INTERNATIONAL
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Consumer Packaged Goods (CPG) Predictive Analytics Models

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SCHOOL OF SCIENCE & TECHNOLOGY

A thesis submitted for the degree of

Master of Science (MSc) in Data Science

NOVEMBER 2018

THESSALONIKI – GREECE

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Abstract

This dissertation was written as a part of the MSc in Data Science at the International Hellenic University. It aims at analyzing the marketing mix of a retail company's product through the use of data science techniques and algorithms.

Initially, an introduction is written in terms of marketing, marketing mix and modeling. Thence, the challenges faced by retailers in modeling marketing mix are analysed and some policies to address these situations are proposed.

Afterwards, some examples take place of cases where data science is involved in procedures relating to retail companies. Finally, the algorithms used for retail analysis are analyzed and the procedure followed for a product's sales prediction is explained, using multiple linear regression.

Next, a detailed description of the dataset used for the analysis and the variables according to which the result was extracted, was made. Furthermore, exploratory data analysis was applied by visualizing the dataset's features using the R language, SAP HANA Studio and SAP Predictive Analytics.

The next step was the implementation of multiple linear regression algorithm purposing to predictive modeling for retail sales forecasting using the aforementioned tools, concluding that this method has proven to be very effective.

At last, some conclusions are drawn and some issues for future research are suggested.

Acknowledgements

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1 Introduction

Within the competitive environment we have, businesses in order to prevail on the market must exploit all the given opportunities. Towards following the path of success, the decisions taken in each sector should be made after extensive research. Data science is ideal to exploit all the information of an enterprise's internal and external environment and through various processes to accurately predict the consequences of their decisions.

In this dissertation, the concept of marketing developed, so that a further analysis of the marketing mix, which is one of the main concepts of marketing and relates to the most important factors influencing the direction of a company's product, followed. The main factors are known as the 4Ps , Price, Product, Promotion and Place. They are really popular in the field of marketing as they form the core elements where each business would have to invest.

However, it is inadequate for a company to know these factors. The business must build on this knowledge to follow clearer paths through which it could reach the top. In order to achieve this, marketing mix modeling is necessary. This tool evaluates the company's available choices, as well as reveals choices that were not known in the past and are capable of suggesting a major development in the company.

Marketing Mix Modeling follows various strategies depending on the complexity of the business situation and the challenges need to be addressed in each specific case. The main strategies analyzed in this union are “longitudinal” and “cross-functional”.

Afterwards, an introduction to the kinds of variables affect Marketing Mix Modeling is made. These variables may concern some marketing mix elements, as mentioned above (4Ps), in addition to some market forces that engage marketing, such as consumers’ behavior and competitors’ position. These are the elements on which modeling is based and differentiated by.

Additional, marketing mix modeling creates new challenges which become pronounced in business and technical level. Business challenges are related to company’s target or recognition of useful procedures such as uplift drivers identification and decision time reduction. Technical challenges are related to the barriers arise from a technical point of view, like the instability of coefficients.

The second chapter of the literature review, refers to the connection between data science and retail trade. Initially, some applications through which data science contributed to the upward path of retail companies are briefly explained. The second part of this chapter refers to a particular use case of data science in retail, which is crucial for a company to address. This is sales forecasting, for which the algorithms that are used more frequently are explained. The most prevalent of them is being implemented in the chapter which concerns modeling, on a real dataset.

In the fifth chapter, a dataset concerning Consumer Packaged Goods industry is analytically explained. Building on this dataset, exploratory data analysis and predictive modeling will be made, using R programming language and SAP's tools.

The exploratory data analysis part includes a descriptive statistics projection conducted using R language running in Rstudio environment. Also, it includes data visualization, which is the core concept of this kind of analysis. The tools used for data visualization are R language, SAP HANA Studio and SAP Predictive analytics, in order to make use of both open source and commercial tools.

In the next chapter, multiple linear regression algorithm was implemented for the predictive modeling, using the same tools as before. This function slightly differs from the one tool to the other. The procedure followed after modeling using R is visualizing residual plots, which consists an important path that assesses regression models. With SAP Predictive Analytics the modeling process is specific with unique differentiation the variables that were selected for modeling and the function choice. The result in both cases was highly accurate, proving multiple linear regression is really suitable for such kind of analysis.

The last chapter refers to the conclusions drawn following the research carried out in the context of the present diplomatic work as well as by the model's application in real data. Finally, some suggestions for future research have been made, with the aim of further contribution of data science to similar kinds of cases.

2 Research Method

This chapter refers to the methodology followed for the compilation of the third and fourth chapter, which compose the literature review of this dissertation.

2.1 Goal and Research Questions

The goal of this research is to point out the data science use cases in retail companies and explain the way multiple linear regression is used for sales forecasting, after a brief introduction to the marketing mix and marketing mix modeling concepts. The formulated research questions that used to achieve the goal described above are:

RQ1: What is Marketing Mix Modeling?

RQ2: What are the retail business cases where data science applications are being used?

RQ3: How does Multiple Linear Regression contribute to sales forecasting?

2.2 Search Process

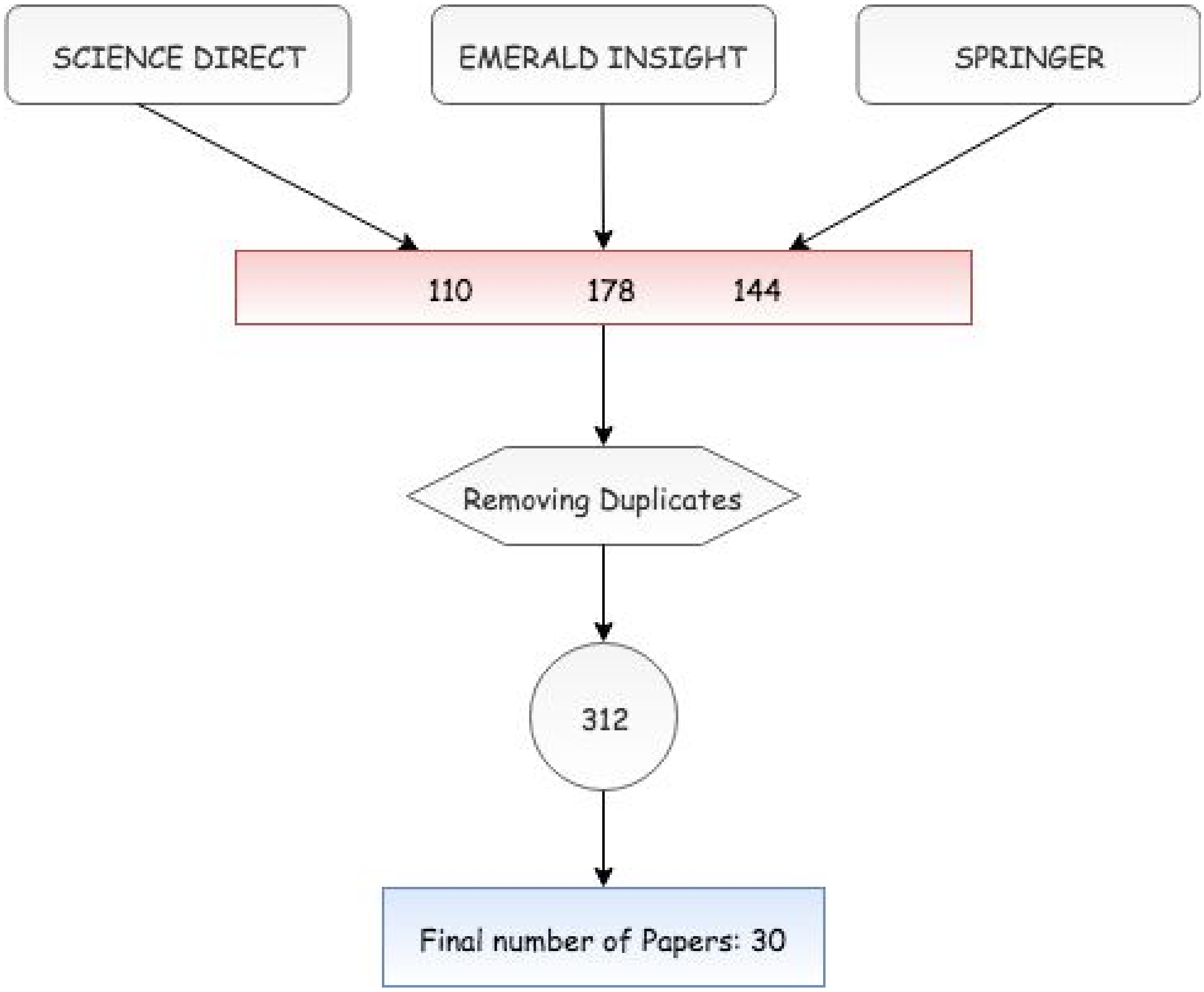
In this literature review, the approach which was followed is proposed by Kitchenham 2007 [1]. In order to cover a large spectrum of relevant publications, the following widely recognized libraries were used:

a) Science Direct
b) Emeraldinsight
c) Springer Link

Google Scholar used as well in cases where some topics were not fully covered by the previous libraries.

Some of the keyword strings that were used are “Marketing Mix”, “Marketing Mix Modeling”, “Data Science and Retail”, “Sales Forecasting Algorithms”. At the next step, the fields where the results could be useful were decided. In order to get a reasonable number of results, the keyword strings were searched in the title, abstract and keywords. No restrictions regarding the paper release date were used.

The procedure for literature selection was conducted until September 2018, so it contains papers that were published up to that date. The final number of papers gathered after removing duplicates is 312. Then, papers with irrelevant title and abstract were removed. The number of papers finally used is 30.



3 Introduction to Marketing Mix Modeling and Business Challenges

Business market is constantly growing and becoming more competitive as many similar products and services have been introduced to the same market so as to meet consumer needs.

3.1 Marketing

Towards addressing market needs, companies follow different policies and choose the suitable techniques through which they try to achieve the best possible result in maximizing the profit and sales of their products.

Success is the result of integrated operations and processes that are related to strategic decisions determining the course of each company and its products.

Applying the principles of modern marketing and adopting in depth this simple to interpret but extremely difficult to implement definition of what marketing is, every company and product moves towards the future with greater safety.

According to Armstrong and Kotler (2011), "*Marketing* is a set of steps that deliver value, which could be remembered by customers and can create a relationship with them, as well as providing benefits to the organization". [2]

With the intention of value delivery, some marketing expenditure and investment decisions should be made. This requires the analysis of marketing mix, which is considered one of the core concepts of marketing theory.

3.2 Marketing Mix

Neil Borden, Emeritus Professor of marketing at the Harvard Business School, was the first to suggest the term "Marketing Mix". The term was inspired from his associate, Professor James Culliton. In 1948, Culliton described the business execute as "a mixer of ingredients".

The creation of a profitable company is largely depended on the combination of appropriate marketing procedures and policies. A company's marketing mix is a set of actions the company follows to promote its brand or a specific product in the market.

The main areas where marketing managers should concentrate in order to achieve their goals are widely known as the "4Ps". These are Price, Promotion, Product and Place. The first to introduce these four marketing variables was E. Jerome McCarthy in 1960.

According to McCarthy, marketing management faces some issues regarding customer analysis and product, channels, promotion and pricing analysis. The suggested solution was the use of a framework that emphasizes on customer importance and has the 4Ps mentioned above as fundamental variables.

In 1981, Bernard H. Booms and Mary J. Bitner further developed the traditional marketing mix into the extended marketing mix or services marketing mix. This is also called as the 7Ps model, as Booms and Bitner included three additional Ps to accommodate trends towards a service or knowledge-based economy; they added "People" in order to recognize human element importance, "Process" to reflect the fact that services are experiences as processes, and "Physical Evidence" referring to the whole environment in which the service is presented.

All of the above are only the primary principles developed around the marketing mix concept. This term is continuously enriched with more elements according to the needs of each season/period. These theories are the foundations of marketing mix, but there are more theories about the variables added over the years. The rest of the variables as well as those which mentioned above will be discussed in another chapter.

Marketing managers should learn how to select the appropriate variables for an accurate and targeted analysis of their company's marketing mix, for the purpose of attracting customers via their buying behavior and, thus, keep them satisfied.

For this reason, models have been created that aim to claim and analyze the available data that facilitate marketing managers. The analysis of such cases is called Marketing Mix Modeling. [3][4][5][6]

3.3 Marketing Mix Modeling

"Marketing mix modeling" has been applied to a variety of marketing models. In this way, many different business strategies could be evaluated, which have emerged from the commercial development each company has shaped according to its objectives. Some of the marketing policies followed by businesses are related to the way the advertisements are used by the company to promote the company itself or its products, the type of promotions applied, packaging procedures, sales forecasting, all combined with the policy and the moves followed by competitive companies.

There are several models implemented in order to contribute in the optimization of the above situations. However, the most prevalent model for this type of analysis is multiple linear regression. This model is based on a number of variables that are related to each other which must necessarily be taken into consideration for each type of decision making.

Whichever modeling solution technique is being used, it is important to be validated throughout the model's development. Once this procedure is followed, the input variables can be used to determine some valuable information for the company. Usually these predictions concern business profit or sales. For example, a marketing manager, knowing that an investment on advertising could result in a big profit for the company, if made on a specific time, it could make some decisions about the amount of money to invest on advertising at the right time. In other words, it is necessary for the marketing manager to understand in depth how each one of the variables affect the company's sales and profits towards following the optimal strategy. Therefore, Marketing Mix modeling could lead in decision making as well as creating a knowledge platform which the company could easily reclaim. [9][10]

3.3.1 Marketing Mix Modeling on Retail

Marketing mix modeling is a very useful tool with many analytical capabilities that gives retailers the opportunity to create an inclusive fact base. Its usability is that it enables them to take data-driven marketing and activity decisions. Marketing mix modeling is based on econometrical modeling and a tool through which the performance of the marketing mix can be measured so as to follow some optimization solution through advertising or other means, such as promotions and pricing.

In general, there is a perception that retail management is concerned with the aesthetics of products and how they will look on the TV screen, on the shelf and, therefore, in the consumer's mind. However, this is the least retail management is about. As it is much more complicated than that, both marketing and sales department need a concise and simple basis to record the facts they need to make strategic decisions. There are many issues the executives would like to know how to handle and marketing mix modeling could give the answer.

The objective of the marketing mix modeling is to provide a complete real base for the executives involved in the retail management in order to help them make strategic decisions. A very important issue about which they are called to decide is the allocation of funds to various business departments and levers as well as their investment.

There are three main types of analysis that could be applied through marketing mix modeling. These are Performance driver analysis, Impact analysis and Optimization of marketing spend. The first one relates to the factors that drive the company's performance and specifically, it provides the answer to which of the factors affect directly an organization's success. Impact analysis associates with marketing investments and their impact on revenue. Last but not least, Optimization of marketing spend is concerned with the marketing budget, the capital sales and their reinvestment to revenue and profit.

