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The management of the Retail
network in the fashion system

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INTRODUCTION

This work will take in consideration the retail sector in the fashion industry, with particular attention to the direct sales channel.

The opening of a network of owned shops indeed is a choice adopted by a growing numbers of actors in the industry, starting from the luxury brands till the operators of the lower segments of the market. This strategy is due to the increasing need to establish a relation with the final consumer, as long as the competition has intensified due to the entrance of the market of companies like H&M and ZARA that made fashion always available and cheap. During their growth the personal owned shops played a fundamental role, becoming part of their promotional strategy.

Therefore, this aspect of retail stimulated our interest, making us question about what kind of factors influence the results of a store and how it is possible to generate attachment to the brand through the shopping experience.

In particular, we wanted to find evidence of those variables that affect the sales of a shop through an analysis based on a real case. As a consequence, the final result will not be a list set *a priori* of those aspects we should take in consideration when managing a store, but it will focus on the importance of two variables in particular.

The number of variables observed was limited because in order to be able to affirm that a particular factor influences something else (a final result, the revenues of a company, etc.), it is necessary to consider a situation in which all the other aspects of the business remained unchanged. In other words, it is possible to test only one variable at time, comparing two or more years (or seasons) in which a relevant change on the variable observed is traceable. This makes necessary to find a context in which the factor under observation can be isolated from the rest, reducing the number of situations we could study.

For this reason, we want to underline that this work does not pretend to include all the different aspects we should take in consideration in the retail management. This is even more significant if we think that in this sector it is not possible to adopt a proper scientific approach during the analysis, since it is not possible to isolate completely a variable from the others. Indeed, the retail industry is highly affected by a number of social factors that cannot be controlled or monitored. In this way, pretending to carry out an analysis with scientific precision would be impossible and misleading. The economical science itself actually is a social science, meaning that its study requires a multidisciplinary approach.

As a consequence, this turned our attention to the second aspect faced in this work: the adoption of an effective information system to support decisions. Therefore, while implementing the analysis we tried to show how adding new analytical tools to the information system already adopted by the company (object of our case study) can be useful to get more knowledge about customers' behavior. In our opinion, in an environment that is not possible to control, the capacity to observe and understand it turns to be one of the most important skill to develop.

So, the work will be divided into six chapters:

- 1) the first will be an introduction to the fashion's world, focusing in particular on its sociological evolution;
- 2) in the second we will present the company on which we applied the analysis, paying attention to its structure and to the information system adopted;
- 3) in the third chapter we will present the theoretical tool we used to carry out the analysis on the sales data. We applied it on three different years. Moreover, it will be presented also the theoretical framework adopted to study the changes occurred on the first variable observed;
- 4) in chapter four we will present the results of the analysis on two out of the three years analyzed;
- 5) after the explication of what changed in the shop over the two years, we will find how the first variable analyzed can explain the modifications occurred in the sales data during the timeframe considered;
- 6) in chapter 6 we will implement the analysis on the third year taken in consideration. First of all, we will present the changes occurred in the shop during this period and later we will apply the analysis on the sales data. As before, from the modifications occurred we will be able to assess the effect of the second variable observed on the results of the shop.

CHAPTER 1: THE FASHION INDUSTRY, A SOCIOLOGICAL OVERVIEW

1.1 DEFINITION AND EVOLUTION

If we look at the dictionary fashion is defined as "an habit that becomes prevailing in a society, and imposes itself in costumes, ways of life and ways of dressing". It's interesting to underline that the definition of fashion does not involve only the clothing industry, but it is related to different ways of expression of the human being.

The common term used in english is fashion, that comes from latin *facere*: doing, building ,realize something. However, in the common meaning fashion is intended as something that in a given time and place has reached an high degree of diffusion in the society, or in a part of it. This particular definition is better represented from the less used term, *mode*, that derives from the latin *mos*: habit, tradition, rule.

In our opinion, this second interpretation of the term is more interesting as it gives importance to the sociological aspect of the phenomenon, underlying that the emergence of a new taste, even when it is the result of the expression of an individual orientation, needs the "approval" of the society. Indeed, fashion has to be studied first of all on a sociological side, as it arises from the natural tendency of people to imitate each others. Moreover fashion is what distinguish a group of people from another group and it is what define the membership to a given social class or to another. However, this social "role" has changed during the years and the borders between upper and lower classes are no more defined by exterior appearances. Fashion is no more the border line between richer and poorer, as the increase of the average quality of life made available a lot of benefits that before were accessible only to wealthier classes. What has remained is its' representative function of different social, historical and geographical contexts. Indeed, we can see by the way people dress the degree to which the society they live in is dynamic, updated and evoluted.

For example, people living in rural zones dress differently from people living in the cities, where the contact between different cultures is higher. Other examples of this function of fashion were the affirmation of "men-like" style in womens' dress code during the 80's, when women entered the business world, or the recent movement to a western dress code of chinese people, due to the process of democratization after Mao's dictatorship.

Thus, the "power" of fashion is its capacity to represent the picture of a society in a given period following its habits and costumes' evolution. For this reason fashion has a peculiarity, the cyclicity, for which it is one of the most dynamics industries.

1.2 THE FASHION'S CYCLE

The fashion's cycle is defined as the time frame between the introduction of a new trend and its' substitution by another one. This substitution can involve the main characteristic of the products (materials, design, structure) or just its variants (e.g. the color). Basically, the fashion's life cycle is comparable with the traditional product's life cycle, being composed of three phases: *introduction*, *diffusion* and *decline*.

1) *Introduction*: the product is adopted by the opinion leaders, those people that want to distinguish themselves from the mass. Typically they are seen as those ones that are able to understand before the others the new trends and to adopt them;

2) *Diffusion*: The fashion reaches an high degree of diffusion and is adopted by large segments of the market. This phase is characterized by an aspirational dimension, as the mass market wants to imitate the opinion leaders;

3) *Decline*: it can be of two kinds, of short term and long term. The first case is typical of the renovation of the fashion system, with the substitution of a trend with a new one. The second is a long term phenomenon, that is characterized by the disappearance of a particular type of product (for example the hats or the garter).

The reasons of the renovation cycle of fashion can be found in the natural cycle of seasons (which implies different functional needs) and in two other factors:

- the need of the industrial fashion system to generate turnover of the products. It can be called as a sort of "forced obsolescence" induced in order to nourish new demand. On a technical point of view the products would still last, but economically their life period is much shorter;
- The fashion's representative role of society's evolution, given the modifications of costumes and habits that are considered "acceptable" in a given place and time.

Actually, the two factors described above are interrelated, as the continuous change of the fashion's system due to the first factor generates new criteria in the evaluation of what is considerable "acceptable" or not. This is particularly true with the entrance of the market of companies like H&M and ZARA, that introduced new collections more times in a year, losing almost any relation with the seasonal (and functional) aspect of the renovation's cycle of fashion. If this is true, the relationship between fashion and social habits results inverted, with the "artificial" generation of new costumes across the society (what about the "Hipster" phenomenon?), and a faster modification of dress codes.

1.3 "THE IMITATION GAME"

As we have seen above, the second phase of the fashion's cycle is characterized by an aspirational dimension, by which some people want to imitate the way in which some others behave and dress. This second type of people are called the "opinion leaders", those who are able to understand before the new trends and to adopt them.

In this view, the fashion's cycle can be seen as a "run away-chasing" game, in which the opinion leaders try to differentiate themselves from the mass, that in turn wants to reach their status. Actually, this phenomenon is universal and exists since from the first populations, where the dress code was represented just by some leaves covering the intimate parts of the body. What have changed over time indeed is the part of the society that has been the model to imitate. This is clearer looking at the process that fashion has followed over the years, starting from the Italian Renaissance until the diffusion in all Europe and in Paris in particular, where we assisted to the affirmation of the *ateliers*. It is in the french city that we can trace the birth of the concept of "annual collection" with the activity of Charles Friedrich Worth, the first tailor that started to produce the dresses from his own ideas (the others before produced only "on commission"). In this phase fashion is still a privilege of the nobility and the upper classes, that constituted that niche to which the rest of the society aspired to.

A century later, after the second world war and with the diffusion of the industrialization, we assisted to the first signals of expansion of fashion's scope. A central role in this process was played by the designer Pierre Cardin, that made deals with industrial producers and dealers in order to expand the numbers of consumers able to buy his products, finding a compromise between a wider diffusion and the maintenance of the image of the luxury item. This new trend signed the rising of Milan as the new capital of "*pret-a-porter*" fashion, that

represented the new partnership between designers and industrialists (in this context brands as Armani, Versace and Ferré gained success): fashion exit the exclusivity of the atelier and entered the mass market. Moreover, the passage from the "atelier" to the "pret-a-porter" was representative of the social change brought by the advent of the mass production: the new middle class started to emerge, representing an important new share of the final market.

In this context the clothing industry followed a process of "democratization" in which the social model to imitate was changed: now the new luxury brands found their ambassadors in those people who economically succeeded.

During the years, these changes generated more dynamism between the social classes and the economic development stimulated greater variety in the society. In this context, new values and new models to emulate arose giving life to an increasing number of different "tribes" in which people recognized and indentified themselves. This evolution is well represented by the passage from the theoretic approach of the "*trickle down effect*" to the newer theory of the "*trickle across*".

The first theory asserts that fashion is firstly introduced in the higher levels of the social structure, to be later transferred to the lower ones and progressively expanding to the masses. This assumes the form of a cycle that periodically starts from the beginning. As we can see, this approach mirrors a situation in which there is still a clear division between social classes, as that one before the advent of the mass production. After it indeed the second theory can better explain the mechanism that underlies fashion's diffusion, especially among younger people. In the *trickle across theory* instead the adoption of a new trend is explained not only by a vertical movement (a top-down approach) but by an *horizontal movement* as well, where people belonging to different "tribes" find their own models to imitate. The consequence is the simultaneous affirmation of different fashion's trends at the same time and in the same geographical (and cultural) context.

The aim of the stylist then becomes the interpretation of the values that people want to transmit through the membership to a particular group, materializing them into a new style or dress-code. This makes of the capacity to create a clear image or a status the base of a fashion company's success, allowing to gain competitive advantage and to avoid a competition based exclusively on costs.

1.4 THE COMMUNICATION OF THE COMPANY'S VALUES

The recent growth of the dynamism and the competition in the fashion system has increased the importance of the marketing strategies for the companies operating in the industry. As we said before, the need of the identification by the customer within a set of values is the key to be able to gain a solid position in the market, creating a customer base and attracting new people that identify with those values. In order to do that, we can look at the four "P" of the Marketing of fashion system: *the product, the price, the place and the promotion.*

1) The Product

In the modern society, the purchase of a pair of shoes or a suite is no more amenable to the satisfaction of a primary need, as the necessity to shelter from the cold, but to the purchase of an image and some values, through which we can be recognized. Of course, the functionality of the product remains important, but it is not enough to induce the purchase: the desires have become the new needs.

2) Price

The logic behind the setting of the price doesn't mirror just the cost of production, but is tightly related to the positioning strategy that the company wants to pursue. Thus, the price is set in relation to what the consumer expects, or what the company wants to be expected, about the value of the product and the brand. For this reason, a product won't have success in the marketplace not only if it is too costly for the target which is directed to, but also if it is too cheap, as the final customer will not feel represented by the brand. This is one of the reasons why the luxury brands never applies discounts or promotions. In relation to the price a company can decide to position in four segments: "High", "Premium", "Medium" and "low". It starts from the lower one in which it is followed just a logic of costs, until the highest one, that is aspirational.

3) Place

The decision regarding the place, or the location, is related to two aspects: the choice of the best place in which to present and promote the collection of the brand, and the choice of the distribution channel.

Starting from the first aspect, the main ways in which a company promotes its' collections are through the events dedicated to the sector (as Pitti in Florence or the fashion week in Milan). It is not enough to decide to participate to them, but it is necessary to decide the right location, depending on the proposal, the collection and the public to which is directed. The main cities in this sense are Milan, Paris, London and New York, each one representing the center of a particular kind of fashion.

The second choice is fundamental for the company, affecting both the image of the brand and its commercialization. Indeed, the distribution channels of the product have to be based on the positioning strategy, as the perception of the brand varies in relation to the location in which it is possible to find it. In this sense, we can consider the distribution strategy as an integral part of the promotional strategy. It will be necessary to decide whether to apply a selective or capillary distribution system, the geographical location of the stores, and, first of all, whether to sell only in mono-brand or in multi-brand stores as well. We will talk about the role of retail in the next paragraph.

4) Promotion

It is the essential condition for the product to achieve success. The traditional media as the newspaper, the radio and tv are still heavily adopted by every brand that wants to be recognized in the marketplace. In many cases, there is no specific object advertised, or, at least, the clothes are not at the center of the scene: what has to be transmitted is always the "atmosphere", in order to link the brand to a particular world through the force of images. Of course, when talking about promotion, we cannot avoid to take in consideration the importance of Internet.

1.5 THE ROLE OF RETAIL

First of all, with retail we mean the sale of products to final customers in a physical shop, excluding the e-commerce from our scope. However, we don't want to present a series of rules that should be followed in order to get the perfect store. For the aspects to consider when managing a retail channel indeed, we preferred to apply an analysis to a real case, obtaining from the data some evidence of what we should consider important or not.

Thus, the aspect we want to talk about is the role that retail has assumed in the fashion system's evolution described. Indeed the store is still the place in which the

company obtains the final results, or in other words where it gets the profit of its job. However, there have been a lot of modifications in the context in which a retailer competes that have to be taken in consideration if he wants to be still effective and have success.

Indeed, with the increasing number of actors operating in the retail industry, the new challenge is to be able to create an environment (the shop) in which the customers are willing to spend their time. The real question nowadays is: "why should shoppers be willing to spend some time in my shop?": it is the experience inside the store that is becoming the key to attract and retain them.

Moreover, there is the increasing affirmation of the e-commerce. It's evident that it has an impact on the activities of the traditional retailers but it's not always clear how does it affect them. Most of all, is it going to substitute them at all or taking only a part of their share?

As a lot of wrong forecasts show, it is difficult to predict the future, especially in this field where social factors are tricky to quantify. What we should focus on is to implement mechanisms that improve our capacity to analyze the present, as long as the monitoring of its evolution can provide us with useful hints about the future.

