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RECOMMENDING RECOMMENDER SYSTEMS

TACKLING THE COLLABORATIVE FILTERING ALGORITHM SELECTION PROBLEM

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Recommending Recommender Systems: tackling the Collaborative Filtering algorithm selection problem

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"The world is woven from billions of lives, every strand crossing every other.
What we call premonition is just movement of the web.
If you could attenuate to every strand of quivering data, the future would be entirely calculable.
As inevitable as mathematics."

Sherlock Holmes

Resumo

A internet tem se tornado uma ferramenta indispensável, quer para uso pessoal ou profissional. No entanto, a vasta quantidade de informação *online* impede um utilizador da Internet de manter-se ao corrente dos seus interesses. Os Sistemas de Recomendação surgiram com o intuito de resolver este problema, sugerindo itens potencialmente interessantes aos utilizadores. Já existem várias estratégias estudadas e implementadas para este tipo de sistemas, que seguem diversos paradigmas para computar as recomendações. Apesar de existir uma forte presença em vários *websites* hoje em dia, ainda existem vários desafios que necessitam de ser ultrapassados no que toca a Sistemas de Recomendação. Entre esses desafios, o facto de ainda não existir uma conceptualização bem definida sobre quais são as melhores estratégias de recomendação para cada tipo de problema limita a progressão segura e válida desta área de investigação.

Atualmente este problema é abordado através da avaliação experimental de vários algoritmos de recomendação em alguns conjuntos de dados. No entanto, estes estudos requerem uma quantidade considerável de recursos computacionais, especialmente em termos de tempo. Para evitar estes problemas, alguns investigadores procuraram aplicar técnicas de meta-aprendizagem para o problema de seleção do melhor algoritmo de recomendação. Apesar de efectivamente se terem provado eficazes e terem demonstrado o potencial destas soluções, estes estudos não possuem a escala e maturidade essenciais para ser possível generalizar o meta-conhecimento obtido.

Desta forma, esta tese foca-se em várias limitações identificadas nos trabalhos relacionados de forma e melhorar as soluções existentes em diversas vertentes do problema. Nomeadamente, pretende-se encontrar mais *metafeatures* informativas, *metatargets* mais ricos e *metalearners* especialmente dedicados para a seleção de algoritmos de Collaborative Filtering. Todas as contribuições são validadas através de estudos empíricos, que são continuamente aprimorados no decorrer do documento. A tese foca-se em algoritmos de *Matrix Factorization* e usam o processo experimental maior e mais complexo conhecido até à data.

As conclusões apontam para o facto de que todas as contribuições propostas têm um impacto positivo no problema de seleção de algoritmos de Collaborative Filtering. Nomeadamente, foram identificados cinco novos conjuntos de *metafeatures* (criados através da extensão e generalização de metafeatures de trabalhos relacionados e de técnicas de *Representational Learning*), duas novas classes de *metalearners* (em que um deles aborda o problema de seleção de algoritmos sem metafeatures e o outro combina o uso de *performance ratings* com múltiplas outras *metafeatures*) e um novo *metatarget* (que é capaz de criar *rankings* de algoritmos para cada conjunto de dados, tendo em consideração várias métricas de avaliação). Para além disto, os estudos efetuados permitem perceber qual o impacto das *metafeatures* e dos *metalearners* considerados em diversos problemas de recomendação e para diversos algoritmos de recomendação.

Abstract

The internet has become an essential everyday tool, both for professional and personal use. However, the large amount of online information does not allow internet users to keep up with their interests. Recommender Systems address this problem by suggesting potentially interesting items to users. Several recommendation strategies have been developed and studied to compute these recommendations. Despite their strong presence in many websites today, there are still several challenges to cope with. One of them is the fact that there is still no knowledge regarding which is the best recommendation method available for a given problem.

The current trend to solve this problem is the experimental evaluation of several recommendation methods in a handful of datasets. However, these studies require an extensive amount of computational resources, especially in terms of time. To avoid such drawbacks, some researchers used Metalearning to tackle the selection of the best recommendation algorithms for new problems. Despite proving effective and showing the potential of such solutions, these studies lack the proper scale and maturity required to generalize the metaknowledge obtained.

Therefore, this Thesis addresses several limitations identified in the related work by improving upon the existing solutions in multiple dimensions of the problem. Namely, it focuses on finding more informative metafeatures, richer metatargets and tailor-made metalearners for Collaborative Filtering algorithm selection. All contributions are validated through an empirical study, which is continuously improved throughout the document. The Thesis focuses on Matrix Factorization algorithms in the largest and most complex experimental setup available to date.

We conclude that all proposed contributions positively impact the CF algorithm selection problem. Namely, we identify five new sets of metafeatures (created by extending and generalizing the state of the art metafeatures from other domains and automatic Representational Learning techniques), two classes of metalearners (one which performs algorithm selection without any metafeatures and another which leverages performance ratings in combination with other metafeatures) and one novel metatarget (which is able to create a single ranking of algorithms per dataset while considering the input of multiple evaluation measures). Furthermore, we identify the impact of metafeatures and metalearners on multiple recommendation datasets and algorithms.

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Glossary

ALS	Alternating Least Squares
AUC	Area Under the Curve
AVG	Average Rankings
CF	Collaborative Filtering
CFS	Correlation Feature Selection
CM	Comprehensive Metafeatures
DM	Data Mining
GR	Graph-based metafeatures
HYB	Hybrid Filtering
IR	Item Recommendation
LDA	Latent Dirichlet Allocation
LR	Label Ranking
MAE	Mean Average Error
MAP	Mean Average Precision
MF	Matrix Factorization
ML	Machine Learning
MtL	Metalearning
MRR	Mean Reciprocal Rank
MSE	Mean Square Error
NDCG	Normalized Discount Cumulative Gain
NMAE	Normalized Mean Average Error
NN	Nearest Neighbors
RM	Rating Matrix systematic metafeatures
RMSE	Root Mean Squared Error
ROC	Receiver Operating Characteristic
RP	Rating Prediction
RS	Recommender System
SGD	Stochastic Gradient Descent
SL	Subsampling Landmarkers
SVD	Singular Value Decomposition
UBCF	User Based Collaborative Filtering

Chapter 1

Introduction

The shift towards an online economy increased the number of customers, markets and revenue streams. Although it has facilitated the presentation of large product catalogs to potential customers, it has inadvertedly created a problem: every platform has more information than its customers can consume. This issue, present in most online digital economy website, is known as the information overload problem (Bobadilla et al., 2013).

In early days, Information Retrieval systems were the answer to this problem. They are able to fulfill user needs by processing an user query and match it with the contents in the business database. The result was a ranked list of results, expected to fulfill his user needs as closely as possible. Although useful, such approach requires the user to explicitly state the needs, usually by a set of keywords. More importantly, this process is repeated every time the user has a new need. Considering how this negatively affects the user experience, better alternatives were sought after.

A solution was provided by Recommender Systems (RSs) (Adomavicius et al., 2005). These systems avoid explicitly inquiring the user regarding his needs, by creating and leveraging user profiles instead. Each user profile is enriched by data collected regarding the user behavior and interactions with the platform, meaning the user needs are now implicitly formulated and permanently available. Machine Learning (ML) algorithms can then be used to make inferences regarding user preferences and thus make recommendations of relevant items at any time.

However, each online platform is different. This difference impacts directly in the data collected and, in turn, in the richness of user profiles and the ML solutions applicable. Thus, the RS research community has striven to create domain agnostic strategies, in order to be able to formalize solutions that can be used in multiple domains. This is why the same recommendation strategy can be used in multiple websites, whether the recommended items range from material objects (books, DVDs, CDs, movies) to non-material entities (Jobs, Dates, Friends) (Lü et al., 2012).

Among the most important recommendation strategies, a few must be highlighted due to its significance (Bobadilla et al., 2011): Content-based Filtering, Social-based Filtering, Context-aware Recommendations and Hybrid Recommendations. All of them rely on a different hypothesis to model the user profile and, by extension, the recommendation problem. However, the earliest and most iconic recommendation strategy is known as Collaborative Filtering (CF) (Sarwar et al.,

2000). It recommends items found relevant by other users with similar preferences. CF popularity arises from the fact that it requires only transactional data, common in online platforms. Thus, this recommendation strategy employs user feedback (e.g., user purchased a book or an user viewed a movie) to define user profiles.

1.1 Problem overview

One of the open research issues in RSs is the lack of guidance regarding which algorithm would be more adequate for a new recommendation task, and, more importantly, why. This problem becomes even more evident when several recommendation strategies are considered, each with several suitable algorithms. To deal with this issue, the practitioner is forced to evaluate every available algorithm for a new task before selecting the best suited (Park et al., 2012). This process has a high cost, not only regarding time, but also human and computational resources. An alternative to reduce such costs is to automate the algorithm selection process.

A prime candidate for this automation is Metalearning (MtL) (Brazdil et al., 2009). It employs ML algorithms to find the relationship between a set of characteristics extracted from tasks (i.e. metafeatures) and the performance of algorithms when applied to those tasks (i.e. metatarget). Thus, in any MtL solution, learning occurs in two levels: baselevel and metalevel. In the first, baselearners accumulate experience on previous learning tasks. In the latter, metalearners accumulate experience on the behavior of multiple baselearners on multiple learning tasks. This allows to generate metaknowledge, which refers to the knowledge about the learning process (Vanschoren, 2010). Although useful in multiple tasks, MtL is primarily used to address the algorithm selection problem (Rice, 1976). It refers to the act of using a metamodel (i.e. a ML model which identifies the mapping between metafeatures and metatargets) to predict the best algorithm(s) for a new task.

There are few works investigating the use of MtL in RSs (Adomavicius and Zhang, 2012; Griffith et al., 2012; Matuszyk and Spiliopoulou, 2014; Zapata et al., 2015). Although this helps in justifying the need for further research in the topic, it also opens too many possibilities. Therefore, this Thesis limits the scope of research in this topic by addressing only the problem of algorithm selection for a single recommendation strategy is considered: CF. This strategy was chosen because it is the only with a large amount of public datasets and algorithms, essential to create a meaningful metadataset. Another advantage is the existence of a large number of related work approaches to serve as baselines.

Having defined the scope of this thesis, it is important to clarify the problems to be addressed. Although there is some related work in this topic, which obtained relevant results and showed the potential of these solutions, they are limited in several aspects. In particular, there are problems regarding (1) the proper formulation and evaluation of the algorithm selection tasks, (2) there is no empirical comparison of the proposed solutions, making it difficult to understand their relative merits, (3) there is no systematic proposal and validation of CF metafeatures that leverage upon the merits found in other ML domains, (4) the metatargets considered are usually very simple and

differ among solutions and (5) there are no tailored solutions in terms of metalearners and metatargets to allow further improvement in terms of predictive performance. All of these issues impede to make proper generalizations about the CF algorithm selection task, which consequently prevents to obtain significant metaknowledge. This Thesis aims to reduce the effect of these previous considerations by tackling various issues in the metafeatures, metatargets and metalearners.

1.2 Thesis Statement

In this thesis, the algorithm selection problem in CF is addressed by introducing multiple contributions in order to improve upon the existing solutions. In essence, two hypothesis are considered:

Hypothesis 1. *It is possible to leverage the relationships between the CF data characteristics (i.e. metafeatures) and the performance of CF algorithms (i.e. metatargets) in order to predict the best CF algorithm(s) for new CF datasets.*

Hypothesis 2. *The CF algorithm selection problem can be posed using multiple metafeatures, metatargets and metalearners, thus creating different use cases concerning a different perspective of the problem.*

Hypothesis 3. *The CF algorithm selection solutions can be evaluated in a way which allows to extract meaningful metaknowledge regarding the CF task.*

To investigate this hypothesis, 3 essential research questions must be addressed:

(RQ1) How mature are the CF algorithm selection approaches available in the literature? The answer to this question aims to determine the merits of existing approaches both in terms of theoretical coverage and empirical efficacy. To answer this question, a systematic literature review and empirical study are performed. Their goal is to aid in clarifying the issue and thus motivate and justify further lines of research.

(RQ2) How can the current CF algorithm selection solutions be improved? After considering the horizon established by the previous studies, each individual dimension of the problem is addressed via the introduction of proposals aimed for their improvement. The improvement is made by proposing new metafeatures, metalearners and metatargets. Notice that many of such contributions, although designed for CF, are also applicable to multiple other domains.

(RQ3) What metaknowledge is obtained and how does it affect RS research? Lastly, after improving the existing solutions on the topic, it is important to reason about the patterns observed. To do so, it is important to assess the impact that metafeatures and metalearners on the baselevel datasets and algorithms. Such analysis will be performed throughout the various stages of the research conducted, thus assessing the merits of MtL on multiple perspectives of the CF algorithm selection problem.

1.3 Contributions

The main contributions in this Thesis are:

- **Systematic literature review and empirical study:** This study focused on previous work on algorithm selection for RSs. It addresses several critical dimensions of the MtL methodology, used to review and formalize the related work on this novel research area. Furthermore, it performed an experimental study to assess the merits of the current approaches, thus establishing a starting point for further research.

- **Empirical Research:** The empirical nature adopted in this Thesis allows to continuously build upon the algorithm selection process by iteratively proposing new solutions and assessing their merits. Thus, throughout the Thesis, multiple solutions for CF algorithm selection will be presented, which include solutions both from the related work and the proposed contributions. By doing so, one is able to validate the existing contributions to the problem in a unified scenario and understand which dimensions require further work and which are already suitable. Furthermore, the experimental setup used is considerably expanded, increasing the confidence of the conclusions.

- **Metafeatures:** Alternative metafeatures were proposed, especially designed for CF. To do so the first proposals took advantage of metafeatures used in other ML domains and make adaptations to be able to create CF metafeatures. As result, 4 sets of metafeatures were designed: Systematic Rating matrix metafeatures, Subsampling Landmarkers for CF, Graph-based metafeatures and Comprehensive metafeatures. Afterwards, a technique that allows to automatically create metafeatures recurring only to a Representational Learning ML model is also proposed: `cf2vec`.

- **Metatargets:** The problem is first addressed using standard metatargets, namely by considering only the best algorithm per dataset. However, due to limitations of this approach, the research shifts towards a setup where rankings of algorithms are used instead. Here, two approaches are considered: single criterion and multicriteria metatargets. While the first creates rankings by using the straightforward ordering performance scores obtained by a single evaluation measure, the latter takes advantage of multiple evaluation measures to create a single ranking of algorithms. To do so, it takes advantage of Pareto frontiers, which allows to create fairer rankings of algorithms.

- **Metalearners:** The metalearners used in this Thesis are concordant with the metatargets used. Thus, while at the start, standard classification algorithms are used to address algorithm selection problem when the metatarget contains only the best algorithm, this paradigm changes by using ranking based approaches when the metatargets follow suit. Here, a Label Ranking approach for algorithm selection is formalized, which allows to make predictions of the relative position for all available recommendation algorithms. This solution is also

improved by considering data and algorithmic nuances from such formulation. First, a metalearner based on CF algorithms is proposed in order to predict the best ranking of CF algorithms, while disregarding the influence of metafeatures: CF4CF. Furthermore, one improves on the data and algorithmic advantages of both approaches by proposing an hybrid solution: CF4CF-META. The results show the solution achieved the best performance on the experimental setup, thus materializing as the best solution to the problem yet.

- **Metaknowledge:** Another important issue in the algorithm selection problem is to understand how do the metafeatures and metalearners influence the relative performance of recommendation algorithms on particular baselevel datasets. Thus, extensive metaknowledge analysis are provided throughout the Thesis in multiple perspectives of the problem in order to clarify which are the most meaningful meta-approaches for each specific case (i.e. baselevel dataset and algorithm). To do so, metafeature importance analysis, baselevel dataset impact analysis and algorithm footprints are employed (and adapted) throughout the Thesis.

1.4 Implications of Research

First and foremost, the studies developed here allow to formalize the research area of algorithm selection for CF. This is a very important contribution, since the few existing approaches do not address the algorithm selection problem in the most correct and complete way. Therefore, critical dimensions of the problem are identified, which guide the contributions introduced in the Thesis and, more importantly, to properly organize the problem for future contributions.

Furthermore, this Thesis presents the most extensive and deep study to the problem known to date. In fact, it addresses many problems found in the literature review on the subject, namely experimental setup design flaws and incomplete validation procedures. To deal with this issue, the same experimental setup is used throughout the Thesis. Furthermore, an exhaustive experimental validation procedure is proposed, which is replicated in every single Chapter. This yields a wide range of performance assessments, which compare multiple aspects of the problem throughout the Thesis.

Another important implication of this research is the wide range of the proposals. Namely, 5 new sets of CF metafeatures, 3 new classes of metalearners and 1 novel metatarget are introduced. More importantly, all have proven useful to the CF algorithm selection problem, even if in different aspects of the problem. Thus, all proposed contributions allow to push the state of the art in this research area, proven by the multiple metalevel evaluation scopes considered. In fact, one must notice that many of the contributions introduced may also be useful for other domains.

Lastly, this Thesis has an important implication for research in RS: it provides meaningful help in order to guide the RS community towards MtL solutions to address the algorithm selection problem. Namely, by investigating the important metafeatures and metalevel patterns found in the mapping between metafeatures and metatargets, one is able to establish the groundwork for future design and development of RS algorithms.

1.5 Document Structure

This document is organized as follows:

- Chapter 2 presents an overview of the research areas associated with this Thesis: RS, MtL, the algorithm selection problem in CF and Representational Learning.
- Chapter 3 provides a literature review on the existing CF algorithm selection solutions and an empirical study comparing them.
- Chapter 4 introduces four CF metafeatures proposals designed through systematic procedures: Rating Matrix, Subsampling Landmarkers, Graph and Comprehensive metafeatures.
- Chapter 5 describes the proposed formalization that uses Label Ranking to address the algorithmic selection problem. Furthermore, it also includes the proposal for multicriteria metatargets.
- Chapter 6 builds upon the previous Label Ranking formulation by proposing two different classes of metalearners: CF4CF and CF4CF-META.
- Chapter 7 presents a Representational Learning approach to CF metafeatures: `cf2vec`.
- Chapter 8 discusses the main conclusions found and the directions for future work.

Chapter 2

Background

This chapter presents the State of the Art regarding several research issues important to this Thesis: Recommender Systems (Section 2.1), Metalearning (2.2), Algorithm Selection and Collaborative Filtering (2.3) and Representational Learning (Section 2.4). Every concept is detailed in order to introduce and position the contributions of the remaining Chapters to this Thesis.

2.1 Recommender Systems

The information overload problem refers to the impossibility of an online user to process all information required, since the volume of relevant information available largely surpass the user capability to understand it. Hence, automatic alternatives able to filter the information, keeping only relevant contents and in a manageable quantity are desired (Yang et al., 2014; Bobadilla et al., 2011). Such Machine Learning models are known as Recommender Systems (RSs).

Despite usually having the same purpose, RSs can take advantage of different recommendation strategies. Such strategies depend on the data available and can be sourced from different aspects of the domain of interest. RSs aim to capture patterns that explain how items are related and, as a consequence, in which circumstances they should be recommended.

The first and foremost recommendation RS strategy is Collaborative Filtering (CF) (Goldberg et al., 1992; Sarwar et al., 2000; Deshpande and Karypis, 2004). Despite research in the area have started almost 30 years ago, it is still actively researched and widely used in real world scenarios (Chen et al., 2018). Although this thesis focuses on CF, this chapter also briefly reviews other RS strategies: Content based Filtering (CBF) (Diaby et al., 2013; Tan et al., 2014), Social based Filtering (SBF) (Kazienko et al., 2011; Bugaychenko and Dzuba, 2013), Social Tagging Filtering (STF) (Song et al., 2011; Jin and Chen, 2012), Hybrid Recommendation (HYB) (Cai et al., 2014; Saveski and Mantrach, 2014) and Context-aware Recommendation (Adomavicius et al., 2005; Burke, 2007). The reader is directed towards more appropriate literature (Resnick and Varian, 1997; Burke, 2002; Adomavicius and Tuzhilin, 2005; Wei et al., 2007; Tintarev and Masthoff, 2007; Verbert et al., 2012; Shi et al., 2014; Yang et al., 2014).

2.1.1 Collaborative Filtering

CF recommendations are based on the premise that a user should like the items favored by a similar user. Usually, it does not assume that the current user is aware of preferences from similar users. Instead, the RS is charged with finding similar users based on the preferences of the current user and then decide which are the most interesting items to be recommended.

The data used in CF, named user feedback, states the degree of preference (feedback) an user has provided towards a given item (Bobadilla et al., 2013). User feedback can be categorized in:

- **Explicit feedback**: such data assumes the user knowingly assigns preference to items. These can be numerical (a rating value from a predefined Likert scale issued to a specific item), ordinal (a ranked list of preferred items, with no rating value assigned) or binary (whether the item is favored or not).
- **Implicit feedback**: this data is collected from the user's behavior within the domain, for instance from click-through data from the search engine and the duration of time spent, on a web page. It is also known as positive-only feedback, meaning it only allows to express interest, never the lack thereof.

Collecting user feedback through explicit and implicit methodologies have positive and negative aspects: implicit methodologies are considered unobtrusive and allow to substantially increase the amount and diversity of feedback available, but explicitly acquired data is more accurate in expressing preferences (Belén et al., 2009).

The data structure used in CF is known as rating matrix R (see Figure 2.1). It is described as $R^{U \times I}$, representing a set of users U, where $u_j \in U, j \in \{1,\ldots,N\}$ and a set of items I, where $i_k \in I, k \in \{1,\ldots,M\}$. Each element of this matrix is the feedback provided by an user u_j to an item i_k, represented by $r_{j,k}$. The non-existence of a specific feedback value $r_{j,k}$ is usually represented by the character $\varnothing$.

	i_1	i_2	i_3	$\ldots$	$i_{\lvert I\rvert}$
u_1	$r_{1,1}$	$r_{1,2}$	$r_{1,3}$	$\ldots$	$r_{1,\lvert I\rvert}$
$\vdots$	$\vdots$	$\ddots$	$\ddots$	$\ddots$	$\vdots$
$u_{\lvert U\rvert}$	$r_{\lvert U\rvert,1}$	$r_{\lvert U\rvert,2}$	$r_{\lvert U\rvert,3}$	$\ldots$	$r_{\lvert U\rvert,\lvert I\rvert}$

Figure 2.1: Rating matrix formulation.

CF algorithms can be divided into two classes: memory- and model-based (Bobadilla et al., 2013; Yang et al., 2014; Lü et al., 2012). Memory-based algorithms apply heuristics on a rating matrix to compute recommendations, whereas model-based algorithms induce a model from a rating matrix and use this model to recommend items. Memory-based algorithms are mostly represented by Nearest Neighbor algorithms, while model-based algorithms are mostly based on Matrix Factorization.

Nearest Neighbors CF using Nearest Neighbor (NN) algorithms (Sarwar et al., 2000; Deshpande and Karypis, 2004) can be divided into two sub-categories: user-based and item-based. In common, they have the following steps: to compute the degree of similarity between entities (either users or items); to create a neighborhood of K entities (users or items) having the highest degree of similarity; to predict the rating for a specific item based on previously calculated similarities (Said and Bellogín, 2014). However, there are substantial differences in both approaches.

User-based NN finds users with similar item rating patterns. This is achieved by employing suitable similarity functions, such as Cosine similarity (Equation 2.1) and Pearson's Correlation (Equation 2.2). Thus, the similarity between two vectors v and w, extracted from the rating matrix is given by:

$$sim(v,w) = \frac{v.w}{||v||w||} \tag{2.1}$$

$$sim(v,w) = \frac{\sum_{k=1}^{K}(v_k - \overline{v})(w_k - \overline{w})}{\sqrt{\sum_{k=1}^{K}(v_k - \overline{v})^2 \sum_{k=1}^{K}(w_k - \overline{w})^2}} \tag{2.2}$$

with $\overline{v}$ and $\overline{w}$ representing the average value in each vector.

Having established the neighborhoods, then the following function can be used to predict the missing rating of an user u_j to an item i_k:

$$pred(u_j, i_k) = \overline{r}_{u_j} + \frac{\sum_{n \subset neighbors(u_j)} sim(u_j, n).(r_{n,i_k} - \overline{r}_n)}{\sum_{n \subset neighbors(u_k)} sim(u_j, n)} \tag{2.3}$$

where r_{u_j,i_k} is the rating of the user u_j to an item i_k and $\overline{r}_u$ is the average value of recommendations for the user u_j.

However, in item-based NN, similarity is used differently: instead of calculating user similarity directly by the respective user feedback vectors, now an item-item similarity is sought after. This means the item feedback vectors are now used to build a similarity matrix. The same similarity functions can be used in this context: Cosine similarity (Equation 2.1) and Pearson's Correlation (Equation 2.2).

Then, item-Based NN uses the ratings assigned by each user to items identified as similar and predicts the rating for any item using the following expression (Sarwar et al., 2001):

$$pred(u_j, i_k) = \overline{r}_{i_k} + \frac{\sum_{l \in ratedItems(u_j)} sim(i_k, l).(r_{u_j,l} - \overline{r}_{i_k}}{\sum_{l \in ratedItems(u_j)} sim(i_k, l)} \tag{2.4}$$

Notice that the formulations presented are used in explicit numerical feedback. Thus, the usage of any other data type requires changes to the similarity function.

Matrix Factorization Matrix Factorization (MF) is currently one of the most efficient and robust approaches for CF (Koren et al., 2009). It assumes that the original rating matrix values can be approximated by the multiplication of at least two matrices with latent features that capture the underlying data patterns (Takács et al., 2009). The computation is iterative and optimizes

a performance measure, usually RMSE. In its most simple formulation, the rating matrix R is approximated by the product of two matrices: $R \approx PQ$, where P is an $N \times K$ matrix and Q is a $K \times M$ matrix. P is named the *user feature matrix*, Q the *item feature matrix* and K is the number of latent features in the given factorization. This process is illustrated in Figure 2.2.

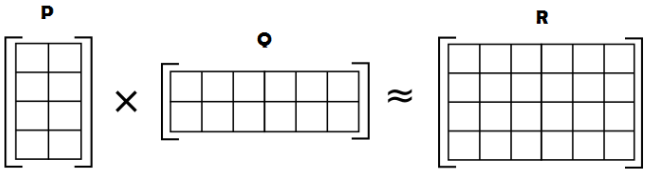


Figure 2.2: Matrix Factorization procedure.

Consider two vectors: the rows $p_u \in P$ and the columns $q_i \in Q$ extracted from the factorized matrices. The elements in p_u measure the extent of the user preference over the latent factors and the elements in q_i represent the presence of these factors in the item. Thus, the users and items are described using a set of latent features that are available in both matrices. After the factorization process, the resulting matrix contains the approximation found to the original matrix. These values are then used to provide the recommendation.

The predictions provided by MF use Equation 2.5 (Koren et al., 2009). MF estimates the predicted preference $pred(u_j, i_k)$ by the user u_j towards the item i_k by multiplying the factor vectors:

$$pred(u_j, i_k) = q_{i_k}^T p_{u_j} \tag{2.5}$$

To learn the factor vectors used in the previous equation, a regularization formula is used to minimize the regularized squared error, in an attempt to minimize the difference between the predicted ratings and the original values for known instances Bokde et al. (2015):

$$\text{argmin} \sum_{(u_j, i_k)} (r_{u_j, i_k} - q_{i_k}^T p_{u_j})^2 + \lambda_i ||q_{i_k}||^2 + \lambda_u ||p_{u_j}||^2 \tag{2.6}$$

where λ_u and λ_i refer to the user and item bias regularization terms, respectively. These terms aim to compensate specific user/item differences against the average values of the preferences stated by either users or items. The purpose is to consider the fact that users have different rating habits, which should be correctly normalized in the factorization process, under the penalty of incurring in overfitting.

In essence, MF algorithms solve an optimization problem in which the provided formula is subjected to multiple iterations until the values converge to a satisfactory solution. Afterwards, the MF model is able to predict the ratings for the missing instances, since the preference formula can be used for any pairs of user/item, according to Equation 2.5. Several optimization methods have been successfully used in CF to perform MF. The most frequent are Stochastic Gradient Descent (SGD) and Alternating Least Squares (ALS).

SGD In SGD, the original rating r_{u_j,i_k} is first compared with the predicted value (Koren et al., 2009) in order to obtain an error measure: $e_{u_j,i_k} = r_{u_j,i_k} - q_{i_k}^T p_{u_j}$. This error measure is used to update the factor vectors p_{u_j} and q_{i_k} using the following equations:

$$\begin{aligned} q_{i_k} &\leftarrow q_{i_k} + \gamma(e_{u_j,i_k} p_{u_j} - \gamma q_{i_k}) \\ p_{u_j} &\leftarrow p_{u_j} + \gamma(e_{u_j,i_k} q_{i_k} - \gamma p_{u_j}) \end{aligned} \tag{2.7}$$

where γ is a scaling value. Therefore, this algorithm uses the error of each prediction to update the respective factor vectors in the opposite direction of the gradient. By performing several iterations, the error is reduced and the model converges to a satisfactory solution. This solution was adopted in (Baltrunas et al., 2010; Pálovics et al., 2014) and a variant, Stochastic Gradient Ascent, was used in (Shi et al., 2012).

ALS The ALS algorithm alternates between two steps: the $P-step$, which fixes Q and recomputes P, and the $Q-step$, where P is fixed and Q is recomputed. The re-computation on the P-step employs a regression model for each user, whose input is the vector q_i and the output is the original user rating vector. The process continues for several iterations until the solution converges. ALS has been used in CF by (Pilászy et al., 2010; Takács and Tikk, 2012; Saveski and Mantrach, 2014).

2.1.2 Other recommendation strategies

This Section presents CF recommendation alternatives. The purpose is simply to present a summary introduction, thus leaving more advanced discussion to other works (Yang et al., 2014).

2.1.2.1 Content-based Filtering (CBF)

CBF recommendations propose the use of item properties to drive recommendations. This rationale implies that if an user bought an item from a specific category in the past, the user will be probably interested in a new item from the same category in the future.

Most CBF methods take advantage of items the user found interesting in the past to serve as initial feedback. Next, similarity calculations are performed to find and recommend the most similar items (Bobadilla et al., 2013). Each item is described by several properties, which depend on the domain used. For instance, movies can be described by their actors and studio, while in music, artists and album properties can be used.

CBF typically uses a vector space model (Salton et al., 1975) to represent items and their properties. In this representation, each row represents a different item and each column is a property of this item. With this formulation, similarity between items is simply given by the similarity of their vectors (i.e. rows in the vector space model). Common similarity measures are Cosine similarity and Euclidean Distance. However, the literature also offers examples of other algorithms: AR (Aciar and Zhang, 2007; Xie, 2010), kNN (Dumitru et al., 2011), MF (Pilászy and Tikk, 2009) and Latent Dirichlet Allocation (LDA) (McAuley and Leskovec, 2013; Tan et al., 2014).

2.1.2.2 Social-based Filtering (SBF)

SBF provides recommendations taking into account user's social relationships and embedded social information (Yang et al., 2014). It assumes that recommendations made while taking into account the taste of friends are better than those from users with similar tastes (Lü et al., 2012).

The user relationships required establish connections between entities and are usually stored in a graph, where nodes represent entities and edges the relationship between them. These connections can adopt a user-user or user-item connection (Huang et al., 2005; Lee et al., 2011). These relationships can be classified as explicit, if there is a direct connection between two entities in the data (e.g. social network connecting users), or implicit, if there is an intermediate entity to connect other entities (e.g. users that declare similar tags, consume similar documents, etc.) (Guy et al., 2009). Such relationships can even be enriched with extra information, which enables them to take advantage of more advanced methods. One example is the Trust-aware recommendations paradigm, in which social relationships are accompanied by a degree of trust. Such data can be represented with explicit trust values (Golbeck and Hendler, 2006) or simply via unary assignments of trust (Yang et al., 2012).

SBF methods typically use NN algorithms to compute the recommendations. They usually extend the CF prediction process by weighting the predictions accordingly to the feedback from friends towards each specific candidate item. Furthermore, they employ graph traversing techniques to find neighbors to be used as candidates. The literature provides several examples of SBF approaches that employed Depth-first search (Golbeck and Hendler, 2006; Guy et al., 2009; Silva et al., 2010; Kazienko et al., 2011), random walk (Yin et al., 2010; Jamali and Ester, 2009; Bugaychenko and Dzuba, 2013), heat-spreading algorithm (Zhou et al., 2010), PageRank (Lee et al., 2011) and Epidemic protocols (Anglade et al., 2007).

2.1.2.3 Social Tagging Filtering (STF)

STF recommendations are based on the relationships stated by users towards specific items, whose preferences are expressed by similar tags. In essence, it is an extension of CF where the feedback is given by tags, rather than using numeric feedback. However, ordinary CF approaches are not suitable to such data, since the tags do not have a numeric nature. Hence, STF approaches draw inspiration also from CBF and SBF paradigms to perform recommendations.

The data used in SBF, also known as social bookmarks, is defined as a set of triplets specifying the user, item and tag (Niwa et al., 2006; Shepitsen et al., 2008). The literature shows examples adopting either a vector space model representation (Niwa et al., 2006; Shepitsen et al., 2008; Zanardi and Capra, 2008; Krestel et al., 2009), a bipartite graph (Song et al., 2011) or instead tensors (i.e. matrix representation with order greater than 2) (Symeonidis et al., 2008, 2010).

STF methods include adaptations of well-identified methods used in CF, CBF and SBF: IR techniques (Niwa et al., 2006; Shepitsen et al., 2008), kNN (Zanardi and Capra, 2008), LDA (Krestel et al., 2009). Higher Order SVD (HOSVD), an extension of Matrix Factorization, has also been used in tensors (Symeonidis et al., 2008, 2010).

2.1.2.4 Hybrid Filtering (HYB)

HYB RS combines multiple recommendation strategies in an attempt to overcome the problems that each strategy poses by using positive functionalities from others. Early HYB approaches investigated the combination of CF and CBF strategies (Bobadilla et al., 2013). As result, 4 different hybridization solutions were proposed: (A) implement CF and CBF algorithms separately and combine their predictions (Christakou et al., 2007; Belén et al., 2009), (B) incorporate some CBF characteristics into a CF algorithms (Melville et al., 2002) , (C) build a general unifying model that incorporates both CF and CBF characteristics (Gunawardana and Meek, 2009; Wu et al., 2014; Saveski and Mantrach, 2014) and (D) include some CF characteristics into a CBF algorithm (Jeong, 2010; McAuley and Leskovec, 2013). Notice that although these RS use only CF and CBF, the hybridization strategies can be applied to any pair of recommendation strategies.

Nowadays, many other hybridization strategies exist (Burke, 2002; Çano and Morisio, 2019). Namely, Weighted (i.e. combines scores from multiple recommendation strategies to create a single recommendation), Switching (i.e. a recommendation agent decides which strategy works best depending on the situation), Mixed (i.e. provide recommendations from multiple individual recommenders without any attempt to merge the strategies in algorithmic terms), Feature Combination (i.e. merge data from different strategies into a single recommendation algorithm), Cascade (i.e. one recommender refines the recommendations given by another), Feature Augmentation (i.e. the recommendations created by one strategy are used as input feature in another) and Metalevel (i.e. the model learned by one strategy is used as input to another).

2.1.2.5 Context-aware Filtering (CAF)

CAF uses contextual information to enrich the recommendation model, hoping to increase the accuracy of the recommendations (Bobadilla et al., 2013). The rationale implies that recommendations for the same user should be different depending on the current time or location, for instance. Thus, in this strategy, the context has as much importance as the other dimensions used (i.e. users and items). Therefore, CAF can be classified as a special type of HYB, since (1) it uses context data - which is a special type of side information - and (2) it requires a non-contextual base strategy to compute the recommendations - and not necessarily multiple recommendation strategies. There are three different ways of incorporating context information into RSs (Adomavicius and Tuzhilin, 2011): (1) pre-filtering, (2) post-filtering and (3) modeling.

In contextual pre-filtering, the context is applied to the data selection and data construction phases of the learning process (Adomavicius et al., 2005; Kuang et al., 2012; Levi et al., 2012; Gupta et al., 2013). Contextual post-filtering only considers the context in the final stage of recommendation, after the execution of a typical non-contextual RS. Finally, in contextual modeling, the context information is incorporated into the modeling phase, as a part of the rating estimation (Yu et al., 2006; Ricci and Nguyen, 2007; Boutemedjet and Ziou, 2008; Karatzoglou et al., 2010; Xie, 2010; Domingues et al., 2009; Natarajan et al., 2013; Cheng et al., 2014). For further details, the reader is directed to (Villegas et al., 2018).

2.1.3 Evaluation

Much like any other ML problem, RSs also require extensive evaluation in order to assess their merits. Here, two different kinds of evaluations are discussed: offline and online.

2.1.3.1 Offline Evaluation

Offline evaluation uses only a data snapshot to assess model performance. To do so, the recommendation dataset is divided into training and testing sets. While the first is used to induce the recommendation model, the latter is used to assess the performance on new, previously unseen, data. Common data splitting strategies are used to assign different ratings to each set, usually hold-out or k-fold cross-validation (Herlocker et al., 2004). However, more advanced techniques exist and depend on the domain selected. For instance, there are examples of prequential evaluation useful for streaming scenarios (Vinagre et al., 2015).

The test phase in RSs has an important difference when comparing to supervised ML evaluation: since there is not a clearly defined target variable to be predicted, the user feedback is used both as feedback for prediction and as the target. Thus, the feedback f for every user u is randomly split into two vectors: initial feedback and target. Formally, $f_u = i_u \cup t_u$. When the predictions $p_u = recommendation(i_u)$ are calculated, comparisons between p_u and t_u can be performed to assess the impact of recommendation for each user in the test set. When the procedure is repeated for all users in the test set, a global evaluation score can be obtained representing the entire RS predictive performance. It is important to notice that, at each fold of the cross-validation, the feedback f_u should be split differently into i_u and t_u, to provide a fair evaluation.

There are multiple ways to compare p_u and t_u, each depending on the scope of the recommendation to be evaluated (Bobadilla et al., 2013; Lü et al., 2012; Yang et al., 2014). The scopes identified, originally proposed for other ML tasks, are:

- Rating accuracy: assess the point-wise difference between a predicted rating value and its actual rating. Examples include the NMAE (Normalized Mean Absolute Error) and RMSE (Root Mean Squared Error);

- Rating correlation: calculate pairwise correlations between sets of predicted and real ratings. Examples include Pearson correlation and Kendall's Tau;

- Classification accuracy: evaluate correct and incorrect decisions about item relevance in each recommendation. In RS, the evaluation is usually performed in a Top-K scenario. Thus, only K items in the top of the predicted items are used in the evaluation. Metrics such as Precision@K, Recall@K and Area Under the Curve (AUC@K) are often used;

- Ranking accuracy: assess how well does the predicted ranking of algorithms match the true ranking, ignoring the ratings. Examples include NDCG (Normalized Cumulative Discounted Gain) and MRR (Mean Reciprocal Rank);

RS evaluation also includes metrics designed for specific recommendation requirements. Examples include catalog coverage, user satisfaction, recommendation diversity and novelty. All offline evaluation measures discussed here are detailed in Appendix A. Further discussion on this topic is available in (Jalili et al., 2018).

Offline evaluation provides an easy way to assess recommendation performance. However, important unanswered issues must be considered: there is no consensus on which metrics should be used for each RS, or even which are the best metrics (Lü et al., 2012). Recently, there has been some advances on this issue regarding real world scenarios. For instance, while earlier works focused on rating accuracy performance even though the goal was to predict rankings of items, nowadays this practice has been abolished and its inadequacy well documented (Lee et al., 2011; Diaz-Aviles et al., 2012).

2.1.3.2 Online Evaluation

Despite efforts to find a bridge between offline evaluation metrics and the feedback provided by real world scenarios, the literature shows no offline analysis can truly determine whether users will prefer a particular system. The main reason lies in the fact that human factors are not included in the process (Herlocker et al., 2004; Beel et al., 2013). Hence, suitable evaluations must use directly the user feedback collected from real users.

These online evaluation methodologies can be characterized by whether they explicitly require the user feedback or if the user behavior is inferred. The first employs surveys, interviews and questionnaires (Bostandjiev et al., 2012), while the second is usually an analysis of user behavior (Herlocker et al., 2004). A common approach to perform the latter analysis is through A/B testing Kohavi et al. (2009). The idea is to compare two recommendation solutions used in two different groups: control and treatment. Each recommendation solution is evaluated using the same performance metric and, afterwards, the results of both groups are compared. The comparison typically involves assessing if the change in the solution performance is statistically significant or not, in order to either accept or reject the new recommendation solution.

With A/B testing, for each RS being evaluated, it is also possible to compare the predictions and real feedback per user. However, in this case, feedback f_u is not split into initial feedback and target. Instead, f_u is considered as the initial feedback provided to the RS, hence allowing to obtain $p_u = recommendation(f_u)$. After obtaining p_u, future user actions are analyzed in order to create the actual t_u. Thus, p_u and t_u can once again be compared and evaluation for the entire RS be performed.

Within this problem frame, all offline evaluation measures can be used to ascertain the merits of each RS. However, since an A/B test requires a real world RS, usually there are domain-specific goals (such as KPI, for instance) which can be used instead. The most popular online metric used is the user acceptance ratio (also known as conversion rate) (Herlocker et al., 2004). The value of this ratio is given by the number of items which the user finds acceptable (either by watching, purchasing, etc.) divided by the total amount of recommended items. The literature also provides examples of other metrics: Interest Ratio (ratio between the number of positive

and negative recommendations (Guy et al., 2009))and novelty (Blanco-Fernández et al., 2010; Bugaychenko and Dzuba, 2013).

Ideally, all RSs should be evaluated using online evaluation measures. In practice, most domains (in particular, academic) rarely have access to a suitable infrastructure. Furthermore, the amount of resources required to perform this evaluation is much higher than the amount required using an offline evaluation procedure, which poses further impediments to the adoption of this evaluation procedure (Bugaychenko and Dzuba, 2013). Hence, despite its faults, offline evaluation cannot be entirely discarded. In fact, it is argued that offline evaluation can have some inherent value, especially if the online performance is poor and the offline evaluation results are good (Beel et al., 2013). The justification lies on the fact that users who contributed to the offline dataset know better than users receiving recommendations.

2.2 Metalearning and Algorithm Selection

There have always been efforts towards developing a super-algorithm able to obtain the best possible performance for every instance of a given task. This goal has been theoretically refuted by the No Free Lunch Theorem (Wolpert and Macready, 1997). It states that, if all possible data distributions are equally likely, any pair of learning algorithms will, on average, have the same performance. Thus, for any algorithm, superior performance over one group of task instances is compensated with inferior performance over another group. Therefore, it is impossible to build a single best, universal learning algorithm (Vanschoren, 2010).

Therefore, the goal must be to understand each algorithm's behavior in order to ascertain where they will be most successful. This behavior, henceforth denominated as algorithm bias, refers to any preference for choosing one data-independent hypothesis to explain the data over another (equally acceptable) hypothesis (Brazdil et al., 2009). In fact, the reason why learning algorithms perform differently on the same data is that they are all biased towards finding certain types of regularities (Vanschoren, 2010). Therefore, if one can find the bias of existing algorithms, one should be able predict the best algorithm for a new dataset.

MtL, a research area that studies the behavior of algorithms, focuses on using ML to understand ML algorithms (and their configurations) in order to improve their results in future applications (Rossi et al., 2012; Nguyen et al., 2012). To do so, there are two basic approaches (Vanschoren, 2018): to learn metamodels purely from model evaluations (van Rijn et al., 2015; Abdulrahman et al., 2018) or to learn metamodels which find the relationships between data characteristics and learning performance (Soares et al., 2004; Rossi et al., 2014). This Thesis will present examples of both approaches, with emphasis on the latter.

Although many other tasks can be tackled by either approach (Rossi et al., 2012), MtL is mostly used to support the task of selecting a suitable predictive algorithm (Brazdil et al., 2009): this is also known as the algorithm selection problem and was first conceptualized by (Rice, 1976). It states that given:

- the problem space P representing the set of instances of a problem class;
- the feature space F containing measurable characteristics for each instance of P;
- the algorithm space A as the set of all available algorithms for solving the problem;
- the performance space Y that shows the mapping from algorithms to performance metrics,

the problem of algorithm selection can be stated as: for a given problem instance $x \in P$, with features $f(x) \in F$, find the selection mapping $S(f(x))$ into the algorithm space A, such that the selected algorithm $\alpha \in A$ maximizes the performance mapping $y(\alpha(x)) \in Y$ (Smith-Miles, 2008). Refer to Figure 2.3 for a schematic overview of the procedure.

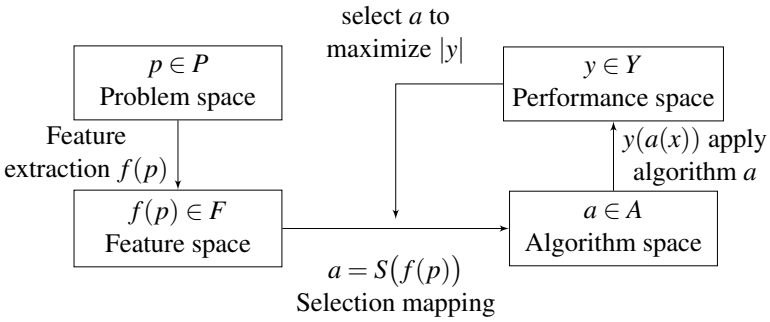


Figure 2.3: Rice's Algorithm Selection conceptual framework (Smith-Miles, 2008)).

MtL addresses the algorithm selection problem as a traditional ML task. For such, MtL uses two levels of learning algorithms: baselearners and metalearners (Brazdil et al., 2009). Baselearners accumulate experience on a specific learning task. They are the learning algorithms whose performance are evaluated in a group of datasets. Metalearners accumulate experience on the performance of multiple baselearners in several datasets and induce a metamodel that can be used to recommend the best baselearner for a new dataset. In this Thesis, the baselearners are always CF algorithms while the metalearners will vary depending on the approach used.

In order to perform algorithm selection, one requires data. This metalevel dataset, i.e. metadatabase, is composed by a collection of meta-examples. Each meta-example corresponds to a different instance of the problem, which in the setup means each baselevel dataset. Each meta-example is described by metafeatures ω from a feature space F and the metatarget π corresponding to the best baselevel algorithm(s) from space A. A generic metadatabase is shown in Figure 2.4.

P	$f_1()$	$\dots$	$f_{\lvert F\rvert}()$
p_1	ω_1	$\dots$	$\omega_{\lvert F\rvert}$
$\vdots$	$\vdots$	$\ddots$	$\vdots$
$p_{\lvert P\rvert}$	$\dots$	$\dots$	$\dots$

A
π_1
$\vdots$
$\pi_{\lvert P\rvert}$

Figure 2.4: Metadatabase.

To build the metadatabase, two essential steps are required: 1) to extract metafeatures from all baselevel datasets, which will be used as the independent variables of the MtL problem (see Section 2.2.2) and 2) to create the metatarget by selecting the best algorithm(s) for each baselevel dataset (see Section 2.2.1). Afterwards, one can train a metalearner on the metadatabase, hence creating a metamodel which is able to predict the best algorithm(s) for new datasets (Serban et al., 2013). This process is illustrated in Figure 2.5.

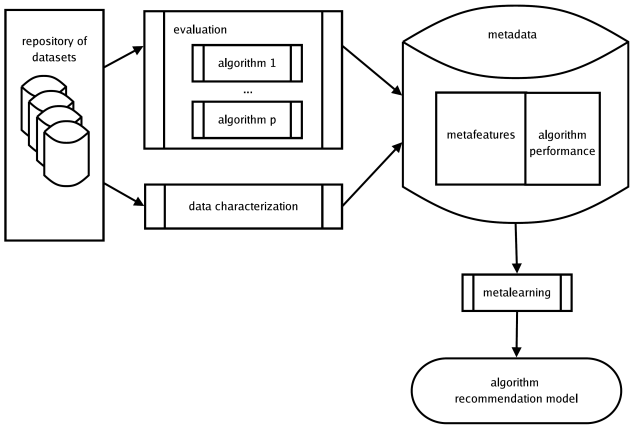


Figure 2.5: Metalearning process (Brazdil et al., 2009)

2.2.1 Metatarget and Metalearner

The metatarget (i.e. the target variable of the algorithm selection problem) is the element that dictates which ML task must be used. The literature shows the following examples:

- To predict the best algorithm: this setup assumes that each meta-example is associated with a single best algorithm. Thus, MtL can be seen as a classification task;
- To predict an un-ordered set of algorithms: here, the desired output is a set of algorithms that will perform well for the new dataset. This task can be modelled as a Multi-Label classification task.
- To predict algorithm performance estimate: here the goal is to predict the real-valued performance of an algorithm, hence it is best described as a regression task.
- To predict the best ranking of algorithms: requires a model from Learning to Rank or Label Ranking tasks, which is able to order the algorithms according to their fit to the problem. Thus, it can be seen as a ranking classification task.

Notice that the metatarget also defines which class of metalearners can be used, since it depends on the ML task chosen. In this Thesis we will focus on the first and last metatarget types.

2.2.2 Metadata

Metafeatures are descriptors able to describe relevant aspects of a dataset. They should correlate well with the performance of the models learned by different algorithms (Brazdil et al., 2009; Kalousis and Hilario, 2003). This is considered the greatest challenge in MtL (Smith-Miles, 2008), since it is uncertain which will be the problem characteristics which are in fact informative. To address the problem, several classes of metafeatures exist:

- Statistical and/or information-theoretical measures: describe the dataset characteristics using a set of measures from statistics and information theory. These metafeatures assume that there are patterns in the dataset which can be related to the most suitable algorithms for these datasets. Examples include simple measures, such as the number of examples and features in the dataset, to more advanced measures, such as entropy, skewness and kurtosis of features and even mutual information and correlation between features Brazdil et al. (2009).

- Model-based characteristics: properties extracted from fast and/or simple models induced from the dataset. In a classification or regression MtL scenario, they refer, for instance, to the number of leaf nodes in a decision tree Brazdil et al. (2009).