An ideal analysis of Marketing Mix modeling deals with the impact of key marketing factors on revenue and profits of the enterprise with the purpose of determining the actual performance drivers. Moreover, it separates these variables from other, external factors that could not be affected by the company. For example, weather or demographic trends belong to this category, while promotional flag and advertising are some of the factors that affect the result and could be modified by the company with the purpose to affect the revenue and profits of the company. Marketing Mix modeling provides the needed information about the measurements of all the above. This kind of analysis belongs to the second type of analysis mentioned in the previous paragraph, Impact analysis. An example is that it could provide information about advertisements and promotions as well as which one of them would be more effective driver for a company in a specific case. In addition, Marketing Mix modeling offers the company the opportunity to extract knowledge about consumer perceptions on product pricing. An effective way to increase the revenue would be to reduce the price of the product by adding a discount to it. However, the impact of this discount on the long-term profit of the business is even more important. For the purpose of balancing the short-term with the long-term benefits of the business, a sensitivity test is necessary. Marketing mix modeling enables retailers to investigate the possible after-effects of their actions, with the result of enabling them to support their decisions in simulation results, rather than making actions based on their instinct. [7][9][10][11]

3.3.2 Marketing Mix Modeling Strategies

There are two main strategies that could be applied to Marketing Mix models. These are “longitudinal” and “cross-functional”.

In the longitudinal approach, the analysis focuses on the sales and profits per period of time combined with the market inputs of each period. This time period depends on the company’s target.

The cross-sectional analysis, also known as side-by-side analysis, is an approach where each one of the different sales territories receive its own inputs at the same period of time; alternately these inputs are distributed across the territories of sales and correlated to the outcomes of profits and sales.

Both of the aforementioned methods are effective and each one of them can be applied in specific cases. However, sometimes the combination of these methods has a more accurate result and is more efficient than using only one of the two methods.

None of the methods mentioned above can have an efficient result, unless the data used for the analysis are suitable. The data should be accurate and highly specific, as the modeling process is based on them. Initially, a data warehouse should be designed, targeting modeling support, as misleading data constitute the most important barrier for successful modeling. The second step is data collection and preprocessing as well as data import into the data warehouse. Another important detail is that in some cases of continuous data modification, the collection and cleaning of data along with entering new data into the data warehouse should be controlled constantly. Towards achieving a successful modeling, clean, accurate and specific data are needed. The data must be reported in subdivisions of the company, such as specific brands and product lines and not in the whole company. This is because the data analysis cannot be done correctly at a global level, since each sub-assembly has its own attributes, which would be able to output a false representation for a subset with totally different data. [3][9][10][11]

3.3.3 Marketing Mix Variables

Every company and product are special and unique. For the development of a successful marketing mix modeling, variables relevant to marketing mix should be identified. Then, the measurement of each one of them should be calculated according to how they affect the marketing mix. Moreover, Data Warehouse should be updated constantly, as marketing mix is continuously changing. The variables on which modeling is based on are some elements that compose marketing programs in addition to other external factors encountered in the external environment.

Elements of the Marketing Mix

Product:

This is the first of the four Ps included in marketing mix concept. The product either has material or non-proprietary form, meaning it is a service. In both cases, its purpose is to address customer needs. Thus, it is of major importance that the business offering a product on the market knows exactly which needs the product is covering and understands completely the nature of the product as well as what makes it unique. That is the only way to make a product successful. A very important process to be followed is product planning. This includes procedures about product lines, product's market direction and Research and Development programs when it comes to a new product.

Price:

Determining the price of a product is one of the most important marketing mix processes, as it affects the profit margins on a specific product. The pricing strategy of a company should take into account what its product represents and what its reflection on the market is. The product's price must also cover its total cost of production. In addition, a price survey of competing products should always be conducted. Marketing Mix modeling could help in the product pricing segment by predicting what price adoption is best suited to maximize the company's profit in combination with other factors.

Place:

This variable refers to the methods and locations about product hosting in order to make it easily accessible to the customers who belong to its target group. It is critical to evaluate possible locations and identify where the product should be located. Place includes the distribution channels through which a product passes until it reaches out to the customers. These channels are related to procedures and policies about retailer-wholesaler relationship.

Promotion:

A common way to increase the sales of a product is through promotions. It is necessary to look at the different ways in which product information is distributed to consumers in order to differentiate the price of the product for a certain period of time and in a different way depending on the circumstances. The procedures related to promotions are the identification of promotion type and the optimization of financial burden of promotion selling plans and devices. There are two types of promotions, consumer and trade promotion:

Consumer promotions: There is a variety of consumer (end-user) promotions that we come across. However, all of them share a common characteristic which regards the immediate effects that they cause on the market as compared to advertising. Promotions such as temporary price reductions, buy one-get one free or cent-off coupons constitute some fundamental examples of promotions which are designed in a robust way to directly affect sales. We feel it is wise that these kind of promotions need to be well understood and measured before incorporated into the business models.

Trade promotions: These are discounts that are not made for consumers but for shops to buy large quantities of them for resale. It is a common policy of products that appear on the market for the first time.

Advertising:

Through this process, the consumer community is informed about and influenced by the existence and use of a marketed product. There are several means of advertising, which are based on product needs and used according to the consumer group to which it is addressed. Some of the policies related to it are the decision taking about spend amount and mix of advertising.

Branding:

Branding refers to the way a customer understands the product or service provided. It consists of policies and procedures concerning the choice of the product or the company logo, brand policy and commercial label choices.

The variables mentioned above are the ones that affect marketing mix the most. Nevertheless, there are much more elements that contribute to marketing mix concept, such as personal selling, packaging, display, servicing, physical handling and fact finding and analysis. [3][9]

Market Forces that engage Marketing

Consumers Behavior:

The consumer market is the total of people who purchase or acquire goods and services for personal use. Their behavior is determined by their purchasing motivation, buying and living habits, environment and their buying power. These elements should be taken into account in order to properly promote the products on the market.

Trading Behavior:

This term refers to the behavior of wholesalers and retailers. It concerns their motivations as well as the goal they have set, their structure and way of thinking and their changing trends in the structure and the processes they follow.

Competitors Position and Behavior:

The behavior adopted by a company's competitors is affected by several elements. One of these is the business-to-industry relationship, which involves the strength and size of competing firms, the number of competitors, the concentration of industry and indirect competition, i.e. competition generated by other kinds of products. Other factors influencing the behavior of competitors is supply-demand relationship, product characteristics such as the quality and price offered to consumers by the product sector, the level at which competitors compete against non-discount base prices, incentives and attitudes of competitors like their possible response to actions by other companies and technological and social changes that change supply and demand.

Governmental Behavior and Marketing Controls:

The company's attitude depends on the information concerning government control of marketing. Controls over marketing concern regulations over products and pricing, rules on competition practices and restrictions on advertising and promotion policy. The greater influence of governmental control on marketing is to act as a great educational campaign to get to know all parties involved in the routes and distribution processes and to achieve a wider use of good practices already in place. [3]

3.4 Challenges on Marketing Mix Modeling

For better investment initiatives, every organization depends on the optimal distribution of funds across different marketing channels. Thus, an analytical approach such as Marketing Mix Modeling is required to enhance marketing budgets. Taking into consideration its wide adoption across industries, MMM serves as a recommendation tool for efficient fund allocation across multiple marketing channels. Despite these facts, it is pivotal that the MMM technique should be appropriately implemented to achieve maximum results.

3.4.1 Business Challenges

Cannibalization effect measurement for every product and its competitors

Cannibalization is a maintenance procedure according to which an operational component is extracted from a larger set of components which are considered unserviceable. This helps in servicing and maintaining other equipment of the same type by using similar, operational sub-components of unserviceable items. The reason to that is usually lack of stock parts available in the market or difficulty in retrieving it from the vendor or manufacturer.

Revenue growth

Several factors affect the revenue growth. It is of great importance the reasonable proof of product value as well as benchmarks for initial executive sponsorship, ensuring the sponsors' engagement by using a proof-of-value pilot. Various analytics that provide meaningful insight and prioritize the needed changes within the organization shall be implemented throughout the revenue estimation process. For achieving maximum results, a combination of the aforementioned practices is recommended, along with the use of a thorough implementation plan.

Proper Pricing

The success of each business is largely due to the correct pricing of its products. The foundation of the prosperity of an enterprise is the pricing of products, thus enhancing the number of sales and revenue of the business. However, the existing pricing methods need many adaptations depending on product, business and market types. To address this challenge, there are several algorithms could be used, as there is excessive quantity of data on consumer profiles, which is one of the key elements of this procedure.

Promotional effectiveness measurement

As price promotions are increasingly applied for the stimulation of a company's performance, new methods have been also introduced to further enhance as well as quantify their effectiveness. The introduction of scanner data and persistence modeling are two innovative means of promotional effectiveness.

Volume uplift drivers identification

The success of each company depends on a number of internal and external factors. The identification of uplift drivers of sales and evidences of store performance is a crucial challenge to be addressed. The major focus should be on measurable key drivers responsible to record the progression of the company, while being correlated in the same time with a certain standard, i.e. a budget or an average.

Decision time reduction

The successful implementation of different ideas is determined by the shortening of decision time. This can be achieved through converting the internal setup operations into external ones. However, key factors such as cost or safety should be taken into consideration for the most appropriate setup technique to stand out. [12][13][14][15][16][17]

3.4.2 Technical Challenges

State of Data

For each kind of analysis, as well as for marketing mix modeling, it is necessary to evaluate the current data state. Unfortunately, in many cases the marketing department does not fully exploit the given information. When the data state is not correct, modeling could fail. A proposed policy to prevent such situations is to identify the necessary types of information and needed data for future analysis.

Multicollinearity

When the marketing activities coincide with each other, they generate a collinearity in the analysis model. These variables typically appear when analyzing by using observation data. The most important issue is the kind of impact they have on our analysis, which sometimes is negative. A recommended solution to avoid such situations is the removal of highly correlated input variables or the use of information overlapping methods.

Lack of Measurement Standards

The development of better measures of marketing variables is essential for knowledge evolution. The measurement process concerns “rules for assigning numbers to objects to represent quantities of attributes” . The measurements with which marketers work are often inadequate. For that reason, emphasis should be placed on their development through careful programming of data collection and analysis.

Lack of Transparency

The lack of transparency can have an impact on manipulation of information and issuing of false or misleading information. There are four types of transparency that contribute to information technology exploitation and transparency development: cost, supply, organizational and technological transparency.

Measurement of Advertisement Content

Advertising content is a complicated element to measure. The substantial factor of advertising measurement is sales. Direct sales results constitute a criterion of advertising effectiveness measurement. However, this does not represent the degree of completeness the content of an advertisement can have. On account of this, evaluation models of advertisement effectiveness have been developed.

Dynamic Effects

At the start of a business move, the results are not immediately apparent. In many cases, even months have passed until the efficiency of some moves has emerged. During this time, it would be useful to consider the different aspects of creating a model process. A proposed policy of addressing this issue is to identify the required time to show results and to address the variables and the effects on it.

Interaction Effect between Advertisements

Different marketing activities can have a better effect on sales, providing they are properly coordinated. In many cases, the coexistence of promotions and advertisements, instead of increasing profit through the sales of a product, has a negative effect on it. Whilst the direct effect of these methods is positive, the use of pricing has a negative impact on the influence of the consumer community through advertisements and the opposite. However, there are several ways to control this issue by applying classification algorithms where relationships between marketing activities can be recognized and there is the possibility of their application optimization.

Nonlinear Effects

There are cases where the effect of altering a variable on the desired result is specific and others where their relationship is linear. However, this relationship is often quite complex and there is a need to identify and describe it. For example, in some cases of activity implementation, customer responsiveness is relatively predictable. Other times, it is difficult to predict their effects as the relationship of consumers with certain advertising spots, such as television, is not linear, making modeling process difficult.

Instability of Coefficients

In many cases, when modeling a marketing mix of a product, there are columns that are related to each other and, as mentioned above, they are almost collinear. Thus, when the independent variables of the model are highly correlated, an instability effect on the least square coefficients is caused. To deal with this issue, biased estimators are often used which aim at greater stability.[18][19][20][21][22][23][24][25]

4 Data Science and Retail

Data is becoming more and more important to businesses that want to make profitable decisions. Retailers analyze the data as they have found that their beneficial value produces positive results for their businesses.

4.1 Data Science Use Cases in Retail

Bellow, there are some cases in which data science contributes to the upturning of enterprises by solving certain problems and optimizing different processes.

Recommendation Engines

A very useful tool for predicting consumer behavior is Recommendation Engines. In this way trends are dictated resulting in increased sales.

Market Basket Analysis

The most necessary process of analyzing retail data is the Market Basket Analysis. For this process, it is very important to organize the transaction data correctly. Rule mining algorithms are the core tool behind this type of analysis. Through Market Basket Analysis the profits from sales reach the peak.

Warranty Analytics

The tool used to monitor warranty claims, reduce costs, improve quality and detect illegal activities is Warranty Analytics. It is a good opportunity to convert Warranty challenges into active intelligence.

Price optimization

A major advantage gained through the use of optimization mechanisms is to determine the appropriate price of a product. Pricing depends on various factors, such as the cost of production, customer target group as well as competition's prices and offers.

Inventory management

The procedure which refers to the storage of goods for future use is called inventory management. The supply chain is analyzed in depth, taking into account the product offer at the right time on the right side. Machine learning algorithms are used to identify correlations and patterns between the available elements and the supply chain.

Location of new stores

Data Science seems to be extremely important in terms of new stores location. The algorithms used for this issue are quite simple but simultaneously effective. In this type of analysis, the demographic data and data relating to the location of other stores are of utmost importance.

Customer sentiment analysis

The analysis of data extracted from social networks and e-Services, is a part of customer sentiment analysis. The implementation of analytical tools on social platforms is easy as they are directly available. A common policy is to monitor words that are positive or negative in order to understand the view that the client has shaped.

Merchandising

The purchasing decisions taken by customers through optical channels are easy to be manipulated through merchandising tools. Some important elements that contribute to this are the brand names of the product or the company in combination with the attractive packaging. Data on consumer priorities, taking into account market trends, are essential for a proper analysis.

Lifetime value prediction

The total value of the profit which is acquired by a particular customer throughout his / her relationship with the business is called customer lifetime value. In this forecasting procedure, historical data identifying consumer preferences are of particular importance. The result obtained after analyzing the mentioned data reflects the value of customers for the business.

Fraud detection

In order for a client not to suffer any kind of fraud with a negative effect on the company, a fraud detection process is a must. There are Big data platforms to detect such activities that allow continuous monitoring of any move. The Data Science Algorithms used in these cases should not only identify fraudulent activities but also predict future similar activities. This way, the customer and the company are protected.

As is apparent from the cases mentioned above, data science has many useful applications for businesses operating in the retail trade. All the data that can be claimed for the benefit of an enterprise are analyzed and processed in order to find the right marketing policy and to optimize the commercialization processes.

However, there are still many applications where data science contribute to the upward path of companies. Only the most common cases have been reported above. A very useful application of data science is the sales forecast of a product, which is presented in the next chapter.

4.2 Retail Sales Forecasting

A crucial task of a store's management is sales prediction. Predictive analytics is a powerful tool which allows retailers discover the factors that drive products sales. Various algorithms have been used to periodize sales of products. The most widely used of them are Neural Networks and Multiple Linear Regression.