So, for example, we assist to an increasing integration between the "real world" and the virtual one, with the implementation of in-store mobile technologies that allow to establish a new approach to the shopping experience. At the same time, these kinds of solutions create the possibility to mine new shopper analytics and to leverage them in the store planning process. Still, there a lot more of other tools availables to get knowledge of what is happening in our shops, helping us to understand the dynamics described by the sales process and the consumer's behavior.

Therefore, these analytical tools have to be adopted in order to design a proper experience inside the store, that has to be consistent with the expectations of the customers about the brand. Indeed, we think that in the new competitive environment the key aspect to gain success is to become the representation of a specific set of values shared by a target of people. This is what the major brands (Nike, Paul Smith, Diesel) are doing. In this way they stimulate the attachment to the brand, with the return of the shoppers to the stores of the company.

For these reasons we think that a shop is succeeding when it is able to involve emotionally the customer and to stimulate the desire to identify himself with the lifestyle the company represents. Once obtained this result indeed, the competition will no more based on costs, as the brand will have found its own position in the market place,(partially) isolated from the competitors.

1.6 CONCLUDING REMARKS

After this considerations, we can explain the goal and the scope of our work.

We carried out an analysis on the sales data of a shop of an Italian SME competing in the kidswear fashion, pursuing two goals:

1) firstly, we wanted to understand what are those factors that have some effects on the sales of the shop. In particular, the aspect we wanted to analyze is what influence the capacity to sell *by look*, or in other terms, to sell complementary Items in the same transaction.

2) secondly, given the increasing need of fashion's companies to be provided with an effective system to support decisions, we wanted to introduce a new tool (it will be presented in Chapter 3) that can be adopted in order to improve the quality of the informations availables. Through the analysis carried out we will provide some examples of how it is possible to integrate this tool with the analysis already operated by the company. This is particularly relevant for the case we took under examination, as the growth it has been experienced requires the company to reach an higher level of organization, addressing its resources to the strategic aspects of the business and optimizing the final results.

In the next chapter we will present the company taken under consideration in this work.

CHAPTER 2: THE PRESENTATION OF THE COMPANY

2.1 THE STORY

Il Gufo was born in 1980 as a kidswear manufacturer, founded by the President of the company Giovanna Miletta. It started as an artisan reality, when Giovanna Miletta still used to stitch manually the bibs for her sons. However, through the years, the company has grown in the industry paying more and more attention to the fashion side of the product, until it entered the competition of the luxury system.

During the recent years the brand has seen a strong international growth, finding important markets in particular in Russia and in the United States, other than in the rest of Europe and in some parts of the East (Japan, China). Moreover, it was expanded the network of personal owned shops of the company, opening flagship stores in the main cities of fashion, such as Milan, Paris and New York. Aside this, two corner shops in London and Dubai were opened.

The most important characteristic of the company is that it has not entered the industry of men and women's clothing yet, focusing only on kidswear: this constitutes still one of its main strengths. Differently from the competitors indeed, what characterizes the brand is the concentration of the efforts since the beginning on the children's segment, starting as a contractor for other companies until producing just for its own trademark. If on one side this could present problems of identification of the brand just with this part of the market, on the other side this strategy constitutes the main strength, as it allows the company to be recognized for the value of its products. Indeed this is a segment in which is required a strong specialization, for the particular attention that has to be given to the materials used, the design of the products and the determination of the sizes. Thus, the accumulation of the experience in the solution of peculiar problems related to these aspects of the industry are at the base of the affirmation of the company in the recent years.

2.2 THE STRUCTURE

The company is divided into two parts, Il Gufo spa and Il Gufo Retail srl. The first completely owns the second.

However, the two societies have different scopes, as the first deals with the production and sale of the product to the independent shops while the second manages the network of owned shops. The total revenues of Il Gufo spa (including

il Gufo Retail) has been of 26 millions in 2014, with a forecasted growth to 30 millions in 2015. The greater part of this result is produced by the manufacturing and the commercialization to third parts, so by il Gufo spa.

This is because the company was born as a manufacturer, and only later it opened its own retail channel, seeing an acceleration in the last years with the opening of new flagship stores.

The production model

The company does in house the phases of concept, design of the product and choice of the materials. The production is partially contracted and partially in house. In particular the phases of application of the details to the final product are still done by the company. Two collections are produced annually: the Autumn/Winter collection (AI) and the spring/summer collection (PE).

However, the aspect we want to focus on is the commercial part of the production, meaning with it the management of the relation between the production and the commercialization. In line with the main manufacturing model of the firms operating in the high fashion segment, the production system implemented mirrors the *programmed model*. Indeed, the process starts with the initial phase of design of the product and production of the samples of the collection, continues with the presentation of the samples to the sales agents and proceed only in the final part with the actual production. This organization gives the companies, in particular those ones operating in the high segments of the market, two kind of advantages: the first is the low level of inventories in the warehouse, the second derives from the affirmation of a specific brand identity, with the presentation of the collections at the special events. As a disadvantage, this way the lead time and the time to market are longer, together with the low possibility to provide restocks during the season.

Given these issues, the company mixes the programmed model with the *ready model*, typical of the contractors, where it misses the phase of production and presentation of the samples. In this model, the production takes place when the season is already started and follows the requests of the market and the emerging trends.

So, the final result is a model in which the concept and the design of the product, (with the samples) are still the core part of the process, but at the same time a part of the collection (in relation to the trends forecasted) is overproduced. In this way the company is able to ensure all the season long a wider range of products and

sizes, giving greater support to the sales. As we have seen in the first part of the work indeed during the last years the fashion system has seen a strong acceleration, till the introduction of *flash collections* within the main collection. In this context it is necessary to be able to answer the market's requests always and in short time, establishing a stronger relation with the customers.

On the other side, from this evolution is understandable also the choice of reinforcement of the direct sales channel, that will be presented in the next paragraph.

2.3 THE RETAIL CHANNEL: THE FLAGSHIP STORES AND THE OUTLETS

The shops of the company are divided into two categories: the *boutiques* and the *outlets*. The boutiques are represented by the flagship stores of Milan, Paris, New York, Florence, Rome and Treviso, while the outlets are set into the McArthur Glen centers of Noventa di Piave, Serravalle and Marcianise. These two typologies of shops sell different collections: in the boutiques indeed we find the new collection (AI or PE), while the outlets sell the collection of the year before, constituted by the unsold items of the boutiques and the inventories of the warehouse (what Il Gufo spa didn't sell to the independent shops). As a consequence, it's possible to find the new and the old collection at the same time every year.

The purchasing process

The purchasing process of the collection by the boutiques happens two times a year: in February for the Autumn/Winter collection and in July for the Spring/Summer collection. The main event for the company is Pitti, that opens the purchases of each season. In this occasion (that takes place in January and in June) the new collections are presented and the first orders collected.

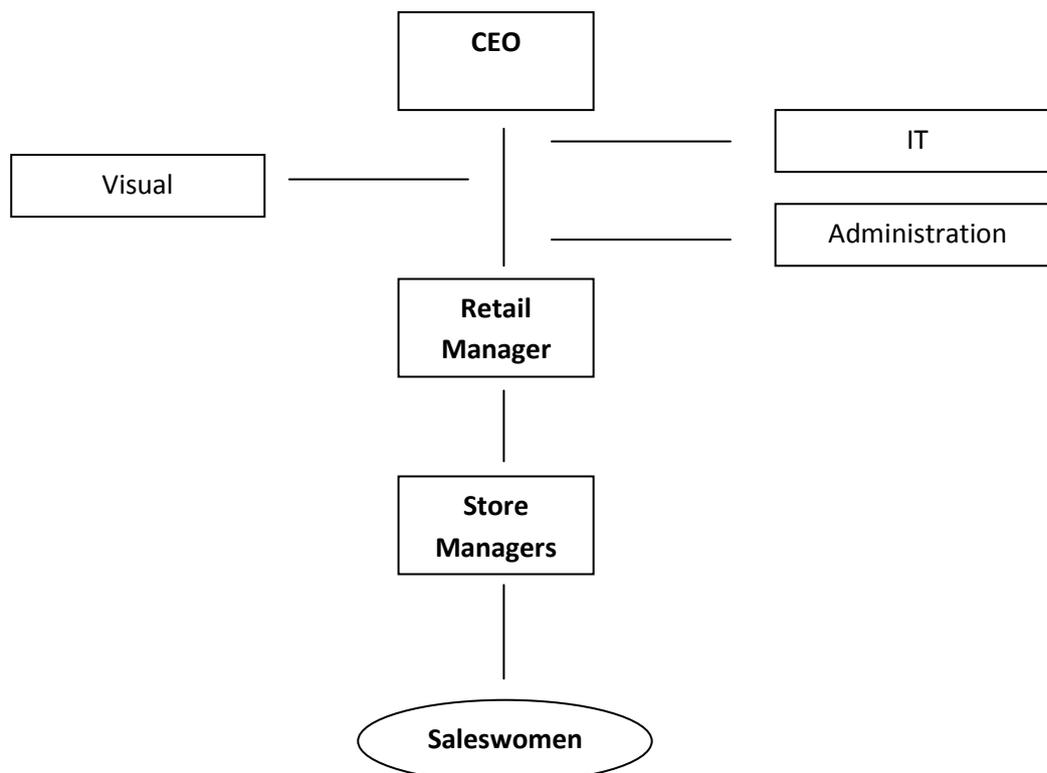
The sale process is the same of that one followed with the external sales agents, with the presentation of the samples to the Retail Manager and then, in collaboration with the Store Managers, the choice of what to buy. The main difference with the purchase done by the independent shops is that the owned shops have to keep in store a wider range of products, in order to guarantee the complete representation of the brand image.

As we said above, it is possible to restock during the season, in relation to the stock's availability of the parent company, Il Gufo spa. The outlets instead, for the reasons already described, don't follow the same process, as they receive the material depending on the inventories available (indeed in this case we don't talk of purchase but of transfer). So, for this type of shop it is not under control what they are going to receive. However, the division of the remaining stocks between them is still really important, as the range of products available in store is critical for the sales' success.

In general, we can say that the purchasing campaign is one of the most important phases of the shops' management, being the moment in which the offer to the final customer is determined. This point indeed will be studied deeper in the analytical part of the work.

The organizational structure of Il Gufo Retail

The organizational structure of Il Gufo Retail is representable the following way:



The CEO is at the top of the whole organization (in this case the CEO of Il Gufo Retail is the CEO of Il Gufo spa as well).

Under the CEO (the IT, the Visual and the Administration are staff units) we find the *Retail Manager*, in charge of the management of all the shops of the company. Under him there are the *Store Managers*, that are in charge of the management of their single shop (there is no difference between the store Managers of the boutiques and the store Managers of the outlets). Finally we find the *saleswomen* of every single store.

The role of the Retail Manager is to carry out strategical policies to increase the sales of the channel, ensuring at the same time the correct transmission of the brand's image to the final customers. In this sense he has to take decisions about the purchases at the beginning of the season, the realization of promotional campaigns, the analysis of the sales data and the implementation of human resources policies. So, he represents a particular figure, having to be able to combine analytical skills with human resources management capabilities, given the need to collaborate with the store Managers. Indeed, an important part of his job is given by the frequent visits to the shops, where the activity of the Store Managers is checked and the analysis done on the sales data are discussed. These kind of visits are crucial, as the sales of the shop are still determined in greater part by the activity of the saleswomen. For this reason, it is important to compare the analysis done "in office" with the specific reality of the shop and the people that work in it.

As a consequence the Store Managers have to be able to manage all the operational aspects related to their shops, as the shifts of the saleswomen, the stock of the warehouse and the tidiness. However, at the same time they have to be prepared with analytical skills, being able to integrate the in-store experience with the capacity to read the data. In this way they will be able to fully understand the dynamics that happen during the sales process, returning back important informations to the Retail Manager and the company. For this reason, in the case under examination, the Store Manager is intended as a proper Manager, differently from many cases in which is considered just in charge of the management of the operational aspects of the shops.

2.4 THE ECONOMIC RESULTS AND THEIR MONITORING

In this paragraph we introduce the results obtained by "Il Gufo Retail" during September 2015. We are interested in particular to the presentation of the results through the scheme used by the Management of the company to carry out the analysis of the sales.

Indeed, as already said during the explanation of the purposes of this work, the final aim is not only the understanding of which dynamics influence, at least partially, the results of an operative unit. Moreover, we want to integrate the analysis already operated by the company with new instruments, in order to provide a complete structure that supports decisions. Thus, in the scheme we will present, we will introduce the Key Performance Indicators, in other words those indicators through which the performances of each shop are evaluated.

First of all, the data are gathered through the software Cegid, which has the front-office version adopted by the shops and the back-office version, adopted by the company to extract the results. Then, the data are structured by four dimensions: the total revenues of each shop, the number of checks registered, the KPIs and the reductions from the full retail price (the discounts). This kind of structure allows us to get deeper in the analysis of what happened in the shop during the week, in order to be able to get some hints of how the result (the revenues registered) was obtained. This in turn makes it possible to monitor the situation and to implement corrective actions in "real time" if something is going the wrong way.

In the next page we report an example of the Recap of the month of September. Please note that the figures and the names of the boutiques were changed (maintaining the proportions) for privacy's reasons. The outlets are not reported. For a better visualization, we divided the table into two parts.

If we would have to do an analysis on these data the first thing that we would notice would be the increase of the income over the year before (Table 2.1) for every boutique. This is firstly due to the greater number of checks registered, that improved for every unit but the *Boutique 4*. This makes us suppose that the flows of customers into the shops have increased and/or the conversion rate of the potential shoppers is better than the last year. However, we cannot assess which of the two causes is stronger, as the shops are not supplied with people counters.

For this reason, we should have a look to the KPIs (Table 2.2), to evaluate if the effectiveness of the sales has improved. So, let's explain what the two indicators reported in the table represent:

Units per transaction (UPT): it indicates the average number of Items purchased for transaction;

Average Basket (AVG Basket): it reports the average amount for transaction.