- Landmarkers: fast estimates of the algorithm performance on the dataset. There are two different types of landmarkers: those obtained from the application of fast and simple algorithms on complete datasets (e.g. a decision stump can be regarded as a simplified version of a decision tree) and those which are achieved by using complete models for samples of datasets, also known as subsampling landmarkers Fürnkranz et al. (2002) (e.g. applying the full decision tree on a sample).

2.2.3 Systematic Metafeatures Framework

Regardless of the class of metafeatures used, it is useful to find a formalism that allows the use of a common language to describe them. To that end, a systematic framework has been proposed by (Pinto et al., 2016). This framework provides a theoretical approach to systematically explore a given problem in order to derive metafeatures from any dataset. We shall use this framework throughout the Thesis in order to properly describe metafeatures, both proposed or in the related work.

The framework is based on three essential elements: the set of objects O, the set of functions F and the set of post-functions PF. The framework applies each function to each object and all post-functions to the output from the previous element. At the end of this process, we will have the final metafeature. Thus, any metafeature can be represented using the following notation:

$$\{O\}.\{F\}.\{PF\} \tag{2.8}$$

As an example, consider *user.ratings.mean*. This formulation means that the metafeature represents the average rating value for all users in a specific dataset. Notice that if one wishes to disregard the *PF*, it can be replaced by the character ∅.

This framework can be formulated in a recursive fashion with two levels (i.e. inner and outer levels, respectively IL and OL). The OL considers the actual domain objects and it submits them to the IL to be decomposed and more finely described. When IL finishes processing the provided objects through more exhaustive processes, it returns the outcome to the OL for final processing. In essence: the outcome of the IL application of the framework can be used as the result of the OL. This property is useful in complex scenarios in which the entities to be used are enclosed in a hierarchy or the concepts are not directly obtained. Formally:

$$\{\text{OL-}O\}.\{\text{OL-}F\}.\{\text{OL-}PF\} = \{\text{OL-}O\}.\Big[\{\text{IL-}O\}.\{\text{IL-}F\}.\{\text{IL-}PF\}\Big].\{\text{OL-}PF\} \tag{2.9}$$

Considering the previous example, let us suppose we wish to replace the function *ratings* for a more complex descriptor. To do so, one needs simply to refer to the OL as $OL = user.IL.mean$, thus needing only to describe which is the computation to be performed in the IL. For instance, if one wished to perform a normalization of ratings, the IL can be defined as : $IL = user.normalize.\varnothing$.

2.2.4 Metalevel evaluation

The evaluation of a MtL solution is similar to the evaluation of a conventional learning solution. The dataset is partitioned using a data sampling strategy (hold-out, leave-one-out or k-fold cross-validation) to create the training and test datasets. The metamodel trained using the training metadataset is used to predict the metatarget of the instances in the test metadataset. Figure 2.6 presents this procedure.

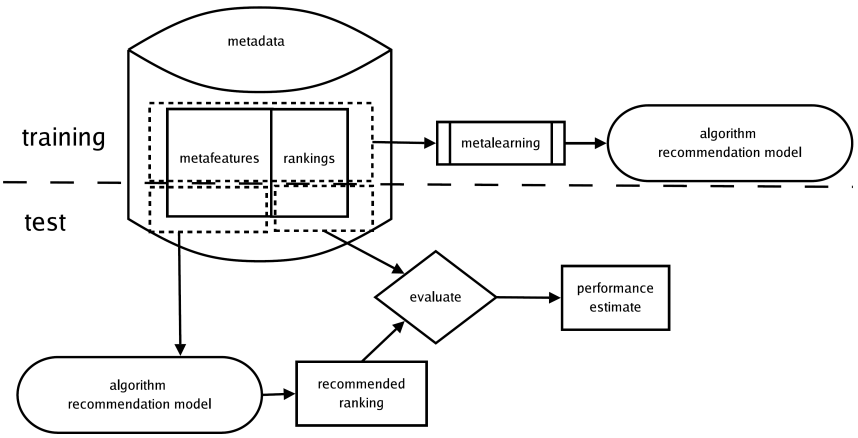


Figure 2.6: Metalearning evaluation process (Brazdil et al., 2009)

The metamodel predictions must be evaluated in two ways (Brazdil et al., 2009): in terms of metalevel accuracy (i.e. to compare predicted and true best algorithm(s)) and to assess the impact on the baselevel performance (compare baselevel performances of the predicted and true best algorithm(s)). Both are essential since they ascertain different dimensions, which may not be aligned. This is particularly important since one wishes to ascertain the best metamodel and it can only achieve this title if it performs well in both tasks.

Metalevel accuracy aims to understand how frequently the metamodel predicts the correct metalabel. The measures depend on the metatarget used, but are mostly characterized by accuracy measures. For instance, when the goal is to predict the best algorithm, classification accuracy measures are suitable. In another example, if the metatarget is rankings of algorithms, ranking accuracy measures must be employed. Thus, this evaluation provides an overall performance score which measures the metamodel's ability to properly match predicted and true metalabels.

On the other hand, the impact on the baselevel performance allows to understand what is the actual cost of failing in the prediction of the best algorithm. This means that even though the best and predicted algorithm may not be the same, what matters is to compare their performance, i.e. the differences in their baselevel performance are most significant to understand the cost of such classification mistake. Therefore, such evaluation uses the baselevel performances obtained by the predicted algorithms for each dataset in the test metadataset as the score. The predictive performance can be assessed using the averaged scores, which illustrate how much baselevel performance is reached, on average, using the metamodel.

Formally, consider for a dataset d_i, the best algorithm $\tilde{a}_{d_i}$ with a performance $P(\tilde{a}_{d_i})$. Now, consider also the predicted algorithm $\hat{a}_{d_i}$ for d_i and its performance $P(\hat{a}_{d_i})$. Notice that the goal is to have $P(\hat{a}_{d_i}) \approx P(\tilde{a}_{d_i})$, even if $\tilde{a} \neq \hat{a}$. Thus, in order to obtain an aggregated score to represent the metamodel's performance for all $d_i \in D$, the impact on the baselevel performance score θ is:

$$\theta = \frac{\sum_{i=1}^{|D|} P(\hat{a}_{d_i})}{|D|} \tag{2.10}$$

In order to facilitate comparison between metamodels, it is useful to calculate a relative score, which considers their deviation from the baseline. Thus, the percentage lift θ_L, which indicates the percentile improvement against the baseline, is employed. Formally, considering the performances of the best algorithm (i.e. oracle), the predicted algorithm by a metamodel and the predicted algorithm by the baseline as $P(\tilde{a}_{d_i})$, $P(\hat{a}_{d_i})$ and $P(\dot{a}_{d_i}$, respectively. This results in the following revised score:

$$\theta_L = \frac{\sum_{i=1}^{|D|} \frac{P(\hat{a}_{d_i}) - P(\dot{a}_{d_i})}{P(\tilde{a}_{d_i}) - P(b_{d_i})} * 100}{|D|} \tag{2.11}$$

Using this revised score, then the interpretation is simple: a positive score means one performs better than the baseline; plus, the performance value refers to the percentage of possible improvement, where 100% refers to the oracle's score.

2.3 Algorithm Selection and Collaborative Filtering

Before dwelling on the related work on algorithm selection approaches for CF, it is important to investigate the related work that merges the research areas of CF and MtL.[1] This is essential in order to position the work to be developed in this Thesis. Recall that using the MtL paradigm, there are two levels with ML algorithms. As a consequence, the potential research areas are those which use CF algorithms in the metalevel, the baselevel or both. Thus, three alternative algorithm selection categories can be formulated: 1) ML meta-approaches to recommend CF algorithms; 2) CF meta-approaches to recommend ML algorithms and 3) CF meta-approaches to recommend CF algorithms.

Our extensive analysis of the literature has shown that several works exist on the first two categories. While the ML meta-approaches to recommend CF algorithms are reviewed in Chapter 3 in the respective Systematic Literature review, here the focus lies on the second category. This separation is used since our major goal is to address the first solution, regardless of whether CF algorithms are used or not as the metalearner. However, we review other works in order to provide complete review of the related work. On this note, as far as the authors are aware, there is only one solution to address the third category and it is proposed in Chapter 6 of this Thesis.

In terms of CF meta-approaches to recommend ML algorithms, the literature provides a few examples (Stern et al., 2010; Smith et al., 2014; Wang and Hebert, 2015; Mısır and Sebag, 2017). An overview of such works is presented in Table 2.1. This table presents several dimensions on this issue: application domain, data, algorithms, metatarget, evaluation metrics and whether the work addresses the Cold Start Problem or not.

Table 2.1: Related work on CF meta-approaches to recommend ML algorithms.

Reference	Domain	Data	Algorithm	Metatarget	Evaluation metrics	Cold Start
(Stern et al., 2010)	Constraint Solving and Combinatorial Auctions	Algorithm Performance and Metadata	custom MF	Best Algorithm	Time and Number of solved instances	No
(Smith et al., 2014)	Classification	Algorithm Performance	k-Means, MF, PCA	Best Algorithm Ranking	Accuracy	No
(Wang and Hebert, 2015)	Computer Vision	Algorithm Performance	SVD, MF	Best Algorithm	Mean Average Precision	No
(Mısır and Sebag, 2017)	Propositional Satisfiability and Constraint Satisfaction	Algorithm Performance	custom MF	Best Algorithm Ranking	Ranking Accuracy, Time, Ratio of solved instances and Regret	Yes

The results show that the domains investigated vary widely, including for instance Constraint Solving and Computer Vision. Regarding the data used in these approaches, they all use algorithm performance as the feedback to CF algorithms as expected. However, the work developed by (Stern et al., 2010) also uses metadata, thus making it more similar to a Hybrid strategy.

[1] As this Thesis focuses on algorithm selection approaches alone, previous works on AutoML using CF (Fusi and Elibol, 2017; Yang et al., 2018) were left out.

Regarding algorithms, most approaches use MF algorithms (either standard or customized versions), which is expected as MF is a widely used and effective approach for CF. There are also examples of the use of k-means and PCA, despite not being standard CF algorithms.

The metatargets are evenly balanced: two approaches recommend the best algorithm (Stern et al., 2010; Wang and Hebert, 2015) and two others the best algorithm rankings (Smith et al., 2014; Mısır and Sebag, 2017).

Regarding the evaluation metrics, some of them are not commonly used in the evaluation of CF algorithms, namely: number or ratio of solved instances (Stern et al., 2010; Mısır and Sebag, 2017) and Regret (Mısır and Sebag, 2017). This happens because they are related to the baselevel task rather than the metalevel task. Furthermore, it can be observed that only the earliest work (Stern et al., 2010) fails in evaluating the accuracy of the recommendations. But this practice has changed, especially when considering the latest work (Mısır and Sebag, 2017), which presents both metalevel accuracy and impact on the baselevel performance analysis.

One particularly important issue in RSs is the Cold Start Problem, which is the need to provide recommendations when there is none or little data. This issue is harder in this case because there is no information about the performance of any of the algorithms and, thus, the performance matrix which is used as rating matrix, is empty in the corresponding row. In MtL, this is a trivial task: one simply extracts the respective metafeatures and uses the predictive abilities of the metamodel. However, since in CF there are no metafeatures, it is necessary to develop strategies able to deal with this problem.

We found only one work (Mısır and Sebag, 2017) that tackles this problem, thus making it the only suitable candidate for comparison. The authors take advantage of two models: a MF algorithm and a multi-output regression algorithm. The first is used to learn latent representations for both datasets and algorithms, much like in similar related works (Mısır, 2017; Alcobaça et al., 2018). The second learns the mapping between metafeatures and the respective dataset latent matrix representations. Thus, for a new problem, it is necessary only to provide the respective metafeatures to the regression model in order to obtain a prediction of the latent representation. Afterwards, the performance prediction is calculated by standard matrix multiplication operation.

2.4 Representational Learning

Lastly, we briefly review a research area which focuses on finding alternative representations for learning problems: Representational Learning (RL) (Bengio et al., 2013). Although such approaches can serve multiple purposes, this Thesis dwells on this subject as a way to provide related work for Chapter 7. Particularly, we use this technique to create alternative CF metafeatures to those presented in Chapters 3 and 4.

RL uses ML algorithms and domain knowledge to learn alternative and potentially richer representations for a given problem to enhance predictive performance in other ML tasks. Examples of successful applications of RL are text classification (Bengio et al., 2013) and image recognition (He et al., 2016).

Although there are alternatives, like probabilistic models and manifold learning (Bengio, 2011; Bengio et al., 2013), the purest RL technique is the Autoencoder (Bourlard and Kamp, 1988; Lecun, 1987). Autoencoders are obtained by training a neural network to reproduce the input vector in the output vector using a hidden layer with different amount of neurons than the output layer. The most interesting aspect of such technique is the fact that it operates in a fully unsupervised fashion. For such, the network learns two functions: an encoding function f and a decoding function g. Since the hidden layer is able to preserve useful properties of the data, it can represent the input (Goodfellow et al., 2016; Lecun et al., 2015; Schmidhuber, 2015). There are multiple versions of Autoencoders specifically designed for the CF scope (Sedhain et al., 2015; Wu et al., 2016).

A better alternative is the distributed representations (Lecun et al., 2015). As the name suggests, each entity is represented by a pattern of activity distributed over many elements, and each element participates in the representation of many different entities (Rumelhart et al., 1986). In essence, they also represent the input as a real-valued vector, but using a different network architecture. The most significant techniques for this problem are discussed next:

- `word2vec` (Mikolov et al., 2013) assumes that two words are similar (and have similar representations) if they have similar contexts. In this case, the context refers to a predefined amount of neighboring words. One architecture proposed to learn these representations is the skipgram, which predicts surrounding words given the current word. For such, each target word w_t, represented as one-hot encoding for a vocabulary V, is connected to a hidden layer h. This hidden layer, where the distributed representations are, has a predefined size d. Each distributed representation is connected to the previous and next c context words (i.e. $w_{t-c}, w_{...}, w_{t-1}, w_{t+1}, w_{...}, w_{t+c}$).

- `doc2vec` (Le and Mikolov, 2014) learns distributed representations for sequence of words with different lengths (i.e. paragraphs, documents, etc.). One of the introduced algorithms (i.e. Paragraph Vector Distributed Bag of Words (PV-DBOW)) allows a straightforward adaptation of `word2vec`'s skipgram: instead of predicting context words based on a current word, now the neural network predicts sequences of words belonging to a particular document.

- A variation of `doc2vec` is `graph2vec` (Narayanan et al., 2017): by considering each graph as a document, `graph2vec` can represent each graph by its underlying nodes. The process has two stages: 1) create rooted sub-graphs in order to generate vocabulary and 2) train the PV-DBOW skipgram model. WE will present this technique in more detail in Chapter 7.

Lastly, one should notice that many more Representational Learning techniques exist. Notice that we did not cover them in this brief review, since they fall outside the scope of this Thesis. Nevertheless, various works can be consulted for further information (Bengio et al., 2013; Goyal and Ferrara, 2018).

Chapter 3

Systematic Literature Review and Empirical Study

This Chapter discusses seminal works regarding the problem of algorithm selection for RSs, with focus on CF approaches. The discussion aims to understand the current state of research in order to help motivate and guide the work to be conducted in this Thesis. To achieve this goal, this Chapter provides two contributions:

- Systematic literature review (Section 3.1). The related work is reviewed on the key dimensions required to solve the algorithm selection problem. In each dimension, the extent of the research conducted so far is discussed, thus exposing advantages and disadvantages in existing contributions. With this, one can highlight lines of research for future work. Notice that contributions addressed in this Thesis are clearly marked in the appropriate key dimensions.
- Empirical study (Section 3.2). The most suitable CF metafeatures proposed in the related work are experimentally evaluated in order to ascertain their performance on the same experimental conditions. To that end, a large experimental study of baselevel datasets, algorithms and evaluation metrics is conducted. Afterwards, each meta-approach is implemented and evaluated on the same metalevel setup, i.e. same metatarget, meta-algorithms and evaluation measures. Finally, conclusions are drawn from the behavior of the current state of the art meta-approaches with regards to several aspects of the algorithm selection problem. This also allows to establish a baseline, which we take into account in future Chapters.

3.1 Systematic Literature Review

This Section is organized as follows: Section 3.1.1 presents the methodology chosen to collect relevant related work. Afterwards, Section 3.1.2 poses the identified key dimensions as research questions. Section 3.1.3 presents each meta-approach and Section 3.1.4 answers the research questions identified previously. Lastly, Section 3.1.5 presents a summary of the main findings and discusses possible improvements.

3.1.1 Methodology

In order to perform the literature review on the subject of algorithm selection for RSs, several online databases were consulted: Elsevier's Scopus, Thomson Reuters's Web of Science, IEEE Xplore Digital Library, Google Scholar and ACM Digital Library. The search queries combined the keywords: *"recommender system"*, *"metalearning"*, *"algorithm selection"* and *"performance prediction"*. This yielded a total of 6 suitable documents, at the time of this search[1].

3.1.2 Research Questions

Considering the MtL work flow described in Section 2.2, the most important dimensions of the algorithm selection problem for RS were identified: learning problem, data, algorithms and evaluation measures. The dimensions, which have been split into of base and metalevels, are now translated into Research Questions (RQ):

(RQ1) Which recommendation strategies have been included in MtL studies?

(RQ2) Are the public datasets used representative and sufficient for metalearning?

(RQ3) Is the pool of recommendation algorithms suitable and complete?

(RQ4) How well are the RSs performance measures covered?

(RQ5) Are the metafeatures used diversified in nature and enough?

(RQ6) In the studies, what is the typical metatarget?

(RQ7) Which algorithms are employed in the metalevel?

(RQ8) Are the evaluation measures used in the metalevel suitable?

3.1.3 Related work

The previous search literature has yielded a few approaches for RS algorithm selection problem. These are presented next in chronological order, identified by a specific letter. Furthermore, notice the metafeature nomenclature presented in Section 2.2.3 is used in order to formalize the proposed metafeatures in each meta-approach.

A This meta-approach studies the CF algorithm selection problem by mapping the data onto a graph instead of a rating matrix (Huang and Zeng, 2011). Graph-dependent metafeatures are derived and then used to select the most appropriate NN algorithms. These are based on clustering coefficients and clustering participation measures. The selection process uses a domain-dependent rules-based model instead of using a ML algorithm.

[1] Search conducted on November-December 2016, yet still up to date.

B The next study to appear (Adomavicius and Zhang, 2012), extracts metafeatures directly from the ratings matrix: *dataset.density.∅*, *dataset.shape.∅*, *dataset.density.∅*, *item.count.gini*, *item.count.skew*, *user.count.gini*, *user.count.skew* and *dataset.ratings.variance*. The problem was addressed as a regression task, optimizing for RMSE. The outcome is a linear regression model which states the meaningful dimensions for the experimental setup used.

C This meta-approach, proposed by (Ekstrand and Riedl, 2012), resembles meta-approach B in the sense that it too used a regression algorithm, optimized towards RMSE. However, the metafeatures proposed are extracted per each user instead per each dataset. The metafeatures, which use always the user perspective, can be formalized as: *user.count.∅*, *user.mean.∅* and *user.variance.∅*.

D The following work studies the expected error of the recommendations of a NN algorithm using a decision tree regression model (Griffith et al., 2012). Once again, this approach focuses on describing user-level metafeatures: *user.mean.∅*, *user.count.∅*, *item.count.∅*, *user.std.∅*, *item.mean.∅*, *user.neighbors.∅*, *user.similarity.∅*, *user.clustering.∅*, *coratings.jaccard.∅*, *user.TFIDF.∅* and *item.entropy.∅*.

E This meta-approach creates an auxiliary data structure, i.e. co-ratings matrix, from which the metafeatures are extracted (Matuszyk and Spiliopoulou, 2014). First, equivalence classes (EC) are created, which include users with similar amount of ratings. Then, the EC matrix is created by pairwise comparison of EC in terms of the average number of co-rated items in common. The metafeatures are: *dataset.sparsity.∅*, *EC.co-ratings.gini* and *EC.co-ratings.entropy*. The process uses a regression model to predict the RMSE performance of NN and MF algorithms.

F The algorithm selection problem was extended beyond CF, when a Group Recommendation (GR) meta-approach was proposed (Zapata et al., 2015). It derived domain-dependent metafeatures and used several classification algorithms to rank the best vote aggregation algorithms.

All these works are presented in Table 3.1. Each work is described in terms of the RQ identified earlier, with some sub-divided for readability purposes:

- The baselevel algorithms (RQ3) are organized by type - Heuristics (H), Nearest Neighbors (NN), Matrix Factorization (MF) and others (O).
- The baselevel evaluation measures (RQ4) are organized into error based (E), classification accuracy (CA) and ranking accuracy (RA).
- The metafeatures (RQ5) are divided according to the subject evaluated: user (U), item (I), ratings (RT), data structure (S) and others (O).
- The metatargets (RQ6) are: 1) best algorithm (BA), 2) ranking of algorithms (RA) and 3) performance estimation (PE).
- The metalevel (RQ7) uses classification (C), regression (RG) or other (O) algorithms.

Table 3.1: Related work on ML meta-approaches to recommend CF algorithms.

	Ref.		A	B	C	D	E	F
Baselevel	RQ1		CF	CF	CF	CF	CF	GR
	RQ2		3	4	1	3	4	4
	RQ3	H	2	-	1	-	-	11
		NN	2	2	2	1	1	-
		MF	-	1	1	-	1	-
		O	-	-	1	-	-	-
	RQ4	E	-	1	1	1	1	1
		CA	3	-	-	-	-	-
		RA	1	-	-	-	-	-
Metalevel	RQ5	U	-	1	3	11	-	5
		I	-	1	-	-	-	-
		RT	-	1	-	-	-	-
		S	2	3	-	-	3	-
		O	2	-	-	-	-	-
	RQ6		BA	PE	BA	PE	PE	RA
	RQ7	C	-	-	1	-	-	4
		RG	-	1	-	1	1	-
		O	1	-	-	-	-	-
	RQ8		AUC	Correlation	AUC	MAE	Correlation	MRR

3.1.4 Discussion

3.1.4.1 Recommendation strategies

Since this research area is still in the early stages (all works were published in the last 6 years[2]), it is expected that only a few RS strategies would have been studied. In fact, like in the RS research area, the majority of the researches has been performed on CF. This is justified by the lack of public frameworks and datasets beyond this recommendation strategy. The exception is a recent study on the algorithm selection problem for Group Recommendation (GR) (Zapata et al., 2015). Therefore, it is essential to 1) expand the scope of RS strategies studied and 2) perform a deeper analysis of the algorithm selection problem for CF.

3.1.4.2 Datasets

The related works use at most 4 datasets to investigate algorithm selection. While on some cases this may be acceptable if the problem is appropriately modeled (for instance, select the best algorithm for each user instead of per each dataset (Ekstrand and Riedl, 2012; Griffith et al., 2012)), this is usually a drawback. In fact, algorithm selection meta-approaches must use a large amount of diverse datasets to ensure a proper exploration of the problem space P. This dimension must

[2]Recall that this study has been completed in 2017.

be improved, although there are few public datasets. In this Thesis, we shall extend to 38 recommendation datasets. The metafeature extraction process involves applying all strategies discussed in Section 3.2.1 to all CF datasets listed in Table 3.2.

The public datasets used in the related work are: BookCrossing (Ziegler et al., 2005), Epinions (Richardson et al., 2003), Flixter (Zafarani and Liu, 2009), Jester (Goldberg et al., 2001), LastFM (Bertin-Mahieux et al., 2011), MovieLens (GroupLens, 2016) and Netflix (Netflix, 2009). Only two works use private data (Huang and Zeng, 2011; Zapata et al., 2015), which are excluded from further analysis since we cannot access its characteristics.

The results show a large variation in how frequent each dataset is used in these works. The most common dataset belongs to the MovieLens category (used 4 times out of 6). This follows the trend in the RS research area, where these datasets are considered benchmarks. The second choices fell on the Netflix datasets, which became popular after a world-wide competition that finished in 2009 (Koren et al., 2009). The remaining datasets appear only once.

These observations point to the idea that the choice of datasets is suitable since they are all CF datasets. However, for algorithm selection purposes, the amount and diversity are extremely scarce. The main drawback lies in the fact that empirical conclusions drawn from such a small sample will most probably lead to incorrect conclusions. Hence, it is of the utmost importance to include more diverse datasets in future CF algorithm selection studies.

3.1.4.3 Baselevel algorithms

The baselevel algorithms frequently used are distributed in the following categories: Heuristics (14), NN (8), MF (3) and Others (1). The fact that NN approaches are abundant is expected, since they are the earliest and easier to implement in CF. The large amount of heuristics refers mostly to the GR approach, which studies 11 algorithms of this nature. In CF, heuristics are typically associated with naive approaches, such as random and most popular algorithms, which can also be considered baselines. One important note lies in the fact that MF algorithms are widely underrepresented, even though they are the current standard in CF.

The most frequently used algorithms are user-based NN and SVD++, closely followed by item-based NN. This represents the most basic approaches for CF and are therefore available in a larger amount of recommendation platforms. Newer approaches, such as MF, are usually more difficult to find in recommendation platforms. This is an important limitation, but it also justifies their exclusion from the related work. Averages and most popular algorithms are more common than random. This is expected, since they are better baselines (Koren et al., 2009).

Although the algorithms used are suitable for CF, the studies fail to reach a state where there are enough algorithms which allow to extract meaningful conclusions. Therefore, in order to properly explore the algorithm space A for CF, it is important to include new algorithms.

3.1.4.4 Baselevel evaluation

The study shows that most evaluation measures are error based (used in 5 out of 6 works). On the other hand, classification accuracy measures are only used in 1 work. The most frequently used error measures are RMSE and MAE and classification accuracy evaluated through precision and recall. Although suitable for Rating Prediction problems, such measures do not follow the current needs in RSs, where the goal is now to predict rankings of items. Hence, none of the related works is currently relevant given that the way CF is approached is outdated. This Thesis addresses both kinds of problems for completeness purposes.

It is important to notice that the evaluation procedures usually assess only one aspect of the recommendation process, contradicting the guidelines from the RS literature (Herlocker et al., 2004). In fact, only 1 work expanded the evaluation scope to classification measures (Huang and Zeng, 2011). Furthermore, newer evaluation measures such as novelty, satisfaction and diversity are never employed. This demonstrates the incompleteness of the evaluation in the related work. On the other hand, such measures are still not entirely validated, thus explaining their exclusion.

Further investigations are required to improve the exploration of the performance space Y, including increase the scope of offline evaluation measures and to perform the same studies using online rather than offline evaluation procedures.

3.1.4.5 Metafeatures

The metafeatures used in the related works are all statistical and information-theoretical measures. They can be organized into several categories: user (19), data structure (8), item (1), ratings distribution (1) and others (2). The fact that most metafeatures are focused on the user is not surprising, given its central position in the CF problem. In fact, some research considers this perspective so important that only metafeatures of this dimension are used (Ekstrand and Riedl, 2012; Griffith et al., 2012; Zapata et al., 2015). Characteristics related to the data structure are also common and are available in 3 out of 6 works. Notice that only one metafeature per item and rating distribution appear, showing how understudied these are.

The number of metafeatures used usually ranges from 3 to 11. Although one aims to avoid the curse of dimensionality by using few but informative metafeatures, the current state of affairs does not allow to understand whether the metafeatures proposed are the best suited to tackle the problem. Hence, in order to properly explore the feature space F, more and more complex metafeatures must be proposed and their merits validated. Afterwards, feature importance techniques must show which are the most informative and, therefore, the best metafeatures.

The analysis of metafeatures in a deeper level allows us to understand which type of statistical and information-theoretical measures used: mostly ratios, averages and sums. This is expected, since they are the simplest metafeatures found in the MtL literature. Entropy and Gini index appear in the second position (in 3 works). All other functions appear only once.

Despite the fact that diverse metafeatures are proposed, few studies look towards different aspects of the problem. In fact, 4 studies focus their metafeatures on a single subject, which

typically is the user. Plus, there are few examples of metafeatures that look towards relationships between the different subjects of the problem. This makes difficult to find complex patterns in the data, restricting the metaknowledge extracted. To address these issues, one must: 1) propose and adapt new metafeatures for other RS strategies; 2) propose problem-specific (and eventually domain-specific) metafeatures and 3) study new metafeatures besides statistical and/or information-theoretical, such as for instance, landmarkers.

3.1.4.6 Metatarget

Related work on CF algorithm selection has adopted several metatargets. The most common is the performance estimation (PE), available in 3 out of 6 works. There are also two examples of best algorithm (BA) and one ranking (RA) selections. Although all metatargets are suitable and important, it is the authors belief that the most beneficial way to address the problem is using RA. The main reason why is based on the fact that when the metatarget is a ranking, although the learning problem becomes more complex, it also provides more information. Hence, the authors suggest that future works address the problem towards RA.

3.1.4.7 Metalevel algorithms

Usually, only one algorithm is used in the metalevel. This algorithm must match the required metatarget. When PE is used as metatarget, regression algorithms are used (mainly linear regression algorithms). For BA and RA, popular classification algorithms, like rule-based classifiers, Naive Bayes, SVM and kNN, are used. An exception happens when a custom procedure based on rules is used (Huang and Zeng, 2011).

Although the number of algorithms used in the metalevel does not have the same impact as the number used in the baselevel, the use of a larger and more diverse set of algorithms in the metalevel increases the chances of uncover hidden relationships in the metadataset. Only one study uses more than one algorithm in the metalevel (Zapata et al., 2015). A relevant future work is the application of RS on the metalevel. Although this topic has not received any attention so far for the selection of recommendation algorithms, it has been successful in other domains (Stern et al., 2010; Smith et al., 2014; Wang and Hebert, 2015; Mısır and Sebag, 2017). Such works are important to understand whether MtL approaches are indeed the best way to tackle the algorithm selection problem.

3.1.4.8 Metalevel evaluation

The last RQ focuses on the evaluation measures used in the metalevel. Once again, these must be in conformity with the metatarget and meta-algorithm. This is noted by the usage of error based measures or correlation assessments for PE (Griffith et al., 2012; Adomavicius and Zhang, 2012; Ekstrand and Riedl, 2012; Matuszyk and Spiliopoulou, 2014), classification accuracy measures for BA (Huang and Zeng, 2011) and ranking accuracy measures (Zapata et al., 2015). Thus, one concludes all related work perform suitable validation for the algorithm selection task.

However, it is paramount to understand that no related work does ever analyze the impact on the baselevel performance, which is arguably the most important measure of efficacy in algorithm selection problems. For more details, please see Section 2.2.4.

3.1.5 Summary

After reviewing in extent each key topic of the algorithm selection problem for CF, the following key conclusions were found:

- With the exception of one study on Group Recommendation, only CF has been studied on the algorithm selection problem. Furthermore, the study of algorithm selection in CF is limited. This Thesis addresses exclusively the second challenge in all remaining chapters of this document, for which an extensive list of contributions is made.

- Since related work uses at most 4 datasets in each study, it is safe to state that the amount of datasets is not enough to properly analyze the algorithm selection problem. This Thesis addresses this issue by extending the set of datasets to a grand total of 38. Notice that all experiments conducted from this point onward use this collection of datasets.

- The pool of recommendation algorithms studied in algorithm selection studies is always suitable, but never complete. Particularly, there is noticeable absence of MF algorithms, one of the most meaningful class of recommendation algorithms. In this Thesis, this issue is solved by using 10 MF algorithms in all experiments in all remaining Chapters.

- Most approaches evaluate CF with a single error-based measure. This is outdated, since the standard is now to evaluate using rank-based measures and more than one measure is required to evaluate RS. This Thesis directly tackles this issue by investigating both the Rating Prediction problem (using error based measures) and the Item Recommendation one (using classification and ranking-based measures).

- Although a diverse set of metafeatures is available, the related works typically use few metafeatures and usually focused on a single aspect of the CF problem. This Thesis contributes extensively to this subject by proposing 3 different sets of metafeatures in Chapter 4. While the first type focuses on tackling the problems of the metafeatures proposed in the related work by proposing a systematic procedure to analyze the rating matrix, newer metafeatures such as subsampling landmarkers and graph metafeatures are also proposed. Furthermore, Representational Learning techniques are used in Chapter 7 to attempt to derive metafeatures without human interaction.

- Although the typical metatarget is performance estimation, this is not the best choice. If rankings of algorithms are predicted, then there is more knowledge to be obtained. This Thesis addresses this issue from Chapter 5 onwards (Chapters 3 and 4 predict only the best algorithm per dataset). Furthermore, in Chapter 5, a new proposal is introduced which

provides a way to score each baselevel algorithm using multiple evaluation measures in order to create the multicriteria metatargets.

- Despite most studies working with regression algorithms to build metamodels, the change in metatarget has fueled the shift in meta-algorithms. This Thesis shows the usage of classification algorithms (see Chapters 3 and 4), Label Ranking algorithms (see Chapters 5 and 7) and even CF algorithms to select CF algorithms (see Chapter 6).
- Suitable metalevel evaluation measures were used in all related works. Since these depend on the metatarget used, this Thesis uses measures from different scopes: classification accuracy, ranking correlation and ranking accuracy. Furthermore, it evaluates the impact on the baselevel performance, whose nonexistence in the related work is a major deficiency.

3.2 Empirical study

This empirical study aims to compare the performance of all related work metafeatures on the same experimental setup. This Section is organized as follows: Section 3.2.1 discusses which meta-approaches are considered in this analysis, while Section 3.2.2 presents the experimental setup. Lastly, Section 3.2.3 presents the results and discusses the findings.

3.2.1 Related work

In order to choose the meta-approaches to use in the experimental study, certain requirements must be established to ensure a fair evaluation. This means some will be adapted and others discarded:

- The recommendation strategy must be the same: this study will devote its attention to CF, since it is the most popular. This filters meta-approach F (Zapata et al., 2015), since the metafeatures designed for GR cannot be reproduced for the CF domain.
- The metafeatures must be specific to the dataset and not to users: the goal here is to compare meta-approaches that select the best algorithm for a whole dataset. Therefore, studies which devotes attention to the selection of algorithms per CF user should be ruled out (Griffith et al., 2012; Ekstrand and Riedl, 2012). However, in an attempt to enrich the analysis, such metafeatures have been adapted to the dataset-level. The procedure samples users and extracts the metafeatures for such set. Then, it aggregates the results using averages of such metafeatures. Due to experimental restrictions, the amount of users sampled is given by $max(|U|, 1000)$. This way, meta-approaches C and D are kept.
- The metafeatures must reflect the characteristics of either implicit or explicit feedback datasets: since the majority of approaches are designed for explicit feedback, meta-approach A (Huang and Zeng, 2011) must be filtered. This is required because the comparison of metafeatures for different rating scales would yield unfair and unreliable results.

Hence, this experimental setup will focus on meta-approaches B, C, D and E presented in 3.1.3.

3.2.2 Experimental setup

The experimental procedure used to compare the merits of the several meta-approaches presented earlier is now presented. Figure 3.1 presents the base and metalevels in terms of data, algorithm and evaluation measures in a similar representation to the one presented in Figure 2.5. Notice the baselevel configuration is constant for all approaches, and so are the meta-algorithms, metatarget and metalevel evaluation measures. The only difference is the set of metafeatures employed by each meta-approach. More formally, the search spaces P, A and Y are fixed, while space F varies.

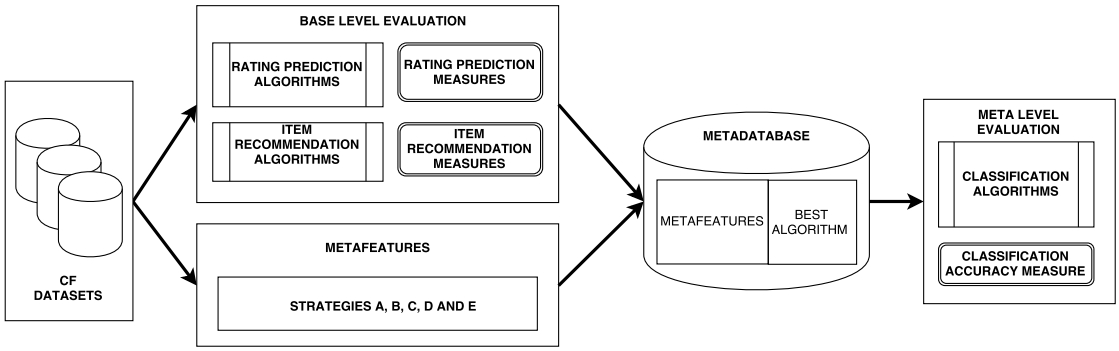


Figure 3.1: Experimental procedure used in the best algorithm selection problem.

All metalevel experiments are performed in a workstation with Intel Core i7-5500U CPU with 16GB RAM using Ubuntu 16.04. Baselevel experiments are performed in a Grid Computing[3].

3.2.2.1 Baselevel

The baselevel experiments refer to the CF problem, where a collection of datasets is evaluated on a pool of suitable algorithms. The 38 datasets used are split up into several domains, namely Amazon Reviews (McAuley and Leskovec, 2013), BookCrossing (Ziegler et al., 2005), Flixter (Zafarani and Liu, 2009), Jester (Goldberg et al., 2001), MovieLens (GroupLens, 2016), MovieTweetings (Dooms et al., 2013), Tripadvisor (Wang et al., 2011), Yahoo! Music and Movies (Yahoo!, 2016) and Yelp (Yelp, 2016). Table 3.2 presents the datasets and some characteristics.

Experiments were carried out with MyMediaLite (Gantner et al., 2011). Two types of CF problems were addressed: Rating Prediction (RP) and Item Recommendation (IR).

Rating Prediction In RP, the goal is to predict the missing rating an user would assign to a new instance. The following algorithms were used in this work:

- *Matrix Factorization* (**MF**), which uses a standard factorization strategy without user/item bias and employs SGD to perform the learning process;
- *BiasedMatrixFactorization* (**BMF**) is an extension of the previous MF algorithm which includes user/item bias (Salakhutdinov and Mnih, 2008);

[3]More details available in: https://grid.fe.up.pt/dokuwiki/doku.php?id=clusters

Table 3.2: Summary description about the datasets used in the experimental study.

Dataset	Acronym	#users	#items	#ratings	Reference
Amazon Apps	AMZ-apps	132391	24366	264233	(McAuley and Leskovec, 2013)
Amazon Automotive	AMZ-automotive	85142	73135	138039	
Amazon Baby	AMZ-baby	53188	23092	91468	
Amazon Beauty	AMZ-beauty	121027	76253	202719	
Amazon CD	AMZ-cd	157862	151198	371275	
Amazon Clothes	AMZ-clothes	311726	267503	574029	
Amazon Digital Music	AMZ-music	47824	47313	83863	
Amazon Food	AMZ-food	76844	51139	130235	
Amazon Games	AMZ-games	82676	24600	133726	
Amazon Garden	AMZ-garden	71480	34004	99111	
Amazon Health	AMZ-health	185112	84108	298802	
Amazon Home	AMZ-home	251162	123878	425764	
Amazon Instant Video	AMZ-video	42692	8882	58437	
Amazon Instruments	AMZ-instruments	33922	22964	50394	
Amazon Kindle	AMZ-kindle	137107	131122	308158	
Amazon Movies	AMZ-movies	7278	1847	11215	
Amazon Office	AMZ-office	90932	39229	124095	
Amazon Pet Supplies	AMZ-pet	74099	33852	123236	
Amazon Phones	AMZ-phones	226105	91289	345285	
Amazon Sports	AMZ-sports	199052	127620	326941	
Amazon Tools	AMZ-tools	121248	73742	192015	
Amazon Toys	AMZ-toys	134291	94594	225670	
Bookcrossing	BC	7780	29533	39944	(Ziegler et al., 2005)
Flixter	FL	14761	22040	812930	(Zafarani and Liu, 2009)
Jester1	JT1	2498	100	181560	(Goldberg et al., 2001)
Jester2	JT2	2350	100	169783	
Jester3	JT3	2493	96	61770	
Movielens 100k	ML100k	94	1202	100000	(GroupLens, 2016)
Movielens 10m	ML10m	6987	9814	10171590	
Movielens 1m	ML1m	604	3421	1069260	
Movielens 20m	ML20m	13849	16680	20365520	
Movielens Latest	ML-latest	22906	17133	21111760	
MovieTweetings latest	MT-latest	3702	7358	39097	(Dooms et al., 2013)
MovieTweetings RecSys2014	MT-RS14	2491	4754	20913	
Tripadvisor	TA	77851	10590	151030	(Wang et al., 2011)
Yahoo! Movies	YH-movies	764	4078	22135	(Yahoo!, 2016)
Yahoo! Music	YH-music	613	4620	30852	
Yelp	YE	55233	46045	211627	(Yelp, 2016)

- *LatentFeatureLogLinearModel* (**LFLLM**) (Menon and Elkan, 2010) is an algorithm inspired on logistic regression, instead of the standard MF. Although is uses SGD for optimization, it has no user/item bias;

- *SVDPlusPlus* (**SVD++**) is a MF strategy that extends the basic SVD strategy to include the items rated by the users and user/item bias in the optimization formula (Koren, 2008).

- Three algorithms, which adapt the standard MF algorithm by modelling the user (or item) factors by which items were rated by the users (or by which users rated the items), were also included. The algorithms focus on asymmetric changes on *item* (**SIAFM**), *user* (**SUAFM**) and *both user and item* (**SCAFM**) (Paterek, 2007). These algorithms assume that by modeling the problem in an asymmetric fashion, the prediction formula in SVD can be linearly combined with these factors to obtain more accurate results. All these algorithms have user/item bias and optimization performed by SGD.

- A MF-based algorithm was adopted as baseline: *UserItemBaseline* (**UIB**) (Koren, 2010). It

uses the average rating value plus a regularized user/item bias in the optimization formula. Learning is achieved using ALS;

- Three algorithms are also included as baselines: *GlobalAverage* (**GA**), *ItemAverage* (**IA**) and *UserAverage* (**UA**). These algorithms make the predictions based on the average rating for all ratings, items and users, respectively.

The RP algorithms were evaluated using the Normalized Mean Average Error (NMAE) and the Root Mean Squared Error (RMSE) (Herlocker et al., 2004).

Item Recommendation In IR, the goal is to recommend a list of ranked items matching the user's preferences. Here, the algorithms used are:

- **BPRMF** which optimizes a criterion based on Bayesian logic (Rendle et al., 2009). It reduces the ranking problem to a pairwise classification task, optimizing the Area under the Curve (AUC) metric. It uses SGD as the learning strategy and no user/item bias;
- *WeightedBPRMF* (**WBPRMF**) is a variation of *BPRMF* that includes a sampling mechanism that promotes low scored items and includes user/item bias;
- *SoftMarginRankingMF* (**SMRMF**) is a variation of *BPRMF*, but it replaces the optimization formula in SGD by a soft margin ranking loss from SVM classifiers (Weimer et al., 2008);
- **WRMF** (Hu et al., 2008) uses ALS as the optimization algorithm and introduces user/item bias to regularize the process;
- The only baseline algorithm available in this scope is *MostPopular* (**MP**). Here, items are ranked by how often they have been seen in the past.

The IR evaluation is performed using Normalized Discount Cumulative Gain (NDCG) and AUC (Herlocker et al., 2004).

All performances were assessed using 10-fold cross-validation and the algorithms were trained using the default hyperparameters suggested in the literature or the implementation used. Although this does not lead to the optimal performance, such limitation proved necessary due to the size and complexity of experimental setup used. Conceptually speaking, the authors are aware that this decision does not allow to predict the absolute best algorithms per dataset. Instead, the problem focuses on predicting the best algorithm given its default bias. This means it is up to the practitioner to perform appropriate hyperparameter optimization on the recommended CF algorithm using the predicted CF algorithm.

Notice that despite providing the largest amount of MF algorithms to date, this empirical setup does not include any NN algorithms. This happens due to scalability issues which render these algorithms incompatible with the size of all datasets used. Due to the importance of MF algorithms to CF, it is the authors belief that this limitation can be accepted, since the experimental setup has improved in terms of amount and diversity of datasets, which is a more important aspect in the algorithm selection problem.

3.2.2.2 Metalevel

As illustrated in Figure 3.1, the metalevel refers to the metafeatures, the metatargets and the measures used to evaluate the metamodels.

The metafeature extraction process involves applying all strategies discussed in Section 3.2.1 to all CF datasets listed in Table 3.2. The outcome is 4 different sets of metafeatures, which refer to the independent variables of the MtL problem. Recall they are identified by their appropriate letters, as identified in Section 3.1.3.

The metatarget is built by identifying the best algorithm for each specific dataset (see Table B.1 to understand which are the best algorithms per dataset). Since different baselevel evaluation measures are used, then it is expected that different algorithms are selected as the best choice for a specific dataset for different measures. Thus, NDCG and AUC are used to select the best algorithms in IR tasks, while in RP tasks, RMSE and NMAE are used. This creates 4 different metatargets, which when combined with the 5 different sets of metafeatures, leads to the total amount of 20 metadatasets to be used in the algorithm selection problem.

These problems are addressed as classification tasks where the goal is to predict the absolute best algorithm for each dataset. A total of 11 algorithms were tested on each of those metadatasets, with different biases: C4.5, kNN, SVM (linear, polynomial and radial kernels), random forest, xgboost and a baseline algorithm: majority vote. The majority vote does not take into account any metafeatures and always predicts the class which appears more often. Since the metadatasets have a reduced number of examples, the accuracy of the metalevel algorithms was estimated using a leave one out strategy (LOOCV).

Lastly, please notice the results presented can be reproduced by accessing the repository `https://github.com/tiagodscunha/cf_metafeatures`.

3.2.3 Results

This Section focuses on presenting and discussing the metalevel performance results. To simplify the focus of such analysis, the baselevel results are discussed in Appendix B.

3.2.3.1 Metalevel accuracy

The metalevel performance aims to assess classification accuracy, i.e. whether the true and predicted algorithms are the same. Figure 3.2 presents the mean accuracy for each metamodel for all baselevel datasets considered. The results are presented for each pair meta-approach/metatarget.

The results show all meta-approaches are able to outperform the baseline. This is a very important result in the sense that it proves that all meta-approaches considered provide informative metafeatures. However, they also show the effectiveness of meta-approaches depends on the metatarget chosen: while on NDCG and RMSE the vast majority of metamodels outperform the baseline, in AUC and NMAE there are 3 and 9 cases respectively where the performance is worse.

Although the results do not show any meta-approach consistently better than the competitors, it is possible to observe that xgboost provides the best results across all meta-approaches and

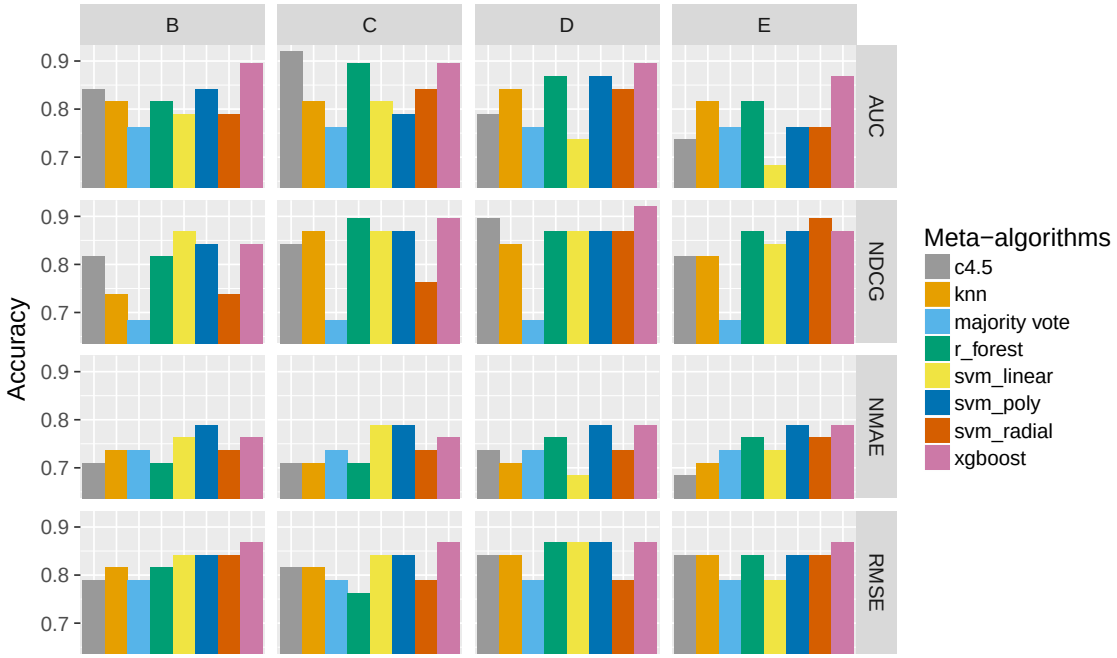


Figure 3.2: Metalevel accuracy.

metatargets. In fact, it is the absolute best metamodel in 11 out of 16 cases and a close second in the remaining.

The previous observations points to the idea that there is no superior meta-approach. To assess this, Critical Difference (CD) diagrams (Demšar, 2006) were employed. They refer to a statistical significance technique which compares multiple algorithms on multiple datasets. To do so, it employs post hoc pairwise Friedman tests. It ranks algorithms based on their accuracy and calculates the CD interval, which state whether the difference in performance is statistically significant or not (i.e. two elements not connected by a line can be considered different).

In order to compare the various meta-approaches using this technique, the best scoring metamodel is selected as its representative. Then, each metamodel is characterized by all accuracy scores, calculated for each baselevel datasets on all metatargets. Figure 3.3 presents the CD diagram for this setup, proving there is no statistically significant difference among meta-approaches.

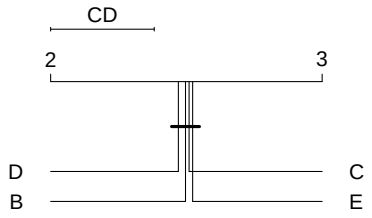


Figure 3.3: Critical Difference diagram comparing several meta-approaches.

3.2.3.2 Impact on the baselevel performance

Figure 3.4 presents the results of the impact on the baselevel performance analysis in terms of percentage lift. Recall the procedure is described in Section 2.2.4.

