ABSTRACT

DEPARTMENT OF MATHEMATICAL SCIENCES

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APPLICATIONS OF GAME THEORY, TABLEAU, ANALYTICS, AND R TO FASHION DESIGN

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This thesis presents various models to the fashion industry to predict the profits for some products. To determine the expected performance of each product in 2016, we used tools of game theory to help us identify the expected value. We went further and performed a simple linear regression and used scatter plots to help us predict further the performance of the products of Prada. We used tools of game theory, analytics, and statistics to help us predict the performance of some of Prada's products. We also used the Tableau platform to visualize an overview of the products' performances. All of these tools were used to aid in finding better predictions of Prada's product performances.

APPLICATIONS OF GAME THEORY, TABLEAU, ANALYTICS, AND R TO FASHION DESIGN

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CHAPTER I

INTRODUCTION

Analysis of fashion data is one of the common methods used to measure and predict market patterns for a company’s products in the fashion world. Analysis of fashion data is just an example of the many methods that can be used to predict the outcome of the company. Researching market patterns and analyzing fashion data helps the company have an idea about its products and how to improve these products. This study, therefore, introduces some of the models that could be helpful in making a performance prediction for a fashion company.

The company of focus in this research will be the Prada company. This research only focuses on data for five years since there is limited data about the company’s products. For the study, only data for four of Prada's products was available. Again, the data obtained was only for five years (2011-2015). This kind of information is mostly not available to the public, or on the internet; it is private and only available for the company. Only a limited amount of data was provided on the internet by the Prada company. Therefore, only the available data provided by the company was scrapped for analysis. The use of three models aided the process of analyzing the obtained data.

One of the models used in this study is taken from game theory. By understanding game theory and some statistical methods, we will be able to estimate the performance of some of Prada's products. This study is focused on the applications of game theory. Many results were computed with the aid of code in R, the open-source programming language. Coding in the R programming language gives us the opportunity to perform simple linear regression on the data obtained, so that we can easily estimate the future profits of a company. This research also shows the mathematical model that illustrates how to predict Prada's future product performance. This model is a tool of game theory. Game theory is an interactive theory that helps us make decisions involving players, payoffs, and strategies. Game theory has great utility in several fields.

Chapter I of this study outlines the meaning and history of game theory, followed by the meaning and history of fashion design. In the end, the research proposes the application of game theory in fashion design. In most of chapter III, the game theory model was selected to help find the expected value of some of Prada's products. In fact, most of the study consists of the performance of Prada's products, products that can be forecasted using game theory and some essential statistical tools. Chapter IV presents several models that are used to estimate Prada's product performance. The R programming language will be used to predict the profits of Prada's products for the first quarter in 2016. At the end of the study, the results of the predictions in both the game theory model and the R programing language model are compared.

Statement of the Problem

This thesis is aimed at predicting profits of some of Prada's products and at predicting future performances. The following models will be applicable: game theory, Tableau, and simple linear regression analysis (via the R programming language). In this comparative study there are expected values found using tools of game theory with values found using other models like the simple linear regression models and data visualization models found using the Tableau platform compared.

Research Method

The collection and the analysis of the data used for predicting future performances of products will involve the use of the following tools:

- Tools such as expected values taken from statistics and utilized a great deal in game theory will be used to estimate Prada's 2016 profits.
- The Tableau platform will be used to graphically visualize the overall performances of Prada's products.
- Statistical tools such as simple linear regression and hypothesis testing using the R programming language will be used to find the best fitting line, and then aid in making predictions about the financial performance of Prada's products.
- The degree of fit of the data to the regression line will be determined as well. The better the fit, the more accurately we are able to make predictions about the financial performance of Prada's products.

Game Theory- Meaning and History

Classical game theory is a deterministic theory and “a well-known mathematical formalization of competitions with rational rules and rational players” (Lässig, 2002, p. 1). Whose strength “lies in the abstraction from a detailed scenario” (Fudenbery & Tirole, 1991, p. 3). As a mathematical theory that attempts to explain socioeconomic phenomenon, game theory “is based on structural procedures of mathematics and directed towards problems in various fields” (Rosenmüller and Trockel, 2001, p. 2). The background foundation of game theory is the human interaction in circumstances or businesses to which it is applied. The theory realizes that human interaction has a varied nature such as that of completion, cooperation, and conflict. Therefore, as a formal theory, game theory allows the making of interactive decisions as a result of the varied interactions in the field to which it is applied (Hauert & Szabo, 2004). Game theory is used to model any decisions involving two, or more than two, decision makers that are termed as players. Each player has their own two, or more than two, ways of acting. This mode of action is called a strategy. The well-defined preferences amidst the possible outcomes are shown by numerical payoffs.

Game theory has six major paradigms which include incomplete information, strategic behavior, mutual anticipation of actions, fairness, bargaining power, and equity. Through these paradigms, game theory employs a probabilistic context (as when it approaches the decision-making problem of a group). It is faced by uncertainty since it deals with a lack of information about the environmental state, the state of opponents’ abilities and incentives, and the state of interpersonal decision processing. The players’ strategic behavior is also randomly influenced. However, the theory is far from being simple: “The simultaneous occurrence of strategic, stochastic and dynamic phenomena, the fundamental role of epistemic aspects like knowledge and information and the impact of institutional and organizational structures make game theoretic analysis a highly complex task” (Rosenmüller and Trockel, 2001, p. 6).

Game theory can be applied in different fields apart from the fashion industry. At the moment, game theory is open to application in various fields. “ The conceptual groundwork of game theory was laid by Zermelo, Borel, Von Neumann and others in the 1920s and 1930s, and the first fully developed version of the theory appeared in *Theory of Games and Economic Behavior* by Von Neumann and Morgenstern” (Colman, 2005, p. 688). As time passed by, game theory began to have a significant impact on the behavioral and social sciences. The early theorist believed that the fundamental goal of game theory was that of prescribing the strategies that rational players should select from to maximize the payoff, making the theory more normative than descriptive. The theory was further augmented by a lesser-known work of König’s paper “On a Method of Conclusion from the Finite to the Infinite,” presented thirteen years after Zermelo. In the paper, Konig applied a general lemma to numerous topics, including game theory (Schwalbea & Walker, 2017). Eventually the theory gained more appeal due to its rationality assumption that people try to do the best for themselves in any circumstance, which made the theory more relevant to behavioral sciences and justified the experimental game.

Fashion Designing- Meaning and History

The word design in fashion designing originates from Latin and it means to symbolize some plan. However, the meaning of the word design has changed from time to time with the word gaining new meanings over time. For instance, initially, the term design was meant as a planning and organizing process but presently, designing not only stands for planning, it also symbolizes the result of a plan. Thus, fashion design is meant "…to make a choice within [the] various styles that clothes can take" (Sharon, 1984, p. 8). Kim and Cho state that "Fashion design consists of three shape parts: silhouette, detail and trimming. Silhouette is outline or outlook shape that expresses whole characteristic of a cloth. Detail is composed of subdivided parts of silhouette including neckline, sleeve, skirt, etc. Trimming is a generic term of all finishing ornaments" (Kim & Cho, 2000, p. 636).