Shop	Income 2015	Income 2014	% Income	N° Checks 2015	N° Checks 2014	% Number Checks
Boutique 1	€ 45.500,00	€ 41.500,00	10%	183	141	30%
Boutique 2	€ 110.500,00	€ 98.500,00	12%	337	327	3%
Boutique 3	€ 235.000,00	€ 163.500,00	44%	471	361	30%
Boutique 4	€ 173.000,00	€ 150.000,00	15%	259	284	-9%
Boutique 5	€ 20.500,00	€ 15.000,00	37%	115	115	0%
Total	€ 584.500,00	€ 468.500,00	25%	1365	1228	11%

Table 2.1: The total income and number of checks registered during September 2015

Shop	UPT 2015	UPT 2014	% UPT	AVG Basket 2015	AVG Basket 2014	% AVG Basket	Discounts 2015	Discounts 2014	% Discounts
Boutique 1	2,50	3,10	-19%	€ 250,00	€ 290,00	-14%	€ 860,00	€ 1.500,00	-43%
Boutique 2	3,60	3,20	9%	€ 330,00	€ 300,00	10%	€ 1.100,00	€ 2.300,00	-52%
Boutique 3	5,20	4,80	7%	€ 490,00	€ 450,00	9%	€ 3.200,00	€ 3.800,00	-16%
Boutique 4	4,20	3,20	31%	€ 670,00	€ 530,00	26%	€ 12.000,00	€ 2.500,00	380%
Boutique 5	2,40	2,00	15%	€ 175,00	€ 145,00	21%	€ 1.400,00	€ 1.800,00	-22%
Total	4,00	3,62	10%	€ 428,21	€ 381,51	12%	€ 18.560,00	€ 11.900,00	56%

Table 2.2: The KPIs and the Discounts during September 2015

At first glance, we can say that the performance of the shops has improved all over the channel. Indeed, we see from Table 2.2 that both the indicators registered better values than the year before for all the shops but *Boutique 1*. In this case the income has increased mainly for an improvement of the flows into the shop. Let's take in consideration *Boutique 2* now. The UPT increased of 0,40 pieces for check, meaning that every 2,5 transactions they were selling one piece more. At the same time, the Average Basket increased of 30 euro for transaction. Thus, if we observe the average prices of some products as the accessories, which ranges between 50/80€, or the shirts and the T-Shirts, that are below 100€, we can suppose that there has been an increase in the sales of these kinds of products. Similar dynamics happen for *Boutique 3* and *Boutique 5*.

Finally, let's observe the result of *Boutique 4*. We notice that this is the only case in which the increase of the average number of Items purchased is higher than the increase of the average amount of the check. To explain this we should watch the total discounts. We see indeed that they have increased of the 380% over the previous year. Given this variation, it's reasonable to think that the reductions from the full price had a greater effect on the increase of the UPT, that in turn improved the average amount. However, the effect on the final check was reduced for the lower average price of the Items bought.

As we have seen, the organization of the sales data in the Tables presented allows us to do some considerations on the performance of the operative units, through an analysis that is not possible to perform just considering the variations of the total income. However, as specified, they remain only considerations, for which we should have the support of other kinds of analysis in order to be able to sustain with greater evidence what we suppose.

This is the reason why we decided to introduce the Market Basket Analysis.

The purpose of the application of this method is to provide the company of another tool to adopt in order to refine the understanding of the results generated. Indeed, as we will see in chapter 5, the results of the Market Basket Analysis can be integrated with the considerations done previously about the KPIs, giving a deeper explanation of the dynamics observed. Moreover, it will be useful to understand some factors that are critical in the generation of the final results.

So, in the next chapter we will present the theory relative to this new tool. Moreover, it will be introduced the theory relative to another kind of analysis we applied to the warehouse's stocks of the company, that will be associated to the Market Basket Analysis to obtain some explications of the results founded.

CHAPTER 3: THE MARKET BASKET ANALYSIS AND THE TEST OF DIFFERENCE BETWEEN TWO POPULATIONS

In this chapter we will introduce the instruments we applied to carry out the analysis on the sales data of the shop of Milan. We will start with the presentation of the theory relative to the Market Basket Analysis to talk later about the methodology used to study the composition of the warehouse's stock.

3.1 How do costumers shop?

"Sales data provide a view of what customers are purchasing but do not provide a view of *how* they are buying, in other words, in what combinations and what quantities. One method that is being used to determine this is the Market Basket Analysis" (Clodfelter, 2012).

The Market Basket Analysis (MBA), or association analysis, "is a data mining solution that identify the relations among items in a costumer's shopping basket" (Clodfelter, 2012), identifying product affinities that provide useful informations for designing various marketing strategies. Indeed, an experienced store manager may know lots of product pairs purchased together, but there could be a lot of associations that are not obvious at all: the MBA is designed to find these type of associations with minimal human interaction. Typically the input to an association analysis is a transaction data at the customer level. MBA extracts many products affinities from the database: the outputs consists in a series of association rules, such as "if customers buy Product A they also tend to buy Product B".

The MBA was originally applied to supermarket transaction data. Actually it takes its name from the fact that consumers in a supermarket place all of their purchased items into the shopping cart or the market basket. Nowadays the application of the association analysis is not limited to the supermarket, but to the retail industry in general, ranging from the industry selling bank products to new sales channels, especially the Internet.

Mainly, the results of the MBA are used to improve the efficiency of marketing strategies and tactics, learning from it which products/services are purchased together. First, the association analysis can be used to manage the space within the shop: it may be decided to stock the associated Items close together, so the

customer would not forget to buy both of them. On the other hand, the associated Items could be stocked far apart such that consumers would spend more time browsing aisle by aisle (Clodfelter, 2012). Second, the MBA can be used for designing various promotional strategies, providing ideas on product bundling. For example, it can be used to design a cross-coupon program where consumers purchasing an Item A get the discount for an Item B.

Finally, MBA with temporal components can be very useful to various marketers for selecting cross-selling Items. For example, it might indicate that customers that have purchased service A tend to purchase service B after three months. This in turn suggests a cross-selling possibility, by which the salesperson should contact the clients with service A (within three months) and try to cross-sell the service B.

3.2 DERIVING MARKET BASKET ASSOCIATION RULES

"The input for a MBA is customer-level transactions data, although is not necessary that each customer be explicitly identified" (Blatteberg, Do-Kim, Neslin 2008).

In our case, the shops of the company record each customer's transaction data with their scanning devices, that register in the system the Items purchased. For each transaction, the shop knows the date, the saleswoman, the Items purchased and the price of each of them.

Table 3.1 shows the transactions from the shop of Milan:

<i>Transaction's number</i>	<i>Items purchased</i>
901	Shirt, Sweater, Long Pant, T-Shirt
902	Socks, Shirt, Long Pant, Sweater
903	Socks, Long Pant, T-Shirt, Sweater
904	Jacket, Long Pant, T-Shirt
905	Shirt, Long Pant, Sweater

Table 3.1: Sample of transactions from the shop of Milan

In the example, there are five transactions and each consists of a set of Items. The main focus of the association analysis is the set of Items purchased for each transaction, from which it provides the series of association rules where we infer which Items are purchased together. Each association rule consists of an antecedent and a consequent. For example, considering the association rule "if a consumer purchases Item A he also tends to purchase Item B", the Item A is the

antecedent while the Item B is the *consequent*. Both the antecedent and the consequent can contain multiple Items.

3.3 FINDING INTERESTING ASSOCIATION RULES

We derive some association patterns from Table 3.1. At first glance, we can see that long pant and T-Shirt are purchased together in four out of five transactions. This observation may tell us that there is a cross selling possibility between long pant and T-Shirt. Moreover, socks and long pant are bought together in two out of five transactions. Again from this pattern, we may suggest an association rule like :*"if a customer buys long pant, then he also buys socks"*. We can generate many association rules from Table 3.1 but we are only interested in selecting *"interesting"* rules. That is, how much are them useful to the Management?

It is difficult to come up with a single metrics quantifying the *"goodness"* of an association rule (Blatteberg, Do-Kim, Neslin 2008). Hence, there have been proposed several metrics. Three of them are the most popular: *support*, *confidence* and *lift*.

The *support* is the percentage of transactions containing a particular combination of Items relative to the total number of transactions in the data-base (Giudici,2005).

We can think of the support for an individual Item as the probability a transaction contains item A, or $P(A)$. However, when we are interested in associations, we are concerned with multiple Items, so the support for the combination A and B would be $P(AB)$. For example, consider the association rule *"long pant and socks"* from Table 3.1. Support measures how often long pant and socks are purchased together, as a percentage of the total number of transactions. They are purchased together two out of five transactions, hence support for the association rule is 0,40.

Support for multiple Items can be interpreted as a joint probability. It measures the probability that a randomly selected basket contains Item A and Item B together. Hence it is symmetric. We know that the joint probability of A and B, $P(AB)$, is not different from the joint probability of B and A, $P(BA)$. For example, support for the association rule *"long pant and socks"* would be the same as the support for the association rule *"long pant and socks"* (Blatteberg, Do-Kim, Neslin 2008).

Support has one disadvantage in evaluating the quality of an association rule. The example in Table 3.1 shows that the association rule *"long pant and socks"* has support of 0,40. However, this does not tell us anything about the *"force"* of the

relation, in other words: we don't get any knowledge about the number of times in which the customer buy the long pant without the socks.

Indeed, Table 3.1 shows that every transaction contains long pant: this Item is so popular that the support for it plus any other product could be large.

For this reason we talk about *Confidence*, that measures how much the consequent (Item) is dependent on the antecedent (Item). In other words, confidence is the conditional probability of the consequent given the antecedent, $P(B|A)$ (Giudici, 2005).

For example, the confidence for the association rule "if sweater then shirt" is 0,75, since four transactions contains sweater and three among the four transactions also contain shirt. In other words, given that the baskets containing sweater is selected, there is 0,75 chance that the same basket also contains shirt. Differently from support, confidence is asymmetric. For example, the confidence of "if shirt then sweater " would be 1. The law of conditional probability states that $P(A|B) = P(AB)/P(B)$, that is, confidence is equal to the support of the association rule divided by the probability or the support of the antecedent. For example, the support of an association rule "if sweater then shirt" is 0,60, while the support or the probability of sweater is 0,80. Hence, confidence is 0,75 ($0,60/0,80$) (Blatteberg, Do-Kim, Neslin 2008).

Finally, there is the *lift*. Consider an association rule "if A then B". The lift for the rule is defined as $P(A|B)/P(A)$ or $P(AB)/[P(A)P(B)]$. As shown in the formula, lift is symmetric in that the lift for "if A then B" is the same as the lift for "if B then A".

$P(A)$ is the probability that a randomly chosen transaction contains Item A. In other words, it is an unconditional probability of purchasing Item A regardless of other Items purchased. It is also used the term, "expected confidence" for $P(A)$.

Hence, the *lift* is said to measure the difference - in ratio - between the confidence of a rule and the expected confidence.

In particular, its' value is significant if it is higher than 1, as a lift ratio larger than 1,0 implies that the relationship between the antecedent and the consequent is stronger than would be expected if the two sets were independent (Giudici, 2005). For example, the lift of the association rule "sweater and T-Shirt" is 1,25, because the expected confidence is 0,60 and the confidence is 0,75. This means that consumers who purchase Sweater are 1,25 times more likely to purchase T-Shirt than randomly chosen customers. The larger the lift, the more interesting the association rules. However, the lift has little practical value when the support of the antecedent Item is very low. For example, consider the relation "jacket and T-Shirt",

with $P(\text{T-Shirt})=0,60$ and $P(\text{jacket})=0,20$ and $P(\text{T-Shirt}\&\text{jacket})=0,20$. The association rule looks like a good rule based on its lift of 1,66. However, only in one transaction a customer bought the jacket and a marketing strategy designed to encourage jacket buyers to purchase T-Shirt may not have an impact.

Summarizing, we have introduced three criteria for evaluating association rules in MBA, defined as follows:

$$\text{Support} = P(AB)$$

$$\text{Confidence} = P(A|B)$$

$$\text{Lift} = P(A|B)/P(A)$$

Every criterion has its advantages but in general we would like association rules that have high values of all three criteria. Association rules with high supports are potentially interesting rules. Similarly, rules with high confidence would be interesting rules. An high value of the lift tells us of a good opportunity, but with low values of the support of the antecedent it is not reliable.

Indeed, whatever criteria adopted, the presence of low-support Items make it difficult to find good association rules. For example, suppose that there is only one transaction including Item A in the entire data-set and this transaction contains also Item B. The confidence of the association rule "if Item A then Item B" would be 1, but it wouldn't be an interesting association rule. We can avoid this problem employing higher levels of aggregation, for example classifying the products by groups. Of course, the aggregation leads to the loss of useful transaction details, and pose the problem of the choice about the right level we should use of it. "One suggested method is to aggregate Items such that each of the resulting groups have roughly the same level of appearance or support in the MBA" (Blatteberg, Do-Kim, Neslin 2008). As a result, Items with smaller unit sales will be grouped together so that we can avoid the problem of bad association rules due to low supports. Otherwise, it could be chosen to form groups of Items belonging to the same merchandising group.

However, none of these rules should be taken too strictly. The needs of the users are the key drivers when deciding the level of aggregation.

3.4 THE APPLICATION OF THE MARKET BASKET ANALYSIS TO THE REAL CASE

Firstly we want to specify the criterion used to evaluate the goodness of the associations founded. We decided to use both the support and the confidence. We didn't apply the lift because of its' low reliability when dealing with Items with low supports, that was the main issue we faced during the analysis. Indeed, the application of MBA to the fashion system requires a different approach than the application to the classical case of the supermarket.

This is first of all because fashion is seasonal, as the clothing collections change every year. Hence, fashion's products of a given collection are outdated the following year, making it difficult to infer what kind of Items are best sold together. Secondly, fashion changes not only year over year, but it follows a cycle within the same season as well. If we take as example the Winter collection of a company, the shopping done in August/September will be different from the shopping done in December. This in turn makes it difficult to find common patterns.

This is especially accentuated from the fact that the company we are analyzing operates in the kidswear industry, where the shopping is driven both by the interest for the fashion world both by the need to take in consideration the functional purposes related to the situations in which the clothe is used (beginning of the school, sports activities, etc). Finally, there are those factors such as the shop window and the internal display that change one time or more in a month. These rotations are at the base of the visual strategies and has some effects on the sales as well, as they are aimed to increase the visibility of specific Items in a given period. We will talk about this aspect in the last chapter of the work.

