Assessing the impact of operational performance improvement on business partners' profitability

The case of a luxury fashion e-commerce

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Abstract

The present dissertation proposes a model that translate an improvement of the fulfillment operations performance of Farfetch partners into a growth of their profitability.

Farfetch itself does not have direct control of the order fulfillment process, so, having operational efficient partners is key for the long-term success of the company. The Fulfillment Development team, where the current project was developed, focuses on reducing the gap between Farfetch and the order fulfillment process, by providing free operational consulting services to its boutique partners. Many times, convincing these partners to engage on these projects may represent a difficult task as they may not understand how they can benefit from it. The described model, that did not exist before, addresses this issue to more easily convince partners to improve performance.

Many are the variables that affect the partner's profitability, but without having deep insight of each partner's resources and structure it would be impossible to build a scalable model. Hence, the proposed model focuses on the two factors that Farfetch has visibility on: sales volume and Service 4.0. return.

Initially, the boutiques were segmented into groups that have similar demand for their stock, by creating two segmentation variables to characterize each boutique's stock. The two variables are: Value Score - represents the attractiveness of the boutique's stock in terms of value transacted; and Demand Score - represents the demand generated by the boutique's stock in terms of order volume. After obtaining such segments, benchmark techniques were applied on actually comparable parts, so one could identify the partner to benchmark for a poor operational performer boutique and understand how the improvement of the operational metrics could affect the orders' growth.

After understanding how a poor operational performer boutique could have performed, in the past, in terms of orders volume, matching the benchmark's operational performance, a forecasting was applied to each boutique's actual and obtained potential orders, creating the boutique's baseline and potential orders. The difference between the two forecasts are the incremental orders due to an improvement of operational performance by the partner.

Finally, the incremental orders were translated into profitability, in addition to the return obtained by the incentive service created by Farfetch - Service 4.0. - that was computed for both scenarios - maintaining the same operational performance or improving to match the benchmark.

The difference between each boutique's baseline and potential revenues are the benefits due to the improvement of operational performance, resulting on model that estimates these incremental cash flows. The expected investment costs required by the boutique, to achieve such operational performance, are an input to obtain some financial metrics, such as ROI. Given the financial metrics, the boutique can then decide whether it is beneficial or not to engage on a consulting service provided by Farfetch to improve operational performance.

Resumo

A presente dissertação propõe um modelo capaz de traduzir uma melhoria da performance operacional dos parceiros da Farfetch num crescimento da sua rentabilidade.

A Farfetch não posssui controlo direto sobre o processamento de encomendas, portanto, ter parceiros operacionalmente eficientes é fundamental para o sucesso a longo prazo da empresa. A equipa de Fulfillment Development, onde o projeto de dissertação foi desenvolvido, dedica-se a mitigar a lacuna entre a Farfetch e o processamento de encomendas, fornecendo serviços de consultoria operacional gratuitos às boutiques. Por vezes, convencer estes parceiros a participar num projeto pode apresentar-se como uma tarefa difícil, pois podem não reconhecer imediatamente os benefícios de uma melhoria operacional. O modelo descrito, que até então não existia, aborda esse problema, para que mais facilmente se possa convencer os parceiros a melhorar a sua performance.

São várias as variáveis que afetam a rentabilidade dos parceiros, mas sem ter uma visão profunda dos recursos e da estrutura de cada um, seria impossível construir um modelo escalável. Assim, o modelo proposto baseia-se nos dois fatores sobre a qual a Farfetch possui visibilidade: volume de encomendas e receitas do Service 4.0..

Inicialmente, as boutiques foram segmentadas em grupos com procura semelhante para o seu stock, criando duas variáveis de segmentação para caracterizar o stock de cada boutique. As duas variáveis são: Value Score - representa a atratividade do stock da boutique em termos de valor transacionado; e Demand Score - representa a procura gerada pelo stock da boutique em termos de volume de encomendas. Após a obtenção dos segmentos, foram aplicadas técnicas de benchmark entre boutiques efetivamente comparáveis, para que se pudesse identificar o parceiro alvo de benchmarking para uma boutique com fraco desempenho operacional e entender como a melhoria das métricas operacionais poderia afetar o crescimento de encomendas.

Após compreensão dos efeitos numa boutique, com fraca performance operacional, teria no volume de encomendas - encomendas potenciais - igualando o desempenho operacional do benchmark, foi aplicado o modelo de previsão às encomendas efetivas e potenciais de cada boutique, criando a baseline e potencial de encomendas. A diferença entre as duas previsões são as encomendas adicionais devido a uma melhoria da performance operacional do parceiro.

Por fim, as encomendas adicionais foram traduzidas em rentabilidade bem como obtido o retorno do serviço de incentivos criado pela Farfetch, Service 4.0., para ambos os cenários - manutenção do desempenho operacional atual ou com a melhoria até igualar o respetivo benchmark.

A diferença entre a baseline e potencial de receitas de cada boutique serão os benefícios devido à melhoria operacional, resultando num modelo que estima esses fluxos de caixa incrementais. Os custos de investimento esperados exigidos pela boutique, para alcançar tal nível operacional, são um input ao modelo, permitindo obter algumas métricas financeiras, como ROI. Dadas as métricas financeiras, a boutique pode, então, decidir se é benéfico ou não envolver-se num serviço de consultoria fornecido pela Farfetch com vista a melhorar o desempenho operacional.

Acknowledgements

Despite being an individual work, the following dissertation would not have been possible to conclude without direction, support and insights from various people.

Firstly, I want to give my gratitude to Farfetch and its culture, specially to the team where the project was developed within. To the guidance given by my supervisor, Tiago Pinto, the support and help by António Freitas and all the insights and collaboration shared with Beatriz Pinto. To the remaining Fulfillment Development team, thank you for making every day at Farfetch a lesson and teaching me the true meaning of causing impact, together. *Todos Juntos!*

To FEUP and my teachers, I want to appreciate all the transmitted knowledge and giving me the necessary tools to become a skilled professional, in particular to my academic supervisor, Professor Isabel Horta, who gave me valuable guidance and insight during the project's development.

I cannot thank enough the support of my parents and my brother, whose unconditional love, understanding and patience allow me to face every challenge with confidence and self belief. To my remaining family, thank you for the inspiration and teaching me the meaning of love and care.

To my friends, I'm grateful for every shared moment and companionship, specially to Alexandre Teles, Gonçalo Pinho and Beatriz Custódio who always succeed on putting a smile on my face.

One does not live isolated and no one grows without cooperation.

"Que quem quis, sempre pôde"

Luís Vaz de Camões

Contents

Acronyms and Symbols

AOV	Average Order Value
ATV	Actual Transaction Value
AW	Autumn Winter
DS	Demand Score
ERP	Enterprise Resource Planning
GBFS	Gender-Brand-Family-Season
GMV	Gross Merchandise Value
IPO	Initial Public Offering
KPI	Key Performance Indicator
NPS	Net Promoter Score
NPV	Net Present Value
NS	No Stock
PDCA	Plan Do Check Act
SQL	Structured Query Language
SS	Spring-Summer
SoS	Speed of Sending
ROI	Return on Investment
VS	Value Score

List of Figures

List of Tables

Chapter 1

Introduction

The current dissertation describes a project developed in the context of Farfetch, a global marketplace for luxury fashion, aiming to address one of the many challenges the company currently faces.

The initial chapter, Chapter 1, contextualizes the environment the project was developed within. It is divided in five sections: a description of the company, Farfetch; the motivation behind the project; a brief description of the project goals; an overview of the methodology used to approach the proposed challenge; and, finally, the structure of the present document.

1.1 The Company

Farfetch presents itself as the global technology platform for luxury fashion. The online marketplace was launched by José Neves in 2008 and has been growing ever since, valued at roughly 6.2 billion dollars after the IPO launch at NYSE in October 2018[1].

Being no longer classified as a startup, Farfetch has currently over 3500 employees with offices in Porto, Lisbon, Guimarães, Braga, London, Los Angeles, New York, São Paulo, New Delhi, Dubai, Shanghai, Hong Kong and Tokyo, covering all time zones for both customer and partner support[2]. With more than 1000 rigorously selected partners, distributed among brands and multi-brand boutiques worldwide, the company connects, in one single platform, the creators with the fashion lovers, shipping to 190 countries. These boutiques and brands expose their best and most exclusive items to a client base of more than 2 million, regardless of the consumer's location.

As the items are owned by the brands and boutiques - named as partners, Farfetch holds no stock itself, establishing the bridge between demand and supply. This business model allows the customers to have access to a vast catalogue of products from more than 3200 brands, which often

[1] in Reuters: Farfetch IPO Lauch - `https://www.reuters.com/article/us-farfetch-ipo-luxury/farfetch-tops-price-range-in-ipo-in-boon-to-luxury-market-idUSKCN1M11BQ` - Accessed 2019-05-10, 15:10.

[2] in Farfetch Investors - `https://www.farfetchinvestors.com/our-company/about-farfetch/default.aspx` - Accessed 2019-05-10, 15:40.

would not be possible to find directly in each brand website, being this one of Farfetch's main competitive advantages.

The orders placed at Farfetch.com are allocated to a partner who has the requested item, who then picks it from their stock and prepares the packaging, being the package collected by a third-party logistic company who delivers it to the final customer.

Although, the absence of inventory is an advantage for Farfetch, it comes with challenges, as the operations and logistics rely on the partners who are typically focused on offline trading. Farfetch must then assure a smooth flow of all complex operations to achieve service consistency and excellence.

1.2 Project Motivation

As upper mentioned, holding no stock comes with challenges, since Farfetch has no control on the order fulfillment process, relying on the partners' operations and capacity. Most of these partners have limited, if none, experience in online operations, so, many not be prepared to respond to the demand that emerged with the fast Farfetch's growth, and thus not being able to fulfill orders that meet customer expectations in terms of speed, accuracy and experience.

With the belief in mind that better operations by the partners lead to customer satisfaction and more committed customers - crucial for the success of the company - arises the department of Fulfillment Development, in which this dissertation was developed. The Fulfillment Development department's aims to mitigate the gap between Farfetch and the control of order fulfillment process. This is accomplished by monitoring partner's operational performance, aiding new partners with complex logistics on-boarding and developing consulting projects to improve their operations.

These consulting services provided to the partners, henceforward mentioned as Performance Projects, aim to improve their processes, set efficient logistics setups and layouts, to guarantee partner's achieve desired level of service and higher capacity, without struggling even when order volume increases. Unfortunately, spending resources on better operational performance, is often seen by partners as a cost rather than an investment with return.

The motivation for the development of this dissertation is to tackle this problem and then be able measure how better operational performance leads to higher partner profitability, in order to more easily convince them to engage on these projects.

1.3 Project Goals

The present dissertation will focus on a clear understanding of how the partners profitability is affected by their operational performance.

The improvement of the operational performance may require financial investment from the partners, thus it is utterly fundamental to understand and evaluate the expected results versus the required investment to achieve them. Having to perform such comparison arises from the need to properly allocate resources and support financial decisions that focus essentially on internal profitability.

This dissertation absolute goal is then, to tackle the uncertainty a partner may have on understanding and evaluating the expected return of improving their operational performance through a project provided by Farfetch. Therefore, is to be developed a model able to:

- predict orders growth from operational performance improvement;
- estimate future incremental cash flows generated from orders growth and Service 4.0.;
- develop a tool to input possible project costs and calculate Return on Investment (ROI).

This way, the Fulfillment Development team can estimate the partner's outcome of undergoing on a consulting project, will be developed focused on the improvement of their operations.

1.4 Methodology

To achieve the proposed goal is fundamental to understand every aspect that affects, directly or not, the partner's profitability. For that, it will be necessary to get full acknowledgment of Farfetch's business as a whole, from processes, architecture and key performance indicators (KPIs), as well as a clear identification of all touching points with partners. These insights will be collected by close interaction with different departments within the company, which aided in aligning the project structure and setting milestones. Alongside, it will be indispensable to get broader knowledge from relevant literature that will guide and support the project structure - explained in greater depth in Chapter 2.

Due to every partner being different from one another, and not being scalable to analyze each one separately, they will be split into groups of similar partners. Once mentioning groups - or segments, as to be explained in the following sections - it is necessary to identify which features should be considered for aggregating the partners.

After the segmentation, it will be fundamental to identify the top operational performers of each segment, and define the metrics for an ideal partner in each segment, to be considered as the benchmark of that segment.

Later, it will be estimated the effect that the improvement of operations has on direct return and potential sales growth of the low performers of each segment. Resorting to the use of forecasting techniques, it will be possible to predict the differential of the return by maintaining operational performance and the potential of each partner.

Finally, the results can be grouped by each partner in order to compute the potential profitability increase and enable the prioritization of performance projects developed by Farfetch.

1.5 Dissertation Structure

The present dissertation is structured in five chapters, including the current one - the Introduction.

Chapter 2 consists on a review of relevant literature considered to be of interest to support the scientific side of the project, reviewing the luxury fashion adaptation to the growing digital channels, how businesses are adapting their supply chain to this new channel and the use of benchmarking techniques. Also, a review is made of clustering technique and the prophet forecasting method.

Chapter 3 scrutinizes both company and department's current processes and metrics, allowing a clear understanding of the two main key performance indicators that affect both the order allocation, as well as other factors that influence partner's return. The framework of the Performance Projects is also scrutinized.

Chapter 4 is dedicated to thoroughly describe the methodology used in the development of the partner's profitability prediction model, together with the followup of a boutique throughout the model. It is divided in 6 parts: partner segmentation, defining the ideal partner, estimation of operational performance improvement orders growth and return, followed by order forecasting per partner and the outcome of engaging on a performance project. Also, the automation of the model is described in the final section of the chapter.

The final chapter, Chapter 5, outlines some conclusions and assess the project's final outcome. Also, a series of recommendations and future opportunities are identified as final consideration, resulting from a deeper understanding of the process and worthy feedback collected.

Chapter 2

State of the Art

The aim of this chapter is to gather and review existing theoretical and empirical research of key subjects and aspects considered to be relevant for the present dissertation.

It is organized in five parts: first, it explores the relationship between the luxury fashion industry and the growing digital world; second, a review of how companies are adapting their supply chain to e-commerce and the digital distribution channel; third, how benchmarking techniques can be used for target setting and operational improvement as well as a small section of how clustering methods can be combined with benchmarking; fourth, a review on clustering models used for pattern detection in data; and finally, a review of a forecasting model proposed by Facebook.

2.1 Luxury Fashion: Adapting to the Digital Future

In 1988, Grossman and Shapiro conceptualized one of the first formal definitions of luxury goods described as products that "bring prestige to the owner, apart from any functional utility" (Grossman and Shapiro, 1988). In addition to the social statement luxury gives, the main driving forces of luxury consumption are exclusivity sensation, emotional and quality value(Melika and Muris, 2009).

The luxury industry includes luxury goods as well as experiences. It comprises nine main segments, led by cars, hospitality and personal goods, representing more than 80 percent of the total luxury market together.

Overall, the luxury market grew 5 percent in 2018, to an estimated €1.2 trillion globally. (Bain&Company, 2019) While the retail channel grew 4 percent, the wholesale channel grew by just 1 percent, facing tough competition from online channels, which continued to accelerate in 2018, growing by 22 percent to nearly € 27 billion. The Americas market accounted for 44 percent of online sales, but Asia is emerging as a new growth engine for luxury online, slightly ahead of Europe. By 2025, the online channel is estimated to represent 25 percent of the market value, up from 10 percent today.

For the coming years, McKinsey&Company (2019) anticipates that risks of trade disruptions and slowing economic growth, even in emerging markets like Asia, could undermine global growth prospects, whereas could uncertainty over events such as Brexit or the possible global economic slowdown. While Europe is facing a deceleration and US growth may have peaked in 2018, Greater China is expected to overtake the US as the largest fashion market in the world in 2019.

The demand for an omnichannel strategy is a natural evolution from the emerging digital technology and ecommerce markets (Deloitte, 2018). A differentiating factor to keep up with this process of change will be the ability of luxury brands to leverage available inventory. Having a physical and an online store increases the chances to get a wider client base and build a strong brand awareness as well. Most luxury brands have adopted the so-called "click and mortar" concept (companies who own both, retail and online stores) to increase sales and awareness. (Castillan et al., 2017)

Now more than ever, the luxury fashion players need to be agile, think digital-first and achieve faster speed to market. Technology leaders such as Amazon, Uber and Netflix have raised customer expectations in terms of speed and convenience, shortening lead times. It is also a crucial aspect for the digital channels of luxury fashion, as well as the whole experience to amaze the customer since product discovery, delivery, until post-sale support. (Okonkwo, 2010)

In the mobile consumer journey, the gap between discovery and purchase has become a pain-point for a more impatient fashion consumer, who seeks to purchase exactly the products they discover, immediately. Also, according to a 2017 millennial survey (Dealspotr, 2017), consumers are more likely to find inspiration from external sources (social media, influencers, TV) than directly from the brand or retailer.

E-commerces should focus on bridging this gap by shortening lead times, increasing the availability of advertised products and new technologies such as visual search. McKinsey&Company (2019) projects that as the race to be the luxury brand platform of choice for both customers and brands heats up, e-commerce players will continue to innovate by adding other profitable services for customers and suppliers.

One of the major keys to establish as a leader in the online luxury fashion industry will be integration of value added services that improve the flow between supplier and consumer, through powerful use of data analytics.

2.2 Adapting Supply Chain to E-commerce

The ability to perform commerce transactions electronically has become an important factor in today's business world. The accelerated proliferation of home broadband connectivity, together with improved search engine technology, has resulted in rapid growth in Internet research and acquisitions (Pentina and Hasty, 2009).

Traditionally, purely retail stores are unique in enabling the consumers to touch and feel the products and providing instant gratification Meanwhile, with the development of technology and growth of internet transactions, online stores are providing wider product choice and better prices (Brynjolfsson et al., 2013).

According to Grewal et al. (2004), Internet retailing offers customers the advantages of easier access to price comparison information, an exclusive shopping experience, and the convenience of a 'store' open 24 hours a day, seven days a week.

The rapid growth of e-tailing as a consumer retail channel has made it a serious competitor to traditional physical channels (Kumar et al., 2016) so, globally, more stores are working to explore synergies between their physical infrastructure and digital channels to build a larger customer base, increase return, as well as extending the physical storefront and complement customer relationships (Gulati and Garino, 2000; Bernstein et al., 2008). However, these strategies comprise several challenges, such as managing channel gaps and extensive online-offline integration.

Saeed et al. (2003) suggests, despite being a complex strategy and demanding high organizational level, the addition of online channels with the maintenance of physical presence, contributes towards the enhancement of the firm's performance.

The online channel and its supply chain differ from traditional ones, within customer types, order fulfilment, costs and profit, logistical requirements, expectations of service quality, degree of market segmentation, access to demand/supply information, and returns policies among other elements (De et al., 2014). The addition of the online channel to the traditional portfolio of retailers can bring opportunities and challenges concerning operations management. According to (Agatz et al., 2008), the integration of channels may yield synergies that reduce e-fulfilment costs. However, these different channels may have different requirements that should be addressed differently.