4.2.1 Neural Networks

In the technical sector, the expression and evaluation of the predictable parameters of a system is done using equalizers. Thus, many complicated problems are encountered, which may have been unlikely to be solved. Neural Networks is a computationally complex method and quite often the solution is easy to find following the fact that has been predicted.

Neural Networks are used for seasonal and non-seasonal sales forecasting as they are the most custom non-linear models. Unlike other models, Neural Networks are flexible in any kind of non-linear pattern analysis, as they don't make any assumptions about underlying data generating process. The most common Neural Networks model is used for sales prediction , is the three-layer network, which is represented as:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_j f\left(\sum_{i=1}^{p} \beta_{ij} x_{it} + \beta_{0j}\right) + \varepsilon_t,$$

with p input nodes, q hidden nodes, a sigmoid function f, a_j a vector of weights of the input to output nodes with $j = 0, 1, 2, \ldots, n$ and β_{ij} the weights of the input to hidden nodes with $i = 0, 1, 2, \ldots, p$ and $j = 0, 1, 2, \ldots, q$. a_0 and β_{0j} are the weights of arcs leading from the bias terms that have always values equal to 1. The inputs x_i are the delayed observations.

4.2.2 Multiple Linear Regression

The modeling technique that is responsible for the analysis of the relationship between a dependent variable y and one or more independent variables $x_1, x_2, \ldots, x_k$ is called regression analysis and it is the most common way of analysis is Sales Forecasting.

This technique aims at recognizing the function that describes the relationship of these variables, so as to predict the value of the dependent variable taking into account the values of the independent variables.

An ordinary form of regression analysis is multiple linear regression, that is used to explain the relationship between a continuous dependent variable and more than one categorical or continuous independent variables. A multiple linear regression model can be formed as: $y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon$, with k predictor variables $x_1, x_2, \ldots, x_k$, a response variable y, regression coefficients $\beta_0, \beta_1, \beta_2, \ldots, \beta_\kappa$ and an error term ε.

In Marketing Mix Modeling and more specifically in Sales Forecasting, multiple linear regression technique is used to predict the volume of sales, which is the dependent variable, taking into consideration factors such as product's actual and base price, prices of competitive products or various promotions that have been applied to the product, which comprise the independent variables.

After the research conducted for writing this diplomatic work, it turned out that this method is the most efficient for prediction with such kind of data. Thus, the multiple linear regression model was applied on a true dataset that includes the data mentioned above. Its implementation and results are developed in Chapter 6. [26][27][28][29][30]

5 Dataset and Exploratory Data Analysis

Exploratory Data Analysis uses visual methods for summarizing dataset main characteristics. This kind of analysis is usually done through programming languages or other tools capable of displaying data through graphs.

5.1 Dataset

In Marketing Mix Modeling, the dataset is provided by the company for which the product sales and prediction analysis are executed. The dataset used is from Consumer Packaged Goods industry.

The dataset includes information about the Volume of Sales, Actual Price, Base Price, Competitors' Price, Promotion Type and Implementation in weekly basis for 146 weeks. The main goal was to analyze the impact of Price reduction and campaigns on Volume of sales for every product. The price reductions of the main competitors of the target product was taken into account as well.

Week: In this column of the dataset, the weeks for which we have data are numbered. As mentioned previously, the weeks contained in the dataset are 146.

Volume of Sales: This feature includes the weekly volume of sales of the company's product for all weeks.

Actual Price: This column relates to the price at which the product was sold.

Base Price: This is an estimation of the product's theoretical basic price, without any promotion or discount applied.

Competitors Price: There are seven columns, each one related to the price of a competitor's product.

Promo All: This is a binary feature whose values are 0 and 1, with "0" meaning no promotion applied and "1" meaning that the specific week a promotion is running.

Type of Promotion: There are five different promotion types and this feature shows which is the type of promotion applied for each week.

Percentage of Promotion: These columns contain information about the rate of price's reduction when during this week promotions have been applied.

5.2 Exploratory Data Analysis

The dataset was explored in two ways. For data visualization, programming language R was used as well as SAP HANA Studio. The reason these two ways were chosen for data visualization is to use both an open source and a commercial tool.

The dataset was in csv form and the first step was to import it in R Studio and SAP HANA Studio, an Eclipse-based tool that constitutes the central development environment and the main administration tool for HANA system. This platform provides us the opportunity to view the data and make some Exploratory Data Analysis.

The next step was to visualize the data with a simple manner, in order to make a better understanding of each variable separately and extract some useful information which help us to process the dataset further later.

5.2.1 Exploratory Data Analysis using R

Below are presented the most important descriptive statistics and plots on dataset's variables as the R language has shown them through R-Studio.

Descriptive Statistics

Initially, for a proper understanding of some key variables of the dataset, it is necessary to know some fundamental statistics about them. Below there is a table of Sales and Actual Price of the product as they appeared through R Studio.

	Statistics	Sales	Actual_Price
1	minimum	36840	0.758
2	maximum	219624	1.222
3	mean	90317.0137	0.9967
4	median	72678	0.9915
5	1st quantile	60561	0.907
6	3rd quantile	117132	1.0953
7	variance, ?^2	1904411473.8343	0.012
8	standard deviation	43639.563	0.109
9	Pearson's moment coefficient of skewness	1.1158	0.0158
10	Pearson's kurtosis	-0.033	-1.0797

The above statistics are quite useful, but their interpretation becomes much clearer after the creation of the below plots.

Data Visualization

Another part of Exploratory Data Analysis is Data Visualization. Below there are the most important plots that developed through R studio.

To start with, a correlation matrix created, in order to illustrate the relationships between the variables.

Correlation Matrix

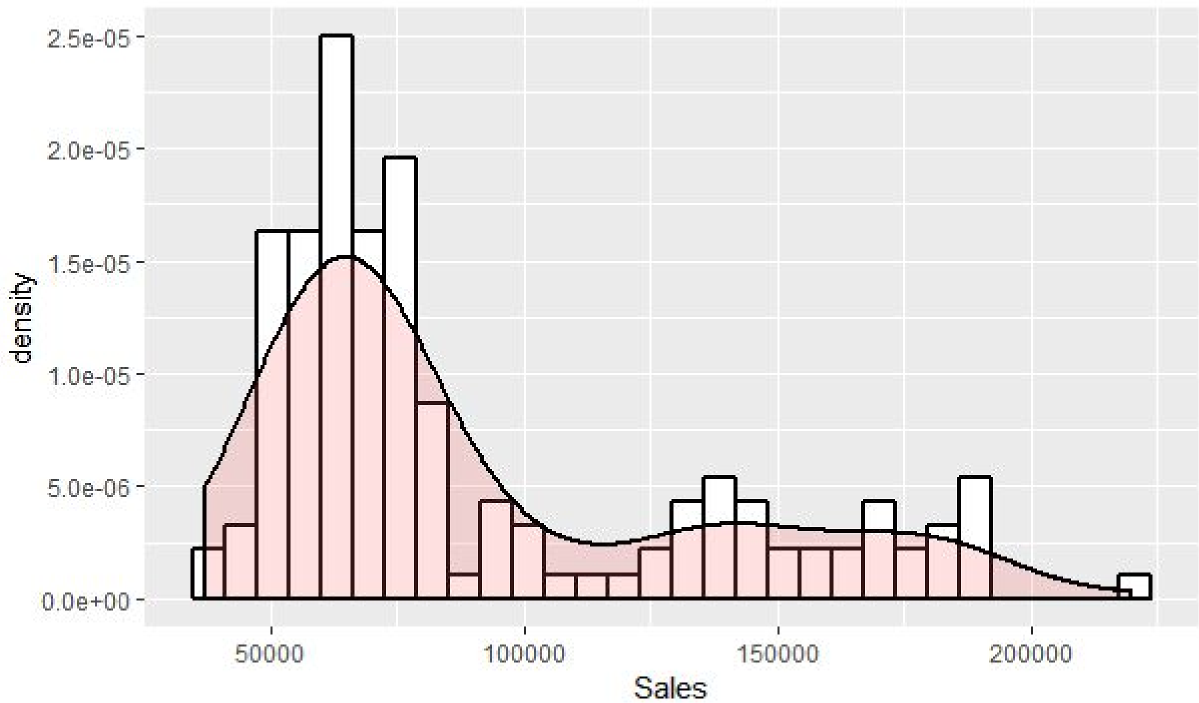
This correlation matrix reveals the relationship between the continuous variables of our dataset. The color bar on the right shows the meaning of each color is in the squares. The more intense the color, the highest linear correlation exists between the variables.

Positively correlated variables: It is evident from the correlation matrix, that Volume of Sales is quite highly correlated with the promotion rate, meaning that the increase of one of them, raises the other. Other positively correlated variables are Competitor 2 Price, with the

Prices of Competitors 4,5,6 and 7, meaning that the price movements of their products are not independent and there is linear relationship among them.

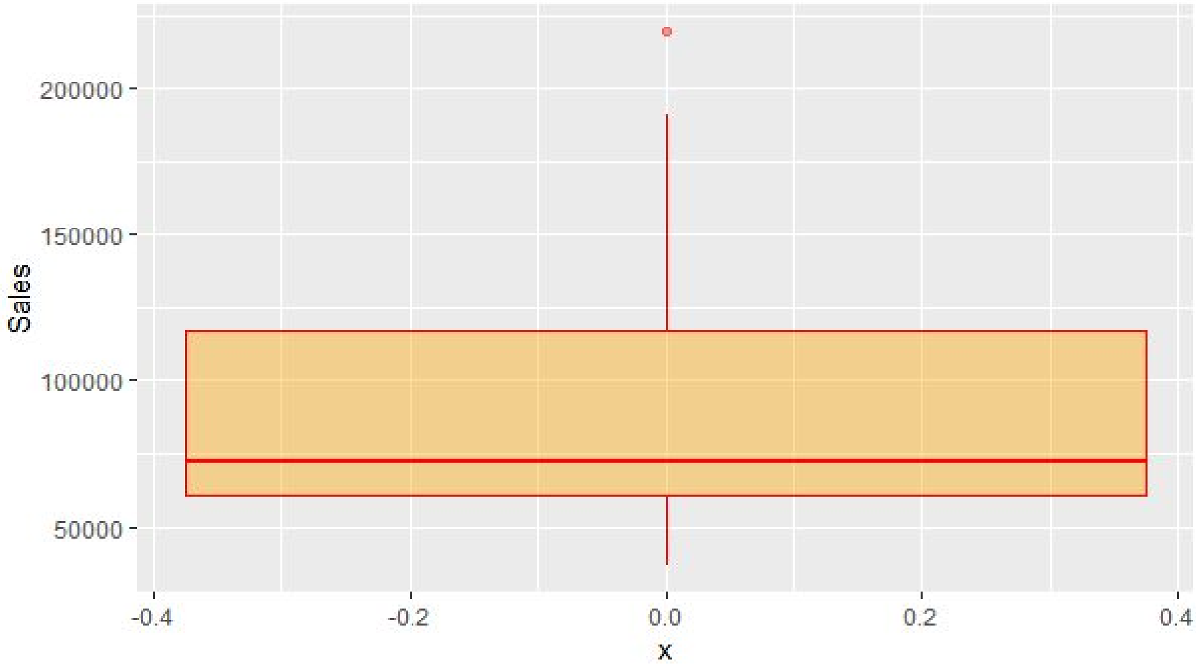
Negatively correlated variables: Some highly correlated variables with negative shift are Volume of Sales and Actual Price. It is perfectly reasonable, as an increase in the price of a product usually causes a drop in its sales. However, the higher correlation is found among the Actual Price and Promotion Rate, as the higher the rate of discount applied, the lower the price at which the product is placed on the market.

Volume of Sales Histogram with density plot



We notice that the above histogram is right skewed. This is perfectly reasonable, as we have seen through the statistics that Sales median is smaller than its mean. The additional information we extract through this histogram is that the highest value of sales is an outlier. It could be more than one outlier, as each bin of the histogram contains sales that belong in a value range. Additionally, the tail of the histogram shows up some small picks, which nevertheless do not make it bimodal.

In this histogram, we have added the density plot of Sales, which visualises the data distribution over the continuous interval of Sales, in order to smooth out the noise. The additional positive feature they have in relation to the histogram is that they are better at determining the distribution shape.

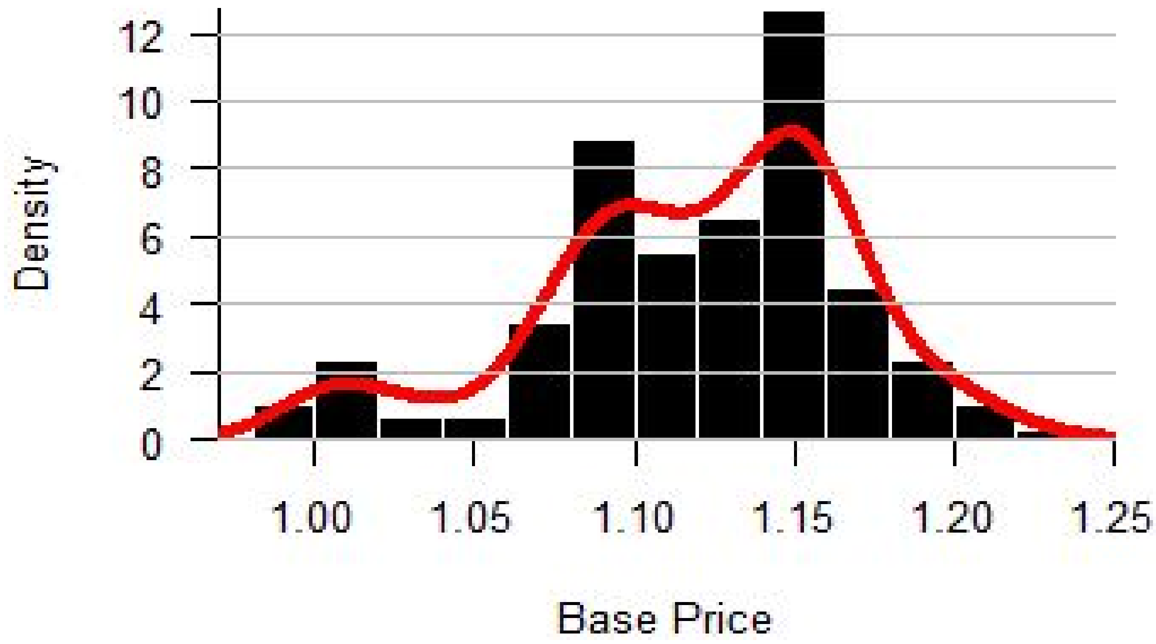


The boxplot which developed, contains completely different information than the histogram. Sales first and third quantiles appear clearly in this boxplot, as they are the down and up sides of the rectangle respectively. The line within the box indicates sales median and seems to be much closer to the first quantile that to the third one, meaning its rightskewness. The outlier is even more obvious in this plot, depicted with an orange dot.