Therefore, for the dynamism of the particular industry we are analyzing, it was difficult to find relations with a support high enough. So, we proceeded the following way:

- we did the analysis by groups of products. In other words, we didn't analyze the associations between the specific products but between groups of them. We used the classification in product's categories already adopted by the company;
- we divided the analysis by month. Given the changes in the shopping drivers between different periods of the same year, we specified the analysis in order to look deeper to the behavior of customers;

- we set in the software used for the analysis (it will be presented in the next paragraph) some minimum values for the confidence and the support. Once obtained those relations that respected the fixed levels we classified the associations by support;
- we did the comparison between the same month of two different years, in order to study the variations occurred.

The most important things to underline of the method we adopted are two: first, we used just the supports to evaluate the importance of the relation and do the comparisons with the other associations. This choice is due to the reasons explained before about the limited number of relations we could find. In this sense, once we set a minimum level of confidence we considered acceptable, it was from the variations of the supports levels that we assessed whether a relation had assumed a different importance in the set of associations founded over the years.

Secondly, the purpose we followed during the analysis was different from the purpose the MBA is usually applied for. Indeed, as we have said in the first paragraph, these kind of analysis are done in order to assess what kind of combinations are most frequently generated and to infer about the behavior of the customer. The final aim is the generation of marketing policies and the assessment of the layout of the store. In our case however, it wasn't of particular benefit to assess that, for example, the sweater is sold together with the long pant, as it is something the company already knows. Indeed, the design of the collection, its promotion and its exposition inside the shop are already studied to sell by *look*. The analysis of the associations would have been useful if some associations between specific Items were presented, but we didn't find results in this sense. For this reason we decided to use the MBA in an alternative way, starting from the modifications of the associations founded between the different years to find what kind of factors influence the sales of the shop. This in turn allowed us to understand some of the variables we should focus on in order to generate more combinations.

Hence, in our analysis is not fundamental the "picture" of a specific moment, but the modifications occurred during the different periods, over the years and over the months. The factors we identified will be presented in chapters 5 and 6.

3.5 PERFORMING MBA USING R

In order to perform the Market Basket Analysis we used *R*. *R* is an open source software adopted to do statistical analysis and data mining. It is freely available on the Internet. Thanks to its libraries, *R* implements a lot of different statistical techniques, that are extensibles through the implementation of the "packages" that upload in the system the specific functions we need. In our case we uploaded the "Arules" package, which implement the Apriori algorithm used to find the most frequent associations .

The Apriori Algorithm

The association rule generation is usually split up into two separate steps:

1. First, minimum support is applied to find all frequent item sets in a database.
2. Second, these frequent item sets and the minimum confidence constraint are used to form rules.

While the second step is straight forward, the first step needs more attention. Finding all frequent item sets (those sets which contain an item with a minimum support) in a database is difficult since it involves searching all the possible items combinations. The set of possible item sets is the power set over I (the set of n Items) and has size $2^n - 1$. Although the size of the powerset grows exponentially in the number of items n in I , efficient search is possible using the downward-closure property of support (also called anti-monotonicity) which guarantees that for a frequent item set, all its subsets are also frequent and thus for an infrequent item set all its supersets must also be infrequent. The Apriori algorithm uses this property to find all frequent associations.

As it is common in association rule mining, given a set of item sets (for instance, sets of retail transactions, each listing individual items purchased), the algorithm attempts to find subsets which are common to at least a minimum number C (the minimum support value) of item sets. Apriori uses a "bottom up" approach, where frequent subsets are extended one item at a time (a step known as candidate generation), and groups of candidates are tested against the data. The algorithm terminates when no further successful extensions are found, using breadth-first search and a tree structure to count the candidate item sets efficiently. It generates candidates of length k from item sets of length $k - 1$. Then it prunes the candidates which have an infrequent sub pattern. According to the downward closure lemma, the candidate set contains all frequent k -length item sets. After that, it scans the

transaction database to determine the most frequent ones to generate the association rules.

You will find in Appendix A the procedure we followed in *R* to get the results of the MBA.

3.6 THE TEST OF DIFFERENCE BETWEEN TWO POPULATIONS

The test is based on the formulation of two hypothesis, and then, after a control over some samples of the populations, on the rejection of one of the two. The hypothesis done are usually the Null Hypothesis, H_0 , and the Alternative Hypothesis, H_1 . Generally, the Null Hypothesis is that one we want to reject.

The strategy to verify the truthfulness of the Hypothesis is to apply a statistical test on the samples, given a probability α by which, supposing the alternative H_0 true, the result is given by random. In other words, the probability α determines the *level of significance of the test*, and if for example it is set at the 5%, it means that with a probability of the 5%, accepting the Alternative Hypothesis we are refusing H_0 when it is true. Of course, the higher the level of significance of the test, the lower the probability to commit an error. The probability of error is associated to the fact that the control of the hypothesis is conducted over samples of the populations, and the result could be by chance. In our case however, the test is conducted in order to establish if the difference between the stocks can be considered the effect of a deliberate choice to increase or decrease the quantity of a given product category, or if it is just the effect of the gradual increase of the purchases of the shop year over year. We can write α as follows:

$\alpha = \text{Probability (reject } H_0, \text{ supposed } H_0 \text{ true)}$

On the contrary, $1 - \alpha$ represents the probability that we are accepting H_0 when it is true, or in other words the probability we are right. The level of probability α has to be set *a priori*, so it's not possible to manipulate the results in order to accept the hypothesis that is more comfortable to us. Usually are chosen low values (between 5% and 1%). Moreover, the level of significance assumes different values in relation to the distribution of the statistical test, which choice depends on the kind of hypothesis we want to verify and on the characteristics of the samples: in the case under examination we will use the statistical test based on the *Chi-squared* (χ^2) distribution.

To carry out this test, we have to build a table of two rows and two columns in which we have to report the number of successes and unsuccesses of each group under consideration. In our case, the number of successes is given by the number of units belonging to a product category, while the unsuccesses will be the rest of the units that compose the total stock of the group.

Here below there is an example for an item:

Sweatshirt	2015	2014	Total
Successes	429	268	<u>697</u>
Unsuccesses	2287	2031	<u>4318</u>
Total	<u>2716</u>	<u>2299</u>	<u>5015</u>

Table 3.2: An example of the table used to carry out the *Chi-Square* test

we formulate the two hypothesis:

$$H_0: \pi_A = \pi_B$$

$$H_1: \pi_A \neq \pi_B$$

where H_0 is the hypothesis that we want to reject. π_A and π_B are the proportions of the populations (the stocks of the product's categories in our case): indeed we want to verify if the quantity of category A over the total warehouse's stock is different from that one of category B. For this reason, we are testing the difference between the *proportions* of the populations.

At this point we can consider the statistical test

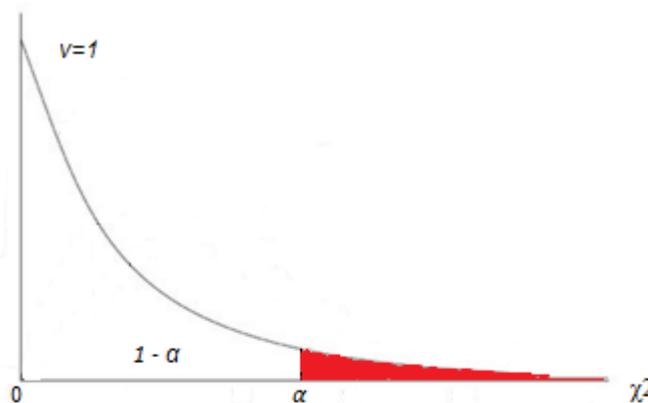
$$\chi^2 = \sum \frac{(f_o - f_e)^2}{f_e}$$

with f_o given by the frequency of the units observed while f_e given by the frequency that we would expect. The final result is given by the sum of the results of the formula calculated for each cell (in this case of the table 3.2).

In other words, f_e is the frequency that the successes (and the unsuccesses) of a given group should have if the Null Hypothesis of equality between the two

proportions was true. In this case, the difference between the two populations should be only the result of casualty. Once determined the values of F_e (by using a combination of the frequencies observed in the two groups) the Null Hypothesis will be accepted or rejected comparing the value of χ^2 with that one of α : H_0 will be considered true if χ^2 is lower than the level of significance set, otherwise it will be rejected.

Below, we report a representation of the distribution of χ^2 with 1 degree of freedom (because the table on which it is calculated is 2x2)



Graph 3.2

The region underlined in red is the region of rejection, while $1 - \alpha$ is the region of acceptance of the Null Hypothesis. For example, chosen an error of the 5%, the value α of the *Chi-square* distribution represented above (with 1 Degree of freedom) will be 3,841.

Finally, we have to specify what the *p-value* is. The *p-value* represents a probability that quantifies the evidence against the Null Hypothesis: the lower it is, the higher is the probability that the results obtained were obtained given the Alternative Hypothesis true. Thus, values of the *p-value* between 10% and 5% means a weak evidence against the Null Hypothesis, between 5% and 1% they are considered significant and under 1% there is a strong evidence in favor of the Alternative Hypothesis.

In this section we presented the *Chi-square* test because the analysis on the warehouse's stocks was carried out through this methodology. *R* is the tool that we

used to apply it to the real case. Moreover, R calculates the p -value as well, giving the possibility to do a double check on the results.

In the next chapter we will present the results of the application of the MBA on the first two years taken in consideration, 2015 and 2014. The analysis of the warehouse's stocks was applied on these two years as well, and it will be presented in chapter 5.

Finally, in chapter 6, we will present the application of the MBA to the last year, 2013. This will be used to evaluate the effect of the second variable considered in this work.

CHAPTER 4: MBA RESULTS

4.1 THE METHODOLOGY

The analysis was done on the product categories in which the clothing collection is divided. We report them in the table below, where each one is associated to a Macro-Group:

Macro-Group	Product's Category
Accessories	<i>Bag Hat Belt Scarf Gloves</i>
Socks	<i>Socks</i>
Shirts	<i>Shirt</i>
Outerwear	<i>Blazer Jackets</i>
Down Jackets	<i>Coats Down Jackets Salopette</i>
Sweatshirts	<i>Fleece Jackets Sweatshirts</i>
Sweaters	<i>Gilet Jumpers Sweaters</i>
Pants	<i>Capri Long Pants Bermuda</i>
Polo	<i>Polo</i>
T-Shirt	<i>Top T-Shirts</i>
Dress	<i>Dress short/sleeves Dress long/sleeves Dress no/sleeves</i>

Tab 4.1: The product categories

The years we analyzed are 2014 and 2015 and the data related to the Autumn/Winter collections. Further, the analysis was done by month: in other words we implemented a separate analysis for September, October, November and December. Each of them was then compared with the same month of the season before. The parameters we used are the 4% for the support and the 50% for the Confidence; in particular the value of support was chosen in order to generate a sufficient number of relations. The associations were then ordered by Support, starting from the higher to the lower

4.2 OVERALL RESULTS

The first consideration is given by the reduction of the number of relations observed going from the month of September to the month of December, for both years.

Secondly, from the comparison between the same month of the two years we see that September 2014 has the higher number of associations, followed by September 2015. The same dynamic is registered in October, while in November and December the numbers are the same.

We report below a table summing up what we just said:

N° of Relations	September	October	November	December
2015	22	8	4	3
2014	28	10	4	3

Tab 4.2: The number of relations founded for each month

In particular, the data analyzed present interesting dynamics in the evolution of 7 product's categories: the sweatshirts, the fleece jackets, the sweaters, the jumpers, the shirts, the polo and the socks. Moreover, aside these categories we founded that the long pants are the product most frequently associated with another product group, while the presence of the others categories is variable. Finally, the relations with an higher support are characterized by the presence of two Items only.

Let's proceed now with the presentation of the results founded for each month, to give then a final overview of the dynamics described by the data during the period taken in consideration.

4.3 RESULTS OF THE ANALYSIS FOR EACH MONTH

Before proceeding with the presentation of the results, we underline that the total number of transactions registered in September 2015 is higher of the 44% than the

number of transactions registered in September 2014, with 471 checks against 361 checks of last year. This extraordinary improvement happened in October as well, mainly due to the higher flow of tourists for the Expo' event. In November and December the number of transactions of 2015 are higher "just" of the 6%.

September

We report below a table comparing the results of the analysis done through *R* on the months of September 2015 and 2014:

	Relation	Support 2015	Support 2014
1	(T-Shirt, Long Pant)	17,2%	18,50%
2	(Sweater, Long Pant)	15%	17,10%
3	(Jumper, Long Pant)	11,40%	12,70%
4	(Sweatshirt, Long Pant)	10,90%	7,70%
5	(Shirt, Long Pant)	10,70%	6,90%
6	(Fleece Jacket, Long Pant)	8,20%	5,80%
7	(Sweatshirt,T-Shirt)	7,50%	5,60%
8	({Sweater, T Shirt},Long Pant)	7,10%	6,90%
9	({Jumper, T Shirt}, Long Pant)	6,30%	8,00%
10	(Skirt, T-Shirt)	6,10%	5,00%
11	(Socks, Long Pant)	5,90%	N/A
12	(Fleece Jacket,T-Shirt)	5,70%	5,10%
13	({Jumper, Sweater}, Long Pant)	5,70%	5,80%
14	({Sweater, T-Shirt}, Long Pant)	5,70%	5,00%
15	({Shirt, Sweater}, Long Pant)	5%	N/A
16	(Polo, Long Pant)	4,80%	1,02%
17	({Shirt, T-Shirt}, Long Pant)	4,80%	4,14%
18	(Socks, Sweater)	4,60%	N/A
19	(Body, Long Pant)	4,40%	N/A
20	(Socks, T-Shirt)	4,24%	N/A
21	({Fleece Jacket, T-Shirt}, Long Pant)	4,20%	4,00%
22	(Polo, Sweater)	4,00%	7,70%

Table 4.3 : The comparison between the association rules founded during September 2015 and 2014. The relations are ranked by support of 2015. N/A means that the relation does not appear in 2014.

	Relation	Support 2014
1	(Jumper, T-Shirt)	10,70%
2	(Polo, T-Shirt)	7,70%
3	(Down Jackets, Long Pant)	6,30%
4	(Coat, Long Pant)	4,90%

Table 4.4.: Relations founded only in September 2014

In Table 4.4 we reported some relations that are not present in Table 4.3, as they didn't appear during 2015. However, we have to take them in consideration during our analysis.