Fashion design has its roots during the time of the industrial revolution. Before the industrial revolution, people made their own clothes or bought from small producers which meant that they only had a few choices. The tides turned in favor of fashion designing only after the industrial revolution enabled mass production of material. The large amounts of clothes that were being produced then offered a big variety of designs for the people to choose from. The market expanded further with the production of bulk cloth in designs (Brockman, 1965). However, despite the high demand and huge amounts of clothes available, not every consumer was good at designing fabrics and setting trends. As a result, there was the development of professional fashion designers.

Just as with other industries like music, book publishing, video game and film, the fashion industry is highly competitive and requires creativity " …this study was first shown in 1989, at the end of the so-called 'designer decade'… There are now 29,000 people working in design consultancies in the United Kingdom, which have sales of 1,600 million per annum" (McRobbie, 2003, p. 1). The field of fashion design widened further as it became embedded into the social and cultural framework, receiving a warm welcome from the consumers, and ultimately, with the application of various textile techniques, became a global business. The past decade has seen combined techniques with the aim of developing better fashion designs. “The challenges of virtual garment simulation are numerous ... First dedicated to the realistic simulation of the mechanical behavior of cloth, it soon evolved towards simulation of virtual garments on synthetic characters. While computer graphics get the most obvious benefits from garment simulation on animated virtual characters” (Volino, Cordier & Magnenat-Thalmann, 2005, p. 593).

Despite there being numerous changes in the meaning of fashion design and there being changes in the techniques employed to the procedure over time, the work of the designer has not changed much when it comes to designing clothes. It all starts with a sketch that is fleshed out into an illustration. Concepts are converted into sample pieces through the sketches, which are then tested for quality, aesthetics, and feel. Lately, computers also aid in this work.

The Strategies of Game Theory

Game theory employs two strategies: pure strategy and mixed strategy. A pure strategy is a complete definition of how a player will play the game (Game Theory, 2015). A pure strategy determines the move a player will make if faced by any situation. In a two-person game, there are two players competing for a market share: player 1 and player 2. Since there are two players, the total market share can be viewed as, player 1 + player 2 = 100%. For example, suppose these two players are two networks battling for viewers. The greater the viewership, the more money the network will make.

Each network can either show sports or comedy. Player 1 has a networking advantage in comedy; and, the other, player 2, has an advantage in sports. If both networks show comedy, then player 1 will get a 56% share of viewers. If both networks show sports, then player 2 will get a 54% viewer share. If player 1 shows comedy and player 2 shows sports then each will get 51% and 49% of the share respectively. And if player 1 shows sports and player 2 shows comedy, the viewer shares will be 50% each.

Table 1 shows all the possible outcomes.

Table 1

Payoff of the Pure Strategy

	Network 2/ Player 2	
Network 1/Player 1	Comedy	Sports
Comedy	56%, 44%	51%, 49%
Sports	50%, 50%	46%, 54%

From the viewpoint of player1, it is a better strategy to show comedy. This strategy is called the dominate strategy. From the viewpoint of player 2, it is a better strategy to show sports, regardless of whether player 1 shows comedy or sports; thus, player 2 also has a dominant strategy. The resulting outcome of a 51% viewer share for player 1 and a 49% viewer share for player 2 is the equilibrium, as none of the players can improve their outcomes unilaterally.

The mixed strategy, on the other hand, refers to a combination of all pure strategies that assign a probability to each pure strategy (Smith, 1988). The mixed strategy allows players to randomly select a pure strategy. Since probabilities bear the characteristic of continuousness, there are many mixed strategies present for a player to choose from. An example of a mixed strategy is found in the rock, paper, and scissors game. This game involves a rock, scissors, and paper which have probabilities of 50%, 25%, or 25%, respectively. Each player decides the pure strategy to use, randomly, based on these probabilities. If these probabilities are associated with the first player, (let us call him Cole), his payoffs versus player 2 will be as shown in Table 2.

Table 2

Payoff of the Mixed Strategy

		Ann		
		Rock	Scissor	Paper
Cole	Rock	0	1	-1
	Scissor	-1	0	1
	Paper	1	-1	0
	Mix of 50-25-25	0	0.25	-0.25

If Cole plays the mixed strategy, the probabilities are multiplied by their outcome in each column. To illustrate, when Ann plays Rock as a strategy (column 1), then there is a 50% probability that there will be a tie (Rock versus Rock) --which is (0 x 0.50 = 0). Now, given that Ann selects Rock as a strategy, if Cole selects row 2, then there is a 25%

probability that Ann wins (-1 x 0.25 = -0.25). Now, given that Ann selects Rock again, there is a 25% probability that Cole will select Paper to win (1 x 0.25 = 0.25). Thus, according to the rules of game theory, the expected value of the game is given by the sum of the products of the probabilities and the payoffs. So, again, if Ann selects Rock, then for Cole, there is a 50% probability that the expected value is zero. Ann can also use mixed strategies. Let's assume that Ann choses a mixed strategy of 25% for Paper, 50% for Scissors, and 25% for Rock. Inserting this mixed strategy is another option for Ann. This payoff matrix will be shown in Table 3.

Table 3

Payoff Matrix for the Mixed Strategies for Player1 and Player2

		Ann			
		Rock	Scissor	Paper	Mix of 25-50-25
Cole	Rock	0	1	-1	0.25
	Scissor	-1	0	1	0
	Paper	1	-1	0	-0.25
	Mix of 50-25-25	0	0.25	-0.25	0.0625

This example of game theory can be used in several fields: fields such as economics, industrial organization, psychology, political science, sociology, and biology to name a few. It can also be applied to fashion design. Game theory can be applied in fashion design to provide answers and to help in decision-making strategies in areas of fashion design. For example, differentiating consumers like those that imitate individuals and buy clothing on sale; and, those who buy clothing at high prices to look original. The rising number of trends and parallel styles also conceives the need of game theory (JØrgensen & Liddo, 2007).

Background in the R Programming Language

Over the last three years, R has had been increasingly useful around the world. R has gained popularity because of its many libraries, its ease of use, its open source availability, its adaptability to large amounts of data, etc. R has been around since 1993. These days, R has become necessary in areas such as data science, which includes data visualization and sentiment analysis, other fields of study. It is a tool that works easily with statistics, linear algebra, operation research, and machine learning. R has been utilized for ventures with banks, political crusades, new tech companies, new nourishment companies, global advancement and help associations, healing centers, and real estate developers (Lander, 2014).

The R programming language can facilitate making predictions, and aid in analyzing data by using many lines of code. In Chapter IV, we will use the R programming language to create a best fitting line, then predict the future performance for Prada's Products.

CHAPTER II

LITERATURE REVIEWS OF APPLICATIONS IN FASHION DESIGN

Introduction

The world of fashion marketing and merchandise is experiencing enormous changes in fashion designs. Manufacturers are in constant battles of producing quality goods with the aim of increasing the consumption power of the consumers. Through all the processes from designing to manufacturing for the entire market, there is need of involvement of related mathematical knowledge as well as skills (Frontoni et al., 2016). The mathematical skills and knowledge associated with fashion design usually involve simple mathematical computations that are normally gained in the process of studying at learning institutions.