Steinfield (2002) states that the the main sources of synergy from integration are common infrastructures and operations. However, a risk of integration is channel conflict, hence, and as stated by the aforementioned author, business owners should align objectives for each channel to coordinate and develop mechanisms of control that promote operational compatibility and develop firms' capabilities to support the integration.

Traditional channels can be integrated with digital ones by using an enterprise resource planning (ERP) system, to provide efficient and effective flow of information (Sarker et al., 2012). In spite of the positive outcome, ERP system implementations are often characterised by high capital investment, long implementation duration, and high chance of failure (Bingi et al., 1999).

Kumar et al. (2016) assumes that the future idealized supply chain can develop into a hybrid supply chain that includes both e-tail and physical retail channels. Retail warehousing practices with cross-docking and consolidation have proved to be an efficient in retail supply chain, as such, these practices should be carefully applied and integrated into future e-commerce operations. The switch from pure traditional retail products to the e-tailing model will eventually become inevitable.

2.3 Benchmarking: Application in Operational Performance

The essence of benchmarking is the process of identifying the highest standards of excellence and quality of any process, product or service, and then implement the necessary changes to achieve or even surpass those standards.

There is no need to reinvent the wheel when we're able to recognize that someone is doing a better job than we are. By learning how things are being done by others, benchmarking forces one to focus on the external environment to become more competitive and may point the way to a more innovative thinking (Landry, 1993).

Andersen and Pettersen (1996) define benchmarking as a process of continuous measurement and comparison of business processes with comparable processes in foremost organizations to obtain information that could help the organization identify and implement improvements.

Benchmarking is also used as a goal-setting process, helping to set targets to achieve performance improvements, and if carried out using the best-in-class companies, these goals are likely to be stretch goals which are important for improving performance and learning (Roth and Marucheck, 1994). In a research involving European companies, Voss et al. (1997) proposed, empirically tested and confirmed a direct link between the use of benchmarking techniques and operational performance improvement.

As a continuous process, Bhutta and Huq (1999) considers that benchmark follows the PDCA cycle (plan, do, check, act) where the "plan" phase focuses on selecting the benchmarking processes and the type of benchmark to be used. In the "do" phase, processes are characterized using metrics and current business practices already documented. In addition, those same metrics and practices are collected from the reference organization. "Check" refers to a gap analysis comparison of findings to determine whether there are positive or negative gaps relative to the benchmarking partner. The final "act" phase refers to launching projects to close down those negative gaps or to maintain the positive ones.

Shetty (1993) identifies three basic types of benchmarking: (1) strategic benchmarking involves the comparison of different business strategies to identify key elements in a successful strategy; (2) operational benchmarking focuses on relative cost position or ways to increase competitiveness, depending on the function under analysis, different factors must be focused on; and (3) management benchmarking which involves an analysis of virtually any support functions, like management information systems, logistics and order processing.

Benchmarking can be carried out in many steps. Some companies have taken up to 33 steps while others have only used four steps (Bhutta and Huq, 1999). Shetty (1993) proposes the use of five basic steps with continuous iterations: (1) identification of the functions to be benchmarked, (2) selection of superior performers (competitive or non-competitive), (3) data collection and analysis of pinpoint gaps in performance, processes and practices, (4) set performance goals for improving and surpassing the best-in-class, (5) implement plans to bridge the gap and monitor results.

Although benchmarking is widely used, it has limitations. It is a difficult process which requires significant time, effort and high financial investment, it can be difficult to collect data from competitors or partners (Prescott, 1989). Boxwell (1994) states that the benchmarking technique should be used as a guide and not for statistical precision.

Cluster Based Benchmarking

As concluded in the section above, the identification of the right partner to rely the benchmark study on, is key for translating the knowledge acquired into relevant and actionable changes in the context of one's area of operation/business. Not only the core activity of the two parts should be similar, but also should be comparable in terms of magnitude.

Sarkis and Talluri (2004), in what the authors considered to be one of the first papers applying clustering methods for benchmarking purposes, recognized that the segmentation, dependent on the right choice of the clustering algorithm, is fundamental to obtain meaningful benchmarking results. In the above mentioned study, the authors used the same three metrics for companies in the energy regulation sector to input on the clustering algorithm, as to further choose the ideal benchmark for each cluster - based on their efficiency. Sarkis and Talluri (2004) supports that the ideal benchmark should be the top performer in each cluster, regardless of being a partner with ideal efficiency, ensuring there is always at least one reference for each cluster.

In a research focused on US airports (Dai and Kuosmanen, 2014), it was stated that the benchmarking between comparable airports is a way for operations managers to ensure competitiveness, allow the relative evaluation of performance and identify useful benchmarks.

In both of these cases, the objects were clustered based on their characteristics and only focused on their efficiency after establishing the clusters, thus allowing the identification of the partners with the most efficient use of resources among groups of comparable parts.

The clustering based benchmarking frameworks proposed by Sarkis and Talluri (2004) and Dai and Kuosmanen (2014) take into account the heterogeneity of parts and the operating environment, and thus leading to a more realistic and valuable benchmarking result.

2.4 Clustering Techniques

Data Mining is known to identify useful, valid and comprehensible patterns in data. Velmurugan and Santhanam (2011) defines data mining as a way of turning raw data into useful information. Clustering, as data mining technique, is the organization of a collection of variables into groups based on similarity (Jain et al., 1999).

Madhulatha (2011) considers it to be "the most important unsupervised learning problem", as it deals with identifying patterns based on similarities found in a selection of unlabeled data. A cluster is then a collection of objects similar between them and dissimilar to the objects belonging to other clusters (Madhulatha, 2011; Han et al., 2001).

There are several clustering methods (Jain et al., 1999; Velmurugan and Santhanam, 2011), the most relevant are as follows:

- Partitioning Clustering;
- Hierarchical Clustering;
- Model-based Clustering.

The most commonly used partitioning based clustering methods are K-Means and K-Medoids. K-means clustering iteratively selects random centroids and assigns every object to the nearest k centroid, where the coordinates of each centroid is the mean of the coordinates of the objects within the cluster. Even though this method is efficient regarding computational time, it is known to be sensitive to the outliers (Park and Jun, 2009). For this reason, K-medoids methods are used where, instead of selecting a random centroid, representative objects called medoids are considered, being the cluster based on the most centrally located, turning the K-medoids method much more robust to outliers in comparison with the K-means (Arora and Varshney, 2016).

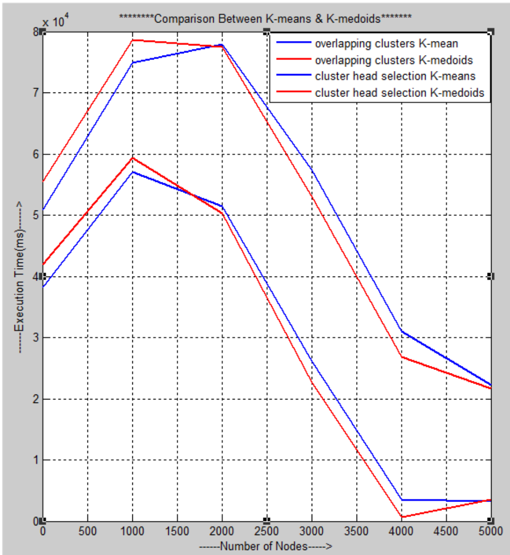

Figure 2.1: Comparison Chart of K-Means and K-Medoids *in* Arora and Varshney (2016).

The results, presented on Figure 2.1, of the comparison of k-means and k-medoids show that in all aspects such as execution time, sensitivity to outliers and noise reduction, k-medoids is much better than k-means but with the drawback that it is much more complex. (Arora and Varshney, 2016)

The most powerful algorithm for k-medoids method is partitioning around medoids (PAM) (Kaufman and Rousseeuw, 1990), however, it is inefficient for a large data sets due to its time complexity (Han et al., 2001).

The two types of hierarchical clustering algorithms are the agglomerative method and the divisive method (Dai and Kuosmanen, 2014) which, based on the selected criteria, combines or divides a set of objects into larger or smaller groups. The most popular criteria used are the single-link algorithm (Trevor et al., 2009), in which the distance between two clusters is the minimum of the distances between all pairs of patterns drawn from the two clusters and the complete-link algorithm (Trevor et al., 2009), in which the distance between two clusters is the maximum of all pair distances between patterns in the two clusters. In both cases, two clusters are merged from a larger cluster based on minimum distance criteria (Jain et al., 1999).

Hierarchical clustering is favored since it is straightforward (Dai and Kuosmanen, 2014), as the results are then shown in a dendrogram representing the nested groups of patterns and similarity levels at which the groups change (Jain et al., 1999). Furthermore, the number of clusters depends on the user's selected granularity, requiring additional effort and care while selecting the desired number of groups to avoid distorting the results.

Model-based methods attempt to streamline the fitness between the data and the model where the data is assumed to be generated (Zhong and Ghosh, 2003). These can be further classified into more exclusive groups. The advantage of this clustering technique is that, in addition to being computationally efficient, the determination of the number of clusters does not rely on user intervention (Dai and Kuosmanen, 2014), delivering more reliable results.

2.5 Forecasting with Prophet

Forecasting is a data science activity central to many activities within an organization. Organizations across all sectors of industry must engage in capacity planning to efficiently allocate their limited resources and set goals to measure performance relative to a baseline.

Nevertheless, analysts capable of producing high quality forecasts are rare since forecasting is a specialized skill that requires experience. Hence, being able to use a robust forecasting method, with few customizable features to adapt to the context of each business, is of high demand.

Figure 2.3 shows results using two alternative automatic forecasting models applied to dataset presented on Figure 2.2. The forecasts were made at three points in the history, each using only the portion of the time series up to that point to simulate making a forecast on that date.

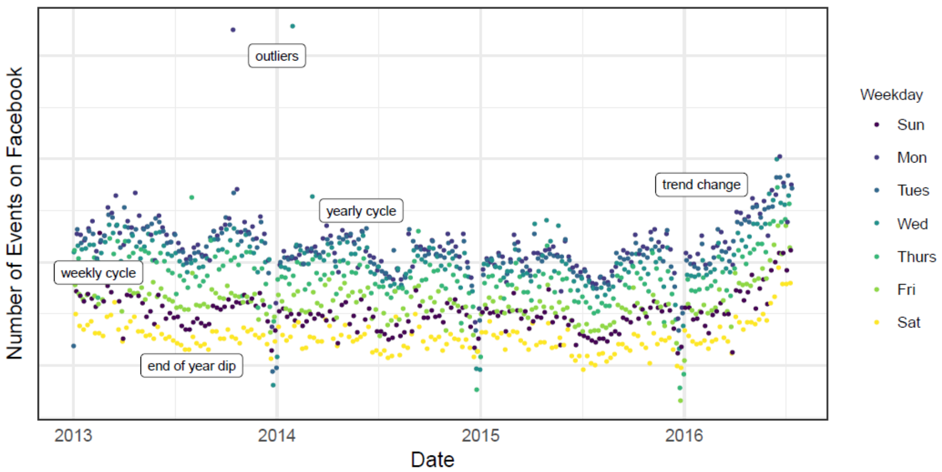

Figure 2.2: Number of events created on Facebook. There is a point for each day, and points are color-coded by day-of-week *in* Taylor and Letham (2018).

The methods shown in Figure 2.3 are: ARIMA, which fits a range of ARIMA models and automatically selects the best one; and TBATS, a model with both weekly and yearly seasonalities.

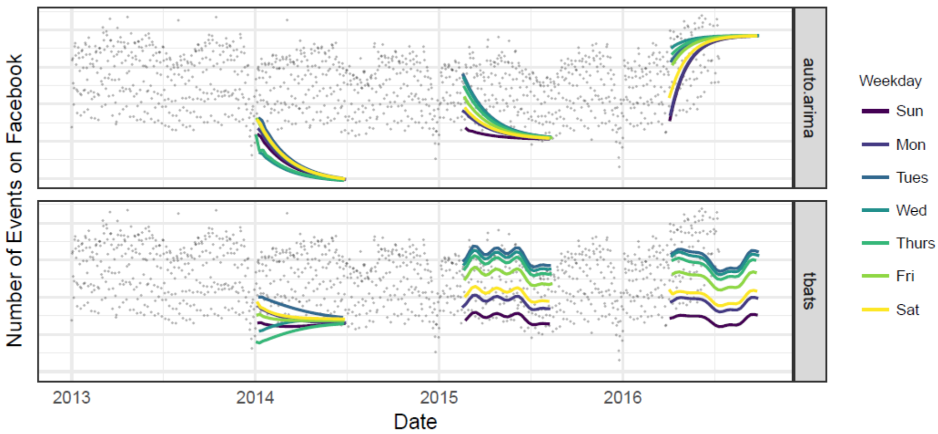

Figure 2.3: Forecasts on the time series from Figure 2.2 using a collection of automated forecasting procedures *in* Taylor and Letham (2018).

Both methods struggle to produce forecasts that match the characteristics of these time series, as well as overreact to the end-of-year dip since they fail to model yearly seasonality. When a forecast produces poor results, is important to tune the parameters of the method to the problem at hand, skills that the typical analyst lack.

The time series forecasting model proposed by Taylor and Letham (2018), called prophet, is designed to handle the common features of business time series seen in Figure 2.2. Importantly, it is also designed to have parameters to be adjusted without knowing the details of the underlying model. The model uses a decomposable time series model with three main model components: trend, seasonality, and special events. They are combined as formulated in Equation 2.1.

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t) \tag{2.1}$$

Here $g(t)$ is the trend function which models non-periodic changes in the value of the time series; $s(t)$ represents periodic changes, i.e., seasonality; and $h(t)$ represents the effects of special events which occur on potentially irregular dates. The error term, $\varepsilon(t)$, represents any changes not accommodated by the model.

Prophet was implemented with two trend models that cover many applications: a logistic growth and a linear growth model. For logistic growth forecasting, the core component of the data generating process is a model for how the population has grown and how it is expected to continue growing, for example, the market size and its expected growth. For other forecasting problems that do not exhibit saturating growth, a constant rate of growth, i.e., linear growth, often provides satisfactory results.

Business time series often present seasonality as a result of the human behaviors. For instance, a week can produce effects on a time series that repeat every week, while the year's seasons or vacation schedules can produce effects that repeat each year. To fit and forecast these effects, seasonality models that are periodic functions of t must be specified. For example, when dealing with a dataset with daily data, specify t equal to 365.25 to support the yearly seasonality.

Also, special events provide large predictable peaks or depressions to many business time series and often do not follow a periodic pattern, so their effects are not well modeled by a common smooth cycle. Prophet allows the analyst to provide a customized list of past and future events, identified by the event unique name. For example, Black-Friday happens every year in November, but not always on the same day. By being able to input to the model the past days where Black-Friday happened and the projected dates, the model will present more accurate results.

Figure 2.4 shows the Prophet model forecast to the Facebook events time series of Figure 2.3. These forecasts were made on the same three dates as in Figure 2.3, as before using only the data up to that date for the forecast.

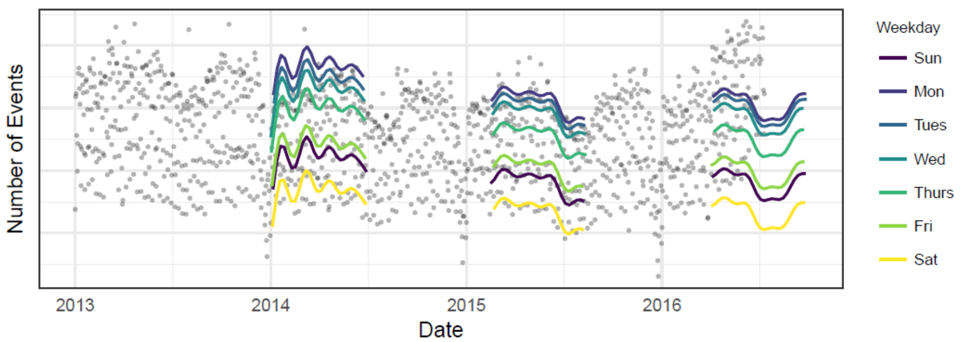

Figure 2.4: Prophet forecasts results corresponding to those of Figure 2.3 *in* Taylor and Letham (2018).

The Prophet model successfully captures both weekly and yearly seasonality, and unlike the forecast models presented in Figure 2.3, does not overreact to the holiday dip in the first year.

A major theme of forecasting at scale is that analysts with a variety of backgrounds must make more forecasts than they can do manually. Prophet uses a simple, modular regression model that works well with default parameters, but also allows analysts to select the components that are relevant to their forecasting problem and easily make adjustments as needed.

Chapter 3

Problem Statement

The present dissertation will focus on providing a clear understanding of how the partners profitability is affected by their operational performance. This problem is contextualized within the Fulfillment Development team, as to support them into more easily convince and encourage partners in engaging on a Performance Project, and keep on aiming for operational excellence.

These Performance Projects aim at improving partner's processes, set efficient logistics setups and layouts, by introducing proper tools and techniques to guarantee that partners achieve higher capacity and performance levels. However, the Fulfillment Development currently fails to provide the partner with an indication of what would be the potential return of their operational improvement. Therefore, the need to formulate a model able to rightfully quantify the return of investing on operations, since it is a very important information for partners to make an investment decision.

Hence, is to be scrutinized in this section, all relevant points to formulate the approach for evaluating the potential return achieved with the consulting project. First, a description of the interaction points the partner has with the order fulfillment process is to be provided, followed by the most relevant operational metrics that define and influence, on a partner level, the internal Farfetch algorithm for order allocation, which also directly affect the partner's return of the Service 4.0.. Finally, a review of the framework of a Performance Project is made.

3.1 Partner's Fulfillment Operations

As already mentioned, the items displayed online and available for purchase on Farfetch.com belong to Farfetch's partners, leading to the order fulfillment process each time an order is placed by a customer.

There are three parts intervening in this process - Farfetch, partner and courier, where each one has clear tasks to complete in the 6 order fulfillment steps, shown in Figure 3.1. Partner's operations on the order process will be deeply described.

Farfetch must approve customer payment and detect a possible fraud, which will lead to a cancelled order if suspicious, known as step 2, actually beginning simultaneously with step 1. The company is also responsible for step 4, by creating an Airway Bill (AWB) - document with the

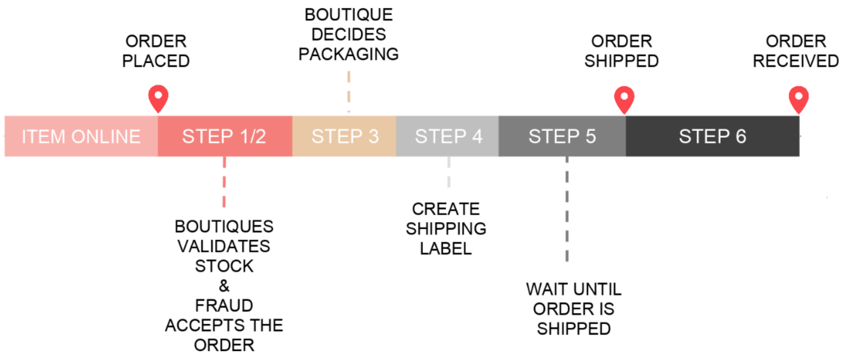

Figure 3.1: Farfetch's order fulfillment steps.

information of the customer and order destination - which in more than 98% of the cases is done automatically and almost instantaneously.

