
# Clustering for Decision Support in the Fashion Industry

Ana Lisa Amorim do Monte

Orientação: Prof. Dr. Carlos Soares
Co-orientação: Prof. Dr. Pedro Brito

Setembro, 2012

Dissertação de Mestrado em Economia e Administração de Empresas


# CLUSTERING FOR DECISION SUPPORT IN THE FASHION INDUSTRY

por

Ana Lisa Amorim do Monte

**Dissertação de Mestrado em Economia e Administração de Empresas**

Orientada por

Prof. Dr. Carlos Soares

Co-orientada por

Prof. Dr. Pedro Quelhas Brito

**2012**

# Nota Biográfica

Ana Lisa Amorim do Monte nasceu a 8 de Novembro de 1981 na cidade da Póvoa de Varzim. Licenciou-se em Gestão na Faculdade de Economia da Universidade do Porto (FEP) em 2005. Durante o curso participou no 44th European Congress of European Regional Science Association (ERSA) como Assistente em 2004.

Após ter terminado a licenciatura, iniciou em 2006 um estágio profissional do IEFP na empresa Monte-SGPS, S.A. na Póvoa de Varzim na área de gestão. Concluído o estágio em 2007, ingressou durante um período de 2 anos no Banco Popular Portugal, S.A., onde executou funções de Caixa e de Gestor de Clientes Particulares numa das suas agências em Portugal. Foi durante a sua permanência no banco, que decidiu integrar o Mestrado em Economia e Administração de Empresas na FEP, tendo iniciado no ano lectivo 2009/2010.

Em 2009, finda a sua passagem pela área da banca, ingressa numa experiência internacional. Participa no Programa de Estágios Internacionais da AICEP, o "Inov Contacto", através do qual colabora, durante um período de seis meses, com a empresa Sonae Sierra, nos seus escritórios localizados em Atenas na Grécia, na área de Reporting Operacional.

Terminado esse estágio internacional em 2010, regressa a Portugal e nesse mesmo ano inicia um estágio interno, com duração de um ano, no Shared Service Center da empresa alemã Infineon Tecnologies, situada no TECMAIA - Parque de Ciência e Tecnologia da Maia - onde integra o departamento de Accounts Payable.

Em finais de 2011, terminado esse estágio interno, a sua dedicação focou-se na finalização do Mestrado, tendo já concluído a parte curricular.

# Agradecimentos

Este trabalho só foi possível realizar através da colaboração e incentivo de um conjunto de pessoas e entidades.

Agradeço ao meu orientador, o Professor Doutor Carlos Manuel Milheiro de Oliveira Pinto Soares, pela atenção, disponibilidade, simpatia, dinamismo, sentido crítico construtivo e acima de tudo pela confiança que depositou neste projecto e na minha pessoa.

Ao meu co-orientador, o Professor Doutor Pedro Manuel dos Santos Quelhas Taumaturgo de Brito, que aceitou contribuir neste projecto com a sua preciosa ajuda e disponibilidade e com os seus incontestáveis conhecimentos na área que mais domina.

Ao LIAAD - Laboratory of Artificial Intelligence and Decision Support, unidade associada do INESC TEC - INESC Tecnologia e Ciência, que me acolheu simpaticamente cedendo o seu espaço e meios para poder realizar este trabalho.

À empresa Bivolino que disponibilizou os seus dados que serviram de base em todo este trabalho, pela sua contribuição e simpatia.

The research leading to these results has received funding from the European Union Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 260169 (Project CoReNet - www.corenet-project.eu).

A todos os meus amigos e colegas, à minha família e ao meu namorado que sempre me apoiaram e incentivaram a não desistir e lutar pelos meus objectivos, que sempre me fizeram acreditar nas minhas capacidades.

# Resumo

O tema deste trabalho é a segmentação das encomendas de uma empresa belga, a Bivolino, cuja actividade se foca essencialmente na comercialização de camisas feitas à medida de cada cliente. Essa segmentação é feita com a ajuda de técnicas de *Data Mining*, tendo sido utilizada neste trabalho a técnica de *Clustering*, a qual é considerada uma das mais importantes técnicas de *Data Mining*. Esta técnica faz a partição dos dados de acordo com um dado critério de similaridade ou distância, sendo a Distância Euclidiana o mais comummente utilizado.

O método de *Clustering* seleccionado para fazer a partição dos dados foi o *K-Medoids*, dado este ser menos sensível a *outliers* do que outros métodos e principalmente por poder lidar com dados nominais. A computação deste método foi realizada com recurso a um *software* para *Data Mining*, o chamado RapidMiner. Das várias experiências efectuadas com os dados no RapidMiner, foram seleccionados os resultados que seriam objecto de análise e interpretação quer numa perspectiva técnica quer numa perspectiva de Marketing.

Os resultados mostram que é possível identificar as tendências de moda nas camisas da Bivolino para apoiar as decisões da empresa a nível do *Design* e do Marketing. Este trabalho contribui para demonstrar a potencialidade da utilização de ferramentas de *Data Mining* para analisar grandes quantidades de dados de empresas transformando-os em informação útil e daí extraírem conhecimento acerca do seu negócio. Será esse conhecimento que lhes vai permitir tomar importantes decisões em tempo útil e obter vantagens competitivas.

**Palavras-chave:** Data Mining, Clustering, K-Means, K-Medoids, Marketing, Segmentação

# Abstract

The scope of this work is the segmentation of the orders of a Belgian company, named Bivolino, which sells custom tailored shirts. The segmentation was done with the help of Data Mining techniques, namely Clustering. Clustering is considered one of the most important Data Mining techniques. Its goal is to partition the data according to some similarity/distance criterion, where the most commonly used is the Euclidian Distance.

In this study, we used the K-Medoids clustering method, because it is less sensitive to outliers than other methods and it can handle nominal variables. The Data Mining software used was RapidMiner. Out of the many experiments that were carried out a few results were selected to be then analyzed and interpreted from technical and Marketing perspectives.

The results show that it is possible to identify fashion trends in Bivolino shirts to support the decisions of the company concerning Design and Marketing. This work provides further evidence of the potential of Data Mining tools to analyze large amounts of business data. The results of this analysis is useful knowledge from which companies can extract regarding their business. This knowledge will allow those companies to make important business decisions in time and, thus, obtain competitive advantages.



**Keywords:** Data Mining, Clustering, Cluster, K-Means, K-Medoids, Marketing, Segmentation

# Table of Contents

# List of Tables

# List of Figures

# Abbreviations

AID – Automatic Interaction Detection

ANN – Artificial Neural Network

BMI – Body Mass Index

CART – Classification and Regression Trees

CHAID – AID for Categorical Dependent Variables

CRISP-DM – Cross Industry Standard Process for Data Mining

DM – Data Mining

KD – Knowledge Discovery

MAID - AID for Multiple Dependent Variables

# PART I

*"Theory helps us to bear our ignorance of facts."*

By George Santayana, a Spanish philosopher

# 1. INTRODUCTION

*"There are no secrets to success.*
*It is the result of preparation, hard work,*
*and learning from failure."*
By Colin Powell, an American statesman

This dissertation is focused on the problem of supporting fashion industry in its production/design and marketing decisions based on Data Mining (DM) approaches. Short life cycles, high volatility, low predictability, and high impulse purchasing is being appointed has characteristics of fashion industry (Lo *et al*, 2008).

The data that companies collect about their customers is one of its greatest assets (Ahmed, 2004). However, companies increasingly tend to accumulate huge amounts of customer data in large databases (Shaw *et al*, 2001) and within this vast amount of data is all sorts of valuable information that could make a significant difference to the way in which any company run their business, and interact with their current and prospective customers and gaining competitive edge on their competitors (Ahmed, 2004).

Given that and the fact that companies have to be able to react rapidly to the changing market demands both locally and globally (Ahmed, 2004), it is urgent that they manage efficiently the information about their customers. So, companies can utilize DM techniques to extract the unknown and potentially useful information about customer characteristics and their purchase patterns (Shaw *et al*, 2001). DM tools can, then, predict future trends and behaviors, allowing businesses to make knowledge-driven decisions that will affect the company, both short term and long term (Ahmed, 2004).

DM is also being used in e-commerce industry to study and identify the performance limitations and to analyze data for patterns and, at the same time, is helping it to increase sale and remove political and physical boundaries (Ahmed, 2004). The identification of such patterns in data is the first step to gaining useful marketing insights and making critical marketing decisions (Shaw *et al*, 2001). In today's environment of complex and ever changing customer preferences, marketing decisions

that are informed by knowledge about individual customers become critical (Shaw *et al*, 2001). Today's customers have such a varied tastes and preferences that it is not possible to group them into large and homogeneous populations to develop marketing strategies. In fact, each customer wants to be served according to his individual and unique needs (Shaw *et al*, 2001). Thus, the move from mass marketing to one-to-one relationship marketing requires decision-makers to come up with specific strategies for each individual customer based on his profile (Shaw *et al*, 2001).

In short, DM is a very powerful tool that should be used for increasing customer satisfaction providing best, safe and useful products at reasonable and economical prices as well for making the business more competitive and profitable (Ahmed, 2004).

## 1.1. Structure

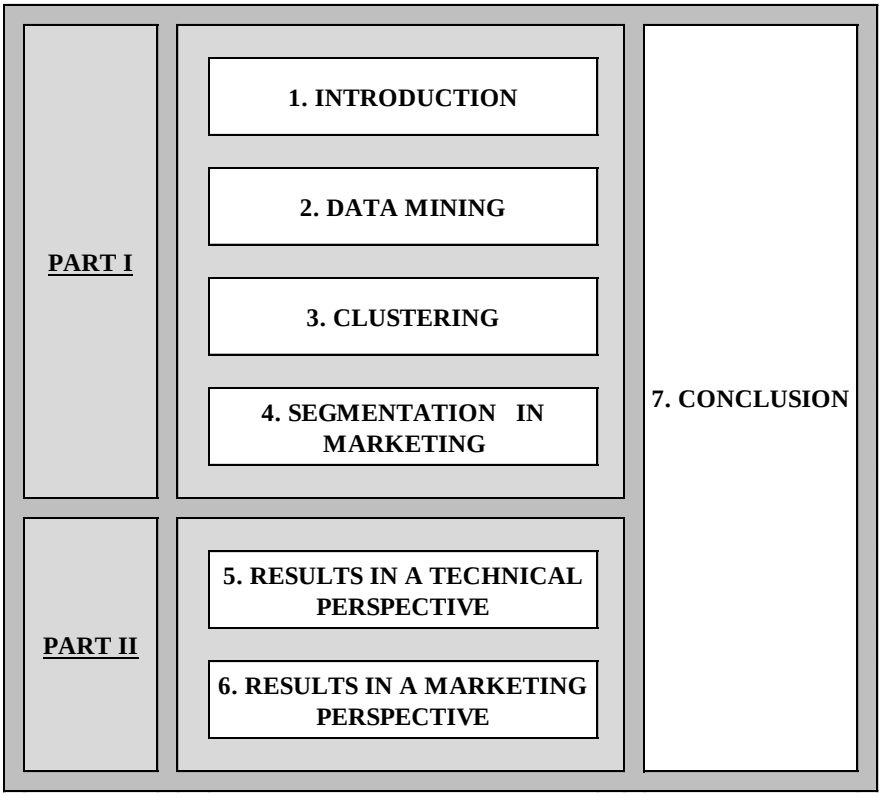
This dissertation is divided mainly in two parts: PART I, that refers to literature review concerning Data Mining, Clustering and Segmentation concepts, and PART II, that refers to the practical applicability of those theoretical concepts to the Bivolino case study and where the results are presented and analyzed.

PART I covers Chapter 1 – Introduction, Chapter 2 – Data Mining, Chapter 3 – Clustering and Chapter 4 – Segmentation in Marketing. Chapter 2 refers to a brief overview about DM including its definition, tasks, process and methodology. Chapter 3 describes in more detail the task of DM that is the focus of this work, i.e., the Clustering, and comprises its definition, goals (or its most common types of problems), stages, algorithms and its validation. With respect to clustering algorithms, we describe in some detail the K-Means that is the most used in practice and cited on literature and also one of its extensions, the K-Medoids. Chapter 4 describes the Segmentation, a very important dimension of Marketing, starting on its definition, and then exposing the requirements for its effectiveness, its process, its different levels, bases, methods and finally its methodology (the clustering methods).

PART II covers Chapter 5 – Results in a Technical Perspective and Chapter 6 – Results in a Marketing Perspective. In Chapter 5 and Chapter 6 are presented the two results of the clustering process that were chosen to be analyzed, the first in a technical perspective and the second in a marketing perspective.

Chapter 7 is the last chapter of the dissertation and comprises the final conclusions of the study. It is divided in four sections: summary, recommendations, limitations (or difficulties found during the study), and future work.

In summary, the dissertation structure can be presented as follows:



# 2. DATA MINING

*"Almost all quality improvement comes via*
*Simplification of design, manufacturing*
*...layout, processes, and procedures."*
By Tom Peters, an American businessman

## 2.1. Data Mining Definition

According to Berry and Linoff (1997) Data Mining is "the exploration and analysis, by automatic or semiautomatic means, of large quantities of data in order to discover meaningful patterns and rules." They assume that "the goal of data mining is to allow a corporation to improve its marketing, sales, and customer support operations through better understanding of its customers."

Another widely used definition, even by Berry and Linoff (1997), is the one given by the Gartner Group which says that "DM is the process of discovering meaningful new correlations, patterns, and trends by sifting through large amounts of data stored in repositories and by using pattern recognition technologies as well as statistical and mathematical techniques."

## 2.2. Data Mining Tasks

The tasks presented in this section on Table 2.1 are suggested by Berry and Linoff (1997), however in the literature we can find some slightly different terminologies or even more tasks in addition to these.

| Task | Definition |
|---|---|
| Classification | Consists of examining the features of a newly presented object and assigning it to one of a predefined set of classes. |
| Estimation | Given some input data, we use estimation to come up with a value for some unknown continuous variable. |
| Prediction | Is the same as classification or estimation except that the records are classified according to some predicted future behavior or estimated future value. |
| Affinity grouping | The task of affinity grouping, or market basket analysis, is to determine which things go together. |
| Clustering | Is the task of segmenting a heterogeneous population into a number of more homogeneous subgroups or clusters. |
| Description | The purpose is simply to describe what is going on in a complicated database in a way that increases our understanding of the people, products, or processes that produced the data in the first place. |

**Table 2.1** – Data Mining Tasks

DM tasks are used to extract and identify patterns from large datasets (Shaw *et al*, 2001) which in turn is the first step to gain useful marketing insights and make critical marketing decisions.

## 2.3. Data Mining Process

According to Berry and Linoff (1997), the DM process has four stages: (1) Identify the business problem, (2) Use DM techniques to transform the data into actionable information, (3) Act on the information and (4) Measure the results. This process is illustrated on Figure 2.1.

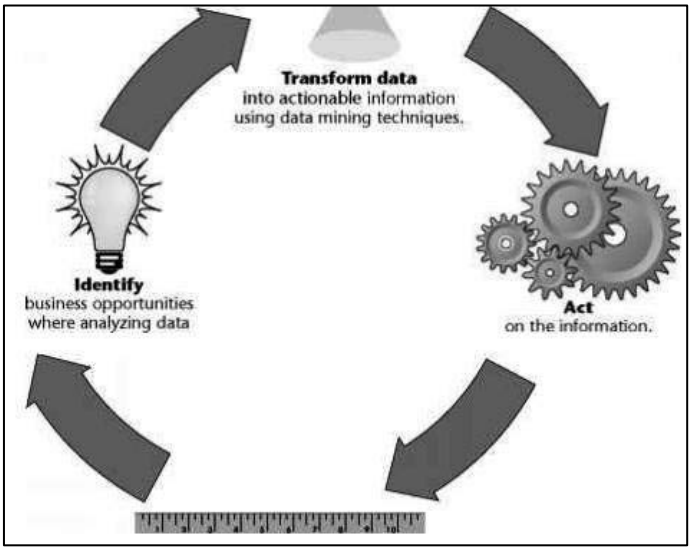



**Figure 2.1** – The four stages of Data Mining Process

As these steps suggest, the key to success is incorporating DM into business processes. These stages are highly interdependent since the results from one stage are the inputs to the next phase. The whole approach is driven by results whereas each stage depends on the results from the previous stage (Berry and Linoff, 1997).

### 2.3.1. Identify the Business Opportunity

Identifying the business opportunity is the stage that occurs throughout the organization wherever increased information could enable people to better perform their jobs. Its purpose is to identify the areas where data can provide value. These, in turn, are the input in the DM stage. There are several different approaches to this stage, but the goal is to identify areas where patterns in data have the potential of providing value. (Berry and Linoff, 1997)

### 2.3.2. Transform Data using Data Mining Techniques

DM takes data, business opportunities and produces actionable results for the Take Action stage. However, it is important to understand what results it must give to make the DM process successful and also to pay attention to the numerous problems that can interfere with it. Some usual problems are, for example, bad data formats, confusing data fields, lack of functionality, timeliness (Berry and Linoff, 1997).

### 2.3.3. Take Action

This is where the results from DM are acted upon and results are fed into the Measurement stage. The question here is how to incorporate information into business processes. The business processes must provide the data feedback needed for the DM process be successful (Berry and Linoff, 1997).

### 2.3.4. Measure the Results

Measurement provides the feedback for continuously improving results. Measurement here refers specifically to measures of business value that go beyond response rates and costs, beyond averages and standard deviations. The question here is what to measure and how to approach the measurement so it provides the best input for future use. The specific measurements needed depend on a number of factors: the business opportunity, the sophistication of the organization, past history of measurements (for trend analysis), and the availability of data. We can see that this stage depends critically on information provided in the previous stages (Berry and Linoff, 1997).

In short, DM process places DM into a context for creating business value. In the business world, DM provides the ability to optimize decision-making using automated methods to learn from past actions. Different organizations adapt DM to their own environment, in their own way (Berry and Linoff, 1997).

## 2.4. Data Mining Methodology

DM methodology refers to stage two of DM process, i.e., the stage where the actual mining of data takes place and where the resulting information is smelted to produce knowledge (Berry and Linoff, 1997).

There are, essentially, two basic approaches of DM, the *hypothesis testing* and the *knowledge discovery*. The first is *a top-down* approach that attempts to substantiate or disprove preconceived ideas. The second is a *bottom-up* approach that starts with the data and tries to get it to tell us something we didn´t already know (Berry and Linoff, 1997).

### 2.4.1. Hypothesis Testing

A hypothesis is a proposed explanation whose validity can be tested. Testing the validity of a hypothesis is done by analyzing data that may simply be collected by observation or generated through an experiment, such as test mailing (Berry and Linoff, 1997).

The process of hypotheses testing comprises the following steps: (1) Generate good ideas (hypothesis); (2) Determine what data would allow these hypotheses to be tested; (3) Locate data; (4) Prepare data for analysis; (5) Build computer models based on the data; (6) Evaluate computer models to confirm or reject hypotheses (Berry and Linoff, 1997).

### 2.4.2. Knowledge Discovery

Knowledge discovery can be either *directed* or *undirected*. In the first, the task is to explain the value of some particular field in terms of all the others; we select the target field and direct the computer to tell us how to estimate, classify, or predict it. In the second, there is no target field; we ask the computer to identify patterns in the data that may be significant (Berry and Linoff, 1997). In other words, we use undirected KD to recognize relationships in the data and directed KD to explain those relationships once they have been found (Berry and Linoff, 1997).

#### 2.4.2.1. Directed Knowledge Discovery

Directed KD is characterized by the presence of a single target field whose value is to be predicted in terms of the other fields in the database (Berry and Linoff, 1997). It is the process of finding meaningful patterns in data that explain past events in such a way we can use the patterns to help predict future events (Berry and Linoff, 1997).

The steps of this process are: (1) Identify sources of preclassified data; (2) Prepare data for analysis; (3) Build and train a computer model; and (4) Evaluate the computer model (Berry and Linoff, 1997).

#### 2.4.2.2. Undirected Knowledge Discovery

Undirected KD is different from directed KD, in the way that there is no target field. The DM tool is simply let loose on the data in the hope that it will discover meaningful structure (Berry and Linoff, 1997).

The process of undirected KD have the following steps: (1) Identify sources of data; (2) Prepare data for analysis; (3) Build and train a computer model; (4) Evaluate the computer model; (5) Apply computer model to new data; (6) Identify potential targets for directed KD; and (7) Generate new hypothesis to test (Berry and Linoff, 1997).

In this work the DM methodology used was the undirected KD, more precisely, the CRISP-DM methodology. This methodology and its different steps are described in Annex B.

# 3. CLUSTERING

*"Science never solves a problem*
*without creating ten more."*
By George Bernard Shaw, an Irish dramatist

## 3.1. Clustering Definition

According to Velmurugan and Santhanam (2010) clustering consists of "creating groups of objects based on their features in such a way that the objects belonging to the same groups are similar and those belonging to different groups are dissimilar."

In operational terms, clustering can be defined as follows: "Given a *representation* of *n* objects, find *k* groups based on a measure of similarity such that the similarities between objects in the same group are high while the similarities between objects in different groups are low" (Jain, 2009).

For Mirkin (2005), clustering is "a discipline on the intersection of different fields and can be viewed from different angles" and therefore he finds it useful to distinguish the different perspectives of statistics, machine learning, data mining and classification about clustering, which are presented on Table 3.1.

| Perspective | Description |
|---|---|
| Statistics | Tends to view any data table as a sample from a probability distribution whose properties or parameters are to be estimated with the data. |
| Machine learning | Tends to view the data as a device for learning how to predict pre-specified or newly created categories. |
| Data mining | Assumes that a dataset or a database has already been collected and the major concern is in finding patterns and regularities within the data as they are, despite how bad or good it reflects the properties of the phenomenon in question. |
| Classification/ | Is an actual or ideal arrangement of entities under |

| Perspective | Description |
|---|---|
| Knowledge-discovery | consideration in classes to: (1) shape and keep knowledge; (2) capture the structure of phenomena; and (3) relate different aspects of a phenomenon in question to each other. |

**Table 3.1** – Clustering Perspectives

## 3.2. Clustering Goals

Clustering goals are types of problems of data analysis to which clustering can be applied. Mirkin (2005) enumerates some objectives for clustering, which are not mutually exclusive nor do they cover the entire range of clustering goals. They are:

1. *Structuring*, that is representing data as a set of groups of similar objects.
2. *Description* of clusters in terms of features, not necessarily involved in finding the clusters.
3. *Association*, which is finding interrelations between different aspects of a phenomenon by matching cluster descriptions in spaces corresponding to the aspects.
4. *Generalization*, that is making general statements about data and, potentially, the phenomena the data relate to.
5. *Visualization*, which is representing cluster structures as visual images.

## 3.3. Clustering Stages

The clustering process is similar to DM process described on section 2.3, however we find it useful to distinguish the stages of the clustering process. According to Mirkin (2005), clustering, as a DM activity, typically involves the following stages:

1. Developing a dataset
2. Data pre-processing and standardizing
3. Finding clusters in data
4. Interpretation of clusters
5. Drawing conclusions

In the first stage it is necessary to develop a substantive problem or issue and then determine what dataset, related to the issue, can be collected from an existing database or set of experiments or surveys, etc.

The second is the stage of preparing data processing by a clustering algorithm. It normally includes developing a uniform dataset from a database, checking for missing or unreliable entries, rescaling and standardizing variables, deriving a unified similarity measure, etc.

Finding clusters in data is the third stage and involves the application of a clustering algorithm which results in a cluster structure[1] to be presented, along with interpretation aids, to substantive specialists for an expert judgment and interpretation. At this stage, the expert may not see relevance in the results and suggest a modification of the data by adding/removing features and/or entities. The modified data is subject to the same processing procedure.

The final stage is drawing conclusions from the interpretation of the results regarding the issue in question. The more focused the regularities are implied in the findings, the better the quality of conclusions are.

## 3.4. Clustering Algorithms

Clustering algorithms can be divided in two groups: (1) *hierarchical* and (2) *partitional*. Hierarchical clustering algorithms (Figure 3.1) recursively find nested clusters either in *agglomerative* mode (starting with each data point in its own cluster and merging the most similar pair of clusters successively to form a cluster hierarchy) or in *divisive* (top-down) mode (starting with all the data points in one cluster and recursively dividing each cluster into smaller clusters). Partitional clustering algorithms (Figure 3.2) find all the clusters simultaneously as a partition of the data and do not impose a hierarchical structure (Jain, 2009).

Input to a hierarchical algorithm is a $n$ x $n$ similarity matrix, where $n$ is the number of objects to be clustered while a partitional algorithm can either use a $n$ x $d$ pattern matrix, where $n$ objects are embedded in a d-dimensional feature space, or a $n$ x $n$ similarity matrix (Jain, 2009)

The most well-known hierarchical algorithms are *single-link* and *complete-link* (Jain 2009) and the most popular and simplest partitional algorithm is *K-Means*. Figure 3.3 synthetizes these clustering approaches.

[1] According to Mirkin (2005), a *cluster structure* is "a representation of an entity set *I* as a set of clusters

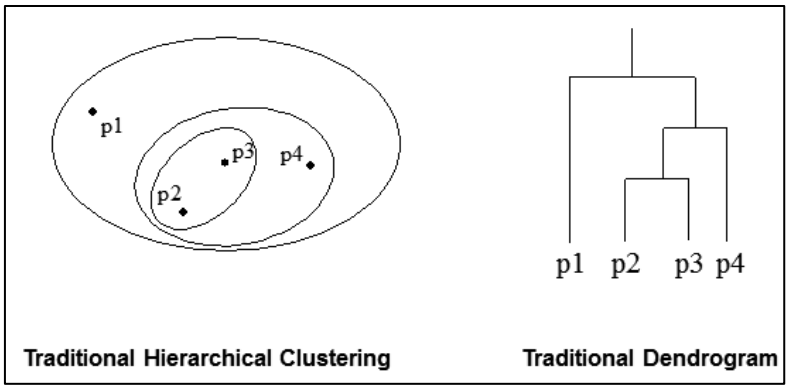



**Figure 3.1** – Hierarchical Clustering

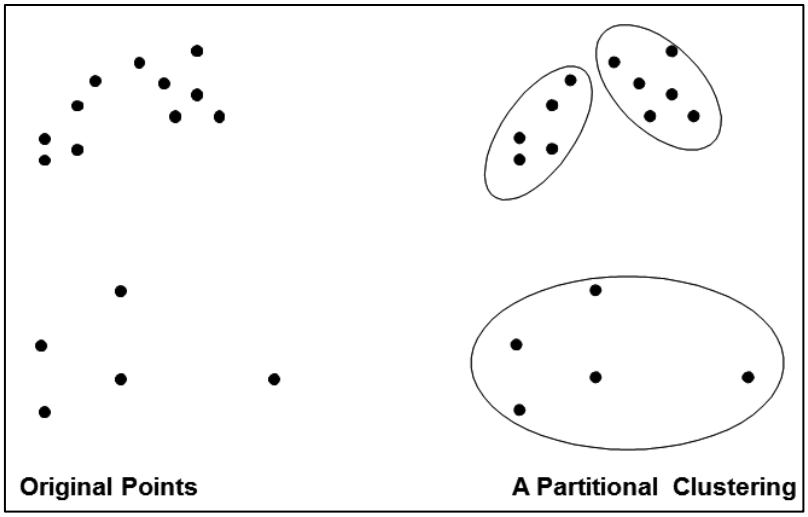



**Figure 3.2** – Partitional Clustering

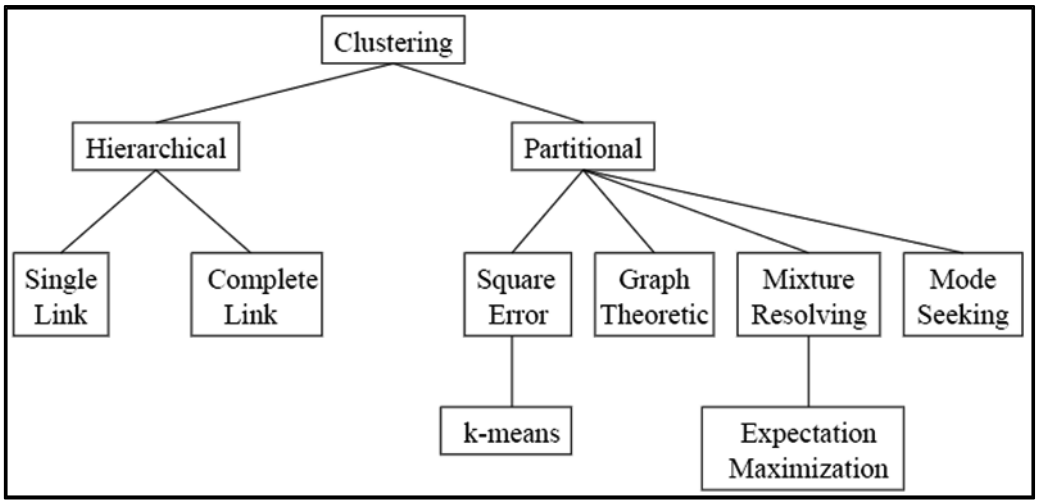



**Figure 3.3** – A Taxonomy of Clustering Approaches (Jain *et al*, 2000)

### 3.4.1. K-Means Clustering

K-Means is one of the most widely used algorithms for clustering. The main reasons for its popularity are: (1) ease of implementation, (2) simplicity, (3) efficiency, and (4) empirical success (Jain, 2009). Likewise, Mirkin (2005) finds K-Means computationally easy, fast and memory-efficient. However, he points out some problems related to the initial setting and stability of results.

Mirkin (2005) defines and resumes K-Means as "a major clustering method producing a partition of the entity set into non-overlapping clusters along with within-cluster *centroids*[2]. It proceeds in iterations consisting of two steps each: one step updates clusters according to the *minimum distance rule*[3]; the other step updates centroids as the centers of gravity of clusters. The method implements the so-called alternating minimization algorithm for the *square error criterion*[4]. To initialize the computations, either a partition or a set of all *k* tentative centroids must be specified."

An example of a K-Means algorithm is given by Jain (2009) and is described as follows:

Let $X = \{x_i\}$, i = 1,…, n be the set of *n* d-dimensional points to be clustered into a set of *K* clusters, $C = \{c_k\}$, k = 1,…, *K*. K-Means algorithm finds a partition such that the squared error between the empirical mean of a cluster and the points in the cluster is minimized. Let $\mu_k$ be the mean of cluster $c_k$. The squared error between $\mu_k$ and the points in cluster $c_k$ is defined as $J(c_k) = \sum_{x_i \in c_k} ||x_i - \mu_k||^2$. The goal of K-Means is to minimize the sum of the squared error over all the *k* clusters, $J(C) = \sum_{k=1}^{K} \sum_{x_i \in c_k} ||x_i - \mu_k||^2$. K-Means starts with an initial partition with *K* clusters and assign patterns to clusters so as to reduce the squared error. Since the squared error always decreases with an increase in the number of clusters *K* (with J(C) = 0 when K = n), it can be minimized only for a fixed number of clusters.

[2] According to Mirkin (2005), a *centroid* is a multidimensional vector minimizing the summary distance to cluster's elements. If the distance is Euclidean squared, the centroid is equal to the center of gravity of the cluster.

[3] According to Mirkin (2005), *minimum distance rule* is the rule which assigns each of the entities to its nearest centroid.

[4] According to Mirkin (2005), the *square error criterion* is the sum of summary distances from cluster centroids, which is minimized by K-means. The distance used is the Euclidean distance squared which is expressed by the equation $d(x_i, x_{i'}) = \sum_{j=1}^{P} (x_{ij} - x_{i'j})^2 = ||x_i - x_{i'}||^2$ (Hastie *et al*, 2001).

So, the main steps of K-Means algorithm are:

1. Select an initial partition with *k* clusters (repeat steps 2 and 3 until cluster membership stabilizes).
2. Generate a new partition by assigning each pattern to its closest cluster center.
3. Compute new cluster centers.

Figure 3.4 illustrates this process, as well Figure 3.5. Starting with two random points as centroids (1), the stage (2) assigns each point to the cluster nearest to it. In the stage (3), the associated points are averaged out to produce the new location of the centroid, leaving us with the final configuration (4). After each iteration the final configuration is fed back in to the same loop till the centroids converge.

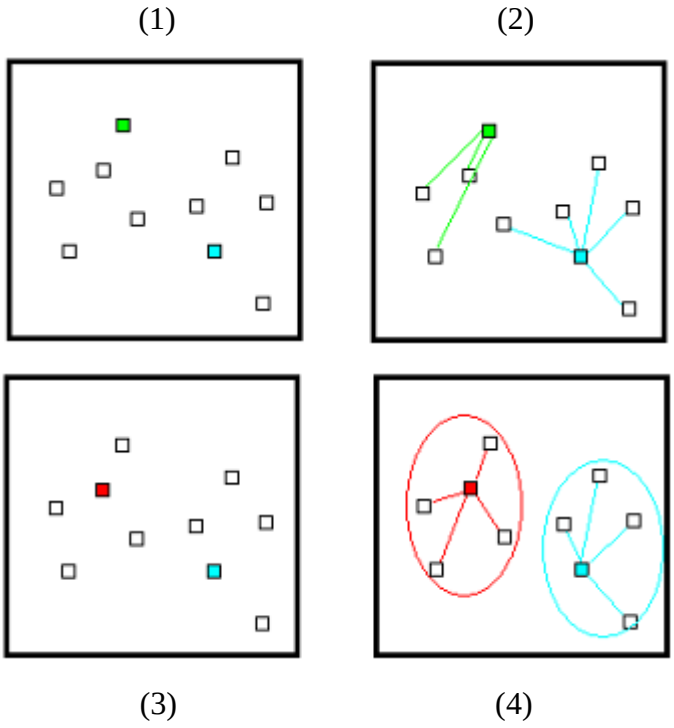



**Figure 3.4** –K-Means Clustering Steps

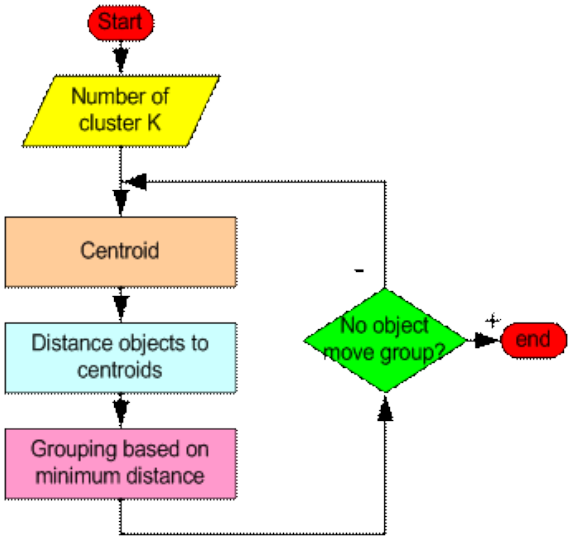



**Figure 3.5** – K-Means Algorithm Process

Table 3.2 presents some distance functions, including the Euclidean distance while Table 3.3 indicates the most common choices for proximity, centroids and objective functions specially for K-Means. The Eucliden distance is the distance metric that we are going to use in this study.

| Distance Function | Formula and Comments |
|---|---|
| Euclidean distance | $d(\mathbf{x},\mathbf{y}) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$ |
| Hamming (city block) distance | $d(\mathbf{x},\mathbf{y}) = \sum_{i=1}^{n}\lvert x_i - y_i\rvert$ |
| Tchebyschev distance | $d(\mathbf{x},\mathbf{y}) = \max_{i=1,2,\ldots,n}\lvert x_i - y_i\rvert$ |
| Minkowski distance | $d(\mathbf{x},\mathbf{y}) = \sqrt[p]{\sum_{i=1}^{n}(x_i - y_i)^p},\ p > 0$ |
| Canberra distance | $d(\mathbf{x},\mathbf{y}) = \sum_{i=1}^{n}\frac{\lvert x_i - y_i\rvert}{x_i + y_i}$, $x_i$ and $y_i$ are positive |
| Angular separation | $d(\mathbf{x},\mathbf{y}) = \frac{\sum_{i=1}^{n} x_i y_i}{\left[\sum_{i=1}^{n} x_i^2 \sum_{i=1}^{n} y_i^2\right]^{1/2}}$<br>Note: this is a similarity measure that expresses the angle between the unit vectors in the direction of **x** and **y** |

**Table 3.2** – Selected Distance Functions between Patterns x and y (Pedrycz, 2005)

| Proximity Function | Centroid | Objective Function |
|---|---|---|
| Manhattan | median | Minimize sum of the distance of an object to its cluster centroid |
| Squared Euclidean | mean | Minimize sum of the squared distance of an object to its cluster centroid |
| cosine | mean | Minimize sum of the cosine similarity of an object to its cluster centroid |
| Bregman divergence | mean | Minimize sum of the Bregman divergence of an object to its cluster centroid |

**Table 3.3** – K-Means: Common choices for proximity, centroids, and objective functions (Adapted from Tan *et al*, 2006)

### 3.4.2. K-Medoids Clustering

K-Medoids is an extension of the basic K-Means algorithm (Jain, 2009). In K-Medoids, clusters are represented using the median of the data instead of the mean (Jain, 2009). Taking as reference point a *medoid*, which is the most centrally located object in a cluster (Velmurugan and Santhanam, 2010) this algorithm, compared to the K-Means, is less sensitive to *outliers*[5] that produce very large distances. Despite the advantage of K-Medoids relatively to K-Means, K-Medoids is far more computationally intensive than K-Means (Hastie *et al*, 2001).

K-Medoids method can be, as well, performed based on the principle of minimizing the sum of the dissimilarities between each object and its corresponding reference point (Velmurugan and Santhanam, 2010).

According to Velmurugan and Santhanam (2010), the basic strategy of K-Medoids clustering algorithms is to find *k* clusters in *n* objects by first arbitrarily finding a representative object (the medoids) for each cluster. Each remaining object is clustered with the medoid to which it is the most similar. K-Medoids method uses representative objects as reference points. The algorithm takes the input parameter *k*, the number of clusters, to be partitioned among a set of *n* objects.

[5] *Outlier* is an item whose value falls outside the bounds enclosing most of the other corresponding values in the sample. May indicate anomalous data, however should be examined carefully because may carry important information.

Velmurugan and Santhanam (2010) present a typical K-Medoids algorithm for partitioning based on medoid, as follows:

Input: K = number of clusters and D = dataset containing *n* objects

Output: A set of *k* clusters that minimizes the sum of the dissimilarities of all the objects to their nearest medoid.

Method: Arbitrarily choose *k* objects in D as the initial representative objects.

Repeat: Assign each remaining object to the cluster with the nearest medoid; Randomly select a non medoid object $O_{random}$; Compute the total points S of swap point $O_j$ with $O_{random}$; If S<0 then swap $O_j$ with $O_{random}$ to form the new set of *k* medoid until no change.

Velmurugan and Santhanam (2010) compared the two algotrithms and concluded that "K-Means algorithm is more efficient for smaller datasets and K-Medoids algorithm seems to perform better for large datasets."

## 3.5. Cluster Validity

After applying a clustering algorithm, we would like to know if the results reflect or not an innate property of the data (Mirkin, 2005). In other words, we want to know whether the cluster structure found is valid or not (Mirkin, 2005).

So, *cluster validity* refers to formal procedures that evaluate the results of cluster analysis in a quantitative and objective manner (Jain, 2009). Before a clustering algorithm is applied to the data, we should determine if data has, in fact, a clustering tendency[6] (Jain, 2009).

In literature we can find several measures for cluster validation, including many cluster validity indices which can be defined based on three different criteria: *internal*, *relative* or *external* (Jain, 2009). Internal indices assess the fit between the structured imposed by the clustering algorithm (clustering) and the data using only the data. The better the indices value, the more reliable is the cluster structure Mirkin (2005). Relative indices compare multiple structures (generated by different algorithms, for example) and decide which of them is better in some sense. External indices measure the performance by matching cluster structure to the *a priori* information. Typically, clustering results are evaluated using the external criterion.

[6] Mirkin (2005) defines *cluster tendency* as a description of a cluster in terms of the advantage values of relevant features.

Furthermore, according to Mirkin (2005), it is still possible to use another procedure for validating a cluster structure or clustering algorithm, it is called *resampling*. A resampling is used to see whether the cluster structure is stable when the data is changed. The cluster *stability* is measured as the amount of variation in the clustering solution over different subsamples drawn from the input data and different measures of that variation can be used to obtain different stability measures (Jain, 2009). For instance, in model based algorithms, as K-Means, the distance between the models found for different subsamples can be used to measure the stability.

In general, cluster validity indices are usually defined by combining *compactness* and *separability*. Compactness measures the closeness of cluster elements, being a common measure of that the variance. Separability indicates how distinct two clusters are being the distance between representative objects of two clusters a good example. This measure has been widely used due to its computational efficiency and effectiveness (Rendón *et al*, 2011).