There is a need for fashion marketers to obtain a sufficient amount of mathematical knowledge. This will serve the purpose of enabling fashion marketers to understand the design of fashion manufacturing items as well as to understand the whole manufacturing process. The knowledge and skills gained will result in determining the correct measurement of costs in the market. Mathematical skills as well as knowledge are essential (Lee et al., 2014). Today, there is need for focusing on how to integrate related mathematical concepts into the merchandise and marketing industry. Mathematical knowledge and skills tend to assist in problem solving in the fashion and merchandise industry.

In most economies, one is expected to do research on the operations and the market demands of fashion products before thinking of setting up a fashion business. There is also the need of an understanding of different cultures that exist in different regions of the world (Battista & Schiraldi, 2013). Understanding different cultures mitigates the complexities that are involved in importing or exporting products globally. Because of advanced technology as well as innovations globally concerning fashion in different global cultures, the integration of mathematical skills and knowledge of the merchandise is needed to meet the demands of the global fashion market. There is, therefore, a need for fashion producers to familiarize themselves with related mathematical knowledge and skills to empower themselves to understand how to solve problems that tend to emerge; and, to make appropriate decisions regarding the retail and the manufacturing of fashion products.

The following are the mathematical and statistical models that will apply to fashion and design, with a good explanation of how these models work. These models are quite detailed regarding their purpose in the fashion industry.

The Oligopoly Model

This model assumes a finite number*, I,* represents the fashion firms (in which each typical firm is represented by *i)* that are taking part in the production, distribution, and storage of the fashion products. These products compete in a non-cooperatively oligopolistic way (Fujiwara, 2015). Each firm bears an individual product that it produces to the market. It works in the sense that if the firm produces its fashion products, it does not influence the whole fashion market. This is due to the fact that there are numerous fashion companies in the industry and the domination of an individual firm is of small significance. The fashion industry will continue to operate despite the influence the individual firm has in the fashion industry.

The assumption made here is that the demand price function is connected with each fashion firm's product in the demand market. The demand price of a fashion firm, i, is labeled as R_k ; and, the demand price functions are labeled as $P_{ik} = P_{ik}(d)$, k=1,…, $n_{R;i=I,\ldots,\ I,}$ It is the price for the fashion firm i's product at a given demand level in the market that may result due to dependency upon the demand for this particular fashion product, as well the demand of for other substitute fashion products. P_{ik} shows competition on the demand side of the competitive fashion products in the supply chain network. The kind of demand price functions is of the genre that is utilized in the learning of the differentiation of oligopolies.

The demand price functions are limited to being linear and are usually assumed in economics. The model is limited to a single demand market; however, the firms seem to compete in various demand markets.

The Linear Programming Model

The linear programming model is often used in the scheduling and the planning of operations. "One form of planning is by aggregate planning; it entails scheduling of concentration on personnel, production, and inventory stages during intermediate planning levels" (Tiwari, 2017, p. 86). For linear programming models to work efficiently in determining price in the fashion and merchandise market it needs to satisfy the following requirements:

a. The decision determinant variable needs to be continuous in the sense that it needs to have value within some restricted range.

b. The aim determinant function needs to be linear.

c. The left-hand side of the constraints needs to consist of linear functions.

When used in fashion design, the linear programming model tries to deal with product mixing and resource allocation when there is no change in price. The price is fixed by an outward force on a firm's organizational a decision. In the fashion and merchandise market, there is need for controlling the prices of their inputs and their outputs through the number of fashion products they produce and purchase. "For example, a fashion company decreases the price of the fashion product; it aims at selling more by reducing its price" (Mladenov et al., 2017, p. 89). The fashion company's goal is to determine the optimal production, or resource allocation, strategy as it alters the unit price of the product. Thus, there is need to use linear programming models to solve price problems when the underlying demand functions describe the relationship that occurs between demand and price.

When used in problem-solving, the linear programming model dictates that one should construct nine different models, each containing the product prices. Each model needs to have an objective function that is based on the declared product prices, inclusively of the upper limits of the product demand as they vary in price. After solving the nine linear problems, one can then proceed to find the optimal linear solution. We can then set the price of the fashion product.

The Test Store Selection Model

The method is widely used when resolving the key decisions that involve designing a merchandising test. Thus, it involves how many particular depots are needed to carry the test; and, the process to be used to establish a seasonal forecast for the whole chain which is specified for test depots sales. The model assumes:

i. The retailer has selected a set of products that will undergo the test.

ii. A specific time interval within which the products are likely to be sold.

iii. The retailer has determined the set period in which the products will be offered for sale in the chosen depots to test their sale potential.

The model defines the important sales period as the time within which the selling price of the product is likely to be higher than the acquisition cost plus variable selling expenses. The level of inventory in the specific depot is enough to prevent shortages of the present supply. The model assumes the same price is accorded in all depots during this period; however, the time price may vary. The model restricts sales information to the crucial sales period. The model ensures that sample sales are at each depot and are set to maximize the appeal to customers of that particular store.

The actual retail of the fashion merchandise model assumes that the retailer has assembled a sales history that is comprises of comparable products that have the possibility of being on offer during the prior season(s).

- We let n represent the number of depots in the chain
- m represents the number of previous products in which there is the history of sales present

- S_{ip} be the observed sales during the crucial sales period at the depot, I, for the product p
- We shall have, $S_p = \sum(S_{ip})$, as well as the S_{ip} (bar), represent the sales of product, p, in depot i during the time of comparison, in period and duration, to the period in which the test is likely to take place

There is a need for checking the K test depots, where we have the petitioning of the n depots of the chain into k different clusters. "The depot within a particular cluster is selected to maximize the measure of dissimilarity that focuses on the percentage of the total sales that are represented by the sales of a particular product prior in each depot" (Medarac et al., 2016, p. 79). These have the possibility of having the same cluster; and, all the depots within a cluster have the same percentage of each prior product.

The model is first described by optimization as it creates clusters and then chooses the test depot within each cluster. The model is especially meant for the integer program, which is known as the K-median problem. This problem is solved with a highly efficient algorithm.

The model has the following variables present:

Y_i = {1, if the depot j is selected as the test store, or 0 otherwise}

X_{ij} = {1, if depot i is also selected to a cluster denoted by test store j, or 0 otherwise}

The parameters present

I = (1…., n) = depot index set

P = (1…., m) = prior product index set

$W_i = \sum(S_{ip})$

$B_{ip} = S_{ip}/\sum(s_{ip})$

$D_{ij} = \sum(u_p \max(B_{jp} – B_{jp}0) + 0_p \max (B_{jp} – B_{jp}^r0))$

Thus, the test store selection problem is represented by the following integer application

Min $((\sum\sum) (w_i d_{ij} x_{ijr}))$

subject to: $\sum (x_{ij}) = 1$ ……. (i)

$\sum(y_i) = k$. ……. (ii)

Equation (i) represents the condition at each depot that is assigned to a test depot. Equation (ii) is just for the assigned only selected test depots.

"The K-median problem is interpreted through the forming clusters and selecting a test depot in every cluster that minimizes the cost of forecast errors." (Ngai et al., 2014, p. 81) The method is mainly applicable to women's specialty Apparel Retailers, where a different region corresponds to the stores varying in size and format.