Farfetch's partners who receive an order notification are responsible for the following steps:

- **Step 1 - Check Stock**: partners must confirm they still hold the requested item at the moment the order is placed. If the stock is confirmed, the order will move on to the next steps, else a No Stock happens, and if available, the order is allocated to another partner;
- **Step 3 - Decide Packaging**: Farfetch has several boxes of different sizes and each item size has a recommended box depending on the item size. The partner must place the item in the box and is encouraged to include any additional details, to augment the customer experience;
- **Step 5 - Ready (Send Parcel)**: comprises the bridge between the partner and the courier, as after the partner prints the AWB and attaches it to the order's package, the order is ready to leave the stock point towards the customers desired address.

Finally, once the package is prepared to be sent, the courier must then pick the package from the stock point and deliver it to the end-customer. This is considered to be step 6, beginning as soon the order's AWB is scanned by the courier.

3.2 Metrics for Performance Evaluation

Since Farfetch has no direct control on order fulfillment operations, controlling performance is a challenge. Hence, some metrics were developed in order to monitor and evaluate fulfillment performance of its partners. Regarding Fulfillment Development team, it is crucial to have clear vision of each partners' performance.

Currently, Speed of Sending (SoS) and No Stock (NS) are the most important operational KPIs, being considered the most appropriate metrics to evaluate partners' commitment to Farfetch. Net Promoter Score (NPS) also plays an important role on aspects that will affect the partners' profitability.

These three metrics are further explained below.

- **Speed of Sending**

The Speed of Sending (SoS) is a KPI measuring the time, in days, between creating an order and the moment the courier picks it up from the partner's shipping point (time between Step 1 and Step 5 - explained in section 3.1), understood as SoS Gross.

As some partners do not work on weekends and public holidays, there was the need to reformulate the SoS metric in a more partner-oriented way to evaluate its performance, resulting in the SoS Net, that excludes from the SoS Gross the weekends, public holidays in the partner's country and the time the orders may spend on hold due to exceptions.

Speed of Sending is a crucial metric, impacting, together with the time the order spends in transit, the total lead time, affecting the customer experience regarding the expected date for the delivery of the requested item.

Farfetch does not set an operational target level for SoS Net for its partners, the SoS target for the partners is to have 80.0% and 96.3% of their orders with an Speed of Sending under 1 day and under 2 days, accordingly.

- **No Stock**

As mentioned before, it is possible the occurrence of a scenario where the item ordered by the customer is no longer available on partner's stock, creating a situation where a No Stock occurs. Whenever this happens, if possible, the order will be allocated to another partner who has an indication of having the item available.

This metric compares the number of No Stock occurrences with the total of received orders, resulting on a percentage.

In terms of No Stock, Farfetch's target for its partners is 1.30%.

- **Net Promoter Score**

Net Promoter Score (NPS) is a metric used to measure the customer loyalty and level of satisfaction. After every order, once the item is received by the customer, an email is automatically sent with a form.

Two questions are made about how likely the customer would recommend both Farfetch and the partner, in a 0-10 scale, being then used to calculate the NPS for both Farfetch and the partner.

An answer between 0 and 6 represents a "Detractor"; an answer between 7 and 8 represents a "Passive"; and, finally, an answer between 9 and 10 represents a "Promoter".

$$\%NPS = \%Promoters - \%Detractors \tag{3.1}$$

Regarding the Net Promoter Score, although there is no specific target, ideally, it should be over 70%.

The Farfetch's target for these operational metrics can be consulted in Appendix C.

These three metrics are inputs for both the Order Allocation Algorithm and the Service 4.0, explained in Sections 3.3 and 3.4, respectively.

3.3 Order Allocation Algorithm

The allocation algorithm selects which partner will fulfill the order placed by a customer on Farfetch.com. It is set in a way that is believed to optimize the customer's satisfaction.

It works like a sequence of four strainers, beginning with a pool of all partners who claim to have availability of the requested item, narrowing that number down from level to level until only one partner remains.

The first level, selects, from all partners with the requested item, the ones that set the item's price between the lowest available and an internally defined threshold. If more than one partner remains, it moves to the next level.

The second level, checks if any of the remaining partners is based on the customer's country. If positive, it first checks if there's a boutique with the item, and from boutiques within the same country, the tie breaker will be the Operational Score. In the case that no boutique has the requested item, the algorithm will use the same logic for brand partners.

In the third and fourth levels, the same logic as the second level is applied at Region and World level, respectively.

The partners' Operational Score is an integer, obtained depending on three inputs: average SoS Net, NS rate and NPS score. The complete method to calculate this score should remain confidential, but it is possible to say that both the average of SoS Net and NS rate weight much more than the NPS score.

- **Geographical Pricing**

The geographical pricing is a concept where a price of an item is dictated by the brand, in a way that reflects different demands and price sensibilities in different countries or regions. For example, the same item from brand A may cost $500 in the UK and $800 in the USA.

These geo-priced items lead to sales which the boutiques have no control on price. Thus, when an order of a item under geographical pricing is placed, the boutiques with the item available will start off at the same level on the Order Allocation Algorithm, as the price will be equal for all of them, leaving more relevance to the Operational Score on selecting the boutique to fulfill the order.

Approximately, of Farfetch's total orders, 32% were of items marked with geographical pricing [1].

3.4 Service 4.0.

In order to align partner's level of operations with Farfetch's targets, in October 2018, Service 4.0. was introduced after a series of iterations. This service consists on a way to encourage partners to aim for high operational performance, resulting in a policy of monetary benefits or penalties for the partner.

The incentive or penalty is calculated based on various inputs: percentage of orders sent in less than 1 and 2 days, No Stock percentage, percentage of Wrong Items sent and Net Promoter Score. The most impactful metrics are the percentage of orders sent in less than 2 days (% SoS < 2d) and No Stock percentage, thus, given a combination of these two values, the incentive may go from +1.30% to -3.00% of the partner's monthly actual transaction value (ATV). Also, for every No Stock occurrence, the partner is charged 10£ (approximately $12.75) for customer compensation.

In addition to the above mentioned incentive, depending on the percentage of orders sent in less than 1 day (% SoS < 1d), the partner may be eligible to either receive an extra incentive of 0.20% or 0.40% of the monthly ATV, plus the refund of part or the totality of the packaging costs (approximately $1.70 each box).

The complete method for the calculation of the Service 4.0. is available in Appendix B.

As the Service 4.0. results on an extra return or penalty for the partner, depending on its operational level of performance, it has a direct impact on partner's profitability.

3.5 Performance Projects

The Performance Projects provided by the Fulfillment Development team to the partners aim to mitigate the gap between Farfetch and the control of order fulfillment process.

These consulting services are mainly focused on impactful partners for Farfetch who are struggling with their operations, for the purpose of improving their performance which will indirectly affect Farfetch's long term customer commitment and satisfaction.

Once the most critical struggling partners for Farfetch are identified, it is scheduled a call between consultants from the Fulfillment Development team and the person responsible for the brand or boutique. In that call, is provided to the partner an explanation of Performance Projects' purpose, areas of focus and framework. After the parties agree on the development of the project, the following phases are:

[1] Data of Farfetch orders from 2018.

- **Diagnostics:** personal visit to partner's stock point(s) and data collection of current fulfillment process;
- **Identify Root Causes:** use of collected data to identify key factors negatively impacting the fulfillment process;
- **Identify Solutions:** identify the best solutions to tackle the main challenges encountered, adapted to the context of the partner's operational set up;
- **Present Solution Plan:** formulate action plan to deliver the proposed solutions;
- **Implement:** deploy selected solutions according to partner's preference and monitor the progress;
- **Control:** after project sign-off, operational metrics are tracked weekly during 60 days to assess the success of the project, comparing to initial target.

It is relevant to mention that these projects do not represent any cost to the partner. Any possible cost that arises from the project will come from the need to invest on operations, and these needs may vary a lot according to the partner's state. For example, hiring more people, buying new materials, contracting developers to work on software integration, among others.

Currently, the Fulfillment Development team fails to demonstrate to the partner the potential increase on profitability obtained by investing on operational performance improvement, constituting a crucial point in convincing them to engage on these projects. Thence, arose the need to develop a model that could estimate the benefits from the partner's point of view, which the present dissertation pretends to fulfill.

Chapter 4

Developed Model & Achieved Results

The present chapter scrutinizes the methodology used for the creation of the model which will be able to estimate partner's profitability derived from an operational improvement.

It is divided in six sections, as follows: boutique segmentation, modeling the ideal boutique within each segment using benchmarking, the effects that performing under the top performer (identified through benchmarking techniques) have on inefficient performers, orders forecasting based on each boutique's historical and potential orders and, finally, translating the operational performance and orders increase into a potential financial output of engaging with a Performance Project. In every section, some of the obtained results are shown and examples of a boutique going through the model.

Although Farfetch's partners are both brands and boutiques, the present dissertation focuses on building a model suitable for boutique partners, as these account for around 60% of all partners and were responsible for the fulfillment of more than 78% of all Farfetch's orders[1]. Even though brand partners are important on a strategic point of view, Farfetch still holds a special consideration for boutiques, hence the Performance Projects provided by the Fulfillment Development team are only offered without costs to this partner type.

4.1 Boutique Segmentation

As mentioned in Chapter 2, in a benchmarking approach, comparing similar parts is key to obtain useful insight. The same logic is applied to the current dissertation, where the comparable parts should be the boutiques, as their main goal is shared: selling luxury fashion online.

Even though the main goal is shared, there are still many points of divergence, for example, in terms of size, some boutiques can be a small familiar business located in a traditional Italian city, while others can be big department stores located in commercial areas in big cities, plus others may even be a national network of stores with shared ownership.

Unfortunately, these are characteristics that Farfetch has no visibility on, and gathering these kind of data would be a rather complex and time consuming task given the number of boutique

[1] Farfetch data from orders between January 2018 and May 2019

partners Farfetch operates with. Thus, it was necessary to find the characteristics that make the boutiques comparable and that would support the current analysis. For that, a clustering method is to be used, where the inputs are the variables considered to be important.

The information regarding the boutiques that Farfetch has access to are country and city, data related to historical Farfetch.com orders - volumes and operational performance metrics - and the stock that the boutique sets available on Farfetch.com.

Ideally, the segments should be composed of boutiques with similar stock attractiveness, i.e. boutiques that should have similar sales potential of their stock, as to identify within each segment the boutiques that are performing better in terms of sales and operational performance - these will then be considered the benchmark of their segment.

Clustering the boutiques based on orders volume would gather boutiques with comparable number of transactions, which from a strategic point of view is important, but from an operational point of view would not add much value, as it would not give an indication of how much could the orders of a poor operational performer increase.

Segmenting the partners based on their stock - units and monetary value - would give an acceptable idea of the boutique size, but not all stock units are equal. For example, in a case where a boutique A has 10 Gucci bags with a total value of $5,000 in stock and another boutique B has in stock 10 Burberry shirts with a total value of $5,000 , a clustering algorithm would probably place these two boutiques in the same cluster, but these two kind of products might not have the same demand.

4.1.1 Gender-Brand-Family Attractiveness

Knowing that no item has exactly the same attractiveness as another, and even for the same item, the attractiveness will most certainly vary in time, it was necessary to translate these insights into actionable data.

For that reason and given the fashion business specificity, data was collected from Farfetch overall sales covering a complete year, since April 2018 until the end of March 2019, to take into consideration the two seasons - Spring-Summer (SS) and Autumn-Winter (AW) - and sale seasons - Black Friday, X20s, Christmas, among others.

As computing the attractiveness of every single item available on Farfetch's website would be an exhaustive task, it was collected data in terms of number of products sold and value transacted from Gender-Brand-Family-Season (GBFS) combinations and grouped by quarter - from 2018-Q2 to 2019-Q1. An example of a possible GBFS combination could be Women-Burberry-Shoes-AW.

The Product Families considered for the analysis were Bags, Accessories, Clothing and Shoes, which together account for more than 95% of Farfetch sales [2], turning other product Families like Baby and Jewellery residual.

[2] Data from Farfetch order of 2018

After having all this data split into quarters, the Value Score (VS) and Demand Score (DS) of each GBFS combination could be computed. VS correlates to the amount of money generated by the transactions and DS correlates to the number of transactions of the GBFS combination.

For example, 5 sales of Women-Burberry-Shoes-AW could generate a total transacted value of $3,000, while 10 sales of Men-Gucci-Accessories-AW could generate a transacted value of $2,500. In this case the VS of Women-Burberry-Shoes-AW would be higher, though regarding the DS, it would be lower.

For each combination of GBFS, both VS and DS are obtained by a min-max normalization, multiplied by 1000, to facilitate human interpretation. The formulas to obtain VS and DS can be seen in Equations 4.1 and 4.2, respectively.

$$VS_i = \frac{GMV_i - min(GMV)}{max(GMV) - min(GMV)} \times 1000 \tag{4.1}$$

$$DS_i = \frac{QtySold_i - min(QtySold)}{max(QtySold) - min(QtySold)} \times 1000 \tag{4.2}$$

where:

GMV_i is the value transacted of the GBFS i;

$QtySold_i$ is the number of transactions of the GBFS i.

4.1.2 Boutique's Stock Attractiveness

Per quarter, a value of both VS and DS was obtained for every GBFS combination. For each combination, the engineered features - namely VS and DS, provide one with the level of attractiveness regarding the transacted value and number of transactions, respectively, thus allowing the quantification of the boutique's stock attractiveness. Data regarding the boutique's stock was gathered and grouped by quarter, specifying the monetary value and units of every GBFS owned by the boutique.

As time passes, the boutique's stock may suffer some fluctuations, for example, in the case the stock is sold or the boutique uploads more stock into Farfetch.com, the stock units and value will decrease or increase, respectively. For such reasons, arose the need to measure the average stock units and value a given boutique owned of each combination of GBFS during each quarter, engineered as seen on Equations 4.3 and 4.4, respectively.

$$StockValue_{ijk} = \frac{\sum_{m=1}^{3} ValueMonth_{mijk}}{3} \tag{4.3}$$

where:

Value $Month_{mijk}$ is the monetary value in stock of boutique k, at the end of the first day of month m of quarter j, of the i GBFS combination.

$$StockUnits_{ijk} = \frac{\sum_{m=1}^{3} UnitsMonth_{mijk}}{3} \tag{4.4}$$

where:

Units Month$_{mijk}$ are the units in stock of boutique *k*, at the end of the first day of month *m* of quarter *j*, of the *i* GBFS combination.

The next step was to turn this absolute stock's data comparable between the boutiques. Hence, was verified the percentage, in terms of stock units and value, that each GBFS combination, held by a boutique, accounted in the total stock of that GBFS available at Farfetch.com. Table 4.1 shows an example, using only two boutiques, of how the boutique's stock data was displayed and the respective percentages on Farfetch.

Table 4.1: Stock quantity and value of two example boutiques, specified per GBFS combination.

Boutique	GBFS	Quarter	Stock Value	% Value on FF	Stock Units	% Units on FF
A	Women-Gucci-Shoes-AW	19Q1	$ 10 000	67%	10	56%
A	Women-Balenciaga-Shoes-AW	19Q1	$ 2 500	56%	5	50%
B	Women-Gucci-Shoes-AW	19Q1	$ 5 000	33%	8	44%
B	Women-Balenciaga-Shoes-AW	19Q1	$ 2 000	44%	5	50%
B	Women-Prada-Bags-SS	19Q1	$ 6 000	100%	8	100%

The cases where a given boutique held 100% of volume of a certain combination of GBFS, were discarded, as orders of any item within that GBFS could only be fulfilled by that boutique, therefore, the order would not go through the Order Allocation Algorithm.

Having the percentage of possession each boutique has of the combinations of GBFS, and knowing that each one of these combinations has a VS and DS, the boutique's overall VS and DS could be determined.

The boutique's overall VS and DS define analytically the boutique's stock attractiveness, therefore, boutiques with similar VS and DS should be allocated with more or less the same amount of orders. These two features can be obtained as formulated in Equations 4.5 and 4.6.

$$BoutiqueVS_{kj} = \sum_{k=1}^{n} \%ValueonFarfetch_{ijk} \times VS_{ji} \tag{4.5}$$

where:

% Value on Farfetch$_{ijk}$ is the percentage of monetary value held by boutique *k*, in quarter *j*, of the GBFS combination *i*, on Farfetch overall;

VS_{jk} is the Value Score in quarter *j*, of the GBFS combination *i*.

$$BoutiqueDS_{kj} = \sum_{k=1}^{n} \%UnitsonFarfetch_{ijk} \times DS_{ji} \tag{4.6}$$

where:

% Units on Farfetch$_{ijk}$ is the percentage of units held by boutique *k*, in quarter *j*, of the GBFS combination *k*, on Farfetch overall;

DS_{jk} is the Demand Score in quarter *j*, of the GBFS combination *i*.

4.1.3 Segmentation through Clustering

Having the right and relevant features is key to run an effective clustering algorithm. The two boutique variables, VS and DS, respectively, characterize attractiveness of the boutique's stock, as previously mentioned. Hence, these were the two input variables to run the partitioning around medoids (PAM) clustering algorithm on RStudio.

Note that each boutique had different VS and DS values for each quarter, thus the PAM clustering was ran four times, once per each quarter dataset. The number of clusters was 10 and it was defined using the Elbow method.

The Elbow method looks at the total within-cluster sum of square (WSS) as a function of the number of clusters and, even though, one should choose a number of clusters so that adding another cluster does not improve marginally the total WSS, it was chosen a number of cluster higher than what should be normally used, to achieve an higher level of granularity. Figure 4.1 shows the plot obtained for the Elbow method.

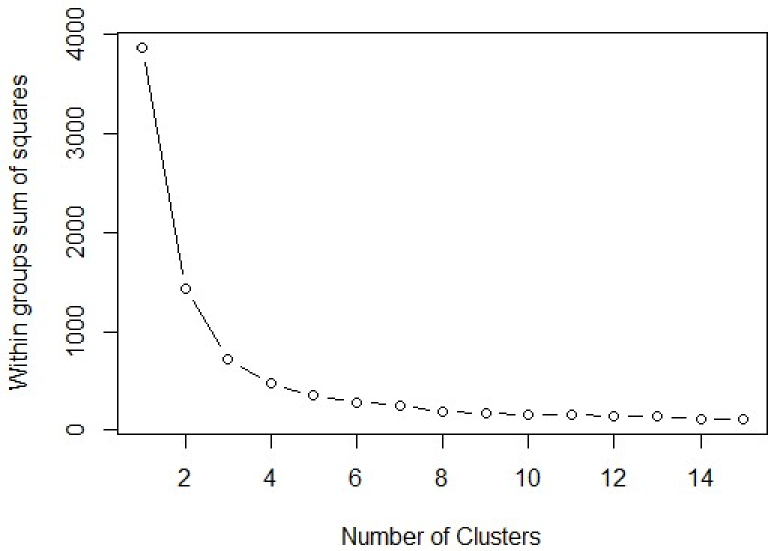

Figure 4.1: Elbow method plot for the boutique's Value and Demand Score dataset.