The following tables describe some of the internal and external cluster validity indices most widely used and Figure 3.6 synthesizes the classification of the validation techniques.

| Name | Expression | Description |
|---|---|---|
| ***Bayesian Information Criterion (BIC)*** | $BIC = -\ln(L) + v\ln(n)$ | - Is devised to avoid overfitting.<br>- $n$ = number of objects<br>- $L$ = the likelihood of parameters to generate the data in the model<br>- $v$ = number of free parameters in Gaussian model<br>- Takes into account both fit of the model to the data and the complexity of the model.<br>- A model that has a smaller BIC is better. |
| ***Calinski-Harabasz*** | $CH = \frac{trace(S_B)}{trace(S_w)} \cdot \frac{n_p - 1}{n_p - k}$ | - $S_B$ = the between-cluster scatter matrix<br>- $S_w$ = the internal scatter matrix |

| Name | Expression | Description |
|---|---|---|
| | | - $n_p$ = the number of clustered samples<br>- $k$ = the number of clusters |
| ***Davies-Bouldin (DB)*** | $BD = \frac{1}{c}\sum_{i=1}^{c} Max_{i \neq j}\left\{\frac{d(X_i) + d(X_j)}{d(c_i, c_j)}\right\}$ | - Aim to identify sets of clusters that are compact and well separated.<br>- $c$ = the number of clusters<br>- $i, j$ = cluster labels<br>- $d(X_i)$ and $d(X_j)$ = all samples in clusters $i$ and $j$ to their respective cluster centroids<br>- $d(c_i, c_j)$ = the distance between centroids<br>- Smaller value of *DB* indicates a better clustering solution. |
| ***Silhouette*** | $s(i) = \frac{(b(i) - a(i))}{Max\{a(i), b(i)\}}$ | For a given cluster, $X_j (j=1,\ldots c)$, it assigns to the *ith* sample of $X_j$ a quality measure, s(i)= ($i$=1,…$m$), the silhouette width. This value is a confidence indicator of the membership of the *ith* sample in the cluster $X_j$.<br>$a$ = the average distance between the *ith* sample and all of samples included in $X_j$.<br>b(i) = the minimum average distance between the ith sample and all samples clustered in $X_k (k=1,\ldots c; k \neq j)$ |
| ***Dunn*** | $Dunn = min_{1 \leq i \leq c}\left\{min\left\{\frac{d(c_i, c_j)}{max_{1 \leq k \leq c}(d(X_k))}\right\}\right\}$ | - $d(c_i, c_j)$ = the intercluster distance between cluster $X_i$ and $X_j$<br>- $d(X_k)$ = the intracluster distance of cluster ($X_k$)<br>- $c$ = the number of cluster of dataset<br>- Large values of index *Dun* correspond |

| Name | Expression | Description |
|---|---|---|
| | | to good clustering solution. |
| ***NIVA*** | $NIVA(C) = \frac{Compac(C)}{SepxG(C)}$ | - $C = \{c_i \mid i = 1, \ldots, N\}$<br>- $v_i$($i$=1,2,…,N)<br>-$N$ = the number cluster from $C$<br>- *Compac (C):* average of compactness product (Esp($c_i$)) of c groups and separability between them (*SepxS*($c_i$))<br>$Compac(C) = \frac{1}{N}\sum_{i=1}^{N} Esp(c_i) * SepxS(c_i)$<br>- *SepxG (C):* average separability of $C$ groups<br>$SepxG(C) = \frac{1}{N}\sum_{i=1}^{N}\left\{\min_{\substack{j\in C \\ j\neq i}}\{d(v_i, v_j)\}\right\}$<br>- The smaller value *NIVA(C)* indicates that avalid optimal partition to the different given partitions was found. |

**Table 3.4 –** Internal Validity Indices (Adapted from Rendón *et al*, 2011)

| Name | Expression | Description |
|---|---|---|
| ***F-Measure*** | $F(i,j) = \frac{2Recall(i,j)Precision(i,j)}{Precision(i,j) + Recall(i,j)}$ | - Combines the precision and recall concepts from information retrieval. Then calculate them of that cluster for each class.<br>$Recall(i,j) = \frac{n_{ij}}{n_i}$<br>$Precision(i,j) = \frac{n_{ij}}{n_j}$<br>- $n_{ij}$ = the number of objects of class $i$ that are in cluster $j$<br>- $n_j$ = the number of objects in cluster $j$<br>- $n_i$ = the number of objects in class $i$<br>- The F-Measure values are within |

| Name | Expression | Description |
|---|---|---|
| | | the interval [0, 1] and larger values indicate higher clustering quality. |
| ***Nmimeasure*** | $NMI(X,Y) = \frac{I(X,Y)}{\sqrt{H(X)H(Y)}}$ | - NMI – Normalized Mutual Information<br>- *I(X,Y)* = the mutual information between two random variables *X* and *Y*<br>- *H(X)* = the entropy of *X*<br>- *X* = consensus clustering<br>- *Y* = the true labels |
| ***Purity*** | $Purity = \sum_{j=1}^{m} \frac{n_j}{n} P_j$ | - We calculate the purity of a set of clusters. First, we cancel the purity in each cluster. For each cluster we have the purity $P_j = \frac{1}{n_j} Max_i(n_j^i)$<br>- $n_j^i$ = the number of objects in *j* with class label *i*<br>- $P_j$ = a fraction of the overall cluster size that the largest class of objects assigned to that cluster represents.<br>- The overall purity of the clustering solution is obtained as a weighted sum of the individual cluster purities.<br>- $n_j$ = the size of cluster j<br>- *m* = the number of clusters<br>- *n* = the total number of objects |
| ***Entropy*** | $E = \sum_{j=1}^{m} \frac{n_j}{n} E_j$ | - Measures the purity of the clusters class labels.<br>- If all clusters consist of objects with only a single class label, the entropy is 0.<br>- As the class labels of objects in a cluster become more varied, the |

| Name | Expression | Description |
|---|---|---|
| | | entropy increases.<br>- To compute the entropy of a dataset, we need to calculate the class distribution of objects in each cluster<br>$E_j = \sum_i p_{ij} \log(p_{ij})$, where the sum is taken over all the classes.<br>- The total entropy for a set of clusters is calculated as the weighted sum of the entropies of all clusters.<br>- $n_j$ = the size of cluster j<br>- $m$ = the number of clusters<br>- $n$ = the total number of data points |

**Table 3.5 –** External Validity Indices (Adapted from Rendón *et al*, 2011)

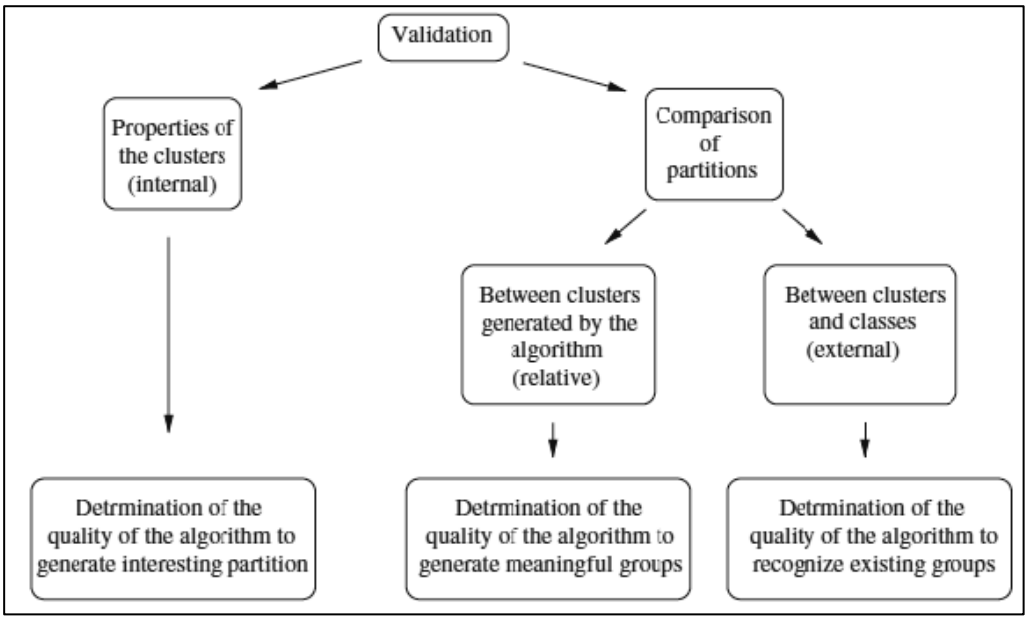



**Figure 3.6** – A Simplified Classification of Validation Techniques (Brun *et al*, 2006)

# 4. SEGMENTATION IN MARKETING

*"Do not buy market share.*
*Figure out how to earn it."*
Philip Kotler in *Marketing Management, 11th Edition*

## 4.1. Segmentation Definition

Kotler (2005) defines market segmentation as "the act of dividing a market into smaller groups of buyers with distinct needs, characteristics, or behaviors who might require separate products and/or marketing mixes." Despite that definition, there is another one that is considered the best by marketers given by Smith (1956): "market segmentation involves viewing a heterogeneous market as a number of smaller homogeneous markets, in response to differing preferences, attributable to the desires of consumers for more precise satisfaction of their varying wants."

According to Wedel and Kamakura (2002), in market segmentation one distinguishes homogeneous groups of customers who can be targeted in the same manner because they have similar needs and preferences. For them, *market segments* are not real entities naturally occurring in the marketplace, but groupings created by managers to help them develop strategies that better meet consumer needs at the highest expected profit for the company. Therefore, segmentation is a very useful concept to managers.

## 4.2. Segmentation Effectiveness

According to Kotler (2000), an effective segmentation must meet some criteria. The segments must be *measurable* (the size, purchasing power, profiles of segments can be measure), s*ubstantial* (segments must be large or profitable enough to serve), a*ccessible* (segments must be effectively reached and served), d*ifferentiable* (segments must respond differently to different marketing mix elements and actions), and a*ctionable* (must be able to attract and serve the segments).

For Wedel and Kamakura (2000) the criteria that determine the effectiveness and profitability of marketing strategies are six and are described on Table 4.1.

| Criteria | | Description |
|---|---|---|
| **1** | **Identifiability** | Is the extent to which managers can recognize distinct groups of customers in the marketplace by using specific segmentation bases. They should be able to identify the customers in each segment on the basis of variables that are easily measured. |
| **2** | **Substantiality** | This criterion is satisfied if the targeted segments represent a large enough portion of the market to ensure the profitability of targeted marketing programs. In the limit, this criterion may be applied to each individual customer. |
| **3** | **Accessibility** | Is the degree to which managers are able to reach the targeted segments through promotional or distributional efforts. |
| **4** | **Responsiveness** | This criterion is satisfied if the segments respond uniquely to marketing efforts targeted to them. It is critical because differentiated marketing mixes will be effective only if each segment is homogeneous and unique in its response to them. |
| **5** | **Stability** | It is necessary, at least for a period long enough for identification of the segments, implementation of the segmented marketing strategy, and the strategy to produce results. Only segments that are stable in time can provide the underlying basis for the development of a successful marketing strategy. |
| **6** | **Actionability** | This criterion is satisfied if the identification of the segments provides guidance for decisions on the effective specification of marketing instruments. The focus is on whether the customers in the segment and the marketing mix necessary to satisfy their needs are consistent with the goals and core competences of the company. |

**Table 4.1** – Requirements for an Effective Segmentation

## 4.3. Segmentation Process

Marketers are increasingly combining several variables in an effort to identify smaller, better-defined target groups. This has led some market researchers to advocate a *needs-based market segmentation approach* (Kotler, 2008). Thus a seven-step segmentation approach was proposed by Best (2005), which steps are described on Table 4.2.

| Steps | | Description |
|---|---|---|
| **1** | **Needs-based Segmentation** | Group customers into segments based on similar needs and benefits sought by customer in solving a particular consumption problem. |
| **2** | **Segment Identification** | For each needs-based segment, determine which demographics, lifestyles, and usage behaviors make the segment distinct and identifiable (actionable). |
| **3** | **Segment Attractiveness** | Using predetermined segment attractiveness criteria (such as market growth, competitive intensity, and market access) determine the overall attractiveness of each segment. |
| **4** | **Segment Profitability** | Determine segment profitability. |
| **5** | **Segment Positioning** | For each segment, create a "value proposition" and product-price positioning strategy based on that segment's unique customer needs and characteristics. |
| **6** | **Segment "Acid Test"** | Create "segment storyboard" to test the attractiveness of each segment's positioning strategy. |
| **7** | **Marketing-Mix Strategy** | Expand segment positioning strategy to include all aspects of the marketing-mix: product, price, promotion and place. |

**Table 4.2** – Steps in Segmentation Process

(Adapted from Kotler, 2008)

## 4.4. Levels of Market Segmentation

Because buyers have unique needs and wants, each buyer is potentially a separate market. Ideally, then, a seller might design a separate marketing program for each buyer. However, although some companies attempt to serve buyers individually, many others face larger numbers of smaller buyers and do not find complete segmentation worthwhile. Instead, they look for broader classes of buyers who differ in their product needs or buying responses. Thus, market segmentation can be carried out at several different levels (Kotler, 2008).

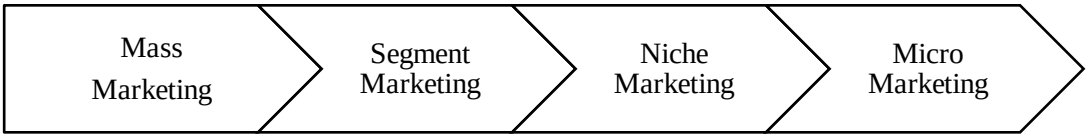



**Figure 4.1** – Levels of Marketing Segmentation

Figure 4.1 shows that companies can practice no segmentation (mass marketing), complete segmentation (micromarketing), or something in between (segment marketing or niche marketing).

| **Levels of Marketing Segmentation** | | |
|---|---|---|
| **Mass Marketing** | Same product to all consumers | No Segmentation |
| **Segment Marketing** | Different products to one or more segments | Some Segmentation |
| **Niche Marketing** | Different products to subgroups within segments | More Segmentation |
| **Micromarketing** | Products to suit the tastes of individuals or locations | Complete Segmentation |

**Table 4.3** – Levels of Marketing Segmentation

### 4.4.1. Mass Marketing

Companies have not always practiced target marketing. In fact, for most of the 1900s, major consumer products companies held fast to mass marketing—mass producing, mass distributing, and mass promoting about the same product in about the same way to all consumers. The traditional argument for mass marketing is that it creates the largest potential market, which leads to the lowest costs, which in turn can translate into either lower prices or higher margins. However, many factors now make mass marketing more difficult. The proliferation of distribution channels and advertising media has also made it difficult to practice "one-size-fits-all" marketing (Kotler, 2008).

### 4.4.2. Segment Marketing

A company that practices segment marketing isolates broad segments that make up a market and adapts its offers to more closely match the needs of one or more segments. Segment marketing offers several benefits over mass marketing. The company can market more efficiently, targeting its products or services, channels, and communications programs toward only consumers that it can serve best and most profitably. The company can also market more effectively by fine-tuning its products, prices, and programs to the needs of carefully defined segments. The company may face fewer competitors if fewer competitors are focused on this market segment (Kotler, 2008).

### 4.4.3. Niche Marketing

Market segments are normally large, identifiable groups within a market. Niche marketing focuses on subgroups within the segments. A niche is a more narrowly defined group, usually identified by dividing a segment into sub segments or by defining a group with a distinctive set of who may seek a special combination of benefits. Whereas segments are fairly large and normally attract several competitors, niches are smaller and normally attract only one or a few competitors. Niche marketers presumably understand their niches' needs so well that their customers willingly pay a price premium (Kotler, 2008).

### 4.4.4. Micro Marketing

Segment and niche marketers tailor their offers and marketing programs to meet the needs of various market segments. At the same time, however, they do not customize their offers to each individual customer. Thus, segment marketing and niche marketing fall between the extremes of mass marketing and micro marketing. Micro marketing is the practice of tailoring products and marketing programs to suit the tastes of specific individuals and locations. Micro marketing includes local marketing (involves tailoring brands and promotions to the needs and wants of local customer groups—cities, neighborhoods, and even specific stores) and individual marketing (tailoring products and marketing programs to the needs and preferences of individual customers) (Kotler, 2008).

## 4.5. Segmentation Bases

Wedel and Kamakura (2000) define segmentation basis as "a set of variables or characteristics used to assign potential customers to homogeneous groups." They classify segmentation bases into four categories, which are presented in Table 4.4.

| Bases | General | Product-specific |
|---|---|---|
| **Observable** | Cultural, geographic, demographic and socio-economic variables | User status, usage frequency, store loyalty and patronage, situations |
| **Unobservable** | Psychographics, values, personality and life-cycle | Psychographics, benefits, perceptions, elasticities, attributes, preferences, intention |

**Table 4.4 –** Classification of Segmentation Bases

(Source: Wedel and Kamakura, 2000)

*General* segmentation bases are independent of products, services or circumstances and *product-specific* segmentation bases are related to customer and product, service and/or particular circumstances. Furthermore, *observable* segmentation bases are measured directly and *unobservable* segmentation bases are inferred.

### 4.5.1. Observable General Bases

In market segmentation, a widely number of bases are used in this category, such us cultural variables, geographic variables, neighborhood, geographic mobility, demographic and socio-economic variables, postal code classifications, household life cycle, household and company size, standard industrial classifications and socioeconomic variables. Also used are media usage and socioeconomic status (Wedel and Kamakura, 2000). The observable general bases play an important role in segmentation studies, whether simple or complex, and are used to enhance the accessibility of segments derived by other bases (Wedel and Kamakura, 2000).

### 4.5.2. Observable Product-Specific Bases

This kind of segmentation bases include variables that are related to buying and consumption behavior, like user status, usage frequency, brand loyalty, store loyalty, store patronage, stage of adoption and usage situation. These variables have been used both for consumer and business markets (Wedel and Kamakura, 2000).

### 4.5.3. Unobservable General Bases

Three groups of variables in this class of segmentation bases are identified: (1) *personality traits*, (2) *personal values* and (3) *lifestyle*.

The first may include dogmatism, consumerism, locus of control, religion and cognitive style. The most frequently used scale for measuring general aspects of personality in marketing is the *Edward's personal schedule*.

Relatively to the second, the most important instrument to measure human values and to identify value systems is the *Rokeach value survey*.

The third is based on three components: *activities* (work, hobbies, social events, vacation, entertainment, clubs, community, shopping, sports), *interests* (family, home, job, community, recreation, fashion, food, media, achievements) and *opinions* (of oneself, social issues, politics, business, economics, education, products, future, culture).The lifestyle typology most used is the *VALS system,* which has been recently reviewed giving its place to the *VALS2 system*. It is defined by two main dimensions: *resources* (income, education, self-confidence, health, eagerness to buy, intelligence, etc.) and *self-orientation* (principle-oriented, self-oriented and status-oriented).These three groups of variables are used almost exclusively for consumer markets giving us "a

more lifelike picture of consumers and a better understanding of their motivations" (Wedel and Kamakura, 2000).

### 4.5.4. Unobservable Product-Specific Bases

This class of segmentation bases comprises product-specific psychographics, product-benefit perceptions and importance, brand attitudes, preferences and behavioral intentions. In these order, the variables form a hierarchy of effects, as each variable is influenced by those preceding it. Many of these variables are used for consumer markets; however they can also be used for segmenting business markets (Wedel and Kamakura, 2000).

All the segmentation bases are summarized on Table 4.5 according to the six criteria for effective segmentation.

| Bases \ Criteria | Identifiability | Sustainnability | Accessibility | Stability | Actionability | Responsiveness |
|---|---|---|---|---|---|---|
| **General, Observable** | ++ | ++ | ++ | ++ | - | - |
| **Specific, Observable** | | | | | | |
| - Purchase | + | ++ | - | + | - | + |
| - Usage | + | ++ | + | + | - | + |
| **General, Unobservable** | | | | | | |
| - Personality | +- | - | +- | +- | - | - |
| - Lifestyle | +- | - | +- | +- | - | - |
| - Psycographics | | - | +- | +- | - | - |
| **Specific, Unobservable** | | | | | | |
| - Psycographics | +- | + | - | - | ++ | +- |
| - Perceptions | +- | + | - | - | + | - |
| - Benefits | + | + | - | + | ++ | ++ |
| - Intentions | + | + | - | +- | - | ++ |
| ++ very good, + good, +- moderate, - poor, -- very poor | | | | | | |

**Table 4.5** – Evaluation of Segmentation Bases

(Adapted from Wedel and Kamakura, 2000)

## 4.6. Segmentation Methods

Many segmentation methods are available and have been used. Wedel and Kamakura (2000) classify segmentation methods in two ways: (1) *a priori* or *post hoc*; and (2) *descriptive* or *predictive*.

A segmentation approach is called *a priori* when the type and number of segments are determined in advance by the researcher and *post hoc* when the type and number of segments are determined on the basis of the results of data analysis. (Wedel and Kamakura, 2000).

A descriptive method analyzes the associations across a single set of segmentation bases, with no distinction between dependent or independent variables. Such method forms clusters that are homogeneous along a set of observed variables. A predictive method analyzes the association between two sets of variables, where one set consists of dependent variables to be explained/ predicted by the set of independent variables. This method forms clusters that are homogeneous on the estimated relationship between the two sets of variables (Wedel and Kamakura, 2000).

This classification of segmentation methods conduct us to four categories that are listed on Table 4.6.

| **Methods** | ***A priori*** | ***Post hoc*** |
|---|---|---|
| **Descriptive** | Contingency tables, Log-linear models | Clustering methods: Nonoverlapping, overlapping, Fuzzy techniques, ANN, mixture models |
| **Predictive** | Cross-tabulation, Regression, logit and Discriminant analysis | AID, CART, Clusterwise regression, ANN, mixture models |

**Table 4.6** – Classification of Segmentation Methods
(Adapted from Wedel and Kamakura, 2000)

Despite this classification, hybrid forms of segmentation are also possible and have been applied, combining *a priori* and *post hoc* approaches. The hybrid procedure can be seen as combining the strengths of the *a priori* and *post hoc* approaches.

### 4.6.1. *A Priori* Descriptive Methods

In *a priori* descriptive segmentation, the type and number of segments are determined before data collection. Cross-tabulation or contingency tables and log-linear models are examples of this kind of segmentation methods. Their main objective is to test segments arising from alternative bases, and to predict one segmentation base from other bases. The methods in this class are suited to quickly obtaining insights about segments and associations among segmentation bases. Although they are not effective, they are used especially in hybrid segmentation procedures.

### 4.6.2. *Post Hoc* Descriptive Methods

In the *post hoc* descriptive approach, segments are identified by forming groups of consumers that are homogeneous along a set of measured characteristics. The number of segments and characteristics of each segment are determined by the data and methodology used. Clustering methods are the most popular tools for *post hoc* descriptive segmentation. The clustering methods mentioned on Figure 4.2 on section 4.7 are described later in this dissertation. The *post hoc* descriptive procedures are powerful and frequently used tools for market segmentation (Wedel and Kamakura, 2000).

### 4.6.3. *A Priori* Predictive Methods

*A priori* predictive approaches require the definition of *a priori* descriptive segments based on one set of criteria, and the subsequent use of predictive models to describe the relation between segment membership and a set of independent variables. There are two types of *a priori* descriptive approaches: (1) *forward* and (2) *backward*.

In forward approaches, background characteristics such as socio-demographics and psychographics are first used to form *a priori* segments that are then related to product-specific measures of purchase behavior. The more common methods used in forward segmentation approaches are cross-tabulation, linear regression and logit model.

In backward approaches, the segments are first defined on the basis of product-specific purchase-related variables and the profiles of those segments are then described along a set of general consumer characteristics. The most used method in backward segmentation approaches is discriminant analysis.

The major disadvantage of the *a priori* predictive methods is that they are based on often relatively ineffective *a priori* segmentation bases in the first stage of the process (Wedel and Kamakura, 2000).

### 4.6.4. *Post Hoc* Predictive Methods

*Post-hoc* predictive methods identify consumer segments on the basis of the estimated relationship between a dependent variable and a set of predictors. The segments formed by *post hoc* predictive methods are homogeneous in the relationship between dependent and independent variables. The methods used for predictive clustering are: automatic interaction detection (AID), which was generalized to multiple dependent variables (MAID) and to categorical dependent variables (CHAID); classification and regression trees (CART); artificial neural network (ANN); conjoint analysis (a two-stage procedure); componential segmentation model; clusterwise regression (a method for simultaneous prediction and classification); and finally, mixture models (there are three categories: mixture, mixture regression, mixture multidimensional scaling models). Currently, the mixture models are considered the most powerful algorithms for market segmentation (Wedel and Kamakura, 2000).

Table 4.7 summarizes the segmentation methods and their evaluation according to the properties of their effectiveness for segmentation and prediction, their statistical properties, their applicability to segmentation problems and the availability of computer programs. This classification of segmentation methods was proposed by Wedel and Kamakura (2000).

| **Criteria / Methods** | **Effectiveness for segmentation** | **Effectiveness for prediction** | **Statistical properties** | **Application known** | **Availability of programs** |
|---|---|---|---|---|---|
| **A-priori, descriptive** | | | | | |
| - Log linear models | +- | -- | + | ++ | ++ |
| - Cross tabs | +- | -- | ++ | ++ | ++ |
| **A-priori, predictive** | | | | | |

| Methods \ Criteria | Effectiveness for segmentation | Effectiveness for prediction | Statistical properties | Application known | Availability of programs |
|---|---|---|---|---|---|
| - Regression | - | ++ | ++ | ++ | ++ |
| - Discriminant analysis | - | ++ | ++ | ++ | ++ |
| **Post-hoc, descriptive** | | | | | |
| -nonoverlapping | ++ | -- | - | ++ | ++ |
| - overlapping | ++ | -- | - | -- | - |
| - fuzzy | ++ | -- | - | +- | + |
| **Post-hoc, predictive** | | | | | |
| - AID | +- | + | - | ++ | + |
| - 2-stage segmentation | + | + | - | + | +- |
| - Clusterwise regression | ++ | ++ | +- | + | + |
| - Mixture regression | ++ | ++ | + | + | + |
| - Mixture MDS | ++ | ++ | + | +- | - |
| ++ very good, + good, +- moderate, - poor, -- very poor | | | | | |

**Table 4.7** – Evaluation of Segmentation Methods

(Adapted from Wedel and Kamakura, 2000)

## 4.7. Segmentation Methodology – Clustering Methods

Cluster analysis is one of the most important segmentation methods and it has long been the dominant and preferred method for market segmentation (Wedel and Kamakura, 2000).

Therefore, clustering methods are commonly used in marketing for the identification and definition of market segments that become a focus of a company´s marketing strategy (Wedel and Kamakura, 2000). Figure 4.2 summarizes the classification of clustering methods.

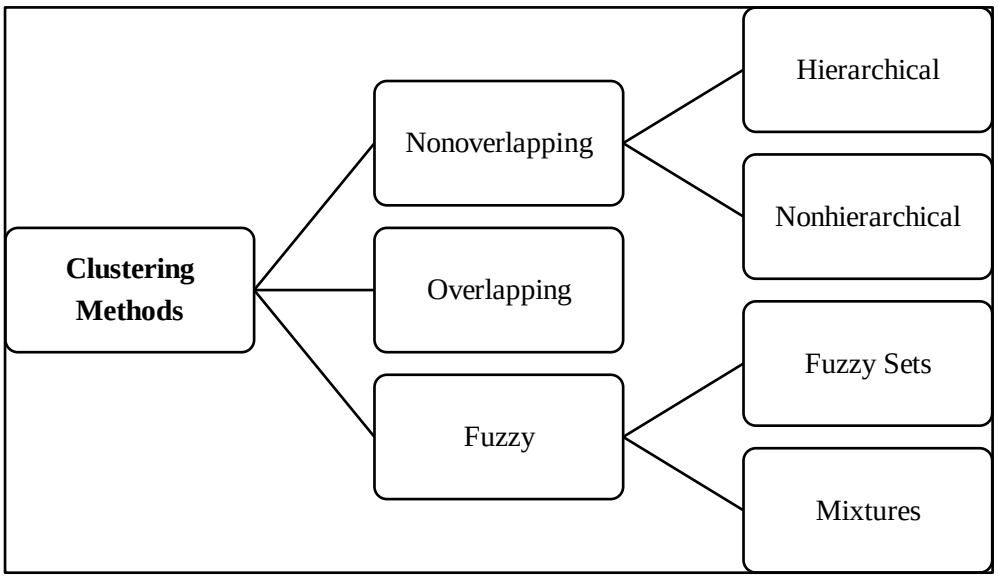



**Figure 4.2** – Classification of Clustering Methods
(Source: Wedel and Kamakura, 2000)

Clustering methods differ between them based on the nature of the clusters formed: *non-overlapping*, *overlapping* and *fuzzy*. In non-overlapping clustering each subject belongs to a single segment only. In overlapping clustering a subject may belong to multiple segments and in fuzzy clustering the membership of a subject in one or multiple clusters is replaced by the degree of membership in each segment.

Overlapping and fuzzy clustering approaches are consistent with the fact that consumers may belong to more than one segment or, in other words, those methods relax the assumption of external isolation of the clusters. In the situation of overlapping clusters, a consumer belongs to one segment. In the case of fuzzy clusters, consumers have partial membership in more than one segment.

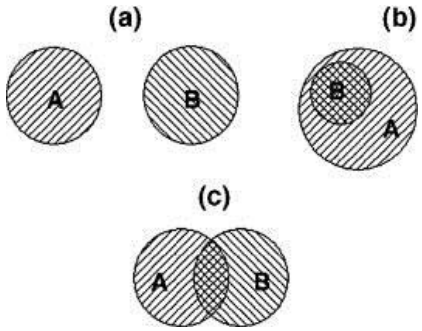



**Figure 4.3** – Clustering Methods: (a) nonoverlapping, (b) overlapping, (c) fuzzy

### 4.7.1. Non-overlapping Methods

Non-overlapping clustering methods have been the most used in segmentation research. There are two types of non-overlapping cluster techniques: *hierarchical* and *nonhierarchical*. Hierarchical clustering methods start with single-subject clusters and link clusters in successive stages; they do not identify a set of clusters directly, rather they identify hierarchical relations among objects on the basis of some measure of their similarity. There are several different hierarchical methods, such as *single linkage*, *complete linkage* and *minimum variance linkage* (or Ward's method). Figure 4.4 illustrates such methods.

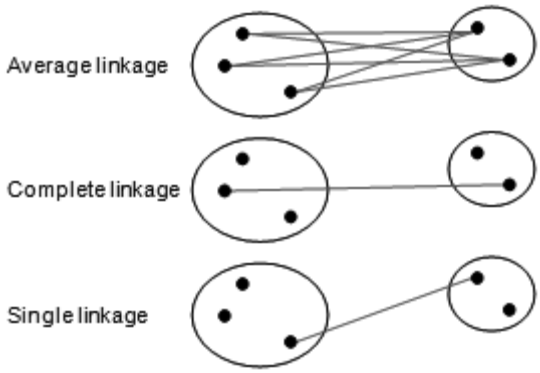



**Figure 4.4** – Non-overlapping Hierarchical Clustering Methods

The single linkage, also called nearest neighbor method, can be used both with similarity measures and with distance measures. Groups are fused according to the distance between their nearest members. The complete linkage, also called the furthest neighbor method, is the opposite of the single linkage method, i.e., the distance between groups is defined as the distance between their most remote pair of individuals. The average linkage defines distance between groups as the average of the distances between all pairs of individuals in the two groups, and is a compromise between the single and complete linkage methods.

Nonhierarchical methods start from a random initial division of the subjects into a predetermined number of clusters, and reassign subjects to clusters until a certain criterion is optimized. These methods derive from a partitioning of the sample into clusters directly from the raw data. A large number of nonhierarchical methods are available, where K-Means is the most widely used.

In literature we find that nonhierarchical methods are superior to hierarchical methods as they are more robust to outliers and to the presence of irrelevant attributes. However the general problem of those methods is the determination of the number of clusters present in data.

### 4.7.2. Overlapping Methods

The overlapping clustering methods have a limited potential regarding segmentation problems.

### 4.7.3. Fuzzy Methods

Regarding fuzzy clustering methods, two types can be distinguished: (1) the *fuzzy sets* and (2) *mixtures*. The first assigns a degree of membership for objects to a class. It assumes that consumers actually have partial memberships in several segments. The second is based on the assumption that the data arise from a mixture of distributions and estimates the probability that objects belong to each class. It assumes that segments are non-overlapping but, because of limited information contained in the data, subjects are assigned to segments with uncertainty, which are reflected in probabilities of membership. Both the fuzzy and the mixture approaches provide membership values between zero and one.

# PART II

*"Practice is the best of all instructors."*

By Publilius Syrus, a Roman writer

# 5. RESULTS ANALYSIS IN A TECHNICAL PERSPECTIVE

*"Whenever an individual or a business*
*Decides that success has been attained,*
*Progress stops."*
By Thomas J. Watson, an American scientist

In this section the results of clustering in a technical perspective, provided by RapidMiner, will be presented and discussed. Our objective here is to answer the business problem at hand in terms of the production of shirts. We aim, through DM techniques (Clustering) and tools (RapidMiner) to detect and understand the fashion trends on shirts based on the shirts orders of Bivolino in 2011. With the information resulting from the clustering process[7], the fashion designers would be able to identify fashion trends. Given that, we are going to focus our analysis mainly on shirts attributes.

## 5.1. Selection of the Clustering Result

Various experiences were done with data in RapidMiner (Annex E) however we had to select one of them to analyze in more detail taking into account the purpose of our study. The result selected is illustrated in Figure 5.1.

| Cluster | Size | Gender | Postal code | Country | Configuratort | Collectiont | Fabric | Collar | Cuff | Placket | Collar white | Cuff white | Shirt gender | Afiliate | Hem |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.282 | men | cv31_3nd | uk | Work Shirt | Retailer1 Man Design | Sheffield | Hai Cutaway | Double inc. Cufflinks | Folded | n | n | men | Retailer1 | Curved Hem with Gussets |
| 2 | 4.889 | men | g41_1ag | uk | Work Shirt | Retailer1 Man Plain | Greenwich | Classic Point | Round Single | Real front | n | n | men | Retailer1 | Curved Hem |
| 3 | 872 | men | 35037 | de | Fashion Shirt | Italian Luxury | Juan_7 | Mao | Round Single | Folded | n | n | men | Bivolino | Straight Hem |
| 4 | 1.570 | men | ec2r_7bp | uk | Work Shirt | Savile Row Plain | london_4 | Italian Semi-Spread | Double inc. Cufflinks | Folded | n | n | men | Retailer1 | Straight Hem |
| 5 | 500 | men | 23558 | de | _ | Fashion Trend | Kiwi_9 | Torino Large 2 Button | Round Single | Real front | y | y | men | Retailer2 | Straight Hem |
| 6 | 1.662 | men | 38106 | de | _ | Fashion Trend | Miro_3 | Classic Point | RoundSingle | Real front | n | n | men | Retailer2 | Curved Hem |
| Total | 10.775 | | | | | | | | | | | | | | |

[7] Due to the lack of space, the details from the data mining process are presented in Appendix A and Appendix B.

| Cluster | Back Yoke Contrast | Fabric color | Fabric design pattern | Fabric finish | Fabric material | Fabric structure | has Monogram | has Pocket | Age Group | BMI Fatness | Height Group | Collar Group | Is Collar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | y | Multicolor | Fine Stripe | Easy iron | 100prcnt Cotton | Dobby | Yes | No | 25/34 | Normal | 180-189 | 60> | Yes | 60kg-80kg | No |
| 2 | y | White | Plain | Easy iron | 100prcnt Cotton | Poplin | No | No | 25/34 | Normal | 170-179 | <_36 | No | 60kg-80kg | No |
| 3 | n | Red & Bordeaux | Plain | Easy iron | Cotton twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100kg-120kg | Yes |
| 4 | y | White | Plain | Easy iron | 100prcnt Cotton | Poplin | No | No | 25/34 | Normal | 180-189 | <_36 | No | 80kg-100kg | No |
| 5 | n | Purple & Lila | Plain | Easy-care kotex 100 | 100prcnt Cotton | Pinpoint | Yes | No | 25/34 | Normal | 180-189 | 40/41 | No | 60kg-80kg | No |
| 6 | n | Blue & Navy | Plain | Easy-care kotex 100 | Cotton twofold | Herringbone | No | No | 25/34 | Overweight | 170-179 | 40/41 | No | 80kg-100kg | No |

**Figure 5.1** – Result of K-Medoids Clustering Extract Cluster Prototype for k=6

The choice for this result, with a k=6 defined *a priori*, was based on various reasons. Before enumerating them, we must tell that this is a very difficult and subjective task, which is a problem usually associated to this clustering algorithm. This is particularly true because the authors are not shirt designers. After doing some experiments with different number of clusters, we had to do decide for the "best" *k*. That decision was made taking into account the amount of the data being clustered (a dataset with 10.775 examples and 29 attributes), the purpose of the analysis and the information it could give us. Given that, if we had chosen a very small *k*, it wouldn't be possible to extract from the results valuable and useful information because it will remain there hidden. And if we have chosen a very big *k*, it was almost impossible to work on and analyze so many data, despite the fact that an increase in *k* reduces the squared error.

After this the clusters will be interpreted one by one based on the attributes that are relevant for production and fashion designers.

## 5.2. Interpretation of Clusters

### Cluster 1

| Cluster | Size | Gender | Postal code | Country | Configuratort | Collectiont | Fabric | Collar | Cuff | Placket | Collar white | Cuff white | Shirt gender | Afiliate | Hem |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.282 | men | cv31_3nd | uk | Work Shirt | Retailer1 Man Design | Sheffield | Hai Cutaway | Double inc. Cufflinks | Folded | n | n | men | Retailer1 | Curved Hem with |

| Cluster | Back Yoke Contrast | Fabric color | Fabric design pattern | Fabric finish | Fabric material | Fabric structure | has Monogram | has Pocket | Age Group | BMI Fatness | Height Group | Collar Group | Is Collar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | y | Multicolor | Fine Stripe | Easy iron | 100prcnt Cotton | Dobby | Yes | No | 25/34 | Normal | 180-189 | 60> | Yes | 60kg-80kg | No |

**Figure 5.2** – Representation of Cluster 1

Cluster 1 grouped 1.282 shirts orders which represented about 12% of the total orders of the company in 2011. This cluster tells us that especially young men from the United Kingdom (uk) have a preference for work shirts from Retailer1 collection that has the following characteristics:

| Attribute[8] | Value |
|---|---|
| Fabric | Sheffield |
| Fabric color | Multicolor |
| Fabric design pattern | Fine Stripe |
| Fabric finish | Easy iron |
| Fabric structure | Dobby |
| Fabric material | 100% Cotton |
| Collar | Hai Cutaway |
| Collar white | no |
| Cuff | Double inc. Cufflinks |
| Cuff white | no |
| Placket | Folded |
| Pocket | no |
| Monogram | no |
| Hem | Curved Hem with Gussets |
| Back yoke contrast | yes |

**Table 5.1** – Shirts Attributes Values of Cluster 1

Besides this information about the fabric characteristics and the different components, it is also important to pay attention to the physical characteristics of the clients. For example, if the client is very tall or obese, the production department should buy more quantity of that fabric since it is not enough to know what the fabric type it needed but also the quantity necessary to produce the shirts. This is an important issue because predicting that an identified group of clients with a certain physical characteristics have specific tastes in terms of shirts and therefore different fashion

[8] The description of each attribute is available on *Annex D*, on Table D.3, Table D.4 and Table D.5 according to the entity it describes (customers, shirts, orders).

trends comparing to other groups, will not only enable the production department to have the necessary material but also to respond in time to the orders.

The information about the orders (shirts and customers attributes) is given by the customers to the company through its website. Figure 5.3 and Figure 5.4 illustrate the process of designing a customized men shirt with a 3D technology, where the first represents shirt attributes and the second the customer attributes. Since Bivolino only produces to fulfill the orders it receives, there is no waste and no stock.

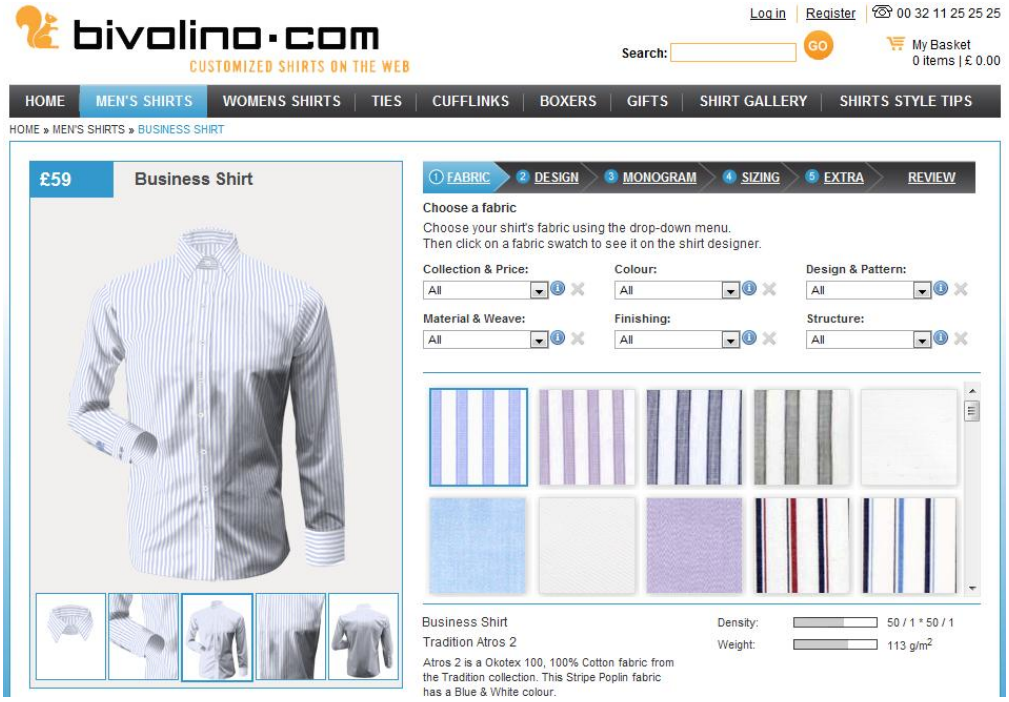



**Figure 5.3** – Illustration of Designing a Men Shirt on Bivolino website – Shirts Attributes

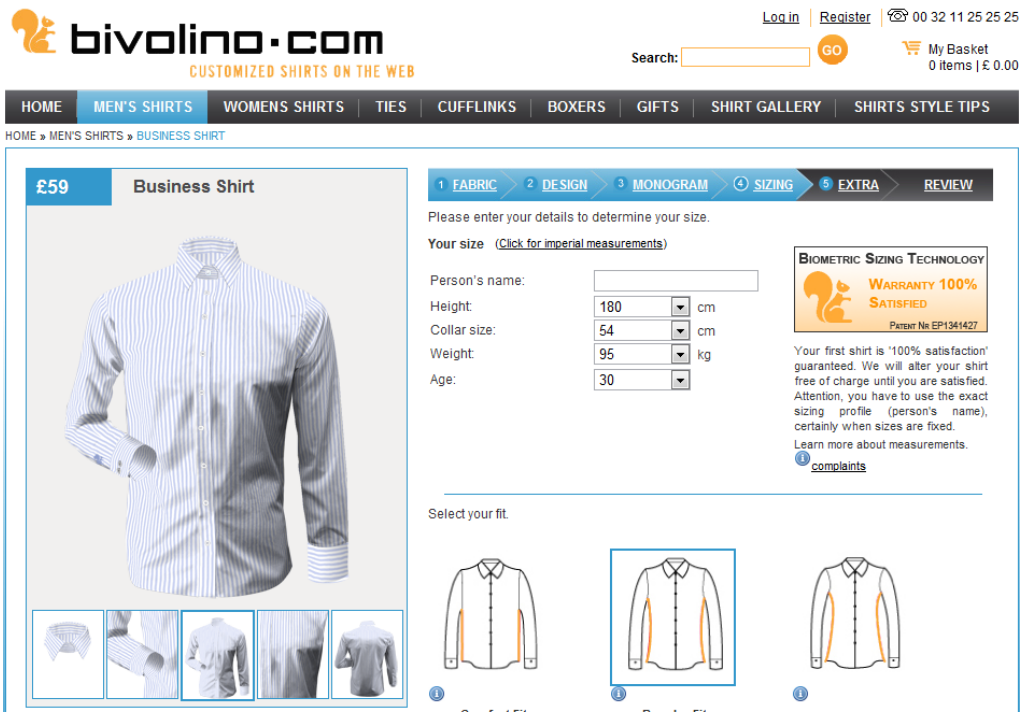



**Figure 5.4** – Illustration of Designing a Men Shirt on Bivolino website – Customers Attributes

In terms of the fabric, the company has about 300 different types available for men shirts. In this cluster the preferred fabric is "Sheffield" and we can see in Figure 5.5 that this type of fabric is on the top 13, since in 10.281 men shirts sold by the company in 2011, 138 were produced with this fabric.

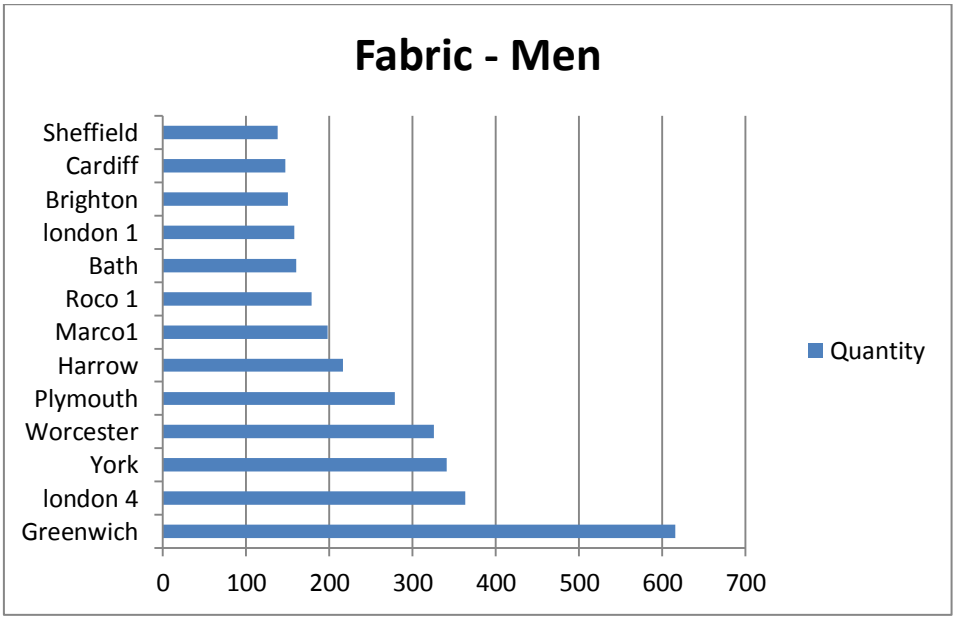



**Figure 5.5** – Fabrics of Men Shirts

In terms of the fabric color, the "multicolor" is the most desired color (Figure 5.6). In a total of 9.815 orders for men shirts, 695 were produced with this color. Company offers about 30 different fabric colors and in 2011 this color was on top 5.