Actual Price Histogram with density plot

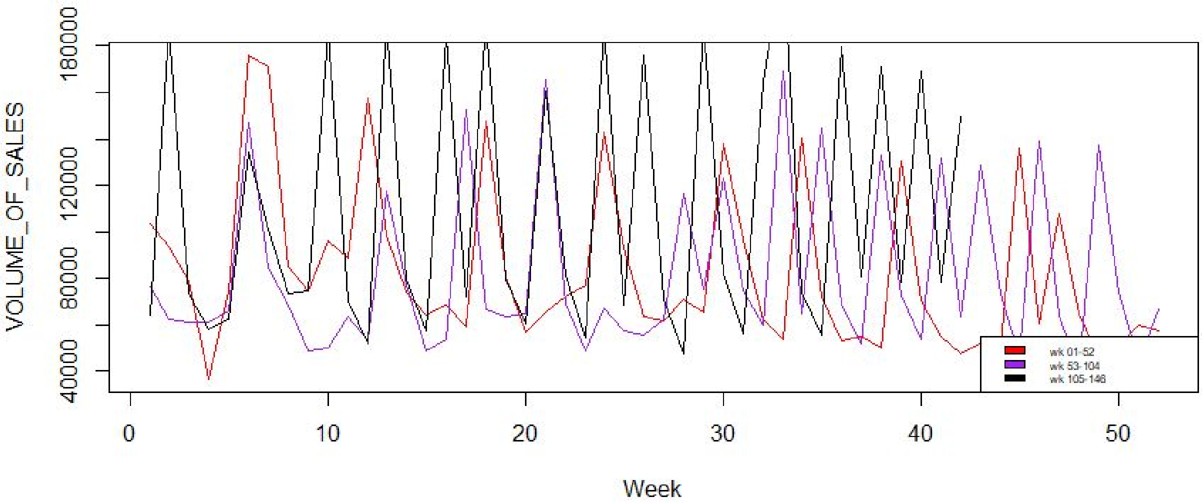
In contrast with the histogram created for the Volume of Sales, Actual Price Histogram is bimodal. The two peaked histogram meaning is that two processes with different distributions combine their outcomes in one set of data. In this case, there is such distribution because of promotions existence. The most likely is the leftmost peak concerns product's price when promotions are running, while the right one concerns the actual price when there is no promotion. The density plot in this case, makes clear the existence of two peaks.

Base Price Histogram with density plot



We notice that the above histogram is bimodal and rightskewed. It is obvious that many of base price's values are gathered close to 1.15 and 1.08. The range of base price's values is quite small in comparison with actual price's range. Additionally, the tail of the histogram shows up a small picks, which probably does not have any particular significance.

In this histogram, we have added the density plot of Base Price, which visualises the data distribution over the continuous interval of Base Price, in order to smooth out the noise. The distribution shape became clearer using the density plot once again.



After we have defined which weeks correspond to each of the three years, we visualized the sales of each year with a different line color. We notice that the sales movement is very similar for the same weeks of each year. However, from the middle of the year onwards, it does not happen anymore.

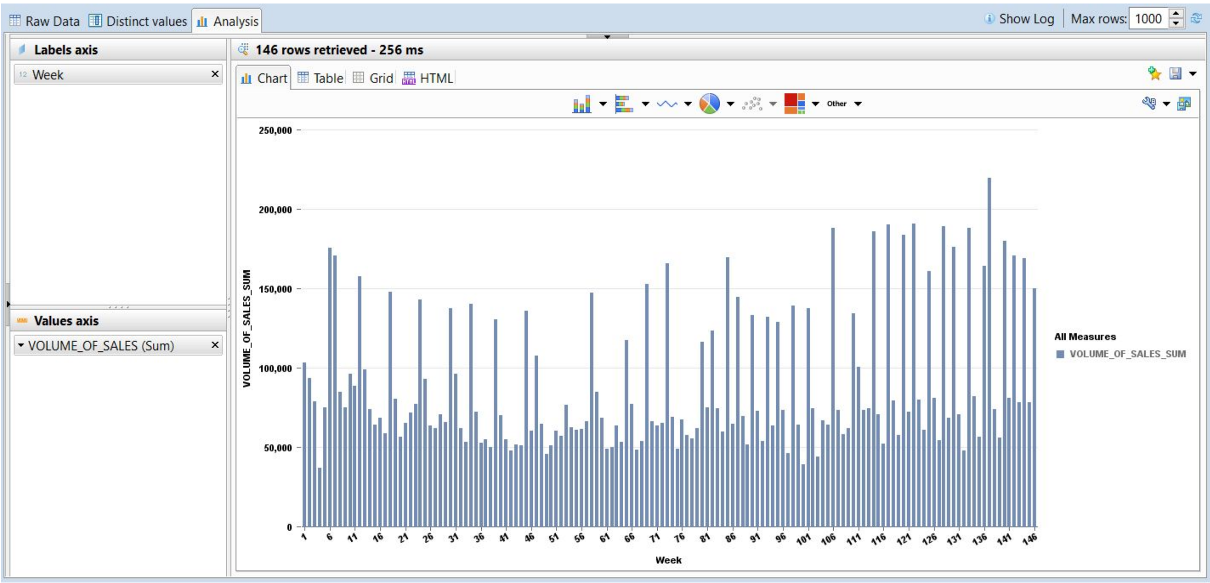
5.2.2 Exploratory Data Analysis using SAP HANA Studio and SAP Predictive Analytics

Below there are some charts as they were created through SAP tools, SAP HANA Studio and SAP Predictive Analytics (Expert Analytics mode).

Data Visualization using SAP HANA Studio

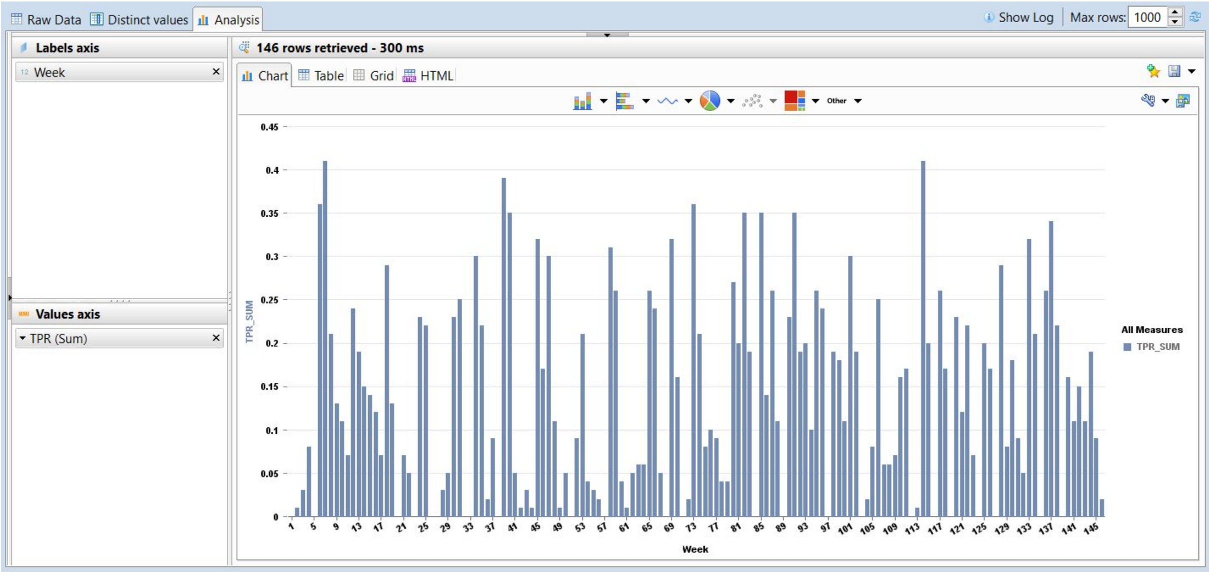
Through SAP HANA Studio, it is possible to display all the charts that were presented above after using the R Studio. However, different charts relating to the same variables have been selected to be presented.

Volume of Sales



In this chart, it is obvious that volume of sales is constantly changing and and no specific trend is observed. This chart is not as helpful as the one was shown previously using R Studio.

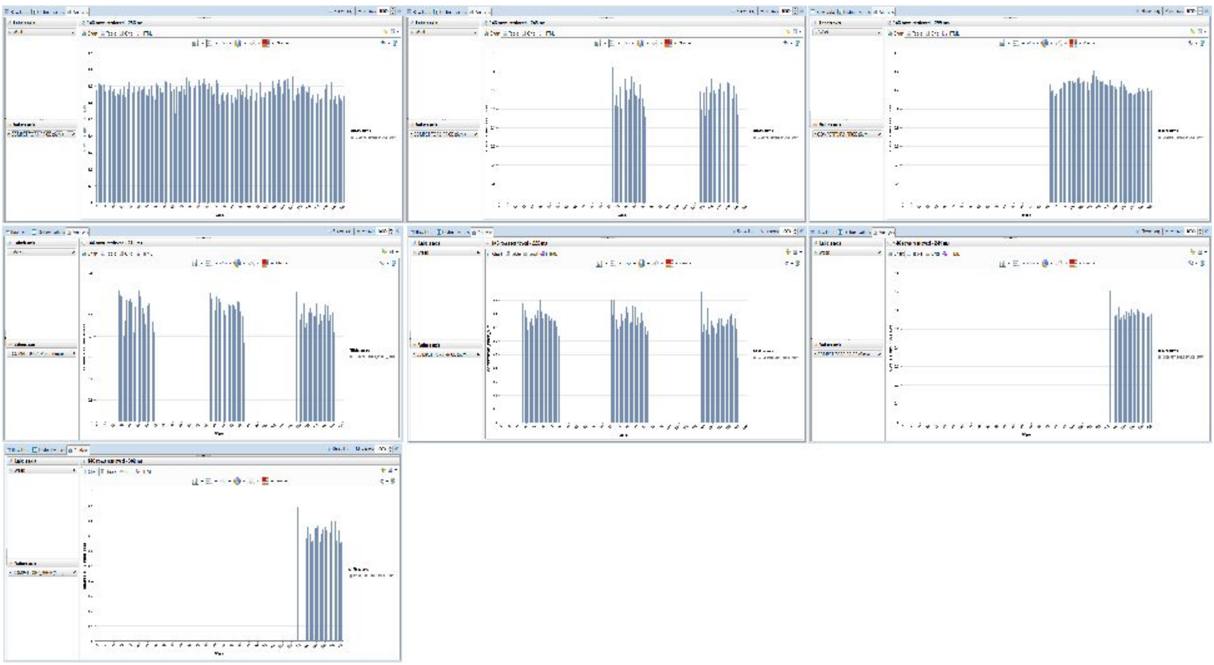
Percentage of Promotion



This chart shows that the promotion rates have a large discrepancy between them. However, as we shall see later, they do not cease to be effective in their own way.

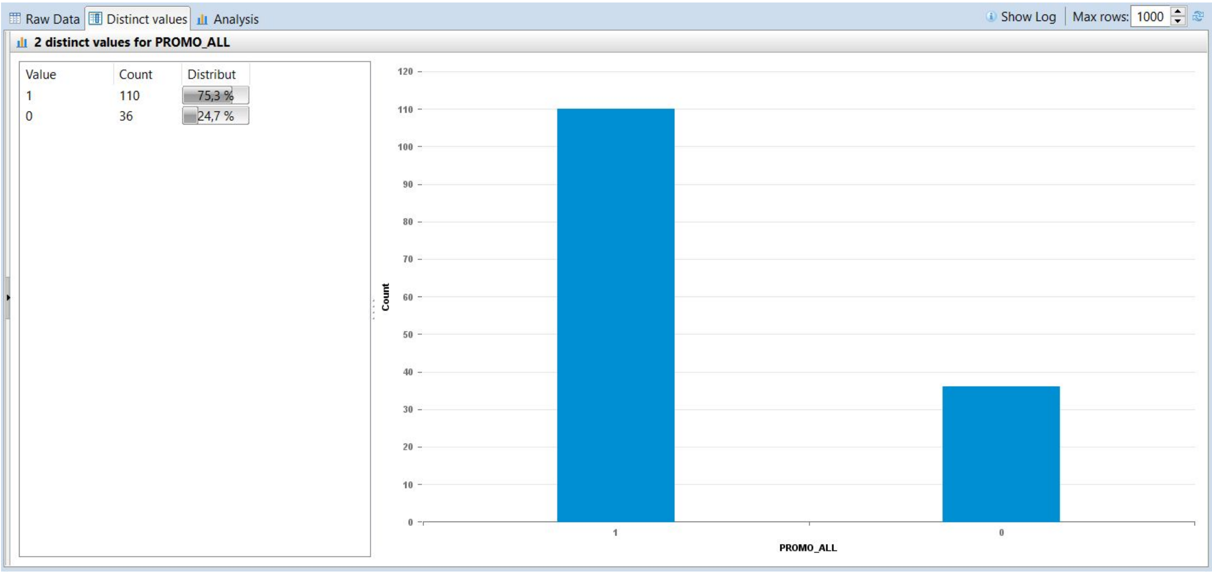
Similar charts were made for all variables but no deduction was made, so only one image containing the price charts of competitors will be presented below.

Competitors Price



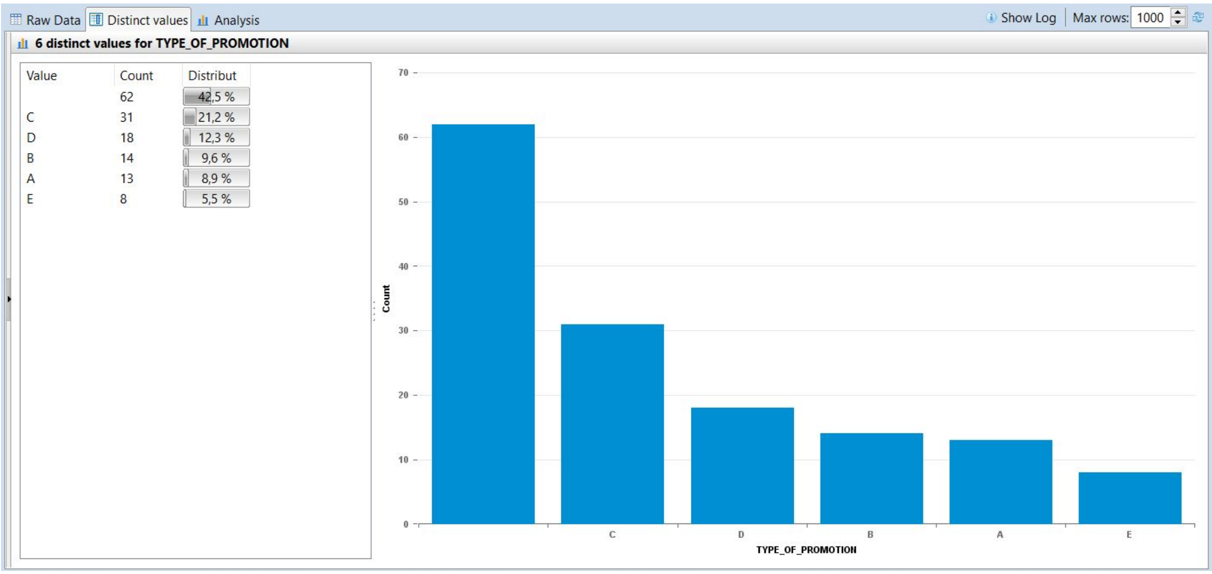
From the above image we infer something very important. This is that some of the competitive products were not available on the market full time. As it seems, only the first competitor was active throughout the whole 146 weeks period.