After these clusters were obtained, the average Boutique's VS and DS, obtained as formulated in Equations 4.5 and 4.6, respectively, was computed for each of the clusters for each quarter. The data was gathered in a table with 40 rows (10 per each cluster of each of the four quarters) and three columns: Quarter-Cluster; Average VS and Average DS.

A second clustering algorithm was ran using the average VS and DS per Quarter-Cluster combination as inputs with a ideal number of clusters of 6. After obtaining the new clusters, there was a need to translate the assigned clusters to a meaningful term, being then ordered from highest to lowest average VS and DS and named from A to F.

This technique allowed to allocate each one of the boutiques belonging to a given cluster in a quarter to a meaningful segment that holds consistency over time. Table 4.2 shows the average VS and DS for the six segments obtained.

Table 4.2: Average Value Score and Demand Score per segment and its meaning.

Segment	Average VS	Average DS	Stock Attractivess	Segment Size
A	1343	1306	Very High	34
B	738	852	High	28
C	434	467	Mid High	109
D	248	271	Mid Low	190
E	127	132	Low	447
F	43	45	Very Low	602

Clustering methods are often used when the dataset has many observations and more than two features, as it turns human visualization and interpretation of the groups of similar parts rather difficult.

In this case, the clustering algorithms were ran using only two variables for the purpose of achieving automated and robust results, as the algorithm creates a collection of objects similar between them and dissimilar to other clusters.

The boutiques distribution among the obtained segments can be observed in Figure 4.2.

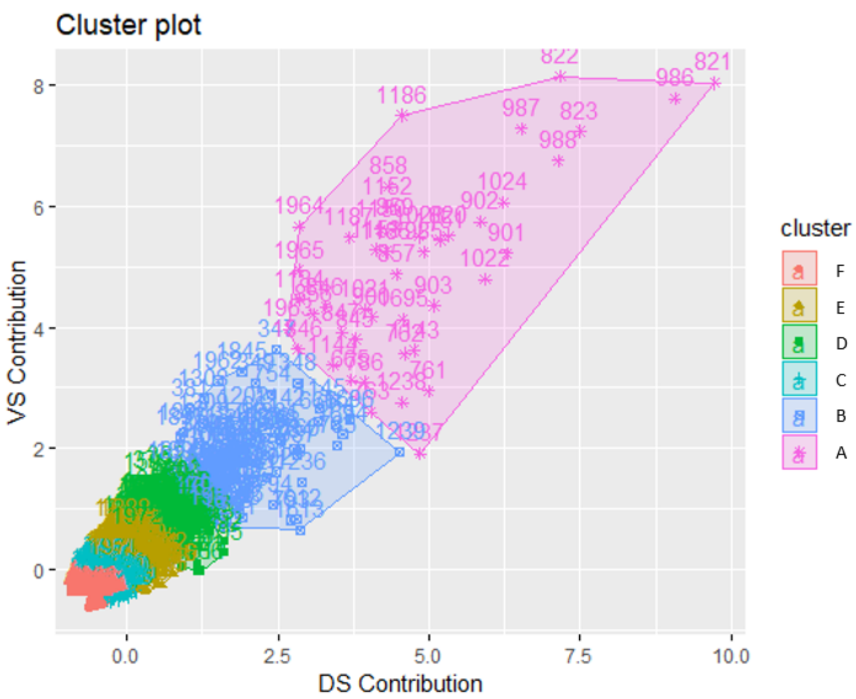

Figure 4.2: Distribution of the boutiques within the segments.

Note to the fact that on Figure 4.2, each boutique is represented by four points: one for each quarter under analysis. As from quarter to quarter, the boutiques may change the segment they belong to, each segment size may not be the same from quarter to quarter. Figure 4.3 shows the average number of boutiques per segment in each quarter.

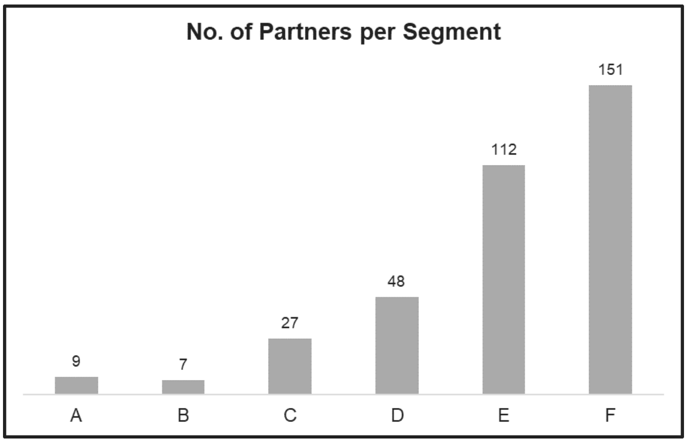

Figure 4.3: Average number of boutiques per segment in each quarter.

The obtained segments were continuously discussed and validated with relevant business experts and project stakeholders from the Fulfillment Development team.

4.2 Segment's Ideal Boutique

Each defined segment comprehends boutiques with similar demand for their stock, who should demonstrate similar amount of orders fulfilled in each quarter. Due to the fact that Farfetch's Allocation Algorithm prioritizes better operational performers, it is expected that these will be assigned an higher amount of orders than the poor performers.

It is, then, fundamental to identify these top operational performers of each segment and define a benchmark to then compare with the other boutiques within the segment's benchmark. With that said, data regarding the orders fulfilled - number of orders, value transacted and operational performance of those - by the boutiques in each quarter was collected.

The number of orders fulfilled by each boutique was split in *Total Sent* and *Sent to Out of Origin Country at GeoPrice*. This was done as, the operational performance has a significant impact on the orders of items marked with geographical pricing and also to prevent the model to be sensitive to the cases where a boutique - even if it has a poor operational performance - is selling more because they set low prices, there is high demand within the country of the given boutique or even given product exclusivity.

It was necessary to model a benchmark of each Segment per Quarter and Region, considered in the Order Allocation Algorithm, as to provide more accurate results when comparing the boutiques of a given segment on a quarter with the benchmark of that same segment on the region of the boutiques for the same quarter.

To select the boutiques that will model the benchmark, the Operational Score - feature relevant to the Order Allocation Algorithm - was simulated based on the operational metrics of the quarter in analysis - SoS Net, NS and NPS. The boutiques were then ordered from highest to lowest based on this Operational Score.

The benchmark was then modeled based on the boutiques that had an Operational Score above the average Operational Score plus one standard deviation, of the group of boutiques being analysed. The characteristics of the benchmark were engineered based on the weighted average of the operational metrics (SoS Net, %SoS < 1d, %SoS < 2d, %NS and NPS), and average number of orders *Sent to Out of Origin Country at GeoPrice*, VS and DS of the boutiques eligible to the benchmark.

Resorting to Excel VBA, a benchmark was modeled for every combination of Segment, Region and Quarter. An example of an obtained benchmark, using the four boutiques with higher Operational Score, can be consulted on Appendix A on Figure A.1.

4.3 Effects of Operational Improvement

For each boutique there is now a respective benchmark, to which it can be compared with in every quarter, as these parts present similar stock attractiveness based on their VS and DS. This analysis is fundamental to understand what could have been the state of the boutique under analysis, if its operational metrics matched the benchmark it is being compared with.

Given that the boutique under analysis belongs to the benchmark's segment, these two parts should have comparable demand of their stock, thus the number of orders *Sent to Out of Origin Country at GeoPrice* should be similar. In fact, this similarities are not often verified, as the boutique's operational performance is below the formulated benchmark.

Assuming that, the boutique under analysis matches the exact same operational metrics as the benchmark, the boutique would present the same level of orders *Sent to Out of Origin Country at GeoPrice* as the benchmark, resulting in a sales increase for the boutique. However, even though the two parts belong to the same segment, their stock attractiveness is not exactly the same, being needed an adjustment factor that keeps loyalty to the boutique's VS and DS.

The adjustment stock attractiveness factor, hereby mentioned as Delta, between the boutique and the benchmark is formulated in Equation 4.7.

$$\%Delta = \frac{VSFactor \times (BtqVS - BenchmarkVS) + DSFactor \times (BtqDS - BenchmarkDS)}{VSFactor \times BenchmarkVS + DSFactor \times BenchmarkDS} \tag{4.7}$$

where:

VS and *DS Factor* are factors to create a weighted average between the *VS* and *DS* of the boutique and benchmark. The sum of the two factors is 100%.

The VS and DS Factor were continuously validated and target of sensitivity analysis with the aim of maximizing the model's Accuracy. The results of the sensitivity analysis can be consulted on Table D.2 of Appendix D. The model Accuracy was defined as 100% minus the percentage of cases the model fails[3]. This might happen in the cases where a given boutique has a very unique and exclusive stock, being then allocated many orders even if their Operational Score is low.

The Delta shows the deviation of the boutique's stock attractiveness from the benchmark, being then this Delta used to estimate the orders that the boutique would have had, if it had the operational metrics of the benchmark. This Delta can be positive or negative, whether the boutique presents higher or lower stock attractiveness than the formulated benchmark.

The potential boutique's orders *Sent to Out of Origin Country at GeoPrice* are calculated as shown in Equation 4.8.

$$BtqPotentialOrders = BenchmarkOrders \times (100\% + \%Delta) \tag{4.8}$$

where:

BenchmarkOrders is the average number of orders *Sent to Out of Origin Country at GeoPrice* by the top performers used for the benchmark.

All the current analysis comes from the assumption that a boutique is allocated with more if they have better operational performance, supported by the relation shown on Figure 4.4.

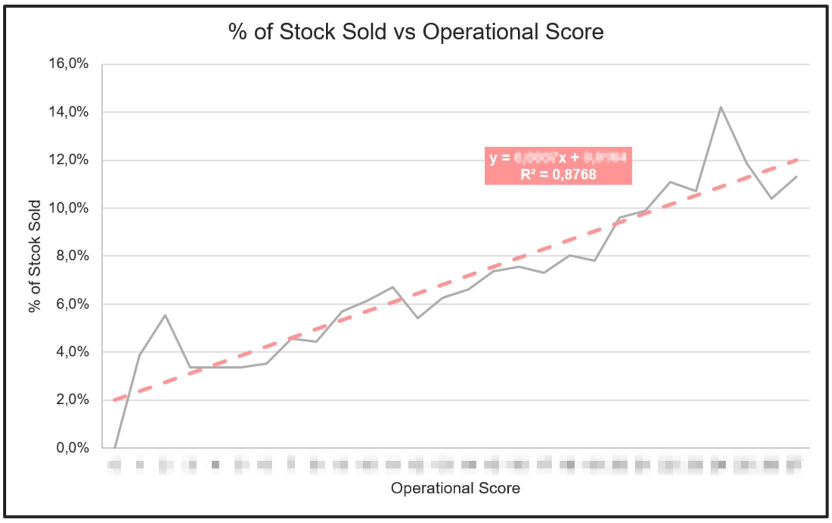

Figure 4.4: Average percentage of stock *Sent to Out of Origin Country at GeoPrice* per Operational Score.

[3] The model is said to fail in the cases where a boutique who could be a potential target for a Performance Project, i.e., below a certain threshold Operational Score defined by the Fulfillment Development team, is said to have a decrease on orders if they improve the operational performance.

As such, it is also of interest to get insight from the regression in Figure 4.4, that shows the average percentage of stock sold of Farfetch's partners to Out of Origin Country at GeoPrice per Operational Score considered in the Order Allocation Algorithm. Due to firm's constraints, the Operational Score distribution, in axis X, together with the equation of the linear regression should remain confidential.

Thus, using the mentioned equation, the Regression Orders were also computed per boutique, based on their stock units and the Operational Score of the assigned benchmark. This regression only takes into account the boutique's number of units in stock and Operational Score, it is not sensitive to the cases where a boutique might have high stock volume, but with very low demand.

The final Boutique's Potential Orders were then obtained from a weighted average between the Boutique's Potential Orders obtained from the benchmark technique and the Regression Orders as formulated on Equation 4.9.

$$BtqPotentialOrders = BenchmarkOrders \times BenchmarkFactor + RegressionOrders \times RegressionFactor \tag{4.9}$$

where:

Benchmark and *Regression Factor* are factors to create a weighted average between the *Benchmark Orders* and *Regression Orders*. The sum of the two factors is 100%.

Also, the *Benchmark* and *Regression Factors* were continuously validated and target of sensitivity analysis in order to maximize the model Accuracy. The results of the sensitivity analysis can be consulted on Table D.1 of Appendix D.

After computing the new final Boutique's Potential Orders, it was obtained, per quarter, a new level of orders *Sent to Out of Origin Country at GeoPrice*. To compute the new total orders sent per quarter, the boutique's actual orders *Sent to Out of Origin Country at GeoPrice* were subtracted to the *Total Sent* orders and then the new Boutique's Potential Orders were added.

Having now per quarter a new Potential of Sent Orders by the boutique, the percentage of orders increase was computed and then applied to monthly orders the boutique had in the year under analysis. This results on a new level of monthly orders that the boutique would have had, in the last 12 months, if its operational performance matched the assigned benchmark's operational metrics. An example of the described operations can be seen on Appendix A, Figure A.3.

4.4 Orders Forecast

Given the project's goal, to understand the impact of improving operational performance on the future profitability of the boutique partners and not based on what it could have been, it was necessary to create two different orders forecast: the first one based on the actual monthly orders the boutique had, and the second based on the new level of monthly orders the boutique would have had if its operational performance matched the benchmark, obtained as explained in Section 4.3.

The monitoring phase of the Performance Projects is six months, thus that was the number of periods selected to predict the level of orders. Given this, data was gathered of every boutique's monthly orders from two years (24 months) historical data.

The current model only analyses boutiques that have been partners with Farfetch for longer than a year. The partners with less than a year within Farfetch are considered to be in an initial phase of the learning curve of dealing with the new demand and adaption of their operations. By only analysing partners with more than one year with Farfetch, some will have less than 24 months of historical data, resulting in inaccurate forecasts. So, firstly it was obtained the average number of monthly orders of each segment, as shown in Figure 4.5.

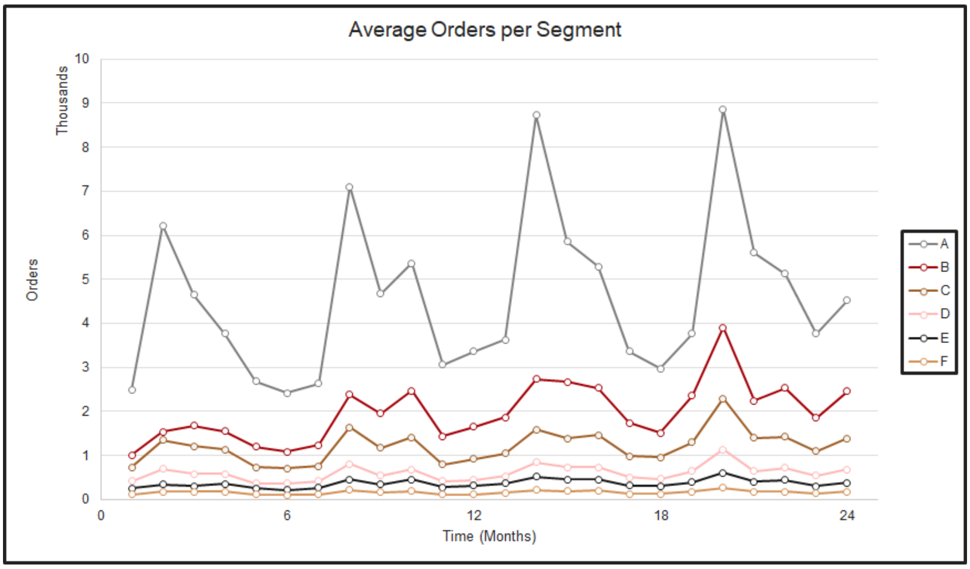

Figure 4.5: Average orders per segment for a 24 month horizon.

Resorting to RStudio and using the prophet forecasting model created by Facebook developers, reviewed on Section 2.5, the forecasting model was ran for each segment for a six month ahead period.

For the prophet inputs, it was used yearly seasonality together with logistic growth where the capacity was computed as the average orders of the last 12 months recorded multiplied by the Farfetch's expected growth for 2019.

After obtaining the six month forecast for each segment, the orders values were turned into a seasonality percentage, obtained by dividing each monthly orders value by the average orders of the last six recorded months as shown in Equation 4.10.

$$\%Seasonality_{ij} = \frac{OrdersForecast_{ij} - L6MAverage_j}{L6MAverage_j} \times 100\% \tag{4.10}$$

where:
$OrdersForecast_{ij}$ are the forecast for month i of the segment j;
$L6M\ Average_j$ is the average of actual orders of the last six months recorded of the segment j.

This results on a vector, per segment, that contains positive and negative percentages per month, depending on how much under or over the average orders of the last six months were for that month, including for the periods being forecast. An example of the obtained seasonality of segment A is shown in Figure 4.6.

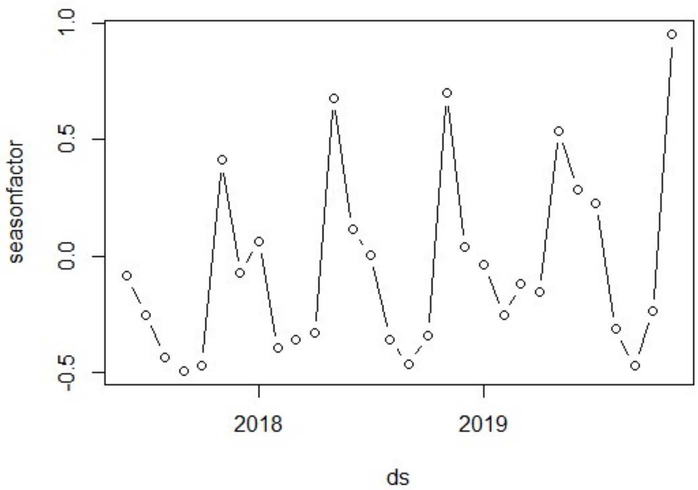

Figure 4.6: Seasonality of segment A.

An algorithm was then produced, to forecast the orders for every boutique partner, according to the flowchart shown on Figure 4.7.

For each boutique, data was collected between 12 and 24 months, depending on the date the boutique joined Farfetch. To increase forecast accuracy, the built algorithm first verifies if, each boutique, has data for of at least 18 months, in order to gather data for at least three complete seasons (AW and SS). For the cases where the boutique does not have sufficient data and most probably the forecast would produce results with low accuracy, the model verifies which segment the boutique belongs to, and computes the forecast based on the average orders of the last six months times the seasonality of its segment.