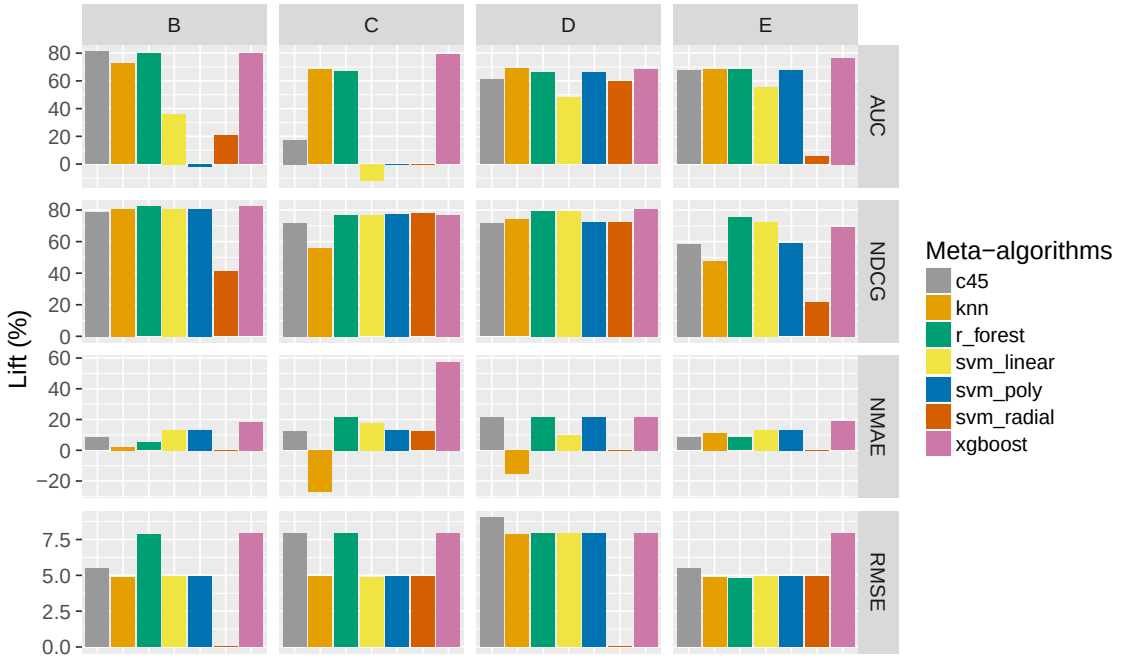


Figure 3.4: Impact on the baselevel performance.

This analysis shows the vast majority of metamodels outperform the baseline. In fact, all metamodels in NDCG and RMSE are better than the baseline, while only on 3 occasions in the remaining metatargets does the performance yields negative scores. Furthermore, one observes that it is harder to beat the baseline in RP than in IR. Notice that the best improvement in RMSE is approximately 8.5% and most metamodels in NMAE show at most a 20% improvement, while it is common in AUC and NDCG to find improvements of 80%.

Overall, all meta-approaches provide comparable performances across all metatargets and xgboost is still the best metamodel. Although now there are more metamodels with comparable performance, this algorithm stands out due to its consistency in all pairs meta-approach/metatargets. These results confirm its superiority in this experimental setup, since the results match with the superiority in terms of metalevel accuracy.

Lastly, one must notice that this analysis proved essential to validate metalevel performance. Despite the proven superiority of xgboost in both evaluation scopes, the results show plenty examples where this is not seen. One example can be found in SVM with linear kernel using meta-approach C in the AUC metatarget, where despite having the same metalevel accuracy as the baseline, it has worse impact on the baselevel performance.

3.2.3.3 Computational Cost

One important aspect to be evaluated in the comparison of related work meta-approaches is the amount of time required for metafeature extraction. Table 3.3 presents the recorded values for the total and average amount of time required. While the first refers to the time required to extract all metafeatures for all datasets, the second indicates the average time for one dataset. This last value serves as an indicator of the time required for the application on a new problem.

Table 3.3: Computational time required to extract related work metafeatures.

Meta-approach	Total time (seconds)	Average time (seconds)
B	16.647	0.438
C	16.142	0.425
D	27.379	0.721
E	206.629	5.438

According to the results, meta-approaches C, and B are the fastest. These results are expected due to fact that their metafeatures are the simplest to calculate and require only the rating matrix to be produced. On the other hand, meta-approach E is the most time consuming. The reason behind it lies with the usage of an alternative data structure and the extraction of more detailed metafeatures. However, the requirements imposed are not prohibitive. Furthermore, the authors acknowledge the performance can be improved by means of parallel computing meta-approaches.

3.2.3.4 Metaknowledge

To understand the metaknowledge is a complex task and usually there is no perfect way to do it. It depends directly on the domain studied and on the MtL approach used. In order to be able to compare MtL approaches with different metafeatures, metalearners and metatargets, this Thesis addresses three metaknowledge analysis tasks, which can be adapted to any learning problem: metafeature importance, baselevel datasets analysis and baselevel algorithms analysis.

Metafeature Importance Metafeature importance analysis aims to understand which are the most important metafeatures per meta-approach in terms of their predictive power. Hence, the procedure compares AUC scores for xgboost metamodels trained on each metafeature of each meta-approach individually. This way, the area obtained by a metamodel with a specific metafeature is the importance score of said metafeature in the overall metamodel. Notice the procedure averages the scores over all metatargets in order to obtain an overall measure of metafeature importance. The results are presented in Figure 3.5. The Figure shows the average AUC scores per metafeature, which are organized by their specific meta-approach.

The results show in meta-approach B, the most informative metafeature is *dataset.density.∅*. It is closely followed by *item.count.gini*, which also scores above 0.2. In meta-approach C, the best metafeature is *user.count.mean*, followed by *user.mean.mean*. Plus, *coratings.jaccard.mean* is by far the most informative metafeature from meta-approach D, with a score approximately 3 times higher than the next competitor. Lastly, in meta-approach E, two metafeatures score above 0.3 and are ranked first, respectively: *EC.co-ratings.entropy* and *EC.co-ratings.gini*.

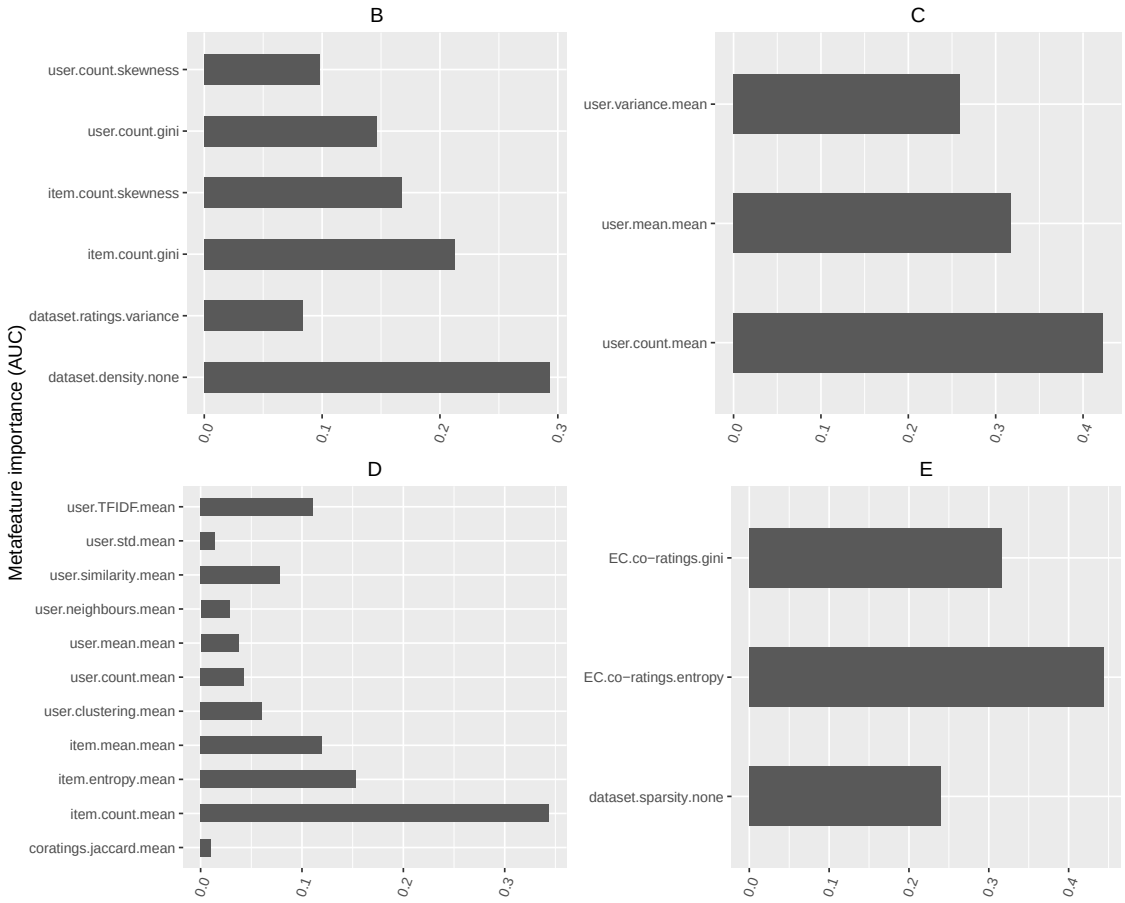


Figure 3.5: Metafeature importance for related work metafeatures.

This analysis shows different metafeatures from different meta-approaches have high predictive power. However, this also means that there is not a definitive set of metafeatures which are acknowledged as best for CF algorithm selection. Further analysis will be performed in order to draw more conclusions regarding the merits of such metafeatures.

Dataset Analysis Now, it is important to understand how do the metamodels affect the baselevel datasets. To do so, the distribution of accuracy scores for all datasets in each meta-approach are presented in violin plots in Figure 3.6. Such representations allow to understand what is the percentage of existing metalearners which are able to predict the best algorithm for each specific dataset. In essence, one is able to understand how difficult it is to predict best algorithm for a particular dataset. Such analysis enables to understand (dis)similarity patterns for multiple meta-approaches with regards to the specific baselevel datasets.

Overall, the results show all meta-approaches work perfectly for the majority of AMZ datasets (this is shown by the existence of a single mark on the right hand side of the plot, meaning that all scores are placed at that position). However, notice there are exceptions within the AMZ domain, since not all meta-approaches are able to always predict the best algorithm correctly. For instance, AMZ-movies fails at least once in all meta-approaches. There are also many datasets which are

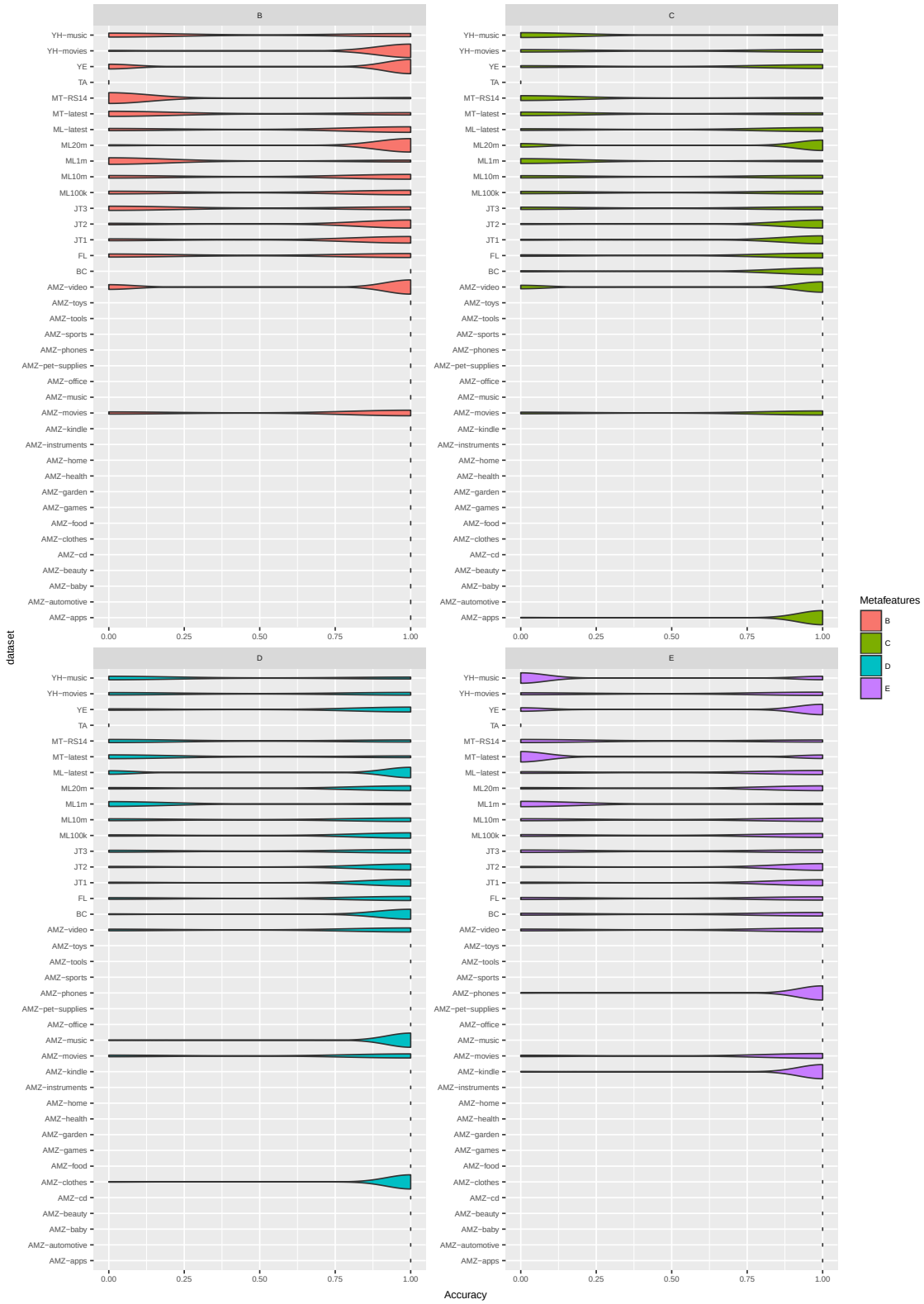


Figure 3.6: Accuracy scores per baselevel dataset for related work metafeatures.

usually wrongly classified (e.g. MT-RS14, ML1m and YH-music) and some which are mostly well classified (e.g. ML20m, JT2, JT3 and BC) in all meta-approaches. Finally, notice TA is always incorrectly classified, regardless of the meta-approach selected.

Comparing now the meta-approaches, there is no clear pattern which explains any favoritism. This happens since the good performance in some datasets is compensated by a worse performance in others. This is expected, as we have seen in the Kendall's tau performance in previous analysis and also because it is the foundation of the algorithm selection problem. Therefore, instead of a global comparison, one must analyze which datasets are favored by which meta-approach, particularly in the cases which it is not favored in the others. Prime examples are YH-movies (well classified by meta-approach B), YE (well classified by B and E meta-approaches), ML-latest (well classified by meta-approach D) and BC (perfectly classified by meta-approach B). Thus, the conclusion of this analysis lies in the fact that different datasets are favored by different meta-approaches. Therefore, the best current approach is to leave to the practitioner to select which is the recommendation domain which is favored by each meta-approach. However, we wish to address this issue in further Chapters in order to attempt to find better representations.

Baselearner Analysis Regarding the baselearners, one wishes to understand how well do the representations explain their performance. Therefore, we draw inspiration from algorithm footprints (Smith-Miles and Tan, 2012). This technique first reduces the dimensionality of any dataset to a 2-dimensional space. Then, it maps instances according to their position in the latent space and assigns a color representing whether the performance is better or worse than a specific threshold. Notice however that such procedure usually explores pairwise algorithm comparisons, effectively showing in which areas one algorithm outperforms the other. However, here we aim to explore each algorithm independently with regards to the impact on baselevel datasets and their respective representations.

The definition of good performance threshold depends on the task's goal. Here, this threshold is defined by whether the baselevel performance scores for all are above or equal those of the 75th percentile. For simplicity, we report only the results for the most frequent baselearners in the metatargets: MP, BPRMF, WRMF, BMF, SUAFM and SVD++ (see Section B.1 for more details). Figure 3.7 presents the results of this analysis.

The interpretation of the results is performed as follows: if the areas of good and bad performance are well identified, then it means the representation is meaningful. If not, then it shows the metafeatures are not the best solution to create representations to such problem. Taking this into account, one observes meta-approaches D and E are particularly good at creating different regions for good and bad performances for all algorithms considered. However, meta-approach B is also quite meaningful in BPRMF, WRMF and MP (i.e. all IR baselearners). Also, meta-approach B creates most overlapping of performance results, thus indicating it is not the ideal solution.

An important observation lies in the fact that the best performances are usually concentrated in the same region, meaning all algorithms have better performance for the same datasets. This shows the difficulty of the algorithm selection task.

Figure 3.7: Algorithm footprints for the related work metafeatures. The threshold for good performance is the third quartile of the distribution of all its performances.

3.3 Conclusions

This work analyzes in depth the problem of algorithm selection for RSs, with focus on CF. It starts with a systematic literature review regarding related work meta-approaches. In this review, the problem is framed within the classical algorithm selection framework and each of the available works is presented and discussed on the several dimensions of the problem. Afterwards, an empirical study is performed to assess the quality of a subset of the approaches discussed on the selection of algorithms. Experimental results regarding the metalevel accuracy, baselevel impact, computational resources and metaknowledge analysis are presented and discussed.

The literature review shows that most work is performed on CF, with a reduced number of datasets, algorithms and evaluation measures in the baselevel. In terms of metalevel, there are several approaches which look at the algorithm selection problem in different and valid perspectives. Most works used regression approaches with a small amount of metafeatures and usually focusing on user characteristics. Here, several issues were highlighted, most of which will be addressed in this Thesis, by taking into account contributions in terms of metafeatures, metatargets and metalearners.

The literature review also showed there was no comparison among metafeatures proposed, which prevents the understanding of their merits. To solve this problem, an empirical study was conducted. It employed the largest and more diverse baselevel empirical setup known to date. Furthermore, the metalevel has been evaluated in multiple scopes, thus addressing an important limitation in the related work: no impact on the baselevel performance exists.

The results have shown that all meta-approaches are able to create effective models to solve the algorithm selection problem, with no statistically significant difference among them. The results are especially good when the meta-algorithm chosen is xgboost. Also, there seems to exist little difference among strategies for the majority of the metatargets and meta-algorithms. Further analysis shows that it is easier to tackle the algorithm selection problem in IR than in RP, due to the different amount of algorithms available in each metatarget. The metaknowledge analysis has shown that the meta-approaches perform differently depending on the baselevel dataset and that some strategies are better at mapping the algorithm performance than others.

In summary, the main conclusion of this study lies in the fact that there is no single best meta-approach that always outperforms the others, but rather aspects on which the performance is better. The authors highlighted the advantages and weaknesses of each work, but the choice of the best metafeatures are still unknown. To tackle this issue, the research moves towards Chapter 4, in which a set of alternative metafeatures is proposed, whose aim is to outperform and complement those reviewed in this Chapter.

Chapter 4

Metafeatures for Collaborative Filtering

One of the most important factors in the success of a MtL approach is the definition of a set of metafeatures that contain information about the (relative) performance of the baselevel algorithms (Brazdil et al., 2009). Despite the effectiveness of the meta-approaches presented in Chapter 3, there are still several approaches which remain to be tested. Hence, it is the purpose of this Chapter to further explore this issue in order to derive powerful metafeatures.

First, it is essential to clarify an issue which directly impacts metafeature design in CF: there is no clear distinction between dependent and independent variables. This means that traditionally powerful metafeatures, such as correlation between features and target variables, are not directly applicable here. This deeply impacts the design of new metafeatures and justifies the need to create CF-specific metafeatures. To do so, the MtL practitioner must rationalize about the CF domain in order to explore alternative metafeatures, possibly adapting metafeatures from other domains. This is the approach used in this Chapter, where 3 different meta-approaches are proposed:

- Rating matrix systematic metafeatures (Section 4.1): these metafeatures describe a CF dataset by systematically analyzing three different perspectives on their ratings distribution: in terms of user, item and ratings. These distributions are aggregated using simple, standard summary statistical functions (Pinto et al., 2016).
- Subsampling landmarkers (Section 4.2): this set of metafeatures describes each CF dataset by the performances obtained by multiple algorithms on several evaluation measures, when using only a sample of said dataset. The study also assesses the effect of using relative landmarkers (Fürnkranz et al., 2002).
- Graph-based systematic metafeatures (Section 4.3): the CF problem is modeled as a CF bipartite graph and metafeatures based on Graph Theory measures are extracted (West, 2001; Godsil and Royle, 2013). The process leverages on a systematic procedure, supported by an hierarchical decomposition procedure (Cunha et al., 2017).

All meta-approaches are experimentally compared in order to understand their merits in selecting the best CF algorithm per dataset. To that end, Section 4.4 presents the wide range of evaluation scopes assessed and Section 4.5 presents the final conclusions in this Chapter.

4.1 Rating Matrix systematic metafeatures (RM)

MtL literature has shown that statistical and/or information-theoretical metafeatures are quite easy and fast to extract, while also obtaining considerable discriminatory power (Brazdil et al., 2009). Furthermore, as shown in Chapter 3, such observation also holds in the CF scope. However, since there is no systematic exploration of the problem in the related work, there may be room for improvement. Hence, this set of metafeatures is based on two pillars: 1) the application of a systematic procedure to develop metafeatures (Pinto et al., 2016) (see Section 2.2.3 for further details) and 2) to extend and generalize the state of the art metafeatures for CF (Adomavicius and Zhang, 2012; Griffith et al., 2012; Matuszyk and Spiliopoulou, 2014).

Consider the rating matrix $R^{|U|\times|I|}$ presented in Figure 4.1, with users $u_j \in U$, items $i_k \in I$ and ratings $r_{j,k}$ representing the ratings user u_j assigned to item i_k. In order to derive metafeatures using the systematic metafeature framework, one needs to identify suitable objects, functions and post-functions.

	i_1	i_2	i_3	$\dots$	$i_{\|I\|}$
u_1	$r_{1,1}$	$r_{1,2}$	$r_{1,3}$	$\dots$	$r_{1,\|I\|}$
$\vdots$	$\vdots$	$\ddots$	$\ddots$	$\ddots$	$\vdots$
$u_{\|U\|}$	$r_{\|U\|,1}$	$r_{\|U\|,2}$	$r_{\|U\|,3}$	$\dots$	$r_{\|U\|,\|I\|}$

Figure 4.1: Rating matrix formulation.

Unlike the related work, which directly explores some perspectives of the problem based on the practitioner's interpretation of the problem, this work aims to perform metafeature extraction in a less restrictive way. Therefore, multiple suitable objects which can be directly derived from the rating matrix R are proposed, while at the same time using a set of functions and post-functions to characterize them. Notice that inspiration is drawn from the related work, since some metafeatures proposed are also available there. The difference, however, lies in the systematic approach used and which promotes a more extensive analysis of the problem.

Hence, the entities from the systematic framework are devised as follows:

- o: the matrix R and the sets of users and items, respectively U and I. These represent three different yet essential perspectives of the problem, which are not well covered in the related work. By assuming all objects are equally important, contrary to the belief practitioners may have, allows to properly explore the CF problem;

- f: depending on the object o, the functions f return several perspectives from the rating data distributions on said objects: original ratings (*ratings*), ratings count (*count*), ratings mean (*mean*) and ratings sum (*sum*). By looking beyond the original ratings, which the vast majority of related work approaches focus on, one allows the exploration of unseen perspectives of the problem;

- pf: the outcome of applying any function to an object can be regarded as a distribution of values. Hence, in order to create a single metafeature, these are aggregated using univariate statistics and Information Theory measures: maximum, minimum, mean, standard deviation, median, mode, entropy, Gini index, skewness and kurtosis. Such post-functions are selected in order to provide a wide range of summary descriptors, which in turn allow to further explore the different perspectives of the CF problem.

For each rating matrix R, the set of meta-features, M, is extracted in two steps: (1) application of a function f to the ratings r_{ui} in each row ($f(U)$), column ($f(I)$) and the entire dataset ($f(R)$) to obtain three different ratings distributions and (2) post-process the outcome of each function f (in the shape of distribution) with the so-called post-functions pf by extracting statistics that can be used as meta-features. Therefore, the set of meta-features is described as:

$$M = pf[f(U)] \cup pf[f(I)] \cup pf[f(R)] \tag{4.1}$$

Additionally, it includes 4 simple statistics: the number of users, items, ratings and the matrix sparsity. Although not properly formulated in the framework, their inclusion lies in the fact that similar concepts have been widely used in the related work in other domains (Brazdil et al., 2009).

As a final note, please note the current selection of objects, functions and post-functions is justified by the analysis performed in the Systematic literature review (see Section 3.1). However, this list is not exhaustive, meaning it is theoretically possible to improve the performance.

4.2 Subsampling Landmarkers (SL)

No approach in the related work investigates the merits of landmarkers as metafeatures in the particular scope of CF, even though they are quite well known in other domains (Pfahringer et al., 2000; Bensusan and Kalousis, 2001; Fürnkranz et al., 2002; Ler et al., 2005; Kück et al., 2016; Kanda et al., 2016). Since these metafeatures use simple estimates of performance to predict the actual performance of algorithms, its efficacy in solving the algorithm selection problem is not only expected but has been demonstrated in various other tasks. Therefore, it is important to understand if their effect is similarly positive in CF.

Landmarkers assume the existence of fast and simple algorithms, since the goal is to extract metafeatures as fast as possible. However, since there are no CF algorithms which meet such demands, the alternative approach of subsampling landmarkers was selected instead. Here, any CF algorithm a_i can be used, since one works only with samples of the data. Hence, the formulation for subsampling landmarkers is based on the estimation of the performance of algorithms a_i on random samples s_j from the original datasets d_j. Then, CF algorithms a_i are trained on and their performance assessed using different metrics m_k. The outcome is a subsampling landmarker for each pair algorithm/evaluation measure, represented as $a_i.m_k$. Figure 4.2 presents the procedure used to extract SL metafeatures. Notice the procedure shown is independent of the algorithms

and evaluation measures selected. In this thesis, all available baselevel algorithms ans evaluation measures in the experimental setup in Section 3.2.2 are considered.

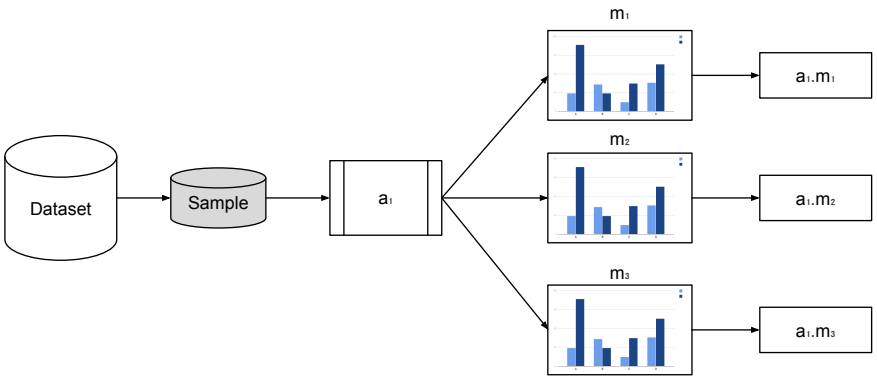


Figure 4.2: SL metafeature extraction procedure. The diagram represents each dataset being processed by one algorithm on multiple evaluation measures.

Furthermore, since a proper exploration of the concept must be ensured, this work employs the concept of relative landmarkers (Fürnkranz et al., 2002). These modify the original performance estimations by comparing them with other landmarkers. The following categories exist:

- **Absolute (AB)**: this approach refers to the original performance values.
- **Ranking (RK)**: landmarkers are ranked according to their score, creating $L = \{l_1, l_2, ..., l_n\}$. The metafeatures are now the respective ranking, with 1 being the best and n the worst.
- **Pairwise (PW)**: this approach performs pairwise comparison for all pairs of landmarkers. Consider two landmarkers l_i and l_j. If the performance of l_i is greater, equal or worse than l_j, then the final metafeature values are 1, 0 or -1, respectively.
- **Ratio (RT)**: calculates the ratio between landmarkers, i.e. given two landmarkers l_i and l_j, the metafeature value becomes l_i/l_j.

As an example, let us consider two CF algorithms, A and B, and the NMAE performance measure. Given a data sample, they are applied to it and the corresponding NMAE score is computed. Table 4.1 illustrates such values and all the corresponding subsampling landmarkers. Notice Absolute is equal to the original NMAE, Ranking assigns the ranking of the algorithms, Pairwise assigns 1 to the best algorithm and -1 to the worst and Ratio presents the ratios of NMAE. It should be noted that the process is repeated for each evaluation measure.

Table 4.1: Example of relative landmarkers.

Algorithm	NMAE	Absolute	Ranking	Pairwise	Ratio
A	0.73	0.73	1	1	0.839
B	0.87	0.87	2	-1	1.192

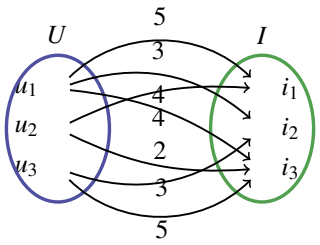
4.3 Graph-based systematic metafeatures (GR)

Given that rating matrix R can be regarded as a (weighed) adjacency matrix, it means that a CF problem can be represented as a (bipartite) graph. The hypothesis, in terms of CF algorithm selection, is that such alternative representation allows to extract meaningful patterns, unattainable otherwise. In fact, it has been shown that RS performance is correlated with multiple graph characteristics (Wang et al., 2018). Supported by this evidence and inspired by the related work approach to derive metafeatures from implicit feedback in CF graphs (Huang and Zeng, 2011), the issue is now addressed in a systematic and exhaustive way.

Hence, this study models the CF problem as a bipartite graph G, whose nodes U and I represent users and items, respectively. The set of edges E connects elements of both groups and represent the feedback of users regarding items. The edges are weighted, representing the preference values (i.e. ratings). Figure 4.3 illustrates an example with the conversion used from standard CF problem to a graph representation, which allows the extraction of the metafeatures proposed here.

	i_1	i_2	i_3
u_1	5	3	4
u_2	4	...	2
u_3	...	3	5

(a) Rating Matrix.



(b) Bipartite Graph.

Figure 4.3: Example for two different and valid CF representations.

The proposed meta-approach is based on Graph Theory (West, 2001; Godsil and Royle, 2013). Although the literature provides several functions for graph characterization, they have a major limitation: the characteristics describe the graph at a high-level, which limits the representation power. To deal with this, the work uses the systematic metafeature extraction (Pinto et al., 2016) (see Section 2.2.3) and hierarchical decomposition of complex data structures (Cunha et al., 2017) approaches for metafeature design. An exploratory approach is adopted in order to obtain and characterize different graph levels. These are now discussed in detail.

4.3.1 Graph-level

When trying to propose metafeatures for a complex structure, it is common to consider high level characteristics first. Although in the context of algorithm selection this is not typically effective (Cunha et al., 2017), it is nevertheless important to verify it. Hence, at this level, only one object is considered for metafeature extraction: the whole bipartite graph G, which can be directly characterized through several Graph Theory measures (West, 2001; Godsil and Royle, 2013). This work selects a subset of potentially useful characteristics to be used as metafeatures. These are:

$$G.\{edge\ density, girth, order, size, radius\}.\varnothing \tag{4.2}$$

The functions refer, respectively, to the ratio of the number of existing edges over the number of possible edges, length of the shortest circle, number of nodes, number of edges and the smallest maximum distance between the farthest nodes of the graph. Since these functions return a single value, no post-processing is required hence the usage of symbol $\varnothing$.

4.3.2 Node-level

This level focuses on the main entities in the graph: nodes. In this bipartite graph, there are two clearly well defined sets of nodes: users and items. Considering their influence in CF, it is important to find and evaluate the importance of suitable metafeatures for each one. Hence, Node-level metafeatures use three different objects: the graph G, the set of users U and the set of items I. These consider all nodes in the entire graph and each subset of nodes independently.

The functions used at this level describe the nodes through their edge relationships. A wide variety of functions suitable to describe bipartite graphs is selected: Bonacich's alpha centrality (Bonacich and Lloyd, 2001), Kleinberg's authority score (Kleinberg, 1999), Closeness centrality, Burt's constraint score (Burt, 2004), Coreness score, Degree, Diversity, Eccentricity, Eigenvector Centrality score:, Kleinberg's hub centrality score (Kleinberg, 1999), nearest neighbor degree (KNN), Neighbors, Local Scan score, Google's PageRank score and Strength.

Since the application of these functions return a distribution of values, these values must be aggregated into a single metafeature value. To do so, several post-processing functions pf are used: mean, variance, skewness and entropy. These functions, based on statistical univariate analysis (central tendency, dispersion and shape) and Information Theory, have performed well in other recommendation metafeatures (Cunha et al., 2017). These metafeatures are described as:

$$\begin{aligned}\{G,U,I\}.\{&alpha, authority, closeness, constraint, coreness, degree, diversity,\\ &eccentricity, eigenvector, hub, knn, neighbors, scan, PageRank, strength\}.\{pf\}\end{aligned} \tag{4.3}$$

4.3.3 Pairwise-level

Pairwise comparisons of simpler elements in a complex data structure have proven themselves successful in other algorithm selection domains (Cunha et al., 2017). Hence, such metafeatures are adapted to this domain by focusing on node comparisons. Due to the complexity of the data structure, the pairwise-level defines 2 layers - inner (IL) and outer (OL) - which are presented next.

Inner Layer (IL) The IL, responsible for node comparison, applies pairwise comparison functions to all pairs of nodes n_i, n_j. The output is stored in the specific row i and column j of a IL matrix, used to keep intermediate records. The functions used to perform pairwise comparisons are based on node similarity (i.e. amount of common neighbors) and the geodesic distance between nodes. The post-processing functions used in this layer are the matrix post-processing functions (mpf). The sum, mean, count and variance functions are applied to each matrix row. The output is a set of summarized comparison values for each function, which are submitted to the OL.

Outer Layer (OL) The OL takes advantage of the recursiveness in the systematic metafeature framework. It does so by using the same objects as used in the Node-level: G,U,I. Each of these sets of nodes are separately submitted to the IL to obtain the actual node comparison scores. Finally, the values returned by each set of nodes are aggregated to create the final metafeatures, using the same post-processing functions as before: mean, variance, skewness and entropy. The formalization of the metafeatures in this level is:

$$\{G,U,I\}.\Big[\{g_i/g_j,u_k/u_l,i_m/i_n\}.\{similarity,distance\}.\{mpf\}\Big].\{pf\} = \{G,U,I\}.\{similarity,distance\}.\{mpf\}.\{pf\} \tag{4.4}$$

4.3.4 Sub-graph-level

So far, measures that characterize the whole graph or very small parts of it (nodes and pairs of nodes) were used. However, a graph may contain parts that have very specific structures, which are different from the rest (e.g. the most popular items will define a very dense sub-graph). Therefore, it is important to include metafeatures that provide information about those sub-graphs. Hence, the metafeatures at this level split the graph into relevant sub-graphs, describes each one with specific functions and aggregates the final outcome to produce the metafeature. Once again, due to complexity, one IL and one OL are defined.

Inner Layer (IL) The IL assumes the existence of a sub-graph. The proposal is to use Node-level metafeatures to describe it. Further functions could be included, such as for instance the Pairwise-level metafeatures. However, they were discarded due to the high computational resources required. Since the outcome is a metafeature value for each node in the sub-graph, the values necessary to describe the overall sub-graph must be aggregated. In order to deal with this issue, the mean, variance, skewness and entropy pf functions are used.

Outer Layer (OL) The OL is responsible to create the sub-graphs to be provided to the IL. The sub-graphs characterized here are communities obtained using the Louvain's community detection algorithm (Blondel et al., 2008) and components, which refer to sub-graphs of maximal strongly connected nodes of a graph. After providing each sub-graph to the IL, one must once again aggregate the results. This is necessary to obtain a fixed-size description of the communities and components that characterizes a varying number of its sub-graphs. These metafeatures are:

$$\{communities,components\}.\Big[\{sub-graph\}.\{Node-level\}.\{pf\}\Big].\{pf\} = \{communities,components\}.\{alpha,authority,closeness,constraint,coreness,degree,diversity, eccentricity,eigenvector,hub,knn,neighbors,scan,PageRank,strength\}.\{pf\}.\{pf\} \tag{4.5}$$

4.4 Results

The experiments conducted here follow the same evaluation procedures as the ones discussed in Section 3.2.3: metalevel accuracy, impact on the baselevel performance, computational cost comparison and metaknowledge analysis. The goal is to create a systematic evaluation analysis, thus ensuring complete results are reported.

4.4.1 Experimental setup

In order to allow fair comparison of metafeatures, this Chapter uses exactly the same experimental setup as the one presented in Section 3.2. The only difference lies in which are the metafeatures employed. Here, the performance of the proposed metafeatures is studied: RM, SL, GR. Furthermore, the Comprehensive Metafeatures (CM), a collection which contains all metafeatures from all meta-approaches is also included. Once again, to simplify the results presentations, we direct all details regarding the implementation of metafeatures in this experimental setup to Appendix C. However, a summary of the metafeatures selected for this experimental setup is provided:

- RM contains 14 out of 74 possible metafeatures, from which the item, user and dataset objects are described by 7,4 and 2 metafeatures. Most metafeatures use the mean function and several post-functions. The number of users is also included.
- All relative landmarkers in SL have been evaluated with a 10% sample size and considering all baselevel algorithms and evaluation measures listed in Section 3.2.2. The results show the AB approach is the best, yielding 11 metafeatures representing IR and RP through 4 and 7 metafeatures, respectively. The most common algorithms are WBPRMF and LFLLM, but there is no evident preference towards any evaluation measure.
- GR metafeatures are adjusted to this experimental setup by reducing the total amount of metafeatures from the theoretical 713 to only 65. The metafeatures do not contain any graph-level characteristic and are divided by node, pairwise and sub-graph levels with 12, 10 and 43 metafeatures, respectively. This means that communities and components are the objects which are most commonly used in this framework, although all objects (user, item and graph) are considered in the remaining levels.
- CM metafeatures contain 49 metafeatures and include metafeatures from all proposed meta-approaches (13, 10 and 26 for RM, SL and GR respectively). These are computed by considering Correlation Feature selection procedure.

Lastly, please notice the results presented can be reproduced by accessing the repository https://github.com/tiagodscunha/cf_metafeatures.

4.4.2 Metalevel accuracy

The results for metalevel accuracy are presented in Figure 4.4.

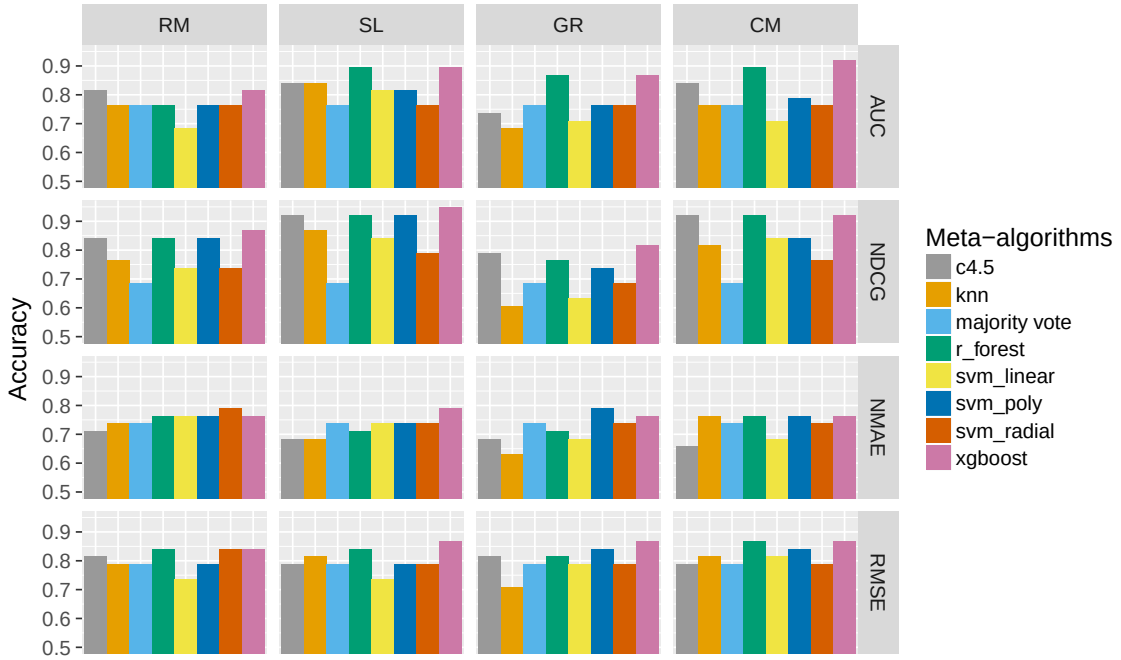


Figure 4.4: Metalevel accuracy performance for proposed metafeatures.

The results show all metafeatures are able to outperform the baseline. This means that all metafeatures proposed so far are suitable for the algorithm selection problem. Furthermore, the effectiveness of meta-approaches depends on the metatarget chosen. In fact, there are no metatargets where all metamodels outperform the baseline. Also, there is no clearly identifiable best meta-approach, although there seems to be a slight advantage of SL and CM meta-approaches. Lastly, although xgboost is usually the best metamodel, this is not always the case. Namely, in the NMAE metatarget, its performance is tied in first place with other meta-algorithms.

In order to properly compare meta-approaches from both Chapters, all 8 meta-approaches are included in the CD diagrams of Figure 4.5.

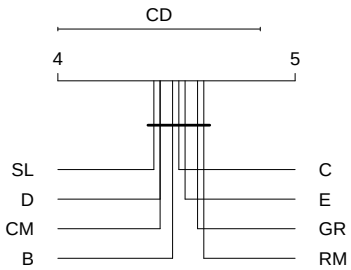


Figure 4.5: Critical Difference diagram comparing proposed meta-approaches.

The results show that there is no difference in terms of metalevel accuracy for all metafeatures when using the best xgboost metamodel. Although this does not favor the ambitions of proposing metafeatures which outperform the related work meta-approaches, it does confirm that all metafeatures proposed are suitable and competitive.

4.4.3 Impact on the baselevel performance

Figure 4.6 shows the results of the impact on the baselevel analysis for the proposed metafeatures. The procedure used is described in Section 2.2.4.

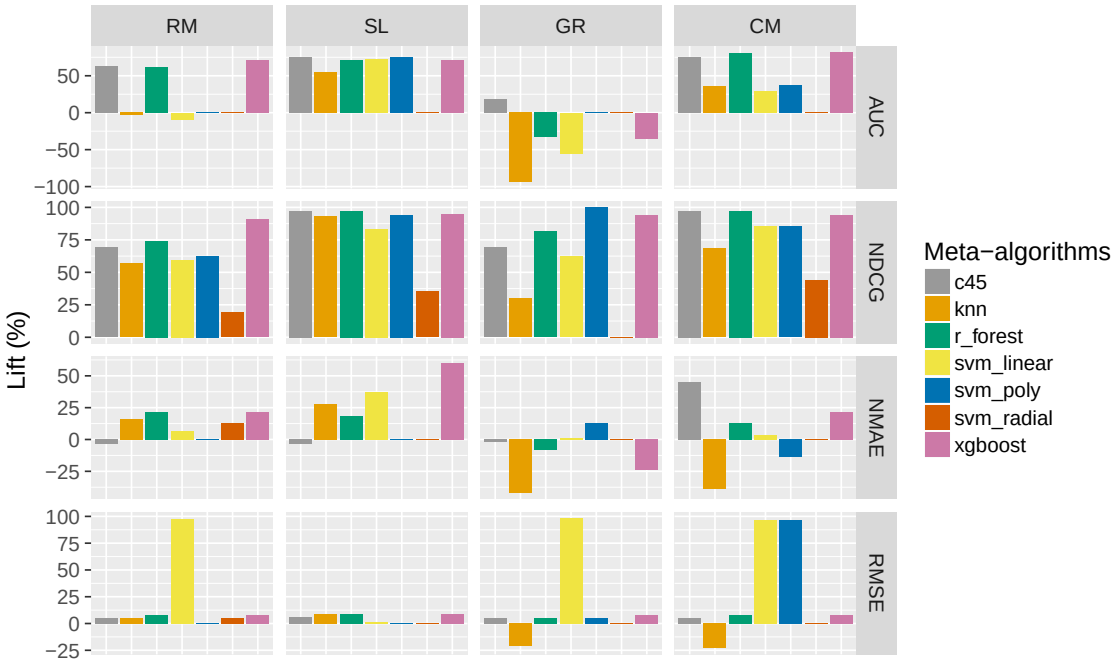


Figure 4.6: Impact of meta-algorithms on the baselevel performance measures for proposed metafeatures.

The results show the majority of metamodels outperform the baseline. However, there are also more metamodels which do not outperform the baseline. Once again, the performance seems to be inconsistent across meta-algorithms. Despite this, there is a substantial improvement in RMSE. While competitors achieved 7.5% lift at best, here there are 4 cases where such a performance is raised to over 90%. This surprising result comes from the fact that even though the amount of misclassifications is similar, the mistakes made are much less costly. The performance is comparable in all remaining metatargets.

Overall, no meta-approach is better than the competitors. Although there are some exceptions, such as SL in the NMAE metatarget, there is not a significant difference among meta-approaches. When comparing to the related work, one observes that the best metamodels reach similar performance levels, although the metamodels trained using the new metafeatures are less consistent in achieving good results. Finally, xgboost is no longer the best metamodel. For instance, in the

RMSE metatarget it is never the best, being defeated by SVM with polynomial kernel. Furthermore, using GR in the AUC and NMAE metatargets it even scores below the baseline. However, it does perform well in most of the examples found in the IR problem.

4.4.4 Computational Cost

Similarly to the analysis reported in Section 3.2.3, we aim to assess the computational cost required to calculate the proposed metafeatures. However, due to impractically high computational resources, it is not useful nor easy to provide such measurements for any another meta-approach beyond RM metafeatures. The overall results show these metafeatures require 112.531 and 2.961 seconds to extract such metafeatures to all datasets and on average per dataset, respectively. This is indeed slower than the results reported for the related work metafeatures, but by a lower margin.

However, one must note that time has not played a central part in the design of these metafeatures. Instead, the goal has always been to perform an extensive and deep analysis of the metafeature generation problem for CF, which required quite complex computations. Such endeavour would always lead to worse computational performance, especially when considering the process would inevitably also include metafeatures which may not be important for the specific experimental setup. However, it is also true that once the best metafeatures are found, it is always possible to filter out the least important and, as a consequence, be more efficient. Furthermore, the computational requirements can differ extensively depending on the implementation and hardware used. For instance, parallel computing procedures could potentially solve the issue.

Having said that, a measure of computational resources is still provided for all proposed meta-approaches. Since it is prohibitively expensive to recalculate all metafeatures for all datasets [1], then a decision has been made to perform a comparative analysis in a small group of datasets. This allows to assess the differences in magnitude among measurements and can be used as a guideline for other datasets. Table 4.2 presents the computational cost measured in seconds for meta-approaches RM, SL and GR for 4 datasets: AMZ-movies, ML100k, YH-movies and YH-music. Notice that CM results are disregarded since they are a sum of the three meta-approaches.

Table 4.2: Computational time required for the extraction of RM, SL and GR metafeatures.

Dataset	RM	SL	GR
AMZ-movies	0.242	361.239	1214.400
ML100k	0.124	339.254	23.506
YH-movies	0.194	658.955	262.734
YH-music	0.266	5814.624	115.759

The results show RM is much faster than the competitors. In fact, it takes less than a second to be calculated for all datasets considered. This was expected since the procedure requires only the rating matrix. However, in the best case scenario, SL is over 1000 times slower than RM. This is mainly due to the high cost in training and evaluating all algorithms for each sample. There is much room for improvement here, if the absolute best metafeatures are found and the experimental requirements reduced. Furthermore, GR works fast for ML100k, but it takes longer for the

[1] It took a grid computing framework running multiple parallel jobs over the course of several days.

remaining datasets. It requires 23 seconds to extract all GR metafeatures from these datasets, but upwards of 100 seconds for the remainder. Such disparity in costs is given by the fact that now, computational costs are caused by the amount of nodes rather than by the amount of ratings, as happens both in RM and SL. However, considering the expected space and time complexity of such process, these results are encouraging.

4.4.5 Metaknowledge

The metaknowledge analysis procedure used here replicates the one introduced in Section 3.2.3.4. Namely, three analysis are performed: metafeature importance, baselevel datasets analysis and baselevel algorithms analysis.

Metafeature importance The metafeature importance results are presented in Figure 4.7. Notice that due to high amount of metafeatures, only those with highest ranking are presented.