In the first month of analysis, we observe the same relations in the first three positions:

(T-Shirt, Long Pant) ; (Sweater, Long Pant) ; (Jumper, Long Pant)

As we see from table 4.3 the values of the supports of the relations are always higher in 2014. To explain why, we should have a look to the behavior of other two product's categories: the sweatshirts and the fleece jackets. Indeed in 2015 we observe a greater frequency of the relations with these two products: for example, if in 2014 we found the sweatshirt with the long pant with a support of 7,7%, in 2015 it increases to the 10,9%.

Moreover, there are two other important relations with the category:

(Sweatshirts, T-shirt) ; ({Sweatshirt, T-Shirt}, Long Pant)

Also In this case, they are at an higher level of the rank, with greater supports (7,50% and 7,10%) than 2014. Secondly, the fleece jacket also has an improvement over 2014, appearing in the following associations:

(Fleece Jacket, Long Pant) ; (Fleece Jacket, T- Shirt) ; ({Fleece Jacket, T-Shirt}, Long Pant)

with supports of 8,20%, 5,7% and 4,20% against the 5,80%, 5,0% and 4% of 2014.

Finally, we underline another relation

(Shirt, Long Pant)

that presents a support higher of 3,8% than 2014.

On the contrary, we notice that the jumpers have lost importance during this year, taking in consideration in particular these three relations:

(Jumper, Long Pant) ; ({Jumper, T-Shirt}, Long Pant) ; (Jumper, T-Shirt)

where the support of the first two decreases from 12,70% and 8% of 2014 to 11,40% and 6,30% of 2015. The third one does not even appear during this season (we find it in table 4.4). Other than the jumpers we find other three categories that used to have a greater frequency in the associations founded during 2014: the polo, the down jackets and the coats. In particular, while the last year the polo appeared in 5 relations with a support ranging from 10,20% to 4,14%, this year we find the category only in two associations, with much lower values: the higher of the two is just the 4,8%. The other two categories, the down jackets and the coats, appeared in the following relations:

(Down Jackets, Long Pant) ; (Coats, Long Pant)

with a frequency of 6,30% and of 4,90%. In 2015 we don't find these relations anymore.

To conclude, we underline the presence of another category that appears only during 2015: the socks. The relations in which we find them are:

(Socks, Long Pant) ; (Socks, Sweater) ; (Socks, T-Shirt)

with supports at 5,90%, 4,6% and 4,2%. In the associations considered until now, they are the only ones in which we find a product belonging to the Macro-Group of Accessories.

We report below a scheme summing up the product categories appeared during the months of September 2015 and 2014. Even if the number of relations founded in 2014 is higher indeed, 2015 turns to be the year with the greater variety, having 12 different categories against 11 of the 2014.

	September 2015	September 2014
1	T-Shirt	T-Shirt
2	Long Pant	Long Pant
3	Sweater	Sweater
4	Jumper	Jumper
5	Sweatshirt	Sweatshirt
6	Shirt	Shirt
7	Fleece Jacket	Fleece Jacket
8	Dress	Down Jacket
9	Socks	Coat
10	Skirt	Skirt
11	Polo	Polo
12	Body	

Table 4.5: The product categories founded during the analysis on September

October

	Relation	Support 2015	Support 2014
1	(Sweater, Long Pant)	13,00%	10,50%
2	(T-Shirt, Long Pant)	12,10%	11,80%
3	(Jumper, Long Pant)	8,70%	10,00%
4	(Shirt, Long Pant)	8,30%	4,00%
5	({Sweater, T-Shirt}, Long Pant)	5,60%	4,90%
6	({Jumper, T-Shirt}, Long Pant)	4,70%	6,60%
7	(Fleece Jacket, Long Pant)	4,50%	N/A
8	({Jumper, Sweater}, Long Pant)	4,30%	4,50%

Table 4.6 : Relations founded during the month of October 2015 and 2014

As before, we report below the relations that do not appear in 2015:

	Relation	Support 2014
1	(Jumper, T-Shirt)	9,8%
2	(Polo, Long Pant)	5,9%

Table 4.7 : Relations founded only in October 2014

As anticipated, the number of relations founded in October is lower for both years. On the point of view of the type of associations discovered, there are no significant differences with September. The most frequent combinations remain the same of the previous month for both the seasons, with the difference that in 2015 the relation *(Sweater, Long Pant)* has a greater support than *(T-Shirt, Long Pant)*, placing at the first position. We notice then that the sweatshirts and the fleece jackets don't cover the same importance they used to have in September: in October 2015 the first disappears from the associations generated while the second has a support just of the 4,5%. The same happens in October 2014.

We underline the still relevant presence of the jumpers in 2014, with the following relations:

(Jumper, Long Pant) ; *(Jumper, T-Shirt)* ; *({Jumper, T-Shirt}, Long Pant)*

with supports at 10%, 9,8% and 6,6%.

In conclusion we observe the polo, that appears in 2014 in one relation with a support of 5,9%, while they are not present during the following year. However, they are substituted in part by an higher value of the shirt bought in combination with the long pant.

November

We report separately the associations founded in November 2015 and 2014, since only two of them are the same between the two years:

	Relation	Support 2015
1	(T-Shirt, Long Pant)	9,9%
2	(Sweater, Long Pant)	8,2%
3	(Shirt, Long Pant)	7,00%
4	(Sweatshirt, Long Pant)	4,20%

Table 4.8: Relations founded in November 2015

	Relation	Support 2014
1	(Sweater, Long Pant)	8,6%
2	(Polo, Long Pant)	7,8%
3	(Shirt, Long Pant)	4,5%
4	(Scarf, Hat)	4,0%

Table 4.9: Relations founded in November 2014

In November, the number of relations is lower than in October: 4 both in 2015 and in 2014. However, the categories present in the associations discovered have some differences in the comparison between the two seasons. As we can see, the only common relations are:

(Sweater, Long Pant) ; (Shirt, Long Pant)

The first has a similar support between the two years, while in the second we observe a greater distance in their values. Moreover, we underline that in 2015 we find again the association *(Sweatshirt, Long Pant)* with a support of 4,2%.

We observe then that the combination *(Shirt, Long Pant)* has a greater frequency in 2015, but this is almost compensated by the presence of the polo in 2014. Finally, we notice the presence of the new relation *(Scarf, Hat)* in November of last season, with a support of 4%. Again, this is the only case in which we find some products belonging to the macro-group accessories.

December

As before, since all the relations generated are different we present the data in two different tables.

	Relation	Support 2015
1	(T-Shirt, Long Pant)	8,7%
2	(Sweater, Long Pant)	6,00%
3	(Shirt, Long Pant)	5,30%

Table 4.10: Relations founded in December 2015

	Relation	Support 2014
1	(Polo, Long Pant)	7,1%
2	(Polo, Sweater)	5,1%
3	(Jumper, Long Pant)	4,5%

Table 4.11: Relations founded in December 2014

The number of associations is the lowest, with three relations during both years. As we see, the T-Shirts and the sweaters place at the first positions in 2015 while the polo prevails in the last season. We don't notice any particular differences with the associations founded in the previous months, confirming the trends already observed.

4.4 SUMMARIZING OUR FINDINGS

In relation to what we have observed, two product categories play the main rule in the composition of the *total look*. Indeed, the relation (*Sweater, Long Pant*) is that one that recurs every month with the highest average support. Still, it is more interesting to observe the dynamics that follow the categories of the sweatshirts, the fleece jackets and the jumpers. In particular, the sweatshirts have an important role in the associations generated during September 2015. On the contrary, during the previous year the combinations with the jumpers had greater importance, while in 2015 a part of their share is substituted by the increase of the sweaters and the sweatshirts. We find the same dynamics for the polo and the shirt: the first one in fact loses some ground in favor of the second one (this is particularly true comparing November 2015 and 2014).

Finally, we have to make some considerations about the socks. This category, in opposition to the others analyzed, doesn't have an ongoing pattern during the four months. Anyway it will be interesting to try to understand the reasons why they appeared in the associations studied, and observe the effects they had on the economical results.

We report below a scheme that sums up the categories presented in this chapter and their variations:

Category	Variations 2015 (Over 2014)
Sweater	+
Sweatshirt	+
Jumper	-
Fleece Jackets	+
Polo	-
T-Shirt	+
Socks	+
Scarf	-
Hat	-
Shirt	+

Table 4.12 : The variation of each product's category over 2014

The next chapter will be divided into two parts: in the first one we will try to find some explanations for the results here presented, while in the second we will show how the associations founded can be integrated with the informations provided by the analysis already operated by the company, to get a completer picture of what happens into the shop.

CHAPTER 5: COMMENTS ON THE RESULTS

In order to find one of the variables that affected the results of the MBA we decided to do a comparison between the stocks of the products at the beginning of the two years, to assess whether they influenced the variations observed in the association rules generated. In other words, we supposed that the assortment of a product category (its stock) has some effects on the final sales of the shop, since it affects the probability the customer will find the Item he/she likes. This in turn would have some effects on the support of the product categories as well.

Therefore, in the following paragraph we report the results of the analysis on the stock's composition of the warehouse. The assessment of its variation indeed should allow us to understand which product categories had a greater (or lower) assortment than in 2014, to study if the modifications occurred in the stocks can be associated to the variation of the relations' supports.

For this reason, in order to carry out this kind of analysis, we will study the variation of the proportion of each category, or in other words, the quantity of units of a product over the total units of the warehouse.

5.1 THE ANALYSIS ON THE VARIATION OF THE WAREHOUSE'S STOCK COMPOSITION

First of all, we divided into four groups the product's categories taken in consideration in the previous chapter:

Group	Product's categories
1	<i>Socks</i>
2	<i>Shirts, T-Shirts, Polo</i>
3	<i>Down Jackets, Coats</i>
4	<i>Sweaters, Sweatshirts, Jumpers, Fleece Jackets</i>

Table 5.1 : The division of the product's categories into four groups

The reasons of the division will be explained later.

In order to study the variation of the stock's composition between the two years, we carried out an analysis on three different levels:

- a) it was applied the *Chi-Square* test (presented in chapter 3) on the total stock of the four groups of product's categories of Table 5.1;
- b) we applied the same test to the stocks' proportions of the single product's categories, in order to see which one of them had a variation over the year before;
- c) we compared the variations between the product categories, in order to see if some of them improved (or decreased) more than the others categories belonging to the same group (Table 5.1).

Let's see in detail the results of our analysis:

a) In order to test the variation of the proportion (over the total stock of the warehouse) of the total stock of the four groups of product categories, we used these hypothesis:

$$H_0: \pi_{Tot\ Stock\ 2015} = \pi_{Tot\ Stock\ 2014}$$

$$H_1: \pi_{Tot\ Stock\ 2015} > \pi_{Tot\ Stock\ 2014}$$

where π is the proportion of each stock. The results of the analysis are reported in table 5.2:

	<i>X-Square</i>
<i>Total stock variation (π)</i>	73,9

Table 5.2: Variation of the total stock. The level of confidence is the 5%

As we can see, there had been a variation of the proportion of the total stock (the X-Square is higher than 3.841). For this reason, we went deeper to analyze on which categories we could observe the most significant variations.

b) So, given a product's category C, we evaluated two orders of hypothesis: the first one was relative to the stock's greater proportion of C in 2015 over 2014, the second to the stock's smaller proportion of the same product's category in 2015. The first type of evaluation was carried out testing the following affirmations:

$$H_0: \pi_{\text{Stock C 2015}} = \pi_{\text{Stock C 2014}}$$

$$H_1: \pi_{\text{Stock C 2015}} > \pi_{\text{Stock C 2014}}$$

where the level of confidence chosen was again the 5%. The second order of hypothesis instead was the following:

$$H_0: \pi_{\text{Stock C 2015}} = \pi_{\text{Stock C 2014}}$$

$$H_1: \pi_{\text{Stock C 2015}} < \pi_{\text{Stock C 2014}}$$

We report in Tables 5.2 and 5.3 the results obtained for every category analyzed (you will find in Appendix B the code applied in R). The first table reports the results of the test over those categories in which we wanted to verify the stock's greater proportion during 2015, while the second table reports the results of the test aimed to verify the opposite hypothesis:

Category	X-Square	p-value
<i>Socks</i>	171,46	0%
<i>Shirts</i>	5,76	0,80%
<i>Sweatshirt</i>	13.215	0,01%
<i>Jacket</i>	5,96	0,70%
<i>Jumper</i>	9,52	0,1%
<i>T-shirts</i>	3,58	2,90%

Table 5.3: Evaluation of the stocks' greater proportions over 2014 .The level of confidence is the 5%

Category	X-Square	p-value
<i>Coat</i>	34,6	0%
<i>Down Jacket</i>	36,52	0%
<i>Sweater</i>	106,98	0%
<i>Polo</i>	10,43	0,06%

Table 5.4: Evaluation of the stocks' smaller proportions over 2014. The level of confidence is the 5%

As we can see from the tables, the results confirm the Hypothesis H_1 and reject the Hypothesis H_0 . Indeed, the values of Table 5.3 are all higher than 3.841. In the same way, the *p-values* are all below the 5%.

We can conclude that in every case taken under consideration in Table 5.3 the stock's proportion has increased over 2014.

We can say the same for the values of Table 5.4, where the *Chi-square* and the *p-value* confirm H_1 .

We can conclude that in every case taken under consideration in Table 5.4 the stock's proportion has decreased over 2014.

c) Finally we compared the variation of the stocks' proportions between the different categories, in order to see if some of them registered an increase greater than the others over the precedent year. In particular, we wanted to test the difference between product categories belonging to the same group (classification of Table 5.1).

Indeed we made the division of the categories into the four groups of Table 5.1 because the MBA suggested that some products substituted some others in the results of the analysis over 2015. Thus, we wanted to check if the data in the warehouse's stocks could support this assumption. For example, we put together the T-Shirts, the polo and the shirts because we noticed some changes that appeared related during the two years, with a category losing ground in favor of another one. The same was done for the others categories.