Promo All



SAP HANA Studio offers the possibility of viewing all the percentages of the qualitative variables, through Distinct values tool choice. In the above chart, we observe that there are promotions for 110 out of 146 weeks, meaning on the 75.3% of the weeks.

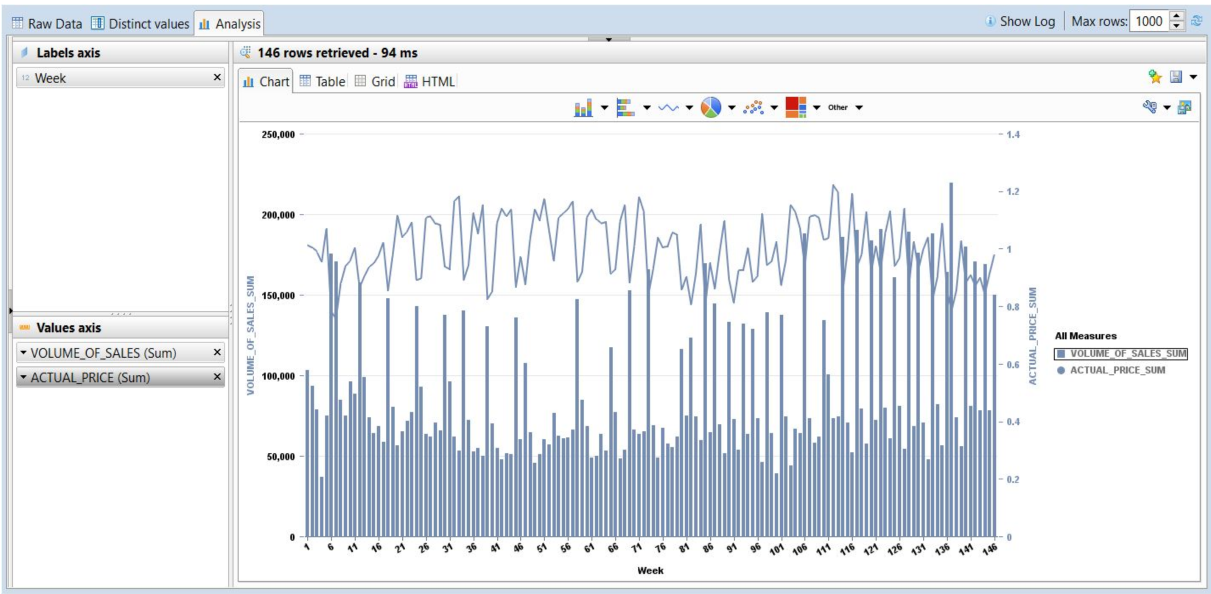
Type of Promotion



In the above chart, it appears which type of advertising is the one that prevailed over the rest, which is obviously promotion type "C". If we compare this to the previous chart, we can deduce that we either have some missing data or most likely there are some individual promotions that do not belong to any of the above types.

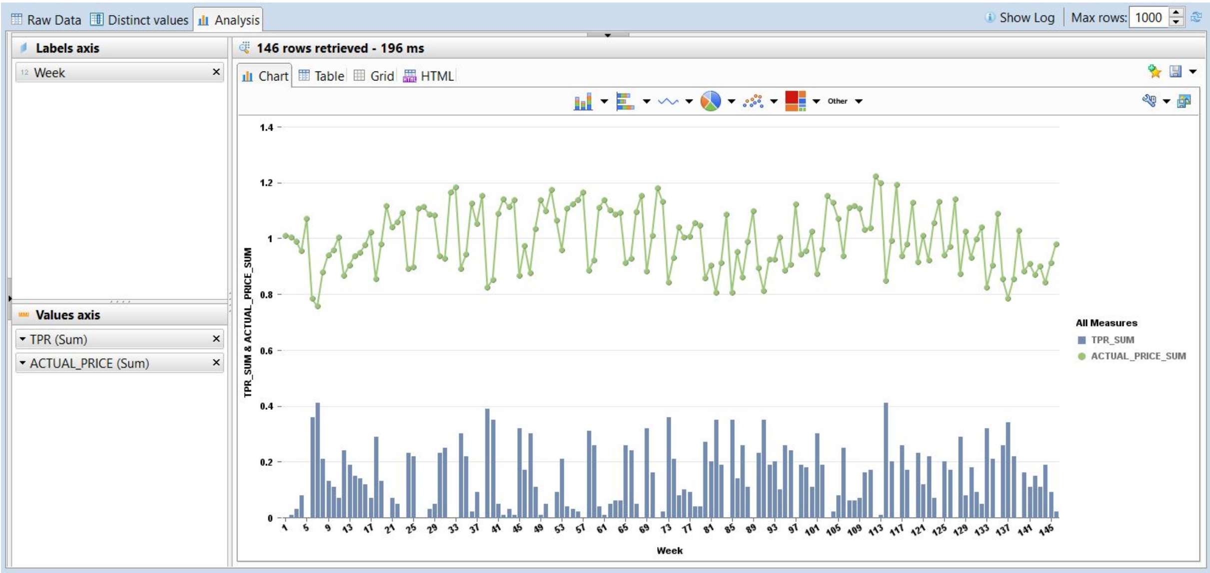
For the purpose of discovering where the movement of the above variables is due, we showed some charts by combining variable pairs. Below are the main results presented by some graphs.

Volume of Sales combined with Actual Price



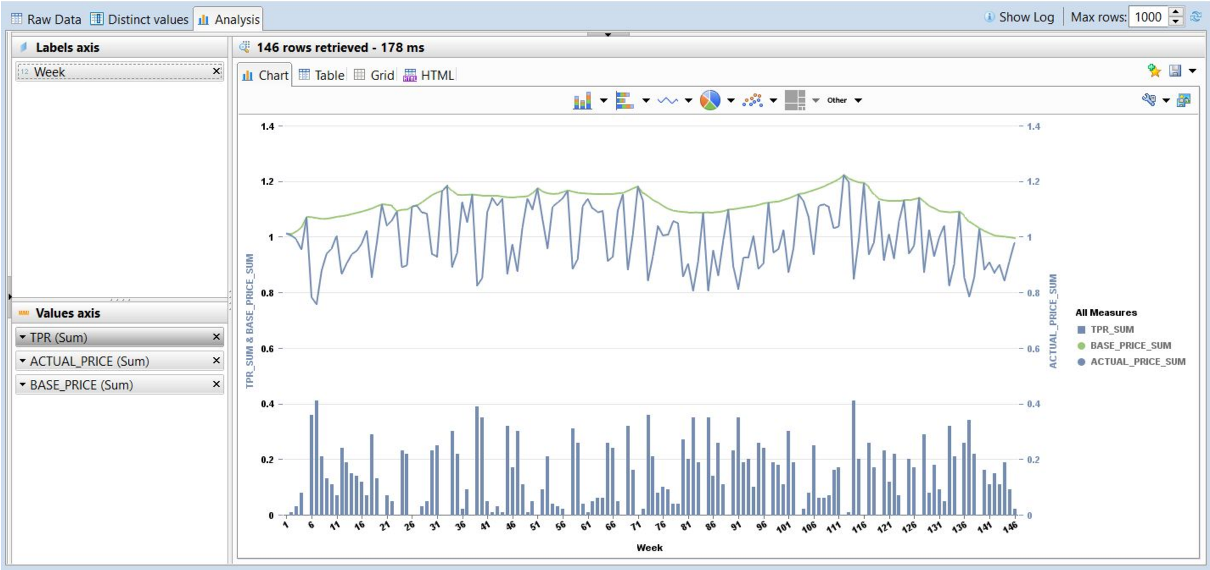
In the previous picture, the relationship between the volume of sales and the actual price of the product on the market appears. The label axis concerns the weeks, while the values axis concerns the Volume of Sales and the Actual Price of the product. It seems that when the Actual Price drops, the Volume of Sales directly increases. However, this is not the only variable that affect Volume of Sales.

Percentage of Promotion combined with Actual Price



As expected TPR and Actual Price move opposite to each other, as each time there is a promotion, Actual Price of the product drops.

Actual Price, Base Price and Percentage of Promotion

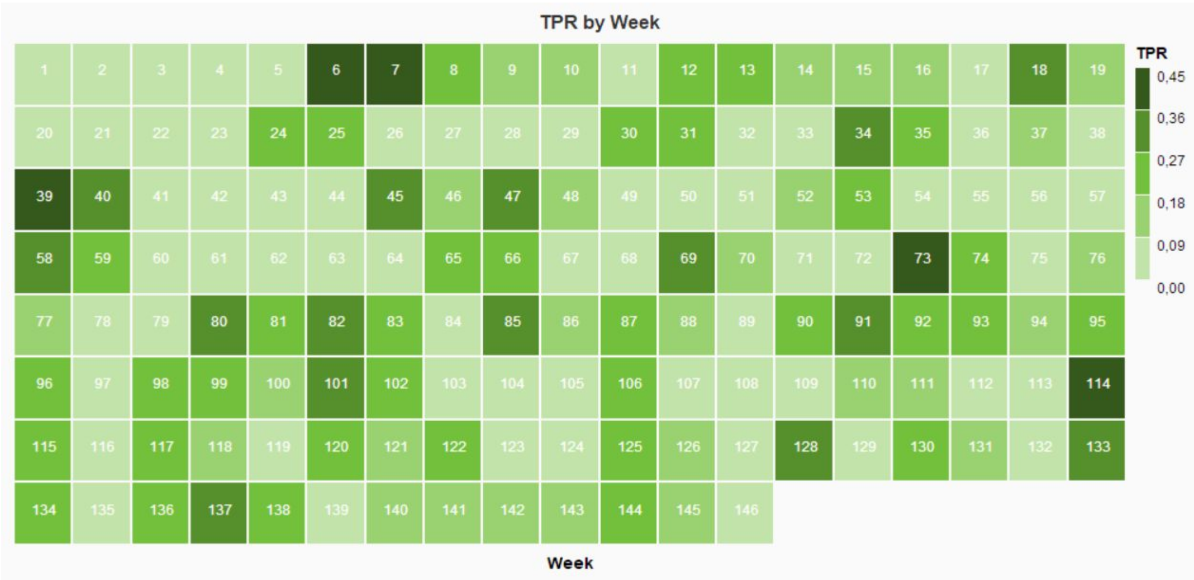


Yet another phenomenon that has been observed is that the actual price deviation from the base price, reflects on Promotion percentage. The same chart is presented above, visualized with SAP HANA Studio.

Data Visualization using SAP Predictive Analytics

SAP Predictive Analytics offers even more options for visualizing the data through its Expert Analytics mode. Below there are some really helpful insights we extracted through this tool.

Promotion Rate by Week:

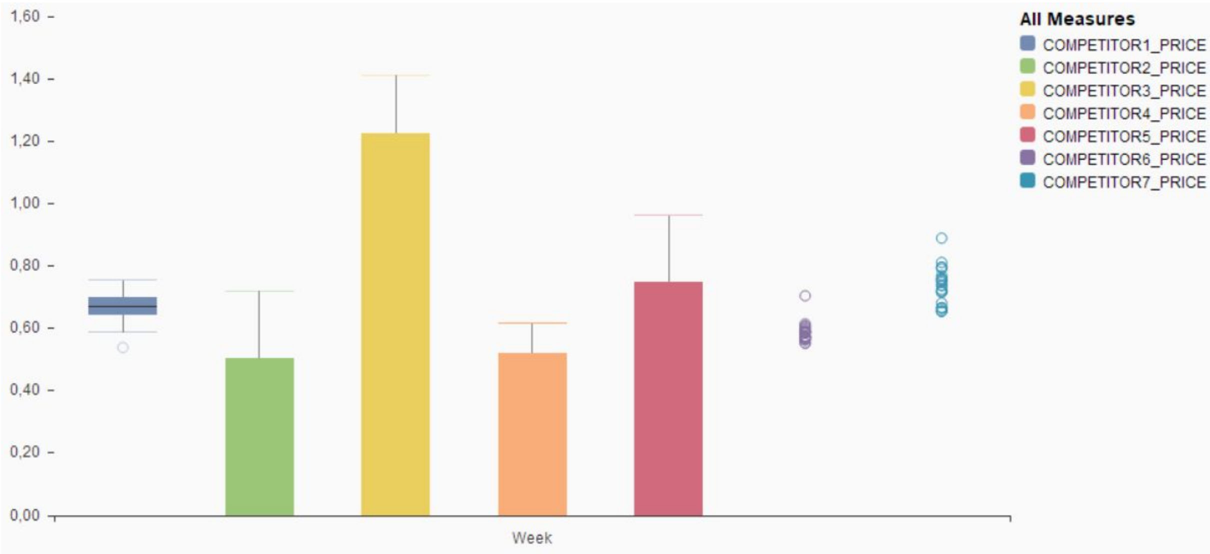


In the above table, it is clear the size of promotion rate applied in each of the 146 weeks. The darker the color within the square, the greater the promotion rate was applied. We can observe that in most of the weeks promotion was applied, the percentage was not high.

Actual and Base Price

In the above picture, we have combined two boxplots of price. The fact that the Base Price is higher than Actual Price was expected. The obvious additional information that is revealed from this chart is that its wide range of Base Price is much smaller of Actual Price's range.

Competitors



The prices of all competitors were depicted in the above image as boxplots. The range of the 1st competitor's prices is quite small, while competitors' 2, 3, 4 and 5 prices values start from zero and are spreading in a huge range. Giver the fact that competitor one is active all weeks and has much more stable prices than the others, it makes him the dominant competitor. On the contrary, competitors 6 and 7 are the ones that are active the shortest time as we observed previously and that is the reason why no boxplots created for them. They appear as purple and blue dots, that are the individual observations.