The model aims at exposing fashion designers and manufacturers to an intellectual, interesting problem context laden with opportunities through the research. The model impacts on the retailer profits regarding fashion in the following ways:

i. Fashion sales of a given product mix vary greatly in the depots of a large chain.
ii. Fashion market and merchandise testing processes exploit this depot based on clustering on the similarity of sales mix, implying different fashion sales in the fashion industry.

iii. The type of relationship between the fashion algorithm on the clusters formed and the micro-merchandising is useful to explore. It entails each cluster being treated as a virtual chain that is controlled separately in a consistent manner concerning fashion products mix, timing delivery, advertising message and the store layout.

The Game Theory Model

"Fashion marketing and merchandise in, game theory model the behavior of fashion designers and fast-fashion imitators in determining how behavior changes the fashion industry experiences in different legal [government]" (Aumann, 2017, p. 29). The model takes into account the weakest government where there is no legal protection experienced by any type in all fashion designs. Secondly, the model considers a government where there is uncertain legal protection for fashion designs, as it is experienced in the current American system. In the current American system, fashion designers aren't in a position of knowing whether a claim of infringement has been litigated successfully. Thirdly, the model takes into account a game through a proposed innovative design that aims at protection and privacy prevention to various design developers. It provides explicit copyright protection to fashion designs.

When there is no legal protection available, there is no remedy for the fashion designer, and no relief from infringement. Thus, the game theory model seeks to act as a problem-solving tool. The model assumes that the one who copies or imitates has a greater economic incentive to select the exact copy than to redesign, since the exact copy will have more imitations than the redesigned fashion. The reasoning is that fast-fashion firms account for the trending in a market industry (Rapoport, 2018). Firms that copy or imitate don't incur the time and money that are connected to redesign.

The ability to copy or imitate helps the firm to make quick decisions between two outcomes: redesign and copy. The copier or imitator is entitled to go for an exact copy since it has a high payoff of, say, one hundred; whereas, the redesign payoff is, say, fifty. To apply principles of game theory, this idea is considered a game. In this game, the combination of strategies is an exact copy. It means that the copier or imitator gains one hundred while the designer loses one hundred. It is a legal game with no legal protection. This game is a zero-sum game model, where one must achieve an optimal outcome as is demonstrated by the copier's choice of redesign and the designer's choice. Based on the above information, it is possible to apply game theory to fashion design. In this thesis, we will use a particular game theory model to make predictions about Prada's products.

In conclusion, there is a need for the incorporation of mathematical models into the fashion market and merchandise industry. These mathematical models are necessary for solving some of the problems that require mathematical concepts. The mathematical models are used to help in creating a sustainable environment in which the fashion industry operates. The variational inequality oligopoly model, on the other hand, helps in the understanding that the firm seeks to maximize its profits while minimizing its production costs. The costs could be accrued during the entire period of the supply chain, given that the process involves activities of manufacturing, distribution, and storage. By utilizing the game model, consumers will have a better vantage point based on their environmental consciousness, as it affects their consumption.

Higher levels of learning at universities and colleges offer mathematical skills and knowledge to be used in the fashion and merchandise industry. The teaching of fashion market and merchandise programs is given to enhance the development of expertise in the industry. The expertise in the industry will then result in the production of fashion products that can correspond to different needs of customers globally. The belief is that fashion programs will gear up the production of graduates, skilled with mathematical knowledge, that will disrupt the industry and push it towards a production of high quality fashion products that will prompt higher demand.

CHAPTER III

APPLYING GAME THEORY AND TABLEAU MODELS IN PRADA'S PRODUCTS

In this chapter, we are going to apply the game theory and the Tableau platform to the field of fashion design. The two models will be expressed as tools used to estimate the future profits for Prada's products. However, before applying the two models, there is need to give a real-life example. Below is a simple experimental example to clarify the idea.

Experimental Example

A small company that makes T-shirts needs to know which types of T-shirts are popular. They have four strategies: Traditional, Contemporary, Sports and Designer. Besides deciding on the most popular T-shirt dependents on the economy during the four quarters of the year. Because of the state of the economy in the 4th quarter, the Traditional T-shirts will achieve the highest profits, while in the 3rd quarter the Contemporary T-shirts will be the best. In the 2nd quarter, the sports T-shirts would do the best. Lastly, in the 1st quarter, the best type of these four T-shirts is the Designer T-shirts. From this information, what should the firm do? They should carefully define the problem. First of all, they need to go back and study each quarter before making any decision.

There are four quarters: 1st quarter, 2nd quarter, 3rd quarter, or 4th quarter. Next, they should list the strategies: Traditional T-shirt's strategy, Contemporary T-shirt's strategy, Sports T-shirt's strategy, and Designer T-shirt's strategy. These can be shown in a payoff matrix. The numbers in the matrix represent profits in thousands of dollars. Observe in Table 4:

Table 4

T-Shirts Payoff Matrix

T-Shirt (Strategies)	1st quarter	2nd quarter	3rd quarter	4th quarter
Traditional	3129	1964	4082	5461
Contemporary	1009	984	1124	654
Sports	584	894	239	754
Designer	2346	1346	1000	1111

If the managers of the company are optimistic thinkers, they will go for the greatest number in the matrix--which is 5461 (representing $5,461,000 in profit). The best strategy in this strategy would be to create the Traditional T-shirts, especially during the 4th quarter. Pessimistic managers of the company need to stay away from the most exceedingly terrible of all bad things that could occur. When the company produces Traditional T-shirts, the most noticeably bad thing that can happen is a profit of $1,964,000. For Contemporary T-shirts, the worst is a profit of $654,000, while the most exceedingly awful thing that can occur from Sports T-shirts is a profit of $239,000. For the Designer T-shirts, the least profit is $1,000,000. The company's strategy here is to produce the Traditional T-shirts.

Let us assume data was captured over the last two years for the sales of four different types of popular T-shirts. The data in each cell is a probability, or ratio, based on data scrapped from companies over the last two years. See Table 5.

Table 5

Fiscal Periods during the Year

		1st quarter	2nd quarter	3rd quarter	4th quarter
Popular T-Shirts	Traditional	0.30	0.15	0.10	0.45
	Contemporary	0.05	0.32	0.60	0.03
	Sports	0.05	0.15	0.35	0.45
	Designer	0.02	0.25	0.30	0.43

Note: Each number in the Table 5 is a probability, and the sum of each row is 1.00:

a) $0 \leq a_{ij} \leq 1$, where a_{ij} is an entry in the Table 5

b) $\sum a_{ij} = 1$ (In each row)

The company can now find the expected value of each possible strategy. The expected value of the game is given by the sum of the product of the probabilities and the profit for each popular T-shirt. This gives us Table 6:

Table 6

The Expected Value of the T-Shirts

T-Shirt	1st quarter	2nd quarter	3rd quarter	4th quarter	Expected Value
Traditional	938.7	294.6	408.2	2437.2	4078.7
Contemporary	50.45	314.88	674.4	19.62	1059.35
Sports	29.2	134.1	83.65	339.3	586.25
Designer	46.92	336.5	300	477.73	1161.15

Here, the best strategy is the Traditional T-shirt; the expected profit is $4078.700. So, it is expected that the Traditional T-shirts will have the best performance over time.