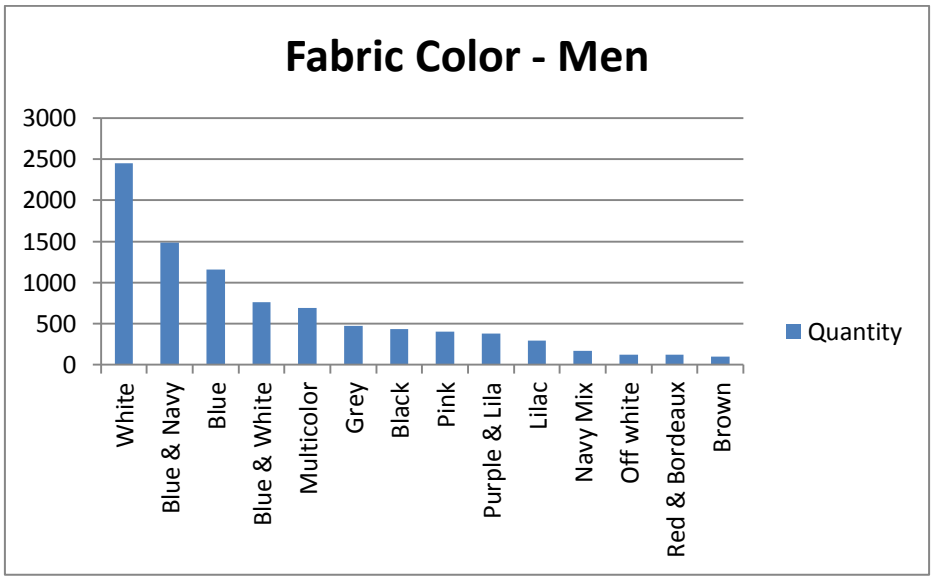



**Figure 5.6** – Fabric Colors of Men Shirts

The fabric design and pattern "Fine Stripe", in the 39 different customers' options, was in 2011 on top 11. In 9.815 men shirts orders, 137 were produced with this fabric design and pattern.

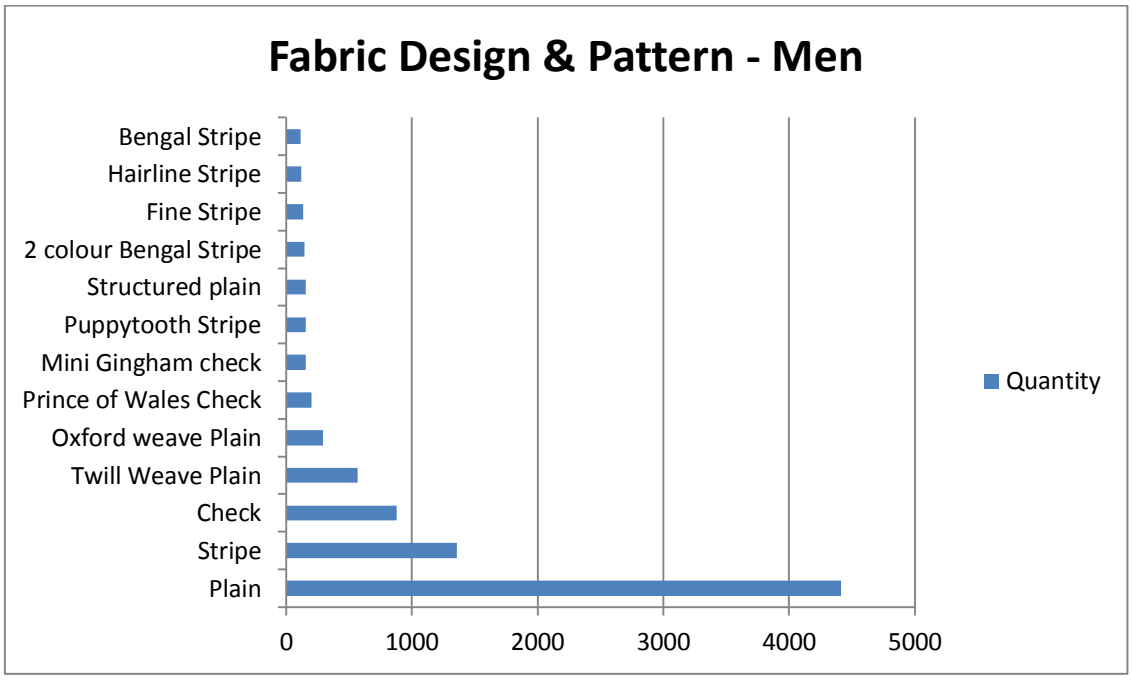



**Figure5.7** – Fabric Design and Pattern of Men Shirts

From 10 different types of fabric finish, the "Easy Iron" is undoubtedly the star. Figure 5.8 shows that in almost 50% of men shirts orders the type of fabric finish applied was this one.

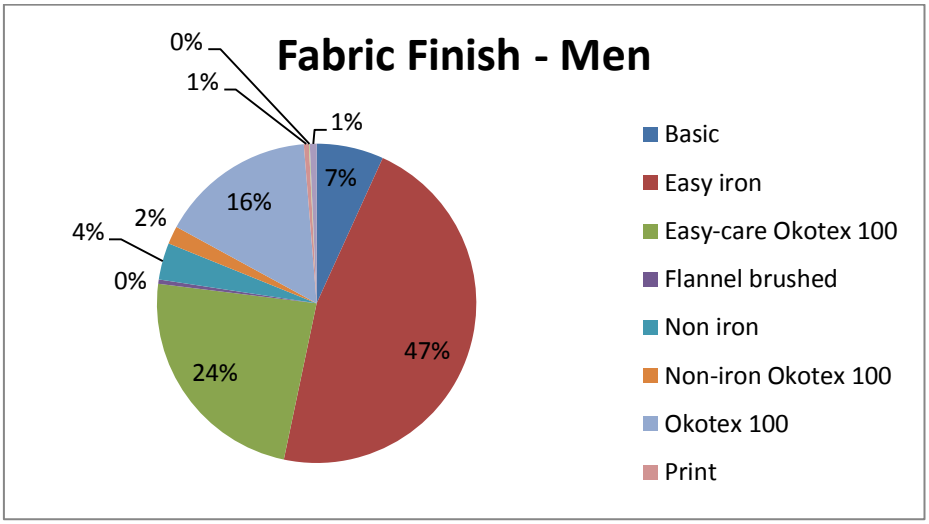



**Figure 5.8** – Fabric Finish of Men Shirts

Among 9 possible options in terms of shirts fabric structure, Figure 5.9 demonstrates that "Dobby" was the third most wanted.

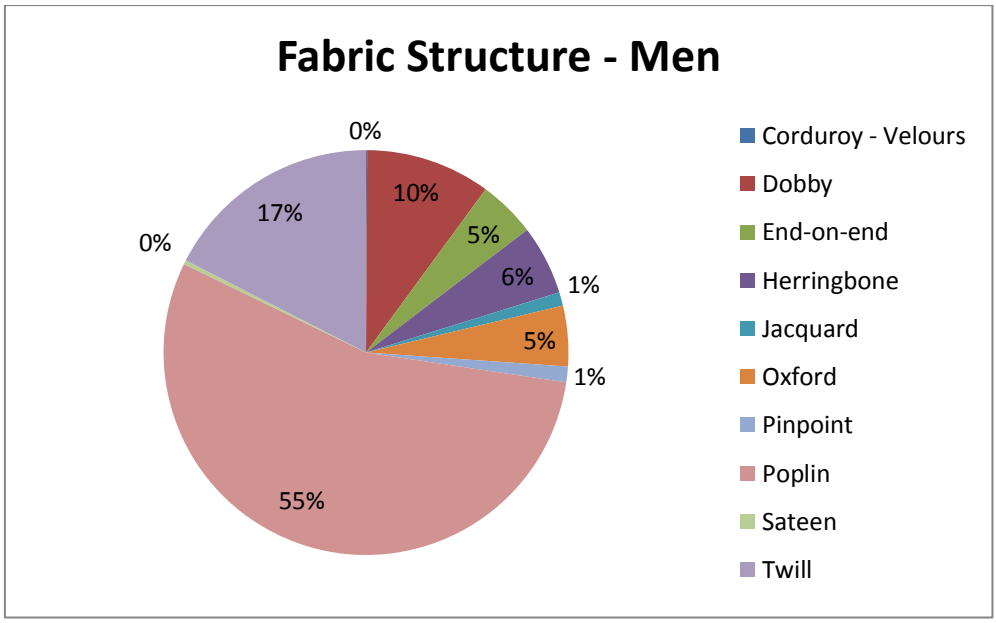



**Figure 5.9** – Fabric Structure of Men Shirts

The fabric material "100% Cotton" is the preferred by the majority of male customers since in Figure 5.10 is shown that more than 80% chose this fabric material.

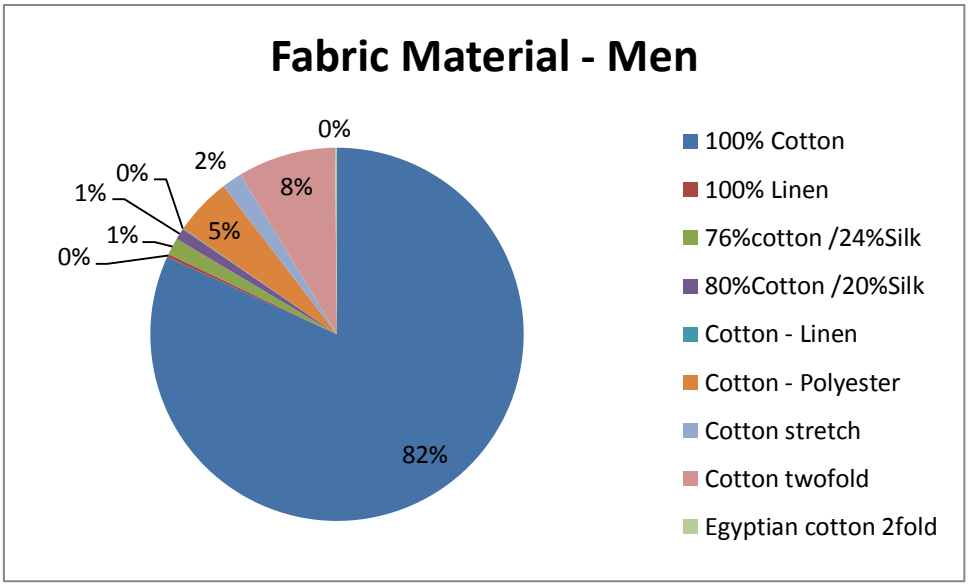



**Figure 5.10** – Fabric Material of Men Shirts

The collar "Hai Cutaway" was the third most wanted in 27 varieties available. In Figure 5.11 we can see that more than 1.000 shirts sold had this type of collar.

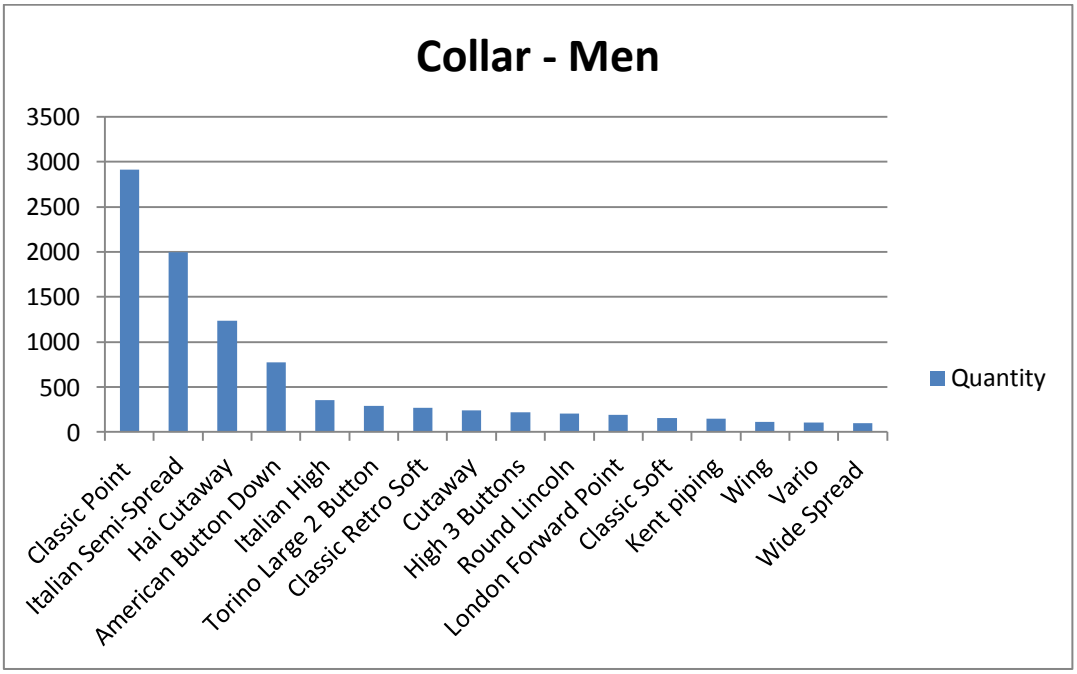



**Figure 5.11** – Collar of Men Shirts

In Figure 5.12 we can note that the cuff "Double inc. Cufflinks" is the second most wanted (24% of total men shirt orders) among 9 different options.

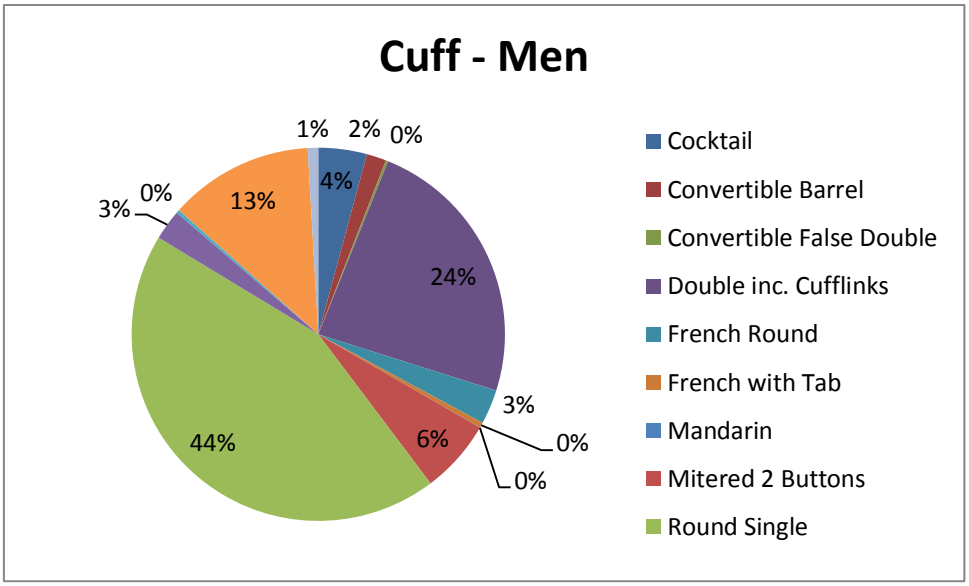



**Figure 5.12** – Cuff of Men Shirts

The placket "Folded" is the second choice of customers since 25% of total shirts orders had this placket type (Figure 5.13).

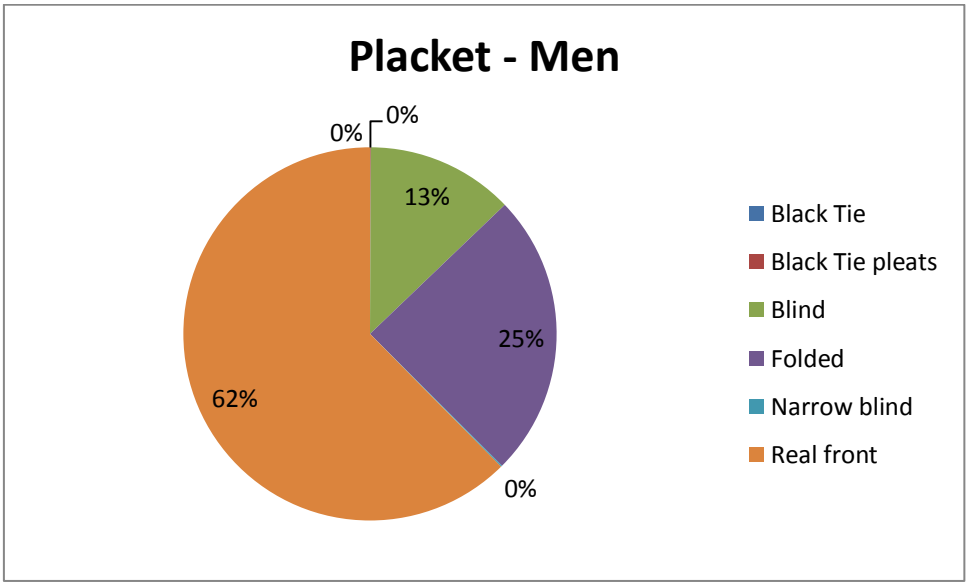



**Figure 5.13** – Placket of Men Shirts

Most of the hem of shirts ordered were "Curved with Gussets" which represented 30% of total orders as we can verify in Figure 5.14.

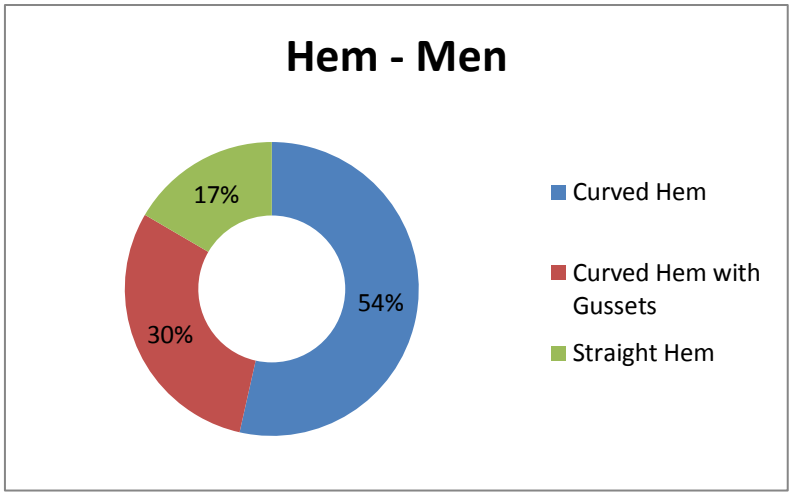



**Figure 5.14** – Hem of Men Shirts

The collar and the cuff of the shirts represented in this cluster are different in color in relation to the shirt (they are both white), and while they do not have pockets or monograms they do have a back yoke contrast. Table 5.2 shows that in general customers do not choose to add these five attributes to their shirts.

In conclusion, cluster 1 gives us information about fashion trends of work shirts for young male workers based on past information from Bivolino shirts orders relative to 2011. Based on that information, the company would be able to predict future fashion trends on shirts, and therefore keeping ahead of its potential competitors.

| **Attribute** | **Value** | **Total** | **Total (%)** |
|---|---|---|---|
| Collar White | Yes | 866 | 9% |
| | No | 8.949 | 91% |
| **Total** | | **9.815** | **100%** |
| Cuff White | Yes | 741 | 8% |
| | No | 9.074 | 92% |
| **Total** | | **9.815** | **100%** |
| Has Pocket | Yes | 3.225 | 33% |
| | No | 6.590 | 67% |
| **Total** | | **9.815** | **100%** |
| Has Monogram | Yes | 2.733 | 28% |
| | No | 7.082 | 72% |

| Attribute | Value | Total | Total (%) |
|---|---|---|---|
| **Total** | | **9.815** | **100%** |
| Back Yoke | Yes | 4.353 | 44% |
| Contrast | No | 5.462 | 56% |
| **Total** | | **9.815** | **100%** |

**Table 5.2** – Representation of Binominal Attributes

**Cluster 2**

| Cluster | Size | Gender | Postal code | Country | Configuratort | Collectiont | Fabric | Collar | Cuff | Placket | Collar white | Cuff white | Shirt gender | Afiliate | Hem |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 4.889 | men | g41_1ag | uk | Work Shirt | Retailer1 Man Plain | Greenwich | Classic Point | Round Single | Real front | n | n | men | Retailer1 | Curved Hem |

| Cluster | Back Yoke Contrast | Fabric color | Fabric design pattern | Fabric finish | Fabric material | Fabric structure | has Monogram | has Pocket | Age Group | BMI Fatness | Height Group | Collar Group | Is Collar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | y | White | Plain | Easy iron | 100prcnt Cotton | Poplin | No | No | 25/34 | Normal | 170-179 | <_36 | No | 60kg-80kg | No |

**Figure 5.15** – Representation of Cluster 2

Cluster 2 grouped 4.889 shirt orders which represented about 45% of the total orders of the company in 2011. It is the biggest cluster of this clustering result. Like cluster 1, this cluster also represents young men from the United Kingdom that have a preference for work shirts from Retailer1 collection but it differs from cluster 1 based in some of the shirts attributes, i.e., for the same shirt attributes some values are distinctly different between each other. They are:

| Attribute | Value |
|---|---|
| Fabric | Greenwich |
| Fabric color | White |
| Fabric design pattern | Plain |
| Fabric finish | Easy iron |
| Fabric structure | Poplin |
| Fabric material | 100% Cotton |
| Collar | Classic Point |
| Collar white | no |
| Cuff | Round Single |

| Attribute | Value |
|---|---|
| Cuff white | no |
| Placket | Real Front |
| Pocket | no |
| Monogram | no |
| Hem | Curved |
| Back yoke contrast | yes |

**Table 5.3** – Shirts Attributes Values of Cluster 2

The shirts attributes that assume the same value as in Cluster 1 are:

| Attribute | Value | Observations |
|---|---|---|
| Fabric finish | Easy iron | See Figure 5.8 |
| Fabric material | 100% Cotton | See Figure 5.10 |
| Collar white | no | See Table 5.2 |
| Cuff white | no | See Table 5.2 |
| Pocket | no | See Table 5.2 |
| Monogram | no | See Table 5.2 |
| Back yoke contrast | yes | See Table 5.2 |

**Table 5.4** – Similarities against Cluster 1

Concerning the remaining shirt attributes, through the observation of Figure 5.5 we can note that the fabric “Greenwich” is the most wanted and used for the production of shirts. Regarding the fabric color, if we look at Figure 5.6 we can see that the more common is the “white” while the fabric design and pattern “Plain” is also the preferred (Figure 5.7). As for fabric structure, “Poplin” represented more than 50% of the total fabric structures used on production of all the orders in analysis (Figure 5.9). The collar “Classic Point” was the option in almost 3.000 orders, representing 27% of total (Figure 5.11) and the cuff “Round Single” is the first choice of the customers, representing 44% of the orders (Figure 5.12). The placket “Real Front” represents the most common option (Figure 5.13) as well the “Curved Hem” (Figure 5.14).

In conclusion, cluster 2 is very representative of the most common customer's choices in terms of shirts attributes. This is visible not only on the cluster size (4.889 orders, i.e., 45% of 10.775 orders) but also in the information given by the figures.

**Cluster 3**

| Cluster | Size | Gender | Postal code | Country | Configuratort | Collectiont | Fabric | Collar | Cuff | Placket | Collar white | Cuff white | Shirt gender | Afiliate | Hem |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 872 | men | 35037 | de | Fashion Shirt | Italian Luxury | Juan_7 | Mao | Round Single | Folded | n | n | men | Bivolino | Straight Hem |

| Cluster | Back Yoke Contrast | Fabric color | Fabric design pattern | Fabric finish | Fabric material | Fabric structure | has Monogram | has Pocket | Age Group | BMI Fatness | Height Group | Collar Group | Is Collar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | n | Red & Bordeaux | Plain | Easy iron | Cotton twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100kg-120kg | Yes |

**Figure 5.16** – Representation of Cluster 3

Cluster 3 grouped 872 shirt orders which represented about 8% of the total orders of the company in 2011. It is smaller than the other two clusters already analyzed and in terms of attribute values, it is very different. This cluster represents a more mature men customers (45 to 54 years old) from Germany (de) that have a preference for fashion shirts from an "Italian Luxury" collection with the following characteristics:

| Attribute | Value |
|---|---|
| Fabric | Juan 7 |
| Fabric color | Red & Bordeaux |
| Fabric design pattern | Plain |
| Fabric finish | Easy iron |
| Fabric structure | Twill |
| Fabric material | Cotton twofold |
| Collar | Mao |
| Collar white | no |
| Cuff | Round Single |
| Cuff white | no |
| Placket | Folded |
| Pocket | yes |
| Monogram | yes |

| Attribute | Value |
|---|---|
| Hem | Straight |
| Back yoke contrast | no |

**Table 5.5** – Shirts Attributes Values of Cluster 3

Despite being very different, this cluster still has some attributes values in common with both cluster 1 and cluster 2.

| Attribute | Value | Similarity to | Observations |
|---|---|---|---|
| Fabric design pattern | Plain | Cluster 2 | See Figure 5.7 |
| Fabric finish | Easy iron | Cluster 1 and 2 | See Figure 5.8 |
| Cuff | Round Single | Cluster 2 | See Figure 5.12 |
| Placket | Folded | Cluster 1 | See Figure 5.13 |
| Collar white | no | Cluster 1 and 2 | See Table 5.2 |
| Cuff white | no | Cluster 1 and 2 | See Table 5.2 |

**Table 5.6** – Similarities against Cluster 1 and Cluster 2

This cluster, unlike cluster 1 and cluster 2, represents a small group of orders with some distinctive characteristics. Starting with the fabric, the "Juan 7"[9] in 10.281 shirts sold by Bivolino in 2011, only 15 shirts were produced with this type of fabric yet the fabric color "Red & Bordeaux" was the 13$^{th}$ choice in a ranking of 31 different colors (Figure 5.6). The fabric structure "Twill" was the second most wanted type (Figure 5.9). Likewise, the fabric material "Cotton twofold" is the second type preferred (Figure 5.10). The type of collar "Mao" it is not a frequent option (it is not represented in Figure 5.11) since in total men shirt orders (9.815) only 31 was this type of collar. The "straight" hem was not chosen by the majority of customers (Figure 5.14) and unlike cluster 1 and cluster 2, cluster 3 represents orders where shirts have pocket, monogram and do not have back yoke contrast.

In conclusion, cluster 3 presents a very different pattern in terms of fashion trends which is probably related to, on one hand, a different class age (25-34 vs. 45-54) and nationality (United Kingdom vs. Germany) and on the other hand, to a different configurator of the shirt used (work shirt vs. fashion shirt) and BMI indices (Normal vs.

[9] The fabric "Juan 7" is not represented in Figure 5.5 – Fabric of Men Shirts because of its little representation on overall 302 different types of fabric.

Obese). Later on this dissertation, we will be able to see that there is effectively a relation between all these factors; that fashion trends or product attributes are not inseparable from customer's physical attributes.

**Cluster 4**

| Cluster | Size | Gender | Postal code | Country | Configuratort | Collectiont | Fabric | Collar | Cuff | Placket | Collar white | Cuff white | Shirt gender | Afiliate | Hem |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 1.570 | men | ec2r_7bp | uk | Work Shirt | Savile Row Plain | london_4 | Italian Semi-Spread | Double inc. Cufflinks | Folded | n | n | men | Retailer1 | Straight Hem |

| Cluster | Back Yoke Contrast | Fabric color | Fabric design pattern | Fabric finish | Fabric material | Fabric structure | has Monogram | has Pocket | Age Group | BMI Fatness | Height Group | Collar Group | Is Collar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | y | White | Plain | Easy iron | 100prcnt Cotton | Poplin | No | No | 25/34 | Normal | 180-189 | <_36 | No | 80kg-100kg | No |

**Figure 5.17** – Representation of Cluster 4

Similar to the analysis to Cluster 1 and Cluster 2, Cluster 4 represents young men from the United Kingdom that have a preference for buying work shirts through Retailer1 website. This cluster grouped 1.570 shirt orders which represented about 15% of the total company orders in 2011. The shirts attributes represented in this cluster are the following:

| Attribute | Value |
|---|---|
| Fabric | London 4 |
| Fabric color | White |
| Fabric design pattern | Plain |
| Fabric finish | Easy iron |
| Fabric structure | Poplin |
| Fabric material | 100% Cotton |
| Collar | Italian Semi Spread |
| Collar white | no |
| Cuff | Double inc. Cufflinks |
| Cuff white | no |
| Placket | Folded |
| Pocket | no |
| Monogram | no |

| Attribute | Value |
|---|---|
| Hem | Straight |
| Back yoke contrast | yes |

**Table 5.7** – Shirts Attributes Values of Cluster 4

Cluster 4 shares the characteristics of clusters 1, 2 and 3 as we can see in Table 5.8.

| Attribute | Value | Similarity to | Observations |
|---|---|---|---|
| Fabric color | White | Cluster 2 | See Figure 5.6 |
| Fabric design pattern | Plain | Cluster 2 and 3 | See Figure 5.7 |
| Fabric finish | Easy iron | Cluster 1, 2 and 3 | See Figure 5.8 |
| Fabric structure | Poplin | Cluster 2 | See Figure 5.9 |
| Fabric material | 100% Cotton | Cluster 1 and 2 | See Figure 5.10 |
| Collar white | no | Cluster 1, 2 and 3 | See Table 5.2 |
| Cuff | Double inc. Cufflinks | Cluster 1 | See Figure 5.12 |
| Cuff white | no | Cluster 1, 2 and 3 | See Table 5.2 |
| Placket | Folded | Cluster 1 and 3 | See Figure 5.13 |
| Pocket | no | Cluster 1 and 2 | See Table 5.2 |
| Monogram | no | Cluster 1 and 2 | See Table 5.2 |
| Hem | Straight | Cluster 3 | See Figure 5.14 |
| Back yoke contrast | yes | Cluster 1 and 2 | See Table 5.2 |

**Table 5.8** – Similarities against Cluster 1, Cluster 2 and Cluster 3

As we can see cluster 4 only differs from the other three clusters in two attributes, on the fabric and on the collar. The fabric “London 4” was the second most common choice (Figure 5.5) with 363 out of 10.281 men shirts ordered with this type of fabric. The collar type “Italian Semi Spread” is also the second more wanted in 27 different types, representing about 20% of the total (Figure 5.11).

In conclusion, cluster 4 is very similar to cluster 1 and cluster 2 except in two attributes. Therefore we can say that young male workers have similar tastes and physical attributes with some differences in terms of fashion trends and preferences.

Once again we can confirm that some common factors like age and nationality have influence on tastes as well as the purpose of the buying (business minded or not).

**Cluster 5**

| Cluster | Size | Gender | Postal code | Country | Configuratort | Collectiont | Fabric | Collar | Cuff | Placket | Collar white | Cuff white | Shirt gender | Afiliate | Hem |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 500 | men | 23558 | de | – | Fashion Trend | Kiwi_9 | Torino Large 2 Button | Round Single | Real front | y | y | men | Retailer2 | Straight Hem |

| Cluster | Back Yoke Contrast | Fabric color | Fabric design pattern | Fabric finish | Fabric material | Fabric structure | has Monogram | has Pocket | Age Group | BMI Fatness | Height Group | Collar Group | Is Collar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | n | Purple & Lila | Plain | Easy-care kotex 100 | 100prcnt Cotton | Pinpoint | Yes | No | 25/34 | Normal | 180-189 | 40/41 | No | 60kg-80kg | No |

**Figure 5.18** – Representation of Cluster 5

Cluster 5 grouped 500 shirts orders which represented about 5% of the total orders of the company in 2011. This cluster is smaller than the other four clusters analyzed and it represents young men customers from Germany (de) that have a preference for fashion shirts from a "Fashion Trend" collection with the following characteristics:

| Attribute | Value |
|---|---|
| Fabric | Kiwi 9 |
| Fabric color | Purple & Lila |
| Fabric design pattern | Plain |
| Fabric finish | Easy Care Okotex 100 |
| Fabric structure | Pinpoint |
| Fabric material | 100% Cotton |
| Collar | Torino Large 2 Button |
| Collar white | yes |
| Cuff | Round Single |
| Cuff white | yes |
| Placket | Real Front |
| Pocket | no |
| Monogram | yes |
| Hem | Straight |

| Attribute | Value |
|---|---|
| Back yoke contrast | no |

**Table 5.9** – Shirts Attributes Values of Cluster 5

This cluster approaches to the others clusters in the following shirts attributes:

| Attribute | Value | Similarity to | Observations |
|---|---|---|---|
| Fabric design pattern | Plain | Cluster 2, 3 and 4 | See Figure 5.7 |
| Fabric material | 100% Cotton | Cluster 1, 2 and 4 | See Figure 5.10 |
| Cuff | Round Single | Cluster 2 and 3 | See Figure 5.12 |
| Placket | Real Front | Cluster 3 | See Figure 5.13 |
| Pocket | no | Cluster 1, 2 and 4 | See Table 5.2 |
| Monogram | yes | Cluster 3 | See Table 5.2 |
| Hem | Straight | Cluster 3 and 4 | See Figure 5.14 |
| Back yoke contrast | no | Cluster 3 | See Table 5.2 |

**Table 5.10** – Similarities against Cluster 1, Cluster 2, Cluster 3 and Cluster 4

The "Kiwi 9" fabric was used to produce only 7 shirts in the total of 10.281 men shirts orders in 2011. This type of fabric is not represented in Figure 5.5, only the ones more commonly used. In Figure 5.6 we can see that the fabric color "Purple & Lila" are among the most sought after and the fabric finish "Easy Care Okotex 100" was second on the top-list of customer's preferences among 8 different options (Figure 5.8). The fabric structure "Pinpoint" seems like an unusual choice since it is under-represented on the overall choices as shown in Figure 5.9, and in a total of 27 collar types the "Torino Large 2 Button" is in 6$^{th}$ place of the list of customer's preferences (Figure 5.11). In this cluster the collar and the cuff have the same color as the shirts, an attribute value ("yes") that only is assumed in this cluster.

In conclusion, and specifically comparing cluster 5 to cluster 3, we can say that despite the nationality (de) and the configurator of the shirts (fashion) being the same, these two clusters present very different fashion trends. This could be partially explained by the age class (25-34 vs. 45-54) and other physical attributes such as BMI indices (normal vs. obese).

**Cluster 6**

| Cluster | Size | Gender | Postal code | Country | Configuratort | Collectiont | Fabric | Collar | Cuff | Placket | Collar white | Cuff white | Shirt gender | Afiliate | Hem |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | 1.662 | men | 38106 | de | _ | Fashion Trend | Miro_3 | Classic Point | RoundSingle | Real front | n | n | men | Retailer2 | Curved Hem |

| Cluster | Back Yoke Contrast | Fabric color | Fabric design pattern | Fabric finish | Fabric material | Fabric structure | has Monogram | has Pocket | Age Group | BMI Fatness | Height Group | Collar Group | Is Collar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | n | Blue & Navy | Plain | Easy-care kotex 100 | Cotton twofold | Herringbone | No | No | 25/34 | Overweight | 170-179 | 40/41 | No | 80kg-100kg | No |

**Figure 5.19** – Representation of Cluster 6

Cluster 6 grouped 1.662 shirt orders which represented about 15% of the total orders of the company in 2011. This cluster represents young men customers from Germany (de) which have a preference for fashion shirts from the "Fashion Trend" collection with the following attributes:

| Attribute | Value |
|---|---|
| Fabric | Miro 3 |
| Fabric color | Blue & Navy |
| Fabric design pattern | Plain |
| Fabric finish | Easy Care Okotex 100 |
| Fabric structure | Herringbone |
| Fabric material | Cotton twofold |
| Collar | Classic Point |
| Collar white | no |
| Cuff | Round Single |
| Cuff white | no |
| Placket | Real Front |
| Pocket | no |
| Monogram | no |
| Hem | Curved |
| Back yoke contrast | no |

**Table 5.11** – Shirts Attributes Values of Cluster 6

This cluster has some similarities between the precedents clusters already analyzed as presented in Table 5.12.

| Attribute | Value | Similarity to | Observations |
|---|---|---|---|
| Fabric design pattern | Plain | Cluster 2, 3,4 and 5 | See Figure 5.7 |
| Fabric finish | Easy Care Okotex 100 | Cluster 5 | See Figure 5.8 |
| Fabric material | Cotton twofold | Cluster 3 | See Figure 5.10 |
| Collar | Classic Point | Cluster 2 | See Figure 5.11 |
| Cuff | Round Single | Cluster 2, 3 and 5 | See Figure 5.12 |
| Collar white | no | Cluster 1, 2, 3, 4 | See Table 5.2 |
| Cuff white | no | Cluster 1, 2, 3, 4 | See Table 5.2 |
| Placket | Real Front | Cluster 2 and 5 | See Figure 5.13 |
| Pocket | no | Cluster 1, 2, 4 and 5 | See Table 5.2 |
| Monogram | no | Cluster 2 and 4 | See Table 5.2 |
| Hem | Curved | Cluster 2 | See Figure 5.14 |
| Back yoke contrast | no | Cluster 3 and 5 | See Table 5.2 |

**Table 5.12** – Similarities against Cluster 1, Cluster 2, Cluster 3, Cluster 4 and Cluster 5

Despite those similarities, cluster 6 distinguishes from them in other attributes like the fabric “Miro 3” which is not a very frequent choice and because of this not represented in Figure 5.5. In other words, this type of fabric was only used on the production of 20 men shirts in a total of 10.281. The fabric color “Blue & Navy” is the second most used (Figure 5.6) and finally, the fabric structure “Herringbone” is the fourth choice in a variety of 10 different types (Figure 5.9).

In conclusion and specifically comparing to cluster 3 and cluster 5, due to the fact they represent customers with the same nationality (de) and orders with the same configurator (fashion), cluster 6 shows that despite these common issues we can still find different patterns, tastes, preferences and fashion trends.

## 5.3. Conclusions of the Clustering Results

In this section we analyzed the results of a K-Medoids clustering for a *k* number of clusters established *a priori* (*k* = 6) based in a dataset of 10.775 examples (n = 10.775) which correspond to the number of shirts orders of Bivolino in 2011.

The analysis was focused on 29 attributes which were divided into three different categories according to the entity it describes, they are the orders, the shirts and the customers (Table D.2, Table D.3 and Table D.4 on Annex D). We focused the study mainly on the attributes that describe the shirts and the orders because our purpose was to identify the shirts fashion trends based on the customers choices in terms of shirts attributes.

Once the most common attributes values in shirts orders were identified, the production and/or purchasing department and the fashion designers would be able to better perform their tasks, because they already have information about the type and quantity of the raw material needed as well the shirts fashion trends.

In short, we can say that DM tools and techniques are indeed valuable instruments to better understand consumer tastes and preferences allowing companies to be more efficient and responsive to customer's requests and gaining a competitive advantage.

# 6. RESULTS ANALYSIS IN A MARKETING PERSPECTIVE

*"The gratification comes in the doing,*
*Not in the results."*
By James Dean, an American actor

## 6.1. Identification of Segments

In order to perform an analysis in a marketing perspective, we found it useful to add more variables[10] (or attributes) to the clustering process. The new variables are mentioned on Table D.2, Table D.3 and Table D.4 on Annex D and are marked in a different color.

As a result of adding more variables to the analysis the results are different from the first ones, even though the number of *k* clusters and *n* examples remains the same. So, for a clustering with a k=6 defined *a priori* and a dataset of n=10.775 but now with 59 attributes and not 29, the new results are as shown in Figure 6.1.

| Cluster | Size | Gender | Postal code | Country | Quantity | Selling price | Delivery price | Voucher | Card type | Configuratort | Collectiont | Fabric | Measures in cm | Fit | Age | Imperial |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2.687 | men | sy2 6lg | uk | 1 | 64 | 3,5 | NULL | mastercard | Work Shirt | Savile Row Design | Canterbury | 2 | Regular | 40 | y |
| 2 | 5.116 | women | 34090 | fr | 1 | 89 | 6 | v92p46nxw | american express | Party Women | Glamour | Vola1 | 1 | Georgia relaxed module | 38 | n |
| 3 | 2.316 | men | sg4 9aq | uk | 1 | 53 | 3,5 | NULL | visa | Party Shirt | Autograph Design | Dubai | 2 | Regular | 48 | y |
| 4 | 80 | men | co4 5bq | uk | 1 | 61 | 3,5 | NULL | visa | Work Shirt | Savile Row Plain | York | 1 | Regular | 49 | n |
| 5 | 564 | men | cv31 3nd | uk | 1 | 52 | 0 | NULL | visa | Work Shirt | M&S Man Design | Sheffield | 2 | Super Slim Fit | 25 | y |
| 6 | 12 | men | 22049 | de | 1 | 60 | 6 | NULL | visa | unknown | Fashion Trend | Miro 7 | 1 | Super Slim Fit | 26 | n |
| Total | 10.775 | | | | | | | | | | | | | | | |

[10] Instead of using 29 attributes to run the clustering, we now have 59 attributes, i.e., an additional 30 than we initially had. However, not all will appear in the new result because despite its importance for running the clustering, they are not of much significant for the analysis.

| Cluster | Collar size | Weight kg | Height cm | Rating | Monogram | collar | Cuff | Placket | Pocket | Collar white | Cuff white | MODEL | Shirt gender | Affiliate | Hem | Back Yoke Contrast | Fabric colour | fabric design pattern |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 18 | 98 | 185 | 1.8 | BARR | Hai Cutaway | Double inc. Cufflin | Real front | NULL | n | n | 51 | men | Retailer1 | Curved Hem | y | Blue | Mini Gingham check |
| 2 | 52 | 110 | 176 | 1.8 | NULL | basic open | Mini puffed | Ruffle | NULL | n | n | 89 | women | Bivolino | Curved Hem with Gussets | n | Multicolor | Print |
| 3 | unknown | 76 | 173 | 1.8 | NULL | Classic Point | Round Single | Real front | Mitred | n | n | 51 | men | Retailer1 | Curved Hem | y | Purple Mix | Oxford Floral print |
| 4 | 41 | 82 | 175 | 1.8 | NULL | Italian Semi-Spread | Double inc. Cufflin | Real front | Mitred | n | n | 51 | men | Retailer1 | Curved Hem with Gussets | y | Blue | Twill Weave Plain |
| 5 | unknown | 75 | 188 | 1.8 | MSM | Hai Cutaway | Double inc. Cufflin | Folded | NULL | n | n | 51 | men | Retailer1 | Curved Hem with Gussets | y | Multicolor | Fine Stripe |
| 6 | 39 | 65 | 182 | 1.8 | NULL | Italian Semi-Spread | Round Single | Real front | NULL | n | n | 51 | men | Retailer2 | Curved Hem | n | Pink | Plain |

| Cluster | Fabric finish | Fabric material | Fabric structure | has Voucher | has Monogram | has Pocket | year | month | day Week | Age Group | BMIFatness | Height Group | Collar Group | IsCollar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Easy iron | 100% Cotton | Poplin | No | Yes | No | 2011 | 11 | 6 | 35/44 | Overweight | 180-189 | < 36 | No | 80kg -100kg | No |
| 2 | Print | Silk/ Cotton | Voile Semi-Transparent | Yes | No | No | 2011 | 10 | 6 | 35/44 | Obese | 170-179 | 52/53 | No | 100kg-120kg | Yes |
| 3 | Easy iron | 100% Cotton | Oxford | No | No | Yes | 2011 | 12 | 7 | 45/54 | Overweight | 170-179 | 60> | Yes | 60kg-80kg | No |
| 4 | Easy iron | 100% Cotton | Twill | No | No | Yes | 2011 | 11 | 2 | 45/54 | Overweight | 170-179 | 41/42 | No | 80kg-100kg | No |
| 5 | Easy iron | 100% Cotton | Dobby | No | Yes | No | 2012 | 1 | 4 | 25/34 | Normal | 180-189 | 60> | Yes | 60kg-80kg | No |
| 6 | Easy-care Okotex 100 | 100% Cotton | Herringbone | No | No | No | 2011 | 5 | 2 | 25/34 | Normal | 180-189 | 39/40 | No | 60kg-80kg | No |

**Figure 6.1** – Result of K-Medoids Clustering Extract Cluster Prototype for k=6 with extra variables

Comparing this clustering result to the previous results on section 5.1, we can see that the clusters are slightly different, both in terms of size, attributes values and patterns, but also in their representation, being cluster 2 the most representative.

| Cluster | Size | Size (%) |
|---|---|---|
| 1 | 2.687 | 25% |
| 2 | 5.116 | 47% |
| 3 | 2.316 | 21% |
| 4 | 80 | 1% |
| 5 | 564 | 5% |
| 6 | 12 | 1% |
| **Total** | **10.775** | **100%** |

Besides that, if we look at Figure 6.1 we can see that cluster 2 differs from all the others and brings us new information, i.e., it represents women that are receptive to sales promotions (vouchers). Its distinct attributes values are represented on Table 6.1.

| Attribute | Value |
|---|---|
| Gender | Women |
| Country | fr |
| Configuratort | Party women |
| hasvoucher | Yes |
| BMIFatness | Obese |
| Weight_Group | 100kg-120kg |
| isObese | Yes |

**Table 6.1** – Representation of Distinct Attributes Values of Segment 2

This means that we could now segment the market of shirts costumers based on a demographic variable, the "gender". Table 6.2 represents a division of the Bivolino shirts orders by gender, where the low representation of women in 2011 is notorious, what is probably related to the fact that Bivolino only introduced the women shirts collection into the market in 2011.

| Gender | Total orders | Total orders (%) |
|---|---|---|
| Men | 9.815 | 91% |
| Women | 960 | 9% |
| **Total** | **10.775** | **100%** |

**Table 6.2** – Representation of Bivolino Orders by Gender

Given that we added some more variables to our study and consequently gained a new clustering result, we have to interpret the new clusters. However since our analysis will now be focused on a marketing perspective, we have first to define our segmentation variables or segmentation bases, taking into account the variables and the information available.