The formula that we used to compute the variation was the following:

$$\frac{p1 - p2}{p2}$$

With

$p1$: the proportion of 2015 of the product category 1 over the total units of the group to which it belongs,

$p2$: the proportion of 2014 of the product category 2 over the total units of the group to which it belongs.

As we can see in the formula, the difference between the frequencies of each year was divided by the frequency of 2014, in order to get a percentage of growth of the category over the previous season.

In the application of this method to the case study we took under consideration two groups in particular: the sweatshirts, the sweaters, the jumpers and the fleece jackets; the T-shirts, the polo and the shirts. Please note that in this case, the proportion of the product category interested was calculated over the total amount of units belonging to the same group. For example, the frequency p_s of the sweatshirts was calculated over the total amounts of units belonging to the group of the sweatshirts, the sweaters, the jumpers and the fleece jackets. This is different from the base adopted during the test of difference between proportions done previously, where we used the total amounts of units of the warehouse. We adopted this decision because we wanted to analyze which product category had the greater increase within a group, while in the previous analysis we wanted to evaluate if the proportion of the category over the total stock of the warehouse had changed over time.

You will find an example of the application of the formula to the category of the sweatshirts in Appendix C. We present in the Table 5.5 the variations that each category registered, divided by the two groups taken in consideration:

Group 1	Variation Over 2014	Group 2	Variation Over 2014
<i>Sweatshirts</i>	35,30%	<i>Shirts</i>	11,81%
<i>Fleece Jackets</i>	23,90%	<i>T-Shirts</i>	3,99%
<i>Sweaters</i>	18,53%	<i>Polo</i>	-27,73%
<i>Jumpers</i>	-40,50%		

Table 5.5: The comparison between the categories' variations

As we can see, in *Group 1*, the product category that had the greater increase over 2014 were the sweatshirts, followed by the fleece jackets and the sweaters. The quantity of jumpers decreased, consistently with the results of the test of difference between two proportions. In the same way, in *Group 2* the shirts' category increased more than the others, followed by the T-Shirts and the polo, with a negative growth.

This paragraph concludes the analysis of the variations of the stocks' quantities between 2014 and 2015. From the results obtained we can draw two conclusions: the first one is that the composition of the warehouse's stock has changed over the two years. As we saw indeed, the stocks' proportions of the categories considered have changed both when studied all together (point a) both when analyzed singularly (point b). This in turn means that their assortment varied over time. Secondly, there are some differences in the variations of the product categories' proportions (point c), with some of them that registered greater improvements than the others (ex. the sweatshirts).

In the next part we will try to understand how these results can provide an explanation of the associations generated through the MBA.

5.2 THE RESULTS OF THE MARKET BASKET ANALYSIS AND THE IMPORTANCE OF THE WAREHOUSE'S STOCKS

Before proceeding, we want to explain why the number of relations founded by the MBA decreases going from September to December. This is due mainly to the segment in which the company operates, the kidswear. Indeed, during September and, in minor part, in October, there is the concentration of the shopping for the school (as it is possible to see every year from all the advertising campaigns "back to school"). This makes the first two months of the winter season those ones with the greater number of associations generated.

On the point of view of the kind of relations observed, in Chapter 4 we noticed that during 2015 the sweatshirts and the fleece Jackets appear an higher number of times in the association rules generated. This is true in particular during September, where there are 6 relations with these categories against 4 in 2014. Moreover, the supports of the relations involved are higher in every case. Now, after the analysis it on the warehouse's stocks, we can understand why.

As we have seen indeed, the stocks' proportions of the two categories are higher than in 2014, and this in turn seems it affected (positively) their sales. In the same way, the greater stocks' proportions of other products as the socks and the shirts had the same effects on the frequency by which we find them in the combinations generated by the MBA.

Moreover, looking at the relations' supports of the down jackets, the coats, the sweaters and the polo we have seen that they decreased during 2015. Indeed, the stocks' proportions of these products are lower in the last season, having as a consequence the diminution of their presence in the association rules generated.

So, reminding that the variation of the stock's proportion represents the variation of the assortment of a product, these results seems to suggest that:

the availability of a wider choice of a product is a critical factor in order to increase the sales of that product in combination with others categories.

This conclusion is even clearer if we think that the analysis carried out on the specific Items (meaning with them a particular type of pants, or a particular sweater, etc) gave a set of 0 rules.

However, the relation between the improvement of the products' assortments and the relations' supports is not always straight forward. About this, let's observe the dynamics of the sweaters and of the T-shirts. As observed in the analysis of their stocks' proportions, we can say that in 2015 the quantities purchased of both of them have been improved. Nonetheless, we saw a weaker effect on the relations' supports of these two products than that one we saw on the supports of other categories. In particular, if we look at September 2015, the frequency of the two relations (*T-Shirt, Long Pants*) and (*Sweaters, Long Pants*) is lower than in 2014, behaving the contrary as we would expect.

So, to understand why, we should take in consideration the results of the comparison between the variations of the stocks' proportions of the product categories (test c in paragraph 5.2), where we founded that the sweatshirts and the shirts are the Items with the greater improvement. This result makes us believe that there has been a substitutive effect in the sales of the sweaters with the sweatshirts and, in part, of the T-Shirts with the shirts.

Actually, in September, this was expected in particular for the first two categories, as during this month the shopping is based on functional purposes (for the school). So, during this period of the year the sweatshirt looks more attractive, as it is more comfortable for kids to use at school and it's not still cold enough to use the sweater (one of the main reasons for which the moms say they prefer to buy sweatshirts for school is that they are worried the sweater is too warm to wear in class). This factor, associated with the greater improvement of the sweatshirts' assortment, increased the possibility that the customers would buy this category, that ended up gaining a greater share in the sales of September. After the initial month however, we see that the importance of the sweatshirts decreases, as the sweaters get back the share (and the support) lost (that turns to be higher than in 2014).

A similar case can be found observing the dynamics of the T-shirts and the shirts. Again, the shirts' stock's proportion had the greater improvement (over the year before) within the group of products categories they were classified in. It's growth over 2014 had been of 11,81% (Table 5.5) while that one of the T-shirts only of 3,99%. As a consequence, we see how the T-Shirts' support didn't register a significant improvement, especially during the months of September and October. In order to get more evidence of this, let's apply the *Chi-Square* test to compare, between 2015 and 2014, the total amounts of transactions in which the T-Shirts and shirts were bought. If the number of times the T-shirts had been bought is not statistically different between the two years (while for the shirts it is) it will be reasonable to believe that there has been a substitution effect between the two categories. The results of the test are reported in table 5.6. The computation is reported in Appendix D.

Shirts	X-Square	T-Shirts	X-Square
September	3,94	September	0,09
October	6,6	October	1,06E-02

Table 5.6: The level of confidence used is the 5% and the relations on which we did the test are (T-Shirts, Pants) ; (Shirts, Pants). The months analyzed are September and October 2015 and 2014.

The test sustains what we supposed: the number of transactions in which the shirts appear is statistically different (higher) than the same number of 2014 (the values of the X-Square are higher than 3.841 for both the months), while this is not true for the T-shirts. This means that the quantity sold of shirts had a significant improvement during 2015 while the quantity of T-shirts had not.

This makes us believe the hypothesis of the substitutive effect between the shirts and the T-Shirts true.

After these considerations, we have a clearer understanding of those factors that seem to influence the kind of associations generated, and, in conclusion, the capacity of the shop to sell by look:

we can affirm that the element that influence with more evidence the kind of associations generated is the assortment of the product categories available in the warehouse.

However, we want to underline that the data analyzed suggest that the need the customers have to satisfy remains a key aspect to take in consideration when designing the shopping experience. This is evident from the fact that the presence of the sweatshirts in the associations generated decreases after September 2015. The fact that the shopping is no more based on needs linked to the beginning of the school indeed moves the attention of the customers to other kinds of products, as for example the sweaters. This in turn means that we should always manage the aspects related to the warehouse taking in consideration the evolution of customers' behavior during the season.

For this reason we will start the last part of the chapter, dedicated to the integration of the MBA into the company's information system, with the presentation of the *Sell Through*, a tool used by the Management to check in "real time" the warehouse's stocks. As we will see, the associations we founded during our analysis can be useful to improve the quality of the decisions we have to take when managing this aspect of the business.

5.3 THE INTEGRATION OF THE MBA IN THE COMPANY'S DECISION SYSTEM

The *Sell Through* is used for two purposes: first, to assess if a particular type of product needs to be restocked during the season, second, to do the annual purchases of the new collections.

Starting from the first, the decision whether it is necessary to restock a product is taken in relation to the time of the year in which it is faced. If, for example, we do an analysis of the *Sell Through* in November finding that the stock of the "Sweatshirts" is low, it's not automatic that we will decide to restock it. In this case the results of the MBA could be useful to take the decision, as we observed that the sweatshirts were sold in particular during September, while later the sweaters turned to be more attractive. So, probably it wouldn't be necessary to restock the product in November.

Moreover, since it is necessary to extend the Sell-Through analysis to the colors availables in the stock, it could be useful to apply the MBA in order to evaluate if they can be easily combined with the colors that will be used to set the inside of the shop during the following weeks. If there is no consistency between the colors founded and those ones that will be exposed, it could be necessary to restock the product under analysis.

So, in both the examples presented the associations generated through the MBA provided useful informations to take the decision.

In order to talk about the second purpose, we report below two tables representing the Sell-Through values of the product's categories considered during the analysis of the warehouse's stocks:

2015			
Category	Qty Purchased	Qty Sold	Sell Through
<i>Socks</i>	765	495	65%
<i>T-Shirt</i>	1341	771	57%
<i>Polo</i>	442	208	47%
<i>Shirt</i>	504	300	60%
<i>Sweaters</i>	1039	530	51%
<i>Jumpers</i>	570	336	59%
<i>Sweatshirts</i>	429	197	46%

Table 5.7: Values of the Sell through of 2015. Shop of Milan

2014

Category	Qty Purchased	Qty Sold	Sell Through
<i>Socks</i>	258	168	65%
<i>T-Shirt</i>	1007	681	68%
<i>Polo</i>	409	278	68%
<i>Shirt</i>	352	199	57%
<i>Sweaters</i>	742	430	58%
<i>Jumpers</i>	809	355	44%
<i>Sweatshirts</i>	268	139	52%

Table 5.8: Values of the Sell through of 2014. Shop of Milan

where the computation of the Sell-Through is given by the following ratio:

$$Sell-Through = \frac{Qty\ Sold}{Qty\ Purchased}$$

From the analysis of the data reported above indeed the Management takes the purchasing decisions for the following seasons.

So, firstly, we notice that the quantities sold improved for all the categories in which the quantities purchased have been improved, while for the others (jumpers and polo) they decreased. Moreover, for categories such as the socks, we can affirm that the greater assortment available had a positive effect both on the sales both on the Sell-Through ratio.

However, there are some categories for which the percentages of *Sell Through* are lower than the year before, as for the examples of the sweaters and the sweatshirts. In this cases we could use the MBA to understand why we didn't observe an improvement of their ratios. The association rules showed us indeed that the two products didn't register an ongoing pattern during 2015, with the sweatshirts having a peak during September and the sweaters starting slower and turning to be more attractive later. As a consequence, the next time we could buy a lower quantity for both the categories, as the trends they followed focused their sales on specific periods of the year.

As the final consideration shows, the results obtained from the MBA provided useful informations to carry out the evaluations related to the second goal of the Sell-Through as well. For this reason we can say that the two kind of analysis should be integrated in order to improve the effectiveness of the decisions of the warehouse's management.

Moreover, the MBA is a tool that the company can associate also to other kinds of analysis. Thus, we want to conclude the chapter giving another example of how the results of the MBA can be used to deepen the understanding of what is happening during the sales process. So, let's see how we can integrate the informations given by the KPIs (already presented in chapter 2) with the results of the association analysis.

The KPIs and the MBA applied together

	September	October	November	December
UPT 2015	5,20	3,00	2,70	2,5
UPT 2014	4,90	3,25	2,80	2,5

Table 5.9 : UPT values for each month of the two years analyzed

	September	October	November	December
AVG Basket 2015	€ 490,00	€ 305,00	€ 275,00	€ 245,00
AVG Basket 2014	€ 445,00	€ 320,00	€ 270,00	€ 246,00

Table 5.10: AVG Basket for each month of the two years analyzed

Consistently with the results of the MBA the values of the UPT (Table 5.9) are higher both in September 2015 and in September 2014, decreasing as they move toward December. Moreover, comparing the two years, we notice that September is the only month of 2015 in which the UPT is higher than in 2014.

The values of the AVG Basket (Table 5.10) are consistent with those of the UPT, registering the highest values during September. However, in the comparison between the two years, the situation is slightly different as, other than in September, we find a greater value of the KPI also in November.

So, at this point, it's interesting to apply the results of the MBA to understand why the indicators follow these dynamics during the months presented. In particular, they will be useful to explain the values the indicators assume during the months of September and November. Starting from the first month, the associations founded show us that the greater value of the UPT registered during September 2015 is due to the presence of the socks. To see this, we did the ratio between the quantity of

socks sold in September and the total number of transactions registered during the month (you find the computation in Appendix D). In other words, we compared how many pair of socks *per* transaction had been sold in 2015 and in 2014. Thus, while in 2015 were sold 0,44 pair of socks for each transaction, in 2014 they were only 0,15. Moreover, the difference between the two ratios is 0,29, meaning that, in average, during September 2015 the shop sold 0,29 pair of socks more for every check.

As the difference between the UPTs of the two months is of 0,30 pieces for transaction we can say that the presence of the socks can explain almost all the increase of the indicator. This makes sense, especially if we consider that in fashion companies the accessory has become a fundamental part of the business, for the importance it covers to improve the values of the KPIs.

November is a particular case, because in 2015 the value of the UPT is lower but at the same time the Average Basket is higher. We can find the explanation in two factors: the first is always related to the kind of relations generated during November 2014, the other is related to strategical choices undertaken by the company. Starting from the first, we see that in the associations of last year we find the presence of two accessories: the scarf and the hat. As we have already seen, this can in part explain the higher UPT. However, this does not tell us why the Average Basket is still higher in 2015: this is due to the sales of the down jackets. Indeed during 2015 the sales of this category were decreasing over all the Retail Channel, requiring the company to boost them. Moreover this type of product is particularly important during the month of November, the less profitable one (after the "school shopping" and before the Christmas period), given its' capacity to sustain the Average Basket thanks to its' high price. For this reason, it was launched a competition (only for the month of November) between all the boutiques on that one that would have been able to sell more Down Jackets over the previous year: the shop of Milan was the winner. At this point, we can explain why even if the UPT is lower the Average Basket is higher. The competition indeed focused the efforts on the sales of the category, that in turn reduced the number of Items sold for each transaction but increased the final value of the check.