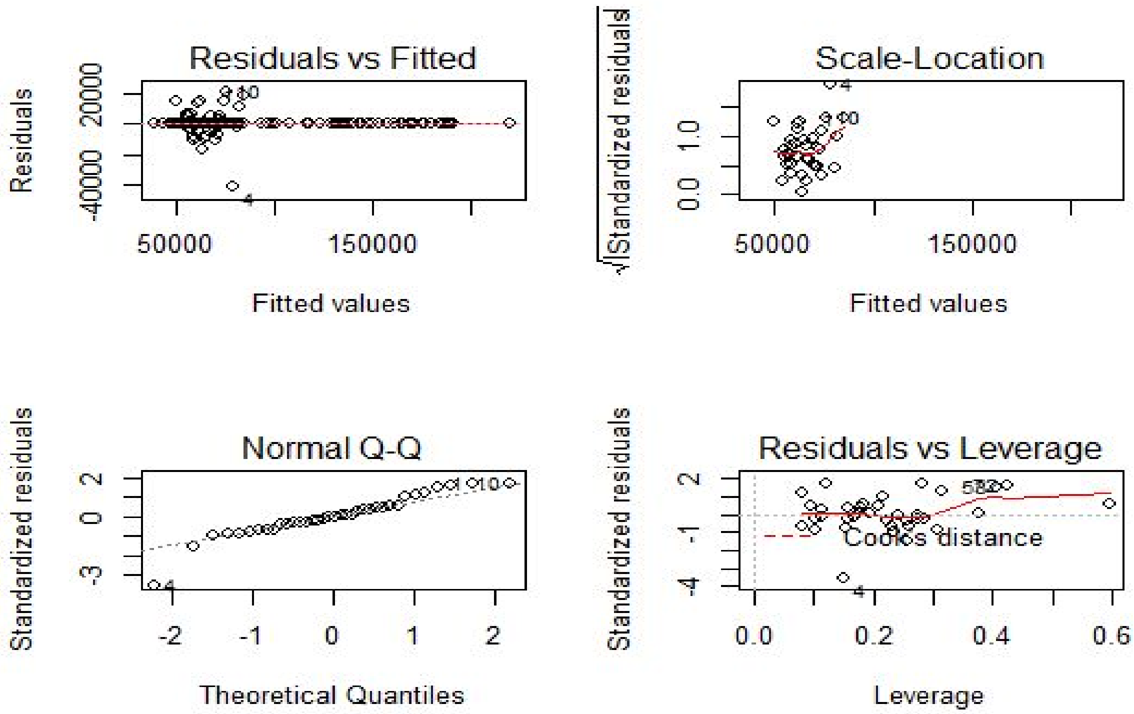
6 Modeling Results

Below are presented the results, after using the multiple linear regression algorithm for modeling through the use of R language and SAP Expert Analytics.

6.1 Modeling using R

The model implemented in R Studio with the implementation of lm function, which stands for "linear model" and is producing the best-fit linear relationship of the variables by minimizing the least squares criterion. lm is used to perform regression and analysis of variance or covariance.

An important part that assesses regression models is visualizing residual plots. With plot(model) command, where model is the result of our analysis, four residual plots will be produced and we can extract some insights.



Residuals vs Fitted:

The most commonly creating plot, when conducting a residual analysis is the "Residuals vs Fitted" plot. On the y axis are the residuals while on the x axis are the estimated responses (fitted values) of this scatter plot. This kind of plots are used to detect non-linearity, outliers and unequal error variances. From our plot, it is obvious that the relationship between the variables of our model is linear as the most of the residuals are on the red line or really close to it.

Scale-Location:

This plot is also called "Spread-Location" plot. It is indicated for homoscedasticity testing, meaning the assumption of equal variance as it shows if the residuals are equally spread along the predictor ranges. In our "Scale-Location" plot , it seems that all the points are randomly spread around the red line.

Normal Q-Q:

This is a normal probability plot. The "Normal Q-Q" plot describes the distribution of the residuals based on the normal distribution. The residuals are considered as normally distributed when the points are close to the diagonal line. When the snaking from the diagonal line is strong or deviations exist, our residuals should be considered as non-normally distributed. From our plot, turns out that the residuals are normally distributed, as the most of them coincide with the diagonal red line.

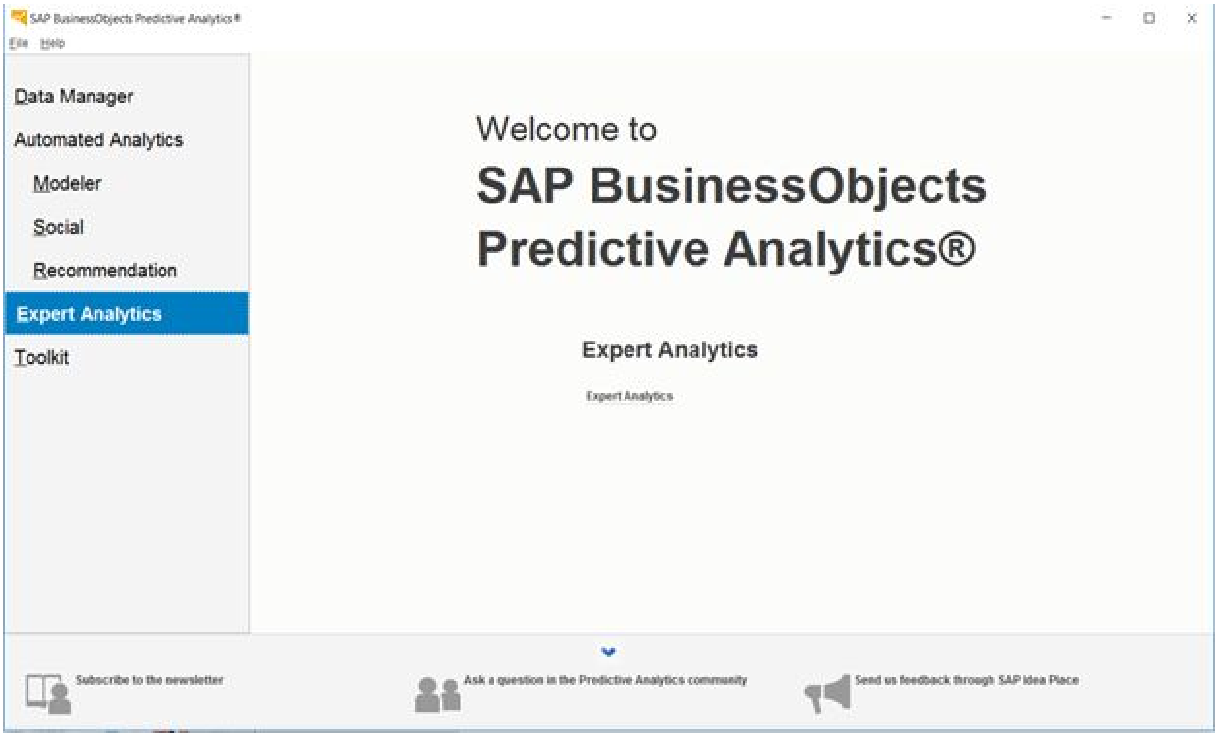
Residuals vs Leverage:

The "residuals vs leverage" plot helps us to identify some influential cases if any exists. In linear regression analysis there are cases where even the outliers could be important so as to be taken into consideration. However, not all of them are influential to determine a regression line, meaning that we could exclude them from the analysis without making any important difference on the result. In most cases they have no meaning and they follow the trend, but in some other they could be really meaningful. The points in the upper right or lower right corners outside the distance line are the ones that could be influential for our model.

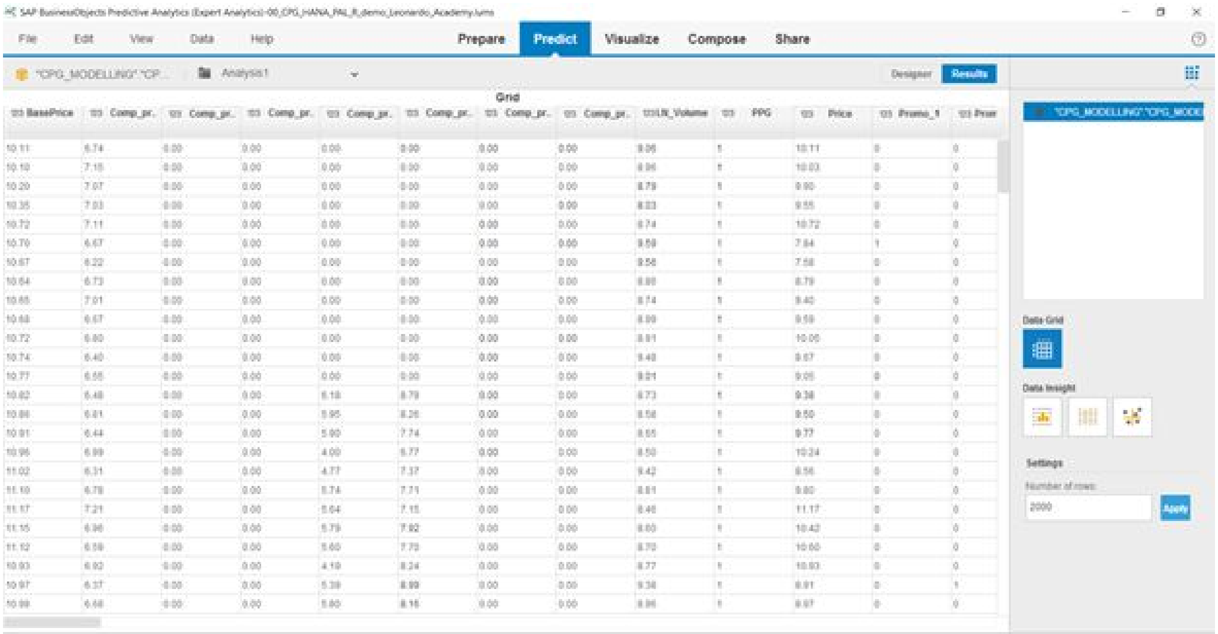
6.2 Modeling using Expert Analytics

Expert Analytics, is a SAP Predictive Analytics tool, which allows statistical analysis, data mining and predictive modeling. Additionally it allows the analysis of data through visualization techniques. This tool also supports the use of R language, offering even more opportunities for predictive analysis.

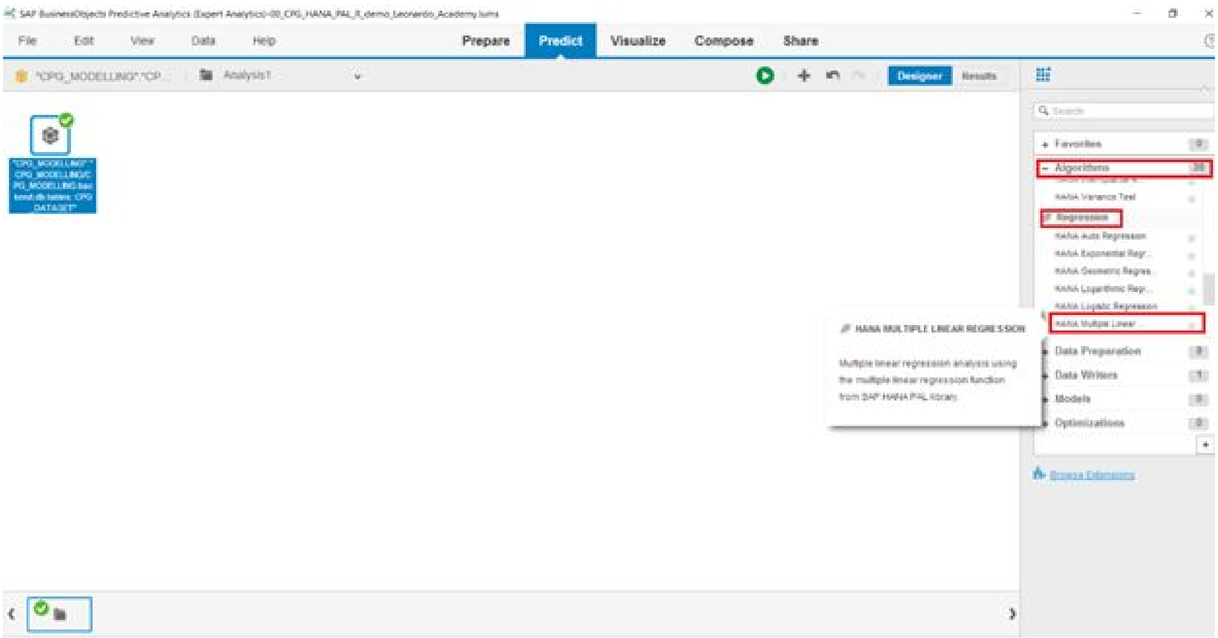
Below it seems that after we opened SAP Predictive Analytics, we select the Expert Analytics mode, which gives us the analytical capabilities mentioned above.



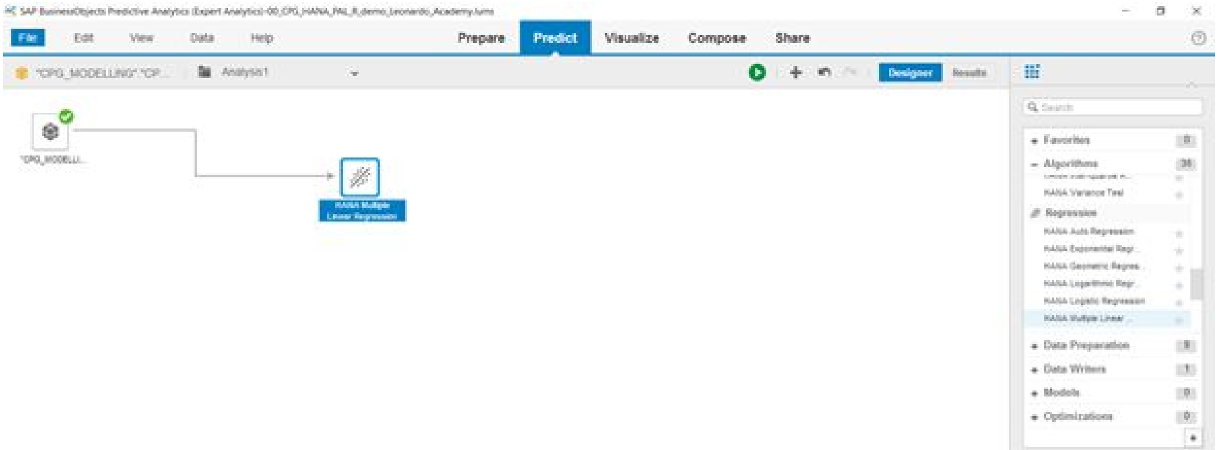
Then we need to link SAP Predictive Analytics Expert to SAP HANA Studio, which we used in the previous chapter for data visualization, to display our table of data. Below is the table that contain the data.



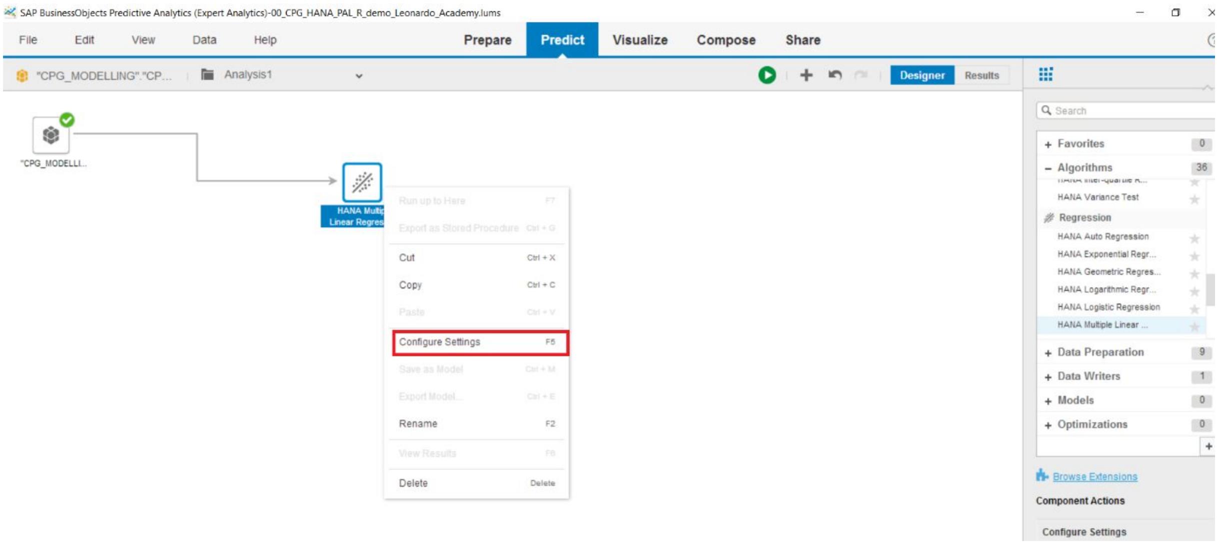
Then we select the predict tab and choose the HANA Multiple Linear Regression algorithm to apply to the dataset.