Hence, it is expected that the Traditional T-Shirts will be doing the best over the next year.

The Application of Game Theory

In this study, it is expected that the researcher finds some historical data on particular items in the fashion industry for at least five years. However, the study was faced with numerous challenges as far as data collection is concerned. First of all, despite going to numerous stores, no relevant data was provided. Those working at stores claimed that they could not provide the data because it is private. Attempts to reach other apparel businesses did not bear fruit. Most of the businesses never replied to emails sent to them. Other businesses demanded payments before the researcher could gain access to their records. Given these frustrations, the researcher took to the internet as a last resort. By conducting searches on the internet about fashion companies around the world, the Prada Company was identified. They listed four products: Leather Goods, Footwear, Clothing and "Others." They listed data on these products from 2011 to 2016.

The Historical Data (A Real -Life Example)

Four products will be used to show applications of game theory to fashion design. We will perform the applications. Frist, we need to have probabilities to calculate the expected value of the products. To identify the probabilities, we need to go back five years for each product. Data was collected and stored in an excel file and then used to calculate the probabilities. Tables 7-10 show the net sales during five years subdivided into four quarters for Leather Goods, Footwear, Clothing and Others respectively. The numbers in Tables 7-10 represent the profits in thousands of euro for Prada over the years from 2011 to 2015.

Table 7

Net Sales of Leather Goods' Product (€ mn)

Year	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
2011	263.7	354	341.9	466.9
2012	417.3	525.8	501.2	593.8
2013	538.4	618	554.4	621.7
2014	479	496	471.8	518.9
2015	485.5	511.6	429.1	493.7
Total	2183.9	2505.4	2298.4	2695
Probability	38%	21%	19%	22%

Table 8

Net Sales of Footwear's Product (€ mn)

Year	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
2011	98.8	176.3	116.3	168.7
2012	134.7	180.6	135	175
2013	118.2	164.2	133	179.2
2014	95.5	113.1	114.7	125.5
2015	128.6	144.3	126.8	137.8
Total	575.8	778.5	625.8	786.2
Probability	21%	28%	23%	28%

Table 9

Net Sales of Clothing 's Product (€ mn)

Year	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
2011	87.8	124.6	125.4	174.9
2012	113.8	134.9	139.3	175.4
2013	108.1	140.7	141.5	191.3
2014	111.2	118.5	129.4	153.1
2015	120.2	128.7	130.8	161.9
Total	541.1	647.4	666.4	856.6
Probability	20%	24%	25%	32%

Table 10

Net Sales of Others' Product (€ mn)

year	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
2011	5.2	7.1	5.6	6.2
2012	7.5	10.2	7.8	4.2
2013	7.9	12.1	10.7	8.8
2014	12.1	16.8	13.7	11.7
2015	15.1	18.4	14.3	12.9
Total	47.8	64.6	52.1	43.8
Probability	23%	31%	25%	21%

Now, we find the probabilities for each product. It is better to collect all these probabilities in one matrix. This matrix will be shown in Table 11. The data in each cell is a probability, or ratio, based on data scrapped from companies over the last five years.

Table 11

The Probabilities of the Products

Product	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
Leather Goods	38%	21%	19%	22%
Footwear	21%	28%	23%	28%
Clothing	20%	24%	25%	32%
Others	23%	31%	25%	21%

Next, after finding the probabilities, we will introduce the net sales for the products in the last year studied. The last year given is 2015 according to Prada's annual report that will be showed in Table 12. There are four possible strategies: Leather Goods, Footwear, Clothing, or "Others." To improve their sales based on the profits in each quarter, Prada needs to use the probabilities to find the expected value of these products. These expected values will be the profits of Prada’s products for the first quarter in 2016.

Table 12

Net Sales of the Products in 2015

	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter
Leather Goods	485.5	511.6	429.1	493.7
Footwear	128.6	144.3	126.8	137.8
Clothing	120.2	128.7	130.8	161.9
Others	15.1	18.4	14.3	12.9

According to Table 12, the 2nd quarter (Leather Goods) achieved the highest number in the Table --which is €511.600-- that will be chosen when the decision makers of Prada are optimists. From the data, the Prada company can predict that of all the products, Leather Goods products will perform the best next year, and this will happen during the second quarter of the year. According to the rules of game theory, we are required to find the expected value using **mixed strategies**. When we multiply the probability and the profit in each cell in Table 12, then sum each row, we will find the expected values. See Table 13:

Table 13

The Expected Value of the Products

	1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	Expected Value
Leather Goods	184.49	107.436	81.529	108.614	482.069
Footwear	27.006	40.404	29.164	38.584	135.158
Clothing	24.04	30.888	32.7	51.808	139.436
Others	3.473	5.704	3.575	2.709	15.461

From Table 13, it can be observed that the expected value of the Leather Goods product is strictly the highest amount of all the products' expected values. The Leather Goods product's expected value is €482.069. Based on this result, the Prada Company should choose Leather Goods over the next few quarters since it is the best possible strategy for the Prada Company. The expected values will be the profits in the future quarter for Prada's products. The exact values for the 1st quarter in 2016 is unknown because it was not available on Prada's website. However, the actual profit for the full year in 2016 is provided on the company's website. As a result, some tools of game theory will be applied to Prada's products for a full year to see how close we are to the exact value of the profits in 2016. Let us look at Table 14 which presents the five full years for these products' profits as provided on Prada's website.

Table 14

Net Sales of the Product (€ mn) – Full Year

Products	2011	2012	2013	2014	2015
Leather Goods	1,426.50	2,038.00	2,090.50	1,965.60	2,103
Footwear	560.1	625.4	376.7	448.7	726
Clothing	512.6	563.3	490.6	512.3	612
Others	24.1	29.7	38.8	54.3	63

To calculate the expected value of Prada's products for the full year of 2016, the probabilities for each product are required. The probabilities already calculated in Table 11 will be applicable for each product. Now, we can find the expected values by calculating the sum of the product of the probabilities and the products' profits. Hence, the expected value for the full year of 2016 is given in Table 15.

Table 15

The Expected Value for Full Year 2016

Products	2012	2013	2014	2015	Expected values	Actual values
Leather Goods	774.44	439.01	373.46	463	2,049.57	1,804
Footwear	131.334	105.476	103.201	203.28	543.291	679
Clothing	112.66	117.744	128.075	195.84	554.319	600
Others	6.831	12.028	13.575	13.23	45.664	56

According to Table 15, it can be confirmed that the expected values in 2016 are similar to the actual values. By being close to the exact values, we are able to use our game theory model to predict the future profits of Prada’s products. Based on Table 15, the expected profit of the Leather Goods' product still is the largest profit amount among all the products' expected values in 2016. However, the performance of Leather Goods in the past years has been better than the expected value in 2016. This is an indicator that expected values for Footwear and Clothing are similar and there is very little difference over the last few years. The "Others" product does not have a large profit, but its performance is going up during the five-year period from 2011 to 2015.

Analysis the Products in Tableau

Let us look at an overall view of the performance of Prada's four products. There are numerous mathematical models provided by the Tableau platform to generate trend lines. Some of these trend lines may be linear, Logarithmic, Exponential or Polynomial. The following graph is a linear model. Trend lines are utilized to predict the continuation of a specific trend of a variable. Additionally, it recognizes the relationship between two factors by following the trend of both factors at the same time.