So, also in this case, we saw how it is possible, through the integration of the KPIs (already adopted by the company) and the analysis carried out through *R*, to go deeper into the understanding of what happened during the sales process. In particular, the adoption of the MBA allowed us to understand where did the values of the indicators came from, as for the example of the greater UPT during September 2015.

With this paragraph we conclude the chapter dedicated to the demonstration of the relation between the product categories' stocks and the associations founded through the MBA. As we have argued, the warehouse seems to be a variable that can help to explain the modifications in the kind of products (and in the associations between them) the company sell. This result was quite expected, as it is logical that a wider choice creates greater possibility to find the clothe the customer is more comfortable with. However, we saw also how the improvement of the products' assortments is not the only variable that affects the sales. Indeed the final choice is still determined by the specific need the shoppers have to satisfy, that in the particular sector taken in consideration is influenced by the period of the year that is occurring.

Other than this last aspect, actually there are other variables that influence the retail activity and we should take in consideration at least another one of them: the layout of the shop and the internal display of the collection. So, during the next and last chapter, we will try to understand whether the visual strategy has some effects on the associations generated between the product categories.

CHAPTER 6: IS IT WORTH TO INVEST MONEY ON THE VISUAL FUNCTION?

6.1 THE ANALYSIS APPLIED ON 2013

Since the generation of relations between complementary products is one of the main purposes of the visual strategies, we applied again the MBA to answer the question. However during the two years taken in consideration in the previous chapters there hadn't been any significant changes in the internal display and in the layout of the shop, making it impossible to determine the influence of these variables on the sales. For this reason, we analyzed another year, the 2013, comparing the differences with the relations founded in 2014.

The changes occurred between these two years are relevant because the shop moved, with relevant improvements in the way the collection is exposed inside the store.

Before describing how the shop has changed, in the next paragraph we describe the main aspects of the visual strategy of a shop.

6.2 THE VISUAL STRATEGY

The visual merchandising is the function through which the company materialize the promotional activities carried out outside the store. Indeed, if the advertising campaigns aim to stimulate the interest for the brand, the visual strategy is the tool by which the communication process finds physical realization. For this reason the layout and the internal display have to be designed in order to be consistent with the expectations of the customers. But what are the main aspects involved in these kind of decisions?

First of all, the atmosphere of the store: this is an immaterial aspect, but really important to generate a positive sensation and to influence the final decision of the shopper. For this reason it is considered as "in-store marketing". The atmosphere is the result of four elements:

- *the window shop*: it is the part that communicate to the customers that have still to enter the shop. It has to be frequently renovated in order to stimulate new interest and attract the shoppers inside;
- *the internal part of the store*: the lighting, the furnitures, the perfume, the music, the colors and the images;
- *the layout*: it's the organization of the selling space in relation to the functional purposes
- *the internal display*: the way in which the clothes are exposed.

All of these aspects are aimed to influence the purchasing behavior increasing the sell out of the shop. We will take in consideration in particular the second two.

The layout is divided into two types: *the layout of the facilities* and the *layout of the merchandise*. The first one is related to the disposal of the facilities used during the sale process, including the cashes and the installations by which the clothes are exposed. The type of facilities chosen will depend on the organization of the merchandising and on the internal display. However, the layout of the facilities can be generally classified into two main types: *grid layout* and *layout by islands or free flow*.

The first kind is given by the division of the internal space in long aisles and different paths, each one corresponding to a product category or a merchandising area. The advantage of this type of arrangement is that it allows to expose a big quantity of products, being for this reason the layout chosen by the big stores and supermarket chains. The *layout by islands* instead is oriented toward the creation of independent spaces, or islands, in which the products can be grouped by different criteria: their function, the brand, the style etc. Anyway, the islands are linked between each others, in order to facilitate the passage of the customer in the different areas of the shop. This is the kind of space's organization chosen by the boutiques and the shops of smaller dimensions.

The *Layout of the merchandise* is constituted by the criteria adopted to divide the assortment of the shop into different areas. Its' purpose is to "drive" the flows of the customers in all the areas of the shop, increasing the possibility that he/she finds the product he/she is looking for. For this reason, the choices that have to be taken regards both the criterion by which the Items are grouped together in a given part of the shop, both the way in which the passage between the different areas of the shop can be facilitated. One thing to pay attention to is to follow a logical sequence placing nearby the different islands: for example if in an electronic shop we expose the smartphones in one area in the next one we will put the covers and the

accessories for smartphones, in order to stimulate the cross-selling of complementary products.

Usually, when we apply a layout by island this is divided into three parts: the display, the central area and the backdrop. The *display* is a sort of window shop, used to put in evidence particular promotions or combinations of products. The *central area* is where the majority of the assortment is exposed, with the greater part of the offer for that kind of products. Finally, the *backdrop* is the part that attract the attention of the customer, as it is given by taller structures with images and pay offs. The shop has always to be provided with the complete assortment of the products exposed in the backdrop, since it is the point the attention is focused on.

The Internal Display is constituted by the way in which the products of a specific area are organized. They will be displayed in relation to the kind of shopping experience the company aims to create. Firstly, the internal display techniques divide into two logics: the *massification* and the exposition by *total look*.

In the first type more products of the same category are exposed together (the sweaters with the sweaters, the pants with the pants, etc). This is the logic adopted by the bigger shops, in which the assistance by the salesperson is lower and the customers have to find by their own the Item (type, color, size) they are looking for. Instead, in the sales by *total look* only one piece for each model is exposed (the other sizes are in the warehouse), combined with a complementary product. For example, a sweater and a pant will be put together, creating in this sense the total look. This kind of exposition is typical of the brands operating in the luxury segment where the focus is on the style of the whole collection. They want to stimulate the purchasing of a complete style and image, that represents the mood of the year interpreted by the company. Of course, it is associated with the personal assistance of a salesperson.

In both these two logics (massification and total look) there are different ways in which we can present the Items, the main ones are the following:

- *Shelving*: the products are put in shelves or wall systems. Adopted in particular for bags and accessories.
- *Hanging*: the Items are hold by hooks and they are hanging. It's used in particular by clothing shops.
- *Folding*: the products are bent and put on a table or other similar supports.

Moreover, we should take in consideration two other important aspects when displaying the Items: the level at which they are exposed and the direction of their exposition. The products can be placed at three different levels: the floor level, the eye level and above the head. The first one and the last one are the less visibles,

we usually find the shoes and the accessories. They don't have to be positioned too low or too high, otherwise the customer won't be able to reach them. The second one instead is the more effective (that's the reason why in multi-brand stores the companies buy these positions) as they immediately get the attention of the shopper.

The direction of the exposition is a distinction applied in particular by the clothing shops when dealing with hanging items: it can be lateral or frontal. In the first one the clothes are put by profile while in the second they face frontally the customer. This last method is the most effective one.

In conclusion, we can say that the application of a good visual strategy allows to reach three goals:

- *Inform* the customer, showing him/her all the alternatives available and stimulating his/her interest;
- *propose*. The exposition has to be able not only to sell single items but to boost the purchasing of complementary products;
- *persuade*, creating a positive shopping experience and inducing the final purchase.

So, after the presentation of the main characteristics of a visual strategy in the next paragraph we will see how this is implemented by "Il Gufo". After, we will present what has changed in the shop of Milan between 2013 and 2014.

6.3 THE VISUAL STRATEGY OF THE COMPANY

The shops of the company apply a layout by islands. However the boutiques have only the backdrop space, without any display or central part. In place of them indeed we find the furnitures used by the saleswomen (tables, etc). In the outlets instead we find both the central part and the backdrop.

Within the shops, the merchandise is divided first of all between the collections of the newborn, the boy and the girl. Moreover, the criteria adopted to divide the collection between the different areas of the store take origin from the following process: from the Design Department, in collaboration with the CEO, the *Key products* are determined, or in other words those items that represent the *mood* of the collection. From this choices then, the Visual Department determines the shop windows' calendar, in which it is decided how and when will be prepared the shop windows of the boutiques (that are renovated every month). In this sense, other

than the clothes chosen for the exposition particular importance is given to the colors, that have to be consistent with the period of the year in which the shop window is implemented. For example, the Autumn/Winter collection of this year has began in August and September with the exposition of the warmer colors of the collection, to pass to the blue and white in November and to finish with the typical colors of the Christmas period in December. Finally, the Items are exposed within the shop in relation to the shop window of the month: we will find the clothes and the colors of the window shop in the first 10 meters on the right, while the remaining part of the collection will be organized by chromatic scale in the other islands of the store.

The internal display adopts the exposition by total look, using mainly hanging clothes, both laterals and frontals. Aside the hanging clothes, we find the shelves in which are put the complementary products, as the accessories, the shoes or some clothes of the basic collection (T-Shirt and sweaters). In particular, the shoes are usually at the floor level, while the accessories above the head. The hanged part of the collection places at the eye level.

You will find in appendix E some pictures of the inside of the shop of Milan.

6.4 THE CHANGES OCCURRED IN THE SHOP OF MILAN

In the next page, we report the changes occurred in the shop of Milan, divided by the different variables of the visual strategy described in the previous paragraphs:

From Table 6.1, we can do three types of considerations.

First of all, looking at the "structure of the shop" and the "layout of furnitures" it appears that the main variable that has changed is the dimension of the shop. Indeed, it increased from 30,9 to 107,8 square meters and number of floors from one to two. In turn this allowed to set a greater number of islands and supports for the clothes (frontals, laterals, etc.). Moreover, the "drawers" (those shelves at the floor level where the shop puts mainly the T-Shirts), increased from 8 to 12. The "shelves" instead (they are installed on the wall and used to put those products that can be easily matched with the collection exposed) passed from 7 to 20. Finally, the "other equipments" (other kinds of furnitures that are functional to the sales process, like the tables) are six times higher than in 2013.

	2015	2014
Structure of the shop		
<i>Number of floors</i>	2	1
<i>Square meters</i>	107,8	30,9
Layout of furnitures		
<i>N ° of islands</i>	7	3
<i>N ° of frontals</i>	7	3
<i>N ° of laterals</i>	12	6
<i>N ° of shelves</i>	20	7
<i>N ° of drawers</i>	12	8
<i>Window shop</i>	double	unique
<i>Other equipments</i>	6	1
<i>Changing room</i>	yes	no
Merchandising Layout		
<i>Division of the collection b/w boy and girl</i>	yes	no
<i>Dision by color</i>	yes	yes
<i>% of collection available exposed</i>	35%	65%
Internal Display		
<i>Sales by total look</i>	yes	yes
Atmosphere		
<i>Payoff</i>	yes	no
<i>Screen/Images</i>	yes	no
<i>Music</i>	yes	not selected
<i>Perfume</i>	yes	no

Table 6.1: The changes occurred in the shop of Milan

Considering the merchandising layout and the internal display instead we find that the way the collection is exposed has not changed. Indeed, also during 2013 the sales were carried out by total look and the frontals and the laterals already adopted (even if they were less). The different areas (islands) were always organized by color. The only difference was that the collections of the boy and the girl were not divided due to space problems.

Finally, in the renovation it has been paid more attention to the atmosphere of the shop. They were introduced new elements, as the payoff on the wall, the perfume and screen transmitting images and cartoon for the kids. It was set a specific kind of music for all the boutiques of the company. Moreover, the new shop has a little garden.

From the changes we described, the main conclusion we can draw is that the movement of the shop had important effects on the dimension and the space available, but not on the way by which the company presents the collection.

This is particularly true looking at the percentage of the collection exposed, that increased from 35% of 2013 to 65% of 2014. This means that the total assortment is almost two times more visible in the new shop, giving the possibility to increase the number of combinations displayed and the choice available. Moreover, this had some effects on the job of the saleswomen as well, speeding up their capacity to assist the customer (they have to go less times to the warehouse of the shop) and giving them greater support through the higher number of furnitures (eg. the tables) they can use during the sales process.

As we will see in the next section, these changes had important effects on the associations we found in the comparison between the two years. In particular, we will see their effect on the number, the variety and the supports of the relations generated.

6.5 MBA RESULTS

We report below the tables relative to the months of September, October and November 2013. As during the previous analysis, they are compared with 2014. In December 2013 we didn't find any set of rules.

	Relation	Support 2013	Support 2014
1	(T-Shirt, Long Pant)	18,00%	18,50%
2	(Sweater, Long Pant)	17,80%	17,10%
3	(Jumper, Long Pant)	12,00%	12,70%
4	(Polo, Long Pant)	6,60%	10,20%
5	(Sweatshirt, Long Pant)	6,35%	7,70%
6	(Shirt, Long Pant)	6,11%	6,90%

Table 6.2 : Relations founded during September 2013

	Relation	Support 2013	Support 2014
1	(Sweater, Long Pant)	16,10%	10,50%
2	(T-Shirt, Long Pant)	11,11%	11,80%
3	(Polo, Long Pant)	4,60%	5,90%

Table 6.3 : Relations founded during October 2013

	Relation	Support 2013	Support 2014
1	(Sweater, Long Pant)	6,30%	8,60%

Table 6.4 : Relations founded during November 2013

We will compare the results of the analysis on 2013 with those ones of 2014 considering three variables: the number of relations founded, their variety and the support of each relation. The *number of relations* will give us an idea of the different ways in which a product is combined with the others. For example, the sweater could be combined with the long pant, the shirt or the polo, or all three of them. By this, we should be able to understand how the increases of the number of furnitures used to expose the collection (in particular the complementary clothes) has an effect on the type of combinations generated during the sales.

With *variety of relations* we mean how many different product groups are present in the associations founded. For example, we saw how during September 2015 the number of categories was higher than in September 2014, determining greater variety in the products sold. This should allow us to understand the effect of the new layout and of the internal display on the values of the UPT.

Finally, the *support of each relation* is the indicator that tells us how many time a relation appears. It will be interesting to verify if a minor variety of the products sold has some effects on the support of the associations founded.