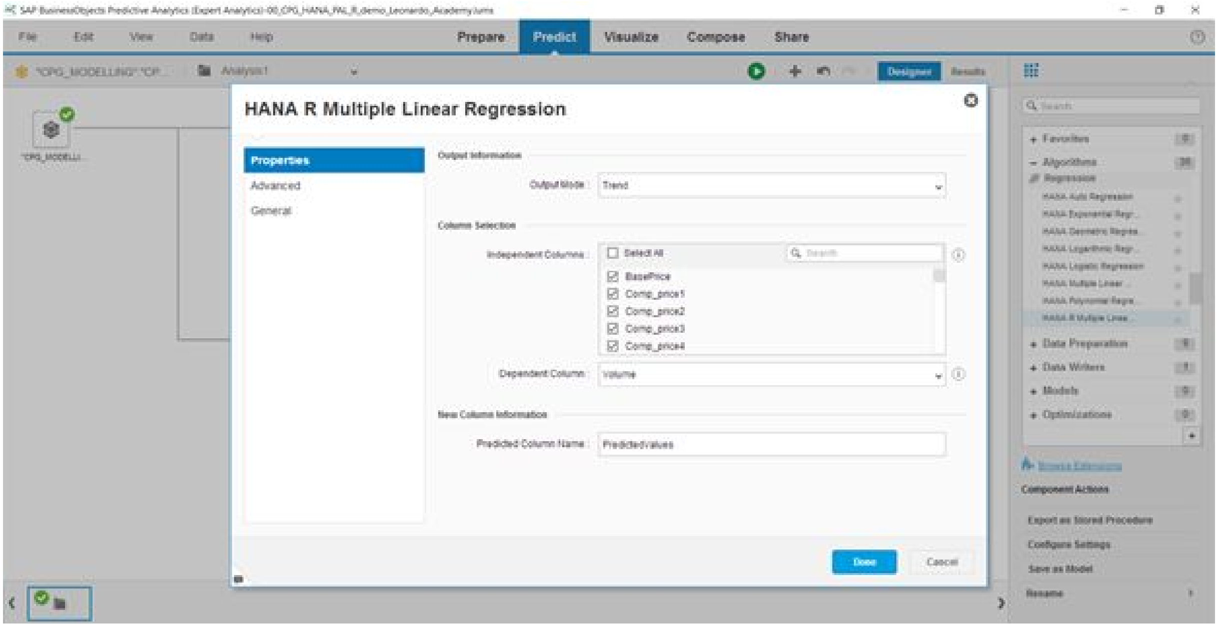
We drag and drop this algorithm to the menu:



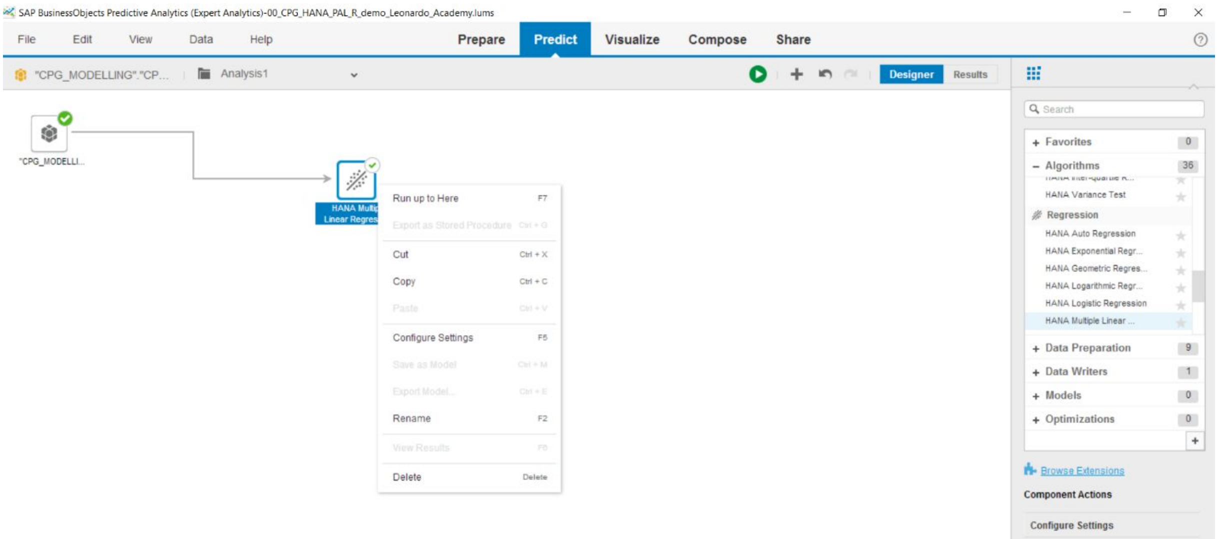
Then, we right click on the algorithm and select “Configure Settings” option:



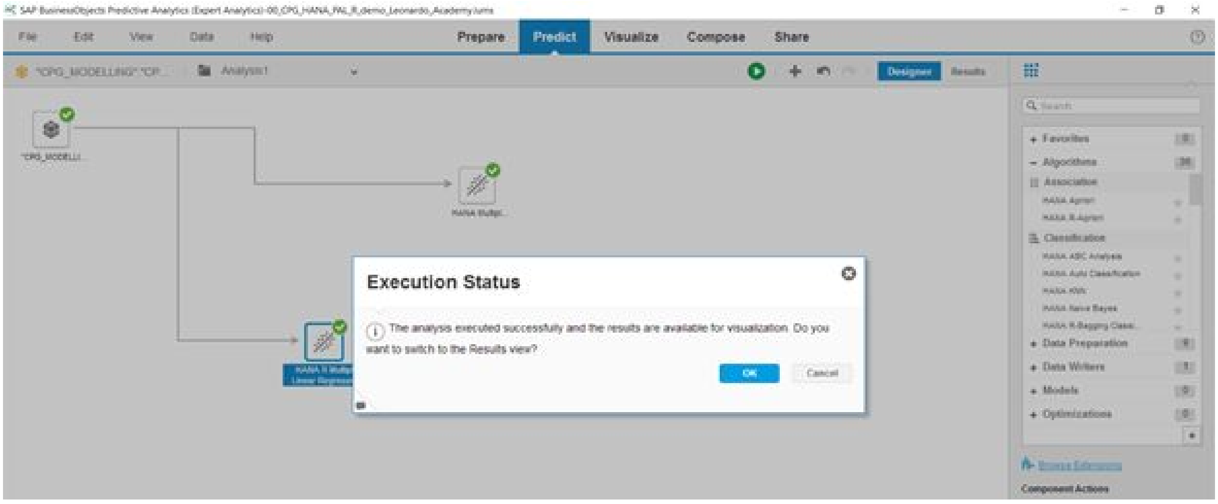
The next step is to select Volume of Sales as target variable and all the other variables except Volume of Sales and Week as Independent Variables.



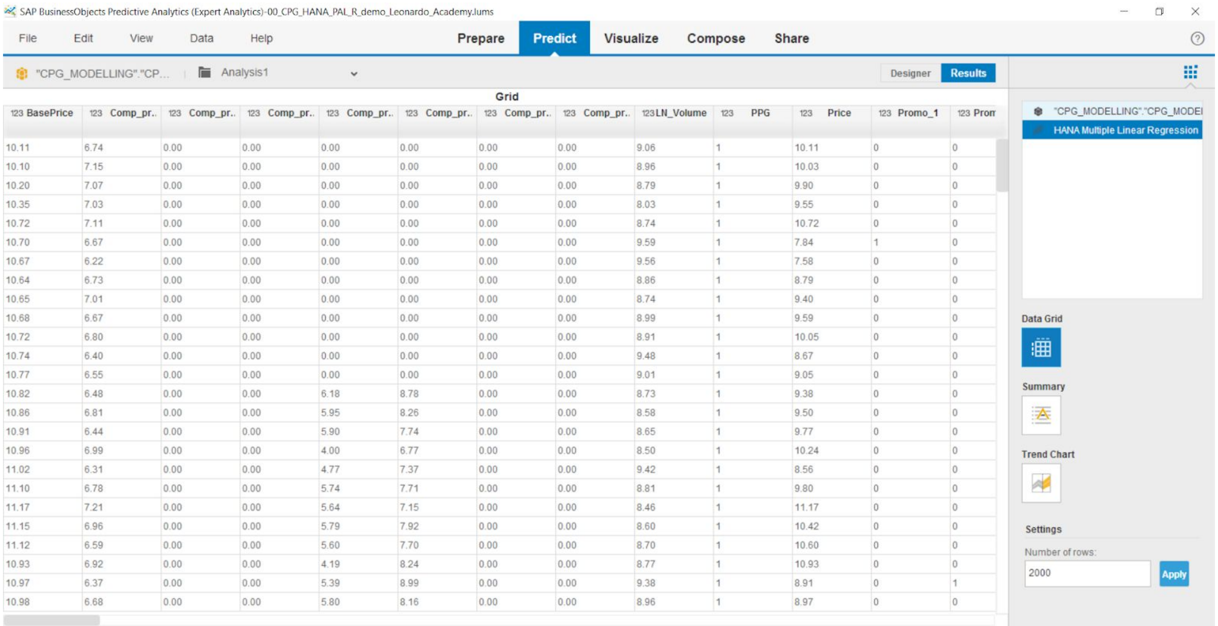
After we are done with this procedure, we right click on the algorithm and select "run up to here".



The image below shows that the model runs successfully.

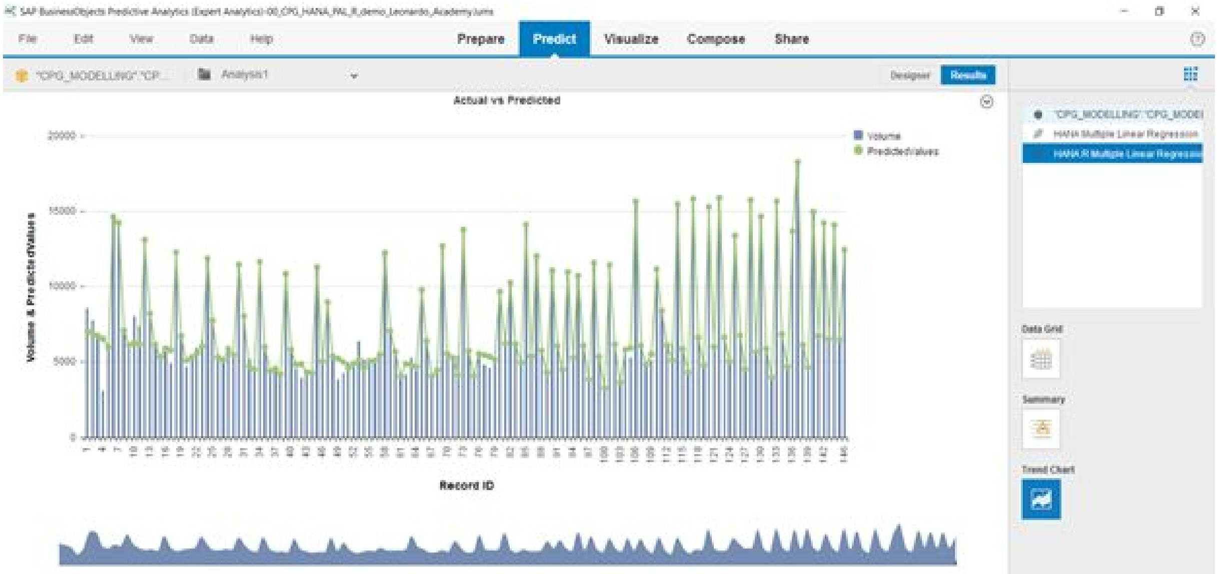


After we press Ok, the next table appears.

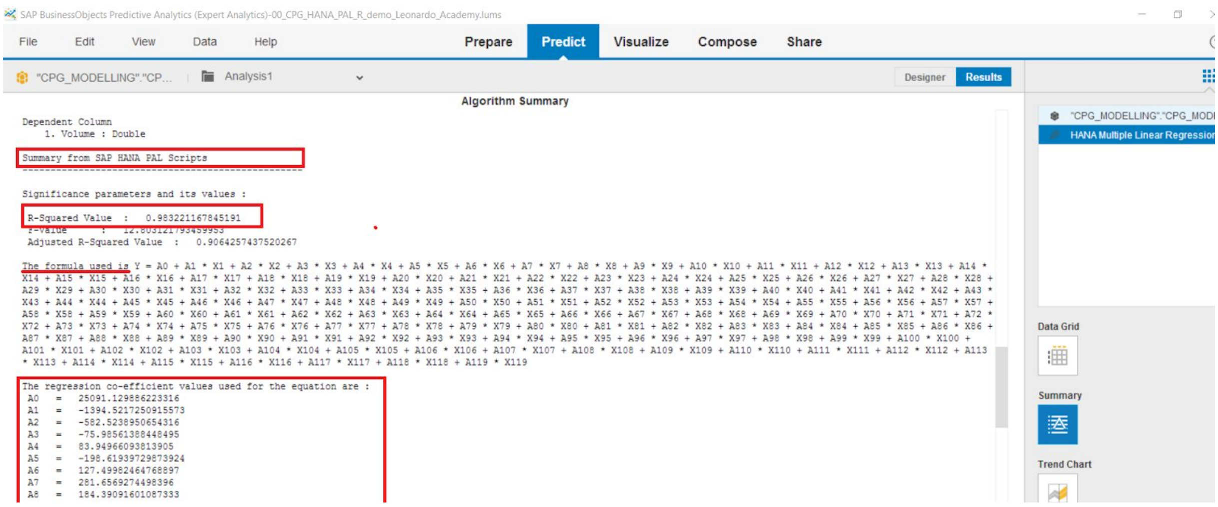


BasePrice	Comp_pr..	Comp_pr..	Comp_pr..	Comp_pr..	Comp_pr..	Comp_pr..	Comp_pr..	LN_Volume	PPG	Price	Promo_1	Prom
10.11	6.74	0.00	0.00	0.00	0.00	0.00	0.00	9.06	1	10.11	0	0
10.10	7.15	0.00	0.00	0.00	0.00	0.00	0.00	8.96	1	10.03	0	0
10.20	7.07	0.00	0.00	0.00	0.00	0.00	0.00	8.79	1	9.90	0	0
10.35	7.03	0.00	0.00	0.00	0.00	0.00	0.00	8.03	1	9.55	0	0
10.72	7.11	0.00	0.00	0.00	0.00	0.00	0.00	8.74	1	10.72	0	0
10.70	6.67	0.00	0.00	0.00	0.00	0.00	0.00	9.59	1	7.84	1	0
10.67	6.22	0.00	0.00	0.00	0.00	0.00	0.00	9.56	1	7.58	0	0
10.64	6.73	0.00	0.00	0.00	0.00	0.00	0.00	8.86	1	8.79	0	0
10.65	7.01	0.00	0.00	0.00	0.00	0.00	0.00	8.74	1	9.40	0	0
10.68	6.67	0.00	0.00	0.00	0.00	0.00	0.00	8.99	1	9.59	0	0
10.72	6.80	0.00	0.00	0.00	0.00	0.00	0.00	8.91	1	10.05	0	0
10.74	6.40	0.00	0.00	0.00	0.00	0.00	0.00	9.48	1	8.67	0	0
10.77	6.55	0.00	0.00	0.00	0.00	0.00	0.00	9.01	1	9.05	0	0
10.82	6.48	0.00	0.00	6.18	8.78	0.00	0.00	8.73	1	9.38	0	0
10.86	6.81	0.00	0.00	5.95	8.26	0.00	0.00	8.58	1	9.50	0	0
10.91	6.44	0.00	0.00	5.90	7.74	0.00	0.00	8.65	1	9.77	0	0
10.96	6.99	0.00	0.00	4.00	6.77	0.00	0.00	8.50	1	10.24	0	0
11.02	6.31	0.00	0.00	4.77	7.37	0.00	0.00	9.42	1	8.56	0	0
11.10	6.78	0.00	0.00	5.74	7.71	0.00	0.00	8.81	1	9.80	0	0
11.17	7.21	0.00	0.00	5.64	7.15	0.00	0.00	8.46	1	11.17	0	0
11.15	6.96	0.00	0.00	5.79	7.92	0.00	0.00	8.60	1	10.42	0	0
11.12	6.59	0.00	0.00	5.60	7.70	0.00	0.00	8.70	1	10.60	0	0
10.93	6.92	0.00	0.00	4.19	8.24	0.00	0.00	8.77	1	10.93	0	0
10.97	6.37	0.00	0.00	5.39	8.99	0.00	0.00	9.38	1	8.91	0	1
10.98	6.68	0.00	0.00	5.80	8.16	0.00	0.00	8.96	1	8.97	0	0