Frist, we store the data of the products in an excel Table. See Table 16.

Table 16

The Data Over Five Years

Year	Leather Goods	Footwear	Clothing	Others
2011	263.7	98.8	87.8	5.2
2011	354	176.3	124.4	7.1
2011	341.9	116.3	125.4	5.6
2011	466.9	168.7	174.9	6.2
2012	417.3	134.7	113.8	7.5
2012	525.8	180.6	134.9	10.2
2012	501.2	135	139.3	7.8
2012	593.8	175	175.4	4.2
2013	538.4	118.2	108.1	7.9
2013	618	164.2	140.7	12.1
2013	554.4	133	141.5	10.7
2013	621.7	179.2	191.3	8.8
2014	479	95.5	111.2	12.1
2014	496	113.1	118.5	16.8
2014	471.8	114.7	129.4	13.7
2014	493.7	125.5	153.1	11.7
2015	485.5	575.8	120.2	15.1
2015	511.6	778.5	128.7	18.4
2015	429.1	625.8	130.8	14.3
2015	493.7	786.2	161.9	12.9

Table 16 shows the profits of four products: Leather Goods, Footwear, Clothing, and "Others" from 2011 to 2015. In general, the profits of Leather Goods achieved the highest amount of all the products. However, the lowest numbers of all the products was "Others". Clothing and Footwear had similar profit amounts over five-year period.

Now let us evaluate the data in Tableau as it shows in Figure 1. We will visualize these products using Tableau, then we will make general predictions.

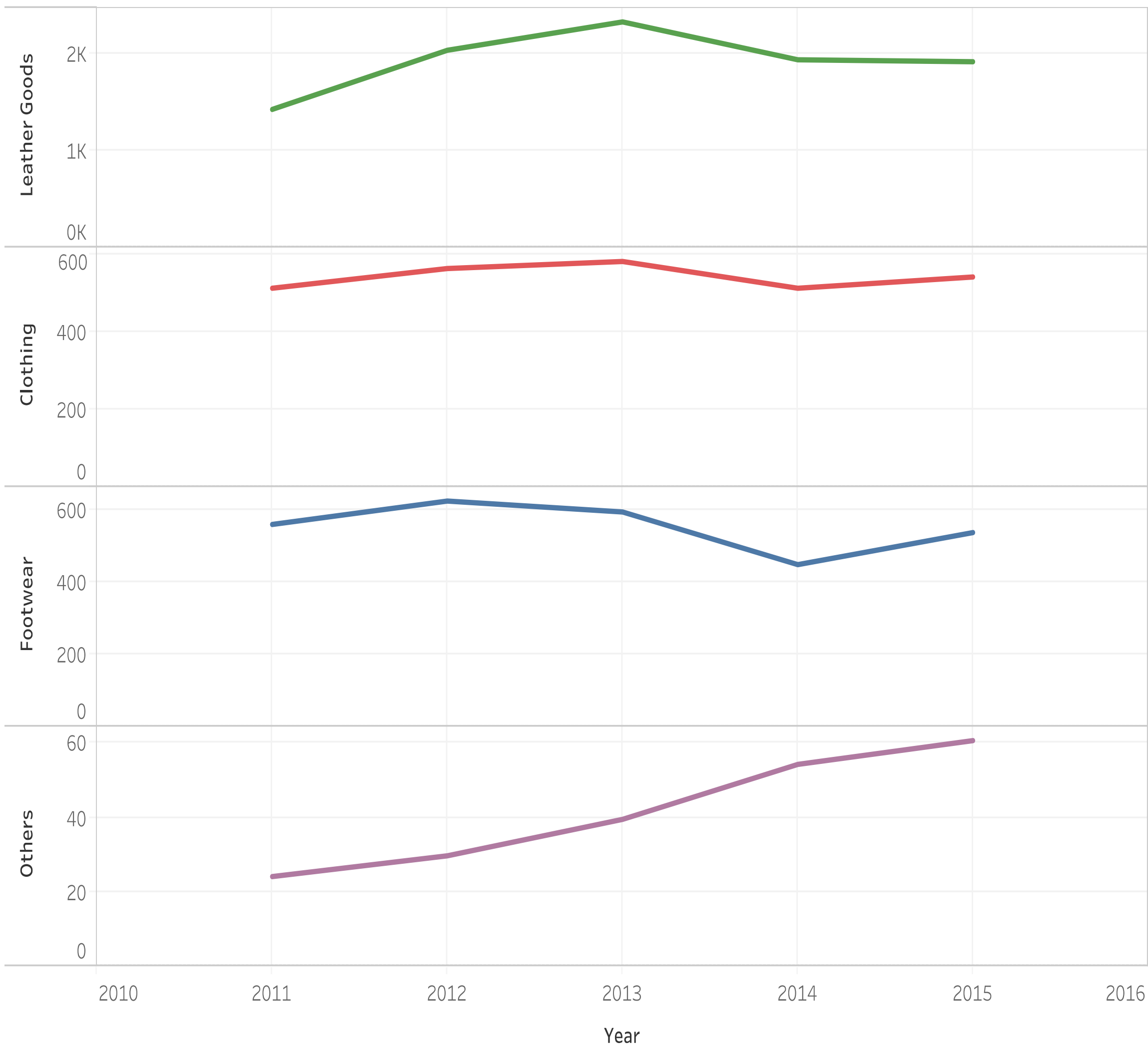

Figure 1. The overview of the products in Tableau. The linear graph of Leather Goods, Clothing, Footwear, and Others products for five years in Prada's company by using Tableau platform.

Figure 1 gives a general overview of Prada's product performances. Each line on the graph shows the performance of the products. The products are Leather Goods, Footwear, Clothing, and Others. Each graph depicts the performance of a product on a particular scale. For instance, for Leather Goods, the profit data is represented on a scale from zero to 2k, but the profit data for Footwear and Clothing are calculated on a scale from zero to six thousand. The "Others" profit data shows numbers on a scale from zero to sixty.

Based on the Figure 1, one can visualize that all the lines do not have a perfect performance here. The "Others" product, on the other hand, seems to have performed better during five years. The "Others" product increased gradually from 2011 to 2014 before a slight growth in 2015. Leather Good, Footwear and Clothing depicted periods of growth in profits between 2011 and 2013. However, they recorded a slight drop during the period between 2013 and 2015. In the year 2013, it seems the conclusion is Leather Goods, Footwear and Clothing are the leading profit gainers for the company.

CHAPTER IV

REGRESSION ANALYSIS FOR THE PRADA PRODUCTS' DATA

This chapter offers analysis of each of four Prada products using tools such as simple linear regression and hypothesis testing. These tools, along with chunks of R code, will be used to find results that will aid in decision making. These tools will also be used to find the best-fitting line so that we are better able to predict Prada's profits for the 1^{st} quarter in the year 2016.

Simple Linear Regression

Simple linear regression is one of the most common techniques used in statistics. This technique helps to predict the value of an outcome between two variables; a variable Y depends on one or more independent predictor variables X. Simple linear regression is used to study the potential relationship between the independent variable (s) and the dependent variable by using a linear relationship (a mathematical formula).