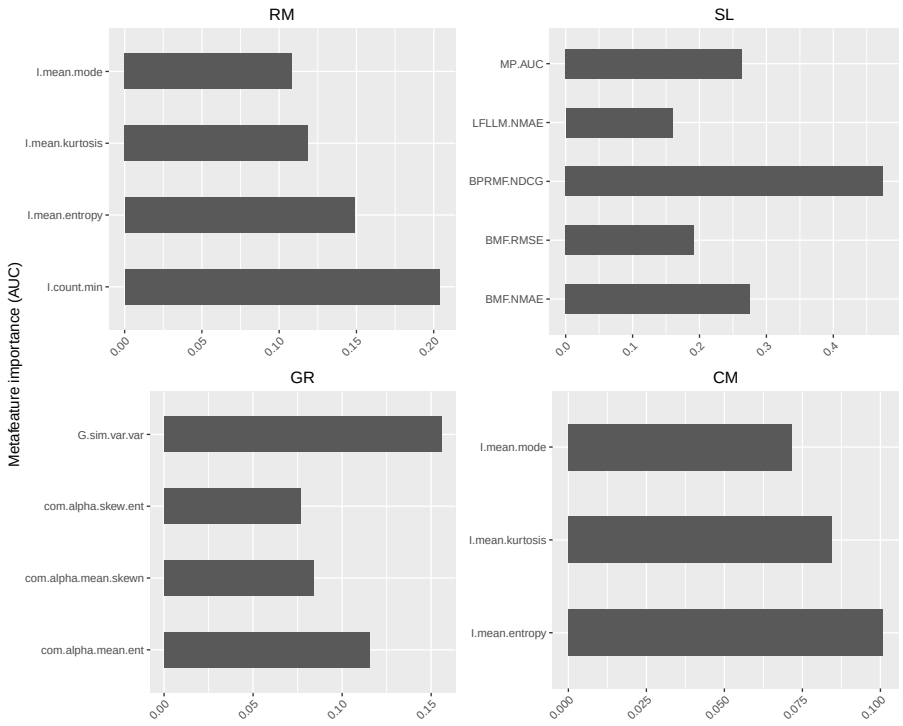


Figure 4.7: Metafeature importance for proposed metafeatures.

The results show that all best RM metafeatures are based on the item ratings distribution. This is an interesting result when considering that related work mostly focuses on user ratings distributions, instead. Furthermore, SL highlights 2 metafeatures belonging to IR and 3 to RP. It is also visible that BMF shows up twice, indicating its performance is paramount in the algorithm selection problem. Regarding GR, 3 metafeatures related to the communities object in sub-graph-level and one in the Pairwise level are selected. This shows two things: 1) the best metafeatures are those which describe more detailed levels of the CF graph and 2) there are many metafeatures

in this domain which are not particularly informative. Lastly, the results in CM show that all best metafeatures belong to the RM meta-approach. This either means RM is more important than the remaining meta-approaches or the procedure used to create CM metafeatures is not ideal.

Dataset Analysis Now, the impact of the proposed meta-approaches on the baselevel datasets is investigated. Particularly, Figure 4.8 presents the violin plots regarding the accuracy scores for all proposed meta-approaches. Notice that the scores consider all metalearners and metatargets.

The results show that, unlike the related meta-approaches, there seems to exist fewer cases where the vast majority of datasets are incorrectly classified. This happens particularly in the RM and SL meta-approaches, where results seem more balanced. This seems to point to the fact that the proposed metafeatures have higher sensitivity to the data properties, even if that does not reflect in superior predictive performance. A prime example is the TA dataset. Recall that this was always incorrectly predicted by related meta-approaches (and still is by RM and SL), but now here are a few cases where GR and CM actually can correctly predict the best algorithm.

However, the results are not optimal. There are now more occasions when AMZ datasets are not perfectly predicted (even though the vast majority of times it is). Furthermore, the fact that some datasets present a balanced amount of correct and incorrect prediction implies that performance depends mostly on the metamodel's tuning rather than on the representation chosen. In summary, one observes that despite similar performances, the metamodels tend to make different mistakes. This analysis then shows which metafeatures should be preferred, depending on the recommendation domain.

Baselearner analysis Now, the focus shifts towards assessing the impact of metafeatures on the baselevel performance. To do so, a procedure inspired in algorithm footprints is applied to all proposed metafeatures. Figure 4.9 presents the results.

The results show an improvement in terms of dataset discrimination for RM, SL and CM meta-approaches, when compared to the related work meta-approaches. This is justified by the clearer separation between good and bad performances for all baselearners considered. However, GR representations yield more compact representations which impedes a proper analysis of results. This happens since PCA is used to reduce dimensionality to 2 dimensions, which is insufficient to represent the level of detail in these metafeatures.

Once more, the algorithms tend to perform better for the same datasets. This is indicated by the fact that regions of good and bad performance are usually the same, regardless of the meta-approach chosen. However, the representations (with the exception of GR) used make it clearer to understand the performance variations.

Lastly, one observes that IR algorithms usually have clearer regions of good and bad performances. One reaches this conclusion since the results show there are fewer outliers in these cases. In this aspect, RM and SL are the best solutions.

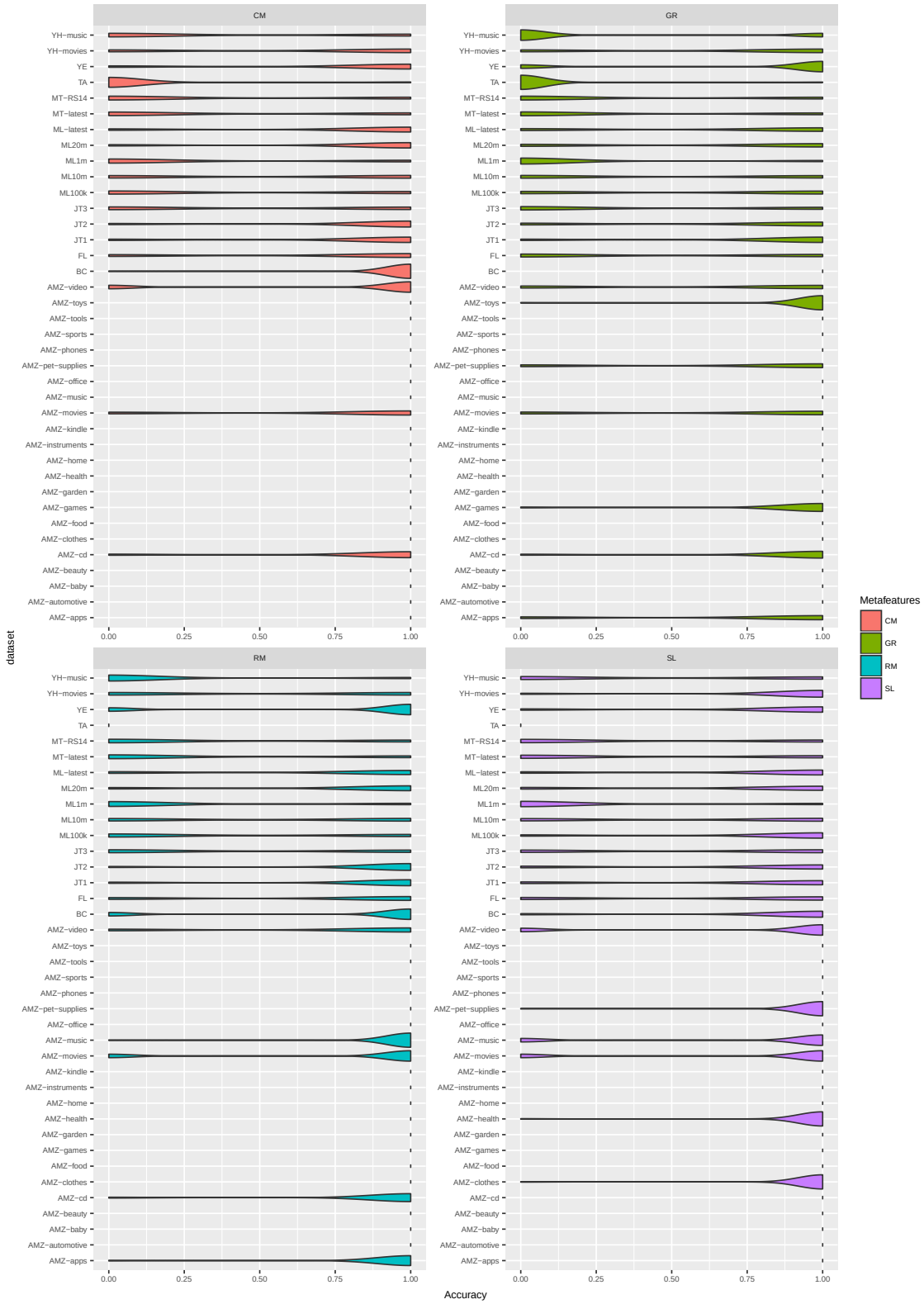


Figure 4.8: Accuracy scores per baselevel dataset for proposed metafeatures.

Figure 4.9: Algorithm footprints for the related work metafeatures. The threshold for good performance is the third quartile of the distribution of all its performances.

4.5 Conclusions

This Chapter has proposed several meta-approaches to generate metafeatures for CF problems, which have been designed to extend state of the art metafeatures discussed in Chapter 3. To that end, the first contribution has been a set of metafeatures which systematically describe a CF dataset and whose functions are inspired in those found in the related work. Furthermore, the merits of subsampling landmarkers in CF were investigated and the research extended by evaluating multiple relative landmarkers meta-approaches, designed to explore the absolute performance values in multiple perspectives. Afterwards, an extensive set of metafeatures based on a graph perspective of the CF problem was proposed. The technique developed has based itself on a systematic and hierarchical decomposition approach, which allowed to obtain metafeatures of extensive detail. Lastly, all metafeatures proposed are combined in a single meta-approach, which are named Comprehensive Metafeatures.

All metafeatures have been validated on the same experimental setup used in Chapter 3. The results show that all proposed meta-approaches perform approximately the same, even though different perspectives of the CF problem have been studied. Metaknowledge analysis has provided several insights into the CF problem: the most informative RM metafeatures are statistics from the item ratings distribution; the fact that BPRMF and BMF are the most important algorithms in SL; how the best GR metafeatures belong to the pairwise and sub-graphs levels, namely on community detection and node similarity statistics; and, that the procedure used to create CM metafeatures is not effective, since all best metafeatures belong to RM. Further analysis on the metaknowledge generated indicates the proposed representations are more sensitive in terms of accuracy per dataset and also in terms of discrimination regarding baselearners. Furthermore, it would be interesting to assess dataset similarity through performance similarity, i.e. two datasets are similar if the best algorithm ranking is similar Nguyen et al. (2012).

The results also point out that there is no statistically significant difference in performances between the proposed metafeatures and the ones in the related work. This is an important result because it proves that the proposals have all been meaningful, even if not the ideal candidates. However, it also makes it obvious that the depth of description employed in designing the metafeatures did not yield the superior discriminatory power anticipated. Associating this limitation with the extensive computational costs required, leads to the conclusion that the metafeatures proposed are not as meaningful as hoped.

The limitations in predictive power can be explained by multiple reasons. However, the main problem lies in limitations in the baselevel experimental setup: 1) too few datasets, meaning there are not enough data points in order to take full advantage of the systematic procedures used; 2) high class imbalance given by the fact that the algorithm selection problem is addressed as classification and 3) the fact that some algorithms fail to appear in the algorithm selection problem. Since there is a limit in terms of how many datasets one is able to include in the setup, these issues will instead be tackled by investigating the discriminatory power of such metafeatures using rankings of algorithms in Chapter 5.

Chapter 5

Multicriteria Label Ranking metamodels for Collaborative Filtering

The related work in CF algorithm selection has never investigated the selection of rankings of algorithms, having focused instead on predicting the best algorithm or assessing performance estimation. This limits the metaknowledge extracted, by not knowing how other methods are expected to perform. However, if one tackles the algorithm selection problem using rankings, then there is a sorted predicted utility for all algorithms (Brazdil et al., 2003). This way, the metamodels are more complex, but also more powerful. By modelling CF algorithm selection using this paradigm, two contributions are introduced:

- **Label Ranking metamodels** Considering CF algorithms as labels in the classification problem, then one can use ranking-based techniques to tackle the problem of selecting the best ranking of algorithms. However, it is important to consider all candidate algorithms in the predictions, since the system is unaware of which recommended algorithms the practitioner will actually choose (Brazdil et al., 2003). This motivates the usage of Label Ranking (LR) metamodels, since it fulfills both requirements. Section 5.1 presents this contribution.

- **Multicriteria metatargets** Currently, ranking metatargets are created using a single evaluation measure. This leads to limited and measure-dependent metaknowledge. However, RS literature clearly states that a single evaluation measure is not enough to properly characterize algorithm performance (Herlocker et al., 2004; Gunawardana and Shani, 2009). Thus, one hypothesizes that MtL can benefit from using more complex metatargets, which include multiple evaluation scopes. To that end, multicriteria metatargets are introduced. This technique creates unique metatargets by taking into creating Pareto-Efficient rankings (Ribeiro et al., 2013). This is presented in Section 5.2.

The remaining of this Chapter presents the experimental results in Section 5.3, where multiple CF metafeatures are evaluated on LR metamodels. The results mimic the analysis in previous Chapters, focusing on metalevel accuracy, impact on the baselevel performance and metaknowledge analysis. Lastly, Section 5.4 presents the conclusions on the contributions proposed.

5.1 Label Ranking for CF algorithm selection

5.1.1 Problem formulation

LR aims to predict a preference relationship among a finite set of labels or alternatives (Hüllermeier et al., 2008; Vembu and Gärtner, 2010). Let us consider a finite set of labels $L = \{l_1, l_2, ..., l_n\}$ for which predictions will be made, where n is the total number of labels available. Consider also that a binary preference relation $\succ_x \subseteq L \times L$ allows to dictate the preference associated to an instance $x \subset X$ regarding sets of two labels. When all possible preference relations are specified for an instance, then a total strict order of L is obtained, i.e. a ranking of labels. This ranking, $\pi_x \subset \Omega$, can be seen as a permutation of $\{1, ..., n\}$, where n is the number of labels. In LR, each instance x is associated with a ranking π_x. The goal of a LR learning algorithm is to find the mapping $g : X \to \Omega$, such that a loss function in Ω is minimized. Typically, ranking accuracy measures, such as Kendall's tau and Spearman's rank, are used for this purpose (de Sá et al., 2016).

Rice's formulation of the algorithm selection problem (Rice, 1976), discussed in Section 2.2, can be straightforwardly used to accommodate a LR approach. Thus, the set of labels $L \in \Omega$, for which predictions will be made, is given by the names of all algorithms $a \in A$. Recall that in order to create the rankings π, the predictive performance of all CF algorithms is assessed regarding a specific evaluation measure. The preference relations $\succ$, which are the basis to the rankings π, are established based on those performance estimates. Therefore, the algorithm selection problem for CF using LR can be defined as follows: for every dataset $p \in P$, with features $f(p) \in F$ associated with the respective rankings π_p, find the selection mapping $g(f(p))$ into the permutation space Ω, such that the selected ranking of algorithms π_p maximizes the performance mapping $y(\pi_p) \in Y$.

5.1.2 Label Ranking Metalearning Process

LR introduces minimal changes regarding the classification task used to address the CF algorithm selection problem so far. The main change required relates to the metatarget, although it does also affect the meta-algorithms and metalevel evaluation measures. To clarify the change in paradigm, Figure 5.1 presents the metadatabase format required for the current formulation. Notice it is an adaptation of the earlier formulation discussed in Section 2.2.

d	mf_1	...	$mf_{\|F'\|}$
d_1	ω_1	...	$\omega_{\|F\|}$
$\vdots$	$\vdots$	$\ddots$	$\vdots$
$d_{\|P\|}$	...	...	...
d_α	$\hat{\omega}_1$	...	$\hat{\omega}_{\|F\|}$

a_1	...	$a_{\|A\|}$
π_1	...	$\pi_{\|A\|}$
$\vdots$	$\ddots$	$\vdots$
...	...	...
$\hat{\pi}_1$	...	$\hat{\pi}_{\|A\|}$

Figure 5.1: LR metadatabase formulation.

The metadatabase is composed by a set of blocks, which are organized into training and prediction data (top, bottom) and independent and dependent variables (left, right), respectively. More formally, all datasets $d_i \in P$ are represented through metafeatures $\omega = mf(d_i)$, i.e. the independent variables of the predictive task. This formulation does not make any assumptions regarding such representations, meaning any type of metafeatures can be used.

To create the dependent variables, each dataset d_i is associated with the respective ranking of algorithms $\pi(d_i)$. Such ranking can be directly obtained based on the performance values for a specific evaluation measure m_k. It considers a static ordering of the algorithms a_j to define the multiple dependent variables. The ranking values assigned, corresponding to the ranking position, refer to permutations of values $\{1,...,|A|\}$.

Modelling the problem this way enables to use any LR algorithm to induce a metamodel. The metamodel can be applied to metafeatures $\hat{\omega} = mf(d_\alpha)$ extracted from a new dataset d_α to predict the best ranking of algorithms $\hat{\pi(d_i)}$ for this dataset.

5.2 Multicriteria Metatargets

In order to define a multicriteria metatarget, one needs first to formalize how a standard ranking of algorithms $\pi_M(d_i)$ is created for each dataset d_i. Consider the baselevel performance $p_{m_k}(a_j|d_i)$, representing how well does algorithm a_j is on dataset d_i through evaluation measure m_k. Thus, the individual ranking can be formalized as follows:

$$\pi(d_i) = SORT\left(p_{m_k}(a_j|d_i)\right)_{j=1}^{|A|} \tag{5.1}$$

where $SORT$ refers to any function able to rank the performance values. Notice that such function should be concordant with optimization goal of evaluation measure m_k, meaning it should create a decreasing ordering when the goal is to maximize and vice-versa.

To define how to address the problem using more than one evaluation measure m_k, Pareto-Efficient Rankings (Ribeiro et al., 2013) are used as inspiration. The original work focused on defining a single ranked list of items for every user, while using rankings of items predicted by different algorithms. Such task is believed to be quite similar to the one considered here. Specifically, if one were to change the words "user", "algorithms" and "items" respectively by "dataset", "evaluation measures" and "algorithms", the parallelism becomes clear. Since the original framework makes no further assumptions, it is believed this technique is suitable to this problem.

To solve this multi-objective optimization problem, one must first create a search space for each dataset d_i: Dataset-Interest space S_{d_i}. This space characterizes each algorithm a_j on a multidimensional representation, with each dimension representing an individual evaluation measure m_k. It is important to consider that all evaluation measures used must have the same optimization bias, i.e. all have a maximization or minimization goal. Alternatively, performance results can theoretically be scaled to fit the same bias. Thus, the Dataset-Interest space is defined as

$S_{d_i} = [p_{m_k}(a_j|d_i)]_{i=1}^{|A|}$. Figure 5.2 shows a Dataset-Interest space with two evaluation measures and fifteen algorithms. These are represented as the axis and data points, respectively.

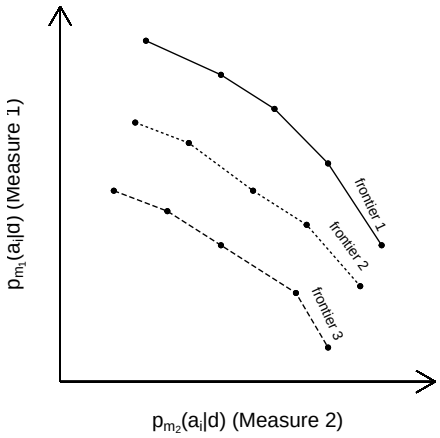


Figure 5.2: Dataset-Interest space. Each axis refers to a different evaluation measure, with points representing each baselearner performance on this multi-dimensional problem. The frontiers, identified by lines, represent baselearners with identical ranking.

An informal interpretation of this illustration allows to understand its convenience in solving the problem: assuming the evaluation measures have a maximization goal, it is possible to intuitively understand that the best algorithms are placed on the top right corner. However, when using multiple evaluation measures, the problem becomes intractable and cannot be solved manually.

The goal is to do this procedure while taking into account performances on a wide range of evaluation measures. Hence, the concept of Pareto frontiers is used, which refers to delimitations in the Dataset-Interest space which identifies the areas of algorithm dominance. These are represented in Figure 5.2 as lines connecting data points, i.e. algorithms. Thus, the frontiers highlight two different relationships: algorithms within the same frontier can be considered similar, while those in different frontiers are effectively different.

If one assigns to any algorithm a frontier, then one is able to obtain a solution to the problem. Similarly to the original work, the frontiers are calculated using the skyline operator algorithm (Lin et al., 2007). Formally, consider that the skyline operator creates a set F of frontiers, where each frontier is represented as $f_k \in K$. Now, each algorithm a_k is associated to a specific frontier f_k, formally $f_k(a_j|d_i)$. Thus, this work proposes to use the frontier of each algorithm $f_k(a_j|d_i)$ instead of the original performance values $(p_{m_k}(a_j|d_i)$ in order to formally define the multicriteria ranking:

$$\pi_M(d_i) = SORT\left(f_k(a_j|d_i)\right)_{j=1}^{|A|} \tag{5.2}$$

where the *SORT* function takes into account the frontiers, rather than the performance scores.

The advantages of multicriteria metatargets are two-fold: (1) since the practitioner is not forced to blindly assign a different ranking to all algorithms, this results in a more representative and fair assignment of algorithm ranking positions and (2) since the process is defined using a multidimensional Dataset-Interest space, any number of evaluation measures can be used simultaneously.

5.3 Results

This Section dwells on the validation of both contributions proposed. The procedure mimics the one used in both previous Chapters, but adapts it to the current ranking setup. The tasks addressed are: metalevel ranking accuracy, statistical validation, impact on the baselevel performance and metaknowledge analysis. Furthermore, the results are reported for all combinations of meta-approach and metatarget employed. However, we present the experimental setup first.

5.3.1 Experimental setup

This section presents the experimental setup used in this new CF algorithm selection paradigm. The baselevel remain the same as the presented in Section 3.2.2. On the metalevel, all metafeatures presented in Chapters 3 and 4 are included: related work metafeatures(i.e. B, C, D, E) and proposed metafeatures (RM, SL, GR and CM). The main difference lies in the metatargets studied:

- **Single criterion**: this metatarget uses the rankings of algorithms based solely on the sorting of algorithm performances for all datasets. Since 4 baselevel evaluation measures are used - NDCG, AUC, RMSE and NMAE -, then 4 different metatargets are created.

- **Multicriteria**: this metatarget takes advantage of the proposed multicriteria metatarget methodology and creates a unique ranking of algorithms for both the Item Recommendation (IR) and the Rating Prediction (RP) problems. The procedure takes into consideration RMSE and NMAE to create the RP metatarget, while NDCG and AUC are used to create the IR metatarget.

Notice that all ranking metatargets are available in Appendix B. Using these metatargets also affects the meta-algorithms and evaluation measures used. In this setup, several LR algorithms are used: KNN (Soares, 2015), Ranking Tree (RT), Ranking Random Forest (RF) (de Sá et al., 2016) and the baseline Average Ranking (AVG). The metamodels are evaluated using Kendall's Tau ranking accuracy. The validation procedure uses leave one out cross-validation and the metamodels are tuned using grid search hyperparameter optimization.

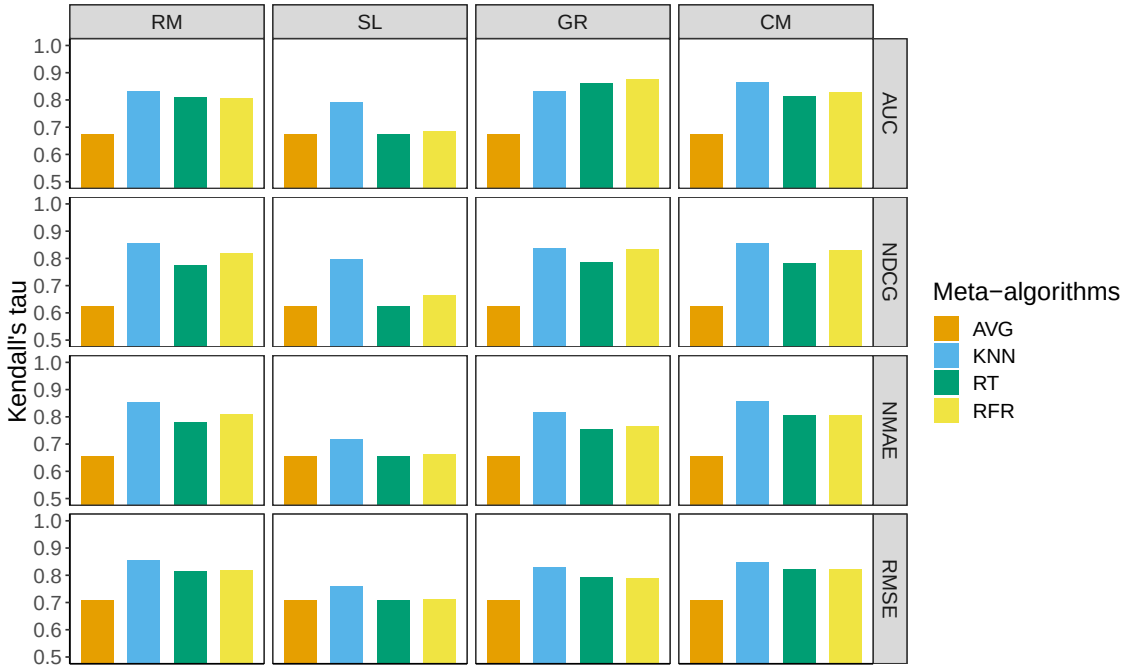
Lastly, please notice the results presented can be reproduced by accessing the repository `https://github.com/tiagodscunha/lr_alg_sel`.

5.3.2 Metalevel ranking accuracy

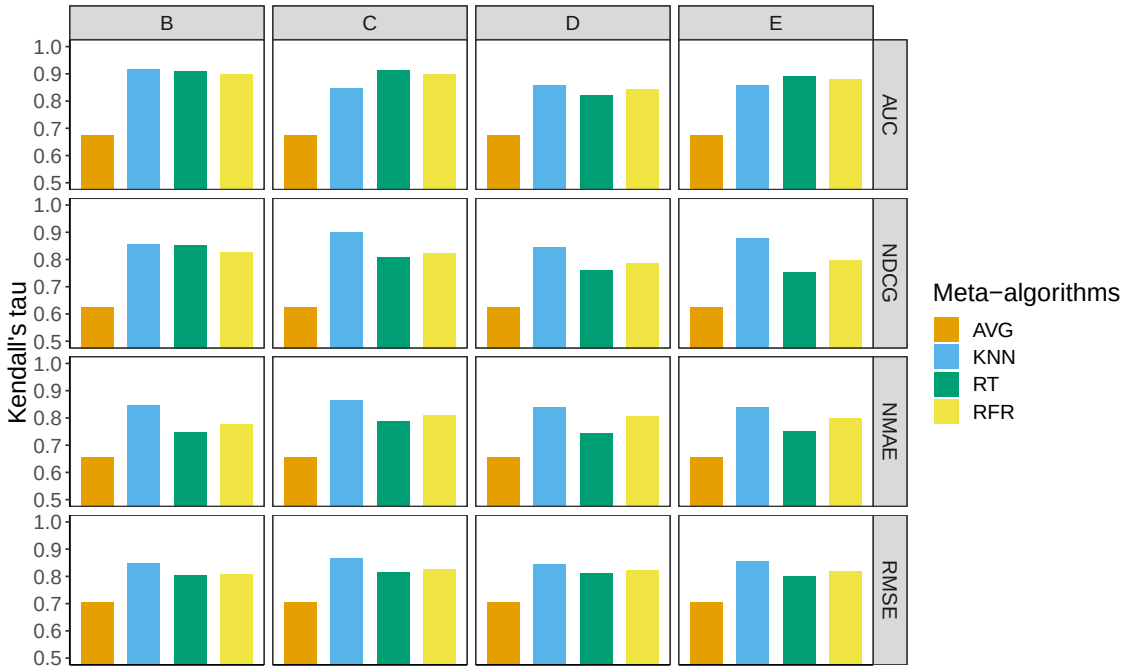
The metalevel predictive performance is measured in terms of ranking accuracy using Kendall's tau coefficient. The results consider both sets of metafeatures (related and proposed) and both metatargets (single criterion and multicriteria). This is done in order to properly validate the multicriteria metatargets proposed and allow comparison among meta-approaches.

5.3.2.1 Single criterion Metatarget

Figures 5.3a and 5.3b present Kendall's tau ranking accuracy for all metamodels for the proposed and related work metafeatures. The results are organized by meta-approach and metatarget.



(a) Proposed metafeatures.



(b) Related work metafeatures.

Figure 5.3: Metalevel accuracy for single criterion metatargets.

Overall, the vast majority of metalearners performs better than the baseline. However, this

behavior is slightly different in proposed and related work metafeatures: while no related work metafeatures fail at this task, SL metafeatures in RT and RFR metamodels fail to beat AVG.

One also observes performance is mostly stable across metatargets. This is supported by the fact that metamodels tend to be ranked similarly and with approximate performance in every column, regardless of the meta-approach considered. This is mostly characterized when considering KNN's performance , which appears to be the best meta-algorithm throughout.

However, when considering the variation in terms of meta-approaches, then there are some significant differences. This difference is particularly evident when considering proposed and related work metafeatures: while all metamodels in the latter are very good, SL underperforms in all metatargets, particularly when using RT and RFR. Thus, this observation indicates SL may not be the most suited approach for ranking metatargets.

In summary, all meta-approaches proposed are suitable for the CF algorithm selection problem. Now, one must validate whether these assumptions holds for the multicriteria metatargets.

5.3.2.2 Multicriteria Metatarget

Figures 5.4a and 5.4b present the Kendall's tau ranking accuracy for all metamodels trained using the multicriteria metatargets, using the proposed or related work metafeatures respectively.

Regarding the proposed metafeatures, the results show RM and CM are the best solutions, with comparable performance, while SL is the worst meta-approach. The related work metafeatures perform very similarly, with quite constant performances regardless of the algorithm used.

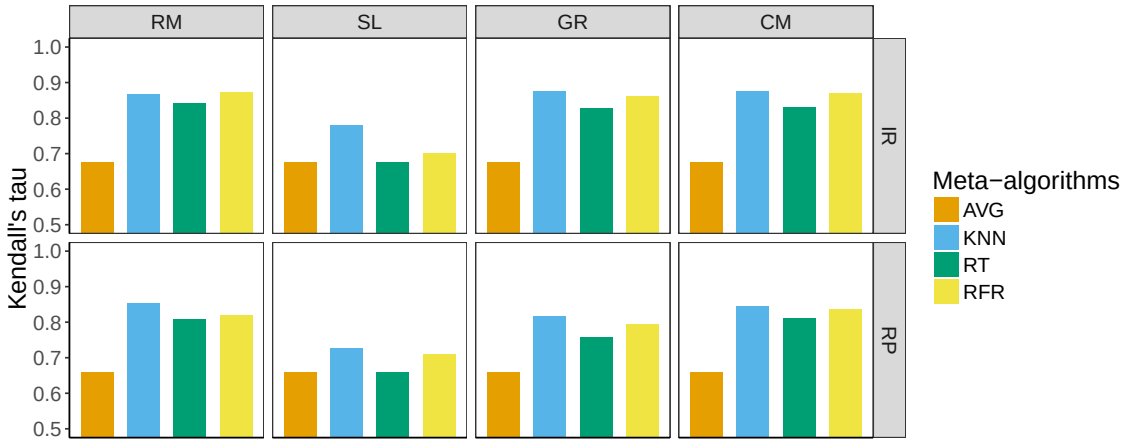
However, more important than the differences are the common observations in both setups: all meta-approaches perform above the baseline, with KNN outperforming its competitors in every case. Furthermore, with the exception of SL metafeatures, all meta-approaches perform approximately equally well. This shows not only that LR is a suitable approach to CF algorithm selection but also that the representation power yielded in terms of best algorithm selection also happens when rankings of algorithms are considered.

Lastly, notice the similarity between single criterion and multicriteria metatargets. This shows multicriteria metatargets are a suitable alternative, since the most important patterns are kept.

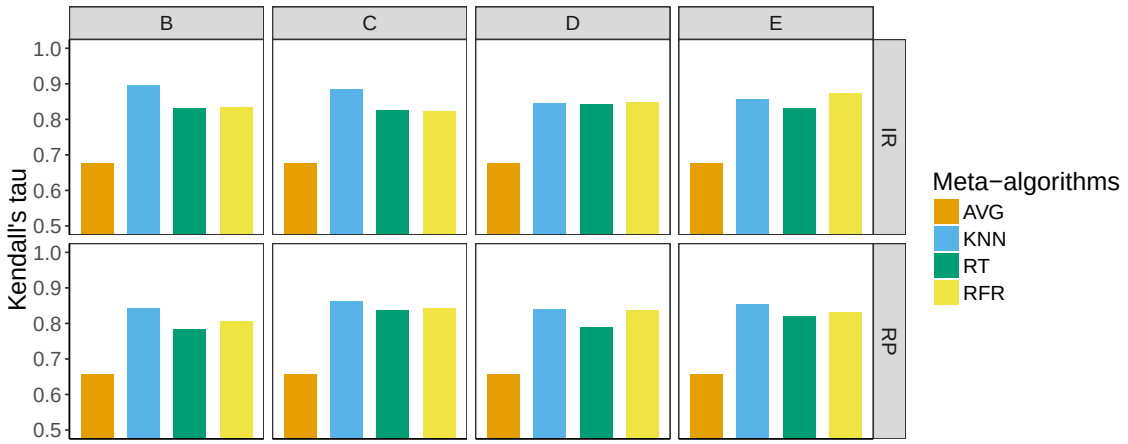
5.3.2.3 Statistical Validation

To validate the observations performed, statistical significance tests using CD diagrams are employed. Each meta-approach is represented by its best metamodel, meaning all Kendall's Tau performances for all datasets are used to characterize said meta-approach. Figures 5.5a and 5.5b present the results for single criterion and multicriteria metatargets, respectively.

The results show all meta-approaches, regardless of the metatarget, are always better than the baseline. However, there are some differences in the merits of meta-approaches depending on the metatarget type. While in single criterion metatarget, all related work metafeatures and RM metafeatures hold the best performance by a clear margin, in the multicriteria metatarget this does not happen. Instead, all metafeatures beyond SL are ranked first.



(a) Proposed metafeatures.



(b) Related work metafeatures.

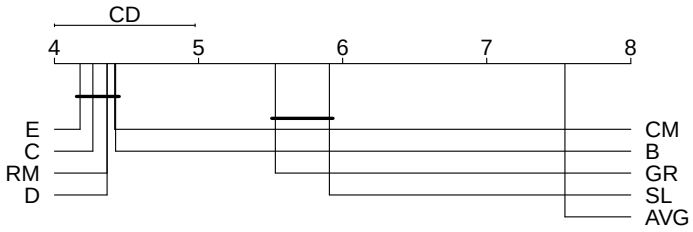
Figure 5.4: Metalevel accuracy for multicriteria metatargets.

The results show that the related work meta-approaches have comparable performance to some proposed metafeatures. Since there seems to not exist any statistically significant difference among them, one concludes that both types of meta-approaches are suitable for the problem.

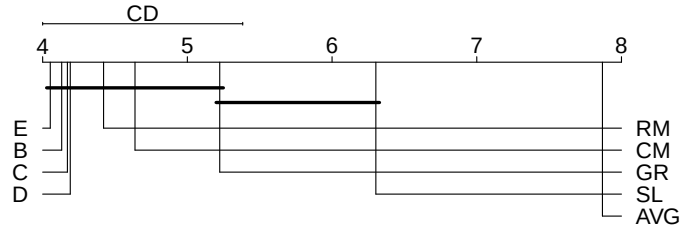
5.3.3 Impact on the baselevel performance

LR metamodels are also evaluated by taking into account the impact on the baselevel performance. Notice that although this has been done before, there is an important difference now: the metatarget is a ranking instead of an algorithm. Thus, such analysis must look towards the baselevel impact on every position of the predicted ranking, defined by a threshold $t \in \{1, |A|\}$. AS a consequence, the graphics generated will also be different, with a measure of impact on the baselevel performance for every position in the ranking predicted. The procedure, which is an adaptation of the one described in Section 2.2.4, is described as follows:

- For a dataset d_i, consider the best ranking of algorithms π_{d_i}. This ranking is directly represented by a performance vector ω_{d_i}.



(a) Single criterion metatarget.



(b) Multicriteria metatarget.

Figure 5.5: Critical Difference diagrams for different metafeatures using LR metamodels.

- Consider now a predicted ranking $\hat{\pi}_{d_i}$ for d_i. The respective performance vector $\hat{\omega}_{d_i}$ is created by obtaining the baselevel performances of every algorithm $\hat{a}_i$ from the original performances ω_{d_i}. To do so, the algorithms from $\hat{\pi}_{d_i}$ and π_{d_i} are matched by name.

- The performance vector $\hat{\omega}_{d_i}$ is regularized to ensure that at each threshold t (i.e. each possible ranking position), the values are set to be either better or the same as the previous threshold value. This is essential due to the nature of the analysis, e.g. if at ranking $t = 2$ the performance is worse than at $t = 1$, then the best performance so far should be preserved in order to fairly evaluate the metamodel.

- The process is repeated for all datasets, obtaining a set of performance vectors. Afterwards, the performance values are averaged for each threshold value t, creating an average performance vector that represents the metamodel performance in terms of baselevel impact.

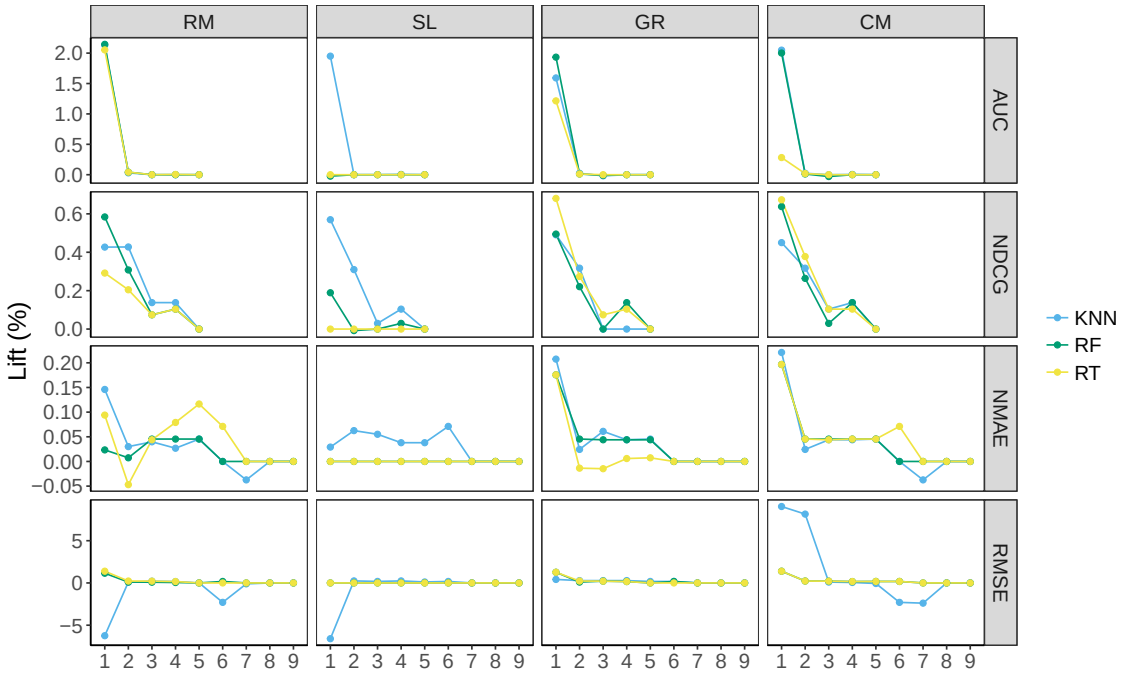
- Since one aims to calculate the percentage lift, then the performance vector is adjusted considering the baseline's performance vector $\dot{\omega}_{d_i}$ and the best absolute performance vector $\tilde{\omega}_{d_i}$. This procedure uses the same calculations presented in Equation 2.2.4, but applied to every threshold t independently.

Now, this analysis is performed for both sets of metafeatures (proposed and related work) and metatargets (single criterion and multicriteria).

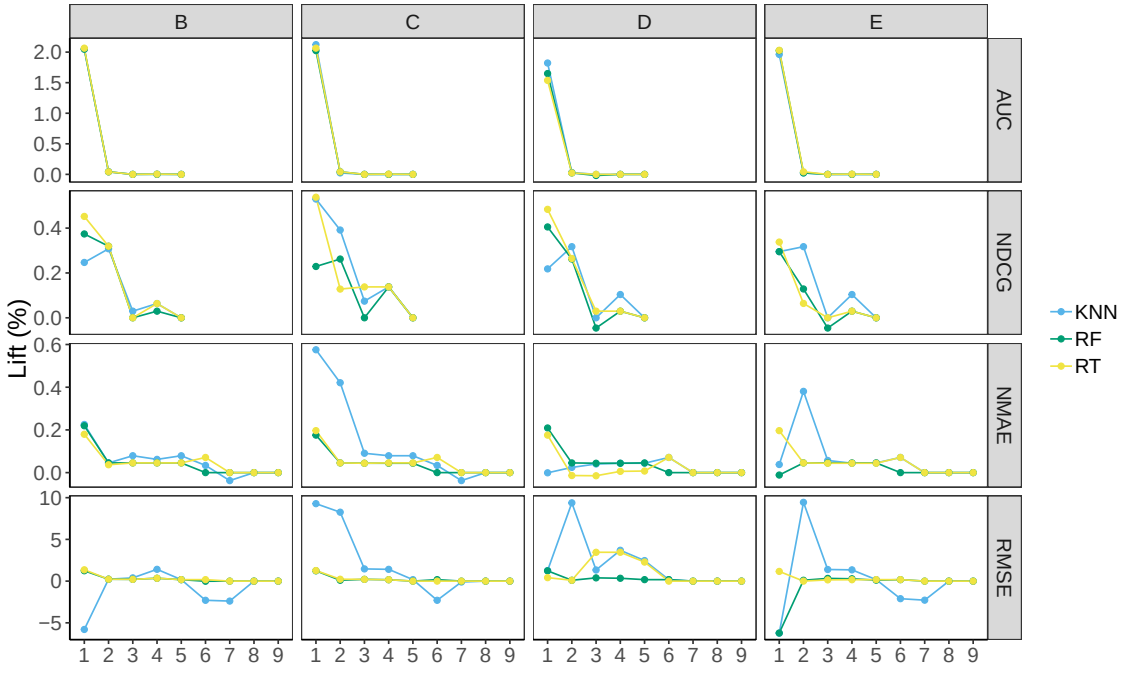
5.3.3.1 Single criterion Metatarget

Figures 5.6a and 5.6b present the percentage lift used to measure the impact on the baselevel performance for metamodels trained using the single criterion metatargets. Notice the results are

presented for every threshold t for all metamodels and that these are different in IR and RP. This happens due to the different amount of baselearners included in the rankings, respectively 5 and 9.



(a) Proposed metafeatures.



(b) Related work metafeatures.

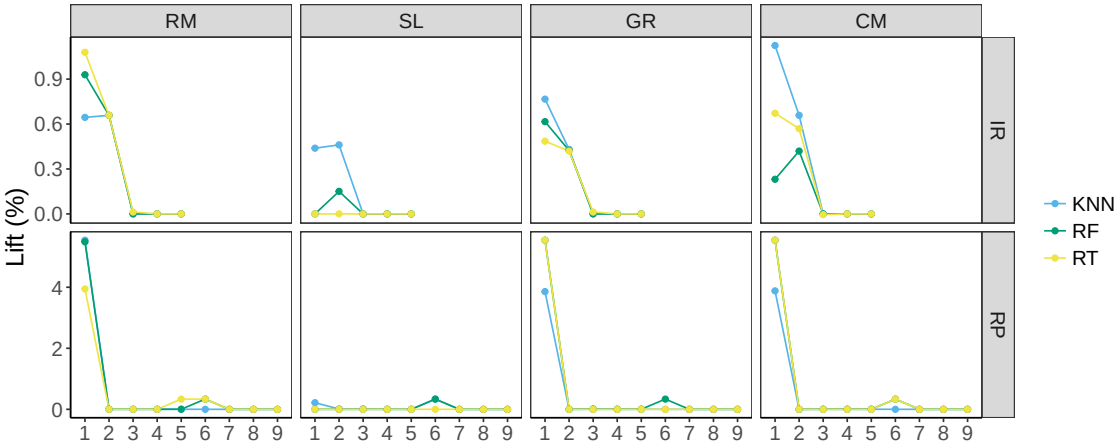
Figure 5.6: Impact on the baselevel performance in single criterion metatargets.

The results show RMSE is the most problematic metatarget, in which only CM, C, D and E are able to obtain meaningful positive impact. On all other metatargets, all metamodels across

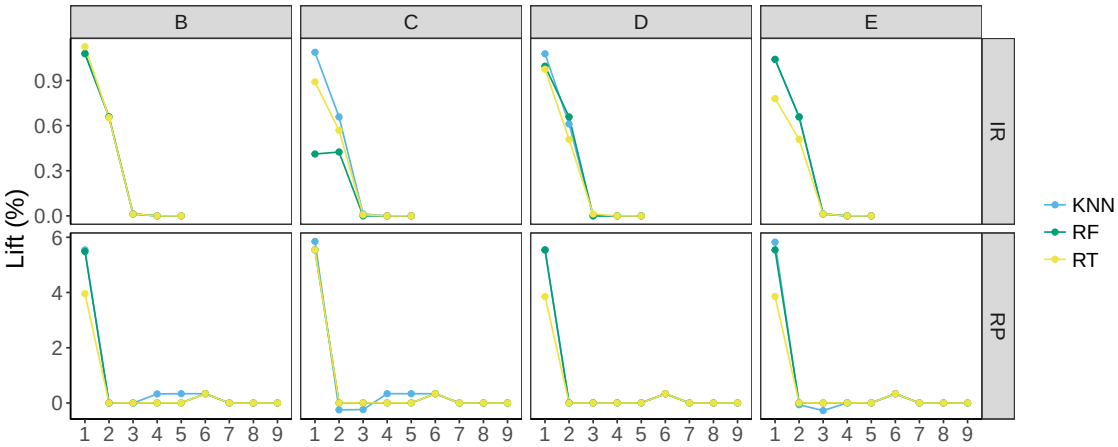
all meta-approaches are able to obtain positive impact. However, the scores obtained depend on the metatarget: AUC, NDCG, NMAE and RMSE usually have positive impact for $t = 1$, $t < 5$, $t < 7$ and $t < 3$. Furthermore, the scores are also different depending on the metatarget: the maximum improvement for AUC, NDCG, NMAE and RMSE is approximately 2%, 0.6%, 0.6% and 10%. These results indicate meta-approaches are particularly effective at finding patterns in all metatargets, with the exception of RMSE. Also, there is no obvious difference between metafeatures. In fact, the differences are given primarily due to the metamodels used and not the representative power of the meta-approach. Overall, KNN performs the best in all metatargets (the only exception is in the RMSE metatarget, where it even achieves negative lift). However, this pattern is more obvious in the proposed metafeatures than in the related work meta-approaches.

5.3.3.2 Multicriteria Metatarget

Figures 5.7a and 5.7b present the percentage lift used to measure the impact on the baselevel performance for metamodels trained using multicriteria metatargets.



(a) Proposed metafeatures.



(b) Related work metafeatures.

Figure 5.7: Impact on the baselevel performance in multicriteria metatargets.

The results show that the performance obtained for all meta-approaches beyond SL are quite similar: the metamodels have positive influence for $t \in \{1,2\}$ and $t = 1$ in IR and RP, respectively. Afterwards, the impact is the same as the baseline. The maximum score achieved is approximately 1% and 6% for IR and RP, respectively. In the case of SL, although the behavior is the same, the performance obtained is lower. This is particularly evident in the IR metatarget. There is a difference, however, in terms of metalearners: while in the proposed metafeatures KNN works best in IR while RT performs best in RP, the related work metafeatures always favor KNN.

5.3.4 Metaknowledge analysis

The analysis shifts now towards metaknowledge analysis, with similar studies as the ones performed in Section 4.4.5: metafeature importance and dataset and baselearner impact analysis.

5.3.4.1 Metafeature importance

Since there is no standard feature importance procedure for Label Ranking, a heuristic strategy is used instead: to traverse all trees in the RFR metamodels, assign all metafeatures with the respective tree level (i.e. its ranking) and average the results per metafeature. This score indicates the metafeature's global ranking, where lower scores are better. Figure 5.8a shows these results.

The results show most RM metafeatures are statistics from the distribution of the number of ratings per item. This behavior is different from what it is found in the best algorithm metatarget, in which only one metafeature of this type was present.

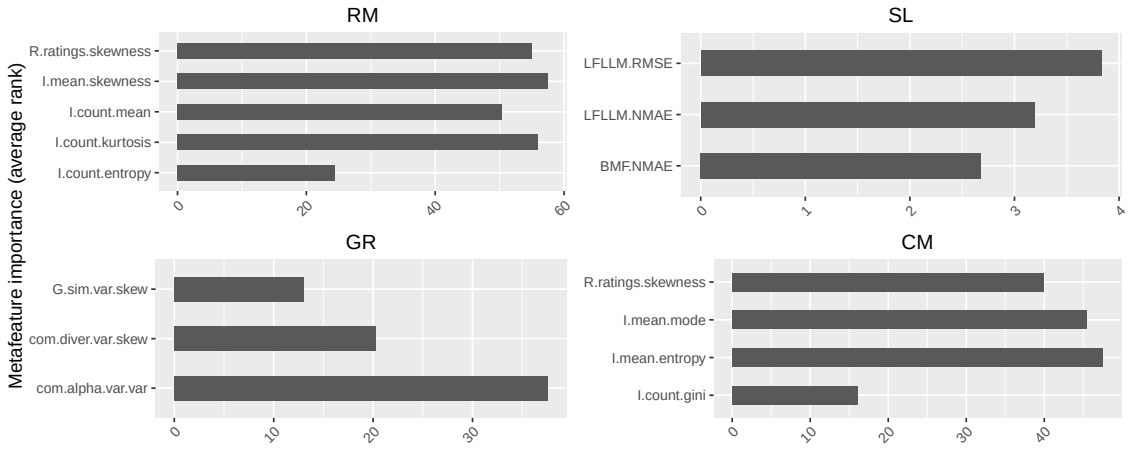
In terms of the SL meta-approach, the best metafeatures belong to RP algorithms. Among these, there is a particular interest in LFLLM's performance since it has 2 out of the 3 most informative metafeatures. However, the most meaningful metafeature overall is BMF.NMAE.

Furthermore, the most important GR metafeatures refer to communities while described by two functions: alpha and diversity. While alpha has been quite important in the best algorithm metatarget contributing with 4 metafeatures, the diversity function was not present. Furthermore, the results show that pairwise and sub-graph levels were the most informative GR metafeatures.