For the boutiques which there are sufficient records, the prophet forecasting method is ran using the same conditions as the ones used to get the segment's seasonality, i.e., yearly seasonality, logistic growth and the capacity calculated based on the average orders of the last 12 months recorded for the boutique times the Farfetch expected growth for 2019.

It was noted that for some cases where a boutique was growing or decreasing exponentially the monthly orders on Farfetch, the prophet model was producing poor results, resulting in negative number of orders for the months with less demand, thus it was incorporated in the model a forecast

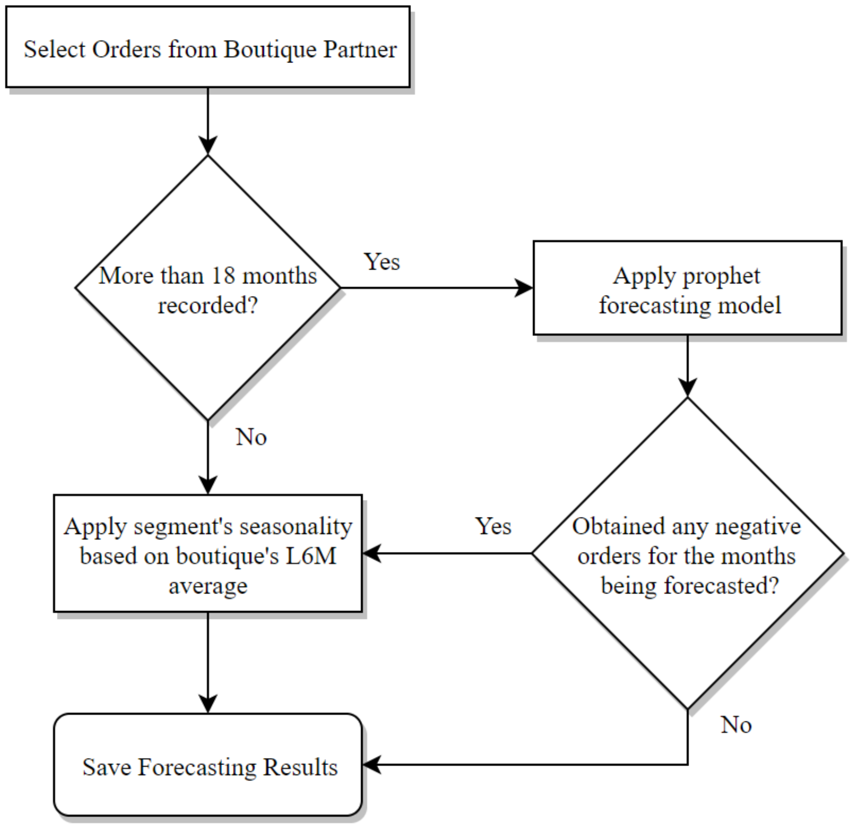

Figure 4.7: Logic used for the forecasting algorithm.

result evaluation. Hence, after running the prophet model for a boutique, it is verified, if for any of the six months being forecast, any negative number was produced. If negative order values are recorded, the forecasting results are discarded and replaced by applying the same method as to the boutiques with insufficient records. If no negative result is produced, the forecasting results are accepted and saved. An example comparing the forecast results obtained applying directly prophet and applying the segment's seasonality with the L6M average orders for a boutique with decreasing orders is shown on Appendix E on Figure E.1 and Figure E.2.

As mentioned initially, there was a need to build one forecast based on the actual orders each boutique had per month, which is considered the boutique's baseline. These are expected number of orders for the boutique if the operational performance remains unchanged. The second forecast, replaces the orders of the last 12 recorded months for the potential orders the boutique could have had if its operational performance matched the benchmark's, obtained as explained in Section 4.3. The forecasts obtained of these is the number of orders the boutique will have if it improves the operational performance in the future.

Figure 4.8 shows the actual and potential orders of a boutique plus baseline forecast together with the potential forecast.

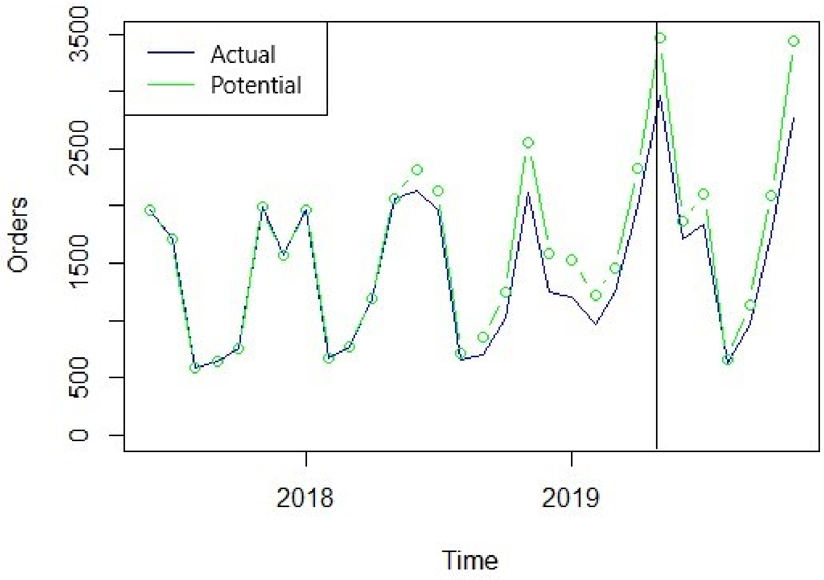

Figure 4.8: Boutique's actual and potential orders and the respective forecasts.

This way, the difference between the two forecasts is the increment on the orders allocated to the boutique due to the improvement of the operational metrics.

4.5 Performance Project Outcome Evaluation

An increase on profitability may have many sources, such as costs reduction, selling the same quantities with higher prices leading to higher margins, or simply sell more for the same price and keep the margin.

Unfortunately, Farfetch has no visibility on boutique's costs and in case a boutique decides to raise their prices to increase profitability, most probably they would reduce the sales volume, as Farfetch's Order Allocation Algorithm prioritizes the boutiques that set the item available to the customer at a lower price.

From Farfetch's point of view, the only way the boutiques can increase profitability is by increasing the quantity sold or by increasing the operational performance which is a direct input for the Service 4.0..

4.5.1 Project Benefits

The potential cash flows generated from a Performance Project should be analysed based on incremental cash flows, i. e., the difference between the expected cash flows the boutique will have from a Performance Project and the cash flows the boutique will keep on having without the project (Lopes, 2014), as formulated in Equation 4.11.

$$ProjectCF = CFwithProject - CFwithoutProject \tag{4.11}$$

As described in the previous sections, each boutique has now an increment on allocated orders per month due to a potential improvement on operational performance. These are the extra orders generated from the Performance Project.

To translate these new orders into revenue, one had to multiply these extra number of orders by the Average Order Value (AOV) the boutique had on the same months being forecast on the previous year. Table 4.3 shows an example of the AOV used for the months being forecast.

Table 4.3: AOV used for the months being forecast for an example boutique.

	MM / YYYY	**AOV**	**Extra Orders**	**Extra GMV**
Actuals	06 / 2018	$ 510	183	$ 93 175
	07 / 2018	$ 554	168	$ 93 067
	08 / 2018	$ 603	56	$ 33 715
	09 / 2018	$ 551	145	$ 80 129
	10 / 2018	$ 554	213	$ 118 201
	11 / 2018	$ 521	439	$ 228 707
	12 / 2018	$ 602	326	$ 196 030
	01 / 2019	$ 570	314	$ 178 944
	02 / 2019	$ 529	251	$ 132 666
	03 / 2019	$ 564	185	$ 104 138
	04 / 2019	$ 535	295	$ 157 783
	05 / 2019	$ 548	440	$ 241 002
Forecast	06 / 2019	$ 510	183	$ 93 234
	07 / 2019	$ 554	272	$ 150 918
	08 / 2019	$ 603	31	$ 18 652
	09 / 2019	$ 551	167	$ 91 965
	10 / 2019	$ 554	329	$ 182 174
	11 / 2019	$ 521	653	$ 340 211

The Extra GMV is obtained as formulated on Equation 4.12.

$$ExtraGMV = ExtraOrders \times AOV \tag{4.12}$$

These extra orders generated from the operational performance improvement represent an extra revenue. To turn these revenue into profit, the Farfetch's commission from every sale must be deducted along with the most probable cost the boutique had to acquire the products and then resell them - cost of goods sold (COGS).

The COGS is obtained as formulated on Equation 4.13.

$$COGS = ExtraGMV \times FarfetchCommission + \frac{ExtraGMV}{BoutiqueMarkup} \tag{4.13}$$

where:

Farfetch Commission is the percentage Farfetch gets of every sale the boutique gets from Farfetch.com.

By consulting business experts with close contact with boutique partners, a markup[4] was assumed for each type of product family - Clothing, Bags, Accessories and Shoes.

For each boutique, it was, then, verified the percentage of stock they held of each product family to further achieve a specific markup per boutique partner. Table 4.4 shows an example of the markup for a virtual Boutique A, where the Contribution is obtained by multiplying the % of Stock that the boutique has of the Product-Family by the respective Markup.

Table 4.4: Example of the markup calculation per partner.

Boutique A	**% of Stock**	**Product-Family Markup**	**Contribution**
Bags	10%	2,2	0,22
Clothing	65%	2,5	1,63
Shoes	20%	2,4	0,48
Accessories	5%	2,2	0,11
	100%	**Boutique A's Markup =**	**2,44**

The actual profit, generated from the extra orders per month, can then be calculated as formulated on Equation 4.14.

$$ExtraProfit = ExtraGMV - COGS \tag{4.14}$$

Table 4.5 shows an example of the sales incremental profit generated from an increase on the orders sent.

Table 4.5: Example of the profitability per month generated by the extra orders.

	06 / 2019	**07 / 2019**	**08 / 2019**	**09 / 2019**	**10 / 2019**	**11 / 2019**
Extra GMV	$ 93 234	$ 150 918	$ 18 652	$ 91 965	$ 182 174	$ 340 211
Farfetch Comission	$ -27 970	$ -45 276	$ -5 596	$ -27 590	$ -54 652	$ -102 063
Product Acquisition	$ -38 289	$ -61 979	$ -7 660	$ -37 768	$ -74 815	$ -139 717
Sales Profit	**$ 26 975**	**$ 43 664**	**$ 5 397**	**$ 26 608**	**$ 52 707**	**$ 98 431**

To measure the success of the Performance project, a baseline operational level must be obtained. Each boutique's operational level baseline metrics (% SoS < 1d, % SoS < 2d and % NS) are calculated based on its performance of the last six months. An example is displayed on Table 4.6.

These are the metrics the boutique is expected maintain if no measures are taken to improve the operational performance. These will be used later to predict the direct return from the Service 4.0..

[4] Markup is the ratio between the selling price of a good or service and its cost. For example: If a product cost is $100 and the selling price is $200, its markup will be $200/$100 = 2.

Table 4.6: Example of the operational performance baseline considered for the forecast months.

	Orders	% SoS <1d	% SoS <2d	% NS
12 / 2018	1253	66,6%	96,7%	3,07%
01 / 2019	1208	76,3%	99,2%	3,48%
02 / 2019	965	75,6%	98,9%	2,71%
03 / 2019	1244	62,9%	94,1%	3,19%
04 / 2019	1987	16,0%	66,7%	4,70%
05 / 2019	2963	20,0%	76,4%	2,29%
Boutique's Baseline =		**43,5%**	**84,4%**	**3,23%**

The improved metrics of the boutique - the projected final state of the Performance Project - are calculated using the same logic that was applied in the boutique's operational baseline, but based on the operational performance of the benchmarks considered for the boutique under analysis. An example can be consulted on Figure 4.14.

In Figure 4.9 is shown the difference of the operational metrics between a boutique and the proposed benchmark for that boutique.

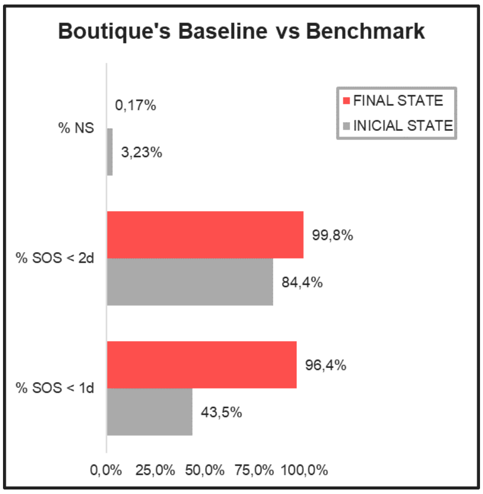

Figure 4.9: Boutique's and its benchmark operational performance comparison.

Considering each orders forecast and the respective GMV per month, it is now possible to predict the expected Service 4.0. return for both the boutique's baseline operational metrics and the improved ones. The difference between the Service 4.0. return with the improved metrics and the baseline are the benefits generated from the Performance Project focused on the improvement of operational metrics.

Consequently, additionally to the incremental profit generated from an increase on the orders sent, the benefits from the Service 4.0. will be the return obtained the potential GMV - considering the orders increase - with the improved operational metrics minus the return with the boutique orders' baseline and the baseline operation metrics.

In Table 4.7, it is presented an example of a possible incremental cash flow for the boutique generated from a operational performance improvement with an ambitious scenario.

Table 4.7: Example of the incremental cash flows generated from an improvement of the operational performance.

	06 / 2019	**07 / 2019**	**08 / 2019**	**09 / 2019**	**10 / 2019**	**11 / 2019**
Extra GMV	$ 93 234	$ 150 918	$ 18 652	$ 91 965	$ 182 174	$ 340 211
Farfetch Comission	$ -27 970	$ -45 276	$ -5 596	$ -27 590	$ -54 652	$ -102 063
COGS	$ -38 289	$ -61 979	$ -7 660	$ -37 768	$ -74 815	$ -139 717
Sales Profit	$ 26 975	$ 43 664	$ 5 397	$ 26 608	$ 52 707	$ 98 431
Service 4.0. - Baseline Performance	$ 6 056	$ 6 522	$ 2 218	$ 3 410	$ 6 188	$ 9 820
Service 4.0. - Improved Performance	$ 12 291	$ 13 611	$ 4 322	$ 7 238	$ 13 263	$ 21 699
Service 4.0. Profit	$ 18 347	$ 20 132	$ 6 540	$ 10 648	$ 19 450	$ 31 519
Project Net Result	**$ 45 321**	**$ 63 796**	**$ 11 936**	**$ 37 256**	**$ 72 157**	**$ 129 950**

Note to the fact that on the Service 4.0. - Baseline Performance entry, the cash flows may be negative or positive, whether the boutique, with its baseline performance, would receive an incentive or penalty, respectively.

4.5.2 Financial Metrics

After obtaining the benefit cash flows, represented as the Project Net Results entry on Table 4.7, the missing piece is the investment cost that the project requires from the boutique.

As previously described, the Performance Projects are provided for free to boutique partners. Any possible cost that arises from the project will come from the need to invest on operations, and will be very specific depending on the partner's initial state. Some examples of possible investments needed from the boutique can be: hiring more people, buying new materials, contracting developers to work on software integration, among others.

Predicting these investment costs without knowing the boutique's structure is an almost impossible task, so, these costs were left as an input to be inserted by Fulfillment Development consultant when analysing a specific boutique partners beneficial cash flow.

After the insertion of possible investment costs by the consultant, the following financial metrics are obtained: Return on Investment (ROI), Net Present Value (NPV), Payback Period, and Benefit/Cost Ratio.

The ROI, NPV and Benefit/Cost Ratio can be calculated based on the formulas show in Equation 4.15, 4.16 and 4.17, respectively.

$$ROI = \frac{Benefits - Costs}{Costs} \times 100\% \tag{4.15}$$

$$NPV = Benefits - Costs \tag{4.16}$$

$$Benefits/CostRatio = \frac{Benefits}{Costs} \times 100\% \tag{4.17}$$

where:

Benefits is the sum of the benefits generated by the Performance Project;

Costs is the sum of the investment required from the boutique.

The Payback Period is the number of months needed for the sum of the projected benefits equal or surpass the investment required.

Having calculated these metrics, both the boutique and the Fulfillment Development consultant can now evaluate whether it is worth it or not to enroll on a Performance Project focused on the improvement of the boutique's operational performance.

In Figure 4.10 it is presented a boutique's project cash flow, corresponding to the data shown on Table 4.7, as well as some predicted costs of the project, in particular, contracting an IT company to develop software integration and hiring two more people to process orders.

PROJECT'S BUSINESS CASE ($)	*t = 0*	*06 / 2019*	*07 / 2019*	*08 / 2019*	*09 / 2019*	*10 / 2019*	*11 / 2019*
Extra Sales		93 234	150 918	18 652	91 965	182 174	340 211
Service 4.0. - Profit		18 347	20 132	6 540	10 648	19 450	31 519
Order Process Time							
Cost of Goods Sold		-66 259	-107 254	-13 256	-65 358	-129 467	-241 780
NET RESULT		45 321	63 796	11 936	37 256	72 157	129 950
Investment Costs	-35 000	-3 500	-3 500	-3 500	-3 500	-3 500	-3 500
PROJECTS CASH-FLOW	**-35 000**	**41 821**	**60 296**	**8 436**	**33 756**	**68 657**	**126 450**

Figure 4.10: Boutique's cash flow plus project predicted investment needed.

Figure 4.11 shows the predicted financial metrics for a boutique taking in consideration the project's benefits and costs.

FINANCIAL METRICS	
ROI	544%
NPV	$ 304 416
Payback Period	*1 month(s)*
Benefit/Cost Ratio	6,44

Figure 4.11: Project financial metrics for a particular boutique.

To safeguard the consultant responsible for the project, it is important to keep track of the assumptions made to estimate a project's predicted cash flows. Figure 4.12 shows the assumptions made in the analysis of the given boutique.

After analysing the predicted project's financial metrics and the assumptions behind the methodology used to obtain such results, one can finally make a decision whether it is beneficial or not to engage on a project aiming for operational improvement.

OPERATIONAL PERFORMANCE	Pre-Project	After Project
% SoS < 1d	43,46%	94,09%
% SoS < 2d	84,45%	99,77%
% NS	3,23%	0,29%

FINANCIAL	
Mark-Up	2,44
Farfetch Comission	30,0%
Packaging Cost	$ 1,70

OTHER ASSUMPTIONS
1. % Wrong Items lower than threshold to be elegible for the incentive
2. NPS score over 4,5 to be elegible for % SoS < 1d extra incentive
3. There won't be drastic changes in the boutique's stock (value, quantity and attractiveness)

Figure 4.12: Assumptions considered to obtain the project cash flows.

In the case of the boutique being followed throughout the model, given the required investments required and the projected incremental cash flows resulting in a ROI of 544%, it can be concluded the boutique would greatly benefit from improving operational performance, thus, engaging on a Performance Project provided by the Fulfillment Development consultants.

4.6 Model Deployment

The model described in the previous sections was continuously built and reshaped by extracting the data and processing it in both Excel and RStudio.