Hypothesis Testing

Hypothesis testing is a method that enables you to draw legitimate statistical conclusions about the estimation of products, or distinction among them. There are two contradictions in hypothesis testing: the null hypothesis and the alternative hypothesis; they are denoted by H_0 and H_1 respectively. When the null hypothesis is false, then the alternative hypothesis is true. So, the alternative hypothesis is the complement of the null hypothesis.

If we reject the null hypothesis, then the alternative hypothesis will be supported by statistical evidence. Otherwise, If we fail to reject the null hypothesis, then the alternative hypothesis well not be supported. So, we can only accept the null hypothesis as a proven theory when the testing fails to reject.

a. ***Level of confidence*** is the probability of making an error that identifies how confident we are in a decision. Examples of levels of confidence are 95% and 99%. We will use the 95% level of confidence

b. ***Level of significance*** is the probability of the null hypothesis being rejected or being accepted. Level of significance is donated by α, and it is calculated as $\alpha = 1- c$, where c is the level of confidence. For instance, when the level of confidence is 95%, this means $c = 0.95$; hence, $\alpha = 1 - 0.95 = 0.05$. So, the value of α will be 0.05.

c. ***Significance of regression*** is simply the hypothesis test of whether the slope of the independent variable is equal zero:

$$H_0 : b = 0$$

$$H_1 : b \neq 0$$

If we may conclude the slope of the independent variable is not zero, then we reject the null hypothesis that $b = 0$; otherwise, we fail to reject. Keep in mind that we need to find a probability of obtaining a sample "more extreme" than the others observed assuming the null hypothesis is true. To draw a conclusion, we need to know the relationship between the P-value and the level of confidence. We reject the null hypothesis when $p < \alpha$, as well as fail to reject when $p > \alpha$. Now, let us look at the data a little more closely and use the R program programing language to help us analyze the data.

Leather Goods

Beginning with Leather Goods, we will use data visualization to view the overall performance of Leather Goods products over a five-year period to predict its profits. Based on the properties of simple linear regression, it is important to identify the independent variable and the dependent variable and to analyze the relationship between them. Here, the independent variable will be the year, and Leather Goods is the dependent variable. The first step in a simple regression analysis is plot the data after importing it from an existing excel file using the R programming language. Plot the data of Leather Goods during five years show in Figure 2.

```
### Simple linear regression
data1<- read.csv("~/Desktop/Desktop - Aisha's MacBook Air/analysis data
CSV.csv")

head(data1)

##   Year Leather Goods Footwear Clothing Others
## 1 2011         263.7     98.8     87.8    5.2
## 2 2011         354.0    176.3    124.4    7.1
## 3 2011         341.9    116.3    125.4    5.6
## 4 2011         466.9    168.7    174.9    6.2
## 5 2012         417.3    134.7    113.8    7.5
```

```
## 6 2012        525.8    180.6    134.9   10.2

## Loading the required package: ggplot2

require(ggplot2)

#### Plot the data in Leather Goods

ggplot(data=data1, aes(x=Year, y=Leather.Goods)) + geom_point() + geom_
smooth(method = "lm")
```

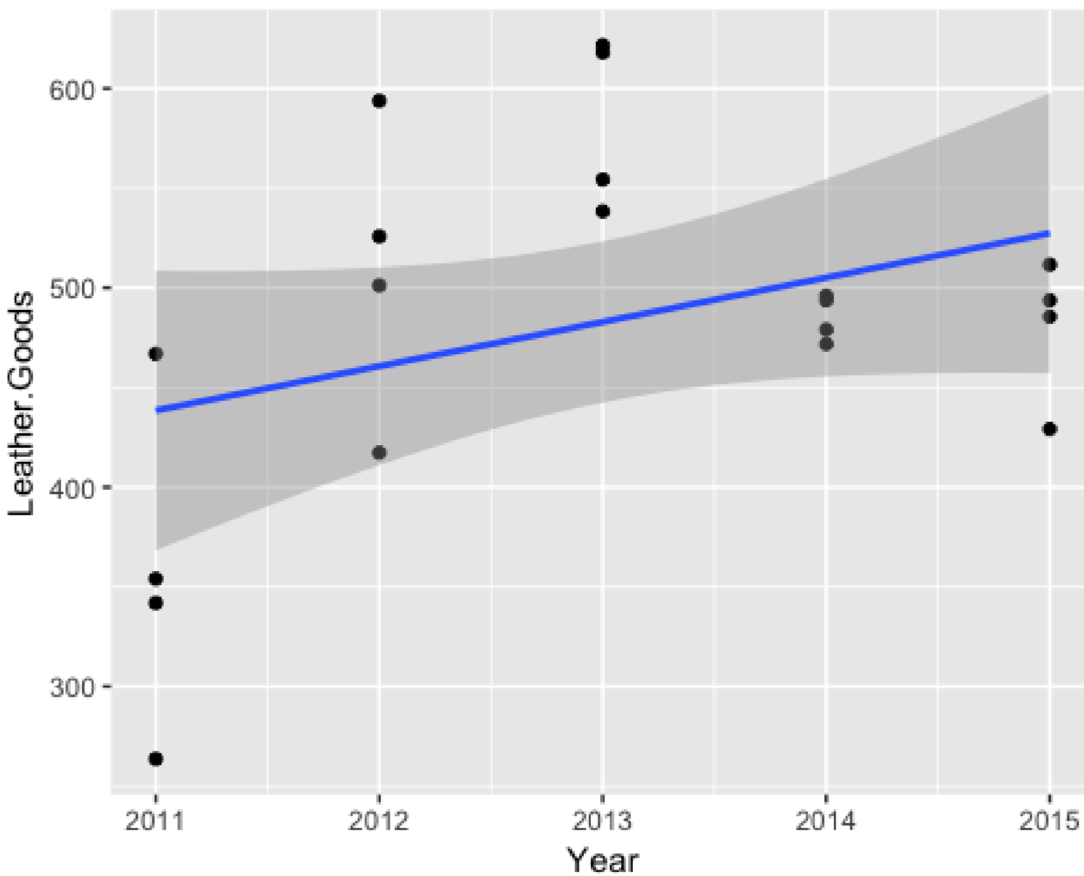

Figure 2. Simple linear regression of Leather Goods product. The simple linear regression of Leather Goods product slightly increases over five years by using the R programming language.

```
cor(data1$Leather.Goods, data1$Year)

## [1] 0.3587859

#### Fitting the model
lm1<- lm(Leather.Goods~Year, data = data1)
lm1
## Call:
## lm(formula = Leather.Goods ~ Year, data = data1)
## Coefficients:
## (Intercept)         Year
##   -44266.12        22.23

summary(lm1)
## Call:
## lm(formula = Leather.Goods ~ Year, data = data1)
## Residuals:
##     Min      1Q  Median      3Q     Max
## -174.72  -42.21  -13.57   57.93  138.82
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -44266.12   27440.29  -1.613    0.124
## Year            22.23      13.63   1.631    0.120
##
## Residual standard error: 86.21 on 18 degrees of freedom
## Multiple R-squared:  0.1287, Adjusted R-squared:  0.08032
## F-statistic: 2.659 on 1 and 18 DF,  p-value: 0.120
```

Correlation = r = 0.3587859. The relationship between Leather Goods and Year is a weak increasing function; it is increasing about 0.3587859 in each year. Thus, it is not good correlation, but there is a line can be plotted as it shows in Figure 2.