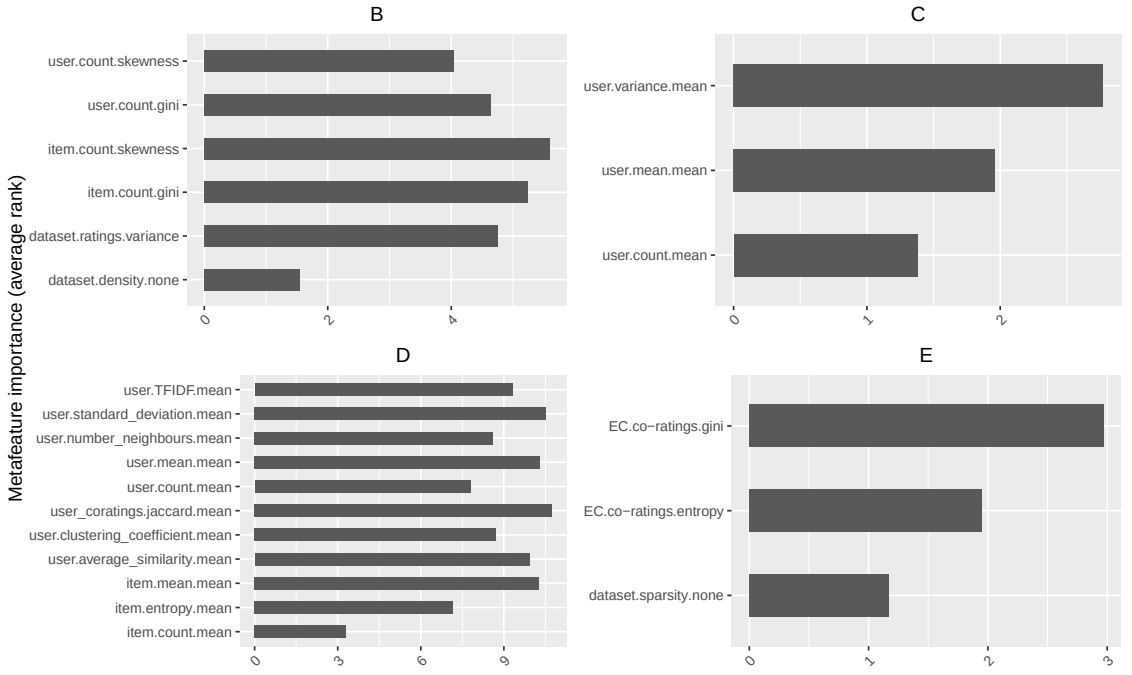
Regarding CM metafeatures, all important metafeatures belong to the RM meta-approach. This behavior has been observed before in the best algorithm metatarget, meaning there is little to be gained by using such metafeatures. Furthermore, the most important CM metafeatures are not the same identified as best in RM, with the exception of *R.ratings.skewness*: now, the mean ratings per item yield 2 metafeatures, while the number of ratings per items appears only once.

Moving now to the related work, meta-approach B now favours *dataset.density.none*. This differs from the results observed on the previous metatarget, with *dataset.ratings.variance* being the best choice. However, *user.count.skewness* ranks second in both problems.

In meta-approach C, the best and worst metafeatures change places whether the metatarget is best algorithm selection or to predict the best ranking of algorithms: now, *user.variance.mean* is more important than *user.count.mean*. The second place is still assigned to *user.mean.mean*.



(a) Proposed metafeatures.



(b) Related work metafeatures.

Figure 5.8: Metafeature importance for LR metamodels using multicriteria metatargets.

Meta-approach D is the one which introduces most changes to the best metafeatures in this setup: *item.count.mean*, followed by *item.entropy.mean* and *user.count.mean*. None of these is among the best metafeatures in the previous metatarget.

Lastly, *dataset.sparsity.none* is still the most informative metafeature in meta-approach E. Then, $EC.co-ratings.entropy$ is better than $EC.co-ratings.gini$ in this metatarget, unlike what happens in the best algorithm metatarget.

One final observation lies in the fact that no metafeature holds the same importance in all meta-approaches. Namely, *user.mean.mean* ranks 2 and 8 in meta-approaches E and D, respectively. This is expected because more metafeatures mean different patterns can be extracted. This

fact indeed makes the metafeature importance analysis volatile, thus inhibiting the definition of metafeatures which are universally good.

5.3.4.2 Dataset Analysis

Now, the metamodel's impact on each baselevel dataset is investigated. The procedure is the same as the one used in Section 4.4.5, but with a difference in the evaluation measure used: now, the results represent Kendall's tau instead of accuracy. Figures 5.9 and 5.10 present the results of such analysis. Notice also that in this setup there are fewer metamodels per meta-approach, thus justifying the less detail in the violin plots created.

The main pattern observed in the best algorithm metatarget still holds in this setup: the predictions for AMZ datasets are usually always correct. However, the performance is not always perfect. This happens due to Kendall's tau nature, which outputs a continuous score in Leave One Out cross validation, unlike accuracy which yields a binary score.

Another difference imposed by the evaluation measure lies in the scale of possible values. Since Kendall's tau lies in the interval $[-1,1]$, then it is possible to have datasets for which the predictions have mostly negative correlation. In this regard all meta-approaches produce negative scores for YH-music, MT-RS14 and ML100k. This shows these datasets are the ones for which is more difficult to find patterns between metafeatures and the current metatargets. However, while TA predictions can be negative using proposed metafeatures, the same does not happen in related work metafeatures.

The results also show the related work metafeatures can attain perfect score in some datasets which the proposed metafeatures cannot: YH-movies, ML10m and BC. The inverse behavior does not occur. However, the difference in the maximum performance obtained is rather small, with multiple proposed metafeatures scoring above 0.9.

Despite these small performance fluctuations, the main pattern observed is the fact that there is little difference between related work and proposed metafeatures. Once again, the differences can be observed mostly on a handful of datasets and usually with small variations in performance. Thus, this analysis concludes that proposed and related work metafeatures are comparable.

5.3.4.3 Baselearner Analysis

The last metaknowledge analysis pertains to the impact of the metafeature representations on the baselearners. To that end, the algorithm footprints procedure (Muñoz et al., 2018; Smith-Miles and Tan, 2012) is adapted to inspect the behavior on the top ranking algorithms. Notice this differs from the previous analysis, where the goal was to establish areas of good and bad performance per baselearner. Now, we shall observe areas where baselearners are ranked in the interval $[1,3]$. Figures 5.11 and 5.12 show the results of this adapted algorithm footprints procedure for the propose and related work metafeatures, respectively. Notice also that datasets which do not assign a ranking in the predefined interval to a specific baselearner are removed in order to facilitate analysis.

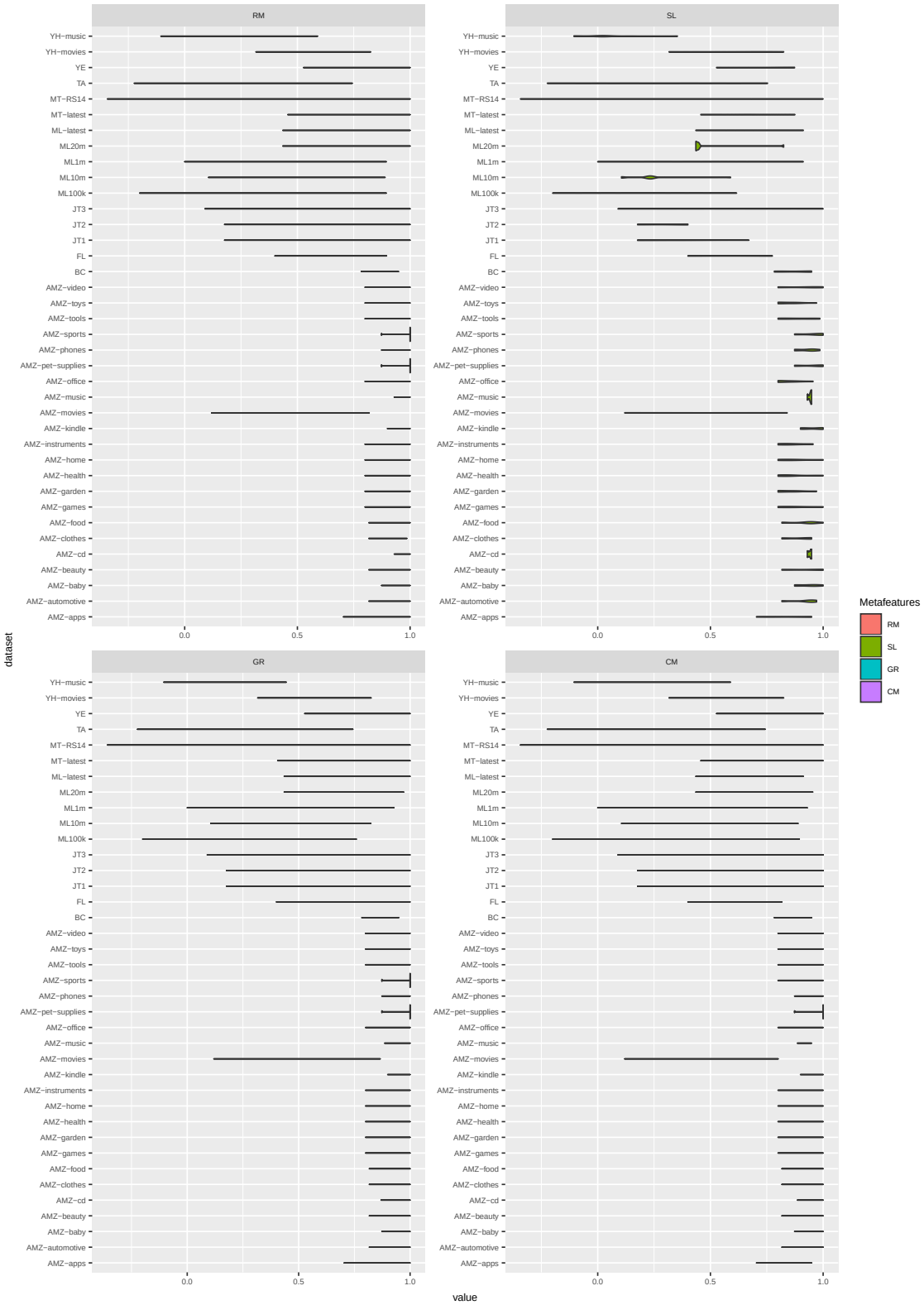


Figure 5.9: Kendall's tau scores per baselevel dataset for proposed metafeatures.

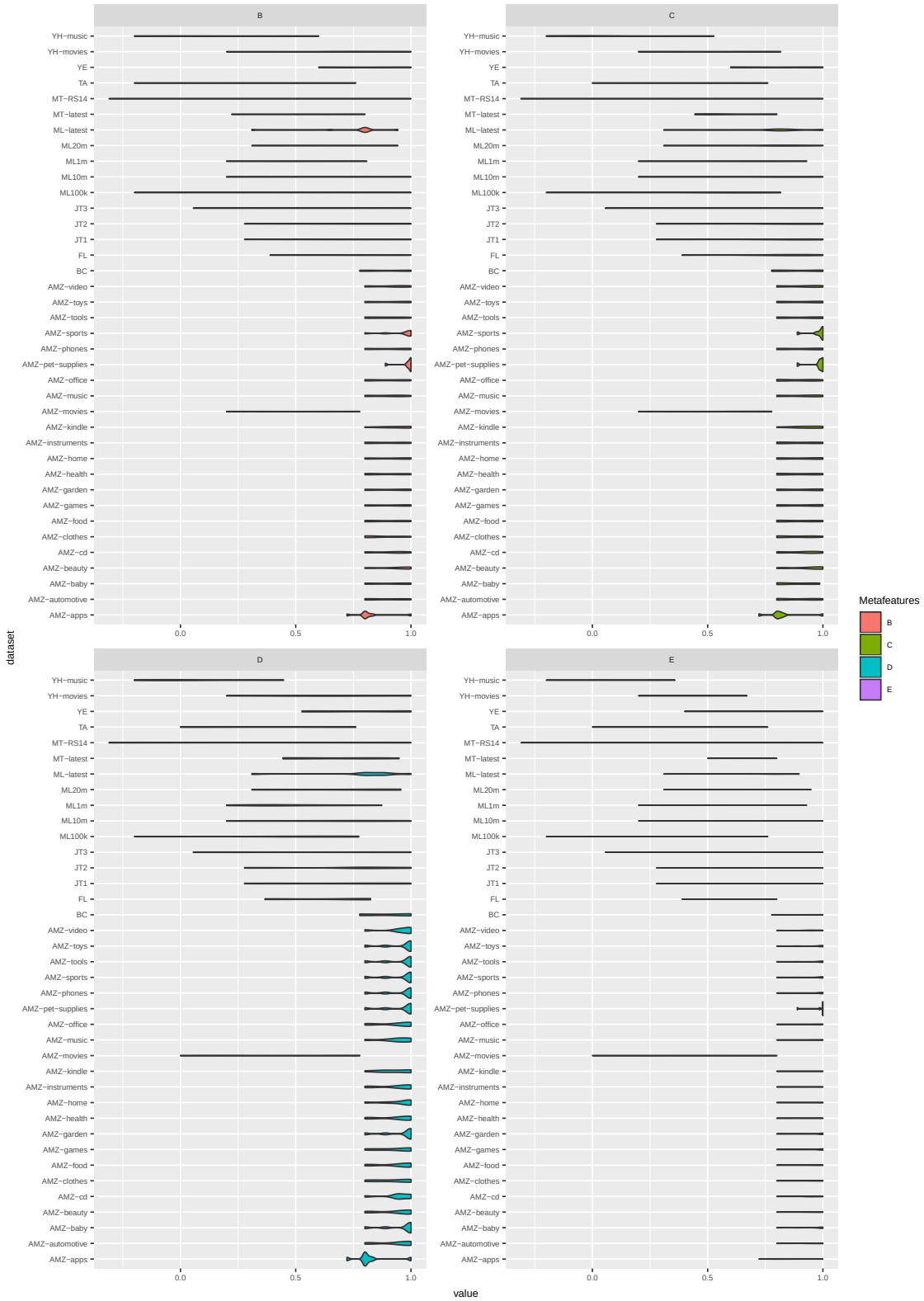


Figure 5.10: Kendall's tau scores per baselevel dataset for related work metafeatures.

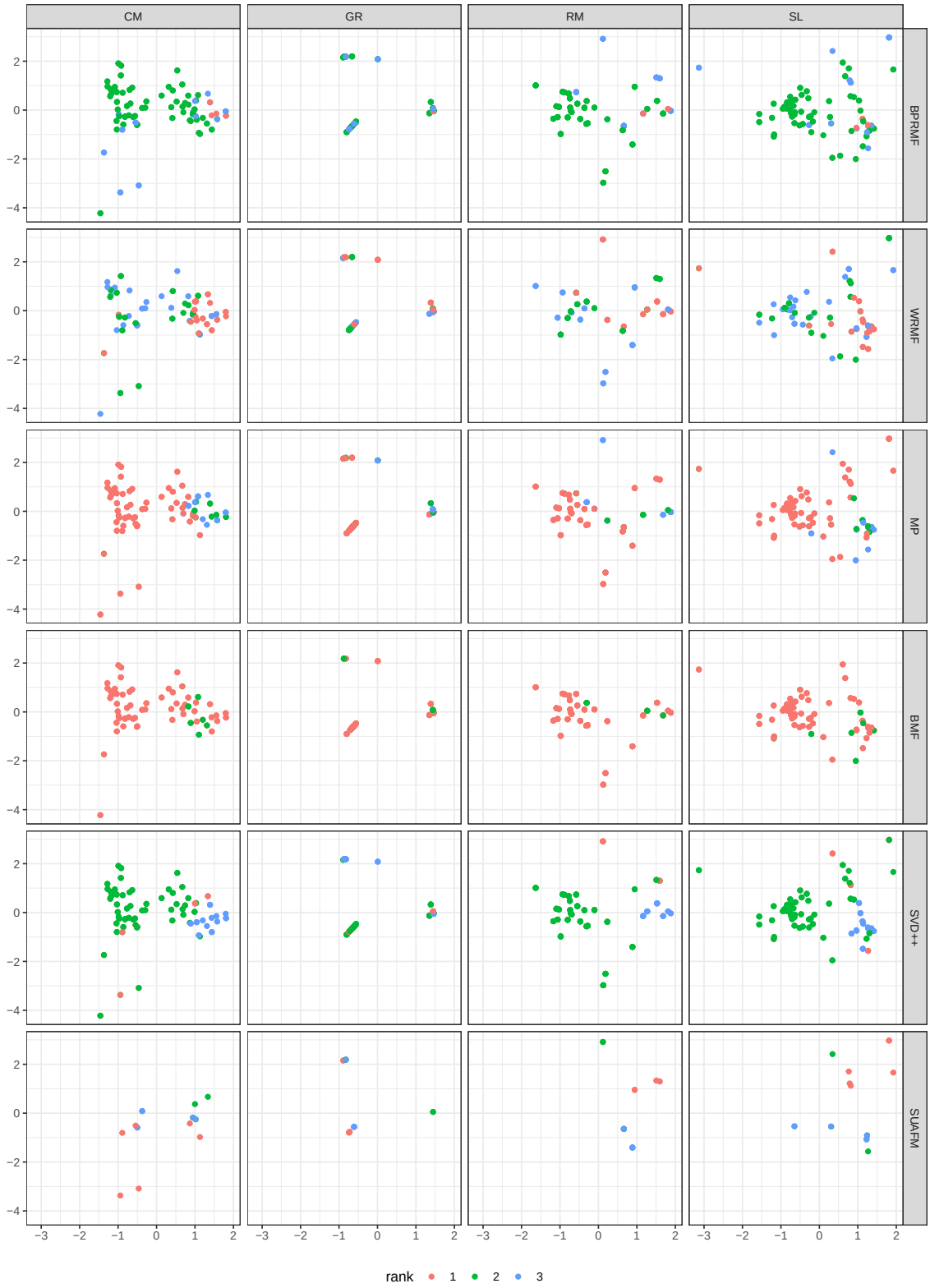


Figure 5.11: Algorithm footprints using rankings for proposed metafeatures.

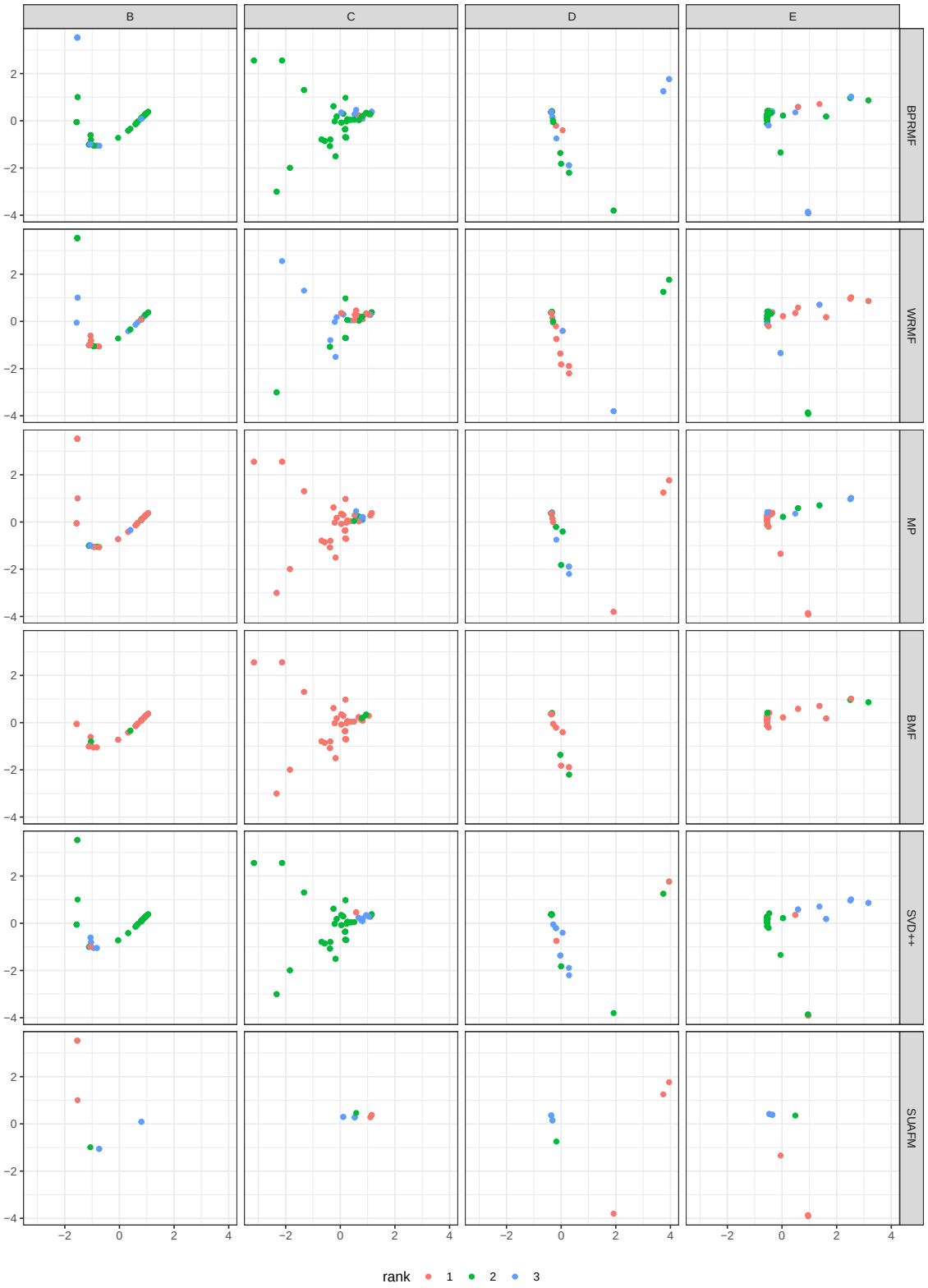


Figure 5.12: Algorithm footprints using rankings for related work metafeatures.

Even before dwelling in details, there is a clear difference to the previous algorithm footprint analysis: this representation does not assign the same the preference regions to all baselearners. Instead, one is able to clearer understand in which areas does one baselearner performs better than other. Thus, the procedure seems better suited to analyze ranking metatargets.

The results for the proposed metafeatures show an interesting result: some algorithms, from different CF tasks, have similar representations. This representation has in common the ranking assigned to the same datasets: while MP and BMF have a similar representation regarding rank 1, BPRMF and SVD++ follow suit but for rank 2. This means that there is a strong relationship between each pair of algorithms for the same datasets at the top positions in each metatarget. Another pattern is that the figures complement one another. Notice how the datasets which yield a rank 1 to MP, also assign a rank 2 to BPRMF.

Furthermore, the results show that all proposed meta-approaches are effective at discerning between the top three positions in the rankings. This differs from the previous analysis where GR yielded confusing results. In this regard, the related metafeatures create less obvious representations, even if in most occurrences there are clear patterns. However, this is mainly due to the fact that points are more concentrated than in the proposed metafeatures, thus preventing to extract more meaningful observations.

As a final note, please consider this analysis is made with regards to each baselearner. Since the metamodels consider more complex and complete metatargets, it is expected the patterns will not be as clearer. The purpose of this analysis is therefore to understand partial patterns which may help understand for which baselearners it may easier to discern metafeature impact on their ranking prediction.

5.4 Conclusions

This Chapter presented a novel way to address CF algorithm selection, where rankings of algorithms are used as metatargets in Label Ranking metamodels. Furthermore, the rankings of algorithms are manipulated through a multicriteria procedure, which creates rankings of algorithms that consider multiple evaluation measures. All perspectives of the problem have been extensively validated, using 8 different sets of metafeatures in conjunction with the standard analysis used so far: metalevel accuracy, impact on the baselevel performance and metaknowledge analysis.

The results show Label Ranking metamodels are suitable to tackle the CF algorithm selection problem. The results have been particularly stable for the KNN algorithm in all meta-approaches and metatargets. Furthermore, these metamodels have been effective at solving two issues from previous experiments, namely class imbalance and limited metaknowledge from not considering all baselearners in the metatargets. For this reason, LR metamodels are now the baseline to beat and shall be compared against in the following Chapters. Also, even though the issue is not approached in this thesis, Learn to rank algorithms directly defined to optimize for ranking accuracy measures could be investigated, given their merits on ranking problems Burges (2010); Nguyen et al. (2016).

Regarding multicriteria metatargets, the results have shown all metamodels assessed using these metatargets yield comparable performances to single criterion metatargets. The small fluctuation in results is justified by the fact that the metatargets are actually highly correlated. On one hand, this impedes further analysis regarding the merits of the proposed approach. On the other, it reduces the effort required to analyze the MtL process. Further investigations are required, particularly using other evaluation scopes.

Furthermore, the results have shown that all metafeatures beyond SL are all comparable in both single criterion and multicriteria metatargets, with no statistically significant differences. Also, other metaknowledge analysis have clarified that there is no obvious difference in their merits. Although, this disproves the belief that the proposed metafeatures would be more informative, the fact is that proposed metafeatures are meaningful, even when considering ranking metatargets. Thus, we shall use this set of metafeatures exclusively in future experiments.

Moving forward, even though the solutions presented are already suitable for CF algorithm selection, there are multiple issues which can still be improved. However, considering the efforts employed so far in terms of metafeatures and metatargets, one argues that the improvement must be achieved in another scope of the algorithm selection problem: the metalearners. This way, the next Chapter introduces two types of metamodels: CF4CF and CF4CF-META. While the first does not use any metafeatures at model fitting, the latter attempts to combine the merits of metafeatures and the previous metamodel.

Chapter 6

Recommending Recommenders

Although several successful approaches to CF algorithm selection have been presented, the results have yielded comparable performances for all metafeatures considered. This behavior, accompanied by the fact that it is difficult to understand what the metafeatures actually mean, may lead to suspicions regarding their predictive power. Therefore, it is essential to understand whether they bear information or if their predictive power comes from noise or chance. To address this issue, two different algorithm selection approaches are proposed, which attempt to verify whether metafeatures are actually important. The goal is to draw conclusions regarding the merits of metafeatures by analyzing metamodel performance. The proposed metalearners are:

- **CF4CF**: this approach focusses on the premise that an algorithm selection solution is essentially a recommendation model. Thus, any recommendation algorithm can theoretically be used to tackle the issue. Therefore, this work proposes CF4CF, a technique which uses CF algorithms to select the best ranking of CF algorithms for a new problem. It does so by taking into account only the algorithm performance (either of the entire dataset or a sample of it - i.e. using subsampling landmarkers). Therefore, this is the only approach known to date which disregards entirely standard metafeatures. Section 6.1 presents the method.

- **CF4CF-META**: This approach builds on the good results obtained by the LR approach presented in Chapter 5 by including algorithmic and metadata changes proposed in CF4CF. The goal is to capitalize on the integration of both approaches in a unified algorithm selection framework in order to attempt to improve the predictive performance. Particularly, the process uses metafeatures from LR and ratings from CF4CF and modifies the LR procedure to deal with partial rankings at prediction time. This way, not only is it possible to answer whether metafeatures from LR are informative but also what is the impact of the ratings used in CF4CF. Section 6.2 presents the proposed method.

This Chapter provides extensive evaluation analysis in order to objectively compare all proposed approaches. The evaluation procedure discussed in Section 6.3 performs the standard evaluation methodologies, namely: metalevel accuracy, impact on the baselevel performance and meta-knowledge analysis. Lastly, Section 6.4 presents the conclusions found.

6.1 CF4CF

The proposal to address CF algorithm selection without explicitly using metafeatures in model fitting is introduced now: CF4CF. To do so, the nomenclature from Section 5.1 is re-used in Table 6.1. Notice that $F = F' \cup F''$, meaning that metafeatures from both dataset and algorithm approaches can be used. They are differentiated here since it helps in clarifying the methods proposed.

Table 6.1: Mapping between Rice's framework and CF4CF and CF4CF-META.

Sets	Description	This setup	Notation
P	instances	CF datasets	$d_i, i \in \{1,\ldots,\lvert P\rvert\}$
A	algorithms	CF algorithms	$a_j, j \in \{1,\ldots,\lvert A\rvert\}$
Y	performance	CF evaluation measures	$m_k, k \in \{1,\ldots,\lvert Y\rvert\}$
F'	CF metafeatures	Systematic metafeatures	$mf_l, l \in \{1,\ldots,\lvert F'\rvert\}$
F''	algorithm characteristics	Subsampling landmarkers	$sl_m, m \in \{1,\ldots,\lvert A\rvert \times \lvert Y\rvert\}$

CF4CF is a method which allows to use any CF algorithm as the metamodel. To do so, it draws a parallelism from standard CF recommendation and MtL: users and items can be represented by datasets and algorithms, respectively. This way, the problem can be formulated as a rating matrix R, where each dataset $d_i \in P$ and the set of algorithms A where each algorithm $a_j \in A$ refer to the rows and columns, respectively. Afterwards, algorithm performance is used to serve as ratings and therefore complete the matrix. This representation is illustrated in Figure 6.1 and is organized into training and prediction steps (top, bottom). The prediction stage shows the subsampling landmarkers ε_{sl} and predicted ratings $\hat{\varepsilon}$.

d	a_1	a_2	a_3	$\ldots$	$a_{\lvert A\rvert-1}$	$a_{\lvert A\rvert}$
d_1	ε_1	ε_2	ε_3	$\ldots$	$\varepsilon_{\lvert A\rvert-1}$	$\varepsilon_{\lvert A\rvert}$
$\vdots$	$\vdots$	$\ddots$	$\ddots$	$\ddots$	$\ddots$	$\vdots$
$d_{\lvert P\rvert}$	$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$
d_α	$\hat{\varepsilon}_{sl1}$	$\ldots$	$\hat{\varepsilon}_{slN}$	$\hat{\varepsilon}_1$	$\ldots$	$\hat{\varepsilon}_{\lvert A\rvert}$

Figure 6.1: CF4CF metadatabase.

Notice that unlike in standard MtL approaches, no metafeatures are used here. Instead, CF4CF uses the rankings of algorithms π for every dataset d_i. Essentially, this algorithm uses only the metatargets form previous LR metamodels as the sole data source to address algorithm selection. However, in order to fit a standard CF algorithm and because ratings have the ability to provide different degrees of preference to each element, the procedure converts such rankings π into ratings

ε by a custom linear transformation *rat*. Formally, to convert the ranking π into a specific ratings scale $S \in [s_{min}, s_{max}]$, the transformation *rat* is applied to each ranking position $l \in \{1, \ldots, |A|\}$:

$$rat(\pi, l) = \frac{(S_{max} - S_{min})(|A| - l)}{|A| - 1} + S_{min} \tag{6.1}$$

This transformation is a combination of an inverse function (to state that high ratings must be assigned to the algorithm of lower ranking value) and a linear re-scaling function (to adapt the ordered values to a specific ratings scale). Thus, every dataset d_i is now described as a ratings vector $\varepsilon = \big(rat(\pi_l)\big)_{l=1}^{|A|}$. The aggregation of all ratings for all datasets produces the CF4CF's rating matrix. Next, a CF algorithm is used to train the metamodel.

The prediction requires initial ratings to be provided to the CF model. However, it is reasonable to assume that no performance estimations exist for any algorithm at prediction time. Hence, CF4CF leverages subsampling landmarkers, a performance-based metafeature to obtain initial data. This way, CF4CF provides N_{SL} subsampling landmarkers to create the initial dataset representation and therefore allow the CF model to predict the remaining $|A| - N_{SL}$ ratings. Hence, a subset of landmarkers $(sl_m)_{m=1}^{N_{SL}}$ for dataset d_α are converted into the partial ranking π'. Such ranking is posteriorly converted into ratings also using the linear transformation *rat*. Thus, the initial ratings are now given by $\hat{\varepsilon_{sl}} = \big(rat(\pi'_n)\big)_{n=1}^{N_{SL}}$. Providing these $\hat{\varepsilon_{sl}}$ ratings, the CF metamodel is able to predict the missing $\hat{\varepsilon}$ ratings for the remaining algorithms. Considering now the entire set of ratings $r(d_\alpha) = \hat{\varepsilon}_{sl} \cup \hat{\varepsilon}$, the final predicted ranking $\hat{\pi}$ is created by decreasingly sorting $r(d_\alpha)$ and assigning the ranking positions to the respective algorithms a_j.

6.2 CF4CF-META

CF4CF-META is a hybrid framework which aims to combine both data and algorithmic approaches from CF4CF and LR metamodels. It is described in Figure 6.2, with datasets d_i represented by a union of both types of metafeatures (regular mf_l and subsampling landmarkers as ratings sl_m) and associated with rankings of algorithms a_j. The process is modeled as a Label Ranking task, similarly to the procedure discussed in Chapter 5. However, the prediction stage is modified to fit CF4CF's ability to deal with incomplete data. Thus, the process is organized into training and prediction stages (top, bottom) and independent and dependent variables (left, right).

d	mf_1	…	$mf_{\|F\|}$	sl_1	…	…	$sl_{\|A\|}$
d_1	ω_1	…	$\omega_{\|F\|}$	ε_1	…	…	$\varepsilon_{\|A\|}$
⋮	⋮	⋱	⋮	⋮	⋱	⋱	⋮
$d_{\|P\|}$	…	…	…	…	…	…	…
d_α	$\hat{\omega}_1$	…	$\hat{\omega}_{\|F\|}$	$\hat{\varepsilon_{sl}}_1$	…	$\hat{\varepsilon_{sl}}_N$	∅

a_1	…	$a_{\|A\|}$
π_1	…	$\pi_{\|A\|}$
⋮	⋱	⋮
…	…	…
$\hat{\pi}_1$	…	$\hat{\pi}_{\|A\|}$

Figure 6.2: CF4CF-META metadatabase.

To build the new metadatabase, every dataset d_i is submitted to a metafeature extraction process, yielding a vector of metafeatures $\omega = mf(d_i)$. Next, the subsampling landmarkers sl_m are converted into ratings and leveraged as the remaining metafeatures. Notice, however, that although this characterization is similar to CF4CF's, there is a major difference: while in CF4CF the ratings from the original performance were used as training data, here one is bound to use ratings from subsampling landmarkers. Otherwise, one would be using ratings created from the original algorithm performance to predict the rankings also obtained from the original algorithm performance, which would be an invalid procedure. Thus, the ratings definition considers the ranking of algorithms π' created from all available sl_m to obtain the ratings $\varepsilon = \left(rat(\pi'_n)\right)_{n=1}^{|A|}$. The independent variables of the algorithm selection problem are now represented as $F = \omega \cup \varepsilon$. To create the dependent variables, each dataset d_i is associated with the respective ranking of algorithms π, similarly to MtL. A standard Label Ranking algorithm is then used to train the metamodel.

In the prediction stage, the new dataset d_α is first submitted to the metafeature extraction process, yielding metafeatures $\hat{\omega} = mf(d_\alpha)$. Next, like in CF4CF, N_{SL} subsampling landmarkers are used to create the initial data. Although CF4CF-META allows to use all subsampling landmarkers, it is important to provide a procedure that allows to calculate fewer landmarkers. This is mostly due to the significant cost in calculating this type of metafeatures, which CF4CF-META's aims to reduce without compromising predictive performance.

Formally, consider a set of landmarkers $(sl_m)_{m=1}^{N}$ for dataset d_α and its respective partial ranking π'. With it, it is possible to obtain the initial ratings $\hat{\varepsilon_{sl}} = \left(rat(\pi'_n)\right)_{n=1}^{N}$. Unlike in CF4CF, no ratings are predicted for the missing values. However, this is not a problem, since CF4CF-META is able to work with missing values (these are represented in Figure 6.2 by $\varnothing$). Aggregating now the metafeatures $mf(d_\alpha) = \omega \cup \varepsilon \cup \varnothing$, one is able to predict $\hat{\pi}$.

6.3 Results

Now, the proposed approaches are validated and compared to some related work competitors. The evaluation procedure involves metalevel accuracy, impact on the baselevel performance and metaknowledge analysis, similarly to what has been done in previous Chapters. However, in this scope a new evaluation perspective is introduced: Top-*N* evaluation, which uses NDCG to evaluate the top of the rankings of algorithms predicted.

6.3.1 Experimental setup

The experimental setup used here is divided in two levels, much like in previous Chapters: baselevel (it remains the same as the one presented in Section 3.2.2) and metalevel. The metalevel used is an extension of the one presented in Section 5.3.1 in the sense that it maintains the usage of multicriteria metatargets and the metalevel evaluation procedure. However, now there are several meta-approaches used, which differ in the algorithms and metadata used. Please notice that the related work metafeatures identified in Chapter 3 are not considered in this setup. The reasons are two-fold: 1) they have performed equally well as the metafeatures proposed in Chapter 4 and

2) one aims to reduce the complexity of results to be analyzed and feel that such analysis has been covered in previous experiments. Having said this, the total set of meta-approaches considered include the proposed approaches and 3 baseline meta-approaches (LR, ALORS and ASLIB):

- **CF4CF** It is analyzed in two variations, given by the CF algorithm used: ALS or UBCF.
- **CF4CF-META** This proposal is analyzed in terms of multiple perspectives: algorithms (i.e. KNN, RT and RFR) and metadata (i.e. RM, GR and CM).
- **LR** This baseline is the one proposed in Chapter 5. All metafeatures (RM, SL, GR and CM) and all meta-algorithms (KNN, RT and RFR) are considered.
- **ALORS** The method introduced by (Mısır and Sebag, 2017) is an algorithm selection approach which uses CF algorithms as metamodels (see Section 2.3). Since the original source code was not available, this work has implemented the solution as similar as possible. Thus, the regression and MF algorithms selected are the Multivariate Random Forest and ALS, respectively. The metafeatures used are RM, SL, GR and CM.
- **ASLIB** The final baseline refers to a general purpose algorithm selection framework (Bischl et al., 2015). This framework is able to address multiple algorithm selection tasks, namely to predict the performance of all algorithms or the best algorithm only, respectively. Thus, it employs standard regression and classification algorithms to do so. However, it does not offer any direct solution to predict rankings of algorithms. The standard procedure is modified by using the regression approach to learn the mappings between metafeatures and targets and posteriorly rank the algorithms according to the scores predicted. This approach is evaluated for multiple metafeatures (RM, SL, GR and CM) and uses the following algorithms from the MLR package (Bischl et al., 2016): Generalized Linear Regression Model (LM), XGBOOST, SVM, Regularized Random Forests (RRF), RPART and RKNN.

The extensive list of results for all variations proposed are listed in Appendix D. The results are presented independently per approach in all evaluation perspectives considered. However, to simplify the readability, only the best solution for each approach is considered as its representative: CF4CF (using ALS), CF4CF-META (KNN with RM metafeatures), LR (RFR with CM metafeatures), ALORS (with CM metafeatures) and ASLIB (RKNN with CM metafeatures).

Lastly, please notice the results presented can be reproduced by accessing the repository `https://github.com/tiagodscunha/cf4cf`.

6.3.2 Meta-accuracy

Meta-accuracy in terms of Kendall's Tau coefficient are analyzed here in two perspectives: first, one aims to understand the effect that the amount of subsampling landmarkers (N_{SL}) holds in both CF4CF and CF4CF-META. Thus, a threshold sensitivity analysis is conducted. Afterwards, all meta-approaches are compared in a similar fashion to what has been done in previous Chapters. Notice that in the latter case, the meta-approaches considered use their best settings.

6.3.2.1 Threshold Sensitivity

The threshold sensitivity analysis results for CF4CF and CF4CF-META are presented in Figures 6.3 and 6.4, respectively. The results present the Kendall's Tau performance for all N_{SL} considered in each metatarget. Recall that $1 \leq N_{SL} \leq |A| - 1$. Furthermore, the baseline is also included to facilitate the analysis.

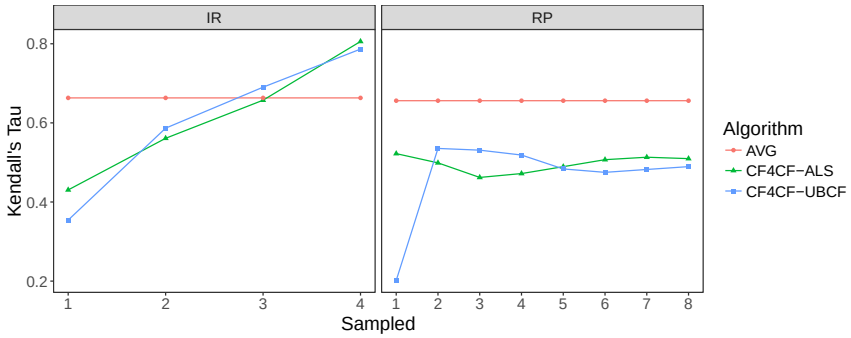


Figure 6.3: CF4CF threshold sensitivity analysis.

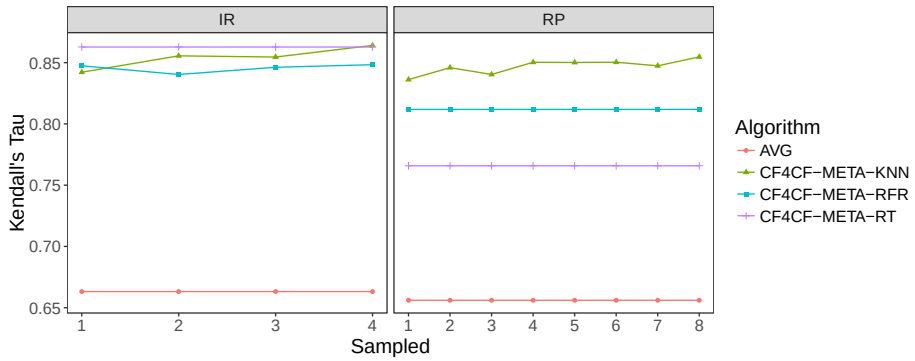


Figure 6.4: CF4CF-META threshold sensitivity analysis.

The results show CF4CF works on IR but not in RP, since it is only able to beat the baseline for $N_{SL} = 4$. However, since it performs poorly otherwise, it shows an inconsistent behavior. On the other hand, CF4CF-META works very well on both metatargets will all metamodels outperforming the baseline in all threshold N_{SL}. More importantly, CF4CF-META works better than CF4CF even for $N_{SL} = 1$. This means that the combination of metafeatures and ratings has positive impact, thus indicating the existence of information in both representations.

In terms of CF4CF metalearners, UBCF and ALS performance is quite similar. This happens in most threshold N_{SL}, although in the best case scenario ALS has a slight advantage. In CF4CF-META's case, the advantage leans towards RT and RFR in IR and RP, respectively. However, KNN is the only metalearner for which the amount of SL has a positive impact. This means only metalearners which use distance-based heuristics are able to capture meaningful relationships from the subsampling landmarkers provided.

Overall, the best performance results throughout are achieved with the maximum amount of subsampling landmarkers. The results show that this has a greater importance in CF4CF than in CF4CF-META. This is another indication that metafeatures are informative.

6.3.2.2 Comparison to related work

Now, the focus lies on the Kendall's tau performance for all meta-approaches considered. The results are presented in Figure 6.5 for all meta-approaches selected.

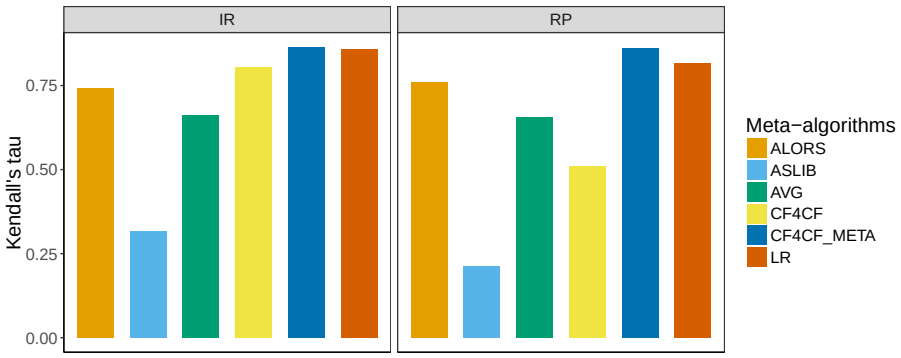


Figure 6.5: Kendall's tau for all meta-approaches.

The results show only three meta-approaches beat the baseline in both metatargets: ALORS, CF4CF-META AND LR. On the other hand, CF4CF only performs well in IR, while ASLIB is worse than the baseline in both metatargets. The first results can be explained by the fact that ratings are not always enough by themselves. As for the ASLIB results, it clearly shows that the adaptation of a regression approach to predict rankings of algorithms is not a suitable approach.

The results clearly show that the best meta-approaches are CF4CF-META and LR, although there seems to be very small differences between them. In order to validate these observations, the statistical validation test used in Section 5.3.2.3 is re-used. The corresponding CD diagram is presented in Figure 6.6.

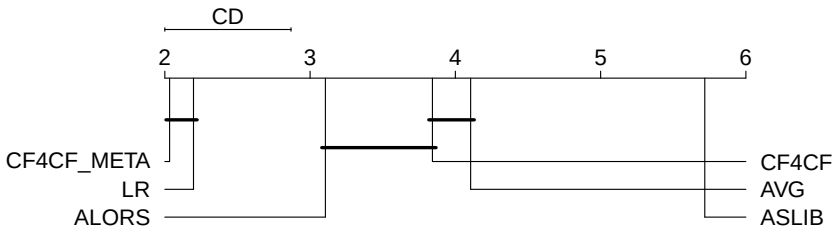


Figure 6.6: Critical Difference diagram.

The analysis confirms the observations, since there is no statistically significant difference between CF4CF-META and LR. Furthermore, ALORS is proven to be better than the baseline, while ASLIB performs much worse. Lastly, there is no significant difference between CF4CF and the baseline.

6.3.3 Top-N Metalevel Accuracy

Notice also that the metalevel evaluation considers now an extra evaluation step: Top-N evaluation. This aims to evaluate how good are the top N positions in the ranking instead of considering the complete ranking of algorithms. The rationale is simple: since the algorithms in the top positions are the most interesting, it is important to assess how well do the metamodels perform in this task. Thus, NDCG is employed to evaluate the predictions of metamodels. Notice that N has different values depending on the metatarget chosen, i.e. $N = \{1,2,3\}$ and $N = \{1,3,5\}$ for the IR and RP metatargets, respectively. This decision is justified by the fact that IR and RP have a different amount of algorithms in the rankings, namely 5 and 9 respectively. Thus, such thresholds were selected since they represent algorithms in the interval between the best ($N = 1$) and mean performances ($N = 3$ or $N = 5$).

Now, the focus lies on analyzing how good are the metamodels considering only the top positions in the predicted rankings of algorithms. To do so, Figures 6.7 and 6.8 presents the NDCG results for all the meta-approaches considered in the IR and RP metatargets, respectively.

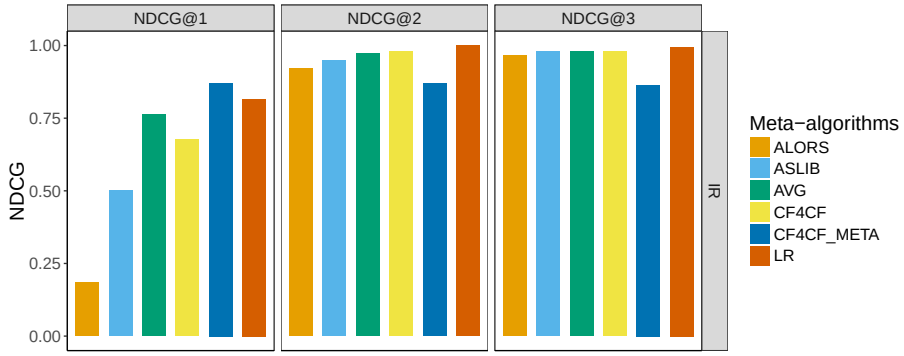


Figure 6.7: NDCG metalevel evaluation in the Item Recommendation problem.

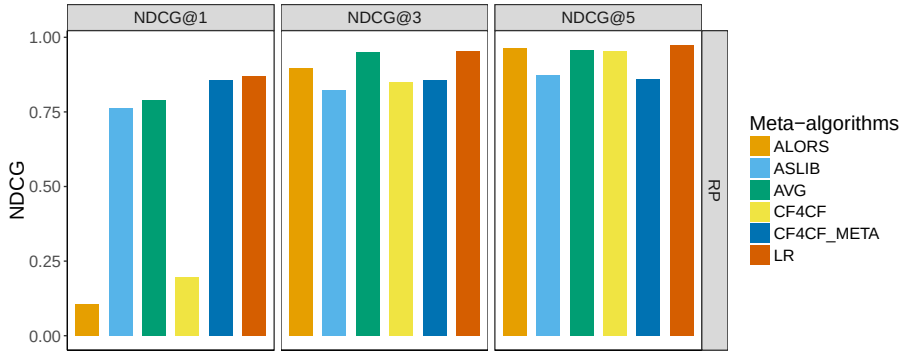


Figure 6.8: NDCG metalevel evaluation in the Rating Prediction problem.

The results show that ASLIB is never able to beat the baseline and that overall CF4CF and ALORS perform poorly, although there are some cases where they marginally beat the baseline. These are important results which mean that their ability to predict the top positions in the ranking is poor or quite similar to the baseline's.

Furthermore, the results also show CF4CF-META works well in terms of NDCG. Unfortunately, it does so only for $N = 1$, while performing worse than the baseline for the remaining thresholds selected. This means that the proposed approach is best suited to select the absolute best algorithm and not necessarily the remaining algorithms in the top positions. Lastly, the results show that LR is the only meta-approach to systematically beat the baseline, even if it doesn't always achieve the best performance. Thus, in this evaluation scope, it is clearly the best approach.

6.3.4 Impact on the baselevel performance

The next analysis is about the impact on the baselevel performance. To do so, the procedure explained in Section 5.3.3 is replicated. The results for this experimental setup are displayed in Figure 6.9.