Despite the processing on Excel, using Visual Basic, being rather time-consuming, it was fundamental for simpler human visualization of the steps the model was going through.

As previously mentioned, the used data was collected from Farfetch sales, boutique's stock and their performance on orders, covering a complete year, since April 2018 until the end of March 2019. Thus, after completion of the model in the beginning of June 2019, there were two more months of data that were not being taken into account, showing that the obtained results would only make sense on April 2019, proving to not be scalable.

To tackle this deficiency, the exact same logic used for the model, was replicated using only RStudio: from updated data extraction by analysing the last complete month at the time the R script was run; all the data processing described from Sections 4.1 to 4.5; to uploading data back to the database and connect it to a final tool on Excel to be used by the Fulfillment Development consultants.

The developed Excel tool of the final automated model has three main views: overview of with a list of all partners and their potential cash flows (Figure 4.13); partner analysis view with their operational performance of the last year and more information regarding the forecast orders (Figure 4.14); and financial analysis of the partner with the estimated cash flows and areas to input the Performance Project costs, to then, compute the Financial Metrics (Figure 4.15).

StoreName	StoreKey	Region	Country	L6M Operational Metrics % SoS < 1d	% SoS < 2d	% NS	6 MONTH - INCREMENTAL CASH FLOWS Conservative	Optimistic	Important Stake Holders PS	PS Supervisor	AM	AM Supervisor
[illegible]	[illegible]	[illegible]	[illegible]	65,4%	98,4%	0,53%	$ -	$ 21 713	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	94,3%	99,7%	0,25%	$ -	$ 1 412	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	99,4%	99,9%	0,36%	$ -	$ 16 057	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	71,0%	97,8%	0,56%	$ 22 061	$ 35 770	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	41,7%	91,2%	2,47%	$ 20 496	$ 60 472	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	82,7%	98,7%	2,22%	$ 15 886	$ 51 787	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	81,3%	98,8%	0,92%	$ 15 129	$ 42 682	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	72,6%	94,2%	6,23%	$ 13 872	$ 28 627	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	79,6%	96,8%	3,54%	$ 11 066	$ 28 549	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	72,9%	98,8%	3,63%	$ 10 009	$ 31 650	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	88,9%	99,2%	1,39%	$ 9 555	$ 35 284	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	85,2%	98,0%	5,73%	$ 9 062	$ 21 254	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	75,8%	98,7%	0,97%	$ 8 711	$ 27 692	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	70,9%	97,1%	8,00%	$ 7 473	$ 48 593	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	89,2%	99,1%	2,21%	$ 7 191	$ 66 341	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	85,0%	99,8%	4,88%	$ 6 260	$ 89 793	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	78,2%	99,3%	3,61%	$ 5 967	$ 19 866	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	83,4%	99,6%	0,47%	$ 5 475	$ 92 029	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	82,4%	99,8%	0,41%	$ 5 007	$ 18 140	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	84,1%	99,9%	0,06%	$ 4 791	$ -2 075	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	86,2%	98,2%	5,53%	$ 3 716	$ 10 526	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	89,9%	100,0%	0,21%	$ 3 081	$ 30 864	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	66,4%	92,9%	6,68%	$ 3 038	$ 17 588	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	68,5%	92,7%	6,08%	$ 2 687	$ 6 955	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	90,7%	99,8%	1,08%	$ 2 379	$ 22 366	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	77,1%	97,2%	6,44%	$ 2 331	$ 5 133	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	84,6%	99,4%	0,76%	$ 2 222	$ 17 118	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	93,7%	99,8%	0,58%	$ 2 106	$ 29 678	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	86,9%	97,0%	3,08%	$ 2 094	$ 3 983	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	92,9%	98,9%	4,31%	$ 1 772	$ -4 729	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	85,9%	100,0%	1,49%	$ 1 057	$ 16 415	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	87,9%	97,2%	0,13%	$ 442	$ 9 727	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	96,3%	100,0%	0,30%	$ -	$ 36 581	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	89,2%	98,7%	0,47%	$ -	$ 5 055	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	92,7%	99,9%	0,00%	$ -	$ -12 887	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	93,3%	99,9%	0,23%	$ -1 889	$ 19 281	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	42,5%	91,7%	1,20%	$ 442 289	$ 1 357 017	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	60,8%	94,9%	0,70%	$ 197 356	$ 537 250	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	72,6%	95,4%	2,89%	$ 183 307	$ 803 570	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	60,2%	93,6%	2,42%	$ 171 852	$ 571 023	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	39,6%	80,8%	2,75%	$ 157 526	$ 374 066	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]	47,6%	80,7%	0,55%	$ 144 060	$ 279 436	[illegible]	[illegible]	[illegible]	[illegible]

Figure 4.13: Model’s Financial Overview per Partner.

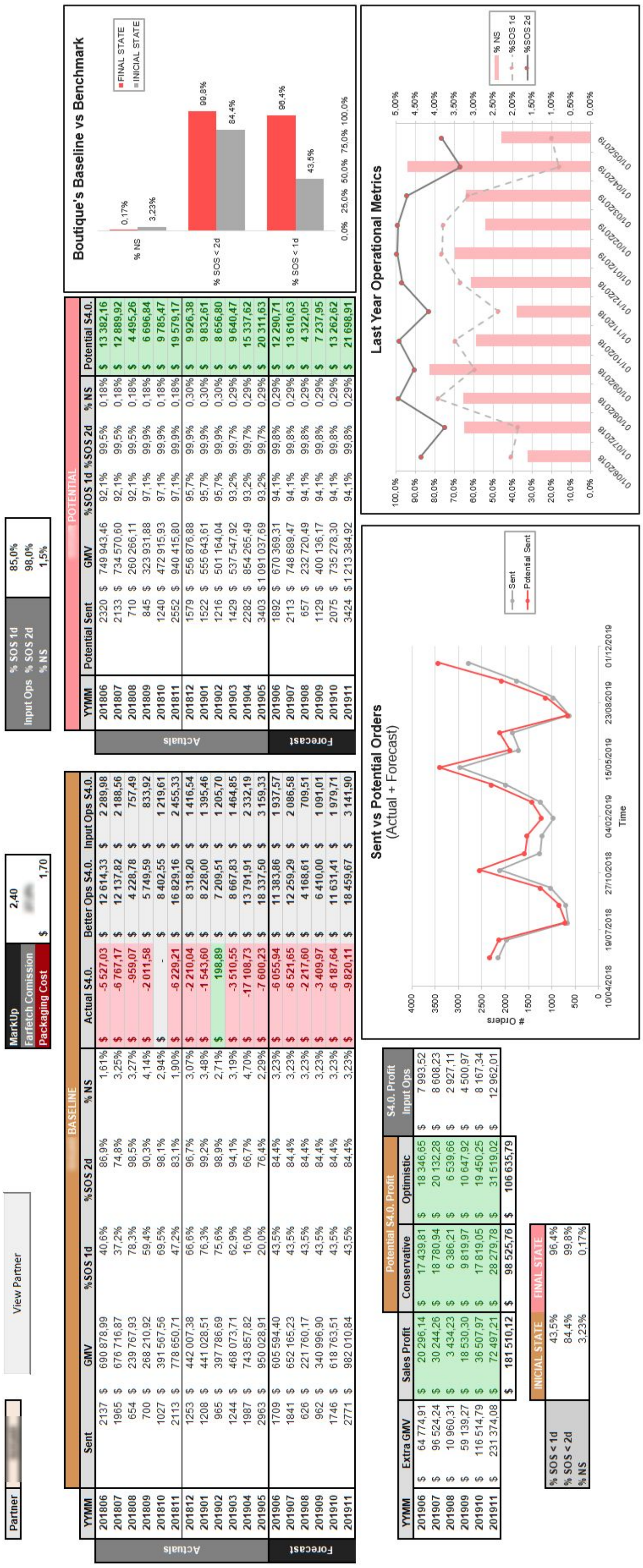

Figure 4.14: Model's Partner Analysis.

- Financial Analysis of Performance Project

SCENARIO: NO SALES INCREASE BUT AMBITIOUS OPS

PROJECT'S BUSINESS CASE ($)	t = 0	06 / 2019	07 / 2019	08 / 2019	09 / 2019	10 / 2019	11 / 2019
Extra Sales		0	0	0	0	0	0
Service 4.0. - Profit		17 440	18 781	6 386	9 820	17 819	28 280
Order Process Time							
Cost of Goods Sold		0	0	0	0	0	0
NET RESULT	0	17 440	18 781	6 386	9 820	17 819	28 280
Investment Costs	-5 000	-1 000	-1 000	-1 000	-1 000	-1 000	-1 000
PROJECTS CASH-FLOW	-5 000	16 440	17 781	5 386	8 820	16 819	27 280

FINANCIAL METRICS		
ROI		796%
NPV	$	87 526
Payback Period		1 month(s)
IRR		323%
Benefit/Cost Ratio		8,96

NET PRESENT VALUE $ 87 526

SCENARIO: SALES INCREASE AND AMBITOUS OPS

PROJECT'S BUSINESS CASE ($)	t = 0	06 / 2019	07 / 2019	08 / 2019	09 / 2019	10 / 2019	11 / 2019
Extra Sales		64 775	96 524	10 960	59 139	116 515	231 374
Service 4.0. - Profit		18 347	20 132	6 540	10 648	19 450	31 519
Order Process Time							
Cost of Goods Sold		-44 479	-66 280	-7 526	-40 609	-80 007	-158 877
NET RESULT		38 643	50 377	9 974	29 178	55 958	104 016
Investment Costs	-5 000	-1 000	-1 000	-1 000	-1 000	-1 000	-1 000
PROJECTS CASH-FLOW	-5 000	37 643	49 377	8 974	28 178	54 958	103 016

FINANCIAL METRICS		
ROI		2520%
NPV	$	277 146
Payback Period		1 month(s)
IRR		770%
Benefit/Cost Ratio		26,20

NET PRESENT VALUE $ 277 146

SCENARIO: NO SALES INCREASE AND INPUT OPS

PROJECT'S BUSINESS CASE ($)	t = 0	06 / 2019	07 / 2019	08 / 2019	09 / 2019	10 / 2019	11 / 2019
Extra Sales		0	0	0	0	0	0
Service 4.0. - Profit		7 994	8 608	2 927	4 501	8 167	12 962
Order Process Time							
Cost of Goods Sold		0	0	0	0	0	0
NET RESULT		7 994	8 608	2 927	4 501	8 167	12 962
Investment Costs	-5 000	-1 000	-1 000	-1 000	-1 000	-1 000	-1 000
PROJECTS CASH-FLOW	-5 000	6 994	7 608	1 927	3 501	7 167	11 962

FINANCIAL METRICS		
ROI		311%
NPV	$	34 159
Payback Period		1 month(s)
IRR		129%
Benefit/Cost Ratio		4,11

NET PRESENT VALUE $ 34 159

Assumptions

OPERATIONAL PERFORMANCE	Pre-Project	After Project	Input Ops
% SoS < 1d	43,46%	94,09%	85,00%
% SoS < 2d	84,45%	99,77%	98,00%
% NS	3,23%	0,29%	1,50%

FINANCIAL	
Mark-Up	2,40
Farfetch Comission	27,00%
Packaging Cost	$ 1,70

OTHER ASSUMPTIONS

1. % Wrong Items lower than threshold to be elegible for the incentive
2. NPS score over 4,5 to be elegible for % SoS < 1d extra incentive
3. There won't be drastic changes in the boutique's stock (value, quantity and attractiveness)

Figure 4.15: Model's Financial Analysis of a Partner.

Chapter 5

Conclusions & Future Work

The present dissertation had the purpose of translating an improvement of the fulfillment operations of Farfetch partners into a growth of their profitability.

As Farfetch itself does not have control of the order fulfillment process, having operational efficient partners is key for the success of the company, leading to customer loyalty growth. The Fulfillment Development team focuses on reducing the gap between Farfetch and the order fulfillment process, by providing free consulting services to its boutique partners. Many times, convincing these partners to engage on a Performance Project may represent a difficult task as they may not understand how they can benefit from it. The described model, that did not exist before, meets the project's goal by addressing this issue.

During the development of the model, a wide range of variables were identified that could affect the partners' profitability, but the model focus on the two that Farfetch has visibility on: sales volume and Service 4.0. return.

By segmenting the boutiques into groups that have similar demand for their stock and applying benchmark techniques on actually comparable parts, it was possible to identify the partner to benchmark for a poor operational performer boutique and understand how the improvement of the operational metrics could affect the orders growth and the return obtained from the incentive service created by Farfetch.

It can be concluded that the project goal was met with the development of a completely automated model, although some points for further analysis can be identified. It should be noted that the chosen approach to address the initial issue is based on the work stream of the current Order Allocation Algorithm.

The boutiques were segmented by similar stock attractiveness based on each boutique's Value and Demand Score. These two variables translate each boutique's stock into values of attractiveness, but it is not possible to identify the stock marked with Geographical Pricing, as the same item may be marked with a fixed price in a region and not in another, generating a fixed price sale or not, depending on the customer's location. The model built assumed then, that the boutique's stock generate orders with fixed price proportional to their stock attractiveness.

Regarding the non-geo-priced orders, given the price threshold considered in the Order Allocation Algorithm, in many cases the Operational Score still is the tie-breaker on selecting the partner to fulfill the order. As the items' prices are managed by the partners, these cases were not addressed by the model, as Farfetch has no control on.

The forecasting takes into consideration the expected Farfetch yearly growth and the historical data from the partners. Hence, the obtained results rely on the assumption that the boutiques will keep a strategy in accordance to their past. It is not expected for the boutiques to drastically change their stock quantities and attractiveness. A further analysis and development of a dynamic forecasting method that could take into consideration each boutique's stock could certainly be a complex task, but with high interest.

Given some business specific constraints, affirming to a boutique partner that it will be allocated more orders if there's an improvement of its operational metrics may be too compromising. There's no guarantee that the boutique's stock will decrease or increase drastically, plus, given the uncertainty of the fashion business, its attractiveness may also change. Hence, in addition to the model described in Chapter 4, there was the need to formulate an additional more conservative scenario where the benefits of operational performance improvement rely on the return obtained from the Service 4.0.. Given the boutique orders' baseline and its GMV, it is computed the difference between of the Service 4.0. return from the improved metrics and the revenue or penalty the boutique incurs by maintaining operational baseline without a change. This uncertainty of the boutique's stock and its demand could certainly be improved by the development of the dynamic forecasting method depending on the boutique's stock.

As Performance Projects are offered without any charge to boutique partners, this model was built only for this partner type. Although, it is still possible for some projects to be developed with brand partners and, in this case, it would be required a completely different model, that was not possible to develop due to the internship's limited duration.

As a final consideration, from Farfetch's point of view, the Service 4.0. is the investment on the firm's order fulfillment operations, but in this case these operations rely on the partners performance. Boutiques still do not see the Service 4.0. as an opportunity to increase profitability, but rather an extra cost they may have to support in case of poor performance. The right communication of this incentive service may be crucial to raise the partner's awareness to operational performance, where a change of strategy to a dynamic Farfetch's commission on sales depending on the performance could be of interest. This change of strategy, could be the right step to shift partner's mentality into acknowledging that the better they fulfill Farfetch orders, the lower the Farfetch's commission, thus, higher direct profits from the items sold through Farfetch.

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Appendix A

Manual Model Overview

Region	[illegible]
Segment	C
Quarter	19Q1

Out	1
GeoPrice	0

Sample Size	4
AVG OpsScore + StDv	[illegible]
Segment Size	24

VS Factor	55%
DS Factor	45%

SLOPE	[illegible]
INTERCEPT	[illegible]

Benchmark Factor	75%
Regression Factor	25%

StoreKey	Store	Country	SOS	NS	NPS	OpsScore	GMVOut	SentOut	TotalSent	StkUnits	VS	DS	Benchmarking		Regression	Target Orders	Orders Increase	Ops Metrics		
													Delta	Orders				%SoS<1d	%SoS<2d	%NS
Benchmark C	19Q1	[illegible]	0,55	0,38%	73,8%	[illegible]	$ 508 531,76	987	7954	11601	423	526			1399	1090		94,92%	99,92%	0,38%
[illegible]	[illegible]	[illegible]	0,51	0,03%	72,8%	[illegible]	$ 541 202,47	1185	13358	11624	415	601	6%	1050	1402	1138	-4%	96,6%	99,9%	0,0%
[illegible]	[illegible]	[illegible]	0,55	0,49%	72,2%	[illegible]	$ 613 302,82	1114	8383	11023	383	400	-17%	822	1330	949	-15%	95,6%	99,9%	0,5%
[illegible]	[illegible]	[illegible]	0,55	0,74%	75,9%	[illegible]	$ 556 399,23	986	4735	13230	517	640	22%	1203	1596	1301	32%	94,2%	99,9%	0,7%
[illegible]	[illegible]	[illegible]	0,63	0,78%	77,1%	[illegible]	$ 323 222,51	664	5339	10528	378	463	-11%	875	1270	973	47%	90,4%	100,0%	0,8%
[illegible]	[illegible]	[illegible]	0,77	0,00%	69,1%	[illegible]	$ 264 812,30	517	10092	13252	371	522	-6%	924	1599	1093	111%	81,6%	96,8%	0,0%
[illegible]	[illegible]	[illegible]	0,62	0,93%	62,1%	[illegible]	$ 269 826,22	496	5551	11241	407	503	-4%	947	1356	1049	112%	94,8%	99,9%	0,9%
[illegible]	[illegible]	[illegible]	0,69	0,56%	71,0%	[illegible]	$ 186 462,00	390	4618	9690	353	424	-18%	809	1169	899	130%	86,6%	99,4%	0,6%
[illegible]	[illegible]	[illegible]	0,71	1,27%	74,3%	[illegible]	$ 507 287,79	1240	9903	15951	601	732	40%	1387	1924	1521	23%	84,2%	99,6%	1,3%
[illegible]	[illegible]	[illegible]	0,78	0,75%	70,8%	[illegible]	$ 427 545,30	595	2645	11266	459	372	-11%	883	1359	1002	68%	77,2%	99,4%	0,7%
[illegible]	[illegible]	[illegible]	0,73	1,29%	72,9%	[illegible]	$ 167 070,16	408	5505	11938	351	581	-3%	956	1440	1077	164%	84,3%	99,1%	1,3%
[illegible]	[illegible]	[illegible]	0,82	0,60%	71,4%	[illegible]	$ 207 892,85	302	2576	9158	352	450	-16%	833	1105	901	198%	72,1%	98,8%	0,6%
[illegible]	[illegible]	[illegible]	0,83	0,84%	62,5%	[illegible]	$ 350 237,47	457	2894	19446	743	423	28%	1260	2346	1531	235%	73,7%	98,8%	0,8%
[illegible]	[illegible]	[illegible]	1,03	0,67%	70,1%	[illegible]	$ 421 528,94	1192	4399	16288	289	446	-23%	756	1965	1058	-11%	59,7%	95,5%	0,7%
[illegible]	[illegible]	[illegible]	0,83	2,05%	73,4%	[illegible]	$ 226 362,28	392	3629	8995	400	370	-18%	813	1085	881	125%	71,7%	98,9%	2,1%
[illegible]	[illegible]	[illegible]	0,97	1,83%	72,3%	[illegible]	$ 286 246,57	681	4579	13115	586	558	22%	1205	1582	1300	91%	60,2%	97,1%	1,8%
[illegible]	[illegible]	[illegible]	0,80	2,53%	75,7%	[illegible]	$ 333 607,40	678	4054	12409	459	466	-2%	972	1497	1103	63%	73,6%	99,0%	2,5%
[illegible]	[illegible]	[illegible]	1,09	0,80%	63,0%	[illegible]	$ 205 350,39	363	4778	14895	561	664	29%	1278	1797	1407	288%	53,9%	92,9%	0,8%
[illegible]	[illegible]	[illegible]	0,92	1,76%	68,4%	[illegible]	$ 476 739,31	871	5667	12181	485	433	-2%	971	1469	1095	26%	69,2%	95,0%	1,8%
[illegible]	[illegible]	[illegible]	1,02	2,32%	70,6%	[illegible]	$ 794 006,91	1056	3543	9358	450	280	-21%	785	1129	871	-18%	61,9%	93,0%	2,3%
[illegible]	[illegible]	[illegible]	0,99	2,83%	75,3%	[illegible]	$ 201 639,89	423	4098	8891	335	361	-26%	729	1072	815	93%	67,7%	93,5%	2,8%
[illegible]	[illegible]	[illegible]	0,98	2,76%	70,2%	[illegible]	$ 33 403,23	158	5609	16249	215	544	-23%	763	1960	1062	572%	60,3%	96,0%	2,8%
[illegible]	[illegible]	[illegible]	1,03	2,57%	72,6%	[illegible]	$ 771 260,68	1345	8876	11783	615	505	20%	1189	1421	1247	-7%	62,2%	94,6%	2,6%
[illegible]	[illegible]	[illegible]	0,86	3,16%	63,7%	[illegible]	$ 315 069,67	524	3417	12168	405	442	-10%	886	1468	1032	97%	71,2%	97,2%	3,2%
[illegible]	[illegible]	[illegible]	1,60	4,09%	44,4%	[illegible]	$ 312 492,64	547	5354	13185	481	433	-2%	966	1590	1122	105%	45,1%	76,6%	4,1%