## 6.2. Identification of Segmentation Variables

Given the variables and the information available, we were able to identify and classify the segmentation variables as following:

- **Demographic** *(Who they are)*
  - Gender: Male, Female
  - Age: [25-34], [35-44], [45-54]
  - Country (or Nationality): United Kingdom (uk), France (fr), Germany (de)

The company can segment its customers market according to the three demographic variables identified; they are the *gender*, the *age* and the *nationality*. This category of segmentation variables is, according to Kotler (2008), very popular in the way that these variables are often associated with consumer needs and wants and are easy to measure.

If company chooses to segment its customers market by gender, it has to take into account that "men and women have different attitudes and behave differently, based partly on genetic makeup and partly on socialization" (Kotler, 2008) and that "they have different expectations of fashion products" (Rocha *et al*, 2005).

If company will segment its customers on the basis of the age, the shirts have to be "designed to meet the specific needs of certain age groups" because "customer wants and abilities change with the age" (Kotler, 2008).

If company decides to segment its customer market based on nationality, it has to pay attention to the "identity attributes because of social and cultural values that inform the self" (Rocha *et al*, 2005).

- **Geographic** *(Where they live)*
  - Country: United Kingdom (uk), France (fr), Germany (de)
  - Postal code: sy2 6lg, 34090, sg4 9aq, co4 5bq, cv31 3nd, 22049

The company can divide its customers market into different countries and also into specific regions given the postal code. This kind of segmentation does not ensure that all customers in a location will make the same buying decision; however it helps in identifying some general patterns (Kotler, 2008).

- **Psychographic** *(How they behave)*

  - Lyfestyle: activities (work; social events or entertainment) and interests (job; fashion)

A psychographic segmentation is based on variables that are inferred such as *personality traits* (consumerism, dogmatism, locus of control, cognitive style, and religion), *personal values* and *lifestyle* (activities: work, hobbies, social events, entertainment, etc.; interests: family, home, job, fashion, etc.; opinions: of oneself, social issues, economics, culture, etc.).

As we did not have access to such kind of personal information we only could infer about it, so we propose to company segment its customers market according their lifestyle based on their activities (if shirt configurator type = work shirt or party shirt, for example) and interests (if shirt configurator type = work shirt or fashion shirt, for example).

- **Behavioristic** *(Why they buy)*

  - Price sensitivity (has voucher: yes; no)

Behavioral variables are considered by marketers "the best starting point for constructing market segments" (Kotler, 2008) and "are related to buying and consumption behavior" (Wedel and Kamakura, 2000). This category comprises variables such as occasions, benefits expectations, brand loyalty, price sensitivity, usage rate, end use, attitude, preferences, etc., where some can be directly measured and others have to be inferred.

Like the psychographic variables, we did not have enough information, however we identified the price sensitivity as a behavioristic variable which can be measured by the use or not of gift vouchers that offers discount on payment.

In summary:

| **Demographic variables** | **Geographic variables** |
|---|---|
| **- Age**<br>[25-34], [35-44], [45-54]<br>**- Gender**<br>Men, Female<br>- **Country (Nationality)**<br>United Kingdom (uk), France (fr), Germany (de)<br>**- Height (cm)**<br>[170-179], [180-189]<br>**- Weight (kg)**<br>[60-80[, [80-100[, [100-120[<br>**- BMI**<br>Normal, Overweight, Obese | **- Country**<br>United Kingdom (uk), France (fr), Germany (de)<br>**- Postal Code**<br>sy2 6lg, 34090, sg4 9aq, co4 5bq, cv31 3nd, 22049 |
| **Psycographic variables** | **Behavioristic variables** |
| **- Lifestyle**<br>Activities (work; social events or entertainment)<br>Interests (job; fashion) | **- Price sensitivity**<br>Vouchers /hasvoucher: yes, no |

**Table 6.3 –** Classification of Segmentation Variables
(Adapted from Kotler, 2008)

After the identification of the segmentation variables we are going to interpret each segment focusing, this time, not on shirt attributes, but on attributes that describe the customers and their relation to the product (shirts).

## 6.3. Interpretation of Segments

### Segment 1

| Cluster | Size | Gender | Postal code | Country | Quantity | Selling price | Delivery price | Voucher | Card type | Configuratort | Collectiont | Fabric | Measures in cm | Fit | Age | Imperial |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2.687 | men | sy2 6lg | uk | 1 | 64 | 3,5 | NULL | mastercard | Work Shirt | Savile Row Design | Canterbury | 2 | Regular | 40 | y |

| Cluster | Collar size | Weight kg | Height cm | Rating | Monogram | collar | Cuff | Placket | Pocket | Collar white | Cuff white | MODEL | Shirt gender | Affiliate | Hem | Back Yoke Contrast | Fabric colour | fabric design pattern |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 18 | 98 | 185 | 1.8 | BARR | Hai Cutaway | Double inc. Cufflinks | Real front | NULL | n | n | 51 | men | Retailer1 | Curved Hem | y | Blue | Mini Gingham check |

| Cluster | Fabric finish | Fabric material | Fabric structure | has Voucher | has Monogram | has Pocket | year | month | day Week | Age Group | BMIFatness | Height Group | Collar Group | IsCollar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Easy iron | 100% Cotton | Poplin | No | Yes | No | 2011 | 11 | 6 | 35/44 | Overweight | 180-189 | < 36 | No | 80kg -100kg | No |

**Figure 6.2** – Representation of Segment 1

Segment 1 comprises male customers from the United Kingdom (uk) that buy work shirts through Retailer1 website. Their buying intention is professional what means that their choices in terms of shirts characteristics are probably conditioned by a formal business dress code. The customers' characteristics in this segment are:

| Attribute | Value |
|---|---|
| Gender | Men |
| Country | uk |
| Age Group | [35-44] |
| Height Group (cm) | [180-189] |
| Weight Group (kg) | [80-100] |
| BMIFatness | Overweight |
| Collar Group | <36 |
| isCollarObese | No |
| isObese | No |

**Table 6.4** – Customers Attributes Values of Segment 1

In Figure 6.3 is shown the geographic representation of male customers where we can see that the majority are from the United Kingdom (uk) representing about 60%

of the total orders of men shirts, followed by Netherlands (nl), Germany (de), France (fr) and Belgium (be).

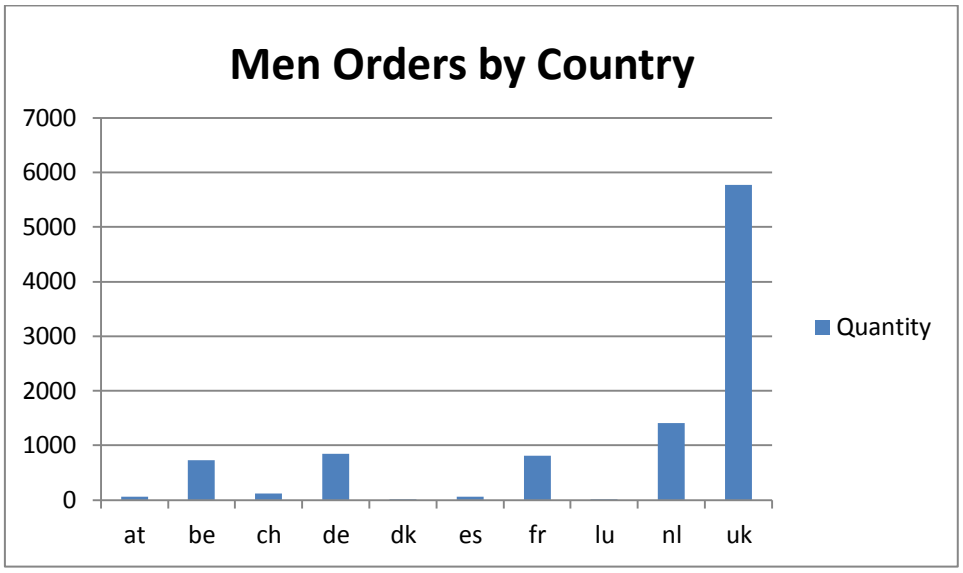



**Figure 6.3** – Representation of Men Orders by Country

In terms of the age, we can see on Figure 6.4 that the customers with an age between 35 and 45 years old are the customers that more buy Bivolino shirts, ensuring almost 30% of the sales.

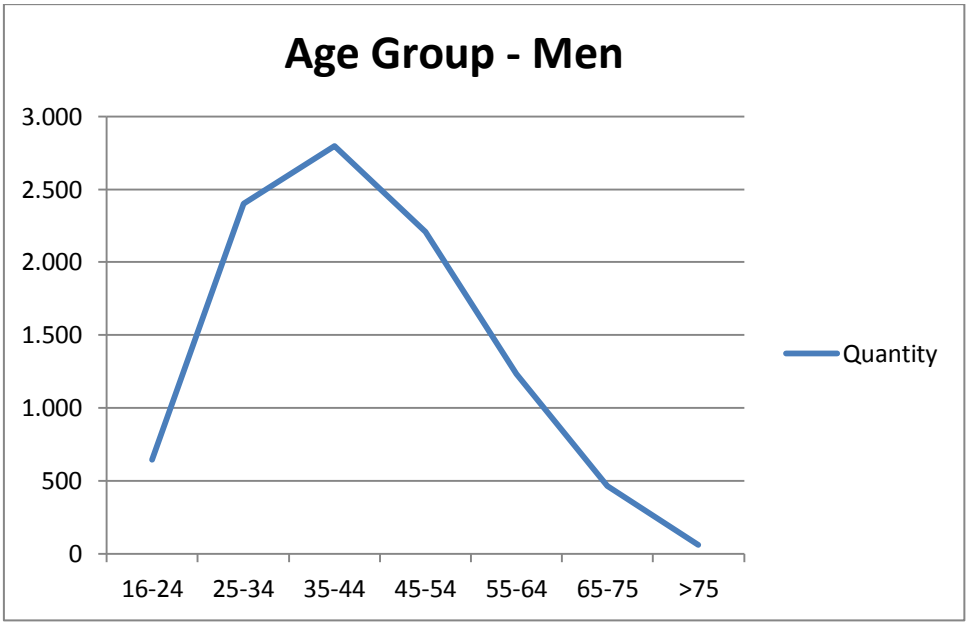



**Figure 6.4** – Age Groups of Male Customers

Figure 6.5 shows that the height groups [170cm-179cm] and [180cm-189cm] (also represented in the first results on Figure 5.1) are very representative of the majority of male customers and that the peak of sales is reached precisely on the group

of heights represented on this segment ([180cm-189cm]) corresponding to about 40% of the sales in 2011.

In terms of the weight groups, similarly we can see that the intervals [60kg-80kg], [80kg-100kg] and [100kg-120kg] are represented on both results (Figure 5.1 and Figure 6.1) and that the two first groups ensure about 74% of the sales (of men shirts) relative to the year of 2011. This is shown on Figure 6.6 where we can see that the peak of sales is attained for the age group represented on this segment ([80kg-100kg]).

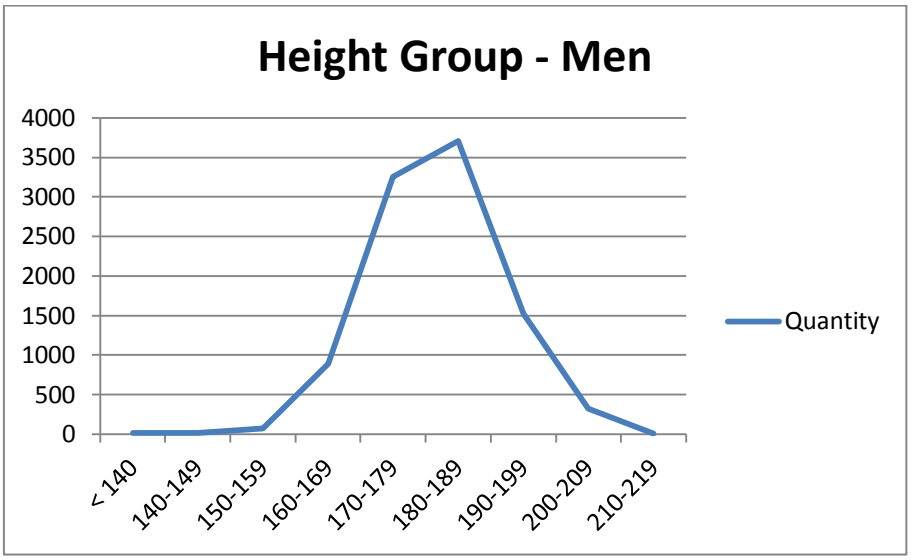



**Figure 6.5** – Height Groups (in cm) of Male Customers

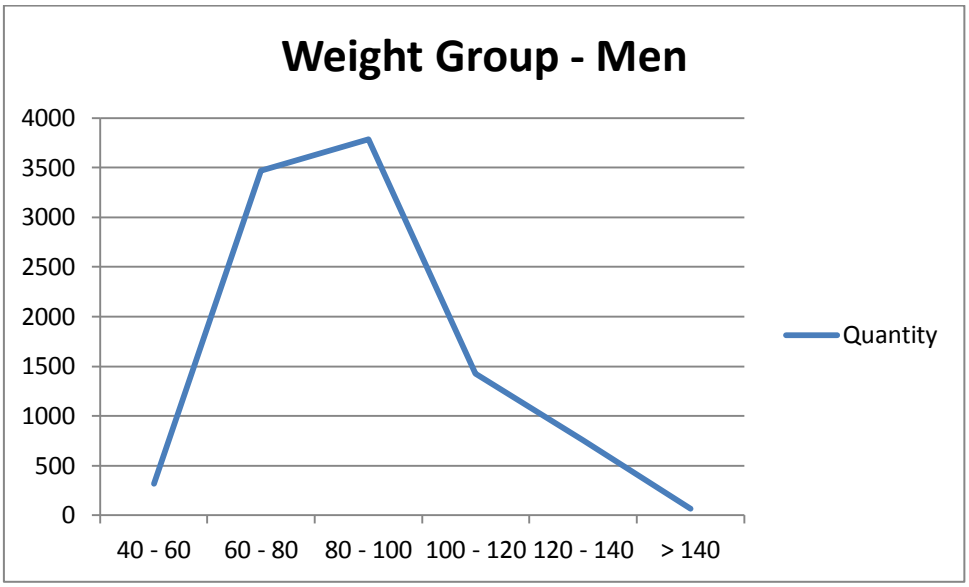



**Figure 6.6** – Weight Groups (in kg) of Male Customers

Still comparing the previous results (Figure 5.1) with the results analyzed in this chapter (Figure 6.1) we can note that the BMI[11] classes represented in both are the same: Normal, Overweight and Obese (Table D.5 on Annex D). In Figure 6.7 we can see that the most representative class is the Normal (42%) followed by the class Overweight (33%), that is represent on segment 1, and the class Obese (20%).

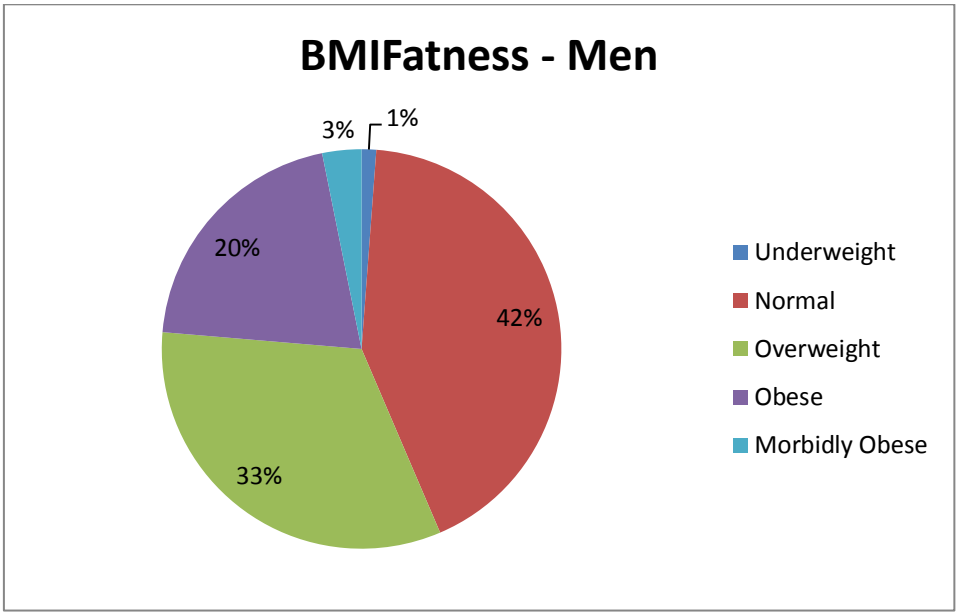



**Figure 6.7** – BMI measures of Male Customers

On Figure 6.8 is shown that the collar groups more representative correspond precisely to the two extreme measures, i.e., the collar group <36 and the collar group >60. Together they represent about 50% of the orders of men shirts, where 23% refers to the collar group represented on this segment, that is <36.

[11] The BMI (Body Mass Index) is a simple index of weight-for-height that is commonly used to classify underweight, overweight and obesity in adults. It is defined as the weight in kilograms divided by the square of the height in meters ($kg/m^2$). Source: WHO – World Health Organization - http://apps.who.int/bmi/index.jsp?introPage=intro_3.html

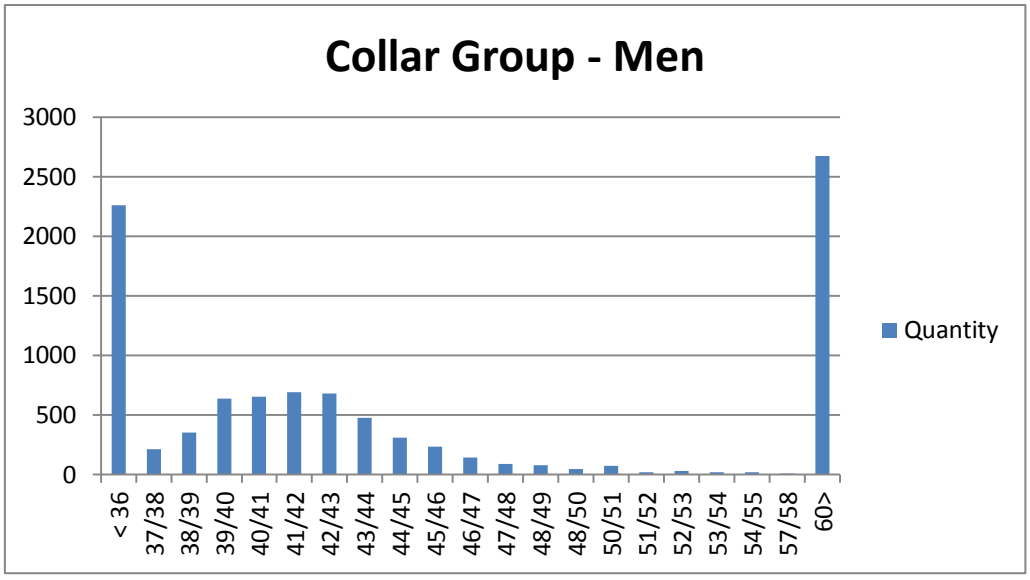



**Figure 6.8** – Collar Groups of Male Customers

The collar size, like the BMI, is used as a measure of the obesity of the customers where for sizes superior to 53 the customer is considered obese (Table D.5 on Annex D). On Table 6.3 we can see that only 28% of men customers are considered obese according to their collar size.

| isCollarObese | Value | Value (%) |
|---|---|---|
| Yes | 2.711 | 28% |
| No | 7.104 | 72% |
| **Total** | **9.815** | **100%** |

**Table 6.5** – Obesity of Male Customers measured by the Collar Size

Table 6.6 summarizes the two mentioned measures of obesity[12] where we can see that only 25% of the male customers are considered obese according to these measures.

[12] This emphasis on obesity measures of the customers is related to the CoReNet project. CoReNet main aim is to meet particular needs and expectations of widely represented European consumer targets - such as elderly, obese, disabled, diabetic people -, that usually look for clothes and footwear with particular functional requirements but, at the same time fashionable, high quality, eco-sustainable and at an affordable price (see *Annex F* for more details or visit http://www.corenet-project.eu/node/155).

| isObese | Value | Value (%) |
|---|---|---|
| Yes | 2.438 | 25% |
| No | 7.377 | 75% |
| **Total** | **9.815** | **100%** |

**Table 6.6** – Obesity of Male Customers

In conclusion, we can say that customers in this segment buy shirts for professional use (probably must follow a formal business dress code) and they do not seem to be price sensitive, since they do not use vouchers to get a discount on payment.

**Segment 2**

| Cluster | Size | Gender | Postal code | Country | Quantity | Selling price | Delivery price | Voucher | Card type | Configuratort | Collectiont | Fabric | Measures in cm | Fit | Age | Imperial |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 5.116 | women | 34090 | fr | 1 | 89 | 6 | v92p46nxw | american express | Party Women | Glamour | Vola1 | 1 | Georgia relaxed module | 38 | n |

| Cluster | Collar size | Weight kg | Height cm | Rating | Monogram | collar | Cuff | Placket | Pocket | Collar white | Cuff white | MODEL | Shirt gender | Affiliate | Hem | Back Yoke Contrast | Fabric colour | fabric design pattern |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | 52 | 110 | 176 | 1.8 | NULL | basic open | Mini puffed | Ruffle | NULL | n | n | 89 | women | Bivolino | Curved Hem with Gussets | n | Multicolor | Print |

| Cluster | Fabric finish | Fabric material | Fabric structure | has Voucher | has Monogram | has Pocket | year | month | day Week | Age Group | BMIFatness | Height Group | Collar Group | IsCollar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 2 | Print | Silk/ Cotton | Voile Semi-Transparent | Yes | No | No | 2011 | 10 | 6 | 35/44 | Obese | 170-179 | 52/53 | No | 100kg-120kg | Yes |

**Figure 6.9** – Representation of Segment 2

Segment 2 represents women from France with an age between 35 and 44 years old that buy shirts through Bivolino website for other purposes than professional related (configurator type = party shirt). The choices of the customers could not be conditioned by a business dress code but could be, for instance, for a special social event.

This segment has an attribute that is distinct from the others, that is the use of gift vouchers (Figure 6.10). In Table 6.7 we can see that 82% of women used vouchers on the orders payment and given that we can say that they are very receptive to sales promotions and price sensitive.

| Gender | Vouchers | Nº Vouchers | Nº Vouchers (%) |
|---|---|---|---|
| Women | Yes | 786 | 82% |
| | No | 174 | 18% |
| ***Total Women*** | | ***960*** | ***100%*** |
| Men | Yes | 5.022 | 51% |
| | No | 4.793 | 49% |
| ***Total Men*** | | ***9.815*** | ***100%*** |
| **Total** | Yes | 5.808 | 54% |
| | No | 4.967 | 46% |
| **Grand Total** | | **10.775** | **100%** |

**Table 6.7 –** Bivolino Gift Vouchers Usage Analysis

Taking into account that in 2011, women Bivolino shirts collection was for the first time introduced into the market, we may comment that these vouchers could refer to a special promotion used to stimulate an experiment based on a new product. Therefore, this kind of promotion could possibly not correspond to a recurring set pattern. Thus, this could just be a specifically targeted promotion, such as an atempt by the company to change its current consumer base, such as increasing the womens shirt sales. Considering these results it should adopt and outline further promotions and strategies of this kind, in an atempt to approach this public in a better way.


**Figure 6.10** – Bivolino Gift Vouchers

| Attribute | Value |
|---|---|
| Gender | Women |
| Country | fr |
| Age Group | [35-44] |
| Height Group (cm) | [170-179] |
| Weight Group (kg) | [100-120] |
| BMIFatness | Obese |
| Collar Group | 52/53 |
| isCollarObese | No |
| isObese | Yes |

**Table 6.8** – Customers Attributes Values of Segment 2

Similar to male customers, female customers from the United Kingdom (uk) lead the Bivolino shirts orders (Figure 6.11), however in this segment the women represented are from France (fr) that is the second country on the ranking representing 25% of total orders of women shirts.

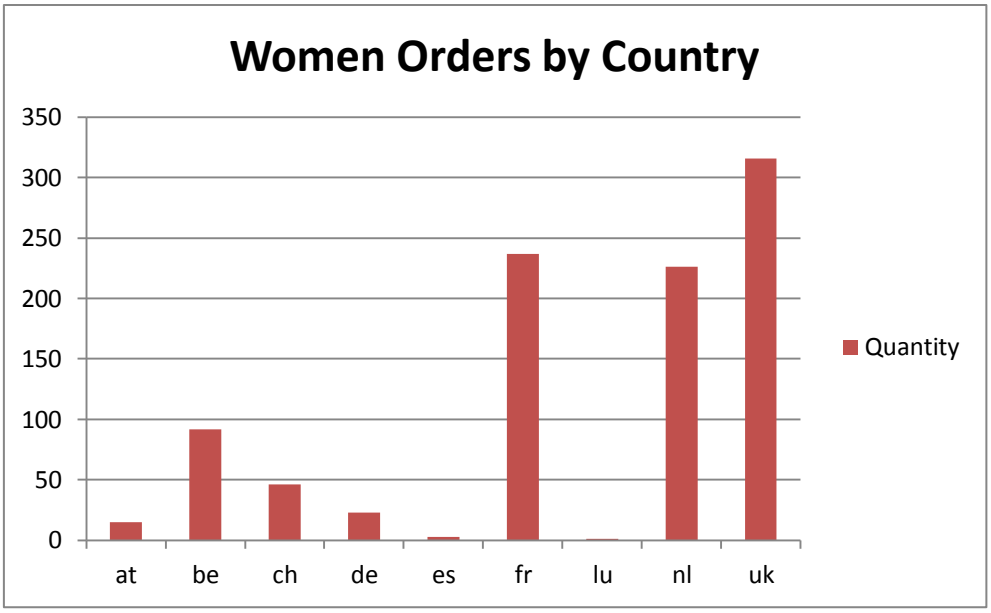



**Figure 6.11** – Representation of Women Orders by Country

Regarding the age (Figure 6.12), young women between 25 and 34 years old are the most representative group of women customers and it could be the most profitable segment. Normally they are considered to be consumerist, fashion addicted, heavy-users of fashion products, enthusiastic buyers and much of the time they buy on impulse. The interval of ages that comes next ([35-44]) is the one represented on this segment and represents about 28% of total orders of women shirts.

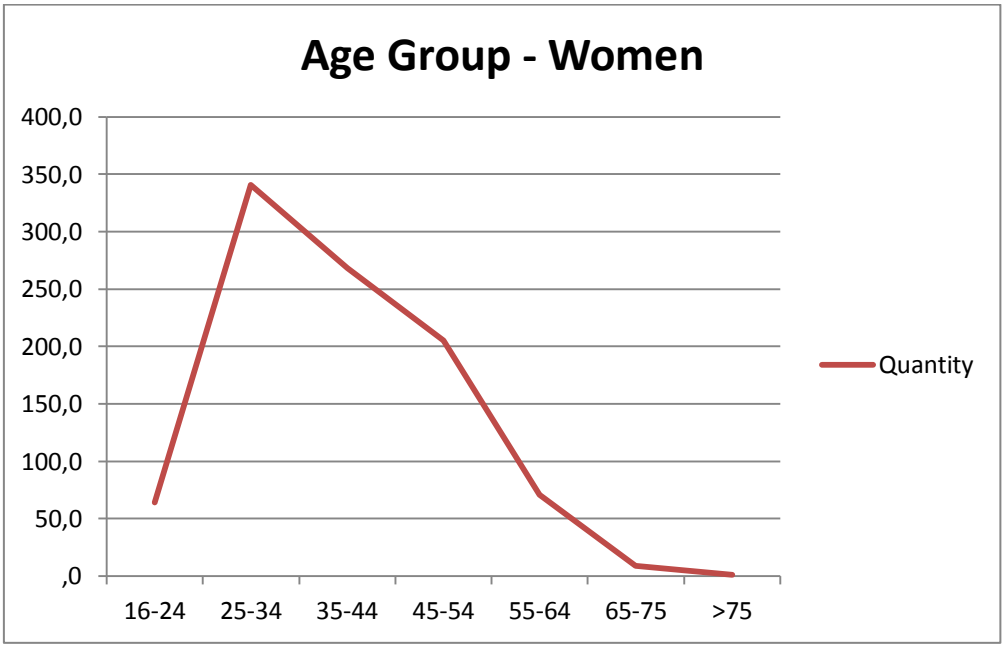



**Figure 6.12** – Age Groups of Female Customers

Women represented on this segment have a height between 170cm and 179cm and, despite not representing the majority of the female customers they represent 33% of the total orders of women shirts (Figure 6.13).

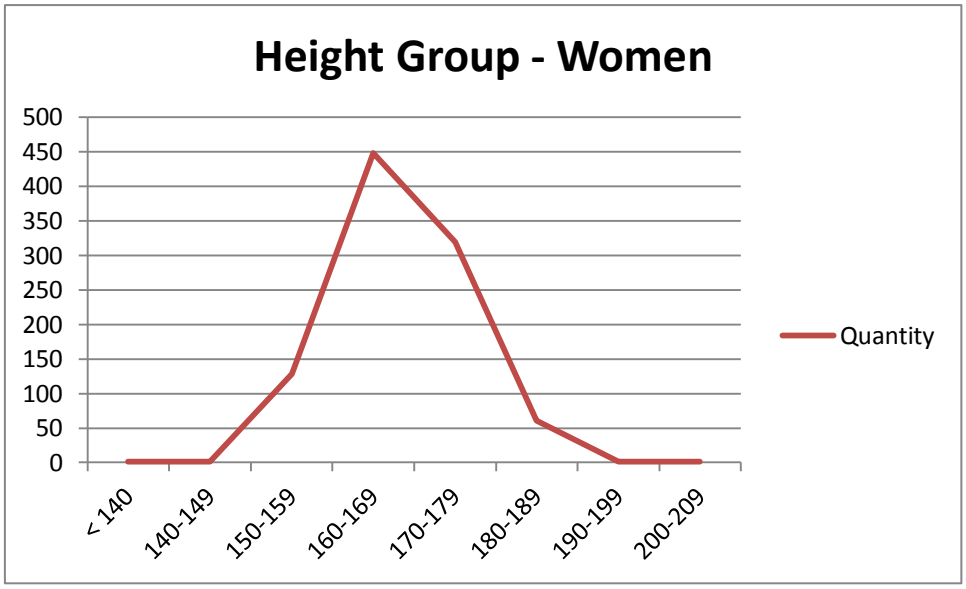



**Figure 6.13** – Height Groups (in cm) of Female Customers

Looking at Figure 6.14 we can conclude that the weight of women represented on this segment ([100kg-120kg]) refers to a minority, i.e., only 3% of women (31 in 960 total orders) that bought shirts from Bivolino on 2011 were overweight.

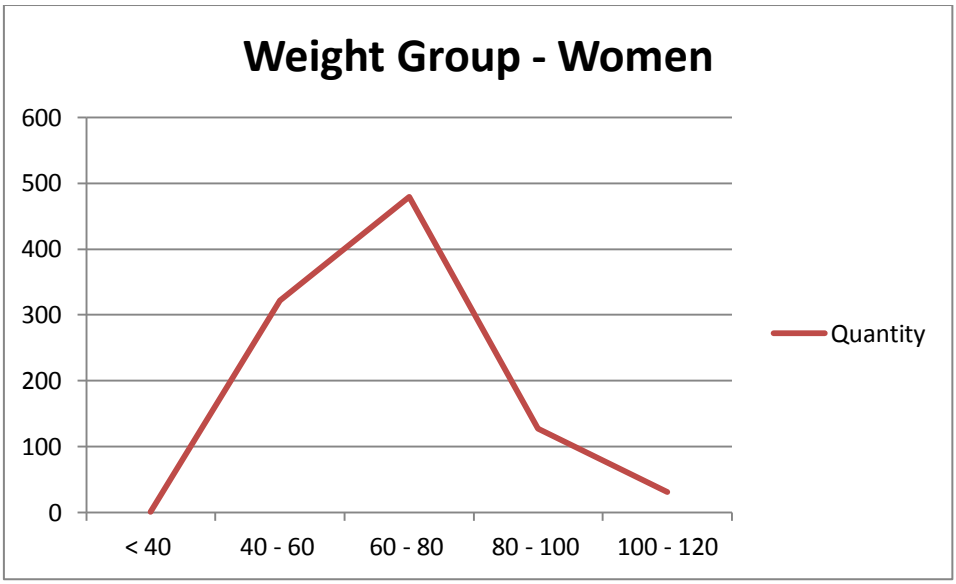



**Figure 6.14** – Weight Groups (in kg) of Female Customers

According to BMI measures women on this segment belongs to the obese class, and on Figure 6.15 we can see that obese women were just 11%, while the majority of the women customers belong to normal class, like the men customers.

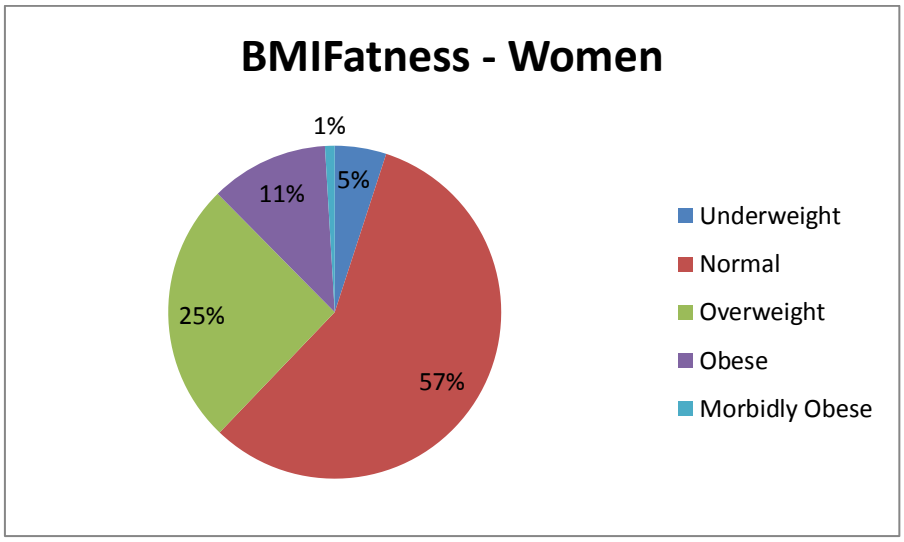



**Figure 6.15** – BMI measures of Female Customers

Likewise we can observe on Figure 6.16 that the collar size of women represented on this segment (52/53) refers to a minority (2%), i.e., only 16 orders in a total of 960 refer to this collar size. In terms of measuring the obesity of women customers based on their collar size, we can see on Table 6.9 that only 1% are considered obese and on Table 6.10 that, in general, obese women are only 4%.

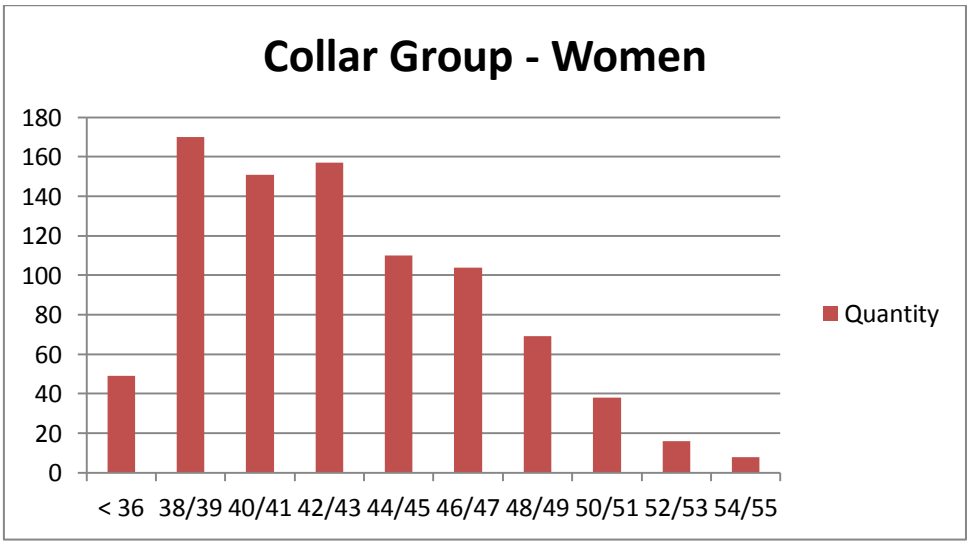



**Figure 6.16** – Collar Groups of Female Customers

| isCollarObese | Value | Value (%) |
|---|---|---|
| Yes | 8 | 1% |
| No | 952 | 99% |
| **Total** | **960** | **100%** |

**Table 6.9** – Obesity of Female Customers measured by the Collar Size

| isObese | Value | Value (%) |
|---|---|---|
| Yes | 39 | 4% |
| No | 921 | 96% |
| **Total** | **960** | **100%** |

**Table 6.10** – Obesity of Female Customers

In conclusion, this segment represents customers that suffer of obesity what means that they may face some difficulties in finding suitable clothing in traditional clothing stores. Shopping online for customized and tailored shirts is very convenient and comfortable for them, since customers do not have to search for stores in which to buy shirts which fit their size and requirements. This in turn, makes them feel more confident.

**Segment 3**

| Cluster | Size | Gender | Postal code | Country | Quantity | Selling price | Delivery price | Voucher | Card type | Configuratort | Collectiont | Fabric | Measures in cm | Fit | Age | Imperial |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | 2.316 | men | sg4 9aq | uk | 1 | 53 | 3,5 | NULL | visa | Party Shirt | Autograph Design | Dubai | 2 | Regular | 48 | y |

| Cluster | Collar size | Weight kg | Height cm | Rating | Monogram | collar | Cuff | Placket | Pocket | Collar white | Cuff white | MODEL | Shirt gender | Affiliate | Hem | Back Yoke Contrast | Fabric colour | fabric design pattern |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | unknown | 76 | 173 | 1.8 | NULL | Classic Point | Round Single | Real front | Mitred | n | n | 51 | men | Retailer1 | Curved Hem | y | Purple Mix | Oxford Floral print |

| Cluster | Fabric finish | Fabric material | Fabric structure | has Voucher | has Monogram | has Pocket | year | month | day Week | Age Group | BMIFatness | Height Group | Collar Group | IsCollar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | Easy iron | 100% Cotton | Oxford | No | No | Yes | 2011 | 12 | 7 | 45/54 | Overweight | 170-179 | 60> | Yes | 60kg-80kg | No |

**Figure 6.17** – Representation of Segment 3

Segment 3 represents men from the United Kingdom (uk), similarly to segment 1, however they differ greatly regarding customers and shirts attributes, since customers represented in this segment are more mature ([45-54] vs. [35-44]), aren´t so tall

([170cm-179cm] vs. [180cm-189cm]), their weight is inferior ([80kg-100kg] vs. [100kg-120kg] and the collar size is precisely the opposite (>60 vs. <36). According to BMI measures they belong to the same class (overweight), however in terms of the collar size the customers represented on this segment are considered obese.

| Attribute | Value |
|---|---|
| Gender | Men |
| Country | uk |
| Age Group | [45-54] |
| Height Group (cm) | [170-179] |
| Weight Group (kg) | [60-80] |
| BMIFatness | Overweight |
| Collar Group | >60 |
| isCollarObese | Yes |
| isObese | No |

**Table 6.11** – Customers Attributes Values of Segment 3

Concerning purchase choices, in this segment the purpose of buying the shirts is not the same as in segment 1, i.e., this time the purchase was not motivated nor conditioned by professional issues (party shirt vs. work shirt).

The customers attributes values that are similar between segment 1 and segment 2 are on the following table:

| Attribute | Value | Observations |
|---|---|---|
| Gender | Men | See Table 6.1 |
| Country | uk | See Figure 6.3 |
| BMIFatness | Overweight | See Figure 6.6 |
| isObese | No | See Table 6.4 |

**Table 6.12** – Similarities against Segment 1

In conclusion, inside the same country (uk) it is possible to identify some more segments that have different needs, tastes and preferences, what means that the company can segment locally however paying attention to local variations.

**Segment 4**

| Cluster | Size | Gender | Postal code | Country | Quantity | Selling price | Delivery price | Voucher | Card type | Configuratort | Collectiont | Fabric | Measures in cm | Fit | Age | Imperial |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 80 | men | co4 5bq | uk | 1 | 61 | 3,5 | NULL | visa | Work Shirt | Savile Row Plain | York | 1 | Regular | 49 | n |

| Cluster | Collar size | Weight kg | Height cm | Rating | Monogram | collar | Cuff | Placket | Pocket | Collar white | Cuff white | MODEL | Shirt gender | Affiliate | Hem | Back Yoke Contrast | Fabric colour | fabric design pattern |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | 41 | 82 | 175 | 1.8 | NULL | Italian Semi-Spread | Double inc. Cufflinks | Real front | Mitred | n | n | 51 | men | Retailer1 | Curved Hem with Gussets | y | Blue | Twill Weave Plain |

| Cluster | Fabric finish | Fabric material | Fabric structure | has Voucher | has Monogram | has Pocket | year | month | day Week | Age Group | BMIFatness | Height Group | Collar Group | IsCollar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 4 | Easy iron | 100% Cotton | Twill | No | No | Yes | 2011 | 11 | 2 | 45/54 | Overweight | 170-179 | 41/42 | No | 80kg-100kg | No |

**Figure 6.18** – Representation of Segment 4

Segment 4 represents, like segment 1 and segment 3, men from the United Kingdom (uk) that ordered men shirts from Retailer1 website. Like segment 1 customers represented in this segment purchased Bivolino shirts for professional use. Comparing the characteristics of work shirts on both segments (segment 1 and segment 4) we can identify some patterns, such as the fit (regular), the cuff (double inc. cufflinks), the placket (real front), the hem (curved), the fabric color (blue), the fabric finish (easy iron) and fabric material (100% cotton). As we have already mentioned before, this could indicate that they may have a formal business dress code to follow.