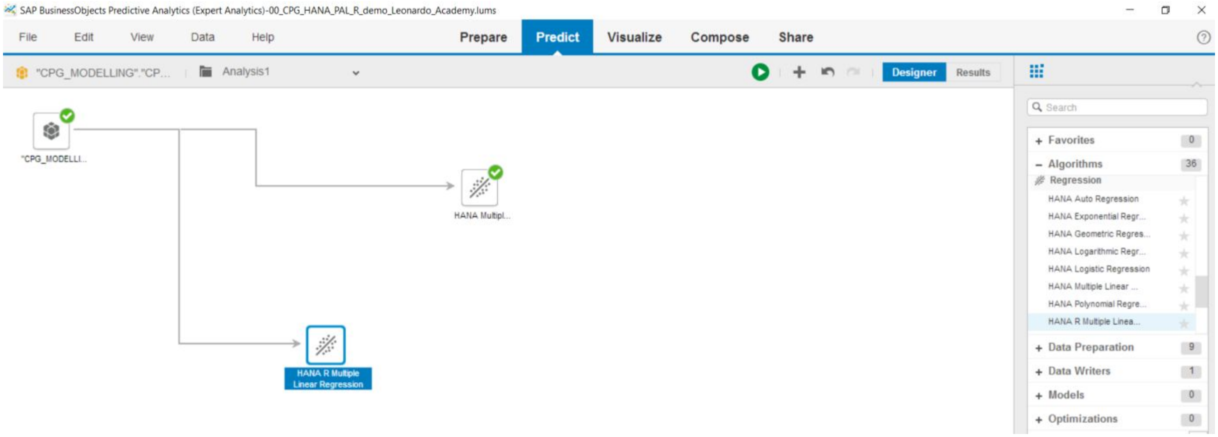
We select “Show the Trend Chart” and it is clear that predicted volume is close to actual volume. We are predicting with great accuracy every Volume Uplift (weekly pick):



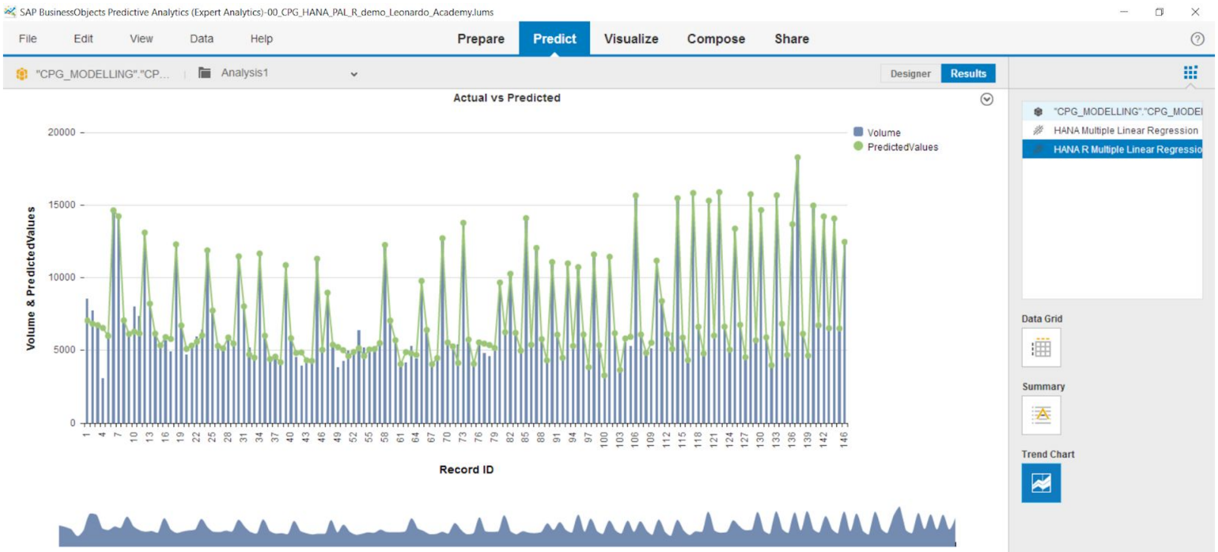
We select “Show the Summary” and we observe that the model accuracy is **98.3** R-Squared. We can also see the formula and the regression coefficient values, that we are using in order to create the What-if simulation tool in our UI app, which will be presented later.



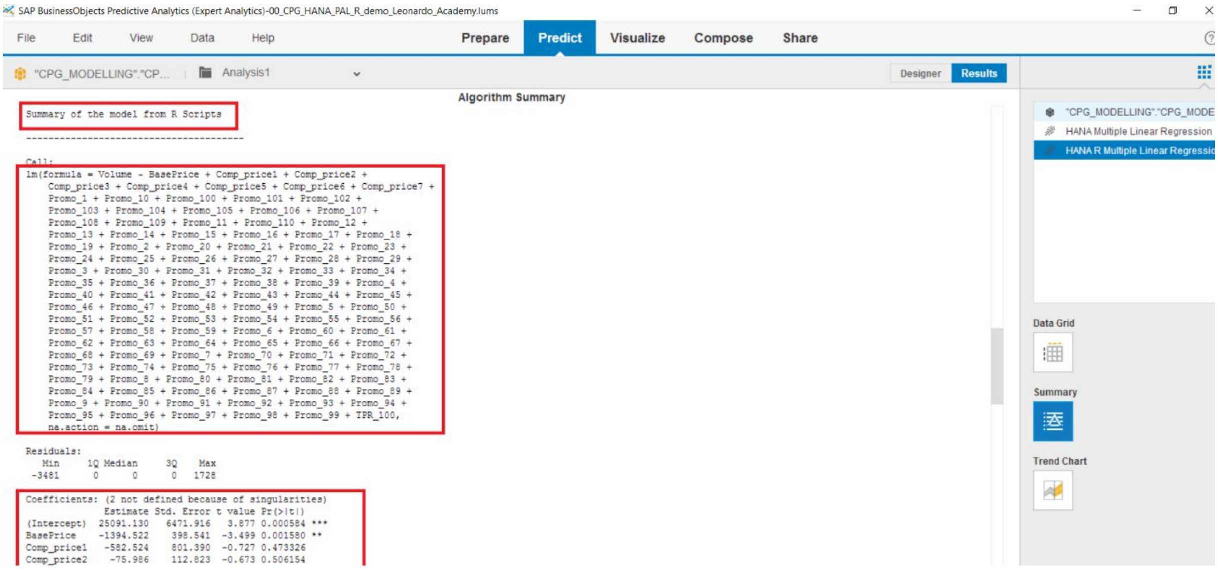
We are going back to the menu and select from the Algorithms the HANA R Multiple Linear Regression. This is the R version of Multiple Linear Regression.



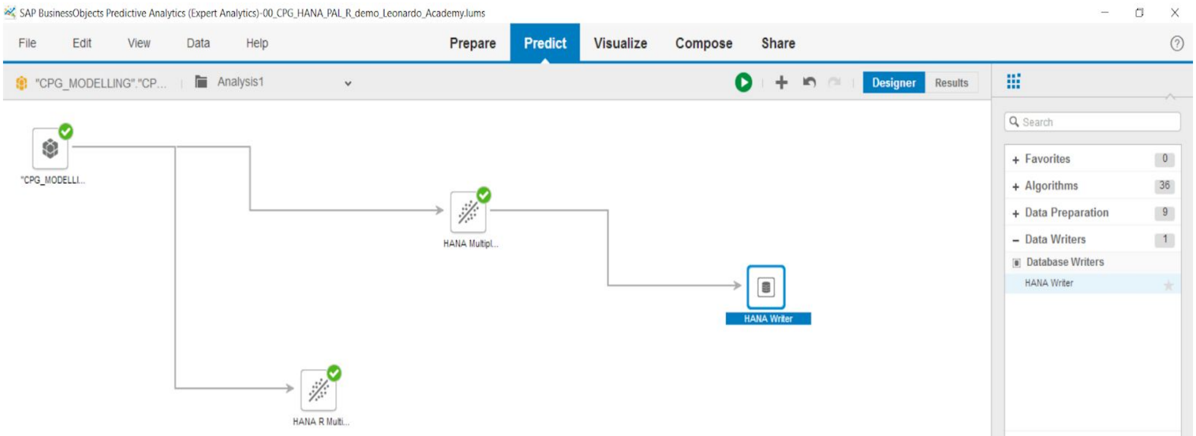
Then we repeat the procedure we followed previously. Finally we present the Trend Chart as before and the accuracy is still great.



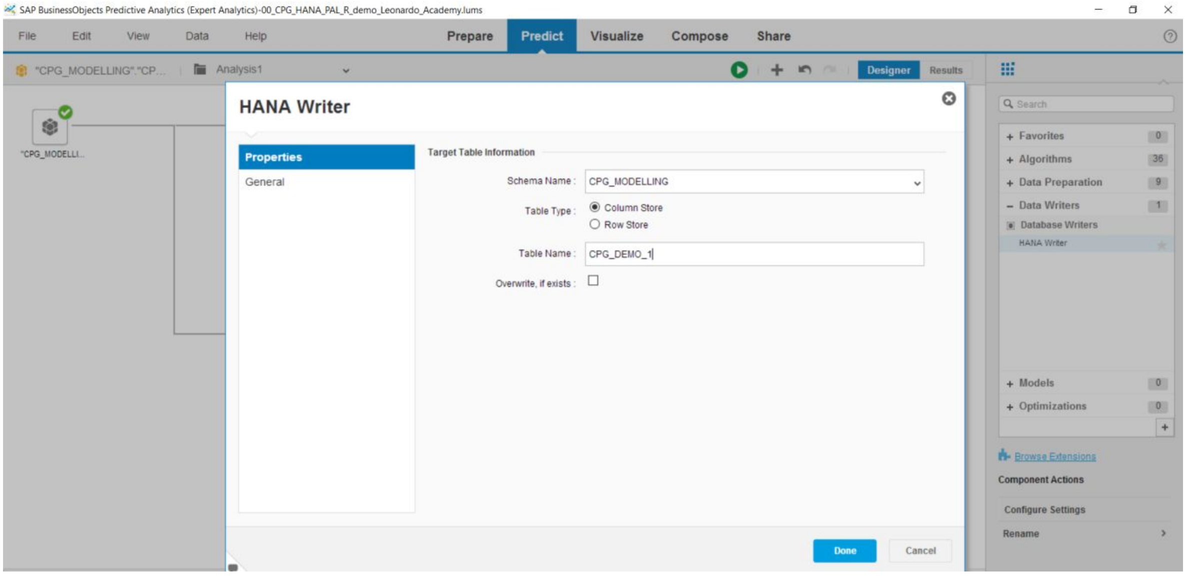
Then we present the Summary as before. Now the model is running as R – script and HANA is using the R function “lm”.



We go back to the menu and select “HANA Writers”:



We select configure settings once again and enter the HANA schema and the table we want to write the results:



The coefficients of the HANA PAL multiple linear regression are used as input for the UI5 application and the Simulation tool. The next step is to present the Automated mode using the same dataset and the UI5 application demo.

7 Conclusions and Next Research Steps

This chapter presents the conclusions that have been drawn through the research made under the present diplomatic work. Then some topics for future research are proposed, which could further contribute to the success of enterprises through data science applications.

7.1 Conclusions

The concept of marketing mix and its components is an important marketing stage for all companies. It is imperative that all marketing managers become aware of its importance in the marketing of products and services. However, new approaches of marketing mix modeling are being created every day due to business globalization and good customer relationship importance, which create requirements for its implementation.

The above has led to the need for modeling of marketing mix. This is a way in which businesses can turn their models into active recommendations, such as the appropriate amount of spending on advertisements and promotions and the time period in which an investment should be made. Thus, marketing mix modeling is the most effective tool for marketing decisions and marketing returns maximization.

The most common way of modeling the marketing mix is through the use of regression algorithms. More specifically, in sales forecasting, multiple linear regression algorithm is applied culminating in great accuracy, as many of the marketing mix variables are correlated to each other. Variables' correlation was obvious after the data visualization process, mainly through the creation of correlation matrix.

Many of the features used for the analysis presented expected results but some others surprised us. One thing is for sure, exploratory data analysis process through data visualization, contributed to the deep understanding of the variables and gave us useful information about the data and the relationship between them.

Then, through the use of multiple linear regression algorithm we forecasted the sales of the product, taking into account the prices of the rest variables. The implementation of this algorithm is possible through the use of open source and commercial tools with great success in both cases, as was determined by this diplomatic work's results. This model is excellent for such kind of data as it predicts sales with great precision.

7.2 Next Research Steps

The next step that could be taken so that marketing mix modeling evolves could be the prediction of a product's sales when there are more and different kinds of available variables.

An interesting case is the use of more data on competitors and their products and the prediction of sales based on them. another idea is the prediction of sales based on consumer personal data combined with existing knowledge of human psychology.

There are many other steps that could be taken, as marketing, like all the sciences, must be based on the information they have and exploit them in order to evolve themselves.

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