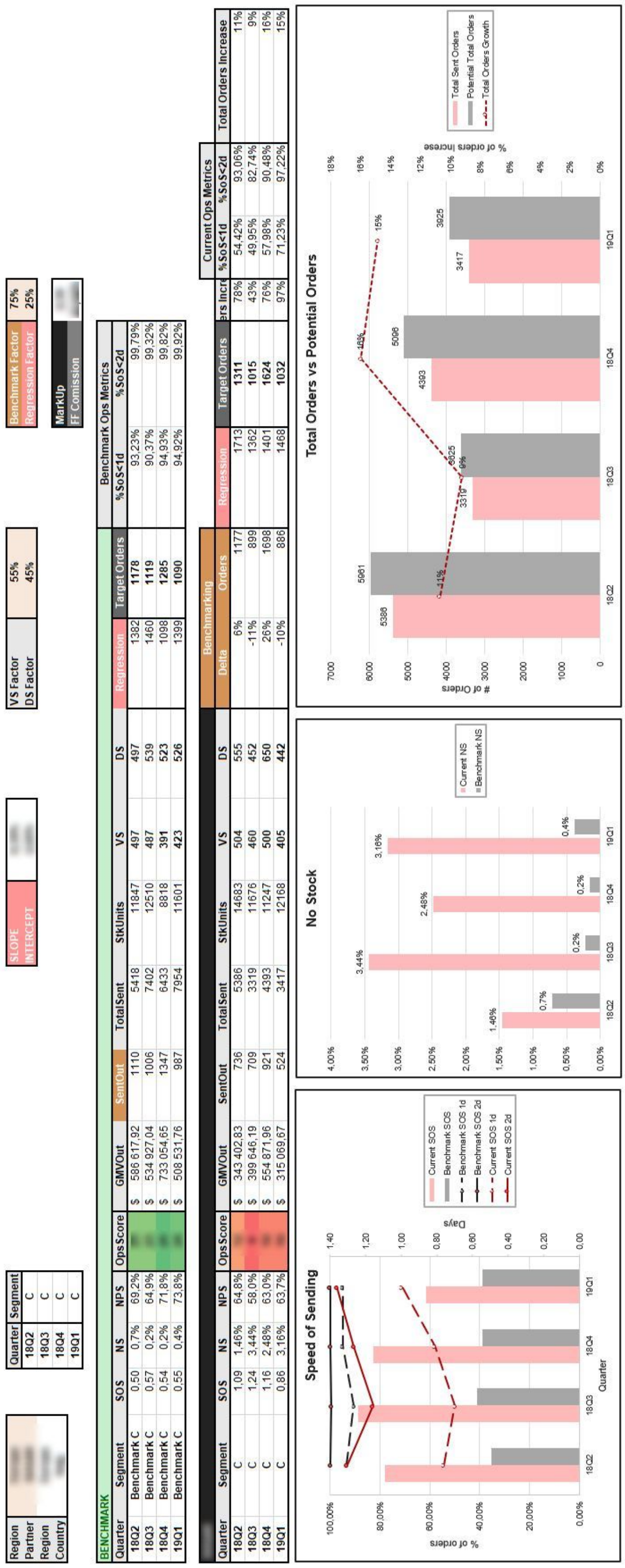
Figure A.1: Benchmark Modeling per Segment, Region and Quarter.

BENCHMARK PER QUARTER

VS Factor	55%
DS Factor	45%

Segment	Quarter	Region	SOS	NS	NPS	OpsScore	GMVOut	SentOut	TotalSent	VS	DS	Ops Metrics %SoS<1	%SoS<2	%NS
Benchmark D	18Q4	[illegible]	0,87	0,52%	78,1%	[illegible]	$ 219 157,93	335	1046	**239**	**214**	64,0%	99,6%	0,5%
Benchmark E	18Q2	[illegible]	0,98	2,23%	57,7%	[illegible]	$ 83 397,11	128	604	**156**	**120**	59,9%	96,5%	2,2%
Benchmark E	18Q3	[illegible]	0,86	0,53%	72,0%	[illegible]	$ 143 220,61	250	850	**171**	**121**	65,5%	98,6%	0,5%
Benchmark E	18Q4	[illegible]	0,56	1,00%	49,7%	[illegible]	$ 426 289,87	1333	4484	**115**	**166**	86,2%	95,8%	1,0%
Benchmark E	19Q1	[illegible]	0,26	0,19%	51,9%	[illegible]	$ 183 564,20	727	2389	**79**	**103**	99,2%	100,0%	0,2%
Benchmark F	18Q2	[illegible]	0,77	0,58%	42,9%	[illegible]	$ 211 722,89	890	2811	**62**	**81**	71,5%	99,1%	0,6%
Benchmark F	18Q3	[illegible]	0,78	0,65%	55,9%	[illegible]	$ 157 879,93	592	1645	**63**	**67**	71,9%	99,6%	0,6%
Benchmark F	18Q4	[illegible]	0,61	0,00%	100,0%	[illegible]	$ 12 872,19	97	269	**19**	**37**	95,9%	100,0%	0,0%
Benchmark F	19Q1	[illegible]	0,61	0,48%	80,0%	[illegible]	$ 5 069,58	16	184	**10**	**15**	94,6%	100,0%	0,5%
Benchmark C	18Q2	[illegible]	0,55	2,75%	62,5%	[illegible]	$ 165 098,89	266	793	**519**	**306**	89,3%	99,6%	2,7%
Benchmark C	18Q3	[illegible]	0,56	4,38%	74,3%	[illegible]	$ 130 657,38	174	626	**457**	**246**	89,6%	99,5%	4,4%
Benchmark C	18Q4	[illegible]	0,75	0,19%	56,5%	[illegible]	$ 27 405,61	53	975	**364**	**294**	86,1%	99,3%	0,2%
Benchmark D	18Q2	[illegible]	0,42	0,14%	58,3%	[illegible]	$ 55 075,63	88	674	**245**	**185**	97,6%	99,7%	0,1%
Benchmark D	18Q4	[illegible]	0,44	0,12%	61,1%	[illegible]	$ 76 885,77	145	779	**230**	**244**	97,3%	100,0%	0,1%
Benchmark D	19Q1	[illegible]	0,60	1,02%	40,0%	[illegible]	$ 81 266,52	192	907	**298**	**231**	92,0%	99,8%	1,0%
Benchmark E	18Q2	[illegible]	0,50	0,65%	73,7%	[illegible]	$ 84 484,60	169	726	**115**	**92**	95,8%	99,8%	0,6%
Benchmark E	18Q3	[illegible]	0,42	0,28%	53,2%	[illegible]	$ 80 652,56	185	675	**177**	**129**	98,5%	99,9%	0,3%
Benchmark E	18Q4	[illegible]	0,53	0,30%	62,8%	[illegible]	$ 132 036,99	310	626	**126**	**129**	92,2%	99,9%	0,3%
Benchmark E	19Q1	[illegible]	0,49	0,23%	71,4%	[illegible]	$ 69 294,94	162	626	**147**	**117**	96,8%	99,9%	0,2%
Benchmark F	18Q2	[illegible]	0,58	0,71%	68,6%	[illegible]	$ 41 962,64	105	536	**63**	**44**	92,0%	99,8%	0,7%
Benchmark F	18Q3	[illegible]	0,52	0,00%	59,6%	[illegible]	$ 34 770,03	82	201	**16**	**15**	92,8%	99,8%	0,0%
Benchmark F	18Q4	[illegible]	0,68	0,21%	78,2%	[illegible]	$ 42 255,89	80	459	**59**	**56**	87,1%	99,8%	0,2%
Benchmark F	19Q1	[illegible]	0,59	0,51%	58,4%	[illegible]	$ 73 655,64	123	699	**74**	**57**	90,4%	99,8%	0,5%
Benchmark A	18Q2	[illegible]	0,47	0,09%	67,6%	[illegible]	$ 1 362 752,27	2623	23000	**1312**	**1352**	95,9%	99,8%	0,1%
Benchmark A	18Q3	[illegible]	0,49	0,10%	61,1%	[illegible]	$ 1 969 322,89	3343	16909	**1019**	**961**	95,2%	99,4%	0,1%
Benchmark A	18Q4	[illegible]	0,66	0,35%	70,9%	[illegible]	$ 2 331 302,60	3790	25129	**1499**	**1712**	88,5%	99,7%	0,4%
Benchmark A	19Q1	[illegible]	0,58	0,11%	68,6%	[illegible]	$ 1 577 813,11	2541	17335	**1212**	**1125**	90,2%	99,4%	0,1%
Benchmark B	18Q2	[illegible]	0,70	0,50%	75,6%	[illegible]	$ 786 267,75	1395	16959	**829**	**989**	85,5%	99,4%	0,5%
Benchmark B	18Q3	[illegible]	0,75	0,26%	68,5%	[illegible]	$ 341 619,24	843	7428	**570**	**705**	81,6%	98,1%	0,3%
Benchmark B	18Q4	[illegible]	0,72	0,13%	63,6%	[illegible]	$ 411 836,41	884	8624	**621**	**1045**	85,5%	99,3%	0,1%
Benchmark B	19Q1	[illegible]	0,68	0,33%	70,3%	[illegible]	$ 399 562,84	813	7213	**662**	**918**	86,1%	99,0%	0,3%
Benchmark C	18Q2	[illegible]	0,50	0,71%	69,2%	[illegible]	$ 586 617,92	1110	5418	**497**	**497**	93,2%	99,8%	0,7%
Benchmark C	18Q3	[illegible]	0,57	0,23%	64,9%	[illegible]	$ 534 927,04	1006	7402	**487**	**539**	90,4%	99,3%	0,2%
Benchmark C	18Q4	[illegible]	0,54	0,15%	71,8%	[illegible]	$ 733 054,65	1347	6433	**391**	**523**	94,9%	99,8%	0,2%
Benchmark C	19Q1	[illegible]	0,55	0,38%	73,8%	[illegible]	$ 508 531,76	987	7954	**423**	**526**	94,9%	99,9%	0,4%
Benchmark D	18Q2	[illegible]	0,53	0,25%	71,6%	[illegible]	$ 434 895,31	891	4631	**265**	**282**	96,4%	99,9%	0,2%

Figure A.2: List of modeled Benchmarks per Segment, Region and Quarter.



Quarter	Segment	SOS	NS	NPS	Ops Score	GMVOut	SentOut	TotalSent	StkUnits	VS	DS	Regression	Target Orders	%SoS<1d	%SoS<2d
18Q2	Benchmark C	0,50	0,7%	69,2%		$ 586 617,92	1110	5418	11847	497	497	1382	1178	93,23%	99,79%
18Q3	Benchmark C	0,57	0,2%	64,9%		$ 534 927,04	1006	7402	12510	487	539	1460	1119	90,37%	99,32%
18Q4	Benchmark C	0,54	0,2%	71,8%		$ 733 054,65	1347	6433	8818	391	523	1098	1285	94,93%	99,82%
19Q1	Benchmark C	0,55	0,4%	73,8%		$ 508 531,76	987	7954	11601	423	526	1399	1090	94,92%	99,92%

Quarter	Segment	SOS	NS	NPS	Ops Score	GMVOut	SentOut	TotalSent	StkUnits	VS	DS	Benchmarking Delta	Benchmarking Orders	Regression	Target Orders	ers Incre	%SoS<1d	%SoS<2d	Total Orders Increase
18Q2	C	1,09	1,46%	64,8%		$ 343 402,83	736	5386	14683	504	555	6%	1177	1713	1311	78%	54,42%	93,06%	11%
18Q3	C	1,24	3,44%	58,0%		$ 399 646,19	709	3319	11676	460	452	-11%	899	1362	1015	43%	49,95%	82,74%	9%
18Q4	C	1,16	2,48%	63,0%		$ 554 871,96	921	4393	11247	500	650	26%	1698	1401	1624	76%	57,98%	90,48%	16%
19Q1	C	0,86	3,16%	63,7%		$ 315 069,67	524	3417	12168	405	442	-10%	886	1468	1032	97%	71,23%	97,22%	15%

Figure A.3: Comparison between a selected Boutique and the respective benchmark per Quarter.

	[redacted]		Baseline	Potential	Baseline	Potential			Potential S4.0. Profit	
	Year	Month	Sent Orders	New Orders	Actual GMV	New GMV	Extra GMV	Sales Profit	Conservative	Optimistic
Actuals	2018	4	1186	1313	$ 422 142,87	$ 467 347,04	$ 45 204,17	$ 15 679,92	$ 10 016,41	$ 10 863,66
	2018	5	2063	2283	$ 734 300,80	$ 812 607,23	$ 78 306,44	$ 27 162,07	$ 17 423,16	$ 18 890,82
	2018	6	2137	2365	$ 760 640,24	$ 841 794,18	$ 81 153,94	$ 28 149,78	$ 18 048,13	$ 19 569,16
	2018	7	1965	2146	$ 699 418,84	$ 763 843,68	$ 64 424,84	$ 22 346,97	$ 16 595,49	$ 17 802,98
	2018	8	654	714	$ 232 783,68	$ 254 139,98	$ 21 356,30	$ 7 407,84	$ 5 523,39	$ 5 923,66
	2018	9	700	765	$ 249 156,84	$ 272 292,83	$ 23 135,99	$ 8 025,16	$ 5 911,88	$ 6 345,51
	2018	10	1027	1191	$ 365 548,68	$ 423 922,56	$ 58 373,89	$ 20 248,09	$ 8 673,57	$ 9 767,65
	2018	11	2113	2451	$ 752 097,72	$ 872 404,87	$ 120 307,16	$ 41 730,81	$ 17 845,43	$ 20 100,30
	2018	12	1253	1453	$ 445 990,74	$ 517 178,41	$ 71 187,67	$ 24 692,79	$ 10 582,27	$ 11 916,51
	2019	1	1208	1387	$ 429 973,52	$ 493 686,48	$ 63 712,96	$ 22 100,04	$ 10 202,22	$ 11 396,36
	2019	2	965	1108	$ 343 480,50	$ 394 379,68	$ 50 899,18	$ 17 655,34	$ 8 149,95	$ 9 103,93
	2019	3	1244	1429	$ 442 787,30	$ 508 635,89	$ 65 848,59	$ 22 840,83	$ 10 506,26	$ 11 740,43
Forecast	2019	4	1480	1547	$ 526 769,87	$ 550 471,17	$ 23 701,30	$ 8 221,24	$ 12 498,96	$ 12 943,18
	2019	5	1884	2330	$ 670 721,17	$ 829 444,62	$ 158 723,45	$ 55 056,23	$ 15 914,57	$ 18 889,46
	2019	6	1942	2633	$ 691 367,70	$ 937 013,48	$ 245 645,78	$ 85 206,88	$ 16 404,46	$ 21 008,50
	2019	7	1973	2504	$ 702 096,56	$ 891 394,96	$ 189 298,40	$ 65 661,73	$ 16 659,03	$ 20 206,97
	2019	8	662	934	$ 235 628,11	$ 332 511,28	$ 96 883,17	$ 33 605,76	$ 5 590,88	$ 7 406,72
	2019	9	906	1121	$ 322 611,78	$ 399 118,54	$ 76 506,75	$ 26 537,81	$ 7 654,79	$ 9 088,72
								$ 274 289,64	$ 74 722,67	$ 89 543,54

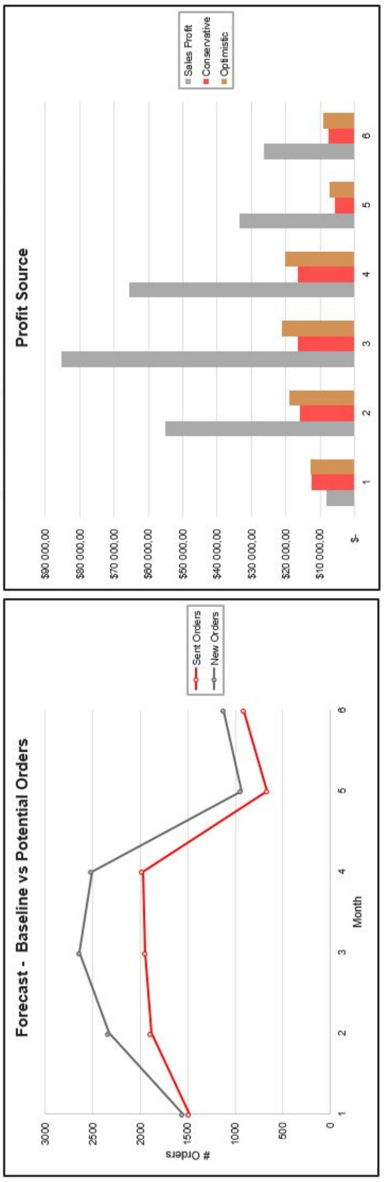


Figure A.4: Selected Boutique baseline forecast and potential forecast with respective sales profit and Service 4.0. return.