Let's consider now the results by month. We underline how, in 2013 as well, the number of relations decreases going from September to December, giving more evidence to the assumptions we made previously about customers' behavior.

September

The number of relations founded in September 2013 is 6, against 28 associations founded in the same month of 2014. Moreover, the combinations are constituted by two Items only in all the cases, always with the long pant as the consequent. In 2014 instead the consequent was constituted by a product belonging to another category (the T-Shirt and the sweater) in 7 different situations. The first four relations are the same between the two years, while during 2014 we find at the fifth position an association with three Items (*Jumper, T-Shirt and Long Pant*) and at the sixth position the relation (*Sweater, Long Pant*). It's interesting to notice that the support of the first two relations (*T-Shirt, Long Pant*) and (*Sweater, Long Pant*) is higher in 2013 than in 2014, while from the third one the situation inverts.

Finally, the variety of the products founded is higher in 2014, where we find 12 different categories against 7 in 2013.

October

During October 2013 we find only three relations, against 8 in 2014. Also in this case the associations are composed by only two Items and the long pant is the consequent for all of them. Differently from 2014, in which the combination with the highest support was (*T-Shirt, Long Pant*), in 2013 the first one is (*Sweater, T-Shirt*). Moreover, its' frequency in 2013 is higher of 5,60% than that one of 2014. This is not true for the others two associations, that present lower supports' values than in 2014. Also in this case, the variety of the Items is lower, presenting only 4 different product categories against 8 in 2014.

November

As we can see, we found just one relation during this month: (*Sweater, Long Pant*). It's support is lower of 2,30% than 2014, where it was the relation with the highest frequency as well. The variety of the Items, of course, is the lowest, with only two categories against 6 in 2014.

6.6. FINAL CONSIDERATIONS

The results presented above suggest us that the visual policies have some effects on the sales. In particular, since the way by which the collection was displayed

hadn't any relevant changes, the improvement we observed during 2014 is determined mostly by the enlargement of the space dedicated to the exposition. Indeed, also in 2013 the relations mirrored the logic of the total look, since the combinations were always between complementary categories. However, the minor possibility to expose more "looks" translated into the little differentiation of the types of associations generated. In other words, if in 2014 the sweater could have been combined with the shirt, the T-Shirt or the polo, in 2013 the only relevant relation founded was with the long pant. This means that the offer of the shop was perceived as focused mainly on one particular type of product (the long pant), with difficulties to propose more types of combinations. It seems instead that a different (and bigger) layout and internal display helped to increase the cross-selling, moving toward a logic that fits better with the sector the company is competing in.

This can be seen by the variety of the categories as well. For example in September, the month in which the inclination to buy a complete basket of goods is higher, the number of Items composing the shoppers' basket is lower compared to 2014 (that was already lower than 2015). This means that the company was losing cross-selling opportunities, leaving the competitors the appropriation of a share of the purchasing power of shoppers. In particular, we underline how, in every month, the accessories missed from the associations founded, representing the minor capacity to involve the customer in a completer experience.

In this sense, the better results of 2014 are also due to the improvements made on the atmosphere of the shop. In particular, let's take in consideration November and December, the less profitable months. In 2013 we have only 1 relation in the month of November while no one in December. This is the period indeed in which the shopping need is no more based on functional purposes, and the attention to the emotional side of the shopping experience becomes relevant. So, for example, during the Christmas period it will be important to play the right music in the shop, while in November it will be important to create a stimulating environment to induce the impulse to buy. During this month in particular the atmosphere becomes the key to boost the sales, as there is no rational need to shop: the results of 2014 confirm us its effectiveness.

Finally, we want to do a consideration on the supports of the relations founded during 2013. It is especially interesting to notice the first two associations of September and the first one of October. As we can see indeed, their supports are higher than those one founded in 2014, seeming to be in contrast with what we said until now. The categories involved in the combinations are the T-Shirt, the sweater and of course the long pant. What got our attention is the fact that in 2013 their frequencies are greater, reaching in one case a percentage higher of 5,60%. In our

opinion, this is explainable considering the greater variety of Items bought during 2014. Indeed, since the last year the choice had been higher for the exposition of a greater share of the collection, the consequence had been the movement of the shoppers' attention toward a more differentiated set of Items, reducing in part the purchase of those combinations of products already founded by the association rules of 2013.

From this section we saw that, again, the considerations we can made employing the MBA are useful to understand the effects of a given variable on the final sales. In this case indeed, they helped us to assess the effect of the layout and of the internal display on the results of the shop.

Moreover, as in the previous chapter, they can be integrated with the tools adopted by the company, in order to carry out a completer analysis.

6.7 THE EFFECTS ON THE UPT

We want to conclude this chapter considering the values of the UPT during the months analyzed, in order to see if the movement of the shop and the new layout adopted had some effects on the KPIs as well.

Here below we report the table indicating the values of the UPT, compared to those ones of 2014:

	September	October	November	December
2014	4,88	3,27	2,81	2,37
2013	3,98	3,02	2,01	1,99

Table 6.5: UPT values of 2013 and 2014

As expected, in 2013 the number of units purchased for each transaction is lower during all the months observed. Two are the main reasons for this result: first of all, there are no relations with more than two Items, reducing the average number of goods bought by each customer. Secondly, no accessories were founded by the analysis, determining a less complete basket of goods purchased.

So, if we were performing an analysis on the sales of the shop using the KPIs we could have looked to the relations generated by the MBA. This in turn would have given us some hints on the reasons why the shop was not performing well enough. For example, we would have seen that we were not selling (with relevant

frequency) more than two Items *per* transaction, and that the customers were mostly buying the sweaters, with minor attention to other goods as the sweatshirts or the fleece jackets. Moreover, they were not "stocking" for the winter season, as there aren't relations in which they were buying two Items with the same function (for example the jumper and the sweater).

As a result, in order to improve the effectiveness of the sales, we could have assessed the goodness of the layout and of the internal display, evaluating if some products had to be changed of position or if it was possible to increase the percentage of the collection exposed.

As we have seen indeed, these two variables have an effect on the capacity of the shop to sell by total look, modifying the kind and the number of associations we observe and increasing the UPT. For this reason, we can conclude the chapter with this answer to the question posed at the beginning: yes, it is worth to invest money on the visual function.

CONCLUSIONS

In the work presented we pursued two goals: the first one was to get some light on those factors that influence the operative results of a shop operating in the fashion industry. The second was given by the integration of the MBA in the analytical system already adopted by the company taken in consideration.

On the first side, we can say that the two factors that we have found through our analysis are the warehouse assortment and the visual strategies. In particular, for what regards the first variable, we saw how the modifications of the stocks available influenced the number of times we found a product category in the associations generated by the MBA. This in turn means that the availability of a wider choice is a factor that affects what the shop is selling. This is evident also from the substitution effects we observed between the categories, when some of the stocks' quantities taken in consideration improved more than the others, generating a substitution between the products sold. However, the results suggested that there are also other variables to take in consideration, since the improvement of the quantity of Items available has a limited capacity to affect the sales. Indeed, during the seasons analyzed the basket of goods purchased changed, independently from the stocks of the warehouse (think at the sweatshirts' support that decreases as the season goes toward December). This means that the functional purpose the customer has to face is still relevant in the purchasing decisions. Moreover, in the sector taken in consideration, it changes in relation to the time period we are analyzing. For this reason, the demonstration of the importance of the second variable observed, the visual strategy, is of particular relevance, as the Visual function will be charged to set the shop consistently with the changing needs of the shoppers during the season.

In this sense, we can understand also why we pursued a second goal during this work: the integration of the analytical system of the company with other tools. As the customers' needs evolve over time indeed, developing the capacity to understand and foresee them becomes fundamental in order to create an environment in which they will return to shop. As we said in the first chapter, the competition in the sector is getting fiercer and the competitors are adopting sophisticated tools to face it. So, in a world in which getting the attention of the customers is increasingly more difficult, the key question to answer to becomes: "why should shoppers be willing to spend some of their time into my shop?". Being provided with an effective supporting decision system is at the base to answer successfully to this question.

APPENDIX A

The application of the "Arules" package on R and the generation of the association rules

We report below the steps we followed to apply the MBA through R. MISET15.csv is the transactional database we used to investigate the relations of September 2015:

1) upload of the "Arules" package on R with the following code:

```
require(Arules)
```

2) upload of the transactional database:

```
DB<-read.transactions("C:\\Users\\Desktop\\MISET15.csv", sep =",")
```

3) application of the Apriori algorithm:

```
rules<-apriori(DB, parameter=list (supp=0.04, conf=0.5)).
```

The last passage generated the associations. We report below a sample of five of them:

	lhs	rhs	support	confidence	lift
1	{POLO M. LUNGA}	=> {MAGLIA}	0.04033970	0.5757576	2.684968
2	{POLO M. LUNGA}	=> {PANTALONE LUNGO}	0.04803227	0.6969697	1.718705
3	{BODY}	=> {PANTALONE LUNGO}	0.04458599	0.5384615	1.327829
4	{CALZINI}	=> {MAGLIA}	0.04600913	0.5365854	2.502294
5	{CALZINI}	=> {PANTALONE LUNGO}	0.05904798	0.6829268	1.684076

Table A.1: A sample of the association rules of September 2015 generated by R

APPENDIX B

The analysis of the variations of the stock's composition.

We describe below the process followed to analyze the variations of the stock's composition with R. The example below refers to the analysis carried out on the socks' category: 765 and 258 are the number of socks of 2015 and 2014. 12.665 and 10.441 are the number of units composing the total warehouse's stock of 2015 and 2014.

(1) Definition of the object of comparison

```
socks<-c(765,258)
```

(2) Definition of the total amount of the sample

```
total<-c(12.665,10.441)
```

(3) Test between the proportions of 2015 and 2014

```
prop.test(socks, total, alternative= "greater")
```

(4) The result

X-squared = 171.46, p-value < 2.2e-16

The stock' proportion of the socks has varied, as the X-Square value is higher than 3,841 and the p-value is next to zero. The level of confidence applied was the 5%.

APPENDIX C

The computation of the stock's variation over 2014

We report below the computation of the variation of the stock of the sweatshirts over 2014:

(1) The stocks

	2015	2014
<i>Sweatshirts' stock</i>	429	268
<i>Total stock</i>	2.716	2.299

Table C.1: The stocks of the sweatshirts and the total stock of the group 4 in the classification of Table 5.1

(2) The computation of the proportion of the sweatshirts' stock over the total population

$$\pi_{\text{sweatshirts } 2015} = \frac{429}{2716} = 0,157 \qquad \pi_{\text{sweatshirts } 2014} = \frac{268}{2299} = 0,116$$

(3) The application of the data to the formula

$$V = \frac{0,157 - 0,116}{0,116} = 0,353 = 35,3\%$$

From the result of the analysis, the sweatshirts had an increase of 35,3% over 2014.

APPENDIX D

The computation of the quantity of socks sold *per* transaction during September 2015 and 2014

In this section we report the computation applied to evaluate the effect of the sales of socks on the value of the UPT during September 2015..

(1) *The number of socks sold and the number of transactions registered during September 2015 and 2014*

	2015	2014
<i>Quantity of socks sold</i>	208	55
<i>Number of transactions</i>	471	361

Table D.1: The number of socks sold and the number of transactions registered during September 2015 and 2014

(2) The computation of the number of pair of socks sold *per* transaction

$$\rho_{\text{socks } 2015} = \frac{208}{471} = 0,44$$

$$\rho_{\text{socks } 2014} = \frac{55}{361} = 0,15$$

As we can see, during September 2015 the shop sold 0,44 pair of socks *per* transaction, while during September 2014 0,15.

APPENDIX E



Picture E.1: View of an island of the shop. Exposition of the girls's collection



Picture E.2: View of an island of the shop. Exposition of the girl's collection

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TEXT REFERENCIES

- Bassi F, *Analisi di mercato. Strumenti statistici per le decisioni di marketing*, Roma, Carocci Editore, 2009
- Blattberg R.C, Byung-Do K., Scott A.N., *Database Marketing:analyzing and managing customers*, Paperback,2009
- Cietta E., *La rivoluzione del fast fashion. Strategie e modelli organizzativi per competere nelle industrie ibride*, Milano, FrancoAngeli, 2008
- Clodfelter R., *Retail buying:from basics to fashion*,4th edition, New York, Paperback, 2013
- Corbellini E., Saviolo S., *Managing fashion and luxury companies*, Milano, Etas, 2009
- De Luca P., Vianelli D., *Il marketing del punto vendita*, Milano, FrancoAngeli, 2007
- Ferraresi M., *Le analisi del punto vendita*, Milano, FrancoAngeli, 2007
- Luceri B., *Prospettive della ricerca di marketing.Business,scienza,spazi e vertigini*, Milano, Egea, 2013
- Marbachn G., *Le ricerche di mercato negli anni della discontinuità*, Milano, UTET, 2014
- Sacerdote E., *La strategia retail nella moda e nel lusso*, Milano, FrancoAngeli, 2006
- Saviolo S., Testa S., *Le imprese del sistema moda*, seconda edizione, Milano, Etas, 2005
- Volontè P., *Sociologia.Concetti,metodi,temi di scienze sociali*, Milano, Einaudi scuola, 2008

WEB REFERENCIES

- Chawla N.V., Raeder T., *Market basket analysis with networks*, in "<https://www3.nd.edu/~dial/papers/ASONAMJ10.pdf>", last access on November 11th, 2015

Chiandotto B., *Test delle ipotesi, versione 2015*, in "http://local.disia.unifi.it/chiandot/INF_STAT/Dispense", last access on November 12th, 2015

Colagrande V., *Alcuni elementi di verifica di ipotesi statistiche con applicazioni nell'ambiente statistico R*, in "http://www.biostatistica.unich.it/mat_didattica/prof_colagrande/Verifica%20Ipotesi.pdf", last access on November 20th, 2015

Giudici P., Passerone G., *Modelli associativi per la market basket analysis ed il web mining*, in "www.ibrarian.net", last access on October 15th, 2015

Hystad G., *Test of hypothesis for comparing two proportions. Tutorial for the introduction of the software R with introductory statistics*, in "<http://math.arizona.edu/~ghystad/Chapter14.pdf>", last access on November 14th, 2015