The attributes that describe the customers of this segment are presented on Table 6.13 and on Table 6.14 the variables that are similar comparing to the segments already analyzed.

| Attribute | Value |
|---|---|
| Gender | Men |
| Country | uk |
| Age Group | [45-54] |
| Height Group (cm) | [170-179] |
| Weight Group (kg) | [80-100] |
| BMIFatness | Overweight |
| Collar Group | 41/42 |
| isCollarObese | No |
| isObese | No |

**Table 6.13** – Customers Attributes Values of Segment 4

| Attribute | Value | Similarity to | Observations |
|---|---|---|---|
| Gender | Men | Segment 1 and 3 | See Table 6.1 |
| Country | uk | Segment 1 and 3 | See Figure 6.3 |
| Age Group | [45-54] | Segment 3 | See Figure 6.4 |
| Height Group (cm) | [170-179] | Segment 3 | See Figure 6.5 |
| Weight Group (kg) | [80-100] | Segment 1 | See Figure 6.6 |
| BMIFatness | Overweight | Segment 1 and 3 | See Figure 6.7 |
| isCollarObese | No | Segment 1 | See Table 6.5 |
| isObese | No | Segment 1 and 3 | See Table 6.6 |

**Table 6.14** – Similarities against Segment 1 and Segment 3

Segment 4 only differs from segment 1 and segment 3 only in one customer attribute, which is the collar group or the collar size (41/42), that is the most common after >60 and <36 (Figure 7.8).

In conclusion, male workers from the same country could present some similarities in terms of shirt characteristics, probably based on a similar business culture, however they could have different physical attributes.

**Segment 5**

| Cluster | Size | Gender | Postal code | Country | Quantity | Selling price | Delivery price | Voucher | Card type | Configuratort | Collectiont | Fabric | Measures in cm | Fit | Age | Imperial |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | 564 | men | cv31 3nd | uk | 1 | 52 | 0 | NULL | visa | Work Shirt | M&S Man Design | Sheffield | 2 | Super Slim Fit | 25 | y |

| Cluster | Collar size | Weight kg | Height cm | Rating | Monogram | collar | Cuff | Placket | Pocket | Collar white | Cuff white | MODEL | Shirt gender | Affiliate | Hem | Back Yoke Contrast | Fabric colour | fabric design pattern |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | unknown | 75 | 188 | 1.8 | MSM | Hai Cutaway | Double inc. Cufflinks | Folded | NULL | n | n | 51 | men | Retailer1 | Curved Hem with Gussets | y | Multicolor | Fine Stripe |

| Cluster | Fabric finish | Fabric material | Fabric structure | has Voucher | has Monogram | has Pocket | year | month | day Week | Age Group | BMIFatness | Height Group | Collar Group | IsCollar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 5 | Easy iron | 100% Cotton | Dobby | No | Yes | No | 2012 | 1 | 4 | 25/34 | Normal | 180-189 | 60> | Yes | 60kg-80kg | No |

**Figure 6.19** – Representation of Segment 5

Segment 5, as segment 1 and segment 4, represents male workers from the United Kingdom (uk) that ordered Bivolino shirts through Retailer1 website. However this segment represents younger customers with ages between 25 and 34 years old.

The characteristics of the customers in this segment are described on Table 6.15.

| Attribute | Value |
|---|---|
| Gender | Men |
| Country | uk |
| Age Group | [25-34] |
| Height Group (cm) | [180-189] |
| Weight Group (kg) | [60-80] |
| BMIFatness | Normal |
| Collar Group | >60 |
| isCollarObese | Yes |
| isObese | No |

**Table 6.15** – Customers Attributes Values of Segment 5

The attributes values that are shared with the other segments already analyzed are presented on Table 6.16.

| Attribute | Value | Similarity to | Observations |
|---|---|---|---|
| Gender | Men | Segment 1, 3 and 4 | See Table 6.1 |
| Country | uk | Segment 1, 3 and 4 | See Figure 6.3 |
| Height Group (cm) | [180-189] | Segment 1 | See Figure 6.5 |
| Weight Group (kg) | [60-80] | Segment 3 | See Figure 6.6 |
| Collar Group | >60 | Segment 3 | See Figure 6.8 |
| isCollarObese | Yes | Segment 3 | See Table 6.5 |
| isObese | No | Segment 1, 3 and 4 | See Table 6.6 |

**Table 6.16** – Similarities against Segment 1, Segment 3 and Segment 4

As we can see, this segment only differs from the other segments in two customers attributes, inamely the age group ([25-34] vs. [35-44] and [45-54]) and in the BMI (Normal vs. Overweight). We noted that as customers go older they tend to be overweight (Figure 6.20), their body shape and abilities change and consequently their choices and requirements in terms of fashion products also change.

In conclusion, the customer age is a segmentation variable that has great influence on fashion choices because with the age the body shape changes and the products must be designed in order to meet their specific requirements.

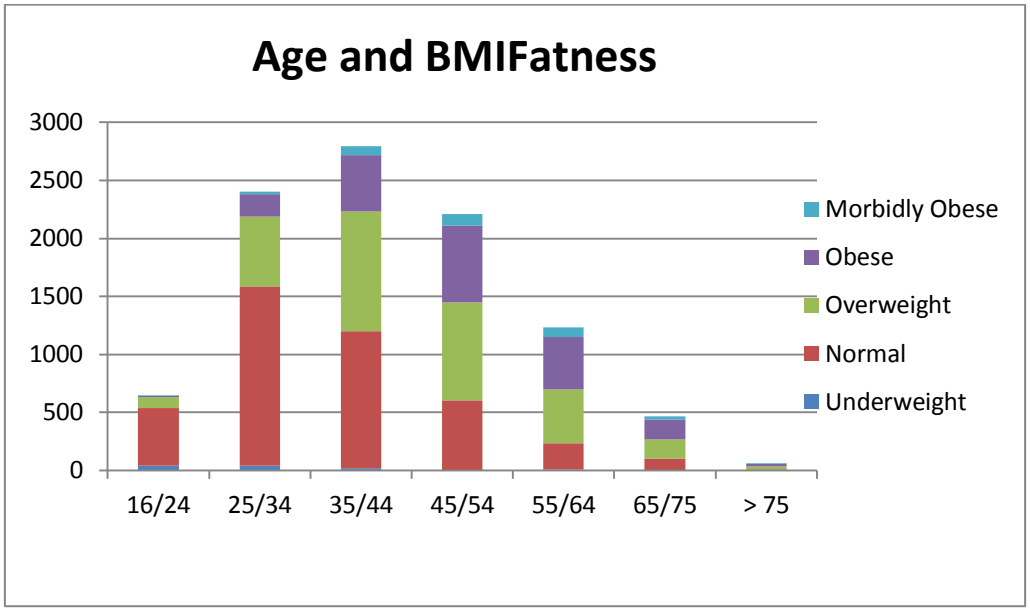



**Figure 6.20 –** Relation between the Age and BMI for Male Customers

**Segment 6**

| Cluster | Size | Gender | Postal code | Country | Quantity | Selling price | Delivery price | Voucher | Card type | Configuratort | Collectiont | Fabric | Measures in cm | Fit | Age | Imperial |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | 12 | men | 22049 | de | 1 | 60 | 6 | NULL | visa | unknown | Fashion Trend | Miro 7 | 1 | Super Slim Fit | 26 | n |

| Cluster | Collar size | Weight kg | Height cm | Rating | Monogram | collar | Cuff | Placket | Pocket | Collar white | Cuff white | MODEL | Shirt gender | Affiliate | Hem | Back Yoke Contrast | Fabric colour | fabric design pattern |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | 39 | 65 | 182 | 1.8 | NULL | Italian Semi-Spread | Round Single | Real front | NULL | n | n | 51 | men | Retailer2 | Curved Hem | n | Pink | Plain |

| Cluster | Fabric finish | Fabric material | Fabric structure | has Voucher | has Monogram | has Pocket | year | month | day Week | Age Group | BMIFatness | Height Group | Collar Group | IsCollar Obese | Weight Group | is Obese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 6 | Easy-care Okotex 100 | 100% Cotton | Herringbone | No | No | No | 2011 | 5 | 2 | 25/34 | Normal | 180-189 | 39/40 | No | 60kg-80kg | No |

**Figure 6.21** – Representation of Segment 6

Segment 6 represents younger customers from a different nationality (de - Germany) compared to the other segments and they ordered shirts of a fashion trend collection through Retailer2 website. The characteristics of the customers in this segment are:

| Attribute | Value |
|---|---|
| Gender | Men |
| Country | de |
| Age Group | [25-34] |
| Height Group (cm) | [180-189] |
| Weight Group (kg) | [60-80] |
| BMIFatness | Normal |
| Collar Group | 39/40 |
| isCollarObese | No |
| isObese | No |

**Table 6.17** – Customers Attributes Values of Segment 6

Comparing this segment to segment 5, we note that the customers physical attributes are identical, such as the age ([25-34]), the height ([180cm-189cm]), the weight ([60kg-80kg]) and BMI (Normal), despite being from different countries. However, comparing segment 6 to all segments, it differs in the nationality (de) and in the collar size (39/40) (Figure 6.8).

| Attribute | Value | Similarity to | Observations |
|---|---|---|---|
| Gender | Men | Segment 1, 3, 4 and 5 | See Table 6.1 |
| Age Group | [25-34] | Segment 5 | See Figure 6.4 |
| Height Group (cm) | [180-189] | Segment 1 and 5 | See Figure 6.5 |
| Weight Group (kg) | [60-80] | Segment 3 and 5 | See Figure 6.6 |
| BMIFatness | Normal | Segment 5 | See Figure 6.7 |
| isCollarObese | No | Segment 1 and 4 | See Table 6.5 |
| isObese | No | Segment 1, 3, 4 and 5 | See Table 6.6 |

**Table 6.18** – Similarities against Segment 1, Segment 3, Segment 4 and Segment 6

In conclusion, we note a trend related to the nationality variable, i.e., we saw that customers from a certain country tend to purchase the shirts through an affiliate of their own country (Figure 6.22). Thus, for instance, customers from the United Kingdom (uk) tend to order the shirts from Retailer1, which represents about 75% of the orders, and customers from Germany (de) from Retailer2, which represents about 76% of the

orders. This could mean that customers are careful when shopping online in the sense that they have preference for brands or stores that they already know and trust.

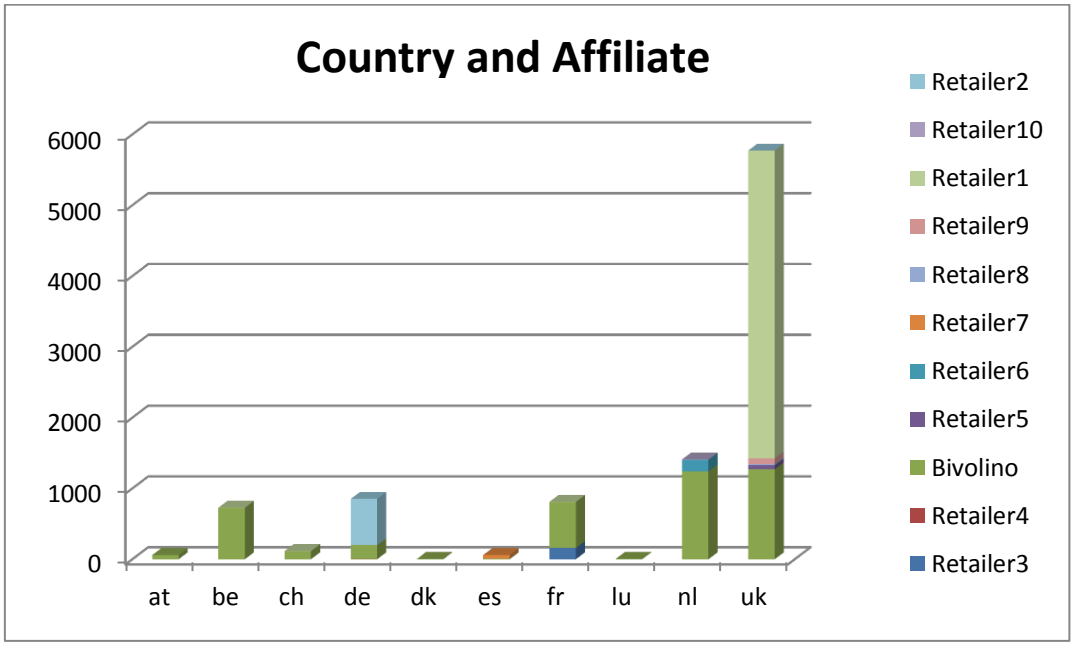



**Figure 6.22 –** Relation between Country and Affiliate for Male Customers

## 6.4. Conclusions of the Results

The clustering results (Figure 6.1) for a number of clusters k=6 defined *a priori* and with more variables than that used in the first clustering process (Figure 5.1), has brought us, in fact, some additional information. One example is given by segment 2 that represents women (Figure 6.9), since it made possible for the company to segment its consumer market on the basis of the gender of the customers, as men and women have different expectations of fashion products.

We also have seen that the company could segment its market based on the age, since the changes in body performance and shape have a great impact on the fashion choices. On example is illustrated on Figure 6.23 where we can see that in terms of shirt fit (level of shirt tightness to the body) choices, the young customers (segments 5 and 6) prefer the "super slim fit" and the older customers the "comfort fit", however remaining the "regular fit" the most common choice (Figure 6.24). Other example is illustrated on Figure 6.25 where we can see that the older customers (segments 1 and 4) are the ones

that like to use pocket on shirts the most, especially the ones of the type "mitred" (Figure 6.26).

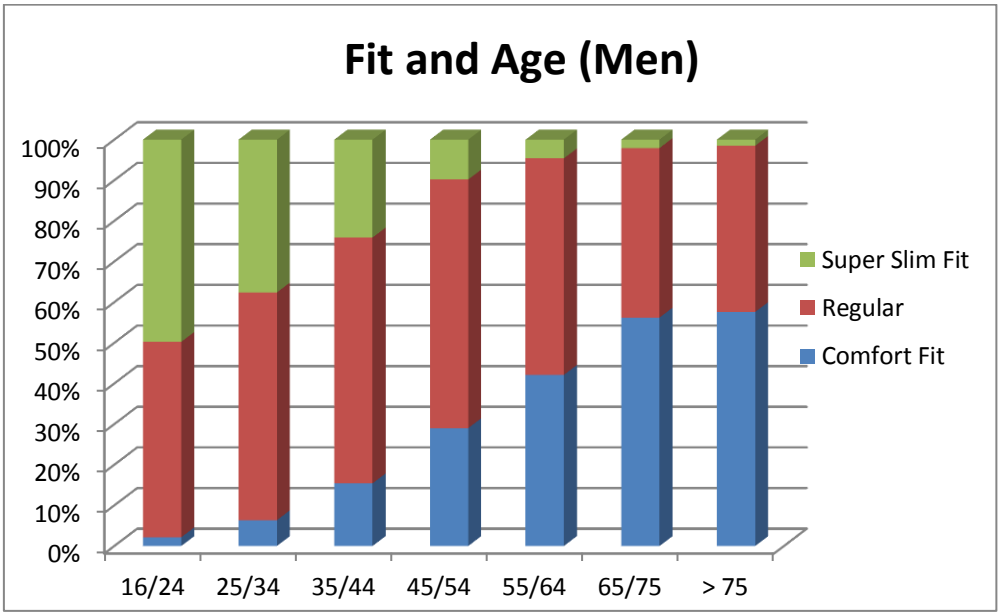



**Figure 6.23 –** Relation between Fit and Age for Male Customers

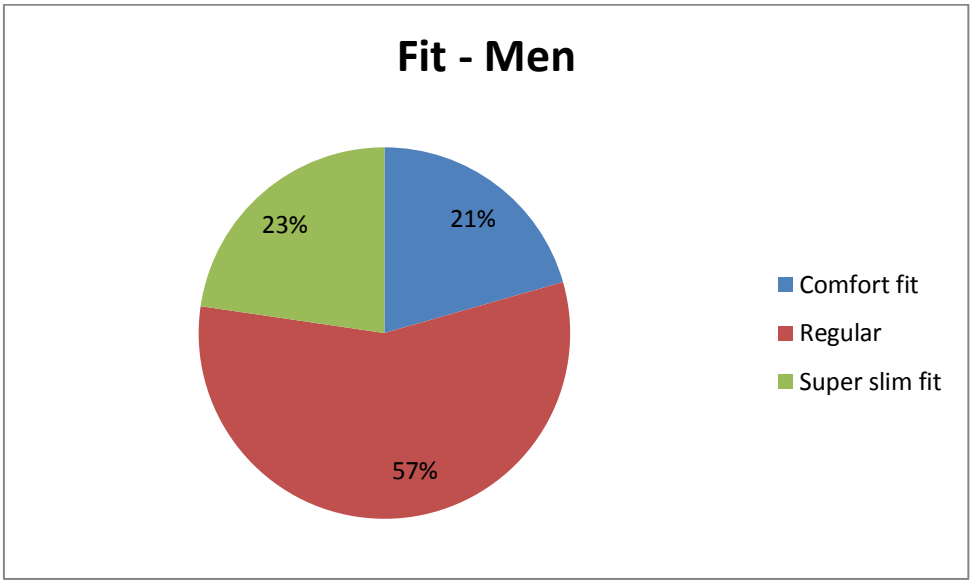



**Figure 6.24 –** Fit choices of Men Shirts

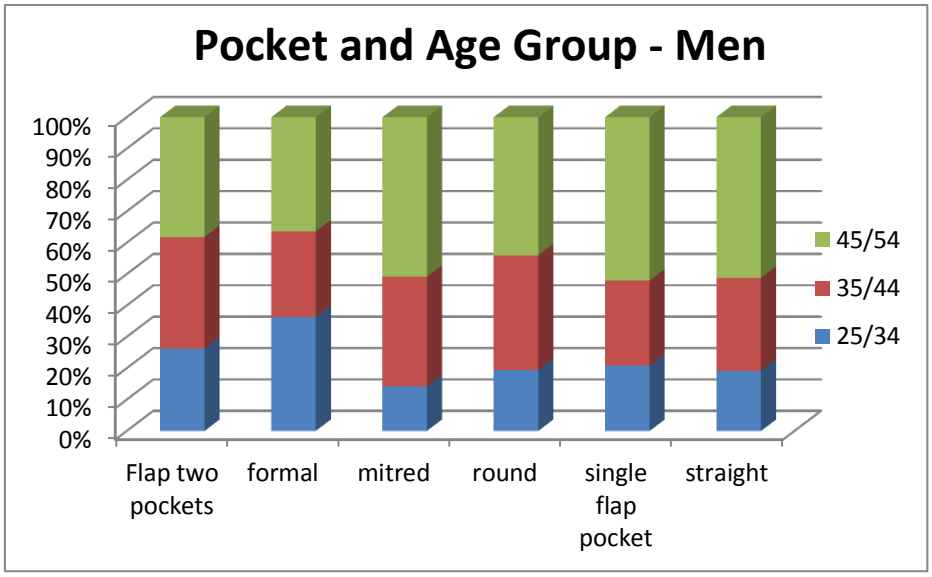



**Figure 6.25 –** Relation between Pocket and Age for Male Customers

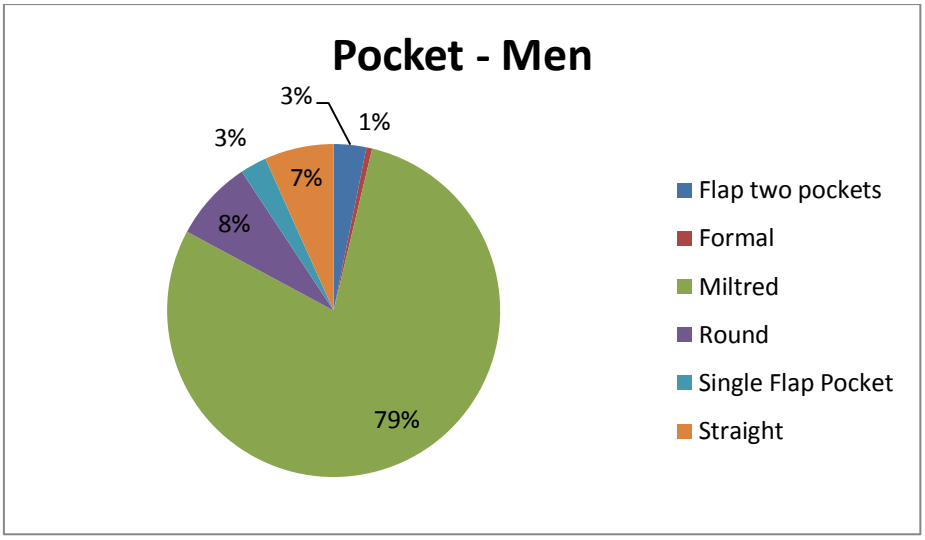



**Figure 6.26 –** Type of Pocket for Male Customers

The more variables we add the more possibilities of segmenting the market. Thus, the company could also segment the market geographically by country or locally (postal code), since costumers from different nationalities have different requirements for fashion and clothing products, and much of the time their choices are influenced by social and cultural values. Figure 6.27 shows the representation of the customer's countries in terms of company orders in 2011 and we can see that the United Kingdom (uk) leads. In Figure 6.28 is shown that the affiliates (Bivolino, Retailer1, Retailer2) through which the company makes much of its sales corresponds to the nationality of some of their best customers (Belgium, United Kingdom, Germany).

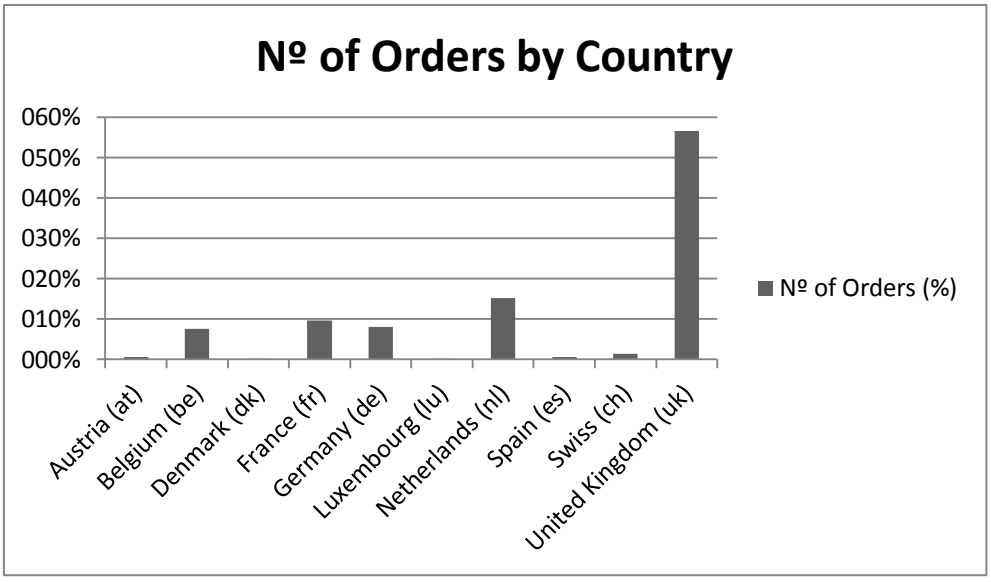



**Figure 6.27 –** Total Orders by Country of Bivolino Shirts in 2011

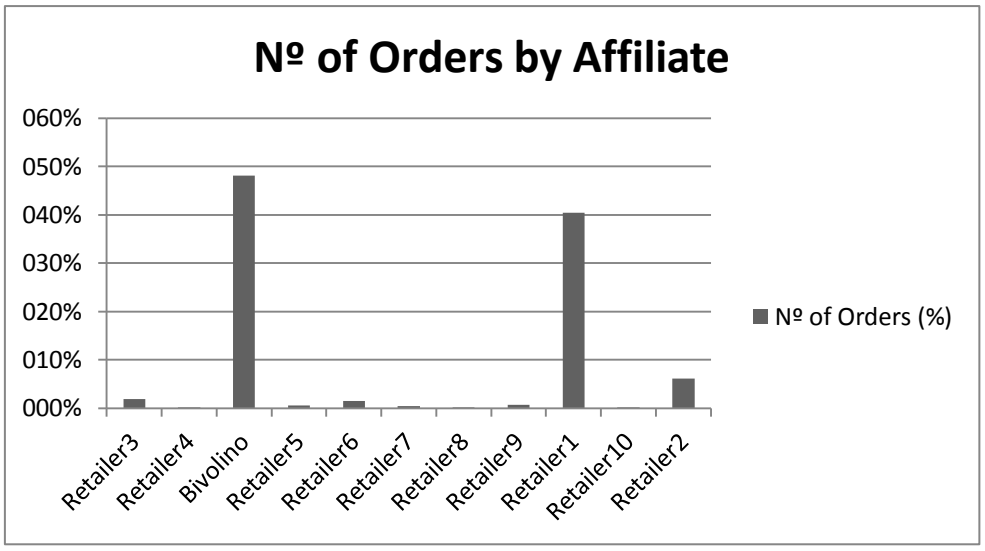



**Figure 6.28 –** Total Orders by Affiliate of Bivolino Shirts in 2011

Another alternative for segmenting the Bivolino costumers market is making it on the basis of the purpose or intention of buying according to, for instance, the categories "work shirt", "fashion shirt" and "party shirt" (configurator or collection type). We can then infer, for example, that they buy motivated by professional requirements (e.g. segments 1, 4 and 5), interest on fashion (e.g. segment 6), or by social events requirements (e.g. segments 2 and 3).

We have also identified another segmentation variable that is the price sensitivity, which could be measured by the usage of gift vouchers to get a discount on payment. We concluded that women are more price sensitive than men given that more

than 82% used a voucher (Table 6.7) on shirts payment. Women are generally more receptive to promotions of this type and more open to experimenting new products than men. However we do not know if it was related to a specific promotion with the intention of allowing the experiment of a new product, however if yes the company should study other ways of attract the female public and improve sales.

In short, in this chapter we analyzed the profile of Bivolino customers and their relation to the product (shirts) based on some segmentation variables that were identified. We concluded that their choices in terms of shirts attributes are greatly influenced and conditioned by numerous factors such as, their physical attributes, age, gender, nationality (country), purpose of buying. Given that, the company must pay attention to those differences and adjust its product and marketing strategies to the different segments identified.

# 7. CONCLUSION

*"It's more fun to arrive a conclusion*
*Than to justify it."*
By Malcolm Forbes, an American publisher

## 7.1. Summary

The aim of this work was to show the practical applicability of Data Mining (DM) techniques and tools to market segmentation in the context of the customized fashion industry. The study was based on data provided by Bivolino, a Belgian company that produces and sells custom tailored shirts, relative to its shirts orders of 2011.

We started the work by doing some literature review about the subjects covered. We aimed to give an overview about DM (definition, tasks, process, and methodology), Clustering (definition, goals, stages, algorithms and validation) and Segmentation in Marketing (definition, effectiveness, process, levels, bases, methods and methodology).

We then described what we did in practice based on those theoretical insights and the data available. We followed the steps of CRISP-DM (business understanding, data understanding, data preparation, modeling, evaluation and deployment), a general methodology to support the DM process. The modeling step was carried out using the DM software RapidMiner. In terms of the segmentation methodology, we adopted a non-overlapping (each subject belongs to a single segment only) non-hierarchical (start from a random initial division of the subjects into a predetermined number of clusters, and reassign subjects to clusters until a certain criterion is optimized) clustering method called K-Medoids. As we know, clustering methods are commonly used in marketing for the identification and definition of market segments that help companies focus their marketing strategies. Then, we proceeded with the market segmentation and identified possible segmentation bases according to the classic segmentation variables for consumer markets (demographic, geographic, psychographic and behavioristic) suggested by Kotler and complemented by Wedel and Kamakura.

In this study we run the clustering process twice for a dataset of n = 10.775 shirts orders and a number of clusters k = 6 defined *a priori*, with the difference on the number of attributes (describing the orders, shirts and customers) used. On the first clustering process we used 29 attributes and on the second we added 30 more. The choice of the attributes to use in each process depended on the scope of the analysis, i.e., the first analysis was based on a technical perspective (production and design of the shirts) and the second on a marketing perspective (segmentation of shirts customers). At the end, we were able to see how results from a clustering process could differ simply changing the number of the attributes.

Given the results we started by analyzing the first results mainly focusing on the attributes that describe the shirts attributes (fabric color, material, design and pattern, finish, structure, etc.) with the purpose of finding some patterns in the data that could be transformed into useful information to support the company's decisions in terms of production and design. Then we analyzed the second result mainly focusing on the attributes that describe the customers (gender, age, country, height, weight, BMI, collar size, etc.) in an attempt to divide the market of Bivolino shirts customers into distinct groups of buyers who have different needs, characteristics, or behaviors, and who might require separate products or marketing programs.

The analysis of both results allows us to conclude that DM techniques and tools are indeed very useful when analyzing vast quantities of data. The first clustering result allowed us to answer one of the aspects from our business problem, i.e., how could the fashion designers identify and predict the fashion profiles and trends. Similarly, the second clustering results enabled us to respond to another aspect of our business problem that is how the company could segment its market in different groups of customers with distinct characteristics, needs, preferences, tastes and behaviors and then adapt or adjust its strategies to respond more effectively to their requirements. It will also allow the company to identify which segments are most profitable and focus its efforts in that direction.

## 7.2. Recommendations

This study gave us new insights about the fashion industry. Thus, based on the data about Bivolino customers database and on the results obtained from clustering and segmenting the data, we recommend:

- The company should strengthen its efforts to expand into the women's clothing market, since they represent a market segment that is very attentive to fashion issues and receptive to sales promotions and to experimenting new products. Gift vouchers were the strategy adopted so far by Bivolino to address this new segment. Given the positive response of this important segment, the company should consider adopting promotions of different types.
- As the older-age consumer market is increasing, the company should also expand in that direction. They should be inclusive in their marketing and promotional campaigns, highlighting the benefits of fashion products as older consumers consider their clothing consumption in a more strategic manner than younger consumers. Understanding the attitudes and behavior of the mature consumers will, on one hand, provide guidance for product development and design and, on the other hand, create opportunities and challenges for the fashion business to focus on this increasingly important market.
- The company should be aware of the implications of the age in fashion consumer choices, since consumers of all ages psychologically need to express their individual style and taste through a choice of better quality products. Designers should add value via fashion products that transcend all ages. They should particularly promote the inclusion aspect of the process of buying clothes, not only in the case of older customers but also in the case of customers with some kind of disability or pathology.
- Beyond the age and physical conditions, other factors have much influence on customers fashion choices and the company must have to take it into account when designing the shirts. They are, for instance, the gender (men and women have different expectations of fashion products), the nationality (customers from different countries have influence of social and cultural values with which they identify), the purpose of the buying (for example, professional), etc.

- The company should focus on the market segments that were identified as being the most profitable and adopt different strategies for each segment taking into account the different customers characteristics they represent (attributes that describe customers) and corresponding fashion choices (attributes that describe the shirts). Not only the shirts should be customized and tailored but also the marketing-mix should be adjusted to each segment unique characteristics.

## 7.3. Limitations of the Study

During our study we faced some difficulties derived from several reasons. The first is related to the inherited limitations of the method adopted. The clustering algorithm K-Medoids, despite being less sensitive to outliers than the K-Means because of the use of the median instead of the mean, still requires the definition of *k* number of clusters *a priori*. Deciding the best or optimal *k* number of clusters is a difficult task, which is well known (Jain *et al*, 2000). According to Jain *et al* (2000) the algorithm, in practice, is typically run multiple times with different starting states, and the best configuration obtained from all of the runs is used as the output of clustering. Therefore, this method results in becoming extremely time consuming even from a computational perspective. Each clustering process on RapidMiner took too much time, which is largely related to the vast quantity of data clustered (too many examples and too many attributes), even though, partitional methods have advantages in applications involving large data sets (Jain *et al*, 2000).Another difficulty related to the clustering method is how to know if the clustering results is a 'good' or a 'poor' one. All clustering algorithms will, when presented with data, produce clusters regardless of whether the data contain clusters or not. If data does contain clusters, some clustering algorithms may obtain 'better' cluster than others (Jain *et al*, 2000). Nevertheless, given the type of the attributes used in the study (binominal and polynomial, i.e., non-numeric) and our task (clustering), the choice of the algorithm was very limited. Most of the clustering algorithms available on RapidMiner did not accept categorical data (data separable into categories that are mutually exclusive, such as age groups). However, the algorithm selected proved to be suitable for the problem at hand.

As we can see, clustering is a very subjective task, i.e., the same dataset may need to be partitioned differently for different purposes (Jain *et al*, 2000). In our study

we clustered the same dataset twice but changing the number of the attributes according to the purpose of the analysis.

Other difficulties are related to the marketing analysis in the way that we have not access to the necessary information about the customers, specially referring to behavioristic and psychographic attributes (personality traits, lifestyles, interests, occupation, education, etc.). However, it was possible to identify same segmentation variables based on the available information. Nevertheless, we couldn't go further in the study.

In sum, the difficulties faced in the study were:

- Deciding the number of clusters *k*;
- High computational cost of the methods;
- Limitations imposed by the types of the attributes, which strongly constraints the selection of the algorithm;
- Subjective nature of the evaluation process;
- Insufficient data to characterize customers.

## 7.4. Future Work

Taking into account the difficulties encountered during this study and the limitations they imposed on it, we find that future work is needed and should focus on the following issues, which are mainly related to the problems of clustering itself:

- Find a general theoretical solution to find the optimal number of clusters for any given dataset;
- Reduce time complexity when dealing with large number of dimensions and large number of data items;
- Find a way to help on the interpretation of the result of a clustering algorithm (that in many cases can be arbitrary itself), as it can be interpreted in different ways;
- Transform the data to enable the use of different clustering algorithms, compare the different results and decide which is the best;
- Reduce the dependency of the effectiveness of the clustering method on the definition of "distance" (for distance-based clustering);
- Alternatively to the previous suggestion, it would be interesting to find a way of defining a distance measure, that is specific to the business problem;

# APPENDICES

# APPENDIX A

## Data Mining Methodology: CRISP-DM

The DM methodology used in this work was the CRISP-DM (**Cr**oss **I**ndustry **S**tandard **P**rocess for **D**ata **M**ining), which is explained in more detail in Annex B. Now we will describe the phases of the DM methodology followed during the study.

### A. Business Understanding

First, we tried to understand the project objectives and requirements from a business perspective, and then convert it into a DM problem. So, our business problem is how *Bivolino*[13] can reach specific market niches while responding more effectively to their unique needs and preferences. This is achieved by identifying profiles of shirts sold. Converting it to a DM problem, the goal is to find clusters in the data provided by Bivolino relative to shirts ordered in 2011. The results of this project are to be useful for marketing purposes but mainly important for the design of new products.

### B. Data Understanding

Understanding the *data*[14] is the first step and one of the most important. In order to become familiar with the data, identify data quality problems, discover first insights into the data, and/or detect interesting subsets to form hypothesis regarding hidden information, we performed an *exploratory data analysis* [15] and identified some interesting insights and patterns (Table A.1).

Besides the findings presented in Table A.1, we can intuitively define some segments with the data for market niches, such as obese and very tall people, for example. These kinds of people face difficulties in finding clothing with appropriate measurements for them, so it is very useful and comforting for them to have a company like Bivolino providing clothing where they do not have to face such a problem.

### C. Data Preparation

Data preparation is the phase where we have to make the data ready to be processed by the DM tools. This is done by working on the initial raw data and applying several operations to construct the final dataset to be modeled by DM tools. This

[13] See *Annex A* to better know the Bivolino Company or visit http://www.bivolino.com/.
[14] See *Annex D*, Table D.1 – Data Table.
[15] *Exploratory Data Analysis* is the use of graphical and descriptive statistical techniques to learn about the structure of a dataset.

includes table, record, attribute selection, transformation and 'cleaning'[16] of data. The initial dataset provided by Bivolino was arranged in order to be modeled on *RapidMiner*[17] (e.g., some missing variables were eliminated, because they were not significant nor in quantity nor in quality for the study; some variables were transformed in a different type, because of the algorithm used thus required). Therefore, not much effort was required for this task.

| Attribute | Attribute Class | Finding |
|---|---|---|
| Gender | Customer | 91% of customers are men (9.815) and 9% are women (960). |
| Country | Customer | 57% of customers are from the United Kingdom (uk). |
| Height (cm) | Customer | 68% of customers belong to interval of height [180-189], [170-179]. |
| Weight (kg) | Customer | 73% of customers belong to interval of weight [60-80], [80-100]. |
| Age (years) | Customer | 76% of customers belong to interval of age [35-44], [25-34], [45-54]. |
| isObese (weight) | Customer | 77% of customers are not obese (weight<100Kg) and 23% obese (weight>100kg). |
| Affiliates | Order | 88% of total orders were made through Bivolino and Retailer1[18] (48% and 40%, respectively). |
| Configurator type | Order | The configurator type preferred by women is "Bespoke Women" (75%) and by men is "Work Shirt" (35%) followed by "Bespoke Shirt" (22%) and "Fashion Shirt" (20%). |
| Collar Group | Shirt | 21% of shirts have the smallest collar (<36) and 25% the biggest collar (>60). |
| isCollarObese | Shirt | 23% of shirts are for obese persons and 77% not. |
| Collection Type | Shirt | The collection type preferred by women is "Charming" (56%) followed by "Simplissime" (11%). |
| Collar White | Shirt | Only 9% of shirt collars are white, i.e., are not the same color |

[16] *Data cleansing* is the process of ensuring that all values in a dataset are consistent and correctly recorded.
[17] See *Annex C* for more details about RapidMiner software or visit http://rapid-i.com/.
[18] For confidentiality reasons, we cannot disclose the names of the retailers.

| Attribute | Attribute Class | Finding |
|---|---|---|
| | | as shirts. |
| Has Monogram | Shirt | Only 27% of shirts have monograms. |
| Has Pocket | Shirt | Only 45% of customers like shirts with pockets. |

**Table A.1** – Findings from Exploratory Data Analysis

**D. Modeling**

After the previous phases were completed, it was time to select and apply a modeling technique. The technique chosen as being the most appropriate to our DM problem type, was the Clustering, more specifically, the K-Medoids algorithm, and given the type of variables at hand (binominal and polynominal). This technique supports nominal variables (the types of variables supported by RapidMiner are described on Table C.1 in Annex C), while other methods, such as the K-Means algorithm, can only deal with numerical data.

**E. Evaluation**

An essential step for the success of a DM project is the careful evaluation of the model built, before proceeding to its final deployment. It is important to evaluate it and review the steps done for its creation, to be certain that the model properly achieves the business objectives. At the end of this phase, a decision on the usefulness of the DM results should be reached. In this study, we tried to evaluate the clustering results on RapidMiner, however we were not capable of interpreting the results of such a measure, as will be discussed later.

**F. Deployment**

When the model expected to be able to achieve the business goals, the knowledge obtained has to be organized and presented in a way that can be operationalized. The deployment could simply consist of a generation of a report or in a implementation of the DM process across the company. Nevertheless, what is important here is that the customer understands what actions need to be carried out in order to actually make use of the model created.

# APPENDIX B

## Clustering using RapidMiner

Here we will describe the steps of the clustering process on RapidMiner with some illustrations.

### 1. Repository

After preparing the dataset for modeling, we were able to import it to the RapidMiner *Repository*[19] and named it as "First Data Set". The *data table*[20] is composed of 29 attributes (or variables), 10.775 examples (number of Bivolino shirt orders) and the values that they could assume. This table represents the so-called *Meta data* which provides information about the data. It includes details such as the number and type of data stored, where it is located, how it is organized, and so on (Delmater and Hancock, 2001). This is typically much less voluminous than the data itself and gives the analyst an excellent idea of which characteristics a particular dataset has. In a certain sense, the Meta data is the warehouse architecture, because it provides the substance upon which all access and applications are based (Delmater and Hancock, 2001).

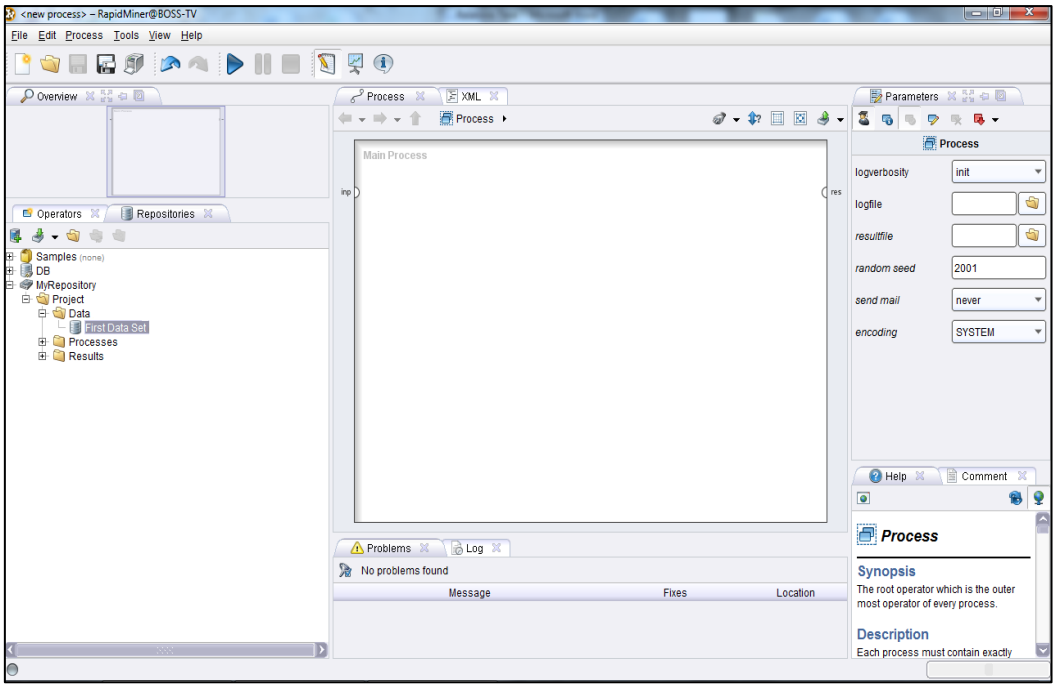



**Figure B.1** – Repository View on RapidMiner

[19] The *Repository* serves as a central storage location for data and analysis processes. (Source: RapidMiner User Manual)
[20] The *Data Table* is presented in Annex D, Table D.1.