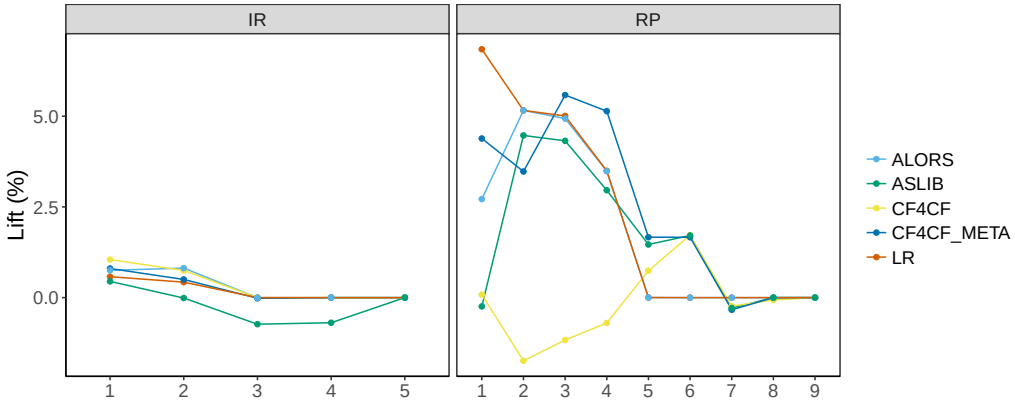


Figure 6.9: Impact on the baselevel performance.

According to the results, most meta-approaches prove useful for $t \in \{1,2\}$ and $t \leq 6$ for IR and RP, respectively. Among these, LR and CF4CF-META perform quite well and reach a maximum improvement of approximately 1% and 7% in IR and RP, respectively. However, the results also show that ASLIB and CF4CF perform quite poorly since they achieve negative lift for most thresholds for IR and RP, respectively. ALORS performs well in both metatargets, but without ever standing out.

6.3.5 Metaknowledge analysis

The current metaknowledge analysis procedures focuses on two issues: metafeature importance and dataset impact analysis. Here, the baselearner impact analysis using algorithm footprints is not investigated since such results are only dependent on the metafeatures and metatargets. Since this Chapter focus entirely on the metalearners, there are no new results to be obtained.

6.3.5.1 Metafeature importance

To perform the analysis regarding metafeature importance, the process used in Section 5.3.4 is reused. Notice that CF4CF-META is used with a RFR metamodel, which takes advantage of both

CM metafeatures and the performance ratings. This has been chosen taking into account the best settings found in previous experiments. Figure 6.10 presents the results of such analysis.

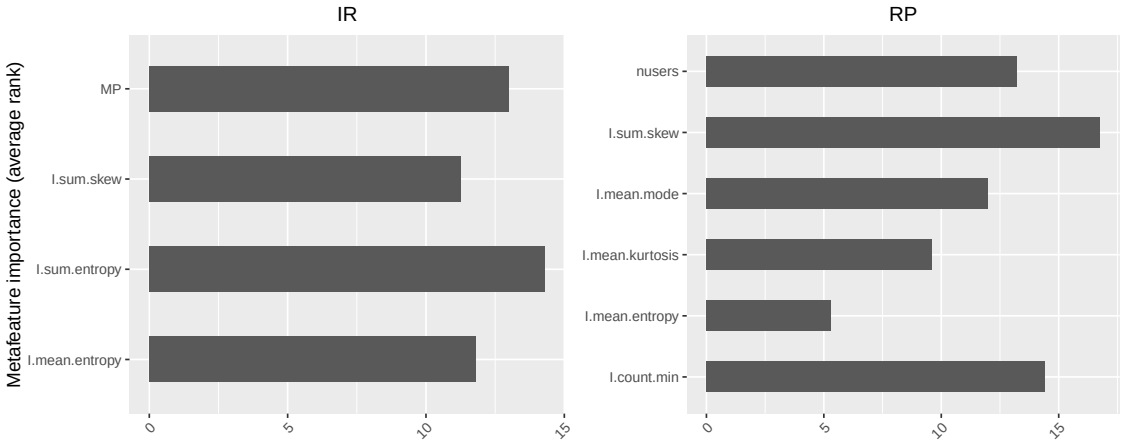


Figure 6.10: Metafeature importance for CF4CF-META metamodels.

The results show that there is no rating-based metafeature in the top metafeatures selected for Rating Prediction, while in Item Recommendation MP ratings are the third best metafeature. This means that rating data is more important to Item Recommendation, while CM metafeatures perform better in Rating Prediction. However, even in this case, no similarities could be found in terms of metafeatures when comparing to CF4CF-META's results without using ratings metafeatures. This points to the observation that ratings actually have influence in the process, changing the patterns that are found within the metamodel.

6.3.5.2 Dataset analysis

This analysis mimics the ones used so far to understand the influence of metafeatures on baselevel datasets through metamodel performance. However, since the focus of this Chapter lies with the MtL frameworks, then the results are aggregated differently. In essence, the results contain the performances for all metalearners trained on all metafeatures and metatargets considered, aggregated by MtL framework. The results are presented in Figure 6.11.

The results show CF4CF-META and LR have similar patterns, with a higher skew towards perfect scores. This is explained by the usage of LR metamodels in both approaches. ALORS appears next with an approximate behavior to the previous frameworks, although with fewer perfect performances. On the other hand, in some datasets the performances have less variation, showing consistency.

CF4CF provides lower average performances than LR, CF4CF-META and ALORS. Its results are more unstable, as shown by the skew of the violin plots. However, it still performs better than ASLIB. This behavior is clear when one considers three observations: there is higher variations of results, the mean Kendall's tau lies near zero and it is the MtL framework with more scores near -1 (i.e. imperfect score).

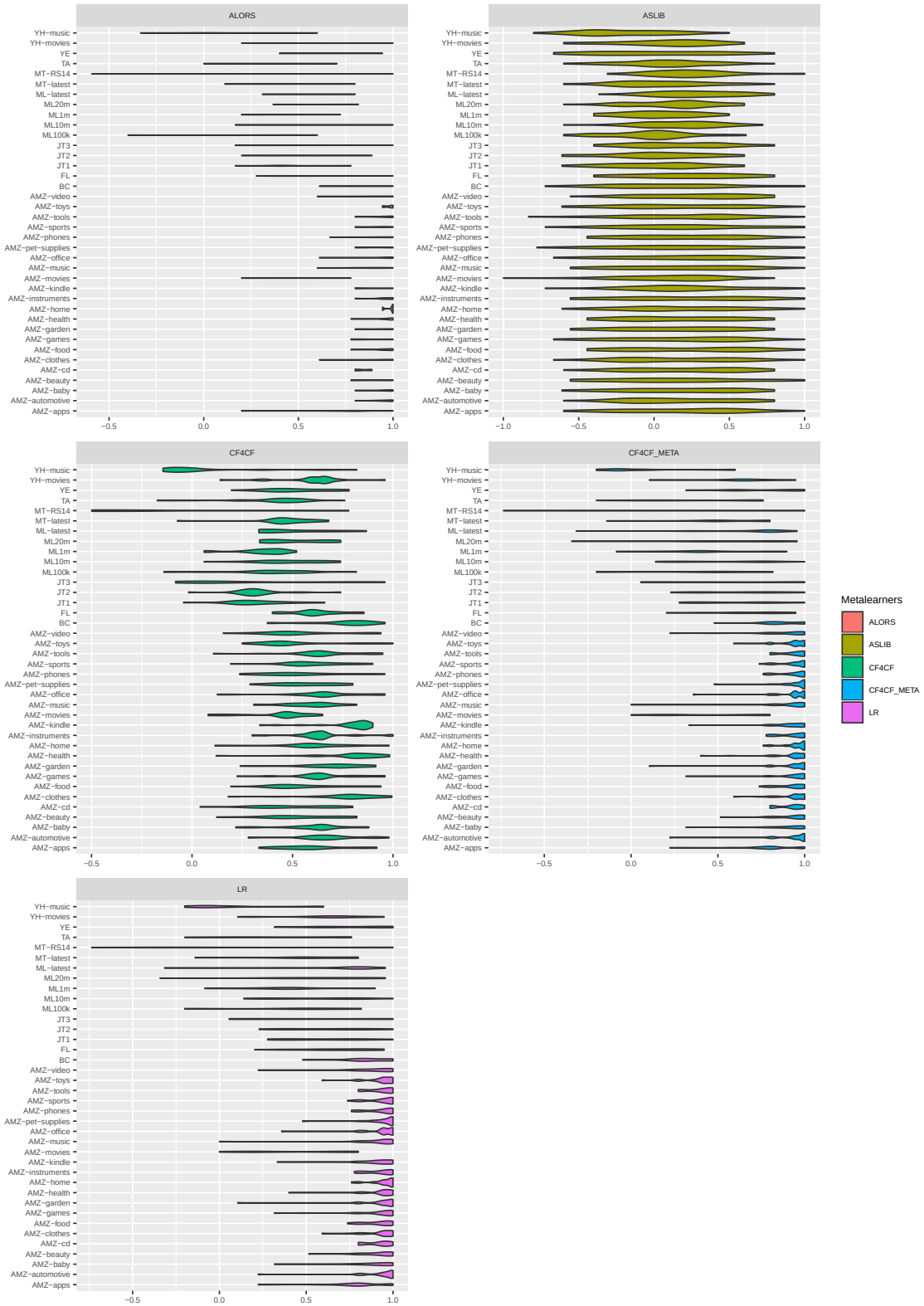


Figure 6.11: Kendall's tau scores per baselevel dataset for all metalearners proposed.

6.4 Conclusions

This Chapter introduced two novel CF algorithm selection frameworks: CF4CF and CF4CF-META. Their main difference lies in the metafeatures used for model fitting and which is the algorithm selected to induce the metamodel: CF4CF uses only algorithm performance as ratings and subsampling landmarkers in a customized CF algorithm, while CF4CF-META leverages standard metafeatures and the algorithm performance as ratings from CF4CF in a LR metamodel.

An extensive experimental analysis has been performed and in which three baselines have been included: the previously proposed LR metamodels, ALORS and the generic algorithm selection framework ASLIB. The results have shown that CF4CF has informative power, especially in the Item Recommendation problem. Thus, it was shown that it is possible to perform algorithm selection without metafeatures. However, it also shows inconsistent results, since it does perform poorly in multiple evaluation scopes. Thus, this behavior puts into question whether using only the ratings from algorithm performance is enough.

CF4CF-META, however, has proved itself consistent throughout the several evaluation analysis, especially in terms of the top position of the ranking. Furthermore, CF4CF-META solves a critical problem in CF4CF, by performing better when using a reduced amount of subsampling landmarkers used at prediction time. Thus, although the primary motivation for the proposal of these approaches has been regarding the investigation of the merits of metafeatures in CF algorithm selection, it is now known that CF4CF-META is the best solution to the CF algorithm selection problem.

Regarding the baselines, the results also show that LR still maintains itself as an excellent solution, even beating CF4CF-META in multiple occasions. In fact, statistical validation has shown that there is no significant difference between them in terms of Kendall's tau. Furthermore, although ALORS works well in all evaluation scopes, it rarely does so as well as LR and CF4CF-META. However, ASLIB performs poorly in all evaluation scopes selected. Although the framework has proven successful in other domains, these results are an indication that it is not properly designed to handle ranking metatargets nor is it a good fit to CF algorithm selection.

The investigations regarding the merits of metafeatures have shown that the data used in CF4CF-META has different impact depending on the CF task addressed: rating data is more important to Item Recommendation, while systematic metafeatures perform better in Rating Prediction. However, by considering the performance of CF4CF and CF4CF-META meta-approaches, one is also able to draw further conclusions regarding the merits of metafeatures: 1) metafeatures are indeed informative, since CF4CF-META is better than CF4CF and 2) there is information in ratings obtained from algorithm performance, since CF4CF-META performs slightly better than LR. Having established that metafeatures are actually meaningful, the focus shifts now towards another approach to metafeature design on Chapter 7, which aims to remove the human from the metafeature generation process.

Chapter 7

cf2vec: dataset embeddings

As seen in Chapters 4 and 5, CF metafeatures tend to perform roughly the same, even when multiple perspectives of the problem are chosen to create the metafeatures. Despite proving that they indeed hold informative power in Chapter 6, the experiments show that it is not possible to obtain a unique dataset characterization technique that outperforms all others. This points to the fact that a new perspective of the problem should be considered in order to achieve the goal.

In this Chapter, the starting point for all current metafeature generation processes is put into question. Namely, notice that all metafeatures are hand tailored, meaning it is the MtL practitioner's experience and perspective of the problem which dictates which characterization measures are suitable for the task at hand. Therefore, the authors argue that an algorithmic-centric approach may be better to approach the problem.

To do so, the work shifts focus to an alternative: Representational Learning (RL) (Bengio et al., 2013). Such techniques use ML algorithms and domain knowledge to learn alternative and potentially richer representations for a given problem. Examples of successful applications can be found in text classification (Bengio et al., 2013) and image recognition (He et al., 2016). However, to the best of the author's knowledge, this approach has never been used for algorithm selection.

In this Chapter, a RL approach is used to automatically design metafeatures for the problem of CF algorithm selection. Namely, a distributed representations technique is employed: `graph2vec` (Narayanan et al., 2017). To do so, inspiration is drawn from the CF graph formulation used to derive graph-based metafeatures presented in Chapter 4. However, instead of attempting to describe the problem using complex hand designed metafeatures, the current proposal aims to use `graph2vec` in order to create a dataset embedding representation. Such representation consists of a set of latent metafeatures, which aim to replace traditional metafeatures.

The Chapter is organized as follows: the dataset embedding technique `cf2vec` is presented in Section 7.1, while Section 7.2 presents the extensive evaluation procedure conducted to verify the merits of such metafeatures. Lastly, Section 7.3 highlights the main conclusions of the impact of the proposed methodology in CF algorithm selection.

7.1 cf2vec: Distributed Representations as CF metafeatures

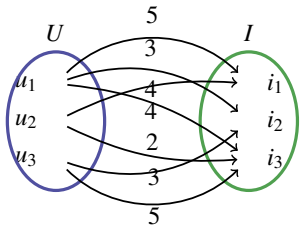
This section introduces the main contribution of this work: `cf2vec`. Next, its essential steps are presented: 1) to create the CF graph, 2) to reduce the problem complexity via graph sampling, 3) to learn the distributed representations and 4) to train a metamodel with alternative metafeatures.

7.1.1 Convert CF matrix into graph

CF is usually described by a rating matrix $R^{|U|\times|I|}$, representing a set of users U and items I. Each element of this matrix is the feedback provided by each user for each item. Figure 7.1a shows a toy example of a rating matrix. Recall that in order to use `graph2vec`, the input elements must be graphs. Thus, the CF graph formulation, discussed in Section 4.3, is re-used here. The process has shown that a CF rating matrix can be seen as an adjacency matrix. This allows to directly construct a bipartite graph G, whose nodes U and I represent users and items, respectively. The edges E connects elements of the two groups and represent the feedback provided by users to items. The edges can be weighted in order to represent preference values (ratings). Figure 7.1b shows the conversion of the toy example from Figure 7.1a.

	i_1	i_2	i_3
u_1	5	3	4
u_2	4	...	2
u_3	...	3	5

(a) Rating Matrix example.



(b) Bipartite Graph.

Figure 7.1: Toy example for two different CF representations.

7.1.2 Sampling graphs

An important part of metafeature design is the effort required (Vanschoren, 2010): if the task is slower than training and evaluating all algorithms on the new problem, then it is useless. Considering how CF graphs can reach quite large sizes, this is a pressing issue and it motivates reducing the problem dimensionality. Since one is not interested in the actual time required, but rather on reducing the amount of data to be processed in order to reduce the time needed, the focus lies on investigating which is the minimum amount of data which allows to maintain a high predictive performance.

Thus, an intermediate (but not mandatory) step is added: graph sampling. In order to find a distributed representation as closely related as possible to the entire graph, a sampling technique able to preserve the graph structural properties must be chosen. According to (Leskovec and Faloutsos, 2006), a good choice is random walk. It performs multiple explorations of graph paths until θ nodes are reached and uses all of them to obtain the respective sub-graph.

7.1.3 Learn distributed representation

Taking advantage of `graph2vec`'s agnostic nature, one argues that the problem can be defined as follows: given a set of CF graphs $G = \{g_1, g_2, ...\}$ and a positive integer σ referring to the distributed representation size, one aims to learn a σ-dimensional distributed representation for every graph. Hence, this process creates a matrix of distributed representations $E^{|G|\times\sigma}$, which can be regarded as the metafeatures for all considered graphs (and by extension, to all CF problems). This procedure requires two steps: 1) to extract of rooted sub-graphs and 2) to learn matrix E.

7.1.3.1 Extract rooted sub-graphs

A rooted sub-graph sg_n^δ is composed by the set of nodes (and corresponding edges) around node $n \in g_i$ that are reachable in δ hops. Learning the distributed representation requires the extraction of rooted sub-graphs for all nodes. Thus, N nodes are used, with $N = |U| + |I|$.

Rooted sub-graphs in `graph2vec` are generated using the Weisfeiler-Lehman relabeling procedure (Shervashidze et al., 2011). Beyond being able to inspect neighboring nodes, it is also able to incorporate information about the neighbors in a single node's name. As a result, it creates a rich textual description for every graph. To do so, it traverses each node in the rub-graph and uses all neighbors as the current node label at each iteration. Next, it replaces the original node labels by new compressed names, which represent a neighborhood structure. The process repeats until d hops are reached. Every rooted sub-graph can be represented by a numeric vector with the frequency that each node (original or compressed) appears in the representation, similar to one-hot encoding.

7.1.3.2 Learn matrix E

Consider now the parallelism between adjacent edges connecting nodes and the sequence of words in a given vocabulary, then the skipgram model can be used straightforwardly. As it can be seen in Figure 7.2, each graph g_i is represented by its identifier and connected to δ context rooted sub-graphs sg. Training such a neural network allows to learn similar distributed representations for graphs with similar rooted sub-graphs.

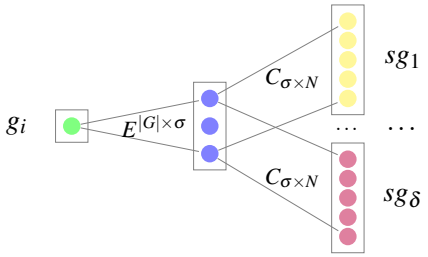


Figure 7.2: Skipgram architecture used in `graph2vec` (Narayanan et al., 2017).

In order to learn the weights, then one must train the network. The learning process, based on Stochastic Gradient Descent, iterates on these steps until conversion is achieved: 1) feedforward

weights from input to the output layer, 2) application of a softmax classifier to compare the output layer's weights with the sub-graph representations and 3) backpropagation of the errors through the network. Doing so, it learns matrices E and C, which represent the distributed representations and context matrices, respectively. Notice the skipgram is trained using Negative Sampling, which refrains from using all sub-graphs of a specific graph. Instead, it takes advantage of few random sub-graphs that do not belong to the graph. This way, training is more efficient.

7.1.4 Learn metamodel

Notice that matrix E can be considered as independent variables to any predictive problem and, as a consequence, can be easily used as metafeatures. Thus, every problem p_i is described by independent variables (the i-th row of matrix E) and the dependent variables (the respective ranking of algorithms). Obtaining these pairs for all g_i, allows to create a metadatabase like the one in Figure 7.3.

P	$f_1()$	$\dots$	$f_{\|F\|}()$
p_1	ω_1	$\dots$	$\omega_{\|F\|}$
$\vdots$	$\vdots$	$\ddots$	$\vdots$
$p_{\|P\|}$	$\dots$	$\dots$	$\dots$
p_α	$\hat{\omega}_1$	$\dots$	$\hat{\omega}_{\|F\|}$

a_1	$\dots$	$a_{\|A\|}$
π_1	$\dots$	$\pi_{\|A\|}$
$\vdots$	$\ddots$	$\vdots$
$\dots$	$\dots$	$\dots$
$\hat{\pi}_1$	$\dots$	$\hat{\pi}_{\|A\|}$

Figure 7.3: Label Ranking Metadatabase.

Formally, the submission of all problems p_i (i.e. g_i) to `cf2vec` produces the metafeatures $\omega = f(p_i)$. To create the dependent variables, each problem p_i is associated with the respective ranking of algorithms π, based on the performance values for a specific evaluation measure $y_k \in Y$. This ranking considers a static ordering of the algorithms a_j (using for instance an alphabetical order) and is composed by a permutation of values $\{1, ..., |A|\}$. These values indicate, for each position l, the respective ranking. Notice also that the work does not make any imposition regarding which is the technique chosen to create the ranking of algorithms. The authors have decided to take advantage of multicriteria metatargets discussed in Section 5.2. A learning algorithm is then used to induce a metamodel which learns the mapping between dataset embeddings and the metatarget. In order to make predictions, the metamodel can be applied to metafeatures $\hat{\omega}$ extracted from a new problem p_α to predict its best ranking of algorithms $\hat{\pi}$. Notice that $\hat{\omega}$ are now obtained by taking advantage of the pre-trained neural network. This means the neural network is able to make the predictions of which is the dataset embedding, simply by considering the CF graph. Therefore, the prediction step is efficient.

Considering how the CF algorithm selection problem has been addressed so far in this Thesis, the ideal solution is Label Ranking, which has been explained in Section 5.1. Although this formulation is favored, since it allows to validate the merits of these metafeatures by considering them

alone, the MtL process is not limited to such metamodels. This means that other meta-algorithms, such as the ones reviewed in Chapter 6, can take advantage of such dataset embeddings.

7.2 Results

Now the focus lies on properly evaluating the aforementioned proposal. To do so, the same evaluation scopes from previous Chapters are re-used, namely: metalevel accuracy, impact on the baselevel performance and metaknowledge analysis.

7.2.1 Experimental setup

The experimental setup used here is divided in two levels, much like in previous Chapters: baselevel (it remains the same as the one presented in Section 3.2.2) and metalevel. This metalevel uses 2 meta-approaches (LR and CF4CF-META), both represented by KNN meta-algorithm which was chosen due to its superior predictive performance. Furthermore, two types of metafeatures (CM and `cf2vec`) are used in conjunction with multicriteria metatargets. Thus, the metalevel differs only from the one in Section 6.3.1 since it adds a new set of metafeatures: `cf2vec`. The complete list of meta-approaches considered here is:

- **LR+CM**: KNN LR meta-algorithm using CM metafeatures.
- **LR+cf2vec**: KNN LR meta-algorithm using cf2vec metafeatures.
- **CF4CF-META+CM**: KNN CF4CF-META meta-algorithm using CM metafeatures.
- **CF4CF-META+cf2vec**: KNN CF4CF-META meta-algorithm using cf2vec metafeatures.
- **AVG**: Average Rankings.

Notice that the best metamodels which use CM metafeatures have been selected based on the experimental results detailed in Appendix D. Furthermore, notice that the results are directly comparable to those presented using multicriteria metatargets in Chapters 5 and 6, since the experimental details are precisely the same, apart from the meta-approaches used.

One important issue to address in cf2vec is the hyperparameter optimization since depending on their settings, different representations are produced. This work pays special attention to δ and σ, since they were shown to be the most important in (Mikolov et al., 2013). An analysis of the sensitivity of such hyperparameters is presented in Section 7.2.2, where all hyperparameters were tuned using grid search (Bergstra and Bengio, 2012).

Lastly, please notice the results presented can be reproduced by accessing the repository `https://github.com/tiagodscunha/cf2vec`.

7.2.2 Hyperparameter sensitivity analysis

Here the aim is to select the best `cf2vec` metafeatures. However, in this setup one does not wish to perform Feature Selection procedures to remove redundant metafeatures. Instead, the interest is knowing which is the best tuning to use in order to obtain the best performance. Therefore, attention is devoted to the effects of `cf2vec`'s hyperparameters instead. The focus lies on three: θ (amount of nodes sampled per graph), δ (amount of context sub-graphs) and σ (representation size).

This analysis investigates the effect of θ (amount of nodes sampled per graph) on Kendall's tau performance when using cf2vec in the original LR formulation, i.e. LR+cf2vec. Figure 7.4 shows the distribution of Kendall's tau scores for all metamodels, with $\theta \in \{25, 50, 100, 200, 500\}$. In these experiments, the performance of the direct competitors is also presented: LR+CM and AVG.

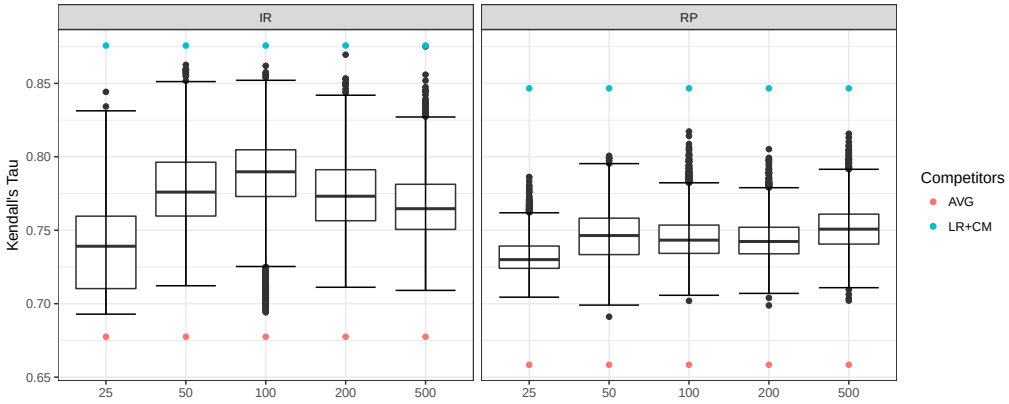


Figure 7.4: Kendall's tau in terms of θ (amount of nodes sampled per graph).

According to these results, `cf2vec` creates informative representations: this is supported by the fact that all their performances are better than the baseline AVG. However, it also shows that `cf2vec` is never better than LR+CM, even though the performance results come very close to CM metamodels. Lastly, one observes that the best settings for this hyperparameter is $\theta = 100$. Such conclusion is reached since although the performances are quite similar overall, this threshold presents the most stable results (notice $\theta = 500$ is better in RP, but clearly worse in IR).

Now, the analysis focuses on hyperparameter σ, referring to the representation size. Figure 7.5 presents Kendall's tau performance for all `cf2vec` metamodels built with $\theta = 100$, since this proved to be the best setting.

The results show that performances for σ are stable: although the best and worst performances fluctuate, the median values remain the same. This observation yields two conclusions:

- The CF algorithm selection problem using the current experimental setup is understudied in the sense that the performances of the embeddings generated are never better than the competitors. The reasons for such results are linked to the experimental setup constraints, such as the limited grid search settings and the reduced amount of meta-examples. Such

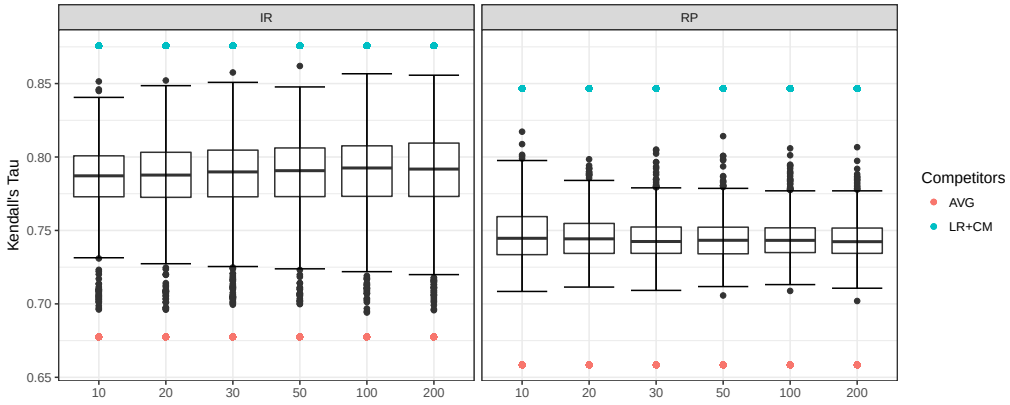


Figure 7.5: Kendall's tau in terms of σ (distributed representation size).

constraints have proven to be too strong for a unsupervised RL technique, which is heavily dependent on the availability of data.

- Furthermore, the results also show that the experimental setup is flawed in the sense that it may be possible to achieve the same results with a even lower σ value. The consequence in this case is that we may be looking at perhaps 2 or 3 metafeatures which may be able to explain the entire mapping between metafeatures and metatargets. In this Thesis, this issue is not approached, but it remains an interesting topic for future research.

This analysis considers the effects of the amount of context sub-graphs (i.e. δ) on Figure 7.6.

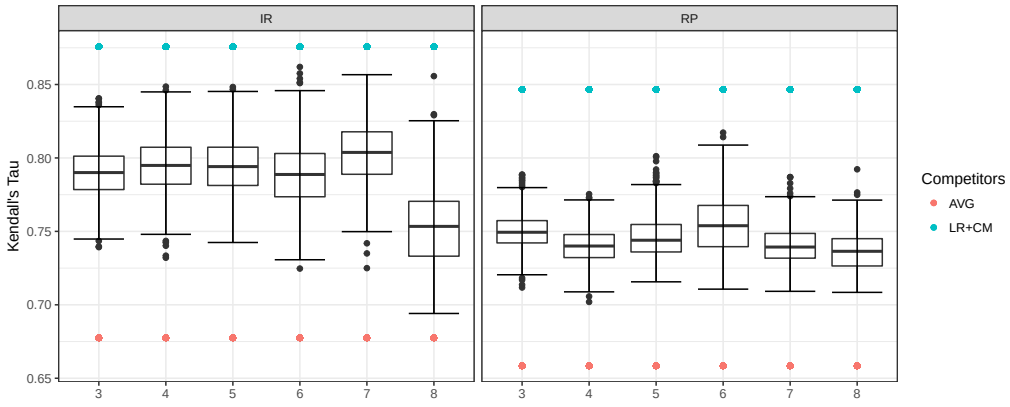


Figure 7.6: Kendall's tau in terms of δ (context sub-graphs).

According to these results, hyperparameter δ has a significant impact on the predictive performance: both metatargets increase their performance until $\delta = 6$. Soon after, their performances decrease. However, lower amounts of context sub-graphs lead to better performance (observe how $\delta \in \{3,4,5\}$ perform better than $\delta = 8$).

7.2.3 Metalevel accuracy

Although the independent impact of hyperparameters has been analyzed, one must select the best `cf2vec` hyperparameter settings for both CF problems. To illustrate how the performance is distributed, Figure 7.7 presents the Kendall's tau performances. Notice the results are zoomed, thus showing only the best performing metamodels. The metamodels are identified by σ and δ.

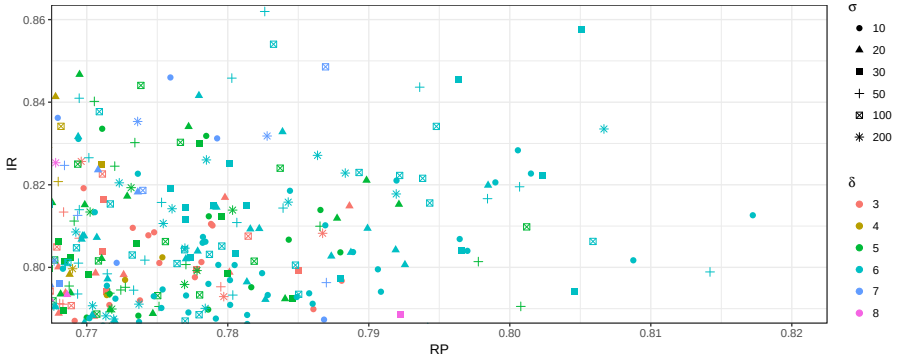


Figure 7.7: Performance scatter plot. Each axis represents the performance that each metamodel has achieved in each CF problem. The metamodels are also characterized in terms of the σ and δ hyperparameters.

The results show that metamodels with $\delta = 6$ occupy the vast majority of performances that simultaneously maximize the performance on both tasks. Among these, the best hyperparameter settings correspond to the performance point placed at $(0.805, 0.858)$, in which $\sigma = 30$. The metamodel trained with this hyperparameter settings is henceforth used as `cf2vec`'s representative.

Taking these settings into consideration, an extensive evaluation in terms of Kendall's tau has been performed for all meta-approaches listed previously. Figure 7.8 presents the results of all meta-approaches.

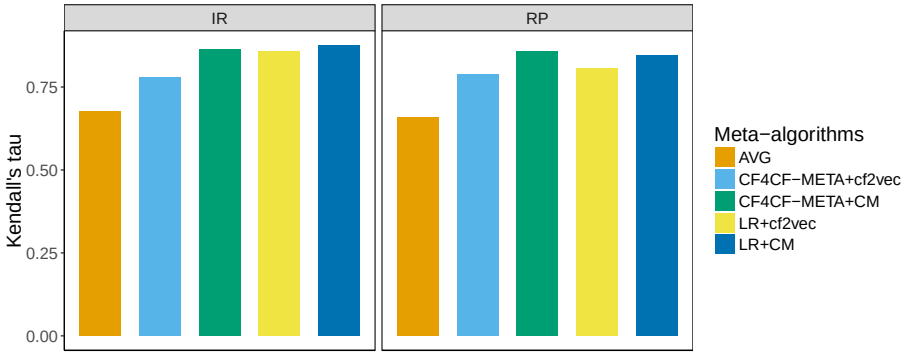


Figure 7.8: Metalevel accuracy.

The results show that all meta-approaches are better than the baseline, thus proving their usefulness. The results also show that LR+CM and CF4CF-META+CM yield the best results, closely followed by LR+cf2vec. In the last position one finds CF4CF-META+cf2vec. These results seem to point out that `cf2vec` metafeatures are not as informative as CM, regardless of whether LR

or CF4CF-META are used. To verify the observations, CD diagrams (Demšar, 2006) have been employed once again. Figure 7.9 shows the results for all meta-approaches considered.

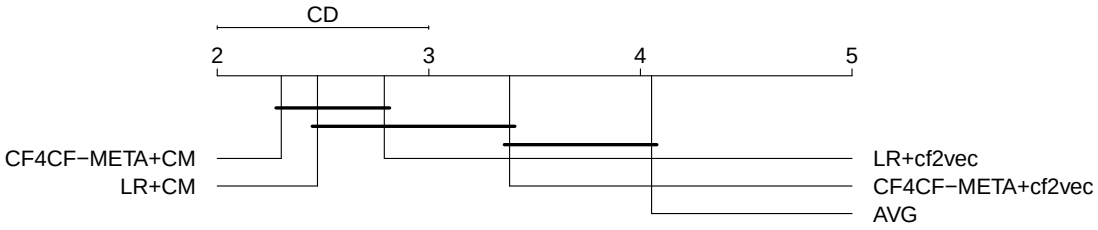


Figure 7.9: Critical difference diagram.

The results confirm the previous observations. Furthermore, they show that there is no statistically significant difference between CF4CF-META+CM, LR+CM and LR+cf2vec, even though the latter is ranked lower. However, it is now possible to see that both CF4CF-META+CM and LR+CM are indeed better than CF4CF-META+cf2vec, while LR+cf2vec only outperforms the baseline with statistically significant differences. In essence, these results show that despite not being able to outperform CM metafeatures, `cf2vec` is able to produce as good metafeatures as the ones proposed in Chapter 4.

7.2.4 Impact on the baselevel performance

The next analysis is about the impact on the baselevel performance. To do so, the procedure explained in Section 5.3.3 is re-used. Furthermore, the results for this experimental setup are displayed in Figure 7.10.

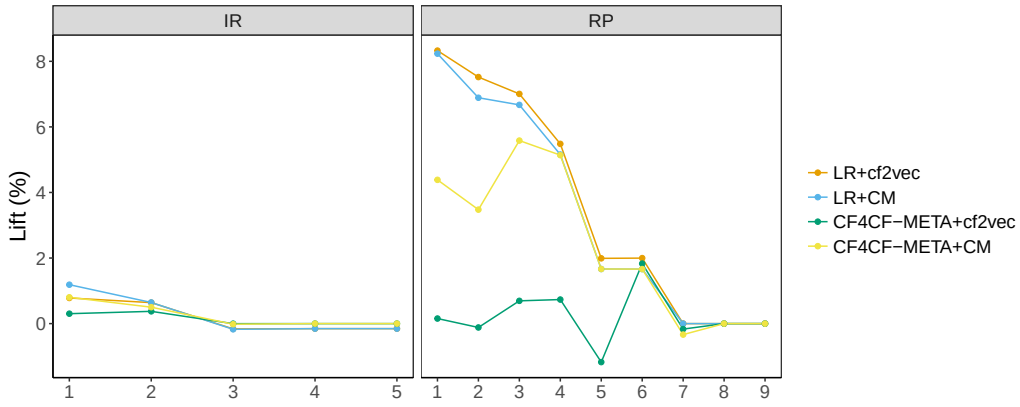


Figure 7.10: Impact on the baselevel performance.

The results show that in IR all meta-approaches perform well for $t \in \{1,2\}$. Among these, the best results are achieved by metamodels with CM metafeatures and achieve over 1% improvement for $t = 1$. However, in RP the results are very different: the best performing metamodels belong to LR technique and they perform above the baseline for $t \leq 7$. Notice that in this case, `cf2vec` metafeatures are the ones which perform best. Furthermore, CF4CF-META metamodels underperform, although those with CM metafeatures are able to perform well for $t \leq 7$, while those

using `cf2vec` metafeatures have inconsistent results, usually close to the baseline's performance. In summary, these results show that `cf2vec` obtains a comparable (and even higher) baselevel performance to the remaining metafeatures, depending on the CF problem addressed.

7.2.5 Metaknowledge analysis

Recall that previous metaknowledge analysis involved ascertaining the most important metafeatures, by means of feature importance procedures. The goal was to understand which of the proposed metafeatures were most meaningful in hope to state which are the CF characteristics which influence algorithm performance. However, `cf2vec` creates latent metafeatures, which have no clear meaning. Therefore, such analysis, although possible, is useless. Thus, this metaknowledge analysis focus instead on assessing the impact of metamodels on the baselevel datasets and also to compare which metafeatures create clearer patterns with regards to the metatargets used.

7.2.5.1 Dataset analysis

This analysis extends upon the procedure used in Section 6.3.5 by considering not only the MtL frameworks but also including the metafeatures used. This way, one is able to assess how these two dimensions impact the baselevel datasets. Figure 7.11 shows the results of such analysis.

The results show metamodels using CM metafeatures perform very similarly regardless of the MtL framework chosen. On the other hand, `cf2vec` seems to favor LR metamodels, given these attain slightly better performances. However, CF4CF-META has less variations in performance, which also indicates merits regarding consistency. Once again, results show there is no universally best meta-approach overall. This provides further evidence metafeatures have equal performance, ultimately validating the proposed `cf2vec` meta-approach.

7.2.5.2 Metafeature analysis

Like in Section 5.3.4, one proposes to analyze the metaknowledge by considering the metafeatures and their relationship to the metatargets. This has been done using adaptations of the algorithm footprint procedure (Muñoz et al., 2018; Smith-Miles and Tan, 2012). However, as seen before, none of the solutions is ideal to consider the complete ranking of algorithms used in Label Ranking metatargets. Thus, a new technique is used to assess such impact, which considers full rankings.

The procedure still performs PCA to reduce the metafeatures to a 2-dimensional space. Notice other techniques have also been studied at this time, namely t-sne (Van Der Maaten and Hinton, 2008). However, the experimental results have shown it did not yield better results than PCA, therefore it was discarded. Also, each metadataset is plotted and associated with data from the metatarget. However, instead of considering the good vs bad performance from algorithm footprints or even the ranking position of algorithms in the posteriorly adapted procedure, one assigns each dataset with the complete ranking of algorithms. To differentiate among metatargets, a color is assigned to each individual metatarget. Notice colors are assigned based on metatarget similarity given by string comparison. This highlights clear patterns between metafeatures and metatargets:

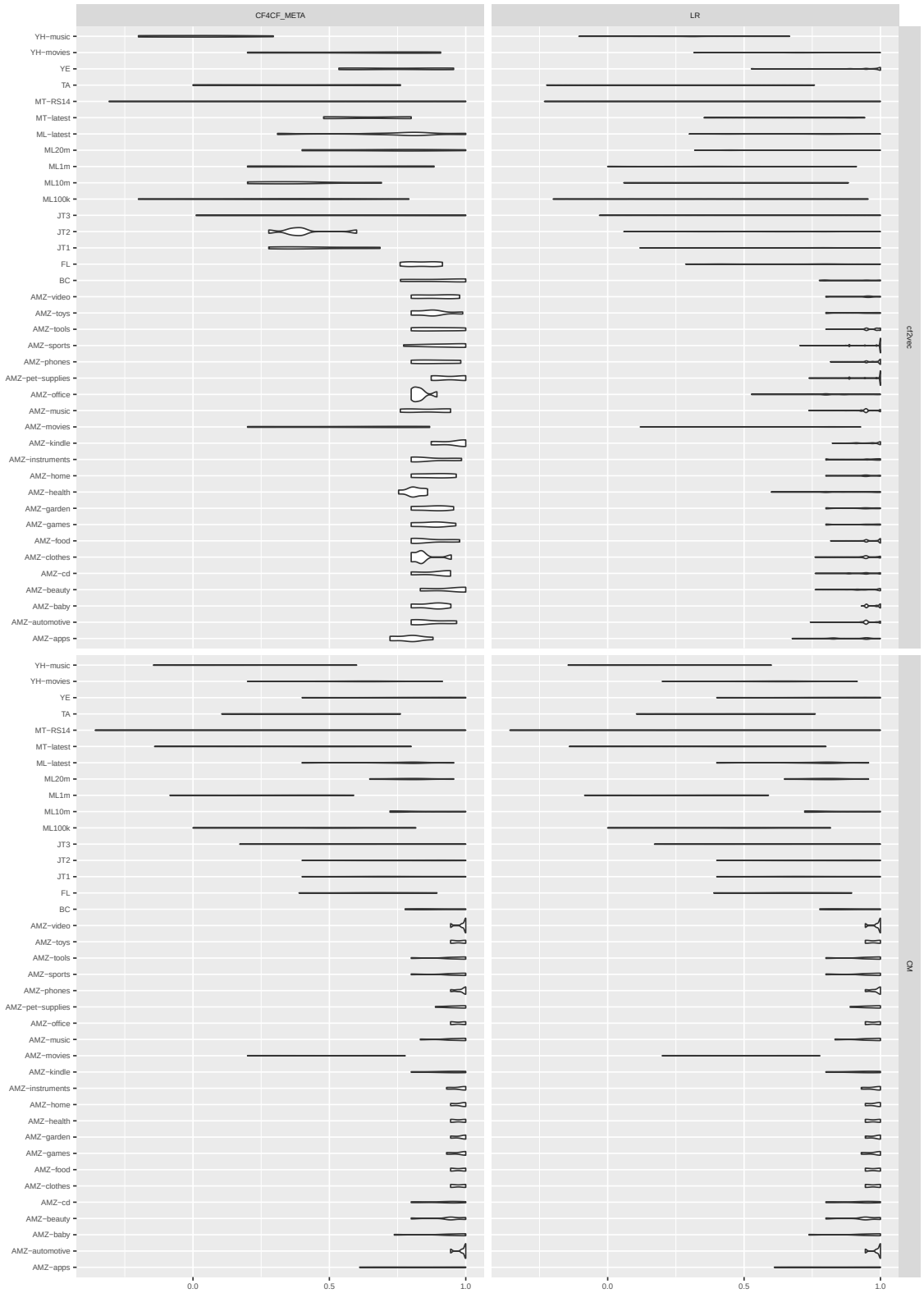


Figure 7.11: Kendall's tau scores per baselevel dataset for all metalearners (i.e. CF4CF-META and LR) and metafeatures (`cf2vec` and CM).

if similar (or the same) metatargets are assigned to two similar datasets (placed near one another), then the representation allows to properly identify the metatarget, thus creating a valid pattern. Figures 7.12 and 7.13 illustrate the results for Item Recommendation and Rating Prediction, respectively.

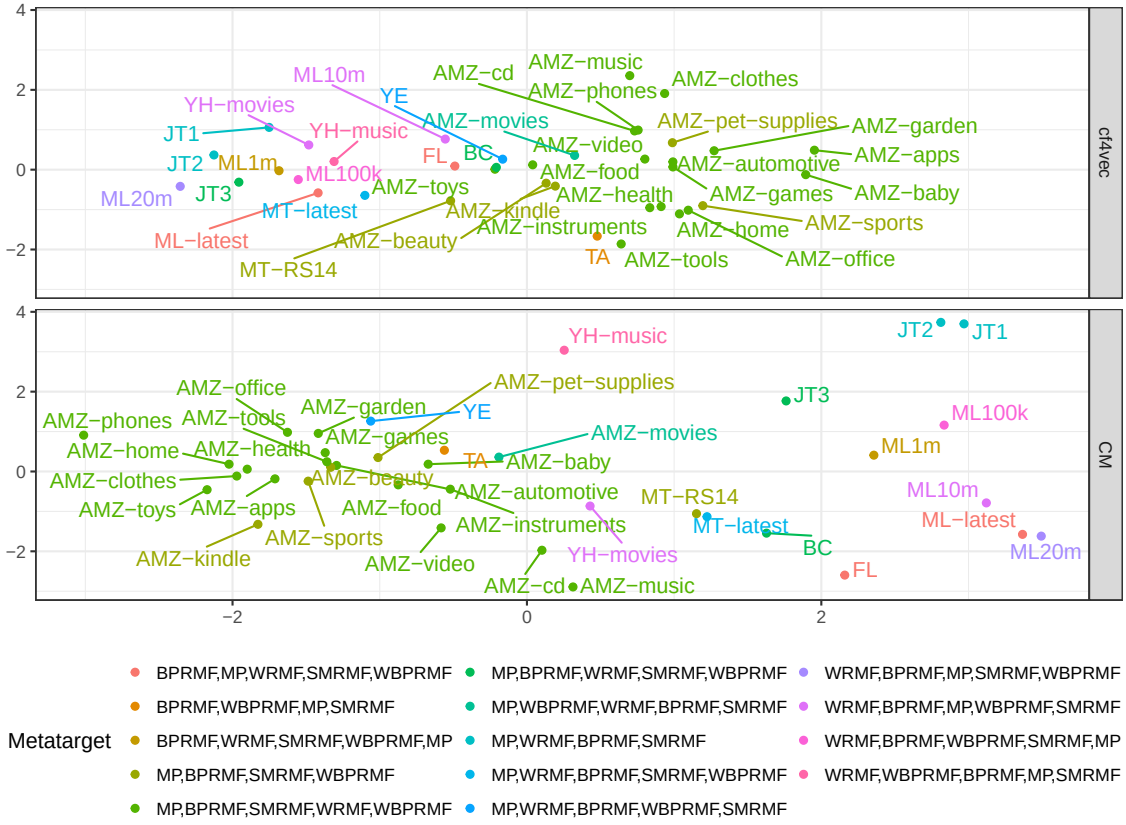


Figure 7.12: Metadata visualization for the Item Recommendation problem.

The results show that both metafeatures work well in two cases, in which the same metatargets are assigned to datasets placed near one another:

- Same domain and similar metatargets: most datasets from the same domain have clearly visible patterns in the mappings between metafeatures and metatargets. This occurs for the AMZ and JT domains, where most data points are placed near each other and have similar colors assigned.

- Different domains but similar metatargets: some datasets from different domains, and sharing similar metatargets, are close to each other. This happens for the BC and FL datasets in Item Recommendation and for the YE and FL datasets in Rating Prediction.

The previous observations refer to the easily predictable meta-instances. The fact that both types of metafeatures are able to properly map the instances together is a good reason to explain why they perform well for the majority of datasets. However, some problems were found:

Figure 7.13: Metadata visualization for the Rating Prediction problem.

- Anomalies: some points are close to others without any apparent reason. This occurs in the TA dataset for both CF problems and the YE dataset in the Item recommendation problem. This means that current metafeatures are not good enough to characterize these datasets.
- Same domain but different metatargets: some datasets from the same domain appear close. However, their rankings are significantly different. This occurs for the ML, YH and MT datasets. A possible reason is difficulty of the metamodel to correctly predict the rankings of algorithms. This difficulty can be potentially be reduced by tuning the metalearner hyperparameters and by choosing metalearners with different bias.

Although not entirely clear, the results seem to point out that CM seems to be generally better than `cf2vec` at mapping the difficult problems. This may be the missing indicator which justifies the differences in predictive performance.

Having said this, it is important to understand that the analysis presented is limited in several aspects: (1) the metafeatures processed via PCA are not directly used in the metamodel and (2) the analysis with regards to the assignment of datasets to metatargets is informal. Thus, the authors acknowledge that the validity of the conclusions observed is limited and must therefore be considered only in terms of exploratory data analysis and not as a proxy for the metamodel's ability to find the mappings between metafeatures and metatargets.

Lastly, the representations provided by PCA, allow a visual inspection of the mapping between metafeatures and metatargets. Although it has been quite helpful in the extraction of metaknowledge, it poses a question regarding whether the metafeatures proposed would benefit from such transformation previous to the metalearner fitting. This issue has not been addressed in this Thesis, yet it remains an interesting research point for future works and applications of the proposed contributions.

7.3 Conclusions

This Chapter introduced a novel technique for CF metafeature extraction: `cf2vec`. It adapts a known distributed representation technique `graph2vec` to the context of CF algorithm selection. To do so, the procedure converts CF datasets into graphs, reduces the problem complexity via graph sampling, learns the distributed representation and uses them as alternative metafeatures.

An extensive experimental study has been conducted, which allowed to understand which are `cf2vec`'s best hyperparameter settings, namely $\theta = 100$, $\delta = 6$ and $\sigma = 30$. However, more importantly, the results show that all hyperparameter settings tried are able to outperform the baseline, thus showing beyond any doubt that `cf2vec` creates informative CF representations. Furthermore, it has been shown that the proposed approach performs approximately the same as other CF metafeatures in terms of metalevel accuracy and impact of the baselevel performance, even though it is unable to surpass them at any point. Despite this, the results have shown that there is no statistically significant difference between them. Furthermore, the results show that a simple LR approach is better suited for `cf2vec` metafeatures, with CF4CF-META performing worse. This observation leads to the conclusion that such representations do not benefit from the added information provided by the performance ratings, unlike what happened in previous Chapters.