Appendix B

Farfetch - Service 4.0.

SERVICE 4.0

Operational Excellence Program

FARFETCH

HOW IS THE **INCENTIVE PROGRAM** CALCULATED?

CALCULATION: Up until now, we've considered Speed of Sending and No Stock separately on our incentives and penalties. From now on, the new Incentive Program will combine your Speed of Sending and No Stock results in a matrix to determine your final payout.

Find your monthly Incentive Service value within the matrix using your position of Speed of Sending & No Stock.

→

Use this value to calculate your monthly payout as follows:

- Incentive Service value x ATV *

The STORM Dashboard includes your Speed of Sending and No Stock results. As soon as we launch the Incentive Program, this dashboard will be upgraded to help you tracking your performance.

We have 2 different matrices depending on your order volume per month.

* We acknowledge the higher impact of a penalty for lower volume of orders.

MORE THAN 76 ORDERS / MONTH

		No Stock Percentage								
	%	0 - 0,25	0,26 - 0,5	0,51 - 0,75	0,76 - 1	1,01 - 1,5	1,51 - 3	3,01 - 5	5,01 - 7	7,01 - 100
Speed of Sending SLA	99,51 - 100	1,30%	1,00%	0,80%	0,40%	0,20%	0,10%	-0,25%	-0,50%	-0,70%
	98,51 - 99,5	0,90%	0,60%	0,30%	0,20%	0,10%	0,05%	-0,35%	-0,75%	-0,90%
	97,51 - 98,5	0,60%	0,30%	0,20%	0,10%	0,05%	0,00%	-0,40%	-1,00%	-1,10%
	96,51 - 97,5	0,40%	0,15%	0,10%	0,05%	0,00%	-0,10%	-0,50%	-1,25%	-1,50%
	95,01 - 96,5	0,30%	0,10%	0,05%	0,00%	-0,10%	-0,20%	-0,60%	-1,50%	-1,90%
	90,01 - 95	-0,05%	-0,15%	-0,20%	-0,25%	-0,30%	-0,50%	-0,75%	-1,75%	-2,30%
	70,01 - 90	-0,30%	-0,40%	-0,50%	-0,60%	-0,70%	-0,80%	-1,00%	-2,25%	-2,70%
	0 - 70	-0,50%	-0,70%	-0,90%	-1,10%	-1,50%	-1,90%	-2,30%	-2,70%	-3,00%

UP TO 75 ORDERS / MONTH

		No Stock Percentage								
	%	0 - 0,25	0,26 - 0,5	0,51-0,75	0,76 - 1	1,01 - 1,5	1,51 - 3	3,01 - 5	5,01 - 7	7,01 - 100
Speed of Sending SLA	99,51 - 100	1,30%	1,00%	0,80%	0,40%	0,20%	0,10%	0,00%	-0,10%	-0,70%
	98,51 - 99,5	0,90%	0,60%	0,30%	0,20%	0,10%	0,05%	-0,10%	-0,20%	-0,90%
	97,51 - 98,5	0,60%	0,30%	0,20%	0,10%	0,05%	0,00%	-0,15%	-0,45%	-1,10%
	96,51 - 97,5	0,40%	0,15%	0,10%	0,05%	0,00%	-0,10%	-0,20%	-0,50%	-1,50%
	95,01 - 96,5	0,30%	0,10%	0,05%	0,00%	-0,10%	-0,25%	-0,30%	-0,55%	-1,90%
	90,01 - 95	0,00%	-0,10%	-0,15%	-0,20%	-0,20%	-0,40%	-0,45%	-0,60%	-2,30%
	70,01 - 90	-0,15%	-0,35%	-0,40%	-0,45%	-0,50%	-0,55%	-0,60%	-0,65%	-2,70%
	0 - 70	-0,50%	-0,70%	-0,90%	-1,10%	-1,50%	-1,90%	-2,30%	-2,70%	-3,00%

EXTRA INCENTIVE for orders sent in < 1 DAY

Applies in addition to the matrix conditions

% Orders with NET SOS < 1 day	Incentive
0% -79%	0% Packaging Cost Refunded
80% -89%	25% Packaging Cost Refunded + 0,2% ATV
90% -100%	100% Packaging Cost Refunded + 0,4% ATV

CONDITIONS:

1. You have received 5 or more NPS responses that month, and the average Packaging rating equals or is higher than 4,5 (out of 5).
2. If you have received 4 or less NPS responses, you will still be eligible, regardless of the packaging rating.

WRONG ITEM RULE

To be eligible to all kinds of incentives (based on the matrix and extra incentive for orders sent in less than 1 day) it is mandatory to comply with the conditions below.

# of Returns	% Wrong Item *
0-5	No Threshold
6-25	50%
26-75	10%
>= 76	6%

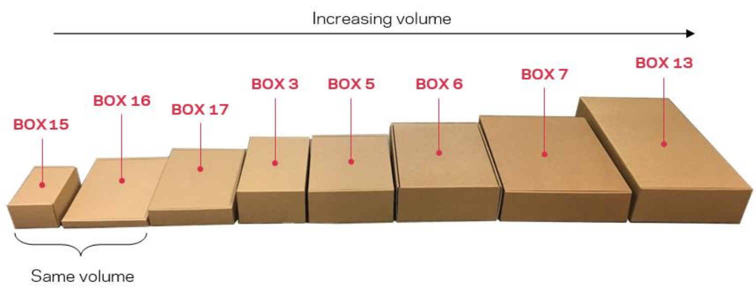
* Wrong item = returns marked by customers as Faulty, Wrong Item and Wrong size.

PACKAGING INCENTIVE

Please note this incentive is contingent to the Wrong Item rule.

Partners will **receive 0.04% of their monthly ATV back** when they follow Farfetch Recommendations or use a more suitable package for 85% of their orders.

This incentive is based on the packaging that you actually use compared to the packaging recommended by Farfetch on STORM at the packaging stage.



Note: Box 14 is missing but it is the biggest one.

The picture shows the various Farfetch Boxes that could be recommended to you.

WHAT ELSE CHANGES?

Service 3.0	Service 4.0
Packaging cost waived per order if order NET SOS < 1 day	New <1 day extra incentive allows for part of packaging costs to be refunded depending on the % of orders with NET SOS < 1 day
Penalty to support customer shipping cost for orders with NET SOS > 2days	No longer applicable
10£ No Stock voucher charged in most cases	10£ No Stock vouchers charged for every order cancellation
10% of canceled item's price charged in case of high No Stock levels	No longer applicable
Free Returns Fee waived if the monthly No Stock rate < 0,75% + compliance with the Wrong Item Rule	Free Returns Fee will never be waived, regardless of your results

METRICS

- **ATV - Actual Transaction Value**

  the aggregate of Sales Prices for all orders less any Cancellations and Returns and Sales Taxes.

- **Speed of Sending (SOS)**

  % of orders sent that month with SOS < or = to 2 Net*. Value corrected after Exceptions are solved.

- **No Stock**

  % of items cancelled by No Stock that month, over all sold items. Value corrected so No Stocks manually changed to Farfetch fault are excluded.

- **% of orders sent in less than 1 day**

  % of orders sent that month with a SOS < or = to 1 day Net*. Value corrected after Exceptions are solved.

- **NPS packaging rate average**

  average of all packaging rate responses given that month (NPS Date).

  *Net SOS excludes the time spent in STORM steps: payment verification & AWB. We also exclude weekends and holidays.

HOW TO MAXIMISE YOUR INCENTIVES

Important aspects to keep in mind:

- Make sure that each month you comply with the Wrong Item Rule

– if you don't comply to the rule, you will not be eligible for the incentives.

**wrong items will be calculated until the end of the following month to allow time to process the orders.*

- Avoid paying additional cost such as the No Stock vouchers by keeping your stock levels up to date.
- Use the No Stock and Speed of Sending to monitor your percentage of ATV
- If your Packaging Rate is over 4.5, you will get an extra incentive if you have shipped at least 80% of your orders in less than one day.
- Always aim to ship 90% or over in less than one day, to enjoy the best incentive. This incentive refunds 100% of your Packaging Costs and 0.4% of ATV.

When calculating the incentives you will need the following information:

1. ATV
2. Number of Orders Sent
3. Speed of Sending (%)
4. Speed of Sending < 1 day (%)
5. No Stock (%)
6. Number of No Stock Items
7. Packaging Rate
8. Number of NPS
9. Wrong Item (%)
10. Number of Returns

EXAMPLE

STEP 1: GATHER YOUR MONTHLY RESULTS

- **Monthly ATV:** 539505,00€ (120 orders)
- **Orders Sent:** 1923
- **SOS%:** 99,24% **SOS% < 1:** 81%
- **Monthly SOS:** 80% (80% orders shipped in 1 working day)
- **Monthly NS%:** 1,00% **NS Quantity:** 18
- **Packaging:** 4,80
- **NPS:** 10
- **Wrong Items sent:** 200 returns arrived, 10 listed as wrong item sent (5% of the returns were due to wrong items sent to the customers, i.e. within threshold.)

STEP 2: CALCULATE YOUR BASIC INCENTIVE FROM THE MATRIX

MORE THAN 76 ORDERS / MONTH

		No Stock Percentage								
Speed of Sending SLA	%	0 - 0,25	0,26 - 0,5	0,51 - 0,75	0,76 - 1	1,01 - 1,5	1,51 - 3	3,01 - 5	5,01 - 7	7,01 - 100
	99,51 - 100	1,30%	1,00%	0,80%	0,40%	0,20%	0,10%	-0,25%	-0,50%	-0,70%
	98,51 - 99,5	0,90%	0,60%	0,30%	0,20%	0,10%	0,05%	-0,35%	-0,75%	-0,90%
	97,51 - 98,5	0,60%	0,30%	0,20%	0,10%	0,05%	0,00%	-0,40%	-1,00%	-1,10%
	96,51 - 97,5	0,40%	0,15%	0,10%	0,05%	0,00%	-0,10%	-0,50%	-1,25%	-1,50%
	95,01 - 96,5	0,30%	0,10%	0,05%	0,00%	-0,10%	-0,20%	-0,60%	-1,50%	-1,90%
	90,01 - 95	-0,05%	-0,15%	-0,20%	-0,25%	-0,30%	-0,50%	-0,75%	-1,75%	-2,30%
	70,01 - 90	-0,30%	-0,40%	-0,50%	-0,60%	-0,70%	-0,80%	-1,00%	-2,25%	-2,70%
	0 - 70	-0,50%	-0,70%	-0,90%	-1,10%	-1,50%	-1,90%	-2,30%	-2,70%	-3,00%

Matrix outcome

SoS %	**99,24%**
NoStock%	**1,00%**
Type Matrix Result	**0,20%**
	1 079,01

STEP 3: CALCULATE ANY ADDITIONAL COSTS SUCH AS:

- Packaging Costs
- No Stock Vouchers

Additional Costs		
Packaging Cost	$	2 884,50
NoStock Vouchers	$	198,00

STEP 4: CALCULATE EXTRA INCENTIVE FOR ORDERS SENT IN < 1 DAY

% Orders with NET SOS < 1 day	Incentive
0% -79%	0% Packaging Cost Refunded
80% -89%	25% Packaging Cost Refunded + 0,2% ATV
90% -100%	100% Packaging Cost Refunded + 0,4% ATV

Incentive/Penalties		
Matrix	$	1 079,01
Extra Incentive SoS	$	1 800,14
No Stock Vouchers	$	-198,00
Wrong Item Rule		Compliant
Total Incentives:	**$**	**2 681,15**

Result: Because this partner was compliant with the Wrong Item Rule, they were able to achieve a total of **$2681.15** in the given month, after the additional costs were deducted.

Appendix C

Farfetch Operational Targets

NO STOCK TARGET 2019

	2018	TARGET	
Boutique	1,4%	1,3%	-6,3%
T0 - Key	1,1%	1,1%	-1,7%
T1 - Important	1,3%	1,3%	-2,3%
Tx - Standard	1,8%	1,5%	-16,3%
Non EU Boutique	3,3%	3,0%	-9,2%
Brand	3,5%	2,2%	-38,0%
B0 - Key	4,7%	2,9%	-38,3%
B1 - Important	4,5%	2,3%	-49,3%
Bx - Standard	2,3%	1,7%	-27,7%
Grand Total	**1,7%**	**1,4%**	**-13,6%**

	2018	TARGET	
APAC	2,3%	1,9%	-18,0%
BR	2,2%	2,0%	-8,5%
CN	3,4%	2,4%	-27,4%
EU	1,5%	1,3%	-10,1%
JP	3,1%	2,5%	-19,5%
US	4,3%	2,8%	-34,1%
Grand Total	**1,7%**	**1,4%**	**-13,6%**

SPEED OF SENDING TARGET 2019 - 2 days

Less than 2 days

	2018	TARGET	
Boutique	96,2%	96,3%	0,2%
T0 - Key	95,7%	96,0%	0,3%
T1 - Important	97,2%	97,0%	-0,2%
Tx - Standard	98,1%	97,5%	-0,7%
Non EU Boutique	92,5%	94,5%	2,2%
Brand	88,2%	93,0%	5,4%
B0 - Key	87,5%	93,0%	6,3%
B1 - Important	91,8%	93,0%	1,3%
Bx - Standard	86,9%	93,0%	7,0%
Grand Total	**95,3%**	**96,0%**	**0,7%**

	2018	TARGET	
APAC	96,8%	96,7%	-0,2%
BR	69,7%	85,8%	23,0%
CN	74,4%	98,0%	31,7%
EU	96,0%	96,6%	0,6%
JP	90,4%	94,8%	4,9%
US	92,1%	94,6%	2,7%
Grand Total	**95,3%**	**96,0%**	**0,7%**

SPEED OF SENDING TARGET 2019 - 1 day

Less than 1 day

	2018	TARGET	
Boutique	75,4%	80,0%	6,1%
T0 - Key	73,3%	79,8%	8,8%
T1 - Important	79,4%	82,2%	3,5%
Tx - Standard	81,8%	83,2%	1,8%
Non EU Boutique	68,9%	76,6%	11,1%
Brand	59,6%	76,9%	29,0%
B0 - Key	56,5%	74,6%	32,2%
B1 - Important	63,1%	76,7%	21,6%
Bx - Standard	59,9%	78,4%	30,9%
Grand Total	**73,7%**	**80,0%**	**8,5%**

	2018	TARGET	
APAC	79,5%	82,2%	3,5%
BR	40,9%	73,7%	80,1%
CN	49,2%	74,0%	50,4%
EU	74,8%	80,3%	7,3%
JP	62,1%	76,5%	23,1%
US	65,7%	76,8%	16,9%
Grand Total	**73,7%**	**80,0%**	**8,5%**

Appendix D

Model's Accuracy - Sensitivity Analysis

Table D.1: Results of Model's Accuracy depending on Benchmark and Regression Factors.

Benchmark Factor	**Regression Factor**	**Accuracy**
0%	100%	**82,16%**
25%	75%	**83,82%**
50%	50%	**85,48%**
75%	**25%**	**86,31%**
85%	15%	**85,89%**
100%	0%	**83,40%**

Table D.2: Results of Model's Accuracy depending on Value Score and Demand Score Factors.

DS Factor	**VS factor**	**Accuracy**
0%	100%	**85,48%**
25%	75%	**87,55%**
45%	**55%**	**87,55%**
50%	50%	**86,72%**
75%	25%	**85,89%**
100%	0%	**84,65%**

Appendix E

Comparing Forecast Results

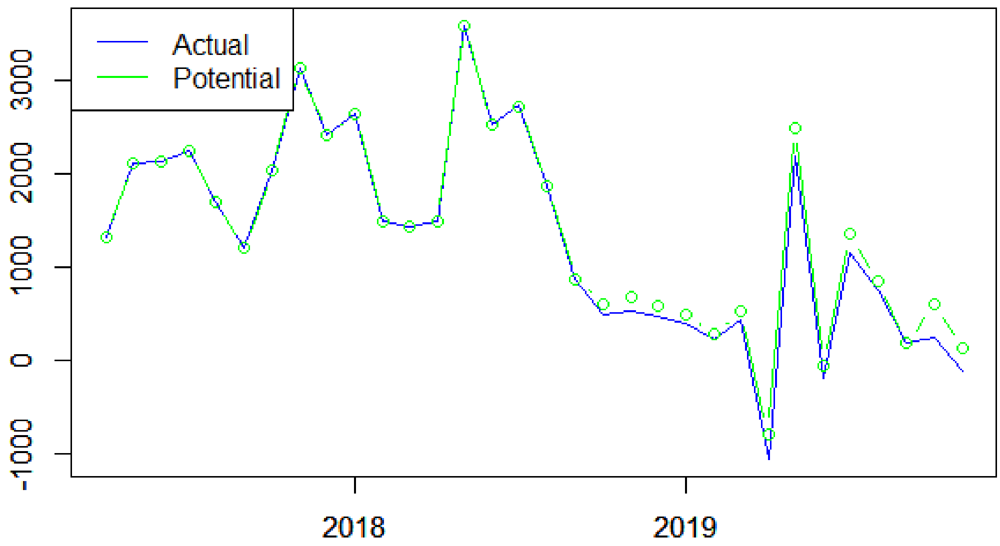


Figure E.1: Forecasting results for a boutique simply applying prophet.

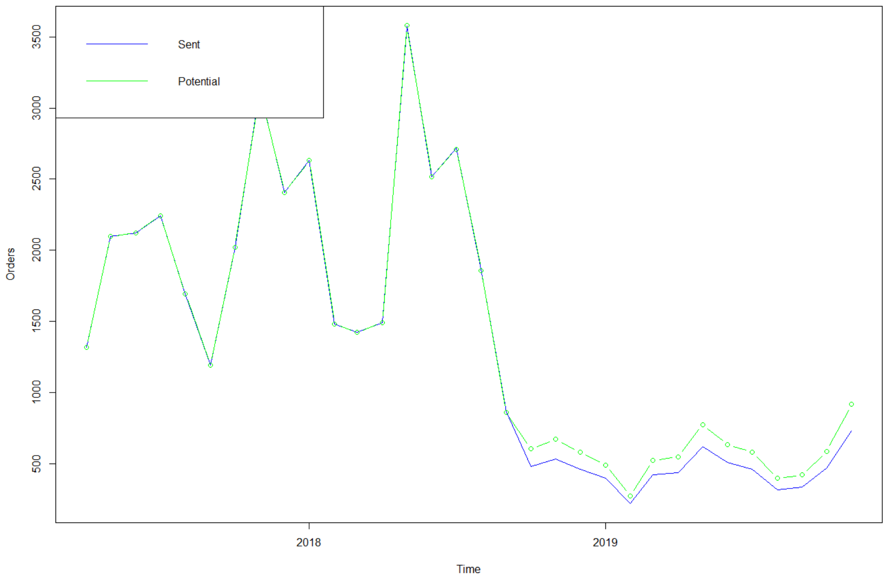


Figure E.2: Forecasting results for the same boutique in Figure E.1, but applying the Segment's seasonality to last six months average orders.