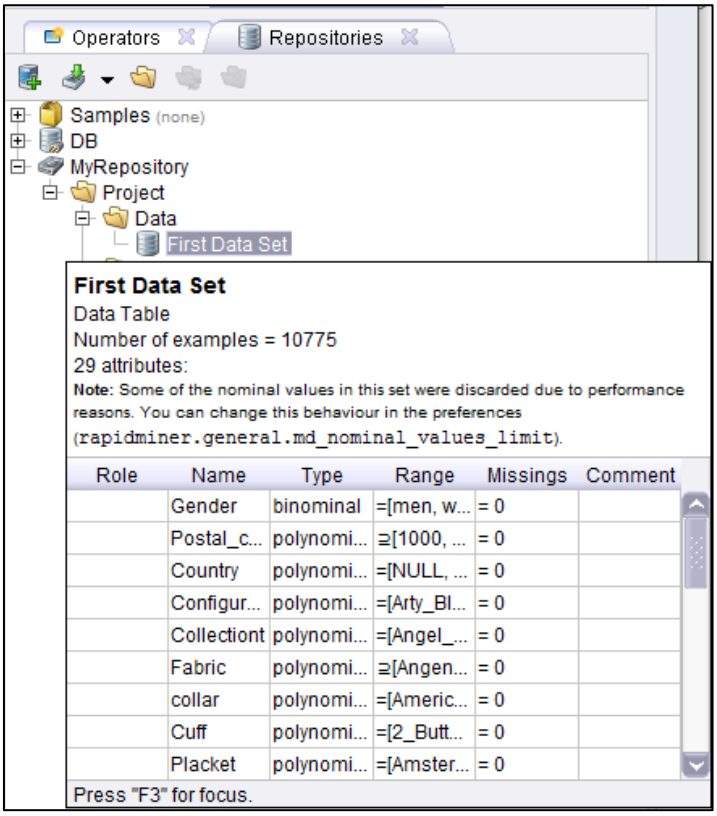



**Figure B.2** – Data Table "First Data Set"

## 2. Process

In order to start the process, we first have to select the operator *Repository Access – Retrieve* to get access to the data table. Then we select the operator *Modeling – Clustering and Segmentation – K-Medoids* and run the process but before running the process we have to define *k*, i.e., the number of clusters and also the number of runs and the measure type. We selected *Mixed Measures*, more precisely the *Mixed Euclidean Distance*, because this is the distance metric most widely used for this algorithm. The process is then ready to run and since it is an intensive task, the results take some time to be ready for display.

After this, the result view didn´t give us the clusters prototype, i.e., the values that each attribute will likely assume so we have also to select the operator *Modeling – Clustering and Segmentation – Extract Cluster Prototypes*. The operator Extract Cluster Prototype generates an ExampleSet consisting of the Cluster Prototypes. Flat cluster algorithms like K-Means or K-Medoids cluster the data around some prototypical data vectors. For example, K-Means uses the centroid of all examples of a cluster. This operator now extracts these prototypes and stores them in an ExampleSet for further

use, requiring the input a centroid Cluster Model, which is precisely the output of the clustering.

We did some experiments for different values of *k* number of clusters and used some dataset samples. In addition to these experiments, we used the operator *Data Transformation – Attribute Set Reduction and Transformation – Selection – Select Attributes* and defined, for different attributes such as affiliates, BMI, etc., values from which the clustering would be based in. Some examples of these experiments are shown in Annex E.

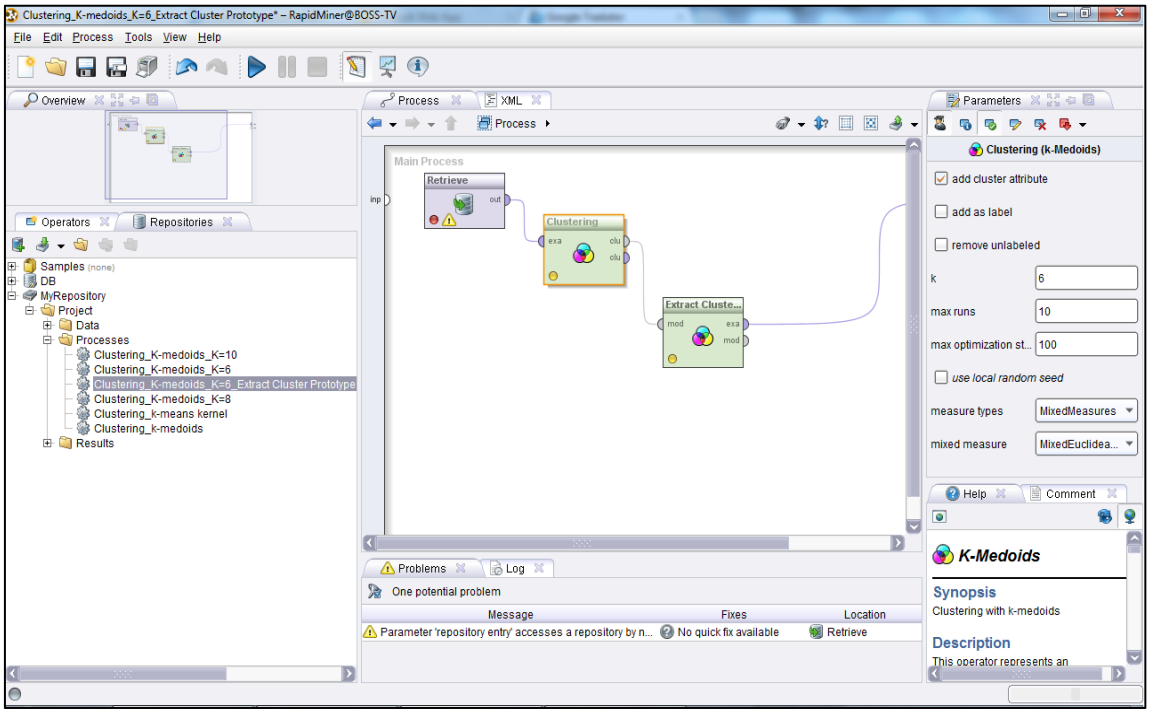



**Figure B.3** – Process View on RapidMiner

### 3. Results

After running the process, the results view is available and we are able to see the ExampleSet in different ways. In the case of the Clustering itself, some of the available views are “Text View”, “Centroid Table” and “Centroid Plot View”. In the case of the extraction of the respective cluster prototypes, some of the result views available are “Meta Data View”, “Data View” and “Plot View”, and even “Advanced Charts”.

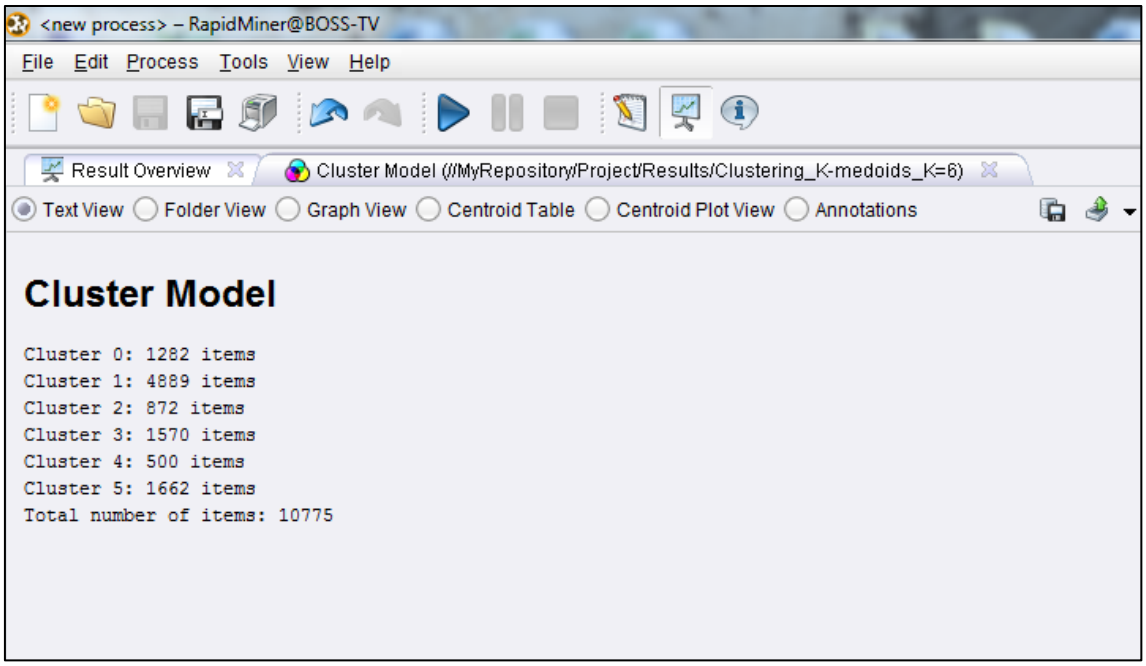
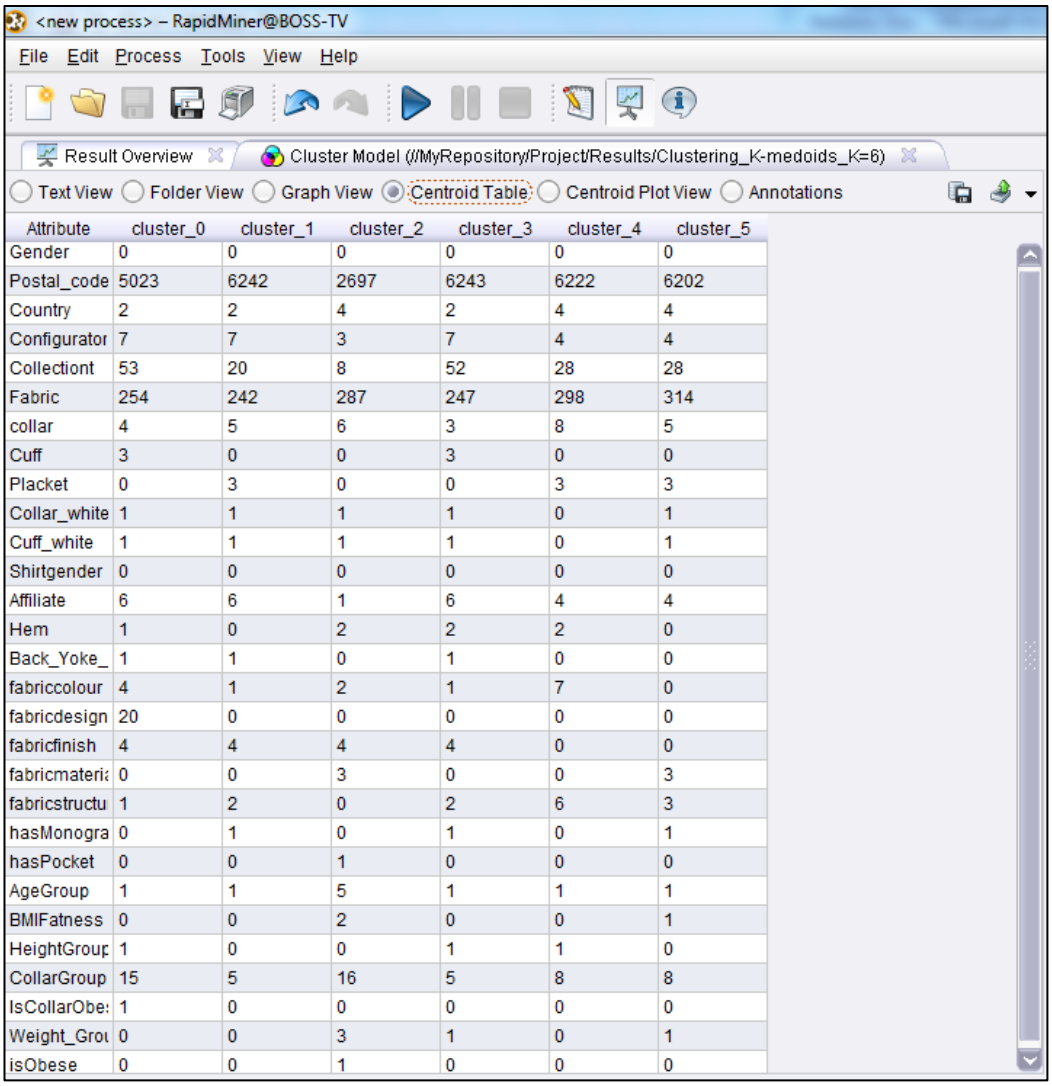



**Figure B.4** – Results View ("Text View") on RapidMiner

In the "Text View" we can see the number of the clusters and their size which is called the Cluster Model.

| Cluster | Size | Size (%) |
|---|---|---|
| 1 | 1.282 | 12% |
| 2 | 4.889 | 45% |
| 3 | 872 | 8% |
| 4 | 1.570 | 15% |
| 5 | 500 | 5% |
| 6 | 1.662 | 15% |
| **Total** | **10.775** | **100%** |




| Attribute | cluster_0 | cluster_1 | cluster_2 | cluster_3 | cluster_4 | cluster_5 |
|---|---|---|---|---|---|---|
| Gender | 0 | 0 | 0 | 0 | 0 | 0 |
| Postal_code | 5023 | 6242 | 2697 | 6243 | 6222 | 6202 |
| Country | 2 | 2 | 4 | 2 | 4 | 4 |
| Configurator | 7 | 7 | 3 | 7 | 4 | 4 |
| Collectiont | 53 | 20 | 8 | 52 | 28 | 28 |
| Fabric | 254 | 242 | 287 | 247 | 298 | 314 |
| collar | 4 | 5 | 6 | 3 | 8 | 5 |
| Cuff | 3 | 0 | 0 | 3 | 0 | 0 |
| Placket | 0 | 3 | 0 | 0 | 3 | 3 |
| Collar_white | 1 | 1 | 1 | 1 | 0 | 1 |
| Cuff_white | 1 | 1 | 1 | 1 | 0 | 1 |
| Shirtgender | 0 | 0 | 0 | 0 | 0 | 0 |
| Affiliate | 6 | 6 | 1 | 6 | 4 | 4 |
| Hem | 1 | 0 | 2 | 2 | 2 | 0 |
| Back_Yoke_ | 1 | 1 | 0 | 1 | 0 | 0 |
| fabriccolour | 4 | 1 | 2 | 1 | 7 | 0 |
| fabricdesign | 20 | 0 | 0 | 0 | 0 | 0 |
| fabricfinish | 4 | 4 | 4 | 4 | 0 | 0 |
| fabricmateri | 0 | 0 | 3 | 0 | 0 | 3 |
| fabricstructu | 1 | 2 | 0 | 2 | 6 | 3 |
| hasMonogra | 0 | 1 | 0 | 1 | 0 | 1 |
| hasPocket | 0 | 0 | 1 | 0 | 0 | 0 |
| AgeGroup | 1 | 1 | 5 | 1 | 1 | 1 |
| BMIFatness | 0 | 0 | 2 | 0 | 0 | 1 |
| HeightGroup | 1 | 0 | 0 | 1 | 1 | 0 |
| CollarGroup | 15 | 5 | 16 | 5 | 8 | 8 |
| IsCollarObe | 1 | 0 | 0 | 0 | 0 | 0 |
| Weight_Grou | 0 | 0 | 3 | 1 | 0 | 1 |
| isObese | 0 | 0 | 1 | 0 | 0 | 0 |

**Figure B.5** – Results View (“Centroid Table”) on RapidMiner

RapidMiner assigns a different number according to the different values that each attribute could possibly assume. For example, it assigns value “0” to attribute “gender” where zero actually means “men” and value “1” to “women”, and so on.

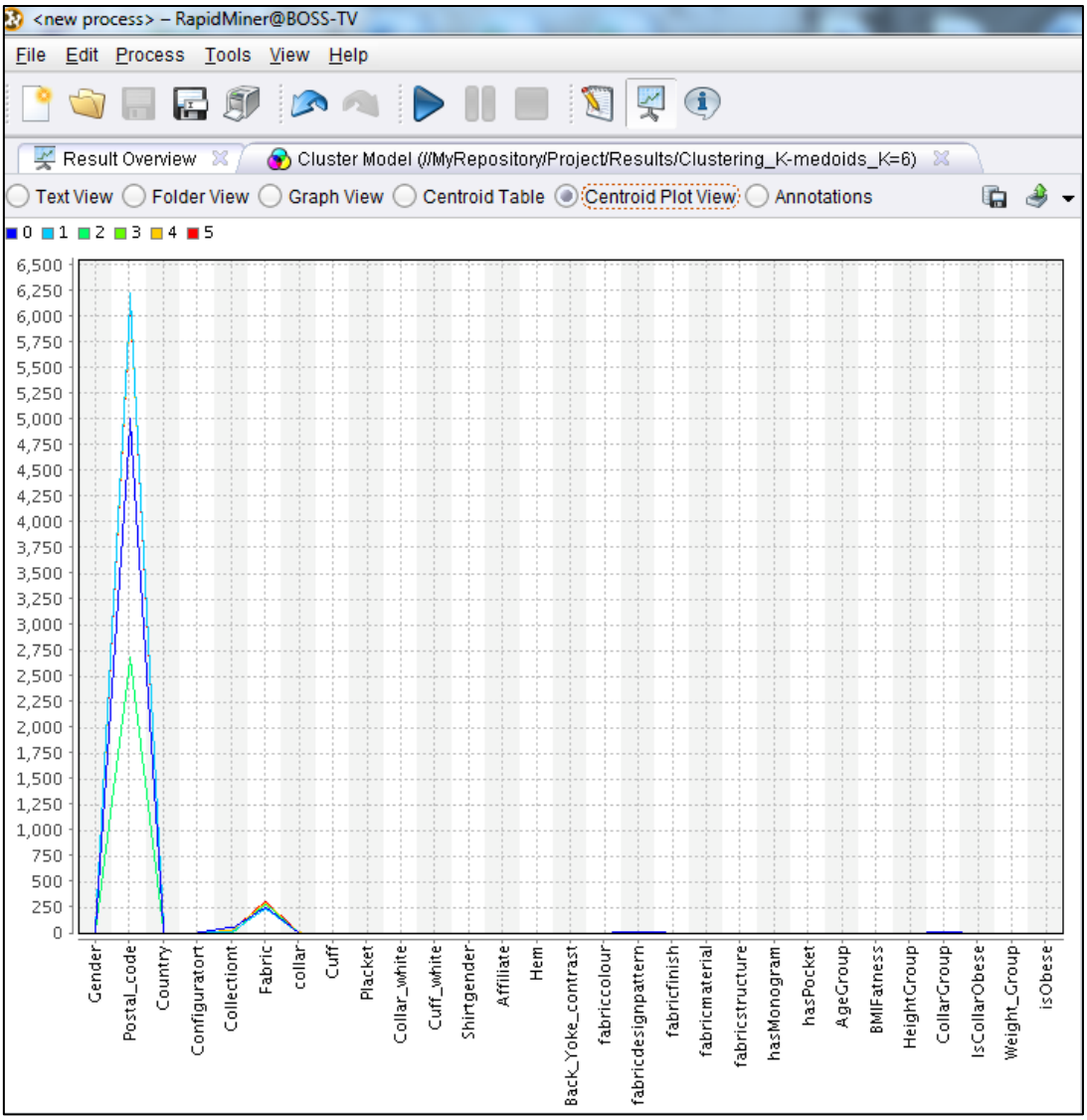
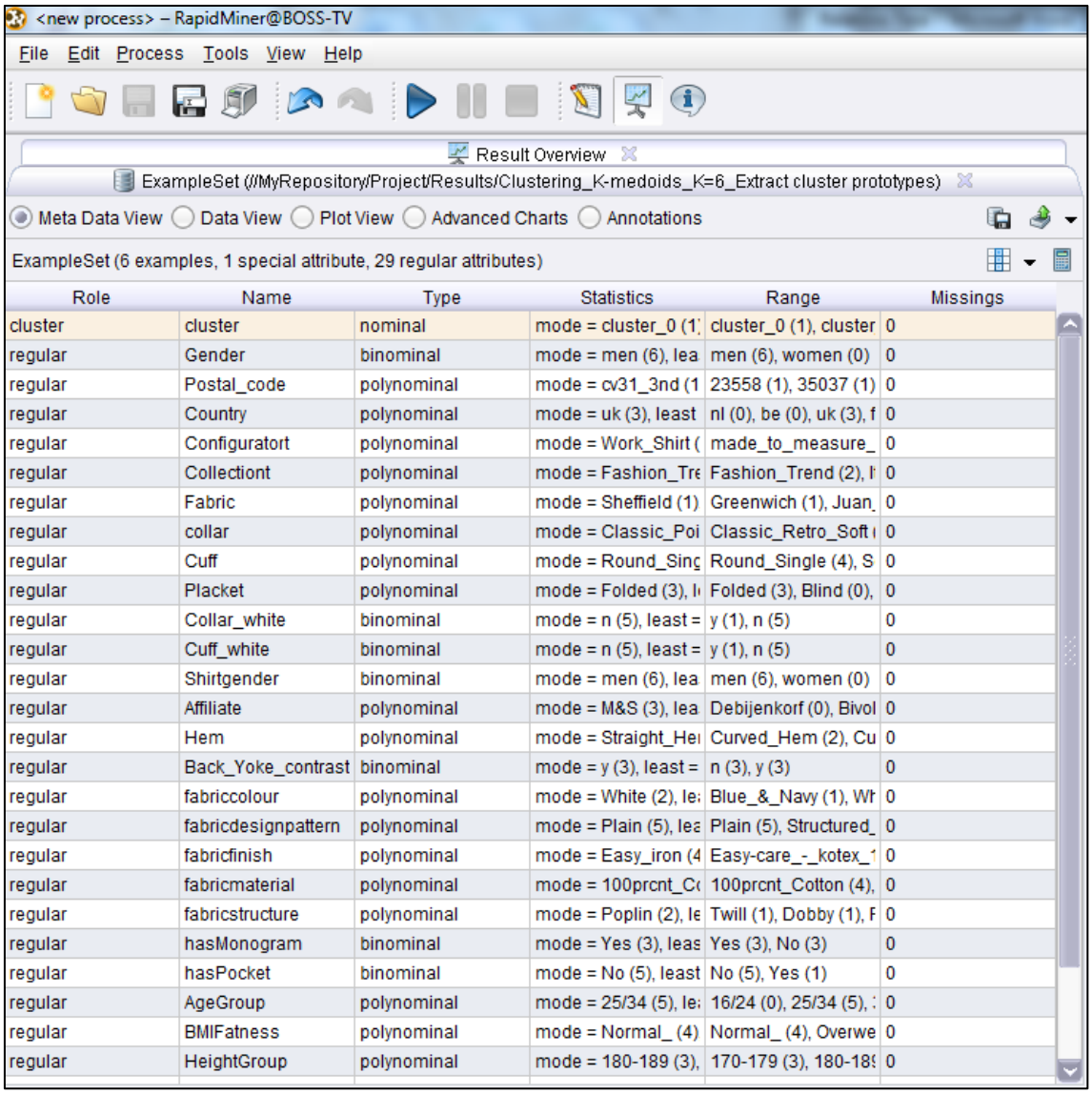



**Figure B.6** – Results View (“Centroid Plot”) on RapidMiner

In centroid plot, the philosophy is the same however the visual presentation is graphical and not tabulated.




| Role | Name | Type | Statistics | Range | Missings |
|---|---|---|---|---|---|
| cluster | cluster | nominal | mode = cluster_0 (1 | cluster_0 (1), cluster | 0 |
| regular | Gender | binominal | mode = men (6), lea | men (6), women (0) | 0 |
| regular | Postal_code | polynominal | mode = cv31_3nd (1 | 23558 (1), 35037 (1) | 0 |
| regular | Country | polynominal | mode = uk (3), least | nl (0), be (0), uk (3), f | 0 |
| regular | Configuratort | polynominal | mode = Work_Shirt ( | made_to_measure_ | 0 |
| regular | Collectiont | polynominal | mode = Fashion_Tre | Fashion_Trend (2), I | 0 |
| regular | Fabric | polynominal | mode = Sheffield (1) | Greenwich (1), Juan_ | 0 |
| regular | collar | polynominal | mode = Classic_Poi | Classic_Retro_Soft ( | 0 |
| regular | Cuff | polynominal | mode = Round_Sing | Round_Single (4), S | 0 |
| regular | Placket | polynominal | mode = Folded (3), I | Folded (3), Blind (0), | 0 |
| regular | Collar_white | binominal | mode = n (5), least = | y (1), n (5) | 0 |
| regular | Cuff_white | binominal | mode = n (5), least = | y (1), n (5) | 0 |
| regular | Shirtgender | binominal | mode = men (6), lea | men (6), women (0) | 0 |
| regular | Affiliate | polynominal | mode = M&S (3), lea | Debijenkorf (0), Bivol | 0 |
| regular | Hem | polynominal | mode = Straight_Hei | Curved_Hem (2), Cu | 0 |
| regular | Back_Yoke_contrast | binominal | mode = y (3), least = | n (3), y (3) | 0 |
| regular | fabriccolour | polynominal | mode = White (2), le: | Blue_&_Navy (1), Wh | 0 |
| regular | fabricdesignpattern | polynominal | mode = Plain (5), lea | Plain (5), Structured_ | 0 |
| regular | fabricfinish | polynominal | mode = Easy_iron (4 | Easy-care_-_kotex_' | 0 |
| regular | fabricmaterial | polynominal | mode = 100prcnt_C( | 100prcnt_Cotton (4), | 0 |
| regular | fabricstructure | polynominal | mode = Poplin (2), le | Twill (1), Dobby (1), F | 0 |
| regular | hasMonogram | binominal | mode = Yes (3), leas | Yes (3), No (3) | 0 |
| regular | hasPocket | binominal | mode = No (5), least | No (5), Yes (1) | 0 |
| regular | AgeGroup | polynominal | mode = 25/34 (5), le: | 16/24 (0), 25/34 (5), : | 0 |
| regular | BMIFatness | polynominal | mode = Normal_ (4) | Normal_ (4), Overwe | 0 |
| regular | HeightGroup | polynominal | mode = 180-189 (3), | 170-179 (3), 180-18 | 0 |

**Figure B.7** – Results View ("Meta Data") on RapidMiner

In data view (Figure B.8) we can see the cluster prototypes, information that complements the Cluster Model (Figure B.4).

Figure B.9 ("Plot View") shows one of the numerous possibilities for visualization of the dataset available on RapidMiner.

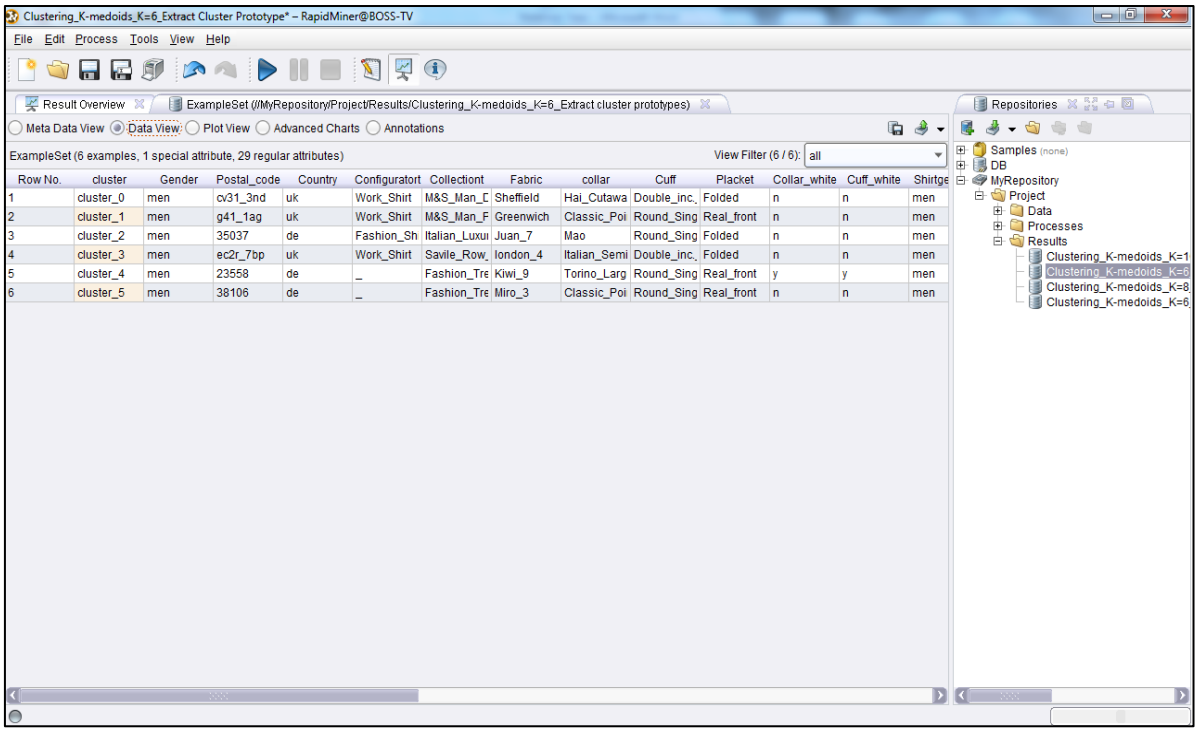



**Figure B.8** – Results View ("Data View") on RapidMiner

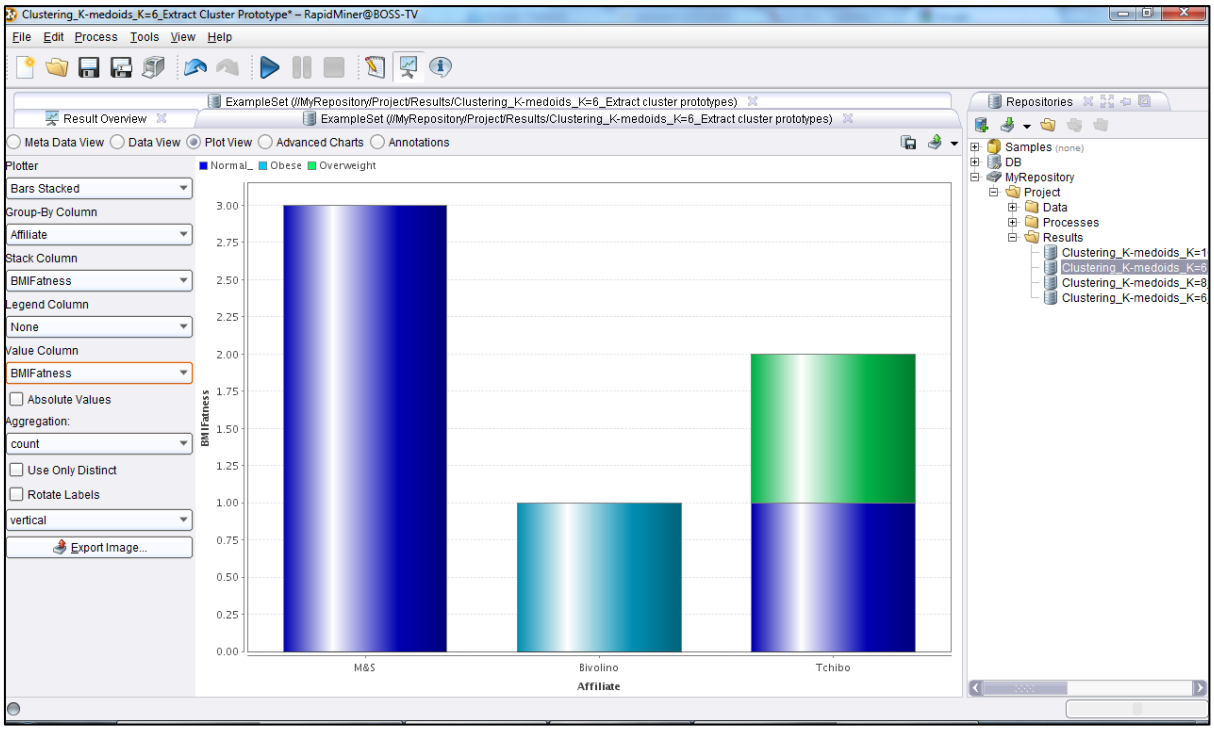



**Figure B.9** – Results View ("Plot View") on RapidMiner

## 4. Evaluation

An important task is the evaluation of the results, i.e., of the clusters resulting from the clustering process. To evaluate the clusters on RapidMiner, we selected the operator *Evaluation –> Performance and Measurement -> Clustering –> Cluster Density Performance*. This operator is used to evaluate a non-hierarchical cluster model based on the average within cluster similarity/distance. It is computed by averaging all similarities/distances between each pair of examples of a cluster and it delivers a performance based on the cluster densities. The inputs required by this measurement are the example set, cluster model and distance measure, being the last one provided through the operator *Data to Similarity*. The Data to Similarity operator creates a similarity measure based on an example set and it calculates a similarity measure from the given data (attribute based). The result of this process is presented on Figure B.11.

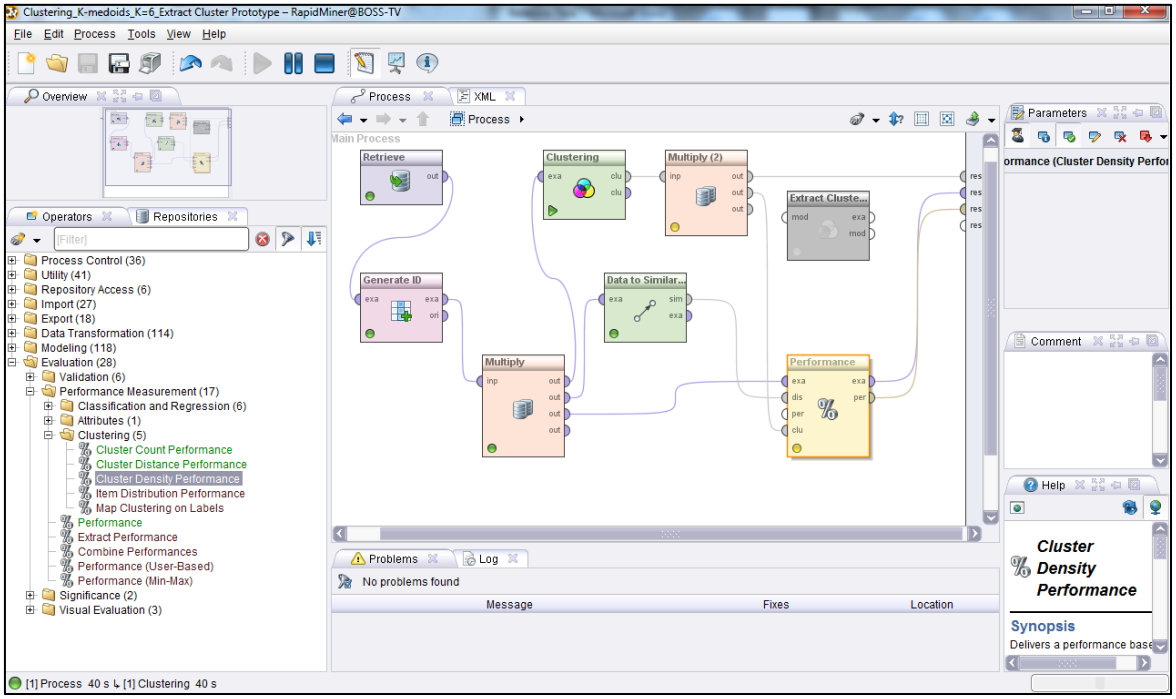



**Figure B.10** – Evaluation View on RapidMiner

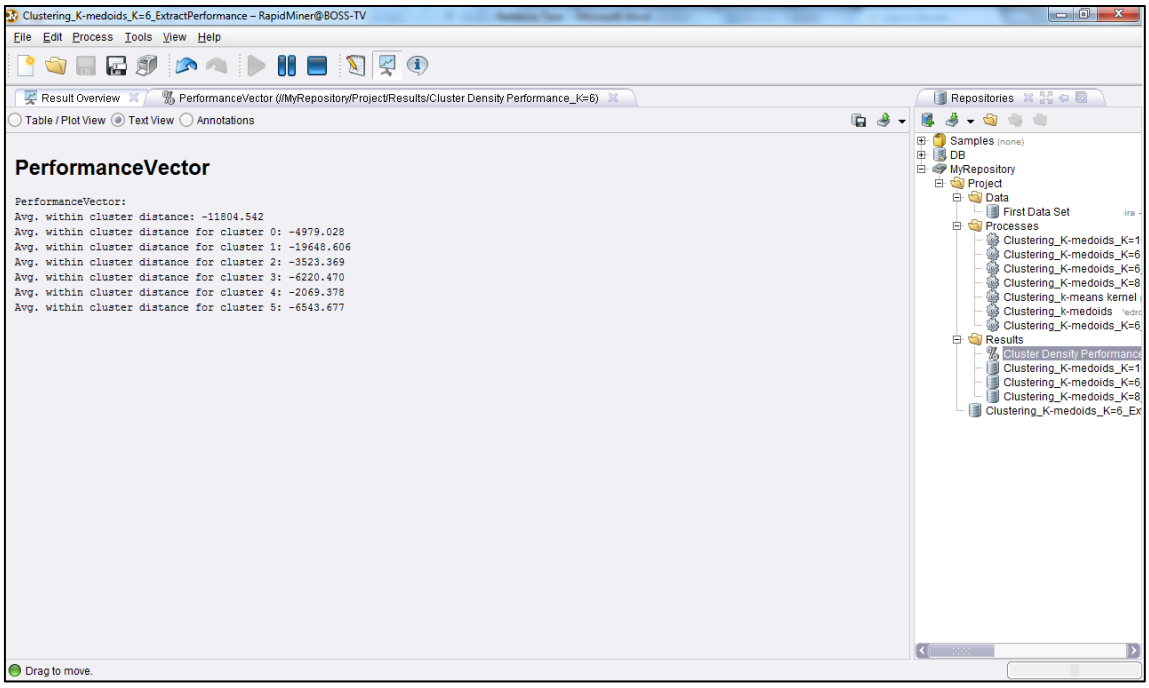



**Figure B.11** – Results of Evaluation View on RapidMiner

# References


AHMED, S. (2004), "Applications of Data Mining in Retail Business", International Conference on Information Technology: Coding and Computing (ITCC'04), IEEE.

ALJUKHADAR, M. and SENECAL, S. (2011), "Segmentation the online consumer market", *Marketing Intelligence & Planning*, Vol. 29, Nº 4, pp. 421-435, Emerald Group Publishing Limited.

ALLENBY, G., FENNEL, G., BEMMAOR, A., BHARGAVA, V., CHRISTEN, F., DAWLEY, J., DICKSON, P., EDWARDS, Y., GARRAT, M., GINTER, J., SAWYER, A., STAELIN, R. and YANG, S. (2002), "Market Segmentation Research: Beyond Within and Across Group Differences", *Marketing Letters*, Vol. 13, Nº 3, pp. 233-243, Kluwer Academic Publishers.

AL-NIMER, THAER (2006), "Data Mining: Techniques and Applications in the Manufacturing Industry", Dissertation for the degree of MSc in Operations Management, University of Nottingham, United Kingdom.

ASPERS, P. (2010), "Using design for upgrading in the fashion industry", *Journal of Economic Geography*, Nº 10, pp. 189-207, Oxford University Press.

AZEVEDO, A. and SANTOS, M. (2008), "KDD, SEMMA and CRISP-DM: A Parallel Overview", IADIS European Conference Data Mining.

BANISTER, E. and HOGG, M. (2004), "Negative symbolic consumption and consumers' drive for self-esteem: The case of the fashion industry", *European Journal of Marketing*, Vol. 38, Nº 7, pp. 850-868, Emerald Group Publishing Limited.

BERRY, M. and LINOFF, G. (2004), *Data Mining Techniques: for Marketing, Sales and Customer Relationship Management*, 2th edition, Wiley Publishing, Inc.

BERRY, M. and LINOFF, G. (1997), *Data Mining Techniques: for Marketing, Sales and Customer Support*, New York: John Wiley & Sons, INC.

BEST, R. (2005), *Market-Based Management*, 4th Edition, Upper Saddle River New Jersey: Prentice Hall.

BROCHADO, ANA (2007), "Segmentação de Mercado e Modelos de Mistura de Regressão: Critérios para a Determinação do Número de Segmentos", Tese de Doutoramento em Ciências Empresariais, Faculdade de Economia do Porto, Porto.

BRUN, M., SIMA, C., HUA, J., LOWEY, J., CARROLL, B., SUH, E. and DOUGHERTY, E. (2006), "Model-based evaluation of clustering validation measures", *Pattern Recognition Society*, Nº40, pp. 807–824, Elsevier Ltd.

CANEVER, M.D., TRIJP, H. and LANS, I. (2007), "Benefit-feature segmentation: a tool for the design of supply-chain strategy", *Marketing Intelligence & Planning*, Vol. 25, Nº5, pp. 511-533, Emerald Group Publishing, Ltd.

CAO, F., LIANG, J., Li, D., BAI, L. and DANG, C. (2012), "A dissimilarity measure for the k-Modes clustering algorithm", *Knowledge-Based Systems*, Nº26, pp. 120–127, Elsevier B.V.

CARDOSO, P. COSTA, H. and NOVAIS, L. (2010), "Fashion consumer profiles in the Portuguese market: involvement, innovativeness, self-expression and impulsiveness as segmentation criteria", Faculty of Social and Human Sciences, University Fernando Pessoa, Porto, Portugal, *International Journal of Consumer Studies*, Nº34**,** pp. 638–647, Blackwell Publishing Ltd.

CARROL, K. and GROSS, K. (2010), "An Examination of Clothing Issues and Physical Limitations in the Product Development Process", *Family & Consumer Sciences Research Journal*, Vol. 39, Nº 1, American Association of Family and Consumer Sciences.

CHEN, M., CHIU, A. and CHANG, H. (2005), "Mining changes in customer behavior in retail marketing", *Expert Systems with Applications*, Nº 28, pp. 773-781, Elsevier Ltd.

CHOO, H., JUNG, J. and CHUNG, I., (2009), "Buyer-supplier relationships in Dongdaemun fashion market: relationship quality model", *Journal of Fashion Marketing and Management*, Vol. 13 No. 4, pp. 481-500, Emerald Group Publishing Limited.

CHOY, K. L., CHOW, K. H., MOON, K. L., ZENG, X., LAU, H., CHAN, F. and HO, G.T.S. (2009), "A RFID-case-based sample management system for fashion

product development", *Engineering Applications of Artificial Intelligence*, Nº22, pp. 882-896, Elsevier Ltd.

CLEVELAND, M., PAPADOPOULOS, N. and LAROCHE, M. (2011), "Identity, demographics, and consumer behaviors: International market segmentation across product categories", *International Marketing Review*, Vol. 28, Nº 3, pp. 244-266, Emerald Group Publishing Limited.

COOIL, B., AKSOY, L. and KEININGHAM, T. (2007), "Approaches to Customer Segmentation", *Journal of Relationship Marketing*, Vol. 6, No 3-4, pp. 9-39, The Haworth Press, Inc.

CUNHA, N. (2009), "Metodologia de Selecção de Segmentações Diversificadas: Um Caso de Aplicação de Técnicas de Data Mining em Dados de Consumo para Avaliação de Portfólios de Cartões Bancários", *Dissertação de Mestrado em Gestão Comercial*, Faculdade de Economia do Porto, Universidade do Porto, Porto.

DELMATER, R. and HANCOK, M. (2001), *Data Mining Explained: a manager's guide to costume-centric business intelligence*, Boston: Digital Press.

DIAS, J. and VERMUNT, J. (2007), "Latent class modeling of website users' search patterns: Implications for online market segmentation", *Journal of Retailing and Consumer Services*, Nº 14, pp. 359-368, Elsevier Ltd.

DIBB, S. and SIMKIN, L. (2009), "Bridging the segmentation theory/ practice divide", *Journal of Marketing Management*, Vol. 25, Nº 3-4, pp. 219-225, Westburn Publishers Ltd.

DING, WEI (2007), "Mass Customization for Clothing Industry – On an E-commerce Environment", Dissertation for the Degree of MSc Operations Management, University of Nottingham, United Kingdom.

DOLNICAR, S. (2002), "A Review of Unquestioned Standards in Using Cluster Analysis for Data-Driven Market Segmentation", Australian and New Zealand Marketing Academy Conference (ANZMAC 2002), Deakin University, Melbourne.

DOLNICAR, S. (2003), "Using cluster analysis for market segmentation – typical misconceptions, established methodological weaknesses and some

recommendations for improvement", *Australasian Journal of Market Research*, 11(2), pp. 5-12.

DOLNICAR, S., and LEISCH, F. (2003), "Data-Driven Market Segmentation – A Structure-Based Conceptual Framework for Management Decision Support", Australian and New Zealand Management Academy Conference, Adelaide, South Australia, 1-3 December.

FAYYAD, U. and UTHURUSAMY, R. (2002), "Evolving Data Mining into Solutions for Insights", *Communications of the ACM*, Vol. 45, Nº 8.

HAND, D., MANNILA, H. and SMITH, P. (2001), Principles of Data Mining, The MIT Press, Massachusetts Institute of Technology.