Thus, the proposed technique holds an important advantage in the sense that the metafeatures are automatically generated without any human intervention, while reaching the same performance as the state-of-the-art metafeatures. However, `cf2vec`'s predictive performance is never able to outperform other metafeatures. This has been justified by the metaknowledge analysis procedure, which showed that CM metafeatures are slightly better at discriminating datasets. These results arise from the fact that RL techniques require much more data than other metafeature generation processes. Therefore, the authors believe that using 38 CF datasets is the only impediment which prevents this technique to reach its full potential.

Furthermore, the results have shown that the current solution still has room for improvement, given by the possibility of having the same predictive performance using representations of even

lower cardinality and that dimensionality reduction techniques may be helpful not only in `cf2vec`, but also in all proposed metafeatures. Such conclusions, even though highlighting the limitations of the current state of affairs, allow to further cement and guide the future research in the field. In this topic, one main idea comes to mind: to change the learning procedure by including simultaneously the embedding learning stage and the MtL predictive procedure. Such approach, which would be the first MtL RL task-specific solution, would enable to find embeddings while taking into account network structure and algorithm performance.

Chapter 8

Conclusions and Future Work

This Chapter provides the main conclusions, limitations and future work research regarding all proposed contributions to the CF algorithm selection problems studied in this Thesis.

8.1 Conclusions

This Thesis has presented a systematic literature review on the CF algorithm selection problem. It was shown that there are few and not properly explored approaches to the problem, mainly characterized by the analysis of Nearest Neighbours performance using at most 4 datasets. This analysis allowed to identify the problems which needed to be addressed and how to position the work developed throughout the Thesis. This Thesis has successfully built on such works in terms of multiple aspects of the problem, namely: metafeatures, metalearners and metatargets.

The research has continued via an empirical study, which compared the related work approaches. This has yielded important results, which served as the starting point for further proposals. The experiments proved that the related work metafeatures contain useful information since their performance has been well positioned above the baseline. In fact, its performance has been proven to be so good that it justified their usage throughout the Thesis. They have maintained a positive performance, making themselves hard to beat in multiple variations of the CF algorithm selection problem studied.

Even so, various efforts were undertaken to improve the solutions available to the problem. These new proposals, varying in terms of metafeatures, metatargets and metalearners, have enabled to deepen the understanding of the task at hand. The experimental results have shown that the vast majority of solutions is able to provide meaningful metamodels, thus showing their importance. In fact, only in two cases this observation does not hold: while using SL metafeatures in LR metamodels and CF4CF metamodels in the Rating Prediction problem. Such results are quite encouraging since it effectively means that the proposals introduced are useful.

In terms of the proposed metafeatures, it is clear that this thesis has gone above and beyond in finding new ways to describe the CF datasets, in an effort to attempt to improve upon the related work metafeatures performance. The wide range of metafeatures proposed included 4 sets

of metafeatures based on the adaptation of standard metafeature extraction procedures to the CF domain (RM, SL, GR and CM) and `cf2vec`, an automatic approach to build CF dataset representations using distributed representations technique. All have proved useful, since they consistently outperform the baseline. However, the results show that there is no statistically significant difference to the metafeatures proposed in the related work. The extensive experimental results have shown that RM and CM seem to be the most consistent and meaningful, even though most RM metafeatures belong to CM. Regarding `cf2vec`, it was observed that the process always provides informative representations, regardless of the hyperparameter settings used.

The metatargets have also been an important topic of study in this Thesis. The initial solutions for algorithm selection problem used only the best algorithm, as it is usual in other MtL solutions. However, it was soon moved towards a ranking approach, since it was observed that there was important information discarded from the process. Thus, the problem has been modeled using LR metamodels in order to predict complete rankings of algorithms. This solution allows to predict the complete ranking of algorithms, having proved to be effective even in Top-*N* analysis. Furthermore, the ranking metatargets used in this solution were modified by incorporating the inputs of multiple evaluation measures in a single ranking of algorithms, thus creating multicriteria metatargets. The validation of this solution has been straightforward since the rankings of algorithms are fairly similar for most datasets. As a consequence, this technique allowed for easier comprehension of results and fairer assignment of algorithms to the respective rank.

Furthermore, multiple classes of metalearners have been introduced. Their arisal has become necessary due to the different nature of metatargets considered. The first experiments, which were modeled as classification tasks, were addressed using standard classification algorithms. The experimental results have shown that xgboost provides the best results by beating its competitors in multiple evaluation scopes. Afterwards, in order to use rankings of algorithms in the metatarget, three novel techniques to CF algorithm selection were introduced: LR, CF4CF and CF4CF-META. The supremacy of LR and CF4CF-META was proved regarding the direct competitors ASLIB and ALORS in multiple evaluation scopes. Although not consistently, CF4CF has shown that it is possible to perform algorithm selection without any metafeatures. In terms of metalearners, KNN has outperformed RT and RFR in several tasks.

Lastly, despite the fact that the Thesis started by empirically comparing only the related work approaches, the entire empirical studies in this Thesis were designed to be both incremental and comparable. To do so, much of the settings from the experimental setups in previous Chapters are re-used. This paradigm has also allowed to incrementally modify the CF algorithm selection pipeline depending on the conclusions found for particular contributions in hope to improve the predictive performance. Furthermore, it was shown that such organization has helped in organizing the Thesis structure and therefore help in the interpretation of results across Chapters. Such procedure has also been extended to metaknowledge analysis, which allowed to increasingly create more advanced and enriched representations to assess the impact of the MtL solutions developed both on the baselearners and baselevel datasets.

8.2 Limitations

However, despite presenting an extensive study on the CF algorithm selection problem, some limitations exist: first and foremost, although this Thesis has effectively improved the experimental setups used in so far related works, there are still elements which are still not ideal in the experimental setup. Three main issues are identified: datasets, algorithms and evaluation measures. First, the amount of datasets used in reduced when compared to other MtL studies in other domains. The main implication is that this prevents us from obtaining a suitable amount of data points in the metadatabase, which impedes to extract more stable conclusions from the MtL analysis performed. However, when considering the CF scope, this is clearly better than the related meta-approaches and even empirical studies (Huang et al., 2007; Panniello et al., 2009; Adomavicius and Zhang, 2010; Vargas and Castells, 2011; O'Doherty et al., 2012; Kluver and Konstan, 2014; Ekstrand et al., 2014; Guo et al., 2014). This issue arises because there are few public datasets available. Regarding the algorithms used, although the selected set is suitable and more extensive than in the related work, it focuses only on MF algorithms. Research in CF has now moved towards more advanced algorithms, including Deep Learning (Wu et al., 2016; He et al., 2017), which it is not covered in this Thesis. Lastly, 4 evaluation measures are used throughout the Thesis in order to evaluate the recommendations, which also proved to be an improvement. However, this selection means that concepts such as novelty, satisfaction and diversity are not considered in these studies.

Another important limitation in this work lies in the fact that only the default hyperparameters are considered for the CF algorithms in the baselevel. Although this directly impacts the results since the optimal results are not considered, such approach was deemed necessary due to computational time constraints. In such cases, the MtL studies tend to reduce the number of configurations tested and thus save valuable time (Vanschoren, 2018). The limitation in this case is that the predictions obtained from the metamodels must be used to use in a warm-start setting alone, i.e. simply to guide the selection process, leaving the hyperparameter optimization in charge of the practitioner.

Lastly, although multiple and diverse metalevel frameworks have been used, the list of available algorithms in each task has not been exhausted. This has been seen in Label Ranking and Collaborative Filtering meta-approaches, where algorithms such as Approximate Ranking Tree Forests (Sun and Pfahringer, 2013) and other MF approaches beyond ALS have been excluded. This decision has been made since the selected set of metalearners is representative and because one does not wish to further complicate the metalevel configurations used. Despite this, it is believed that not using Learn to Rank algorithms may be the main limitation in this issue. The preference towards Label Ranking algorithms lies in the motivation to predict the full ranking of algorithms, considering all their relative positions equally. However, as discussed previously, it is usually the algorithms on the top ranking positions which are most interesting. To minimize the impact of such limitation, a Top-N metalevel analysis using NDCG has been used to assess LR merits on such task.

8.3 Future Work

The following directions for future work are proposed:

- **Baselevel experimental setup** There are several ways to address the limitations identified earlier. However, the authors would like to highlight a selected few, which are considered to be of the utmost importance: to use implicit feedback datasets (since they are now more frequently available), to include other CF algorithms (particularly by extending the experiments to other more updated recommendation frameworks), inclusion of multiple offline evaluation measures from different evaluation scopes and lastly, to replace offline evaluations from the results of online evaluations in order to create the metatargets of algorithms.

- **Expand contributions to other domains** Notice that several contributions presented, although designed for CF algorithm selection, are suitable to many other domains. Namely, it would be interesting to assess the impact of graph-based and `cf2vec` metafeatures, multi-criteria metatargets and all 3 meta-frameworks proposed: LR, CF4CF and CF4CF-META.

- **Other Recommendation strategies** Recall that there is only one related work approach which studies algorithm selection in RS beyond CF. Particularly, the paper studied the prediction of the best ranking of heuristics for Group Recommendations. However, there are multiple other recommendation approaches, such as Content Based or Hybrid RS, which have not yet been addressed. The authors would like to highlight a contribution made in this subject, where a set of tensor metafeatures were proposed to predict rankings of Tensor Factorization algorithms for Context-aware Recommendations (Cunha et al., 2017). Furthermore, the Label Ranking formulation presented in Chapter 5 was also employed. Although the work was removed from this Thesis due to organizational purposes, it is important to acknowledge the existence of this novel technique, especially since it derives from the contributions presented in this Thesis.

- **Representational Learning** Perhaps one of the most interesting contributions of this work is the `cf2vec`, which enabled to automatically create CF metafeatures without any human interaction in the decision process. As far as the authors know, this has been the first attempt to do so in the context of CF. Therefore, this is an interesting direction for future work. As a starting point, we suggest a recent survey on graph embedding techniques, which provides multiple suitable candidates Goyal and Ferrara (2018).

- **Deep Metalearning** One current research trend is the usage of Deep Learning MtL solutions (Santoro et al., 2016; Edwards and Storkey, 2017; Mishra et al., 2017; Li et al., 2017; Vartak et al., 2017). However, as far as the know, there is no existing solution to this issue which applies directly to CF algorithm selection. However, given the maturity of meta-knowledge generated from this Thesis, it may be interesting to explore the application of such techniques to the scope of CF algorithm selection.

- **User Algorithm Selection** Recall that the current work has focused on the selection of the best algorithm(s) per dataset. However, particularly in the context of RS, one could perform algorithm selection on a user level. Despite the fact that this problem has already been addressed in the related work (Griffith et al., 2012; Ekstrand and Riedl, 2012; Collins et al., 2018), there are multiple ways to expand upon it. One example could focus on the adaptation of the methods proposed in this Thesis. Furthermore, techniques such as Contextual Bandits could be an interesting solution to perform an user algorithm selection approach.

- **AutoML** Notice that all contributions presented in this Thesis have focused on the algorithm selection problem. However, the current trend in MtL lies with AutoML solutions, which focus on the entire ML pipeline, including the algorithm selection step. Therefore, it may be important to assess the merits of such solutions on the CF problem, using for instance the wide range of metafeatures proposed. In fact, the research could even approach novel AutoML approaches, which leverage CF as metalearners (Fusi and Elibol, 2017; Yang et al., 2018) and apply it to the CF problem.

Appendix A

Offline evaluation metrics

Here the offline evaluation metrics are presented and organized by type: rating accuracy, rating correlation, classification accuracy, ranking accuracy, satisfaction, coverage and diversity and lastly novelty.

A.1 Rating accuracy

These metrics are characterized by measuring the difference between the predicted rating and the actual rating. Therefore, it is considered the predicted rating for user u to item i as p_{ui} and the real rating as r_{ui}. N and N are the total amount of predicted ratings and the total amount of ratings, respectively Herlocker et al. (2004); Jiang et al. (2011).

$$MAE = \frac{\sum_{k=1}^{N} |p_{ui} - r_{ui}|}{N} \tag{A.1}$$

$$MSE = \frac{\sum_{k=1}^{N} (p_{ui} - r_{ui})^2}{N} \tag{A.2}$$

$$RMSE = \sqrt{\frac{\sum_{k=1}^{N} (p_{ui} - r_{ui})^2}{N}} \tag{A.3}$$

$$NMAE = \frac{MAE}{\frac{\sum_{l=0}^{M} r_{ui}}{M}} \tag{A.4}$$

A.2 Rating correlation

The metrics calculate the correlation between the predicted and the true ratings Lü et al. (2012). Therefore, it is considered the predicted rating for user u to item i as p_{ui} and the real rating as r_{ui}. $\overline{p}$ and $\overline{r}$ are the average of the predicted ratings and the average of real ratings, respectively.

$$Pearson = \frac{\sum_{\alpha}(p_{ui}-\overline{p})(r_{ui}-\overline{r})}{\sqrt{\sum_{\alpha}(p_{ui}-\overline{p})}\sqrt{\sum_{\alpha}(r_{ui}-\overline{r})}} \tag{A.5}$$

The Spearman's correlation is very similar to Pearson's although the ratings p_{ui} and r_{ui} are replaced by the rankings rp_{ui} and rr_{ui}:

$$Spearman = \frac{\sum_{\alpha}(rp_{ui}-\overline{p})(rr_{ui}-\overline{r})}{\sqrt{\sum_{\alpha}(rp_{ui}-\overline{p})}\sqrt{\sum_{\alpha}(rr_{ui}-\overline{r})}} \tag{A.6}$$

In the case of Kendall's Tau, the computation is rather different. The variables used are C and D respectively for the number of concordant and discordant pairs. A pair is concordant if the RS predicts its ranking correctly or discordant otherwise. S_t is the number of object pairs for which the true ratings are the same, and S_p is the number of object pairs for which the predicted ratings are the same.

$$\tau = \frac{C-D}{\sqrt{(C+D+S_t)(C+D+S_p}} \tag{A.7}$$

A.3 Classification accuracy

These metrics are IR based and their formulations are widely known. In the adaptation to RS, one must consider that the precision is the proportion of recommendations that are good recommendations, and recall is the proportion of good recommendations that appear in top recommendations Gunawardana and Shani (2009). It is possible to measure if a recommendation is good by assigning it to a class that is deemed satisfactory. For instance, in explicit feedback it is possible to state a threshold to define when a recommendation is good while on implicit feedback one can consider that it is either good or bad.

Table A.1: Confusion Matrix

	Recommended	Not recommended
Preferred	True Positives (TP)	False Negatives (FN)
Not preferred	False Positives (FP)	True Negatives (TN)

The values used for Precision and Recall can be visually displayed through a confusion matrix (see Table A.1). The Precision and Recall equations are:

$$Precision = \frac{TP}{TP+FP} \tag{A.8}$$

$$Recall = \frac{TP}{TP+FN} \tag{A.9}$$

From these metrics one can extract the F-measure Shin and Woo (2009):

$$F-measure = \frac{2*Precision*Recall}{Precision+Recall} \tag{A.10}$$

The accuracy in RS has the same equation as the precision. It is defined as the ratio of the number of items recommended and purchased to the number of items recommended by the system Lee et al. (2008); Jeong (2010); Talabeigi et al. (2010). Therefore, the items recommended and purchased are the TP and the items recommended are both the TP and the FP.

The ROC curve attempts to measure the extent to which a learning system can successfully distinguish between signal (relevance) and noise (non-relevance) Huang et al. (2007). The ROC curve is obtained by plotting the TP rate (fraction of true positives) as a function of FP rate (fraction of false positives) Diaby et al. (2013). Different values are computed by changing the parameters of the method which will lead to different TP and FP rates. Afterwards, AUC-ROC (Area Under ROC Curve) is calculated via integral calculations. A perfect score is obtained when AUC=1 and it is only representative if AUC>0.5.

A.4 Ranking accuracy

In ranking accuracy metrics, the goal is to assess how good is the order of recommendations. DCG (Discounted Cumulative Gain) at a rank k is defined for an user u with a true rating r_{ui_n} for item i_n ranked at order N by:

$$DCG_k^u = r_{ui_1} + \sum_{N=2}^{k} \frac{r_{ui_N}}{log_2(N)} \tag{A.11}$$

NDCG (Normalized Discounted Cumulative Gain) is the ratio between the DCG and the IDCG, which is the maximum possible gain value for user u Baltrunas et al. (2010):

$$NDCG_k^u = \frac{DCG_k^u}{IDCG_k^u} \tag{A.12}$$

MAP (Mean Average Precision) takes in account the metric Precision@N, where n is the ranking degree evaluated Cheng et al. (2014). $P(i)$ means the precision at cut-off n in the item list.

$$Precision@N = \sum_{i=1}^{n} \frac{P(i)}{N} \tag{A.13}$$

Therefore, the equation for MAP, considering U users, is:

$$MAP = \sum_{i=1}^{U} \frac{Precision@N_i}{U} \tag{A.14}$$

MRR (Mean Reciprocal Rank) equation is the multiplicative inverse of the rank of the first correct answer, where $rank_i$ is the first correctly recommended item for user u Nanopoulos et al. (2010):

$$MRR = \frac{1}{U}\sum_{u=1}^{U}\frac{1}{rank_u} \tag{A.15}$$

Hit ratio calculates the average of true positives in the top raking position Deshpande and Karypis (2004). In this metric, the number of hits H is the number of items in the test set that are also present in the top-N recommended items returned for each user, while U is to total amount of users in the system:

$$Hit - ratio = \frac{H}{U} \tag{A.16}$$

ARHR (Average Reciprocal Hit Rate) is a variation of Hit-Ratio that calculates the impact of the number of hits for each position p_i in the ranked list:

$$ARHR = \frac{1}{U}\sum_{i=1}^{H}\frac{1}{p_i} \tag{A.17}$$

Another metric that evaluates ranking accuracy is the ARP (Average Relative Position) Pilászy et al. (2010). However, this metric is specific for implicit feedback datasets. The relative position of an item i to an user u for a number x of zero ratings is defined as:

$$rpos_{ui} = \frac{pos_{ui}}{x} \tag{A.18}$$

From this metric, ARP is defined for the entire number of ratings R as:

$$ARP = \frac{\sum_{(u,i)\in R} rpos_{ui}}{R} \tag{A.19}$$

A.5 Satisfaction

Satisfaction measures aim to assess how much does the recommendations will have a positive impact on the user. There is one metric to assess the user satisfaction: the half-life utility. The metric attempts to evaluate the utility of a ranked list to the user, by calculating the difference between the user's rating r_{ui} for an item and its "default rating" d. The default rating is generally a neutral or slightly negative rating. Considering that the parameter α is the half-life, this metric can be calculated as follows:

$$Half - life\ utility = \sum_{i=0}^{I}\frac{max(r_{ui}, d)}{2^{(i-1)(\alpha-1)}} \tag{A.20}$$

A.6 Coverage and diversity

Coverage measures the percentage of items for which a recommender system is capable of making predictions. There are two types of coverage: prediction coverage and catalog coverage. While the first calculates the percentage of the items for which the system is able to generate a recommendation, the second one computes the percentage of the available items which effectively are ever recommended to a user Ge et al. (2010). Considering I as the set of available items and I_p as the set of items for which a prediction can be made, prediction coverage can be calculated by:

$$Coverage = \frac{|I_p|}{|I|} \tag{A.21}$$

Catalog coverage is usually measured on a set of recommendation sessions, examining for a determined period of time the recommendations returned to users Ge et al. (2010). Considering I_L^j as the set of items in list L returned by the jth recommendations observed during the measurement time and N as the total number of recommendations observed, the equation for catalog coverage is:

$$Catalog\ Coverage = \frac{|\cup_{j=1...N} I_L^j|}{I} \tag{A.22}$$

Diversity refers to how different the recommended items are with respect to each other. There are two types of diversity: inter-diversity (also known as Hamming distance) that assesses the ability of a method to return different results to different users and the intra-diversity that measures the extent to which an method can provide diverse objects to each individual user Lü et al. (2012). Given users i and j and the $Q_{ij}(n)$ as the number of common objects in the top-n places of the lists, the Hamming distance can be calculated as:

$$Hamming\ distance = 1 - \frac{Q_{ij}(N)}{N} \tag{A.23}$$

To calculate the intra-similarity measure, one is required to use a similarity function $sim(k,l)$ to assess how equal are two items k and l. The intra-similarity measure is given by:

$$intra - similarity = \frac{1}{N(1-N)} \sum_{k \neq l} sim(k,l) \tag{A.24}$$

A.7 Novelty

Novelty refers to how different the recommended items are with respect to what the users have already seen before. The simplest way to quantify the ability of a method to generate novel and unexpected results is to measure the average popularity of the recommended items Lü et al. (2012). For a recommendation list L_i of user i and k_α being the popularity of object α, the equation is:

$$Popularity = \frac{1}{MN} \sum_{i=1}^{M} \sum_{\alpha \in L_i} k_\alpha \tag{A.25}$$

Surprisal is another metric to measure the unexpectedness. Given an object α, the chance that a randomly-selected user has collected it is k_α/M and thus its self-information is:

$$Surprisal = log_2(M/k_\alpha) \tag{A.26}$$

The EPC (Expected Popularity Complement) metric measures the long-tail novelty Vargas and Castells (2014). This metric is calculated per each item i in a recommendation list L by:

$$EPC = \frac{1}{|L|}\sum_{i \in L} nov(i) \tag{A.27}$$

where $nov(i)$ measures the novelty of an item as the probability of not being known by an user.

Appendix B

Metatarget Analysis

This Chapter presents all metatargets used in this Thesis. Namely, it presents the best algorithm metatargets used for classification tasks - which were used in Chapters 3 and 4 - and the single criterion and multicriteria ranking metatargets, used in the remaining Chapters.

B.1 Best algorithm Metatarget

The best algorithms for each dataset and metric at the baselevel are presented in Table B.1. These refer also to the metatargets used to select the best CF algorithm.

Several observations can be made:

- **The most common algorithms are BMF and MP in RP and IR, respectively.** The results show a clear bias towards these algorithms, especially in the Amazon datasets. The behavior can be explained by the fact that these datasets have not been properly processed for RS purposes, hence impeding the best performance possible. However, there is high variance in terms of the best algorithms in the remaining datasets.
- **Some algorithms are never chosen as the best: LFLLM, UIB, IA, UA and SMRMF.** This observation has serious implications in the MtL problem: since these algorithms are never chosen as the best, then they are never used in the metatarget. As a consequence, no information regarding their effects in the algorithm selection problem can be drawn. This shows the limitation in using classification as the task to approach algorithm selection.
- **Two algorithms are the best only in a single dataset (i.e. SCAFM and GA).** This too poses important limitations in the algorithm selection problem: on one hand, algorithms present in very few data points will not provide enough evidence, hence limiting the metalearner's ability to learn. On the other hand, it points to high class imbalance, which allows to foresee a high accuracy performance from the baseline algorithm (i.e. majority voting);
- **The same algorithm is usually the best on both metrics of each problem.** Although not expected, it is not a particularly important issue. In the RP problem specifically, this is even justified by the fact that both evaluation measures are error-based in nature;

Table B.1: Best models obtained on multiple evaluation metrics for each dataset.

dataset	Rating Prediction		Item Recommendation	
	NMAE	**RMSE**	**NDCG**	**AUC**
AMZ-apps	BMF	BMF	MP	MP
AMZ-auto	BMF	BMF	MP	MP
AMZ-baby	BMF	BMF	MP	MP
AMZ-beauty	BMF	BMF	MP	MP
AMZ-cd	BMF	BMF	MP	MP
AMZ-clothes	BMF	BMF	MP	MP
AMZ-digital-music	BMF	BMF	MP	MP
AMZ-food	BMF	BMF	MP	MP
AMZ-games	BMF	BMF	MP	MP
AMZ-garden	BMF	BMF	MP	MP
AMZ-health	BMF	BMF	MP	MP
AMZ-home	BMF	BMF	MP	MP
AMZ-instruments	BMF	BMF	MP	MP
AMZ-kindle	BMF	BMF	MP	MP
AMZ-movies	BMF	BMF	WBPRMF	MP
AMZ-office	BMF	BMF	MP	MP
AMZ-pet	BMF	BMF	MP	MP
AMZ-phones	BMF	BMF	MP	MP
AMZ-sports	BMF	BMF	MP	MP
AMZ-tools	BMF	BMF	MP	MP
AMZ-toys	BMF	BMF	MP	MP
AMZ-video	SVD++	BMF	MP	MP
BC	BMF	BMF	MP	MP
FL	BMF	BMF	WRMF	BPRMF
JT1	SVD++	SUAFM	MP	MP
JT2	SVD++	SUAFM	MP	MP
JT3	SIAFM	SUAFM	MP	MP
ML100k	BMF	BMF	WRMF	WRMF
ML10m	MF	BMF	WRMF	WRMF
ML1m	MF	MF	WRMF	BPRMF
ML20m	BMF	BMF	WRMF	WRMF
ML-latest	BMF	BMF	WRMF	BPRMF
MT-latest	SCAFM	SCAFM	WRMF	MP
MT-recsys2014	GA	GA	MP	MP
TA	SIAFM	SIAFM	WBPRMF	BPRMF
YH-movies	BMF	BMF	WRMF	WRMF
YH-music	SVD++	SVD++	WRMF	WRMF
YE	BMF	BMF	WRMF	MP

- **RP baselines are easier to outperform than in IR.** This happens because CF is known to be biased towards the most popular items, hence making MP very hard to beat. In fact, this is shown in several works both in the academia and in the industry. On the other hand, the baselines in RP are not known for their supremacy, hence making beating them much easier.

B.2 Single criterion Ranking Metatarget

The single criterion ranking metatargets refer to the ranking built using only one evaluation measure. Tables B.2, B.3, B.4 and B.2 refer to the rankings produced using NDCG, AUC, NMAE and RMSE, respectively. Notice that some rankings are incomplete, meaning said algorithms failed to be evaluated in those particular datasets.

Table B.2: NDCG single criterion metatarget.

Dataset	a_1	a_2	a_3	a_4	a_5
AMZ-apps	MP	BPRMF	WRMF	SMRMF	WBPRMF
AMZ-auto	MP	BPRMF	WRMF	SMRMF	WBPRMF
AMZ-baby	MP	BPRMF	WRMF	SMRMF	WBPRMF
AMZ-beauty	MP	BPRMF	SMRMF	WBPRMF	
AMZ-cd	MP	BPRMF	WRMF	WBPRMF	SMRMF
AMZ-clothes	MP	BPRMF	WRMF	SMRMF	WBPRMF
AMZ-music	MP	BPRMF	WRMF	SMRMF	WBPRMF
AMZ-food	MP	BPRMF	WRMF	SMRMF	WBPRMF
AMZ-games	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-garden	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-health	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-home	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-video	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-instruments	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-kindle	MP	BPRMF	SMRMF	WBPRMF	
AMZ-movies	WBPRMF	WRMF	MP	BPRMF	SMRMF
AMZ-office	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-pet	MP	BPRMF	SMRMF	WBPRMF	
AMZ-phones	MP	BPRMF	WRMF	SMRMF	WBPRMF
AMZ-sports	MP	BPRMF	SMRMF	WBPRMF	
AMZ-tools	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-toys	MP	BPRMF	SMRMF	WRMF	WBPRMF
BK	MP	BPRMF	WRMF	WBPRMF	SMRMF
FL	WRMF	MP	BPRMF	WBPRMF	SMRMF
JT1	MP	WRMF	BPRMF	SMRMF	
JT2	MP	WRMF	BPRMF	SMRMF	
JT3	MP	BPRMF	WRMF	SMRMF	WBPRMF
ML-latest	WRMF	WBPRMF	MP	BPRMF	SMRMF
ML100k	WRMF	BPRMF	WBPRMF	SMRMF	MP
ML10m	WRMF	BPRMF	WBPRMF	MP	SMRMF
ML1m	WRMF	BPRMF	WBPRMF	SMRMF	MP
ML20m	WRMF	MP	BPRMF	WBPRMF	SMRMF
MT-latest	WRMF	MP	BPRMF	WBPRMF	SMRMF
MT-recsys2014	MP	BPRMF	SMRMF	WBPRMF	
TA	WBPRMF	BPRMF	MP	SMRMF	
YH-movies	WRMF	MP	BPRMF	WBPRMF	SMRMF
YH-music	WRMF	WBPRMF	MP	BPRMF	SMRMF
YE	WRMF	MP	BPRMF	WBPRMF	SMRMF

Table B.3: AUC single criterion metatarget.

Dataset	a_1	a_2	a_3	a_4	a_5
AMZ-apps	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-auto	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-baby	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-beauty	MP	BPRMF	SMRMF	WBPRMF	
AMZ-cd	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-clothes	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-music	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-food	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-games	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-garden	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-health	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-home	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-video	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-instruments	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-kindle	MP	BPRMF	SMRMF	WBPRMF	
AMZ-movies	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-office	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-pet	MP	BPRMF	SMRMF	WBPRMF	
AMZ-phones	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-sports	MP	BPRMF	SMRMF	WBPRMF	
AMZ-tools	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-toys	MP	BPRMF	SMRMF	WRMF	WBPRMF
BK	MP	BPRMF	WRMF	SMRMF	WBPRMF
FL	BPRMF	MP	SMRMF	WBPRMF	WRMF
JT1	MP	WRMF	BPRMF	SMRMF	
JT2	MP	WRMF	BPRMF	SMRMF	
JT3	MP	BPRMF	WRMF	SMRMF	WBPRMF
ML-latest	BPRMF	MP	WRMF	SMRMF	WBPRMF
ML100k	WRMF	BPRMF	WBPRMF	SMRMF	MP
ML10m	WRMF	BPRMF	MP	WBPRMF	SMRMF
ML1m	BPRMF	WRMF	SMRMF	WBPRMF	MP
ML20m	WRMF	BPRMF	MP	SMRMF	WBPRMF
MT-latest	MP	BPRMF	SMRMF	WRMF	WBPRMF
MT-recsys2014	MP	BPRMF	SMRMF	WBPRMF	
TA	BPRMF	SMRMF	MP	WBPRMF	
YH-movies	WRMF	BPRMF	MP	WBPRMF	SMRMF
YH-music	WRMF	WBPRMF	BPRMF	MP	SMRMF
YE	MP	WRMF	BPRMF	WBPRMF	SMRMF

Table B.4: NMAE single criterion metatarget.

Dataset	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
AMZ-apps	BMF	SVD++	SIAFM	SCAFM	SUAFM	LFLLM	GA	UIB	MF
AMZ-auto	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-baby	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-beauty	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-cd	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-clothes	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-music	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-food	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-games	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-garden	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-health	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-home	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-video	SVD++	BMF	SIAFM	SCAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-instruments	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-kindle	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-movies	BMF	SVD++	MF	SCAFM	SIAFM	SUAFM	GA	UIB	LFLLM
AMZ-office	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-pet	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-phones	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-sports	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-tools	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-toys	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
BK	BMF	SVD++	SUAFM	SCAFM	SIAFM	MF	GA	UIB	LFLLM
FL	BMF	MF	SVD++	LFLLM	SUAFM	SIAFM	SCAFM	GA	UIB
JT1	SVD++	MF	SIAFM	LFLLM	BMF	GA	UIB	SUAFM	
JT2	SVD++	MF	SIAFM	LFLLM	BMF	GA	UIB	SUAFM	
JT3	SIAFM	SVD++	LFLLM	MF	GA	UIB	SUAFM	SCAFM	BMF
ML-latest	BMF	MF	LFLLM	SVD++	SIAFM	GA	UIB		
ML100k	BMF	MF	SVD++	SCAFM	LFLLM	SIAFM	SUAFM	GA	UIB
ML10m	MF	BMF	LFLLM	SVD++	GA	SIAFM	SUAFM	SCAFM	UIB
ML1m	MF	BMF	SVD++	LFLLM	SIAFM	SUAFM	SCAFM	GA	UIB
ML20m	BMF	MF	LFLLM	SVD++	SIAFM	GA	UIB		
MT-latest	SCAFM	SUAFM	SIAFM	SVD++	MF	BMF	GA	UIB	LFLLM
MT-recsys2014	GA	UIB	LFLLM	BMF	SUAFM	SIAFM	SCAFM		
TA	SIAFM	BMF	SCAFM	SUAFM	GA	UIB	LFLLM		
YH-movies	BMF	SVD++	MF	SCAFM	SIAFM	SUAFM	LFLLM	GA	UIB
YH-music	SVD++	SUAFM	SCAFM	GA	UIB	SIAFM	BMF	LFLLM	
YE	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM

Table B.5: RMSE single criterion metatarget.

Dataset	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9
AMZ-apps	BMF	SVD++	SIAFM	SCAFM	SUAFM	LFLLM	GA	UIB	MF
AMZ-auto	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-baby	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-beauty	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-cd	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-clothes	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-music	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-food	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-games	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-garden	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-health	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-home	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-video	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-instruments	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-kindle	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-movies	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-office	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-pet	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-phones	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-sports	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-tools	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-toys	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
BK	BMF	SVD++	SUAFM	SCAFM	SIAFM	GA	UIB	MF	LFLLM
FL	BMF	MF	SVD++	SUAFM	SIAFM	SCAFM	LFLLM	GA	UIB
JT1	SUAFM	SVD++	MF	SIAFM	LFLLM	GA	UIB	BMF	
JT2	SUAFM	SVD++	MF	SIAFM	LFLLM	GA	UIB	BMF	
JT3	SUAFM	SCAFM	SIAFM	LFLLM	SVD++	MF	GA	UIB	BMF
ML-latest	BMF	MF	SVD++	SIAFM	LFLLM	GA	UIB		
ML100k	BMF	SCAFM	SVD++	SIAFM	LFLLM	SUAFM	MF	GA	UIB
ML10m	BMF	MF	SVD++	SIAFM	SUAFM	SCAFM	LFLLM	GA	UIB
ML1m	MF	BMF	SVD++	LFLLM	SIAFM	SUAFM	SCAFM	GA	UIB
ML20m	BMF	MF	SVD++	SIAFM	LFLLM	GA	UIB		
MT-latest	SCAFM	SIAFM	SUAFM	SVD++	MF	BMF	GA	UIB	LFLLM
MT-recsys2014	GA	UIB	LFLLM	BMF	SUAFM	SIAFM	SCAFM		
TA	SIAFM	BMF	SCAFM	SUAFM	GA	UIB	LFLLM		
YH-movies	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	LFLLM	GA	UIB
YH-music	SVD++	GA	UIB	SUAFM	SCAFM	SIAFM	BMF	LFLLM	
YE	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM

The results show:

- **Ranking metatargets are more informative than classification metatargets.** Besides providing more information to the algorithm selection problem, this formulation solves two important problems identified in classification metatargets: class imbalance and missing algorithms in the metatarget.
- **The results are still biased, particularly in Amazon datasets.** Throughout all metatargets, there are ranking that appear more often. For instance, in AUC metatarget the ranking "MP, BPRMF, SMRMF, WRMF, WBPRMF" appears in 18 out of 38 instances. This means that high accuracy performance from the baseline Average Rankings are to be expected, thus meaning the problem not easy to solve.
- **The metatargets present high similarity in terms of average rankings.** The results show that both IR metatargets yield the average ranking of algorithms "MP, BPRMF, WRMF, SMRMF, WBPRMF", although with slightly different scores. In RP, the average ranking is also very similar: in NMAE it is "BMF, SVD++, SIAFM, SCAFM, SUAFM, MF, GA, UIB, LFLLM", while in RMSE only MF and GA switch places. The fact that both metatargets within each CF task are similar is an indication that the application of multicriteria metatargets will be straightforward.

B.3 Multicriteria Ranking Metatarget

Tables B.6 and B.7 present the multicriteria metatargets produced using the procedure explained in Section 5.2 on the experimental setup used in this Thesis.

Table B.6: IR multicriteria metatarget.

Dataset	$a-1$	$a-2$	$a-3$	$a-4$	$a-5$
AMZ-apps	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-automotive	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-baby	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-beauty	MP	BPRMF	SMRMF	WBPRMF	
AMZ-cd	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-clothes	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-digital-music	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-food	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-games	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-garden	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-health	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-home	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-instant-video	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-instruments	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-kindle	MP	BPRMF	SMRMF	WBPRMF	
AMZ-movies	MP	WBPRMF	WRMF	BPRMF	SMRMF
AMZ-office	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-pet-supplies	MP	BPRMF	SMRMF	WBPRMF	
AMZ-phones	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-sports	MP	BPRMF	SMRMF	WBPRMF	
AMZ-tools	MP	BPRMF	SMRMF	WRMF	WBPRMF
AMZ-toys	MP	BPRMF	SMRMF	WRMF	WBPRMF
BK	MP	BPRMF	WRMF	SMRMF	WBPRMF
FL	BPRMF	MP	WRMF	SMRMF	WBPRMF
JT1	MP	WRMF	BPRMF	SMRMF	
JT2	MP	WRMF	BPRMF	SMRMF	
JT3	MP	BPRMF	WRMF	SMRMF	WBPRMF
ML-latest	BPRMF	MP	WRMF	SMRMF	WBPRMF
ML100k	WRMF	BPRMF	WBPRMF	SMRMF	MP
ML10m	WRMF	BPRMF	MP	WBPRMF	SMRMF
ML1m	BPRMF	WRMF	SMRMF	WBPRMF	MP
ML20m	WRMF	BPRMF	MP	SMRMF	WBPRMF
MT-latest	MP	WRMF	BPRMF	SMRMF	WBPRMF
MT-recsys2014	MP	BPRMF	SMRMF	WBPRMF	
TA	BPRMF	WBPRMF	MP	SMRMF	
YH-movies	WRMF	BPRMF	MP	WBPRMF	SMRMF
YH-music	WRMF	WBPRMF	BPRMF	MP	SMRMF
YE	MP	WRMF	BPRMF	WBPRMF	SMRMF

Table B.7: RP multicriteria metatarget.

Dataset	$a-1$	$a-2$	$a-3$	$a-4$	$a-5$	$a-6$	$a-7$	$a-8$	$a-9$
AMZ-apps	BMF	SVD++	SIAFM	SCAFM	SUAFM	LFLLM	GA	UIB	MF
AMZ-automotive	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-baby	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-beauty	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-cd	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-clothes	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-music	BMF	SVD++	SCAFM	SIAFM	SUAFM	MF	GA	UIB	LFLLM
AMZ-food	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-games	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-garden	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-health	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-home	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-video	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	MF	UIB	LFLLM
AMZ-instruments	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-kindle	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	MF	UIB	LFLLM
AMZ-movies	BMF	SVD++	MF	SCAFM	SIAFM	SUAFM	GA	UIB	LFLLM
AMZ-office	BMF	SVD++	SCAFM	SIAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-pet	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-phones	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-sports	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-tools	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
AMZ-toys	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM
BK	BMF	SVD++	SUAFM	SCAFM	SIAFM	GA	MF	UIB	LFLLM
FL	BMF	MF	SVD++	LFLLM	SUAFM	SIAFM	SCAFM	GA	UIB
JT1	SUAFM	SVD++	MF	SIAFM	LFLLM	BMF	GA	UIB	
JT2	SUAFM	SVD++	MF	SIAFM	LFLLM	BMF	GA	UIB	
JT3	SIAFM	SUAFM	LFLLM	SCAFM	SVD++	MF	GA	UIB	BMF
ML-latest	BMF	MF	LFLLM	SVD++	SIAFM	GA	UIB		
ML100k	BMF	MF	SCAFM	SVD++	LFLLM	SIAFM	SUAFM	GA	UIB
ML10m	BMF	MF	LFLLM	SVD++	GA	SIAFM	SUAFM	SCAFM	UIB
ML1m	MF	BMF	SVD++	LFLLM	SIAFM	SUAFM	SCAFM	GA	UIB
ML20m	BMF	MF	LFLLM	SVD++	SIAFM	GA	UIB		
MT-latest	SCAFM	SIAFM	SUAFM	SVD++	MF	BMF	GA	UIB	LFLLM
MT-recsys2014	GA	UIB	LFLLM	BMF	SUAFM	SIAFM	SCAFM		
TA	SIAFM	BMF	SCAFM	SUAFM	GA	UIB	LFLLM		
YH-movies	BMF	SVD++	MF	SCAFM	SIAFM	SUAFM	LFLLM	GA	UIB
YH-music	SVD++	GA	SUAFM	UIB	SCAFM	SIAFM	BMF	LFLLM	
YE	BMF	SVD++	SIAFM	SCAFM	SUAFM	GA	UIB	MF	LFLLM

The results show the multicriteria metatargets produced have high resemblances with the single criterion metatargets seen before. To verify this observation, the correlation between the rankings of algorithms produced by each single criterion metatarget and those in the multicriteria metatarget per each baselevel dataset are calculated. Figure B.1 illustrates the distributions of correlations. The results are zoomed in the $[0.8, 1]$ range, which contains over 93% of the correlations.

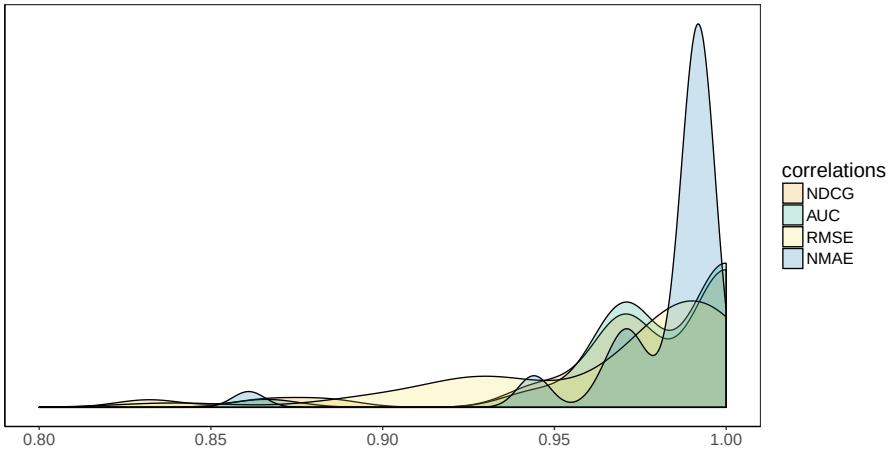


Figure B.1: Distributions of correlations between single criterion and multicriteria rankings.

According to these results, most correlations fall in the $[0.9, 1]$ interval, indicating that the single criterion and multicriteria metatargets are very similar. Therefore, one can conclude that there are very few differences in the metatargets. On one hand, this shows that the procedure keeps the algorithm orderings present in the single criterion metatargets. On the other hand, it also shows that this experimental setup offers little variation in rankings, hence making the problem of finding a consensus metatarget an easy task. This prevents us from proving the efficacy of the procedure, although the results produced are certainly acceptable.

Appendix C

Metafeature Selection

The exploratory nature employed in all proposed meta-approaches has yielded an extensive range of metafeatures. However, in order to properly assess their predictive merits, one needs first to fit them to this particular experimental setup. This Chapter provides details regarding the feature selection procedures employed to achieve that goal.

Feature selection in this Chapter is achieved by means of Correlation Feature Selection (CFS). Although simple, this technique has an advantage of not requiring the target in order to operate. Since the goal is to address algorithm selection using metatargets of different kinds (see Appendix B for further details), then it is of the utmost importance to use a technique which is suitable for all domains to be considered.

CFS assess which features are highly correlated and removes the least meaningful ones. To do so, a correlation threshold θ is defined, which allows to create a cutoff point. Thus, pairs of metafeatures whose correlation lies above the threshold are considered to removal. Based on the frequency each feature appears in such whose correlation is above θ, the procedure decides which must be removed and which must remain. The problem then becomes how to choose the correct θ. Although there is no universal answer, informally one needs to select a value which allows to keep a suitable amount of features, while promoting an overall low correlation score.

C.1 Rating Matrix systematic metafeatures

Now, the RM metafeatures kept after CFS are presented. Threshold $\theta = 0.7$ was found to be the one to provide the best results. Table C.1 presents the metafeatures, organized by object and respective amount.

The Table shows:

- **Most metafeatures are related to the item and user perspectives.** This shows the merits of systematically evaluating each perspective of the rating matrix instead of looking only at the original ratings.

Table C.1: RM metafeatures used in the experiments after CFS.

Object	Metafeatures selected	#
Item	*I.count.minimum*	7
	I.mean.entropy	
	I.mean.kurtosis	
	I.mean.mode	
	I.sum.entropy	
	I.sum.skewness	
	I.sum.maximum	
User	*U.count.maximum*	4
	U.mean.gini	
	U.mean.kurtosis	
	U.mean.minimum	
Dataset	*R.ratings.kurtosis*	2
	R.ratings.standard_deviation	
Other	*nusers*	1

- **Only one simple metafeature is kept.** From the extra metafeatures considered, only *nusers* remains. This is a surprising result since sparsity was expected to appear also, due to its recognized importance in CF domain.

- **Most functions and post-functions proposed are kept.** In fact, only one function is missing - there is no example of the user sum of ratings distribution - and only two post-functions are left out: mean and median. This shows that the wide variety of functions proposed are suitable and important to this setup.

C.2 Subsampling Landmarkers

In order to extract SL, random samples of 10% for each of the original 38 CF datasets are defined. These samples are then used to train CF algorithms, from which performance estimations are assessed via suitable evaluation metrics. This allows the extraction of what are referred as the Absolute relative landmarkers (AB). Afterwards, the remaining relative landmarkers (Ranking, Pairwise and Ratio) are computed based on the values of the Absolute landmarkers.

The entire process creates 4 different sets of metafeatures: AB, RK, PW and RT. These metafeatures are submitted to a similar CFS procedure, maintaining $\theta = 0.7$. This has yielded the metafeatures presented in Table C.2, which are organized by relative landmarker and CF task.

The analysis allows to understand:

- **Different relative landmarkers are characterized by different amounts of metafeatures.** AB, RK, PW and RT are respectively represented by 11, 7, 22 and 13 metafeatures.

- **All evaluation measures are available in all relative landmarkers.** This result shows that SL is dependent on the evaluation measure used.

Table C.2: SL metafeatures used in the experiments after CFS.

Relative Landmarker	CF task	Metafeatures selected	#
AB	IR	BPRMF.NDCG, MP.AUC, WBPRMF.AUC, WBPRMF.NDCG	11
	RP	BMF.NMAE, BMF.RMSE, LFLLM.NMAE, LFLLM.RMSE, SCAFM.NMAE, SIAFM.NMAE, UIB.RMSE	
RK	IR	BPRMF.AUC, MP.NDCG, SMRMF.NDCG	7
	RP	MF.RMSE, SVD++.RMSE, SUAFM.RMSE, UIB.NMAE	
PW	IR	BPRMF.AUC/MP.AUC, BPRMF.AUC/WBPRMF.AUC, BPRMF.NDCG/WBPRMF.NDCG, MP.NDCG/SMRMF.NDCG, SMRMF.NDCG/WRMF.NDCG, WRMF.AUC/WBPRMF.AUC, WRMF.NDCG/WBPRMF.NDCG	22
	RP	BMF.MAE/MF.MAE, BMF.NMAE/MF.NMAE, BMF.NMAE/SVD++.NMAE, BMF.RMSE/LFLLM.RMSE, BMF.RMSE/MF.RMSE, LFLLM.NMAE/MF.NMAE, LFLLM.RMSE/SVD++.RMSE, MF.MAE/UIB.MAE, MF.NMAE/SCAFM.NMAE, SVD++.RMSE/SUAFM.RMSE, SCAFM.MAE/SIAFM.MAE, SCAFM.NMAE/SIAFM.NMAE, SCAFM.RMSE/SUAFM.RMSE, SIAFM.RMSE/SUAFM.RMSE, SUAFM.NMAE/UIB.NMAE	
RT	IR	BPRMF.AUC/SMRMF.AUC, BPRMF.NDCG/MP.NDCG, BPRMF.NDCG/SMRMF.NDCG, SMRMF.NDCG/WRMF.NDCG, SMRMF.NDCG/WBPRMF.NDCG, WRMF.NDCG/WBPRMF.NDCG	13
	RP	BMF.NMAE/MF.NMAE, LFLLM.NMAE/SUAFM.NMAE, MF.RMSE/SCAFM.RMSE, SVD++.RMSE/SUAFM.RMSE, SCAFM.RMSE/SIAFM.RMSE, SCAFM.RMSE/SUAFM.RMSE, SIAFM.NMAE/UIB.NMAE	

- **Not all algorithms are present in SL.** For instance, there is no metafeature for algorithms SMRMF and WRMF in AB.
- **Some metafeatures in derived relative landmarkers are not available in the original AB.** This is an expected behavior since the purpose of relative landmarkers is to find new ways to model the original performance values in the hope of finding more informative representations.
- **The results show that RT keeps fewer metafeatures than PW.** For instance, while in PW there are 5 metafeatures regarding BMF, in RT only one remains. Such results allow to understand that different perspectives of the SL are indeed created, which in turn are translated into different metadata properties.

Despite the observations found, it is still unclear which relative landmarkers has the highest impact in the MtL problem. In order to simplify the results presentation, the predictive merits of the proposed relative landmarkers are investigated. The goal is to find the best relative landmarker, which in turn will be used as the SL representative in further analysis. Since several tasks to address to CF algorithm selection problem are used, each will be discussed individually.

Best algorithm selection In this scope, a full metalevel evaluation procedure for a classification task is conducted. Figure C.1 presents the metalevel accuracy for all the relative landmarkers.

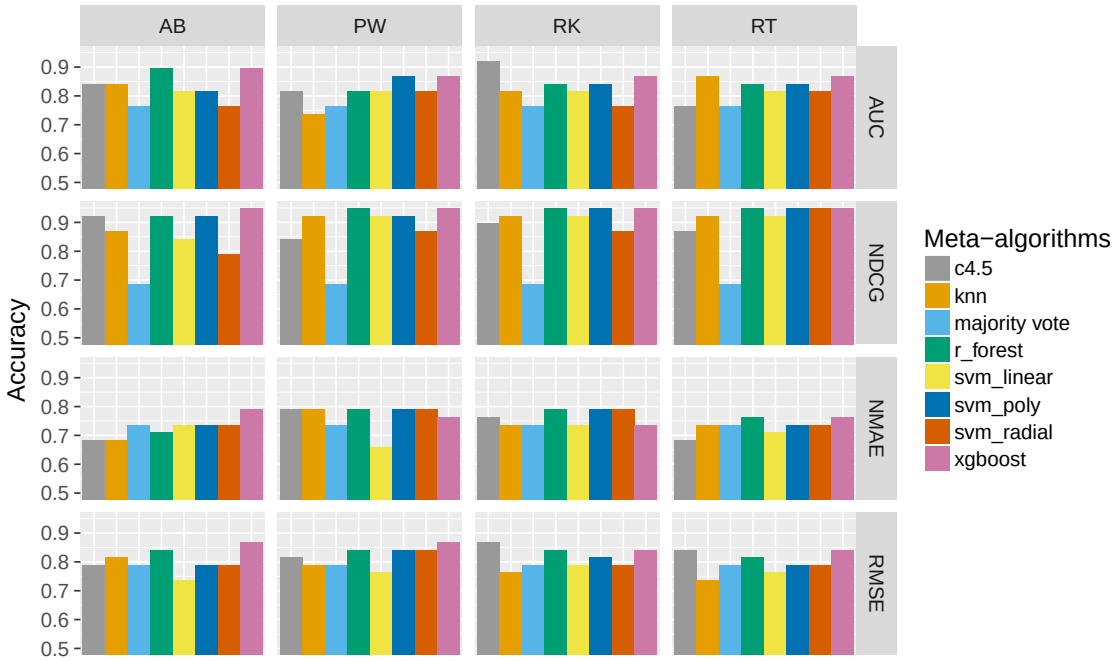


Figure C.1: Metalevel accuracy for relative SL in best algorithm selection.

The results show that all relative landmarkers are able to outperform the baseline, hence proving they are informative. However, there is no clear winner since the results show there is not a

meaningful difference between relative landmarkers in terms of metalevel accuracy. Furthermore, xgboost is the best metamodel since it almost always outperforms the competitors across relative landmarkers and metatargets.

To verify the previous observations, the CD diagram referring to xgboost's performance on all relative landmarkers is presented in Figure C.2. The results confirm the observations, since they state that no statistically significant differences among relative landmarkers.

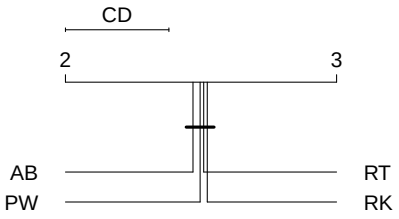


Figure C.2: Critical Difference diagram for relative SL in best algorithm selection.

The impact on the baselevel performance results are presented in Figure C.3

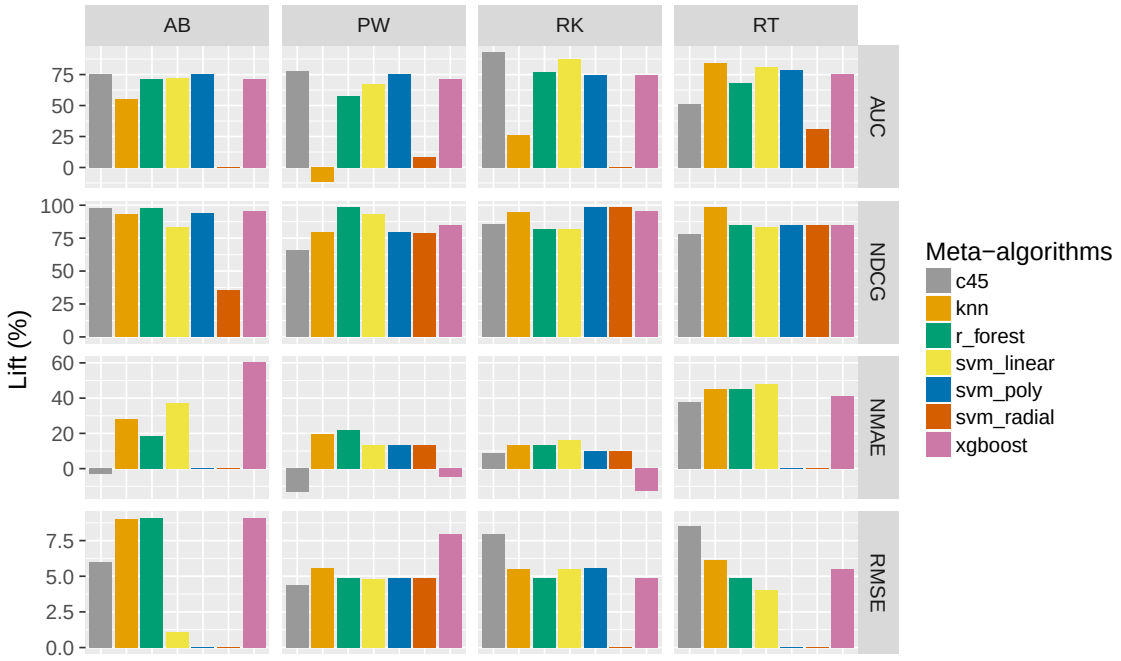


Figure C.3: Impact on the baselevel performance using relative SL in best algorithm selection.

The results show that performance is mostly similar, although there seems to exist a slight advantage of AB. This is particularly evident in the NMAE and RMSE metatargets, where they achieve the best performance. Considering the fact that they represent the simplest and less costly approach in relative landmarkers, AB is selected as SL's representative in the Chapters where a classification task is used to address the algorithm selection problem.

Best algorithm ranking selection Now, the focus shifts towards the metalevel evaluation of relative landmarkers when the task is addressed using Label Ranking algorithm with multicriteria metatargets. For such, Figure C.4 presents the Kendall's tau evaluation for all relative landmarkers proposed.

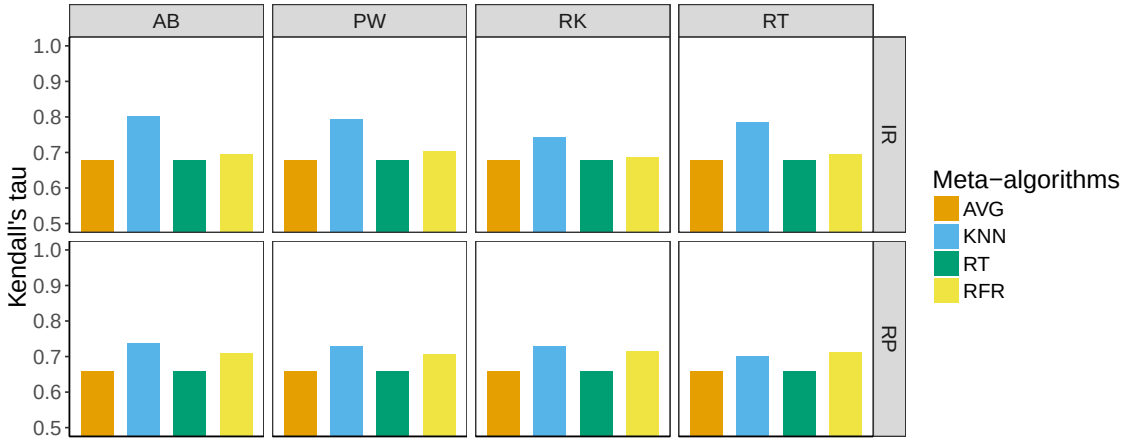


Figure C.4: Metalevel accuracy for relative SL in best algorithm ranking selection.

The results show that KNN presents the best performance throughout, with RT and RF barely beating the baseline in most cases. Furthermore, the results show that its performances are comparable in all pairs meta-approach/metatarget. To validate this assessment, statistical significance tests using CD diagrams were employed. Figure C.5 presents the results comparing the performances of KNN in all relative landmarkers.

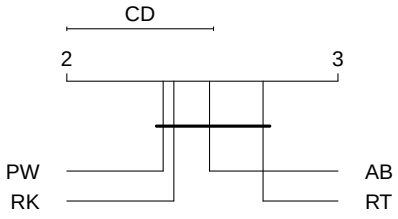


Figure C.5: Critical Difference diagram for relative SL in best algorithm ranking selection.

The results clearly show that despite PW and RK relative landmarkers scoring slightly better than the remaining, the difference in performance is not statistically significant. Now, one evaluates the impact on the baselevel performance, recurring to the same evaluation procedure used before. Figure C.6 presents the results of this analysis.

The results show that most metamodels outperform the baseline, except RK in IR and PW and RT in RP. This shows that in this evaluation scope, the performance is not stable for all the relative landmarkers. However, notice that AB is able to outperform the baseline in this scope in both metatargets for $t = 1$ with KNN. Thus, AB is selected as the SL representative meta-approach, similarly to what happened in the best algorithm metatarget.

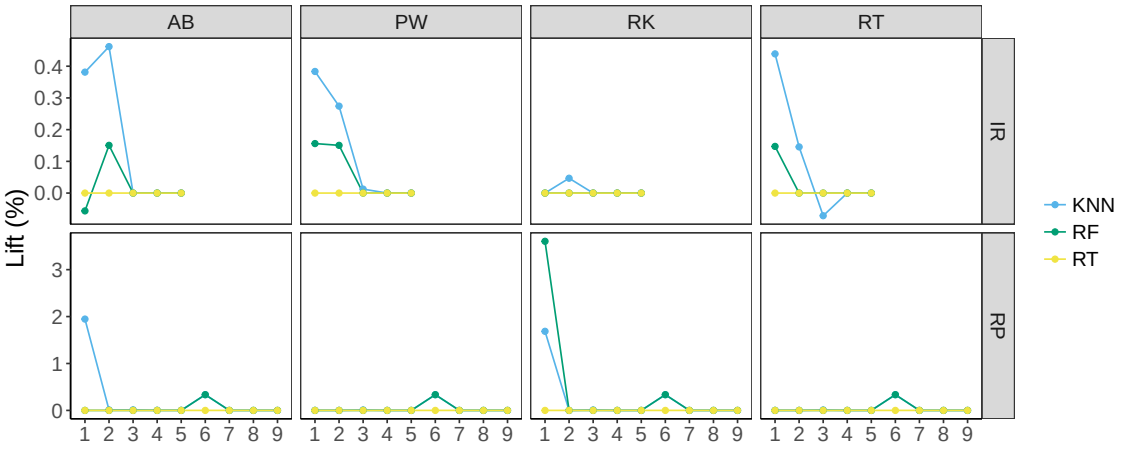


Figure C.6: Impact on the baselevel performance for relative SL in best algorithm ranking selection.

C.3 Graph-based systematic metafeatures

The same CFS technique used before is replicated here. Table C.3 presents the metafeatures selected for $\theta = 0.7$, organized by level and object. Notice that in the cases where a metafeature shares multiple post-functions, these are joined in the nomenclature using the set symbol "{}" in order to facilitate the analysis.

This analysis shows that:

- **No Graph-level metafeatures are kept.** This points out to the fact that they represent concepts which are too simple to be useful in out MtL setup.
- **The remaining levels (Node, Pairwise and Subgraph) keep 7%, 10.4% and 9% of their metafeatures respectively.** Although the percentage of metafeatures kept is small, it still account for 65 metafeatures, a collection larger than its competitors.
- **The vast majority of selected metafeatures belong to the Subgraph level.** This means that the level which takes most advantage of the hierarchical decomposition process is the one with most meaningful metafeatures.
- **The metafeatures include all objects defined.** Although there is a bias towards communities and components, it is always possible to find at least one example of all objects in the remaining metafeatures.
- **Most proposed functions are used.** However, some functions appear more often than others: for instance, *alpha* and *diversity* in Subgraph-level and similarity in the Pairwise level are responsible for the majority of metafeatures in the respective levels.
- **The post-functions used are well distributed.** This means there is no particular preference for any of these functions. However, cases such as $components.coreness.skewness.\{pf\}$ are

Table C.3: Graph metafeatures used in the experiments after CFS.

Level	Object	Metafeatures selected	#
Node	Graph	$G.authority.variance$	2
		$G.closeness.variance$	
	Item	$I.degree.skewness$	4
		$I.diversity.skewness$	
		$I.eccentricity.skewness$	
		$I.PageRank, variance$	
	User	$U.alpha.\{mean, entropy.skewness\}$	6
		$U.closeness.variance$	
		$U.diversity.\{entropy, skewness\}$	
Pairwise	Graph	$G.similarity.variance.skewness$	1
	Item	$I.similarity.count.\{skewness, variance\}$	6
		$I.similarity.mean.variance$	
		$I.similarity.sum.variance$	
		$I.similarity.variance.skewness$	
		$I.distances.sum.skewness$	
	User	$U.similarity.variance.\{entropy, skewness, variance\}$	3
Subgraph	Communities	$communities.alpha.mean.\{entropy, skewness\}$	16
		$communities.alpha.skewness.entropy$	
		$communities.alpha.variance.variance$	
		$communities.authority.skewness.skewness$	
		$communities.closeness.skewness.variance$	
		$communities.coreness.entropy.skewness$	
		$communities.coreness.skewness.\{mean, skewness\}$	
		$communities.diversity.mean.skewness$	
		$communities.diversity.skewness.entropy$	
		$communities.diversity.variance.\{mean, skewness\}$	
		$communities.hub.entropy.mean$	
		$communities.knn.skewness.skewness$	
		$communities.strength.skewness.entropy$	
	Components	$components.alpha.skewness.\{entropy, skewness\}$	27
		$components.alpha.variance.skewness$	
		$components.closeness.skewness.skewness$	
		$components.closeness.variance.\{skewness, variance\}$	
		$components.closeness.skewness.skewness$	
		$components.constraint.skewness.\{entropy, skewness\}$	
		$components.coreness.skewness.\{entropy, mean, skew, variance\}$	
		$components.diversity.entropy.\{mean, skew, variance\}$	
		$components.diversity.mean.\{skewness, variance\}$	
		$components.diversity.skewness.\{entropy, skewness\}$	
		$components.diversity.variance.\{mean, skewness, variance\}$	
		$components.eccentricity.skewness.\{entropy, mean\}$	
		$components.eigenvector.entropy.skewness$	
		$components.eigenvector.skewness.variance$	
		$components.knn.skewness.entropy$	

interesting, since they include all post-functions. This points out the potential informative power of this type of graph characteristics.

C.4 Comprehensive Metafeatures

This work also introduces a new set of Comprehensive metafeatures (CM), which is composed of metafeatures from all proposed meta-approaches, namely RM, SL and GR. This allows to verify whether using characteristics from multiple domains in a single collection does yield better results in terms of algorithm selection. These metafeatures are obtained aggregating all proposed metafeatures and performing Correlation Feature Selection ($\theta = 0.7$). Table C.4 presents the metafeatures selected, organized by meta-approach. Notice that the metafeatures presented shorten the nomenclature using the set symbol "{}" in order to facilitate the analysis.

Table C.4: Comprehensive metafeatures.

Meta-approach	Metafeatures
RM	$I.count.minimum$ $I.mean.\{entropy, kurtosis, mode\}$ $I.sum.\{entropy, skewness, maximum\}$ $U.count.maximum$ $U.mean.\{gini, minimum\}$ $R.ratings.\{kurtosis, standard\_deviation\}$ $nusers$
SL	$BPRMF.NDCG, MP.AUC, WBPRMF.AUC,$ $WBPRMF.NDCG, BMF.NMAE, BMF.RMSE,$ $LFLLM.NMAE, LFLLM.RMSE, UIB.RMSE,$ $UIB.NMAE, SUAFM.RMSE$
GR	$\{I\}.\{diversity, eccentricity\}.\{pf\}$ $\{U\}.\{alpha\}.\{skewness\}$ $\{G\}.\{similarity\}.\{variance\}.\{skewness\}$ $\{I\}.\{similarity\}.\{mpf\}.\{pf\}$ $\{U\}.\{similarity\}.\{variance\}.\{skewness\}$ $\{I\}.\{distances\}.\{sum\}.\{skewness\}$ $communities.\{alpha, authority, closeness, coreness,$ $diversity, hub, knn, strength\}.\{pf\}.\{pf\}$ $components.\{alpha, closeness, constraint, coreness,$ $diversity, eccentricity, eigenvector\}.\{pf\}.\{pf\}$

The analysis shows that:

- **CM contains metafeatures from all proposed meta-approaches.** GR has the highest contribution with 26 metafeatures, while RM and SL provide 13 and 10 metafeatures, respectively. This observation shows that all proposed meta-approaches complement one another. Since this means the correlations among metafeatures from different meta-approaches are not high, it provides evidence towards the fact that the meta-approaches indeed describe different aspects of the CF problem. Therefore, their inclusion has potential to allow to discriminate algorithms more easily.

- **Not all metafeatures are kept.** RM no longer keeps $U.mean.kurtosis$, while in SL, two metafeatures change: SCAFM.NMAE and SIAFM.NMAE are replaced by UIB.NMAE and SUAFM.RMSE. In GR, there are fewer metafeatures represented (for instance, the user alpha distribution is characterized only by the skewness). Also, some metafeatures are entirely removed, namely: $G.\{authority, closeness\}.variance$, $I.\{degree, PageRank\}.\{pf\}$, $\{U\}.\{closeness, diversity\}.\{pf\}$, $components.knn.\{pf\}.\{pf\}$ and $communities.strength.\{pf\}.\{pf\}$

Appendix D

Detailed Evaluation Results

This Chapter presents all evaluation results regarding the experimental setup presented in Chapter 6. It encompasses 5 different algorithmic approaches (CF4CF, CF4CF-META, Label Ranking, ALORS and ASLIB) and all their variations both in terms of metafeatures and meta-algorithms. The analysis shows the Kendall's tau metalevel accuracy, Top-N metalevel accuracy and impact on the baselevel performance analysis. Notice that the models which outperform the baseline at each ranking are highlighted.

D.1 CF4CF

The results in terms of Kendall's tau metalevel accuracy, Top-N metalevel accuracy and impact on the baselevel performance analysis for the CF4CF metamodels are presented in Tables D.1, D.2, D.3 and D.3. Notice that N_{SL} has been selected accordingly to the results presented in Section 6.3.2.1.

Table D.1: Kendall's Tau Ranking accuracy performance for CF4CF approach.

CF task	UBCF	ALS	AVG
IR	**0.787 ± 0.171**	**0.806 ± 0.161**	0.663 ± 0.336
RP	0.489 ± 0.28	0.51 ± 0.279	0.656 ± 0.324

Table D.2: NDCG Top-N accuracy performance for CF4CF approach.

Metric	UBCF	ALS	AVG
ITEM RECOMMENDATION			
NDCG@1	0.668 ± 0.264	0.676 ± 0.243	0.763 ± 0.431
NDCG@2	0.953 ± 0.08	**0.979 ± 0.074**	0.974 ± 0.162
NDCG@3	0.972 ± 0.033	0.981 ± 0.041	0.981 ± 0.057
RATING PREDICTION			
NDCG@1	0.239 ± 0.381	0.195 ± 0.336	0.789 ± 0.413
NDCG@3	0.822 ± 0.166	0.848 ± 0.165	0.949 ± 0.181
NDCG@5	0.949 ± 0.08	0.954 ± 0.086	0.956 ± 0.087

Table D.3: Impact on baselevel performance for CF4CF approach in the Item Recommendation problem.

Algorithm	1	2	3	4	5
AVG	0.533	0.539	0.547	0.547	0.547
ALS	**0.543**	**0.546**	0.547	0.547	0.547
UBCF	**0.543**	**0.545**	0.546	0.547	0.547

Table D.4: Impact on baselevel performance for CF4CF approach in the Item Recommendation problem.

Algorithm	1	2	3	4	5	6	7	8	9
AVG	0.297	0.260	0.255	0.240	0.205	0.205	0.185	0.185	0.185
ALS	**0.296**	0.278	0.267	0.247	**0.197**	**0.188**	0.187	0.185	0.185
UBCF	**0.292**	0.280	0.262	**0.235**	**0.201**	**0.187**	0.187	0.185	0.185

The results allow to perceive:

- CF4CF performs well in terms of Kendall's tau, but only in the IR problem. Both UBCF and ALS are suitable in this case, with a slight advantage for ALS.
- The results in terms of NDCG are poor, since in only one case does the performance beat the baseline: for ALS metamodels in NDCG@2 in the IR metatarget.
- Both ALS and UBCF are able to beat the baseline in terms of impact on the baselevel performance for $t \leq 2$ and $t = 1$ in the IR and RP metatargets, respectively.
- Although the results are not impressive, ALS is the best solution in CF4CF.

D.2 CF4CF-META

The results in terms of Kendall's tau, Top-N metalevel accuracy and impact on the baselevel performance analysis for the CF4CF metamodels are presented in Tables D.5, D.6, D.7 and D.8. Notice that N_{SL} has been selected accordingly to the results presented in Section 6.3.2.1.

Table D.5: Kendall's Tau Ranking accuracy performance for CF4CF-META approach.

Metadata	KNN	RT	RFR	AVG
ITEM RECOMMENDATION				
RM	**0.869 ± 0.208**	0.663 ± 0.336	**0.864 ± 0.226**	0.663 ± 0.336
GR	**0.861 ± 0.204**	0.663 ± 0.336	**0.789 ± 0.33**	
CM	**0.863 ± 0.236**	**0.863 ± 0.266**	**0.845 ± 0.244**	
RATING PREDICTION				
RM	**0.861 ± 0.26**	**0.827 ± 0.265**	**0.815 ± 0.296**	0.656 ± 0.324
GR	**0.847 ± 0.279**	**0.759 ± 0.274**	**0.736 ± 0.32**	
CM	**0.858 ± 0.282**	**0.766 ± 0.28**	**0.802 ± 0.272**	

Table D.6: NDCG Top-N accuracy performance for CF4CF-META approach.

Metadata	KNN	RT	RFR	AVG
ITEM RECOMMENDATION				
NDCG@1				
RM	**0.871 ± 0.203**	0.663 ± 0.336	**0.787 ± 0.33**	0.763 ± 0.431
GR	**0.87 ± 0.216**	0.663 ± 0.336	**0.787 ± 0.33**	
CM	**0.864 ± 0.23**	0.663 ± 0.336	**0.787 ± 0.33**	
NDCG@2				
RM	0.865 ± 0.202	0.663 ± 0.336	0.789 ± 0.33	0.974 ± 0.162
GR	0.859 ± 0.202	0.663 ± 0.336	0.789 ± 0.33	
CM	0.865 ± 0.2	0.663 ± 0.336	0.789 ± 0.33	
NDCG@3				
RM	0.865 ± 0.232	0.863 ± 0.266	0.845 ± 0.244	0.981 ± 0.057
GR	0.864 ± 0.231	0.863 ± 0.266	0.845 ± 0.244	
CM	0.868 ± 0.234	0.863 ± 0.266	0.845 ± 0.244	
RATING PREDICTION				
NDCG@1				
RM	**0.858 ± 0.26**	**0.827 ± 0.265**	**0.815 ± 0.296**	0.789 ± 0.413
GR	**0.854 ± 0.262**	**0.827 ± 0.265**	**0.815 ± 0.296**	
CM	**0.857 ± 0.26**	**0.827 ± 0.265**	**0.815 ± 0.296**	
NDCG@3				
RM	0.847 ± 0.28	0.757 ± 0.277	0.736 ± 0.32	0.949 ± 0.181
GR	0.848 ± 0.278	0.758 ± 0.28	0.736 ± 0.32	
CM	0.848 ± 0.279	0.757 ± 0.276	0.736 ± 0.32	
NDCG@5				
RM	0.857 ± 0.282	0.766 ± 0.28	0.802 ± 0.272	0.956 ± 0.087
GR	0.856 ± 0.28	0.766 ± 0.28	0.802 ± 0.272	
CM	0.856 ± 0.282	0.766 ± 0.28	0.802 ± 0.272	

Table D.7: Impact on baselevel performance for CF4CF-META approach in the Item Recommendation problem.

Metadata	Algorithm	1	2	3	4	5
	AVG	0.533	0.539	0.547	0.547	0.547
RM	KNN	**0.541**	**0.544**	0.547	0.547	0.547
	RT	0.533	0.539	0.547	0.547	0.547
	RFR	**0.536**	0.539	0.544	0.547	0.547
GR	KNN	**0.540**	**0.544**	0.547	0.547	0.547
	RT	0.533	0.539	0.547	0.547	0.547
	RFR	**0.538**	0.539	0.547	0.547	0.547
CM	KNN	**0.541**	**0.545**	0.547	0.547	0.547
	RT	**0.541**	**0.544**	0.547	0.547	0.547
	RFR	**0.538**	**0.543**	0.547	0.547	0.547

Table D.8: Impact on baselevel performance for CF4CF-META approach in the Rating Prediction problem.

Metadata	Algorithm	1	2	3	4	5	6	7	8	9
	AVG	0.297	0.260	0.255	0.240	0.205	0.205	0.185	0.185	0.185
RM	KNN	**0.253**	**0.225**	**0.199**	**0.188**	**0.188**	**0.188**	0.188	0.185	0.185
	RT	**0.234**	**0.209**	**0.205**	**0.205**	0.205	**0.185**	0.185	0.185	0.185
	RFR	**0.252**	**0.225**	**0.222**	**0.205**	0.205	0.205	0.185	0.185	0.185
GR	KNN	**0.244**	**0.225**	**0.204**	**0.191**	**0.188**	**0.188**	0.188	0.185	0.185
	RT	**0.219**	**0.209**	**0.205**	**0.205**	**0.187**	**0.185**	0.185	0.185	0.185
	RFR	**0.279**	**0.245**	**0.223**	**0.222**	0.205	**0.185**	0.185	0.185	0.185
CM	KNN	**0.244**	**0.225**	**0.204**	**0.194**	**0.188**	**0.188**	0.188	0.185	0.185
	RT	**0.218**	**0.209**	**0.205**	**0.205**	0.205	**0.185**	0.185	0.185	0.185
	RFR	**0.246**	**0.209**	**0.205**	**0.205**	0.205	0.205	0.185	0.185	0.185

The results show:

- All metamodels are able to beat the baseline in terms of Kendall's tau, with the exception of the RT metamodel using RM and GR metafeatures. The results also show that there seems to exist an advantage of RM metafeatures, especially when using KNN.
- These metamodels are particularly good for NDCG@1 for both metatargets (although RT does not perform well in IR). However, they are never better than the baseline for the remaining thresholds.
- The impact on the baselevel performance analysis shows that the vast majority of metamodels are better than the baseline for $t \leq 2$ and $t \leq 6$ for IR and RP metatargets, respectively. Although RT achieves the best performance in RP, its performance in IR is poor. However, KNN is able to always outperform the baseline regardless of the metafeatures employed.
- Considering all evaluation scopes, KNN with RM metafeatures seems the best solution.

D.3 Label Ranking

The results in terms of Kendall's tau metalevel accuracy, Top-*N* metalevel accuracy and impact on the baselevel performance analysis for the Label Ranking metamodels are presented in Tables D.9, D.10, D.11 and D.12.

Table D.9: Kendall's Tau Ranking accuracy performance for Label Ranking approach.

Metadata	KNN	RT	RFR	AVG
ITEM RECOMMENDATION				
RM	**0.730 ± 0.335**	**0.839 ± 0.264**	**0.856 ± 0.233**	0.663 ± 0.336
SL	0.527 ± 0.345	0.663 ± 0.336	**0.681 ± 0.306**	
GR	0.597 ± 0.386	**0.844 ± 0.233**	**0.838 ± 0.268**	
CM	**0.714 ± 0.300**	**0.863 ± 0.266**	**0.857 ± 0.227**	
RATING PREDICTION				
RM	**0.764 ± 0.289**	**0.827 ± 0.265**	**0.832 ± 0.301**	0.656 ± 0.324
SL	0.545 ± 0.285	0.656 ± 0.324	**0.674 ± 0.329**	
GR	0.611 ± 0.433	**0.732 ± 0.307**	**0.756 ± 0.316**	
CM	**0.746 ± 0.362**	**0.766 ± 0.280**	**0.818 ± 0.279**	

Considering all results presented, several observations can be made:

- In terms of Kendall's tau, the results show LR metamodels perform better than the baseline for RM and CM metafeatures in both metatargets. Furthermore, RFR is the best metamodel since it is always able to extract the best performances (and beat the baseline) regardless of the metafeatures used.

- Considering now the Top-N evaluation, one observes that RFR still obtains the best performance throughout, although RT is now a strong competitor. The thresholds where such models perform better are $N = 1$ and $N = 3$ for IR and $N = 1$ and $N = 5$ for RP. This means that such metamodels are useful are predicting the absolute best algorithm and the top half of the ranking of algorithms.

- The impact on the baselevel performance analysis shows that most metamodels with RM, GR and CM metafeatures are better than the baseline for $t \leq 2$ and $t \leq 4$ for IR and RP metatargets, respectively. RT and RFR are the best solutions, although they are unable to perform well using SL metafeatures.

- Considering all evaluation scopes, RFR with CM metafeatures seems to be the best solution.

Table D.10: NDCG Top-N accuracy performance for Label Ranking approach.

Metadata	KNN	RT	RFR	AVG
ITEM RECOMMENDATION				
NDCG@1				
RM	0.737 ± 0.446	**0.816 ± 0.393**	**0.789 ± 0.413**	0.763 ± 0.431
SL	0.658 ± 0.481	0.763 ± 0.431	**0.789 ± 0.413**	
GR	0.711 ± 0.460	**0.895 ± 0.311**	**0.868 ± 0.343**	
CM	0.711 ± 0.460	**0.842 ± 0.370**	**0.816 ± 0.393**	
NDCG@2				
RM	0.974 ± 0.162	**1 ± 0**	**1 ± 0**	0.974 ± 0.162
SL	0.868 ± 0.343	0.974 ± 0.162	0.974 ± 0.162	
GR	0.947 ± 0.226	**1 ± 0**	**1 ± 0**	
CM	0.974 ± 0.162	0.974 ± 0.162	**1 ± 0**	
NDCG@3				
RM	**0.990 ± 0.042**	**0.995 ± 0.030**	**0.995 ± 0.030**	0.981 ± 0.057
SL	0.961 ± 0.087	0.981 ± 0.057	0.981 ± 0.057	
GR	0.976 ± 0.063	**0.990 ± 0.042**	**0.990 ± 0.042**	
CM	**0.985 ± 0.050**	**0.990 ± 0.042**	**0.995 ± 0.030**	
RATING PREDICTION				
NDCG@1				
RM	0.763 ± 0.431	**0.842 ± 0.370**	**0.842 ± 0.370**	0.789 ± 0.413
SL	0.605 ± 0.495	0.789 ± 0.413	0.789 ± 0.413	
GR	0.658 ± 0.481	0.737 ± 0.446	0.789 ± 0.413	
CM	**0.842 ± 0.370**	**0.816 ± 0.393**	**0.868 ± 0.343**	
NDCG@3				
RM	0.94 ± 0.183	0.949 ± 0.181	0.945 ± 0.182	0.949 ± 0.181
SL	0.866 ± 0.311	0.949 ± 0.181	0.945 ± 0.182	
GR	0.88 ± 0.313	0.949 ± 0.176	0.913 ± 0.234	
CM	0.892 ± 0.28	0.949 ± 0.176	**0.954 ± 0.174**	
NDCG@5				
RM	**0.962 ± 0.081**	**0.966 ± 0.092**	**0.969 ± 0.077**	0.956 ± 0.087
SL	0.94 ± 0.093	0.956 ± 0.087	**0.958 ± 0.087**	
GR	0.937 ± 0.105	**0.971 ± 0.073**	**0.964 ± 0.082**	
CM	**0.961 ± 0.095**	**0.97 ± 0.073**	**0.974 ± 0.075**	

Table D.11: Impact on baselevel performance for Label Ranking approach in the Item Recommendation problem.

Metadata	Algorithm	1	2	3	4	5
	AVG	0.533	0.539	0.547	0.547	0.547
RM	KNN	**0.538**	**0.542**	0.546	0.547	0.547
	RT	**0.538**	**0.543**	0.547	0.547	0.547
	RFR	**0.538**	**0.544**	0.547	0.547	0.547
SL	KNN	0.529	0.538	0.546	0.547	0.547
	RT	0.533	0.539	0.547	0.547	0.547
	RFR	0.533	0.539	0.547	0.547	0.547
GR	KNN	0.533	0.539	0.547	0.547	0.547
	RT	**0.544**	**0.544**	0.547	0.547	0.547
	RFR	**0.541**	**0.543**	0.547	0.547	0.547
CM	KNN	**0.537**	**0.543**	0.547	0.547	0.547
	RT	**0.541**	**0.544**	0.547	0.547	0.547
	RFR	**0.538**	**0.541**	0.547	0.547	0.547

Table D.12: Impact on baselevel performance for Label Ranking approach in the Rating Prediction problem.

Metadata	Algorithm	1	2	3	4	5	6	7	8	9
	AVG	0.297	0.260	0.255	0.240	0.205	0.205	0.185	0.185	0.185
RM	KNN	**0.264**	**0.225**	**0.223**	**0.205**	0.205	0.205	0.185	0.185	0.185
	RT	**0.234**	**0.209**	**0.205**	**0.205**	0.205	**0.185**	0.185	0.185	0.185
	RFR	**0.234**	**0.225**	**0.205**	**0.205**	0.205	0.205	0.185	0.185	0.185
SL	KNN	0.302	0.265	**0.246**	0.241	0.206	**0.185**	0.185	0.185	0.185
	RT	0.297	0.260	0.255	0.240	0.205	0.205	0.185	0.185	0.185
	RFR	0.297	0.260	0.255	0.240	0.205	**0.185**	0.185	0.185	0.185
GR	KNN	0.309	0.263	0.260	**0.224**	0.208	**0.192**	0.188	0.185	0.185
	RT	**0.221**	**0.209**	**0.205**	**0.205**	0.205	0.205	0.185	0.185	0.185
	RFR	**0.253**	**0.243**	**0.222**	**0.220**	0.205	0.205	0.185	0.185	0.185
CM	KNN	**0.235**	**0.231**	**0.206**	**0.206**	0.205	0.205	0.188	0.185	0.185
	RT	**0.218**	**0.209**	**0.205**	**0.205**	0.205	**0.185**	0.185	0.185	0.185
	RFR	**0.228**	**0.209**	**0.205**	**0.205**	0.205	0.205	0.185	0.185	0.185

D.4 ALORS

The results in terms of Kendall's tau metalevel accuracy, Top-*N* metalevel accuracy and impact on the baselevel performance analysis for the ALORS metamodels are presented in Tables D.13, D.14, D.15 and D.16.

Table D.13: Kendall's Tau Ranking accuracy performance for ALORS approach.

CF task	RM	SL	GR	CM	AVG
IR	**0.732 ± 0.313**	**0.668 ± 0.358**	**0.721 ± 0.356**	**0.742 ± 0.275**	0.663 ± 0.336
RP	**0.783 ± 0.31**	0.614 ± 0.31	**0.681 ± 0.375**	**0.761 ± 0.331**	0.656 ± 0.324

Table D.14: NDCG Top-N accuracy performance for ALORS approach.

Metric	RM	SL	GR	CM	AVG
ITEM RECOMMENDATION					
NDCG@1	0.184 ± 0.393	0.132 ± 0.343	0.184 ± 0.393	0.184 ± 0.393	0.763 ± 0.431
NDCG@2	0.974 ± 0.162	0.947 ± 0.226	0.895 ± 0.311	0.921 ± 0.273	0.974 ± 0.162
NDCG@3	0.971 ± 0.068	0.913 ± 0.093	0.951 ± 0.082	0.966 ± 0.072	0.981 ± 0.057
RATING PREDICTION					
NDCG@1	0.026 ± 0.162	0.184 ± 0.393	0.132 ± 0.343	0.105 ± 0.311	0.789 ± 0.413
NDCG@3	0.906 ± 0.175	0.807 ± 0.303	0.896 ± 0.185	0.896 ± 0.185	0.949 ± 0.181
NDCG@5	0.956 ± 0.125	0.935 ± 0.116	0.933 ± 0.109	**0.965 ± 0.076**	0.956 ± 0.087

Table D.15: Impact on baselevel performance for ALORS approach in the Item Recommendation problem.

Metadata	1	2	3	4	5
AVG	0.533	0.539	0.547	0.547	0.547
RM	**0.542**	**0.544**	0.547	0.547	0.547
SL	0.532	0.539	0.546	0.547	0.547
GR	**0.539**	**0.546**	0.546	0.547	0.547
CM	**0.540**	**0.547**	0.547	0.547	0.547

Table D.16: Impact on baselevel performance for ALORS approach in the Rating Prediction problem.

Metadata	1	2	3	4	5	6	7	8	9
AVG	0.297	0.260	0.255	0.240	0.205	0.205	0.185	0.185	0.185
RM	**0.234**	**0.209**	**0.206**	**0.205**	0.205	0.205	0.185	0.185	0.185
SL	0.300	0.261	0.256	0.240	0.205	**0.185**	0.185	0.185	0.185
GR	**0.270**	**0.245**	**0.209**	**0.208**	0.205	0.205	0.188	0.185	0.185
CM	**0.269**	**0.209**	**0.206**	**0.205**	0.205	0.205	0.185	0.185	0.185

The results allow to observe:

- The vast majority of metamodels are able to outperform the baseline, with the exception of SL metafeatures in the RP metatarget. Here, RM and CM provide the best performance in the RP and IR metatargets, respectively.
- The performance in terms of Top-*N* evaluation is poor since only in one occasion does the performance beat the baseline.
- The impact on the baselevel performance analysis shows that the vast majority of metamodels are better than the baseline for $t \leq 2$ and $t \leq 4$ for IR and RP metatargets, respectively. It is also noticeable that SL performs poorly and there seems to be an advantage to CM.
- The best solution considering all evaluation scopes is CM.

D.5 ASLIB

The results in terms of Kendall's tau metalevel accuracy, Top-*N* metalevel accuracy and impact on the baselevel performance analysis for the CF4CF-ALORS metamodels are presented in Tables D.17, D.18, D.19, D.20 and D.21.

Table D.17: Kendall's Tau Ranking accuracy performance for ASLIB approach.

Algorithm	RM	SL	GR	CM
ITEM RECOMMENDATION				
AVG	0.663 ± 0.336			
LM	0.395 ± 0.314	0.363 ± 0.328	0.268 ± 0.260	0.374 ± 0.375
XGBOOST	0.089 ± 0.311	0.189 ± 0.386	0.374 ± 0.268	0.321 ± 0.379
SVM	0.289 ± 0.236	0.474 ± 0.396	0.337 ± 0.309	0.353 ± 0.333
RRF	0.279 ± 0.321	0.542 ± 0.41	0.332 ± 0.264	0.337 ± 0.251
RPART	0.3 ± 0.443	0.289 ± 0.455	0.4 ± 0.335	0.4 ± 0.481
RKNN	0.305 ± 0.308	0.295 ± 0.365	0.316 ± 0.249	0.316 ± 0.24
RATING PREDICTION				
AVG	0.656 ± 0.324			
LM	-0.026 ± 0.16	0.068 ± 0.282	0.198 ± 0.199	0.037 ± 0.186
XGBOOST	0.154 ± 0.224	-0.137 ± 0.249	0.152 ± 0.213	-0.155 ± 0.279
SVM	-0.004 ± 0.226	-0.095 ± 0.172	-0.198 ± 0.166	0.06 ± 0.248
RRF	-0.158 ± 0.278	-0.199 ± 0.241	-0.171 ± 0.236	-0.19 ± 0.235
RPART	-0.17 ± 0.295	-0.133 ± 0.238	-0.205 ± 0.262	-0.32 ± 0.296
RKNN	-0.079 ± 0.132	0.12 ± 0.269	0.081 ± 0.201	0.214 ± 0.247

Table D.18: NDCG Top-N accuracy performance for ASLIB approach in the Item Recommendation task.

Algorithm	RM	SL	GR	CM
NDCG@1				
AVG	0.763 ± 0.431			
LM	0.474 ± 0.506	0.421 ± 0.5	0.447 ± 0.504	0.211 ± 0.413
XGBOOST	0.184 ± 0.393	0.447 ± 0.504	0.184 ± 0.393	0.263 ± 0.446
SVM	0.289 ± 0.46	0.526 ± 0.506	0.632 ± 0.489	0.158 ± 0.37
RRF	0.447 ± 0.504	0.526 ± 0.506	0.526 ± 0.506	0.342 ± 0.481
RPART	0.395 ± 0.495	0.237 ± 0.431	0.5 ± 0.507	0.395 ± 0.495
RKNN	0.5 ± 0.507	0.526 ± 0.506	0.368 ± 0.489	0.5 ± 0.507
NDCG@2				
AVG	0.974 ± 0.162			
LM	0.921 ± 0.273	0.947 ± 0.226	0.974 ± 0.162	0.974 ± 0.162
XGBOOST	0.974 ± 0.162	0.868 ± 0.343	0.947 ± 0.226	0.895 ± 0.311
SVM	0.974 ± 0.162	0.921 ± 0.273	0.974 ± 0.162	0.974 ± 0.162
RRF	0.947 ± 0.226	0.974 ± 0.162	0.947 ± 0.226	0.974 ± 0.162
RPART	0.921 ± 0.273	0.947 ± 0.226	0.895 ± 0.311	0.921 ± 0.273
RKNN	0.974 ± 0.162	0.947 ± 0.226	0.974 ± 0.162	0.947 ± 0.226
NDCG@3				
AVG	0.981 ± 0.057			
LM	0.942 ± 0.097	0.971 ± 0.068	$\mathbf{0.995 \pm 0.03}$	0.971 ± 0.068
XGBOOST	0.976 ± 0.063	0.937 ± 0.107	0.976 ± 0.063	0.932 ± 0.09
SVM	$\mathbf{0.985 \pm 0.05}$	0.976 ± 0.076	0.981 ± 0.057	$\mathbf{0.995 \pm 0.03}$
RRF	$\mathbf{0.99 \pm 0.042}$	0.966 ± 0.072	0.981 ± 0.057	$\mathbf{0.99 \pm 0.042}$
RPART	0.917 ± 0.111	0.932 ± 0.09	0.956 ± 0.1	0.947 ± 0.095
RKNN	$\mathbf{0.985 \pm 0.05}$	$\mathbf{0.985 \pm 0.05}$	$\mathbf{0.995 \pm 0.03}$	0.981 ± 0.057

The results show:

- No metamodel is able to outperform the baseline in terms of Kendall's Tau.
- A few metamodels are able to beat the baseline for NDCG@3 in IR metatarget. However, they fail to do the same in the other perspectives of Top-N evaluation.
- The results in terms of impact on the baselevel performance show that there are meaningful metamodels for $N = 1$ and $2 \leq N \leq 6$ in IR and RP, respectively. RKNN performs particularly well in this task, since it is the only metamodel able to do so with all metafeatures.
- Despite poor results in terms of metalevel accuracy, RKNN with CM metafeatures seems to be the most appropriate solution.

Table D.19: NDCG Top-N accuracy performance for ASLIB approach in the Rating Prediction task.

Algorithm	RM	SL	GR	CM
NDCG@1				
AVG	0.789 ± 0.413			
LM	0.053 ± 0.226	0.737 ± 0.446	0.026 ± 0.162	0.711 ± 0.46
XGBOOST	0.053 ± 0.226	0.789 ± 0.413	0.763 ± 0.431	0.763 ± 0.431
SVM	0.789 ± 0.413	0.053 ± 0.226	0.763 ± 0.431	0.789 ± 0.413
RRF	0.079 ± 0.273	0.026 ± 0.162	0.053 ± 0.226	0.053 ± 0.226
RPART	0.079 ± 0.273	0.132 ± 0.343	0.053 ± 0.226	0.105 ± 0.311
RKNN	0.079 ± 0.273	0.789 ± 0.413	0.789 ± 0.413	0.763 ± 0.431
NDCG@3				
AVG	0.949 ± 0.181			
LM	0.499 ± 0.47	0.83 ± 0.336	0.434 ± 0.438	0.856 ± 0.313
XGBOOST	0.676 ± 0.406	0.911 ± 0.191	0.872 ± 0.281	0.879 ± 0.24
SVM	0.935 ± 0.179	0.631 ± 0.34	0.843 ± 0.279	0.918 ± 0.241
RRF	0.661 ± 0.402	0.53 ± 0.472	0.372 ± 0.457	0.603 ± 0.376
RPART	0.625 ± 0.409	0.683 ± 0.428	0.545 ± 0.478	0.542 ± 0.458
RKNN	0.63 ± 0.41	0.894 ± 0.241	0.877 ± 0.279	0.824 ± 0.271
NDCG@5				
AVG	0.956 ± 0.087			
LM	0.716 ± 0.11	0.852 ± 0.127	0.687 ± 0.181	0.809 ± 0.161
XGBOOST	0.779 ± 0.088	0.852 ± 0.099	0.791 ± 0.148	0.808 ± 0.142
SVM	0.782 ± 0.106	0.698 ± 0.115	0.87 ± 0.141	0.779 ± 0.103
RRF	0.78 ± 0.086	0.701 ± 0.172	0.698 ± 0.18	0.714 ± 0.134
RPART	0.723 ± 0.119	0.728 ± 0.159	0.77 ± 0.166	0.745 ± 0.112
RKNN	0.699 ± 0.131	0.849 ± 0.139	0.825 ± 0.108	0.872 ± 0.134

Table D.20: Impact on baselevel performance for ASLIB approach in the Item Recommendation problem.

Metadata	Algorithm	1	2	3	4	5
	AVG	0.533	0.539	0.547	0.547	0.547
RM	LM	0.530	0.538	0.539	0.539	0.547
	XGBOOST	0.522	0.538	0.539	0.540	0.547
	SVM	0.529	0.537	0.539	0.539	0.547
	RRF	0.528	0.538	0.539	0.540	0.547
	RPART	0.490	0.535	0.544	0.547	0.547
	RKNN	**0.536**	0.539	0.539	0.540	0.547
SL	LM	0.504	0.538	0.543	0.545	0.547
	XGBOOST	0.474	0.535	0.541	0.545	0.547
	SVM	0.525	0.538	0.539	0.539	0.547
	RRF	0.526	0.538	0.538	0.543	0.547
	RPART	0.515	0.537	0.539	0.544	0.547
	RKNN	0.532	0.539	0.540	0.543	0.547
GR	LM	**0.535**	0.538	0.546	0.547	0.547
	XGBOOST	0.514	0.538	0.546	0.547	0.547
	SVM	0.531	0.538	0.539	0.539	0.547
	RRF	0.532	0.538	0.546	0.547	0.547
	RPART	0.521	0.534	0.540	0.545	0.547
	RKNN	**0.535**	0.538	0.539	0.542	0.547
CM	LM	0.528	0.538	0.539	0.539	0.547
	XGBOOST	0.495	0.536	0.543	0.547	0.547
	SVM	**0.534**	0.538	0.539	0.539	0.547
	RRF	0.532	0.539	0.539	0.541	0.547
	RPART	0.513	0.532	0.539	0.546	0.547
	RKNN	**0.537**	0.538	0.539	0.540	0.547

Table D.21: Impact on baselevel performance for ASLIB approach in the Rating Prediction problem.

Metadata	Algorithm	1	2	3	4	5	6	7	8	9
	AVG	0.297	0.260	0.255	0.240	0.205	0.205	0.185	0.185	0.185
RM	LM	0.381	0.271	0.266	0.249	0.221	**0.195**	0.193	0.188	0.185
	XGBOOST	0.298	**0.244**	**0.231**	**0.228**	0.228	0.226	0.222	0.220	0.185
	SVM	0.297	0.271	**0.248**	**0.231**	0.223	0.223	0.203	0.202	0.185
	RRF	0.780	0.280	**0.248**	0.244	0.221	0.215	0.210	0.205	0.185
	RPART	0.797	0.306	0.258	0.244	0.216	**0.197**	0.195	0.189	0.185
	RKNN	0.297	0.276	**0.228**	**0.209**	0.209	0.206	0.185	0.185	0.185
SL	LM	0.305	0.260	**0.231**	**0.230**	0.208	0.205	0.205	0.188	0.185
	XGBOOST	0.451	0.284	0.270	**0.229**	0.220	0.220	0.212	0.192	0.185
	SVM	0.303	0.284	0.273	**0.227**	0.225	0.224	0.222	0.185	0.185
	RRF	0.430	0.300	0.264	0.251	0.229	0.209	0.208	0.185	0.185
	RPART	0.710	0.286	0.257	**0.225**	0.215	**0.192**	0.190	0.190	0.185
	RKNN	0.297	**0.248**	**0.222**	**0.203**	**0.187**	**0.187**	0.185	0.185	0.185
GR	LM	0.362	0.290	0.277	0.257	0.246	0.228	0.227	0.189	0.185
	XGBOOST	0.361	0.283	**0.247**	**0.220**	0.215	0.212	0.193	0.193	0.185
	SVM	0.298	**0.250**	**0.247**	**0.227**	0.227	0.227	0.227	0.185	0.185
	RRF	0.388	0.292	0.275	0.245	0.213	**0.193**	0.191	0.188	0.185
	RPART	0.705	0.273	0.261	**0.225**	0.217	0.209	0.191	0.191	0.185
	RKNN	0.297	0.268	**0.248**	0.241	0.239	0.239	0.206	0.187	0.185
CM	LM	0.300	0.268	0.264	0.244	**0.191**	**0.191**	0.188	0.185	0.185
	XGBOOST	0.297	0.266	**0.250**	0.243	**0.191**	**0.191**	0.188	0.185	0.185
	SVM	0.297	**0.256**	**0.249**	0.247	0.227	0.224	0.187	0.185	0.185
	RRF	0.302	**0.239**	**0.229**	**0.228**	0.228	0.224	0.222	0.202	0.185
	RPART	0.779	0.311	0.280	0.250	0.227	0.207	0.205	0.195	0.185
	RKNN	0.299	**0.215**	**0.212**	**0.210**	**0.190**	**0.188**	0.188	0.185	0.185

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