HALKIDI, M., BATISTAKIS, Y. and VAZIRGIANNIS, M. (2001), "On Clustering Validation Techniques", *Journal of Intelligent Information Systems*, Vol. 17:2/3, pp. 107-145, Kluwer academic Publishers.

HALKIDI, M., BATISTAKIS, Y. and VAZIRGIANNIS, M. (2002), "Cluster Validity Methods: Part I", SIGMOND Record, Vol. 31, Nº 2.

HARDING, J.A., SHAHBAZ, M., SRINIVAS and KUSIAK, A. (2006), "Data Mining in Manufacturing: A Review", *Journal of Manufacturing Science and Engineering*, Vol. 128.

HASTIE, T., TIBSHIRANI, R. and FRIEDMAN, J. (2001), *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, Springer-Verlag New York, Inc.

HSU, C. (2009), "Data mining to improve industrial standards and enhance production and marketing: an empirical study in apparel industry", *Expert Systems with Applications*, Nº36, pp. 4185-4191, Elsevier Ltd.

JAIN, A.K., MURTY, M.N. and FLYNN, P.J. (2000), "Data Clustering: A Review", ACM Computing Surveys, Vol. 31, Nº 3.

JAIN, A. K. (2009), "Data clustering: 50 years beyond K-Means", Pattern Recognition Letters, Elsevier B.V.

KANTARDZIC, M. (2003), *Data Mining - Concepts, Models, Methods, and Algorithms*, John Wiley & Sons, INC.

KAU, A., TANG, Y. and GHOSE, S. (2003), "Typology of online shoppers", *Journal of Consumer Marketing*, Vol. 20, nº 2, pp. 139-156, MCB UP Limited.

KETTENRING, J. (2009), "A patent analysis of cluster analysis", *Applied Stochastic Models in Business and Industry*, Nº25, pp. 460-467.

KIM, K. and AHN, H. (2008), "A recommender system using GA *K-Means* clustering in an online shopping market", *Expert Systems with Applications*, Nº34, pp. 1200-1209, Elsevier Ltd.

KO, E., KIM, E., TAYLOR, C., KIM, K. and KANG, I. (2007), "Cross-national market segmentation in the fashion industry: A study of European, Korean, and US consumers", *International Marketing Review*, Vol. 24, Nº 5, pp. 629-651, Emerald Group Publishing Limited.

KOTLER, P. and KELLER, K. (2012), *A Framework for Marketing Management*, 5th ed. International ed. - Boston: Pearson.

KOTLER, P. and ARMSTRONG, G. (2012), *Principles of Marketing*, 14th edition, Pearson Education, Inc.

KOTLER, P. and KELLER, K. (2012), *Marketing Management*, 14th ed. global ed. Harlow: Pearson.

KOTLER, P. and KELLER, K. (2008), *Marketing Management*, 13th edition, Prentice Hall.

KOTLER, P., WONG, V., SAUNDERS, J. and ARMSTRONG, G. (2005), *Principles of Marketing*, 4th European Edition, Pearson Education Ltd.

KOTLER, P., RACKHAM, N. and KRISHNASWAMY, S. (2006), "Ending the War between Sales and Marketing", Harvard Business Review.

KOTLER, P. (1999), "*Kotler on Marketing: How to Create, Win, and Dominate Markets"*, USA: The Free Press (FP).

KOZAR, J. and DAMHORST, M. (2008), "Older women's responses to current fashion models", *Journal of Fashion Marketing and Management*, Vol. 12, Nº 3, pp. 338-350, Emerald Group Publishing limited.

LAROSE, D. (2005), *Discovering Knowledge in Data: An Introduction to Data Mining*, John Wiley & Sons, Inc.

LEE, S. J. and SIAU, K. (2001), "A review of data mining techniques", *Industrial Management & Data Systems*, Vol. 101, Nº 1, pp. 41-46, MCB University Press.

LEGÁNY, C., JUHÁSZ, S. and BABOS, A. (2006), 5th WSEAS Int. Conf. on Artificial Intelligence, Knowledge Engineering and Data Bases, Madrid, Spain, February 15-17, pp. 388-393.

LEVINE, EREL (1999), "Un-Supervised Estimation of Cluster Validity – Methods and Applications", MSc Thesis, Feinberg Graduate School, Weizmann Institute of Science, New York, United States of America.

LIM, J., CURRIM, I. and ANDREWS, R. (2005), "Consumer heterogeneity in the longer-term effects of price promotions", International Journal Research in Marketing", Nº 22, pp. 441-457, Elsevier B.V.

LO, W., HONG, T. and JENG, R. (2008), "A framework of E-SCM multi-agent systems in the fashion industry", *International Journal of Production Economics*, Nº114, pp. 594–614, Elsevier B.V.

MACCARTY, J. and HASTAK, M. (2007), "Segmentation approaches in data-mining: A comparison of RFM, CHAID, and logistic regression", *Journal of Business Research*, Nº60, pp. 656-662, Elsevier inc.

MIRKIN, B. (2005), *Data Clustering for Data Mining: A Data Recovery Approach*, Boca Raton: Chapman and Hall.

MOOI, E. and M. SARSTEDT (2011), *A Concise Guide to Market Research*, Springer-Verlag Berlin Heidelberg.

MOORE, M. and FAIRHURST, A. (2003), "Marketing capabilities and firm performance in fashion retailing", *Journal of Fashion Marketing and Management*, Vol. 7, Nº 4, pp. 386-397, MCB UP Limited.

NEWBERY, M., MEULEN, K. (2010), *"Tomorrow's clothing retail: sectors, markets and routes"*, United Kingdom: Aroq Ltd.

NGAI, E.W.T., XIU, L. and CHAU, D.C.K. (2009), "Application of data mining techniques in customer relationship management: A literature review and classification", *Expert Systems with Applications*, Nº36, pp. 2592–2602, Elsevier Ltd.

O'CASS, A. (2004), "Fashion clothing consumption: antecedents and consequences of fashion clothing involvement", *European Journal of Marketing*, Vol. 38, Nº 7, pp. 869-882, Emerald Group Publishing Limited.

PARK, H. and JUN, C. (2009), "A simple and fast algorithm for K-Medoids clustering", *Expert Systems with Application,s* Nº36, pp. 3336–3341, Elsevier Ltd.

PARK, JUNG HYUN (2009), "Technical Considerations for the Design of Smart Apparel for the Overweight", Thesis for the Degree of Master of Science, Faculty of North Carolina State University, Raleigh, United States of America.

PASCUAL, D., PLA, F. and SÁNCHEZ, J. (2010), "Cluster validation using information stability measures", Nº 31, pp. 454-461, Elsevier B.V.

PEDRYCZ, W. (2005), *Knowledge-Based Clustering: From Data to Information Granules,* New Jersey: John Wiley & Sons, Inc.

PHAM, D. T., DIMOV, S. S. and C. D. NGUYEN (2005), "Selection of *K* in *K-Means* clustering", *Journal of Mechanical Engineering Science*, Vol. 219, Part C, IMechE.

PHAU, I., and LO, C. (2004), "Profiling fashion innovators: A study of self-concept, impulsive buying and Internet purchase intent", *Journal of Fashion Marketing and Management*, Vol. 8, Nº 4, pp. 399-411, Emerald Group Publishing Limited.

PRIEST, A. (2005), "Uniformity and differentiation in fashion", *International Journal of Clothing Science and Technology*, Vol. 17, Nº 3/4, pp. 253-263, Emerald Group Publishing Limited.

RENDÓN, E., ABUNDEZ, I., ARIZMENDI, A. and QUIROZ, E. (2011), "Internal versus External cluster validation indexes", *International Journal of Computers and Communications*, Issue 1, Vol. 5.

RYGIELSKI, C., WANG, J. and YEN, D. (2002), "Data Mining techniques for customer relationship management", *Technology in Society*, Nº24, pp. 483-502, Elsevier Science Ltd.

ROCHA, M., HAMMOND, L., HAWKINS, D. (2005), "Age, gender and national factors in fashion consumption", *Journal of Fashion Marketing and Management*, Vol. 9, Nº4, pp. 390-390, Emerald Grouping Publishing Limited.

RUD, O. (2001), *Data Mining Cookbook: modeling data for marketing, risk and customer relationship management*, New York: John Wiley & Sons, Inc.

SCHAFER, J., KONSTAN, J. and RIEDL, J. (2001), "E-commerce Recommendation Applications", *Data Mining and Knowledge Discovery*, Nº 5, pp. 115-153, Kluwer Academic Publishers.

SCOTT, D. (2007), *The New Rules of Marketing & PR*, New York: John Wiley & Sons, Inc.

SHAW, M., SUBRAMANIAM, C., TAN, G. and WELGE, M. (2001), "Knowledge management and data mining for marketing", *Decision Support Systems,* Nº31, pp. 127-137, Elsevier Science B.V.

SIDDIQUI, N., O'MALLEY, A., MCCOLL, J. and BIRTWISTLE, G. (2003), "Retailer and consumer perceptions of online fashion retailers: Web site design issues", *Journal of Fashion Marketing and Management*, Vol. 7, Nº 4, pp. 345-355, MCB UP Limited.

SINGH, S. and CHAUCHAN, N. C. (2011), "K-Means vs. K-Medoids: A Comparative Study", *National Conference on Recent Trends in Engineering & Technology*, B.VM. Engineering College, V. V. Nagar, Gujarat, India.

SIVOGOLOVKO, E. (2012), "Validating cluster structures in Data Mining tasks", EDBT/ICDT Workshops March 26-30, Berlin, Germany, ACM.

SMITH, W. (1956), "Product differentiation and market segmentation as alternative marketing strategies", *Journal of Marketing*, 21, 3-8.

SU, Z. and XU, D. (2011), "Lifestyle of Obese Population and Brand Choosing of Personalized Clothing", IEEE.

TAN, P., STEINBACH, M. and KUMAR, V. (2006), *Introduction to Data Mining: Instructor's Solution Manual*, Pearson Addison-Wesley.

TRINH, G., DAWES, J. and LOCKSHIN, L. (2009), "Do product variants appeal to different segments of buyers within a category?", *Journal of Product & Brand Management*, 18/2, pp. 95-105, Emerald Group Publishing Limited.

TURQUIN, E., WITHER, J., BOISSIEUX, L., GANI, M. and HUGHES, J. (2007), "A Sketch-Based Interface for Clothing Virtual Characters", IEEE Computer Graphics and Applications.

VELMURUGAN, T. and SANTHANAM, T. (2010), "Computational Complexity between K-Means and K-Medoids Clustering Algorithms for Normal and Uniform Distributions of Data Points", *Journal of Computer Science* 6 (3): pp. 363-368, Science Publications.

WEDEL, M. and KAMAKURA, W. (2002), "Introduction to the Special Issue on Market Segmentation, *International Journal of Research in Marketing*, Vol. 19, Nº 3, pp. 181-183, Elsevier Science B.V.

WEDEL, M. and KAMAKURA, W. (2000), *Market Segmentation: Conceptual and Methodological Foundations*, Kluwer Academic Publishers.

WEDEL, M., KAMAKURA, W. and BÖCKENHOLT, U. (2000), "Marketing data, models and decisions", *International Journal of Research in Marketing*, Nº 17, pp. 203-208, Elsevier Science B.V.

WU, J., XIONG, H. and CHEN, J. (2009), "Adapting the Right Measures for K-Means Clustering", KDD'09, Paris, France, ACM.

WU, J., XIONG, H. and CHEN, J. (2009), "Adapting the Right Measures for K-Means Clustering", KDD'09, Paris, France, ACM.

YATSKIV, I. and GUSAROVA, L. (2005), "The Methods of Cluster Analysis Results Validation", *Transport and Telecommunication*, Vol. 6, Nº 1, International Conference RelStat'04.

# ANNEXES

# ANNEX A

## BIVOLINO

The information contained in this annex is from Bivolino website (http://www.bivolino.com/).

*"Made to measure shirts"*

Bivolino was born in 1954 in a sandy area where the squirrel feels at home. Each Bivolino customized shirt is embroidered with the squirrel as the symbol of the perfect biometric fitting guarantee. Today Bivolino supports two projects focusing on preventing the red squirrel extinction: The Save Your Logo initiative as well as the Red Squirrel in South Scotland action.

**Bivolino Brand Story**

### A. The Beginning

Over its 50 year history, Bivolino has built a reputation as a leading supplier of beautifully tailored shirts – crafted with the ultimate combination of precision and design. But few people know the story behind the brand and how it spearheaded the design innovation we see in shirt manufacturing today.

The Bivolino story began in 1954, when brothers Louis and Jacques Byvoet founded the company with a joint investment of 8 million francs. Their grandfather, Jacques, had been in the linen trade since 1900 and the name Bivolino was chosen to represent both the family name of Byvoet and linen – the fabric from which Bivolino shirts would be made from. They based the company in Hasselt, in the heart of Campine in Belgium.

### B. The Origins

With the opening of the Byvoet brothers first premises, the foundations of the Bivolino brand were laid – paving the way for Bivolino to become a pioneer within the shirt market, a symbol that guarantees quality and the perfect bespoke cut with a fashionable twist.

At the time, consumers were looking for something different from the classic white shirt – they wanted fashionable styles in an array of colours, styles and fabrics – and this demand is what formed the cornerstone of the Bivolino concept.

The Bivolino logo, two squirrels sitting on a distaff holding the letter B, was inspired by the location of the brothers' workshop, where they could see squirrels running freely through the sandy pine forests of Hasselt.

### C. The Shirt

Under the direction of Byvoet brothers, the company soon grew to become the market leader in shirt manufacturing, running a small plant with 80 employees producing 350.000 shirts a year. This record productivity was possible due to the Byvoet's investment in the very best modern machinery of the time, highlighting the role of technology in the manufacturing process. At this point, export to Netherlands, Luxemburg, Germany and Switzerland represented 35% of the business.

### D. The Squirrel

The humble squirrel logo chosen in 1954 has today become a symbol of high quality fashion; a guarantee of Bivolino's skillful, professional production techniques that have been honed over many years.

It has been said that the Bivolino brand has similarities to the squirrel – it has a personalized style, and moves quickly and elegantly with freedom. In homenage to the animal that inspired the brand logo, Bivolino currently supports two projects in fighting the extinction of red squirrels in Scotland.

### E. The Science

In 1969, Bivolino built on their early investment in technology by introducing groundbreaking new ergonomic measurement system – allowing each shirt to be individually fitted to the body at first time.

This system was the first of its kind in Europe, and was created in partnership with IBM. Using 1.200.000 measurements of the body, Bivolino was able to reinvent a new fit completely adapted to the body shape.

At the same time as the ergonomic measurement system was introduced, Bivolino was also introducing innovative new fabrics to surprise and excite consumers and the industry, including Terlenka soil release, jacquard and polyester, as well as the

self-ironing popelines Belofast. Meanwhile consumers were looking for bright, bold colours such as blues and reds, along with neutral white, with large stripes and graphic patterns becoming popular.

### F. The Development

During the recession of the 1970's, there was a shift in consumer spending patterns that saw people buying less than before but thinking more consciously about the quality of their purchases. The inherent craftsmanship and quality of Bivolino shirts was therefore more important to the business than ever, and the brand worked hard to produce impeccable products that would stand the test of time, wash after wash wear after wear. In 1981, Bivolino became the first shirt label to take the daring step towards computerized production, which automatically produces the pattern making gradations in a fraction of time – a real revolution in the shirt manufacturing process for the time. By now, and using this new technology, Bivolino was producing 900,000 shirts a year and employing 270 people.

### G. The Fashion

Each season, a select group of designers create a new Bivolino collection under the guidance of a graduate fashion designer from the renowned Academy of Antwerp. The latest fabrics, color trends, styles and cuts are researched and developed by the styling team to create the latest collection of Bivolino shirts for the fashion conscious consumer, ensuring that the brand stays at the forefront of shirt design.

One of the biggest challenges for the Bivolino brand came on 13$^{th}$ October 1987, when an enormous fire ruined the Bivolino factory – taking with it 33 years of passion for shirt making and reducing it to ashes. Over the next year, sales decreased by 80% as the company struggled to recover, and production was moved to Tunisia and Romania. It was during this difficult time for the Byvoet brothers that they decided to pass on the family business to Louis' son, Michel, starting the next step in the Bivolino journey.

### H. The Digital Revolution

The growth of the internet opened up a new world of possibilities for Bivolino and the brand established a new digital studio in the Hight Tech Science Park Limburg. As the company embraced new technology, sewing machines made way for computers

as Bivolino moved into the digital age and in 1997 the first shirt was sold from Bivolino.com.

Customers could now shop online to create a completely bespoke Bivolino shirt with just a few clicks on the mouse. They could choose the fabric, collar and cuffs, or personalize the design with a name or initials with the finished shirt arriving within 2-3 weeks. At this stage customers still had to take their own measurements at home, but Bivolino already had plans to revolutionize this aspect of the design process.

### I. The Biometric Shirt

The year 2000 brought with it the dot com bubble burst, but where others failed, Bivolino saw opportunities. Taking the moto that you have to innovate to survive, Bivolino launched the possibly its most innovative tool yet: biometric sizing technology. After two years of anthropometric research supported by university scientists, the company solved the magic formula to calculate the perfect cut and size for every Bivolino customer – without the need for them to use a tape measure. Bivolino shoppers just need to provide their height, weight, collar size and age, and from this each customer is guaranteed a cut that fits like a second skin. The first shirt ordered is 100% satisfaction guaranteed.

### J. The Awards

Bivolino's innovative approach to shirt design has earned the company numerous awards in several countries. In the Netherlands, Bivolino was given the "Starter Award" from the Dutch home shopping trading association, Thuiswinkle.org. In 2006, the company was awarded the "BeCommerce" prize in Belgium, and this was followed by French magazine Capital giving Bivolino the best position for its cost effectiveness in 2008. In the UK, consumer magazine *Which?* declared Bivolino's biometric sizing technology to be better performing than the bespoke tailors of Savile Row.

### K. The 3D Technology

In 2010, Bivolino launched its latest piece of technology – a 3D shirt design tool. The result of several years of research, the tool was developed thanks to the Open Garments research project, and was supported by European Commission research funds. A new zoom function on the collar, cuffs and pockets means that customers can now

see their shirt presented as realistically as possible, all in real time. Endless design combinations are now also possible – from choosing contrasting fabrics, inner collars, cuffs, yoke and back panels to contrasting sleeves, stitching, removable bones, buttons and more, allowing customers to create the ultimate bespoke shirt. When using the design tool, customers can choose from one of four categories: Business, Fashion, Party and Arty.

### L. The Arty Shirt

At the end of 2010, Bivolino partnered with ten Dutch painters to create bespoke artwork that could be used to customize shirts. This new creative playground for customers was made possible by the Amsterdam Fashion Institute, who brought the group painters together, and digital printing technology. Each artist has their own unique style and themes include mysterious landscapes, Indian culture, the female face and Spring frogs – all of which are available to customers to use a contrasting collars or cuffs, or even as an allover print.

### M. The Women's Shirt

In 2011, Bivolino introduced collection women's shirts for the first time, offering women the luxury of creating a bespoke tailored shirt for any occasion with a few clicks of the mouse.

Customers can experiment with fabrics, choosing different cottons, stretch or transparent options, or mixing and matching prints such as Liberty flowers and stripes as well as adding contrasting collars, cuffs or pockets. Sleeve lengths can be tailored to the season, with full length, three quarter, short and sleeveless options all available. Customers can also add a decorative flower motif, personalized buttons or contrasting stitching to complete the shirt in style.

Bivolino's biometric sizing technology uses the customer's weight, height, age and bra size measurements to create the perfect fit – with a 100% satisfaction guarantee. ELLE called the service "a revolution".

### N. The Planet

Bivolino is passionate about the planet and has developed its service to be as green as possible. Since 2008, each shirt is packaged in a biodegradable envelope, created from non-polluting plastic and Bivolino has made significant progress in

reducing the size of packaging used in delivery. Due to Bivolino's patented biometric sizing technology, the percentage of returns is just 3.8%, reducing the use of transport to return goods. Finally, as each Bivolino shirt is made to order in the company's ethical manufacturing plants in Tunisia and Romania there is no stock of goods – resulting in no waste; in a perfectly adapted business model which Bivolino calls "Mass Customization".

## Bivolino and the Environment

*"By creating, buying and sharing at Bivolino, you go Green!"*

Bivolino is constantly looking for ways to further reduce its environmental impact.

### A. A Sustainable Business Model

At Bivolino, customer creates buys and shares his customized shirt. The making of his bespoke shirt starts immediately in Bivolino apparel manufacturing plans just after his order has been confirmed online. This means that there is no stock of shirts waiting somewhere that eventually need to be absorbed. It is what the company calls a *Made-to-Order business model* or a *Consumer Driven Manufacturing business model* which reduces stock wastes and promotes a real sustainable supply chain. These savings result in a win-win situation for everybody taking part in the supply chain. Customer is part of it and can enjoy a high quality personalized service at very competitive prices. This is also what company calls *"Mass Customization"*.

### B. Reducing Returns

Since 2004, the right size is guaranteed by Bivolino biometric sizing technology (patent Nr EEC-EP1341427 & US-7346421) which means that customer get the right size without trying his shirt or without using any tape measurement. Only by giving his height, weight, age and collar size or cup size for women, he will get a bespoke shirt cut to the bones! For customer first Bivolino shirt the company even remake the shirt if needed till his 100% satisfaction. This worldwide unique biometric sizing technology helps company to make a record low return rate of 3.8% in total. From this amount,

Bivolino repairs as much as possible so that waste is reduced to a strict minimum. Those "default" remaining shirts are then offered to those of us who are in real need through charity organizations.

### C. New Biodegradable Packaging

Since 2008, Bivolino customized shirts are individually or duo packed in a new biodegradable branded bag. The bags are manufactured in a famous environmental-friendly plastic material, the *Ethylene Vinyl Acetate* or also called EVA. Its applications and performance are very similar to PVC while reducing the risk of infringing any toxicity regulations. It is biodegradable after a period of maximum one year with no pollution to environment after disposal and incineration. This green packaging approach is reinforced by the will to reduce packaging waste.

### D. Reducing Packaging Waste

Since 2007, Bivolino has made significant progress to reduce excess packaging in its shipments to customers and has introduced additional types of recyclable packing materials to protect items while in transit. Each Bivolino shirt is packed in a bag to protect its high quality fabric. When customer order two shirts, the company still use the same bag in order to save packaging and call it then a Bivolino duo pack. The bag is put in a bubble envelope which size is perfectly matching with the size of a Bivolino shirt which means that there is no space waste. It is what the company calls a frustration-Free packaging.

### E. Fabric Swatches

Bivolino decided not to send out fabric samples any more. It would be indeed not ecologically responsible (packaging, delivery, fabric waste) if the company would continue to send fabric swatches.

### F. Logistics and delivery

As a matter of fact, online shopping is inherently more environmentally friendly than traditional retailing. The efficiencies of online shopping result in a greener shopping experience. This study explains some of the benefits of the *online shopping model*. It was found that, on average, having goods delivered to your home by parcel

carrier generates significantly less carbon dioxide than making a special trip to the shops to buy the same item. The research compared the carbon footprints of online and conventional shopping for small goods such as books, CDs, clothing, cameras and household items. The work focused on the final stage in the delivery process, the so-called ‘last mile’, when goods are either delivered to the home or customers travel to the shops to collect them in person. It was found that a typical van-based home delivery produced 181g $CO^2$, compared with 4274g $CO^2$ for an average trip to the shops by car. In other words, when a customer drives to the shops and buys fewer than 24 small, non-food items per trip, home delivery is more environmentally-friendly.

### G. Green Digital Clothing

Bivolino provides a vision of the future which encompasses the evolution of digital clothing supply chains, from design to retail, that minimize returns and, in turn, reduce waste. This “webified” supply chain is the “Googlification” of the apparel industry and trade (referring to the book ‘What would Google do?‘ from Jeff Jarvis) focusing on e-configurators, digital design toolkits, online dressing facilities and the development of "controlled" virtual shopping communities. Waste can be controlled as part of a lean manufacturing, or sustainable initiative. Technology also plays a role in developing a more sustainable supply chain. Bivolino uses sustainable technologies including computerized sketching, CAD pattern design, digital grading and marker-making, digital printing and computer numerical control (CAM) single-ply cutting. In fact, any technology which allows the product to remain in digital form until later in the process is considered to be more sustainable. Why is it more sustainable to create and buy a garment in a digital form? Surely you need to see real product samples? Whenever a physical sample is created, waste is introduced into the process. At Bivolino, customer indeed creates and buys a shirt which is digitally displayed and configurated, without real samples or photos. This is worldwide unique!

### H. Ethical Manufacturing Plants

Bivolino offshore manufacturing plants have received the SEDEX label in 2007. This means recognition of Bivolino ethical performance. The points that have been successfully audited were: 1. Employment freely chosen; 2. Freedom of association; 3. Safety & hygienic conditions; 4. Child labour; 5. Wages & benefits; 6. Working hours; 7. Discrimination; 8. Regular employment; and 9. Harsh or inhumane treatment.

# ANNEX B

## CRISP-DM

### The CRISP-DM reference model

The current process model for DM provides an overview of the life cycle of a DM project. It contains the phases of a project, their respective tasks, and the relationships between these tasks. At this description level, it is not possible to identify all relationships. Relationships could exist between any DM tasks depending on the goals, the background, and the interest of the user–and most importantly–on the data.

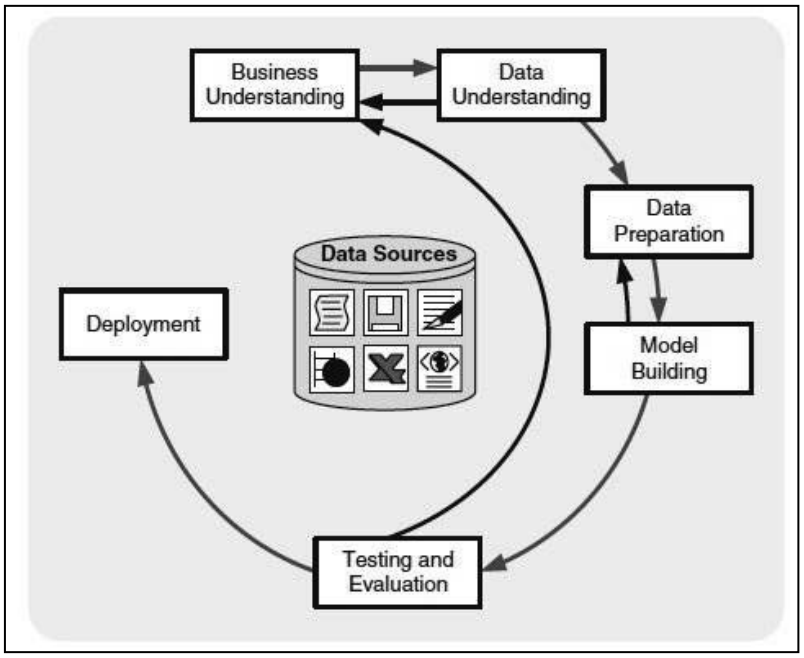



**Figure B.1 –** Phases of CRISP-DM Reference Model

The life cycle of a DM project consists of six phases (Figure B.1). The sequence of the phases is not rigid. Moving back and forth between different phases is always required. The outcome of each phase determines which phase, or particular task of a phase, has to be performed next. The arrows indicate the most important and frequent dependencies between phases.

The outer circle in Figure B.1 symbolizes the cyclical nature of DM itself. DM does not end once a solution is deployed. The lessons learned during the process and

from the deployed solution can trigger new, often more-focused business questions. Subsequent DM processes will benefit from the experiences of previous ones. In the following, we briefly outline each phase:

1. **Business understanding**

This initial phase focuses on understanding the project objectives and requirements from a business perspective, then converting this knowledge into a DM problem definition and a preliminary plan designed to achieve the objectives.

2. **Data understanding**

The data understanding phase starts with initial data collection and proceeds with activities that enable you to become familiar with the data, identify data quality problems, discover first insights into the data, and/or detect interesting subsets to form hypotheses regarding hidden information.

3. **Data preparation**

The data preparation phase covers all activities needed to construct the final dataset (data that will be fed into the modeling tool(s)) from the initial raw data. Data preparation tasks are likely to be performed multiple times and not in any prescribed order. Tasks include table, record, and attribute selection, as well as transformation and cleaning of data for modeling tools.

4. **Modeling**

In this phase, various modeling techniques are selected and applied, and their parameters are calibrated to optimal values. Typically, there are several techniques for the same DM problem type. Some techniques have specific requirements on the form of data. Therefore, going back to the data preparation phase is often necessary.

5. **Evaluation**

At this stage in the project, you have built a model (or models) that appear to have high quality from a data analysis perspective. Before proceeding to final deployment of the model, it is important to thoroughly evaluate it and review the steps executed to create it, to be certain the model properly achieves the business objectives. A key objective is to determine if there is some important business issue that has not

been sufficiently considered. At the end of this phase, a decision on the use of the DM results should be reached.

### 6. Deployment

The creation of the model is generally not the end of the project. Even if the purpose of the model is to increase knowledge of the data, the knowledge gained will need to be organized and presented in a way that the customer can use it. It often involves applying "live" models within an organization's decision making processes—for example, real-time personalization of Web pages or repeated scoring of marketing databases. Depending on the requirements, the deployment phase can be as simple as generating a report or as complex as implementing a repeatable DM process across the enterprise. In many cases, it is the customer, not the data analyst, who carries out the deployment steps. However, even if the analyst will carry out the deployment effort, it is important for the customer to understand up front what actions need to be carried out in order to actually make use of the created models.

Table B.1 presents an outline of the phases accompanied by generic tasks and outputs.

| Phases | Tasks | Outputs |
|---|---|---|
| **Business Understanding** | Determine Business Objectives<br>Assess Situation<br>Determining Data Mining Goals<br>Produce Project Plan | Background, Business Objectives; Business Success Criteria.<br>Inventory of Resources; Requirements, Assumptions and Constraints; Risks and Contingencies; Terminology; Costs and Benefits.<br>Data Mining Goals; Data Mining Success Criteria.<br>Project Plan; Initial Assessment of Tools and Techniques. |
| **Data Understanding** | Collect Initial Data<br>Describe Data<br>Explore Data<br>Verify Data Quality | Initial Data Collection Report.<br>Data Description Report.<br>Data Exploration Report.<br>Data Quality Report. |
| **Data Preparation** | Select Data<br>Clean Data<br>Construct Data<br>Integrate Data<br>Format Data | Rationale for Inclusion/Exclusion.<br>Data Cleaning Report.<br>Derived Attributes; Generated Records.<br>Merged Data.<br>Reformatted Data. |

| Phases | Tasks | Outputs |
|---|---|---|
| **Modeling** | Select Modeling Techniques<br>Generate Test Design<br>Build Model<br>Assess Model | Modeling Technique; Modeling Assumptions.<br>Test Design.<br>Parameter Settings; Models; Model Description.<br>Model Assessment, Revised Parameter Settings. |
| **Evaluation** | Evaluate Results<br>Review Process<br>Determine Next Steps | Assessment of Data Mining Results; Approved Models.<br>Review of Process.<br>List of Possible Actions; Decision. |
| **Deployment** | Plan Deployment<br>Plan Monitoring and Maintenance<br>Produce Final Report<br>Review Project | Deployment Plan.<br>Monitoring and Maintenance Plan.<br>Final Report; Final Presentation.<br>Experience Documentation. |

**Table B.1 –** Generic tasks and outputs of the CRISP-DM Reference Model

# ANNEX C

## RAPIDMINER

The information contained in this annex is from RapidMiner website (http://rapid-i.com/).

RapidMiner is the world's leading open source DM software. RapidMiner does the best among the most important open source DM tools both in terms of technology and applicability. This reflects the focus of the development work which has always been put on a user-friendly combinability of the latest as well as established DM techniques. This combining gives RapidMiner a high flexibility when defining analysis processes. The processes of RapidMiner combine the power of development environments, as known from programming languages, with the simplicity of visual programming. The modular approach also has the advantage that even internal analysis processes can be examined in the greatest detail and utilized.

RapidMiner contains more than 500 operators altogether for all tasks of professional data analysis, i.e., operators for input and output as well as data processing, modeling and other aspects of DM. But also methods of text mining, web mining, the automatic sentiment analysis from Internet discussion forums (sentiment analysis, opinion mining) as well as the time series analysis and prediction are available to the analyst. In addition, RapidMiner contains more than 20 methods to also visualize high-dimensional data and models.

Innovations that have been made on RapidMiner support the optimization of direct mailing and marketing campaigns, churn reduction, the increase of customer retention and the cost-benefit optimized acquisition of customers.

### Data

On RapidMiner there are different value types for attributes and they could also be transformed into other types. We speak of value type *text* in the case of free text, of the value type *numerical* in the case of numbers and of the value type *nominal* in the case of only few values being possible (like with the two possibilities “yes" and “no" for the target attribute).

The values types supported on RapidMiner are presented on Table C1.

| Value Type | RapidMiner Name | Use |
|---|---|---|
| Nominal | nominal | Categorical non-numerical values, usually used for finite quantities of different characteristics. |
| Numerical | numeric | For numerical values in general. |
| Integer | integer | Whole numbers, positive and negative. |
| Real numbers | real | Real numbers, positive and negative. |
| Text | text | Random free text without structure. |
| 2-value nominal | binomial | Special case of nominal, where only two different values are permitted. |
| Multi-value nominal | polynominal | Special case of nominal, where more than two different values are permitted. |
| Date Time | data_time | Date as well as time. |
| Date | date | Only date. |
| Time | time | Only time. |

**Table C.1 –** Types of attributes values supported by RapidMiner

(Source: RapidMiner 5.0 Manual at http://rapid-i.com/content/view/26/84/)

# ANNEX D

## DATA TABLE

| Attribute Name | Type | Range |
|---|---|---|
| Gender | binominal | =[men, women] |
| Postal_code | polynominal | =[1000, 1010, 10115, 10117, 1011_mh, 1013_ad, 1013_bz, 1013_cw, 1013_ha, 1013_tc, 1013_xz, 1013_zg, 1015_ma, 1016_hj, 1016_kx, 1016_pm, 1016_sz, 1017_en, 1017_ew, 1017_pn, 1017_tb, 1017_xj, 1018_ak, 1018_av, 1019_bk, 1019_dn, 1019_hb, 1019_tl, 1019_wt, 1019_xd, 1019rt, 1020, 10245, 1025_vp, 1030, 1031_vd, 1040, 10400, 10409, 10437, 1050, 1051_bv, 1051_ke, 1052_aj, 1052_lw, 1054_at, 1054_ax, 1054_vb, 1054_xz, 1055_mk, 1055_sc, 1056_cs, 1056_da, 1056_kn, 1056_se, 1056_ts, 1056_xr, 1057_hc, 1057_nm, 10587, 1058_am, 1058_gd, 1058_hl, 1058_vt, 1060, 1064_jc, 1065_bt, 1066, 1066_cn, 1066_jr, 1068_ms, 1070, 1071_ks, 1071_td, 1071_zn, 1072_ls, 1072_nj, 1073_nc, 1074_bc, 1075_hn, 1075_hp, 1076_dp, 1076_lt, 1076_tx, 1077_cx, 1077_pc, 1078_ar, 1078_as, 1078_gg, 1079_nj, 1079_pe, 1080, 1081, 1081_at, 1082, 1082_gp, 1083_aw, 1083_hm, 1083_hn, 1083_jp] |
| Country | polynominal | =[NULL, at, be, ch, de, dk, es, fr, lu, nl, uk] |
| Configuratort | polynominal | =[Arty_Blouse, Arty_Shirts, BOXERS, Bespoke_Shirt, Bespoke_Women, Fashion_Shirt, Fashion_Trendy, Party_Shirt, Party_Women, Shirt_Configurator, Sur_Mesure_Femme, Tuxedo_Shirt, Work_Shirt, _, made_to_measure_shirts, made_to_measure_shirts_Women] |
| Collection | polynominal | =[Angel_Skin, Arty, Autograph_Design, Autograph_Plain, Basic, Basic_White, Basics, Bespoke_Basics, Black_&_White, Chamant, Charmant, Charming, Chic_&_Choc, Clearance, Deluxe, Easy-Iron, Easy-to-Iron, Egyptian_Luxury_, Elegant, Fashion_Basics, Fashion_Trend, Fashion_Trends, Flower_Power, Flowerprints, Fundamentals, Gentle_&_Fresh, Glamour, Good_Lucks, Heritage, Italian_Luxury, Luxurious, Luxury, Luxury_, Retailer1_Man_Design_, Retailer1_Man_Plain_, Metropolitan, Minimal, Modieus, Outlined, Poetic, Preppy_Chic, Prestige, Prestige2Fold, Prestige_2ply, Pure, Sale, Savile_Row_Design, Savile_Row_Plain, Scots_Clans_, Simplissime, Super_Deluxe, Superbe, Trends, Trendy_Trends, Ultimate_White, basics, illustrious, linen] |
| Fabric | polynominal | ⊇[Angenelle_Thijsen_3, Antigua_1, Arvik_1, Atros_1, Atros_2, Atros_3, BIA_1, BIA_2, BIA_3, Barbados, Bath, Beijing, Berry_2, Biar3, Biar4, Biar_2, Bodo_1_ë_ë_ë_, Bodo_2_ë_ë_, Bodo_3_ë_ë_ë_, Bodo_4_ë_ë_ë_, Bono1, Bono2, Bono3, Bono4, Boreo_2_ë_ë_ë_, Boston_1, Boston_2, Brama_2, Brama_4, Brama_5, Brighton, Brisbane, Cadiz_1_ë_ë_ë_, Cadiz_2_ë_ë_, Cadiz_3_ë_ë_ë_, Cadiz_4_ë_ë_, Cambridge, Candi_1, Candi_2, Canterbury, Cara_3_, Cardiff, Cees_Andriesen_2, Chester_, Chicago, Combi_1, Combi_2, Consu_1, Cuba, Dalar_1, Dalar_2, Dalar_3, Damo_1, Dante2, Dante_1, Derby, Dex_1, Dex_2, Dex_3, Docra_1, Docra_2, Docra_3, Docra_4, Don_Valentine_1, Don_Valentine_2, Don_Valentine_3, |

| Attribute Name | Type | Range |
|---|---|---|
| | | Don_Valentine_4, Drop_1, Drop_6, Dubai, Durham, Edinburgh, Elasti_1, Elasti_2, Elasti_3, Elasti_4, Elasti_5, Elasti_6, Elasti_7, Elasti_9, Ella_4, Ella_4_, Elor_1, Elor_2, Elor_3, Elor_5, Eton, Exeter, Fakir_1, Fakir_2, Fioco_1, Fiucu_1, Fiucu_1_, Flint_1, Flint_2, Flint_3, Flint_5, Gada_1, Gada_2, Gola1] |
| Colar | polynominal | =[American_Button_Down, Butterfly, Button_Down, Casino, Classic_Point_, Classic_Retro_Soft, Classic_Soft, Claudine, Cortina, Cutaway, Firenze_Button_Down, Hai_Cutaway, Hidden_Button_Down, High-Kent, High_3_Buttons, Italian_High, Italian_Semi-Spread, Kent-low, Kent_piping, LavalliÕŒre, Lido, London, London_Forward_Point, Mandarin, Mandarin_cleavage, Mao, NULL, Napoli_2_buttons, Nehru, Preppy, Revere, Roma_Double_Button_Down, Round_Lincoln, Soft_roll, Straight_Point, Tab, Torino_2_buttons, Torino_Large_2_Button, Vario, Venecia, Wide_Spread_, Windsor_Double, Wing, basic_open] |
| Cuff | polynominal | =[2_Buttons, Cocktail, Convertible_Barrel, Convertible_False_Double, Double_inc._Cufflinks, False_Cuff, Folded, French_Round, French_dantonniÕŒre, French_with_Tab_, High_French, Long_Pointed, Mandarin, Mini_puffed, Mitered_2_Buttons_, NULL, Napolitan, Puffed_, Round_Single, Rounded_Reverse, Short_Sleeve, Short_Sleeve_with_Flap, Sleeveless, Square_2_Buttons__, Square_2_buttons, Square_3_Buttons, Square_Single_with_Pipe, Square_single, Square_single_V, V_Cuff, V_Lapel, V_Reverse, Vintage_turnback] |
| Placket | polynominal | =[Amsterdam, Black_Tie_, Black_Tie_pleats, Blind, Cocktail, Folded, French_dantonniÕŒre, Lido, NULL, Napolitan, No_ruffle, Real_front, Ruffle, Square_3_Buttons, Square_single, Square_single_V, White_Pearl, mother_of_pearl, narrow_blind] |
| Collar_white | binominal | =[n, y] |
| Cuff_white | binominal | =[n, y] |
| Shirtgender | binominal | =[men, women] |
| Affiliate | polynominal | =[Retailer3, Retail4, Bivolino, Retailer5, Retailer6, Retailer7, Retailer8, Retailer9, Retailer1, Retailer10, Retailer2] |
| Hem | polynominal | =[Curved_Hem, Curved_Hem_with_Gussets, Straight_Hem] |
| Back_Yoke_contrast | binominal | =[n, y] |
| Fabriccolour | polynominal | =[Black, Black_mix, Blue, Blue,_Red_&_Brown, Blue_&_Navy, Blue_&_White, Blue_Mix, Brown, Ecru_&_Beige, Green_&_Khaki, Grey, Grey_Mix, Lilac, Lilac_Mix, Multicolor, Navy, Navy_Mix, Neutral, Off_white, Pink, Pink_Mix, Purple_&_Lila, Purple_Mix, Red_&_Bordeaux, Red_Mix, Sky, Teal, White, White_&_Pink, Yellow, black_&_White] |
| fabricdesignpattern | polynominal | =[2_colour_Bengal_Stripe, 2_colour_gingham_check, 3_colour_gingham_check, Bengal_Stripe, Block_Stripe, Bold_Bengal_stripe, Bold_Stripe, Bright_Sateen_plain, Check, Circle_Floral_print, Circle_print, Classic_Bold_Stripe, Diagonal_Semi_plain, Dobby_Stripe, Edged_Butcher_Stripe, Edged_Satin_Stripe, End_on_end_Stripe, Fine_Stripe, Floral, Floral_Spot_Print, Floral_print, Hairline_Stripe, Mini_Gingham_check, Narrow_Stripe, Oxford_Floral_print, Oxford_weave_Plain, Paisley_print, Plain, Prince_of_Wales_Check, Print, Puppytooth_Stripe, Semi_plain, Spot_print, Stitch_Stripe, |

| Attribute Name | Type | Range |
|---|---|---|
| | | Stripe, Structured_plain, Textured_plain, Textured_semi_Plain, Twill_Weave_Plain] |
| Fabricfinish | polynominal | =[Basic, Easy-care_-_kotex_100, Easy_iron, Flannel_brushed, Non-iron_-_kotex_100, Non_iron, Okotex_100, Print, Sanded, Satin] |
| fabricmaterial | polynominal | =[100prcnt_Cotton, 100prcnt_Linen, 100prcnt_Polyester, 100prcnt_Silk, 100prcnt_Viscose, 76prcntcotton_/24prcntSilk, 80prcntCotton_/20prcntSilk, Cotton_-_Linen, Cotton_-_Polyester, Cotton_stretch, Cotton_twofold, Egyptian_cotton_2fold, Silk/Cotton] |
| fabricstructure | polynominal | =[Corduroy_-_Velours, Crinkle_transparent, Dobby, End-on-end, Herringbone, Jacquard, Oxford, Pinpoint, Poplin, Sateen, Twill, Voile_Semi-Transparent, Voile_Transparent] |
| hasMonogram | binominal | =[No, Yes] |
| hasPocket | binominal | =[No, Yes] |
| AgeGroup | polynominal | =[16/24, 25/34, 35/44, 45/54, 55/64, 65/75, >_75, unknown] |
| BMIFatness | polynominal | =[Morbidly_Obese, Normal_, Obese, Overweight, Underweight, unknown] |
| HeightGroup | polynominal | =[140-149, 150-159, 160-169, 170-179, 180-189, 190-199, 200-209, 210-219, <_140] |
| CollarGroup | polynominal | =[37/38, 38/39, 39/40, 40/41, 41/42, 42/43, 43/44, 44/45, 45/46, 46/47, 47/48, 48/49, 48/50, 50/51, 51/52, 52/53, 53/54, 54/55, 57/58, 60>, |
| IsCollarObese | binominal | =[No, Yes] |
| Weight_Group | polynominal | =[100_kg_-_120_kg, 120_kg_-_140_kg, 40_kg_-_60_kg, 60_kg_-_80_kg, 80_kg_-_100_kg, _140_kg] |

**Table D.1**– Data Tabl

| Name | Description | Datatype |
|---|---|---|
| Orderno | Unique id of an order item. This id structure is : "<number of the order>.<number of the item>" <number of item> can be: empty, 01,02, etc. When <number of item> is empty is the same having 00 (that is the first item of the order), the row contains the order summary | Id |
| Date Received | Date of purchase | Date |
| Week | Week of the year | Date |
| Quantity | Quantity of items purchased | Numeric |
| Selling price £ | Total of the price of an order item.<br>Selling Price = Unit Price * Quantity | Numeric |
| Delivery price £ | Cost of delivery | Numeric |
| Voucher | Id of the voucher used to get a discount (see above). | Symbolic |
| Card type | Type of the bank card used for the payment | Symbolic |
| Configurator | Id of the configurator type used in the order (2nd level of the collection dimension although different affiliations may have the same configurator/collection) | foreign key (numeric) |
| Card Number | Card Number (censored) used for payment. Although we do not need to use the full information, partial information may be useful to identify how many different cards the customer is using. | String |
| Configuratort | Configurator type used in the order (2nd level of the collection dimension) | Symbolic |
| Measures in cm | If 1, metric system is used for measures. If 2 the imperial system is used | Boolean |
| Rating | Rating given by the user to the item (only available in some sites) | Numeric (ordinal) |
| Model | Gender of the shirt (51 - men, 89 - women) | Numeric (representing a symbol) |
| Shirtgender | gender of the shirt | Symbolic |
| Affiliate | Website where transaction is made (1st level of collection | Symbolic |

| Name | Description | Datatype |
|---|---|---|
| | dimension) | |
| Affil | Id of the website where transaction is made (1st level of collection dimension) | foreign key (numeric) |

**Table D.2** – Description of Variables that describe Bivolino **Orders**

| Name | Description | Datatype |
|---|---|---|
| Gender | Gender of the customer | Boolean(man/women) |
| Personal Identifier | Unique identifier of the customer | id |
| Postal Code | Postal Code | Symbolic |
| Country | Country code of the customer | Symbolic |
| Age | Age of the customer | Numeric |
| Weight | Weight of the customer in the corresponding units | Numeric |
| Weightkg | Weight of the customer in kg | Numeric (Kilogram) |
| Height | Height of the customer in the corresponding units | Numeric |
| Heightcm | Height of the customer in cm | Numeric (Centimeter) |
| BMI | Body Mass Index. Necessary to define groups (including obese) given the table in a different document | Numeric |

**Table D.3** – Description of Variables that describe Bivolino **Customers**

| Name | Description | Datatype |
|---|---|---|
| Collection | Id of the collection, i.e., line of products (3rd level of collection dimension although different affiliations may have the same configurator/collection) | foreign key (numeric) |
| Collectiont | Line of products (3rd level of collection dimension) | Symbolic |
| FabricID | Id of the fabric type | foreign key (numeric) |

| Name | Description | Datatype |
|---|---|---|
| Fabric | Fabric type | Symbolic |
| Fit | Level of tightness to the body | Symbolic |
| Imperial | If "n", metric system is used for measures. If "y" the imperial system is used | Boolean |
| Collar size | Collar size in the corresponding units | Numeric (Inches) |
| Monogram | Symbol to be stamped in the shirt | Symbolic |
| Colar | Type of collar | Symbolic |
| Cuff | Type of cuff | Symbolic |
| Placket | Type of placket (front button area finishing) | Symbolic |
| Pocket | Type of pocket | Symblic |
| Collar White | Value "y" if the collar has the same color as the shirt or value "n" if not | Boolean (y/n) |
| Cuff White | Value "y" if the cuff has the same color as the shirt or value "n" if not | Boolean (y/n) |
| Hem | Type of hem (shape of the bottom) | Symbolic |
| Back Yoke contrast | Stitching effect for aesthetical purposes | Symbolic |

**Table D.4** – Description of Variables that describe Bivolino **Shirts**

| Category | Value | Variable | Interval |
|---|---|---|---|
| BMI Obesity | Underweight | BMI | [0;18.5[ |
| | Normal weight | | [18.5;25[ |
| | Overweight | | [25,30[ |
| | Obese | | [30;40[ |
| | Morbidly Obese | | [40; Inf[ |
| Age Groups | <16 | Age | [0;16 [ |
| | 16/24 | | [16;25 [ |
| | 25/34 | | [25;35 [ |
| | 35/44 | | [35;45[ |
| | 45/54 | | [45;55 [ |
| | 55/64 | | [55;65 [ |
| | 65/75 | | [65;75 [ |
| | >75 | | [75; Inf [ |
| Weight Group | <45kg | Weight (where Gender is “Man”) | [0;45[ |
| | 45kg-75kg | | [45;75[ |
| | 75kg-95kg | | [75;95[ |
| | 95kg-115kg | | [95;115[ |
| | 115kg-135kg | | [115;135[ |
| | 135kg-155kg | | [135;155[ |
| | 155kg-175kg | | [155;175[ |
| | >175kg | | [175;Inf[ |
| | <40kg | Weight (where Gender is “Women”) | [0;40[ |
| | 40kg-60kg | | [40;60[ |
| | 60kg-80kg | | [60;80[ |
| | 80kg-100kg | | [80;100[ |
| | 100kg-120kg | | [100;120[ |
| | 120kg-140kg | | [120;140[ |
| | >140kg | | [140;Inf[ |
| isObese | No | Weight (where Gender is “Man”) | [0;135[ |
| | Yes | | [135;Inf[ |
| | No | Weight (where Gender is “Women”) | [0;100[ |
| | Yes | | [100;Inf[ |
| Height Groups | <140 | Heightcm | [0;140[ |
| | 140-150 | | [140;150[ |
| | 150-160 | | [150;160[ |
| | 160-170 | | [160;170[ |
| | 170-180 | | [170;180[ |
| | 180-190 | | [180;190[ |
| | 190-200 | | [190;200[ |
| | 200-210 | | [200;210[ |
| | 210-220 | | [210;220[ |
| | >220 | | [220;Inf[ |
| Collar Size Groups | <36 | Collar Size | [0;36[ |
| | 36-37 | | [36;38[ |

| Category | Value | Variable | Interval |
|---|---|---|---|
| | 38-39 | | [38;40[ |
| | 40-41 | | [40;42[ |
| | 42-43 | | [42;44[ |
| | 44-45 | | [44;46[ |
| | 46-47 | | [46;48[ |
| | 48-49 | | [48;50[ |
| | 50-51 | | [50;52[ |
| | 52-53 | | [52;54[ |
| | 54-55 | | [54;56[ |
| | 56-57 | | [56;58[ |
| | 58-59 | | [58;60[ |
| | >60 | | [60;Inf[ |
| isCollarObese | No | Collar Size | [0;53[ |
| | Yes | | [53;Inf[ |

**Table D.5** – Categories of Variables

# ANNEX E

## EXPERIMENTS ON RAPIDMINER

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | shirtgende | Afiliate | Hem | Yoke_cor | fabriccolour | ricdesignpatte | fabricfinish | fabricmaterial | fabricstructures | sMonogra | hasPocket | AgeGroup | BMIFatness | eightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2.847 | men | cv31_3nd | uk | Work_Shirt | M&S_Man_Design | Sheffield | Hai_Cutaway | links | Folded | n | n | men | Retailer1 | with_Gussets | y | Multicolor | Fine_Stripe | Easy_iron | 100prcnt_Cotton | Dobby | Yes | No | 25/34 | Normal_ | 180-189 | 60> | Yes | 60_kg_-_80_kg | No |
| 2 | 7.928 | men | ec2r_7bp | uk | Work_Shirt | Savile_Row_Plain | london_4 | Spread | links | Folded | n | n | men | Retailer1 | Straight_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 180-189 | <_36 | No | 80_kg_-_100_kg | No |
| Total | 10.775 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | shirtgende | Afiliate | Hem | Yoke_cor | fabriccolour | ricdesignpatte | fabricfinish | fabricmaterial | fabricstructures | sMonogra | hasPocket | AgeGroup | BMIFatness | eightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2.490 | men | cv31_3nd | uk | Work_Shirt | M&S_Man_Design_ | Sheffield | Hai_Cutaway | links | Folded | n | n | men | Retailer1 | with_Gussets | y | Multicolor | Fine_Stripe | Easy_iron | 100prcnt_Cotton | Dobby | Yes | No | 25/34 | Normal_ | 180-189 | 60> | Yes | 60_kg_-_80_kg | No |
| 2 | 6.608 | men | ec2r_7bp | uk | Work_Shirt | Savile_Row_Plain | london_4 | Spread | links | Folded | n | n | men | Retailer1 | Straight_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 180-189 | <_36 | No | 80_kg_-_100_kg | No |
| 3 | 1.677 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| Total | 10.775 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | shirtgende | Afiliate | Hem | Yoke_cor | fabriccolour | ricdesignpatte | fabricfinish | fabricmaterial | fabricstructures | sMonogra | hasPocket | AgeGroup | BMIFatness | eightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.346 | men | rm3_0es | uk | Work_Shirt | Savile_Row_Plain | York | Classic_Point_ | links | Real_front | y | y | men | Retailer1 | Curved_Hem | y | Blue | Plain | Easy_iron | 100prcnt_Cotton | Twill | Yes | No | 16/24 | Normal_ | 190-199 | 60> | Yes | 80_kg_-_100_kg | No |
| 2 | 1.799 | men | cv31_3nd | uk | Work_Shirt | M&S_Man_Design_ | Sheffield | Hai_Cutaway | links | Folded | n | n | men | Retailer1 | with_Gussets | y | Multicolor | Fine_Stripe | Easy_iron | 100prcnt_Cotton | Dobby | Yes | No | 25/34 | Normal_ | 180-189 | 60> | Yes | 60_kg_-_80_kg | No |
| 3 | 2.024 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| 4 | 5.606 | men | ec2r_7bp | uk | Work_Shirt | Savile_Row_Plain | london_4 | Spread | links | Folded | n | n | men | Retailer1 | Straight_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 180-189 | <_36 | No | 80_kg_-_100_kg | No |
| Total | 10.775 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | shirtgende | Afiliate | Hem | Yoke_cor | fabriccolour | ricdesignpatte | fabricfinish | fabricmaterial | fabricstructures | sMonogra | hasPocket | AgeGroup | BMIFatness | eightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1.282 | men | cv31_3nd | uk | Work_Shirt | M&S_Man_Design | Sheffield | Hai_Cutaway | Double_inc._Cuffl | Folded | n | n | men | Retailer1 | Curved_Hem_w | y | Multicolor | Fine_Stripe | Easy_iron | 100prcnt_Cotton | Dobby | Yes | No | 25/34 | Normal | 180-189 | 60> | Yes | 60_kg_-_80_kg | No |
| 2 | 4.889 | men | g41_1ag | uk | Work_Shirt | M&S_Man_Plain | Greenwich | Classic_Point | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 170-179 | <_36 | No | 60_kg_-_80_kg | No |
| 3 | 872 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| 4 | 1.570 | men | ec2r_7bp | uk | Work_Shirt | Savile_Row_Plain | london_4 | Italian_Semi-Spre | Double_inc._Cuffl | Folded | n | n | men | Retailer1 | Straight_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 180-189 | <_36 | No | 80_kg_-_100_kg | No |
| 5 | 500 | men | 23558 | de | _ | Fashion_Trend | Kiwi_9 | Torino_Large_2 | Round_Single | Real_front | y | y | men | Retailer2 | Straight_Hem | n | Purple_&_Lila | Plain | Easy-care_-_kotex_100 | 100prcnt_Cotton | Pinpoint | Yes | No | 25/34 | Normal_ | 180-189 | 40/41 | No | 60_kg_-_80_kg | No |
| 6 | 1.662 | men | 38106 | de | _ | Fashion_Trend | Miro_3 | Classic_Point | Round_Single | Real_front | n | n | men | Retailer2 | Curved_Hem | n | Blue_&_Navy | Plain | Easy-care_-_kotex_100 | Cotton_twofold | Herringbone | No | No | 25/34 | Overweight | 170-179 | 40/41 | No | 80_kg_-_100_kg | No |
| Total | 10.775 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | shirtgende | Afiliate | Hem | Yoke_cor | fabriccolour | ricdesignpatte | fabricfinish | fabricmaterial | fabricstructures | sMonogra | hasPocket | AgeGroup | BMIFatness | eightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4.376 | men | g41_1ag | uk | Work_Shirt | M&S_Man_Plain_ | Greenwich | Classic_Point_ | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 170-179 | <_36 | No | 60_kg_-_80_kg | No |
| 2 | 688 | men | cv31_3nd | uk | Work_Shirt | M&S_Man_Design_ | Sheffield | Hai_Cutaway | links | Folded | n | n | men | Retailer1 | with_Gussets | y | Multicolor | Fine_Stripe | Easy_iron | 100prcnt_Cotton | Dobby | Yes | No | 25/34 | Normal_ | 180-189 | 60> | Yes | 60_kg_-_80_kg | No |
| 3 | 466 | men | rm3_0es | uk | Work_Shirt | Savile_Row_Plain | York | Classic_Point_ | links | Real_front | y | y | men | Retailer1 | Curved_Hem | y | Blue | Plain | Easy_iron | 100prcnt_Cotton | Twill | Yes | No | 16/24 | Normal_ | 190-199 | 60> | Yes | 80_kg_-_100_kg | No |
| 4 | 804 | men | 23558 | de | _ | Fashion_Trend | Kiwi_9 | _Button | Round_Single | Real_front | y | y | men | Retailer2 | Straight_Hem | n | Purple_&_Lila | Plain | Easy-care_-_kote | 100prcnt_Cotton | Pinpoint | Yes | No | 25/34 | Normal_ | 180-189 | 40/41 | No | 60_kg_-_80_kg | No |
| 5 | 746 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| 6 | 1.268 | men | ec2r_7bp | uk | Work_Shirt | Savile_Row_Plain | london_4 | Spread | links | Folded | n | n | men | Retailer1 | Straight_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 180-189 | <_36 | No | 80_kg_-_100_kg | No |
| 7 | 2.216 | men | 2550 | be | Fashion_Shirt | Italian_Luxury | Miro_2 | Mao | ns_ | Folded | n | n | men | Bivolino | Straight_Hem | n | White | Plain | Easy-care_-_kote | 100prcnt_Cotton | Herringbone | No | No | 45/54 | Normal_ | 170-179 | 42/43 | No | 60_kg_-_80_kg | No |
| 8 | 211 | men | cv31_3nd | uk | Work_Shirt | M&S_Man_Plain_ | Kingston | Hai_Cutaway | links | Folded | n | n | men | Retailer1 | with_Gussets | y | White | i_Plain | Easy_iron | 100prcnt_Cotton | Herringbone | Yes | No | 25/34 | Normal_ | 180-189 | 60> | Yes | 60_kg_-_80_kg | No |
| Total | 10.775 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | shirtgende | Afiliate | Hem | Yoke_cor | fabriccolour | ricdesignpatte | fabricfinish | fabricmaterial | fabricstructures | sMonogra | hasPocket | AgeGroup | BMIFatness | eightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 2.847 | men | 2550 | be | Fashion_Shirt | Italian_Luxury | Miro_2 | Mao | ns_ | Folded | n | n | men | Bivolino | Straight_Hem | n | White | Plain | _kotex_100 | 100prcnt_Cotton | Herringbone | No | No | 45/54 | Normal_ | 170-179 | 42/43 | No | 60_kg_-_80_kg | No |
| 2 | 2.901 | men | g41_1ag | uk | Work_Shirt | M&S_Man_Plain_ | Greenwich | Classic_Point_ | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 170-179 | <_36 | No | 60_kg_-_80_kg | No |
| 3 | 411 | men | wd24_7dx | uk | Party_Shirt | Autograph_Plain | Cuba | Soft | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Lilac_Mix | Semi_plain | Easy_iron | 100prcnt_Cotton | Dobby | No | No | 16/24 | Normal_ | 160-169 | 60> | Yes | 60_kg_-_80_kg | No |
| 4 | 555 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| 5 | 433 | men | rm3_0es | uk | Work_Shirt | Savile_Row_Plain | York | Classic_Point_ | links | Real_front | y | y | men | Retailer1 | Curved_Hem | y | Blue | Plain | Easy_iron | 100prcnt_Cotton | Twill | Yes | No | 16/24 | Normal_ | 190-199 | 60> | Yes | 80_kg_-_100_kg | No |
| 6 | 363 | men | 23558 | de | _ | Fashion_Trend | Kiwi_9 | _Button | Round_Single | Real_front | y | y | men | Retailer2 | Straight_Hem | n | Purple_&_Lila | Plain | _kotex_100 | 100prcnt_Cotton | Pinpoint | Yes | No | 25/34 | Normal_ | 180-189 | 40/41 | No | 60_kg_-_80_kg | No |
| 7 | 1.082 | men | ec2r_7bp | uk | Work_Shirt | Savile_Row_Plain | london_4 | Spread | links | Folded | n | n | men | Retailer1 | Straight_Hem | y | White | Plain | Easy_iron | 100prcnt_Cotton | Poplin | No | No | 25/34 | Normal_ | 180-189 | <_36 | No | 80_kg_-_100_kg | No |
| 8 | 362 | men | cv31_3nd | uk | Work_Shirt | M&S_Man_Design_ | Sheffield | Hai_Cutaway | links | Folded | n | n | men | Retailer1 | with_Gussets | y | Multicolor | Fine_Stripe | Easy_iron | 100prcnt_Cotton | Dobby | Yes | No | 25/34 | Normal_ | 180-189 | 60> | Yes | 60_kg_-_80_kg | No |
| 9 | 1.188 | men | 38106 | de | _ | Fashion_Trend | Miro_3 | Classic_Point_ | Round_Single | Real_front | n | n | men | Retailer2 | Curved_Hem | n | Blue_&_Navy | Plain | _kotex_100 | Cotton_twofold | Herringbone | No | No | 25/34 | Overweight | 170-179 | 40/41 | No | 80_kg_-_100_kg | No |
| 10 | 633 | men | ig8_9st | uk | Work_Shirt | M&S_Man_Design_ | Brighton | Classic_Point_ | links | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Blue | les_Check | Non_iron | 100prcnt_Cotton | Dobby | No | Yes | 55/64 | Obese | 170-179 | 60> | Yes | 80_kg_-_100_kg | Yes |
| Total | 10.775 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

**Figure E.1** – Clusters – General

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 877 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| 2 | 1244 | men | ig8_9st | uk | Work_Shirt | M&S_Man_Design_ | Brighton | Point_ | Cufflinks | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Blue | Wales_Chec | Non_iron | n | Dobby | No | Yes | 55/64 | Obese | 170-179 | 60> | Yes | 80_kg_-_100_kg | Yes |
| Total | 2121 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1253 | men | ig8_9st | uk | Work_Shirt | M&S_Man_Design_ | Brighton | Point_ | Cufflinks | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Blue | Wales_Chec | Non_iron | n | Dobby | No | Yes | 55/64 | Obese | 170-179 | 60> | Yes | 80_kg_-_100_kg | Yes |
| 2 | 586 | men | 22337 | de | _ | Fashion_Trend | Miro_9 | n_Butto | Round_Single | Real_front | n | n | men | Retailer2 | Curved_Hem | n | Blue_&_Navy | Plain | _kotex_100 | n | one | Yes | Yes | 55/64 | Obese | 180-189 | 45/46 | No | 100_kg_-_120_kg | Yes |
| 3 | 282 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| Total | 2121 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 399 | men | bn20_9bu | uk | Work_Shirt | Savile_Row_Plain | Worcester | _Forwar | Cufflinks | Blind | n | n | men | Retailer1 | Curved_Hem | y | White | e_Plain | Easy_iron | n | Twill | No | No | 35/44 | Obese | 170-179 | 43/44 | No | 80_kg_-_100_kg | Yes |
| 2 | 520 | men | ig8_9st | uk | Work_Shirt | M&S_Man_Design_ | Brighton | Point_ | Cufflinks | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Blue | Wales_Chec | Non_iron | n | Dobby | No | Yes | 55/64 | Obese | 170-179 | 60> | Yes | 80_kg_-_100_kg | Yes |
| 3 | 478 | men | 22337 | de | _ | Fashion_Trend | Miro_9 | n_Butto | Round_Single | Real_front | n | n | men | Retailer2 | Curved_Hem | n | Blue_&_Navy | Plain | _kotex_100 | n | one | Yes | Yes | 55/64 | Obese | 180-189 | 45/46 | No | 100_kg_-_120_kg | Yes |
| 4 | 554 | men | sl7_2eb | uk | Party_Shirt | Autograph_Design | Brisbane | away | Round_Single | Real_front | n | n | men | Retailer1 | ith_Gussets | y | Multicolor | Floral_print | Easy_iron | n | Poplin | No | No | 45/54 | Obese | 190-199 | <_36 | No | 120_kg_-_140_kg | Yes |
| 5 | 170 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| Total | 2121 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 339 | men | bn20_9bu | uk | Work_Shirt | Savile_Row_Plain | Worcester | _Forwar | Cufflinks | Blind | n | n | men | Retailer1 | Curved_Hem | y | White | e_Plain | Easy_iron | n | Twill | No | No | 35/44 | Obese | 170-179 | 43/44 | No | 80_kg_-_100_kg | Yes |
| 2 | 491 | men | 22337 | de | _ | Fashion_Trend | Miro_9 | n_Butto | Round_Single | Real_front | n | n | men | Retailer2 | Curved_Hem | n | Blue_&_Navy | Plain | _kotex_100 | n | one | Yes | Yes | 55/64 | Obese | 180-189 | 45/46 | No | 100_kg_-_120_kg | Yes |
| 3 | 253 | men | sw15_2rz | uk | Work_Shirt | Savile_Row_Plain | York | n_Butto | Cufflinks | Blind | n | n | men | Retailer1 | Straight_Hem | y | Blue | e_Plain | Easy_iron | n | Twill | Yes | Yes | 55/64 | Obese | 170-179 | 60> | Yes | 100_kg_-_120_kg | Yes |
| 4 | 362 | men | ig8_9st | uk | Work_Shirt | M&S_Man_Design_ | Brighton | Point_ | Cufflinks | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Blue | Wales_Chec | Non_iron | n | Dobby | No | Yes | 55/64 | Obese | 170-179 | 60> | Yes | 80_kg_-_100_kg | Yes |
| 5 | 511 | men | sl7_2eb | uk | Party_Shirt | Autograph_Design | Brisbane | away | Round_Single | Real_front | n | n | men | Retailer1 | ith_Gussets | y | Multicolor | Floral_print | Easy_iron | n | Poplin | No | No | 45/54 | Obese | 190-199 | <_36 | No | 120_kg_-_140_kg | Yes |
| 6 | 165 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| Total | 2121 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 174 | men | bn20_9bu | uk | Work_Shirt | Savile_Row_Plain | Worcester | _Forwar | Cufflinks | Blind | n | n | men | Retailer1 | Curved_Hem | y | White | e_Plain | Easy_iron | n | Twill | No | No | 35/44 | Obese | 170-179 | 43/44 | No | 80_kg_-_100_kg | Yes |
| 2 | 419 | men | 22337 | de | _ | Fashion_Trend | Miro_9 | n_Butto | Round_Single | Real_front | n | n | men | Retailer2 | Curved_Hem | n | Blue_&_Navy | Plain | _kotex_100 | n | one | Yes | Yes | 55/64 | Obese | 180-189 | 45/46 | No | 100_kg_-_120_kg | Yes |
| 3 | 121 | men | bn20_9bu | uk | Work_Shirt | M&S_Man_Design_ | Brighton | Point_ | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Blue | Wales_Chec | Non_iron | n | Dobby | No | Yes | 35/44 | Obese | 170-179 | 43/44 | No | 80_kg_-_100_kg | Yes |
| 4 | 356 | men | bn20_9bu | uk | Work_Shirt | Savile_Row_Plain | london_1 | Point_ | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Pink | Plain | Easy_iron | n | Poplin | No | Yes | 35/44 | Obese | 170-179 | 43/44 | No | 80_kg_-_100_kg | Yes |
| 5 | 141 | men | sw15_2rz | uk | Work_Shirt | Savile_Row_Plain | York | n_Butto | Cufflinks | Blind | n | n | men | Retailer1 | Straight_Hem | y | Blue | e_Plain | Easy_iron | n | Twill | Yes | Yes | 55/64 | Obese | 170-179 | 60> | Yes | 100_kg_-_120_kg | Yes |
| 6 | 322 | men | sl7_2eb | uk | Party_Shirt | Autograph_Design | Brisbane | away | Round_Single | Real_front | n | n | men | Retailer1 | ith_Gussets | y | Multicolor | Floral_print | Easy_iron | n | Poplin | No | No | 45/54 | Obese | 190-199 | <_36 | No | 120_kg_-_140_kg | Yes |
| 7 | 92 | women | 34090 | fr | Party_Women | Glamour | Vola1 | pen | Mini_puffed | Ruffle | n | n | women | Bivolino | ith_Gussets | n | Multicolor | Print | Print | Silk/Cotton | mi- | No | No | 35/44 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| 8 | 133 | men | ig8_9st | uk | Work_Shirt | M&S_Man_Design_ | Brighton | Point_ | Cufflinks | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Blue | Wales_Chec | Non_iron | n | Dobby | No | Yes | 55/64 | Obese | 170-179 | 60> | Yes | 80_kg_-_100_kg | Yes |
| 9 | 239 | men | sk23_7qu | uk | Work_Shirt | M&S_Man_Plain_ | Plymouth | Point_ | Round_Single | Real_front | n | n | men | Retailer1 | Straight_Hem | y | Blue_&_Navy | ve_Plain | Easy_iron | n | Oxford | No | Yes | 45/54 | Obese | 180-189 | 60> | Yes | 100_kg_-_120_kg | Yes |
| 10 | 124 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| Total | 2121 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

**Figure E.2** – Clusters – Filtering: BMIFatness=Obese

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 4589 | men | 2550 | be | Fashion_Shirt | Italian_Luxury | Miro_2 | Mao | ttons_ | Folded | n | n | men | Bivolino | Straight_Hem | n | White | Plain | _kotex_100 | n | one | No | No | 45/54 | Normal_ | 170-179 | 42/43 | No | 60_kg_-_80_kg | No |
| 2 | 598 | men | 35037 | de | Fashion_Shirt | Italian_Luxury | Juan_7 | Mao | Round_Single | Folded | n | n | men | Bivolino | Straight_Hem | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | Yes | Yes | 45/54 | Obese | 170-179 | 52/53 | No | 100_kg_-_120_kg | Yes |
| Total | 5187 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1709 | men | cv31_3nd | uk | Work_Shirt | M&S_Man_Design_ | Sheffield | away_ | Cufflinks_ | Folded | n | n | men | Retailer1 | ith_Gussets | y | Multicolor | Fine_Stripe | Easy_iron | n_ | Dobby | Yes | No | 25/34 | Normal_ | 180-189 | 60> | Yes | 60_kg_-_80_kg | No |
| 2 | 2645 | men | ec2r_7bp | uk | Work_Shirt | Savile_Row_Plain | london_4 | emi- | Cufflinks_ | Folded | n | n | men | Retailer1 | Straight_Hem | y | White | Plain | Easy_iron | n_ | Poplin | No | No | 25/34 | Normal_ | 180-189 | <_36 | No | 80_kg_-_100_kg | No |
| Total | 4354 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 155 | men | 23558 | de | _ | Fashion_Trend | Kiwi_9 | Large_2 | Round_Single | Real_front | y | y | men | Retailer2 | Straight_Hem | n | Purple_&_Lila | Plain | _kotex_100 | n | Pinpoint | Yes | No | 25/34 | Normal_ | 180-189 | 40/41 | No | 60_kg_-_80_kg | No |
| 2 | 498 | men | 38106 | de | _ | Fashion_Trend | Miro_3 | Point_ | Round_Single | Real_front | n | n | men | Retailer2 | Curved_Hem | n | Blue_&_Navy | Plain | _kotex_100 | Cotton_twofold | one | No | No | 25/34 | Overweight | 170-179 | 40/41 | No | 80_kg_-_100_kg | No |
| Total | 653 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 64 | men | 3011_xw | nl | ure_shirts | Metropolitan | Juan_8 | Large_2 | French_Round | Real_front | n | n | men | Retailer6 | Straight_Hem | n | Black | Plain | Easy_iron | Cotton_twofold | Twill | No | No | 35/44 | Normal_ | 190-199 | 42/43 | No | 80_kg_-_100_kg | No |
| 2 | 100 | men | 6523_pp | nl | ure_shirts | illustrious | Fakir_1 | Point_ | Round_Single | Folded | n | n | men | Retailer6 | ith_Gussets | n | Blue_&_Navy | Stripe | _kotex_100 | n | Poplin | No | Yes | 45/54 | Normal_ | 180-189 | 40/41 | No | 80_kg_-_100_kg | No |
| Total | 164 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

**Figure E.3** – Clusters – Filtering: Affiliate=Bivolino (Retailer1; Retailer2; Retailer6)

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 8 | men | sw17_8qz | uk | Work_Shirt | M&S_Man_Design_ | Brighton | Point_ | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Blue | Wales_Chec | Non_iron | n | Dobby | No | No | 16/24 | Obese | <_140 | <_36 | No | 40_kg_-_60_kg | No |
| 2 | 11 | men | po16_7aj | uk | Party_Shirt | Autograph_Design | Tokyo | emi- | Cufflinks | Real_front | n | n | men | Retailer1 | ith_Gussets | y | Pink_Mix | Bold_Stripe | Easy_iron | n | Poplin | No | No | 45/54 | bese | <_140 | 60> | Yes | 100_kg_-_120_kg | Yes |
| Total | 19 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 9 | men | cv12_0ew | uk | Work_Shirt | M&S_Man_Design_ | Leeds | Point_ | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | Neutral | pe | Easy_iron | n | Dobby | No | Yes | 35/44 | Obese | 210-219 | <_36 | No | 120_kg_-_140_kg | Yes |
| 2 | 2 | men | 7060 | be | Fashion_Shirt | Italian_Luxury | Juan_7 | Retro_S | Cocktail | Real_front | n | n | men | Bivolino | ith_Gussets | n | Red_&_Bordeaux | Plain | Easy_iron | Cotton_twofold | Twill | No | No | 35/44 | Underweight | 210-219 | 38/39 | No | 60_kg_-_80_kg | No |
| Total | 11 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | uff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 205 | men | eh12_5yt | uk | Work_Shirt | M&S_Man_Plain_ | Greenwich | Point_ | Cufflinks | Real_front | n | n | men | Retailer1 | Curved_Hem | y | White | Plain | Easy_iron | n | Poplin | Yes | No | 25/34 | Normal_ | 200-209 | 60> | Yes | 80_kg_-_100_kg | No |
| 2 | 115 | men | e16_1dz | uk | Work_Shirt | M&S_Man_Design_ | Sheffield | emi- | tons__ | Folded | n | n | men | Retailer1 | Curved_Hem | y | Multicolor | Fine_Stripe | Easy_iron | n | Dobby | No | No | 35/44 | Overweight | 200-209 | <_36 | No | 100_kg_-_120_kg | Yes |
| Total | 320 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

**Figure E.4** – Clusters – Filtering: HeightGroup=<140 (210-219; 200-209)

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | Cuff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 454 | men | sl7_2eb | uk | Party_Shirt | Autograph_Design | Brisbane | away | Round_Single | Real_front | n | n | men | Retailer1 | ith_Gussets | y | Multicolor | Floral_print | Easy_iron | n | Poplin | No | No | 45/54 | Obese | 190-199 | <_36 | No | 120_kg_-_140_kg | Yes |
| 2 | 303 | men | ml3_7dl | uk | Work_Shirt | M&S_Man_Plain_ | Kingston | Point_ | Round_Single | Real_front | n | n | men | Retailer1 | Curved_Hem | y | White | mi_Plain | Easy_iron | n | one | No | Yes | 55/64 | bese | 170-179 | 60> | Yes | 120_kg_-_140_kg | Yes |
| Total | 757 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

| cluster | size | Gender | Postal_code | Country | Configuratort | Collectiont | Fabric | collar | Cuff | Placket | ollar_whi | Cuff_whit | hirtgende | Afiliate | Hem | Yoke_co | fabriccolour | ricdesignpatt | fabricfinish | fabricmaterial | pricstructu | sMonogra | hasPocket | AgeGroup | BMIFatness | HeightGroup | ollarGro | CollarObe | Weight_Group | isObese |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 39 | men | 3672 | at | Fashion_Shirt | Italian_Luxury | Juan_4 | pread_ | ttons_ | Real_front | n | y | men | Bivolino | ith_Gussets | n | Blue_&_Navy | Plain | Easy_iron | Cotton_twofold | Twill | Yes | No | 25/34 | bese | 180-189 | 52/53 | No | >_140_kg | Yes |
| 2 | 24 | men | rh8_9jf | uk | Party_Shirt | Autograph_Plain | Grenada | Point_ | Short_Sleeve | Real_front | n | n | men | Retailer | Curved_Hem | y | Blue | n_plain | Easy_iron | n | Sateen | No | Yes | 45/54 | bese | 180-189 | 52/53 | No | >_140_kg | Yes |
| Total | 63 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |

**Figure E.5** – Clusters – Filtering: Weight_Group=120kg-140kg (>140kg)

# ANNEX F

## CORENET

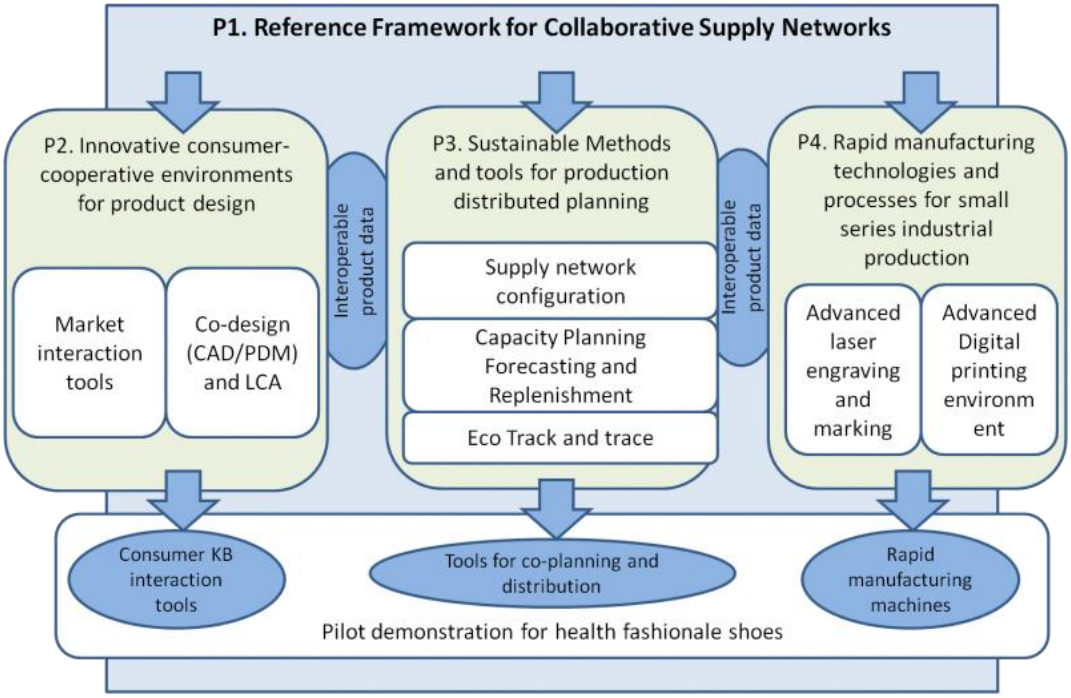
The information contained in this annex is from CoReNet website (http://www.corenet-project.eu/).

**Summary**

CoReNet project was launched the 1st June 2010 under the framework of the call FoF.NMP.2010-2 (Grant Agreement: 260169).

CoReNet main aim is to meet particular needs and expectations of widely represented European consumer targets - such as elderly, obese, disabled, diabetic people -, that usually look for clothes and footwear with particular functional requirements but, at the same time fashionable, high quality, eco-sustainable and at an affordable price.

Adopting the CoReNet framework, based on methods and tools for a cost and eco-efficient collaborative networking, the European Textile, Clothing and Footwear Industry (TCFI) will be able to provide small series of customized fashionable goods for such relevant social niches by enabling products to stay as long as possible digital and to produce on-demand.




The most important pillars of the project are:

- Reference model enabling sustainable and collaborative supply networks to address, orientate and integrate organizational, technological and knowledge management issues.
- Web virtualization systems enabling Integrated and collaborative design and configuration environment of healthy clothes and shoes.
- Supply network coordination services for process configuration, forecasting and replenishment planning, real-time control and finally tracking and tracing including sustainability KPIs.
- Radical innovation of production processes related to product personalization, by the adoption of Rapid Manufacturing technologies for optimized digital printing and laser engraving.

The large commitment of SMEs of the TCFI is the main strength of the consortium that includes important actors of the value chain, from technology providers, components suppliers to manufactures, in order to demonstrate with different pilot cases how the CoReNet solutions will impact on the overall value of TCFI supply networks.

Within CoReNet framework, all partners of the value chain will be able to actively collaborate in value creation processes where the end consumer is the driving actor.

CoReNet methods and tools will enable design changes and production processes adaptation for easy and sustainable product customizations.

CoReNet results will be tested and demonstrated within industrial plants, showing the full potential of the proposed sustainable collaborative networking approach.

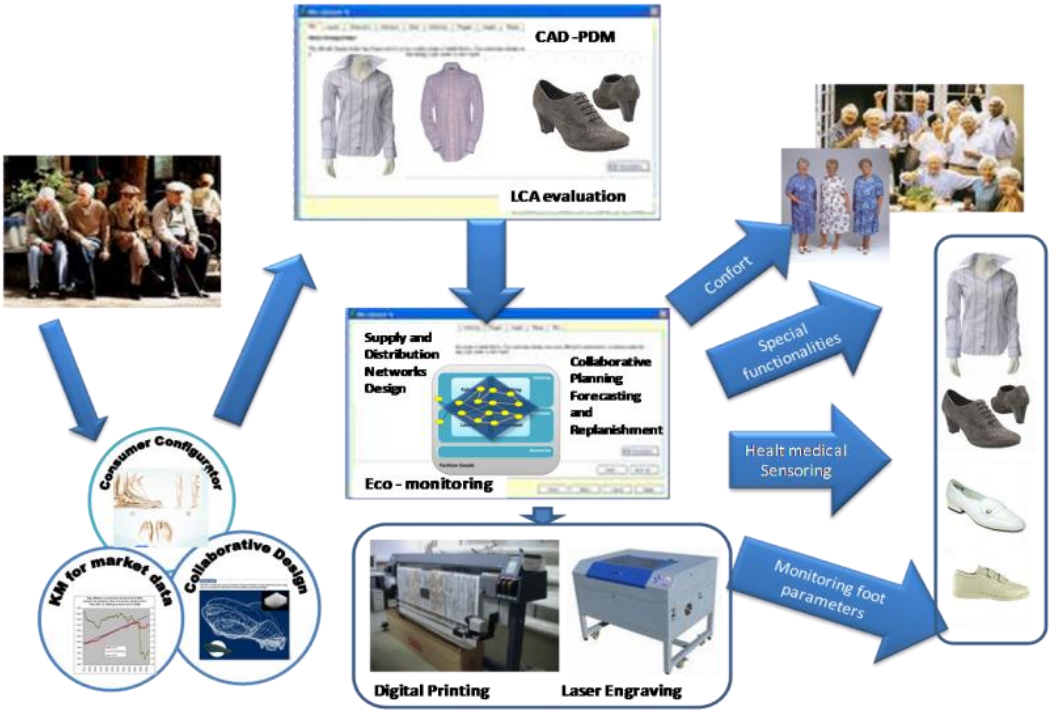
**Approach**

CoReNet project addresses the design, production and distribution of small series of healthy fashionable goods for specific target groups of wide impact in terms of market for the European industry as elderly, disables, diabetics and obese people.

CoReNet will do this supporting the whole value chain to:

- get and manage consumer data to know their needs,
- involve consumer into design and product configuration phases,
- exchange consumer data through adequate data models and secure systems,
- manage the collaboration with suppliers in order to plan and distribute on time,
- implement innovative manufacturing machines in particular for Digital Printing and Laser Engraving,
- delivering the product to the final customer,
- monitoring the quality and sustainability of products.

The CoReNet approach is based on a new holistic framework, meant as a set of methods, tools and technologies for sustainable small series industrial value creation of health fashionable goods.




Specific addressed consumer-oriented market segments will be footwear and accessories, textile and garments with major focus on differentiated consumer-centered products in order to guarantee not only aesthetic requirements but also comfort, health, well-being and to provide new functionalities to the consumer with a sustainable approach to production and consumption.

Such market needs have been identified by the stakeholders of the European Technology Platform on Footwear Products and Processes and of the European Technology Platform for the Future of Textile and Clothing as core pulling segments for innovation and are taken into consideration in the development of this proposal

To achieve the above objectives a strong SME driven consortium has been set up, including major research centers active in the addressed sectors and highly innovation oriented SMEs along the considered value chains.

## Expected Results

### A. Reference Framework for Collaborative Supply Networks

The reference framework will address, orientate and integrate all aspects both at organizational and technological level concerning interaction of organizations and business processes in two concurrent sectors, considering co-ordination and

synchronization of contents, as well as information exchange and software application modularity, in order to create a seamless flow of information from market to design and development, to production and distribution.

### B. Innovative consumer-driven environments for product design

This result will address the implementation of innovative environments for collaboration and knowledge management during design phase. The goal is to create a novel concept that enables the vision of an "empowered-to-design" consumer from one side, and the creation of market and design knowledge from the history of consumer-to-designer, consumer-to-consumer and designer-to-designer interactions within a social network environment.

### C. Methods and tools for supply network configuration and distributed production planning including consumer-oriented Collaborative Planning

Innovative and adaptive services for production process modeling and supply networks formation and management will be based on a distributed interaction system to integrate different actors (components suppliers, outsourcers, service providers, retailers, customers) of different sectors collaborating in dynamic networks. Product quality control based on environmental impact parameters will be developed through a shared platform for eco-monitoring.

Small series and personalized products will require totally different supply networks structures, where each company should be able to produce the complete product (all or most of the operations) and will be specialized by the type of product or market segment.

In this context a supply network will have to be configured for each customer order and tend to include a small number of companies. The key selection criteria will be the ability to perform the required operations for the desired delivery date, with the expected cost.

### D. Rapid manufacturing technologies for small series industrial production

This result will enable the flexible, energy and eco-efficient production of specific added value components/parts of consumer personalized goods through rapid manufacturing multi-purpose machines. In particular reduction of set-up time is crucial in the production of small series in order to avoid loss of time when changing models.

Two particular phases of production process (printing and engraving) will be taken into consideration because they represent critical steps for the personalization of fabric and leather in the definition of the new collections.

These results will be all integrated in real demonstration environments. Integrated demonstrator can be considered a result in terms of functioning pilot collaborative supply network offering integrated small series of clothing and shoes to target groups. The pilot demonstrator will be composed of manufacturing companies collaborating with technologies providers along product lifecycle where coordination has to be managed at supply network and not at company level.