In the R programing language, we use the lm() function to determine an intercept and a slope for simple linear regression. The slope is positive: 22.23. When the year increases, Leather Goods slightly increases by 22.23. The y-intercept is -44266.12. R-square = 0.1287 (12.87%). According to R-squared, the fitting line is not good because R-squared is a small number. Moreover, P-value = 0.1203 > α=0.05. So we fail to reject the null hypothesis. That means there is not sufficient evidence to support the alternative. Hence, the slope of the independent variable may equal zero with a 5% level of significance.

```
#### Confidence intervals on the regression
confint(lm1, level = 0.95)

##                     2.5 %     97.5 %
## (Intercept) -1.019160e+05 13383.7977
## Year        -6.408797e+00    50.8688

#### Prediction (defind=95% confidence)
predict(lm1,data.frame(Year=2016), interval = "confidence")

##       fit      lwr      upr
## 1 549.565 454.5809 644.5491
```

The 95% confidence interval for the next quarter (the first quarter in 2016) is between 454.5809 and 644.5491. Hence, we are 95% confident that the fitting value for Leather Goods, in the first quarter in 2016, is 549.565.

Footwear

To analyze the performance of Footwear, we first plot the simple linear regression line for the Footwear product's performance, over a five-year period, by using chunks of R code. See Figure 3.

```
#### Plot the data in Footwear
ggplot(data=data1, aes(x=Year, y=Footwear)) + geom_point() + geom_smoot
h(method = "lm")
```

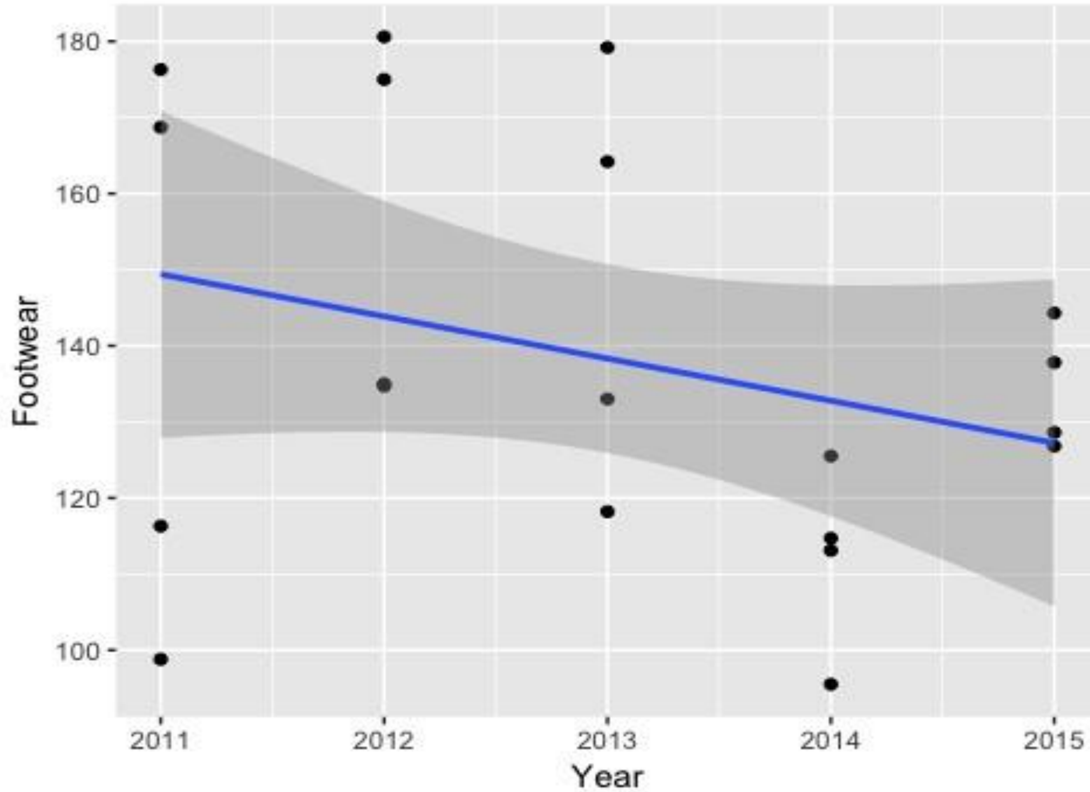

Figure 3. Simple linear regression of Footwear product. The simple linear regression of Footwear product slightly decreases over five years by using the R programming language.

```
cor(data1$Footwear, data1$Year)

## [1] -0.2984152

#### Fitting the model
lm2<- lm(Footwear~Year, data = data1)
lm2
## Call:
## lm(formula = Footwear ~ Year, data = data1)
## Coefficients:
## (Intercept)         Year
##   11295.367       -5.542

summary(lm2)
## Call:
## lm(formula = Footwear ~ Year, data = data1)
## Residuals:
```

```
##      Min      1Q  Median      3Q     Max
## -50.600 -18.473  -2.873  20.946  40.885
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 11295.367   8410.838   1.343    0.196
## Year           -5.542      4.178  -1.327    0.201
##
## Residual standard error: 26.43 on 18 degrees of freedom
## Multiple R-squared:  0.08905,    Adjusted R-squared:  0.03844
## F-statistic:  1.76 on 1 and 18 DF,  p-value: 0.2013
```

Correlation = r = -0.2984152. The relationship between Footwear and Year is a weak decreasing function; it is decreasing in Footwear performance about 0.2984152 over the years. Thus it is not a good correlation. Observe the Footwear regression line in the Figure 3.

According to the Footwear scatterplot (Figure 3), the slope is negative 5.542. When Year increases, the Footwear lightly decreases by 5.542. The y-intercept is 11295.367. R-square = 0.08905. So it is only 9% of the variation in the dependent variable (Footwear) is accounted by the year. The line of regression is not a good fit based on R-squared. Now, the P-value of year is 0.2013, and it is greater than α=0.05. Hence, we fail to reject the null hypothesis, and the regression coefficient equal zero with 5% level of significance.

```
#### Confidence intervals on the regression Analysis
confint(lm2, level = 0.95)

##                   2.5 %       97.5 %
## (Intercept) -6375.1480 28965.883014
## Year          -14.3207     3.235697

#### Prediction (defind=95% confidence)
predict(lm2,data.frame(Year=2016), interval = "confidence")
```

```
##         fit      lwr      upr
## 1 121.6875 92.57351 150.8015
```

The confidence of interval of 95% for the next quarter in the year 2016 is 92.57351 to 150.8015. Hence, we are 95% confident that the predicted value for the 1st quarter in 2016 is 121.6875.

Clothing

Now, let us look at the relationship between Clothing and Year as it shows in Figure 4, then make the prediction.

```
#### Plot the data in Clothing
ggplot(data=data1, aes(x=Year, y=Clothing)) + geom_point() + geom_smooth(method = "lm")
```

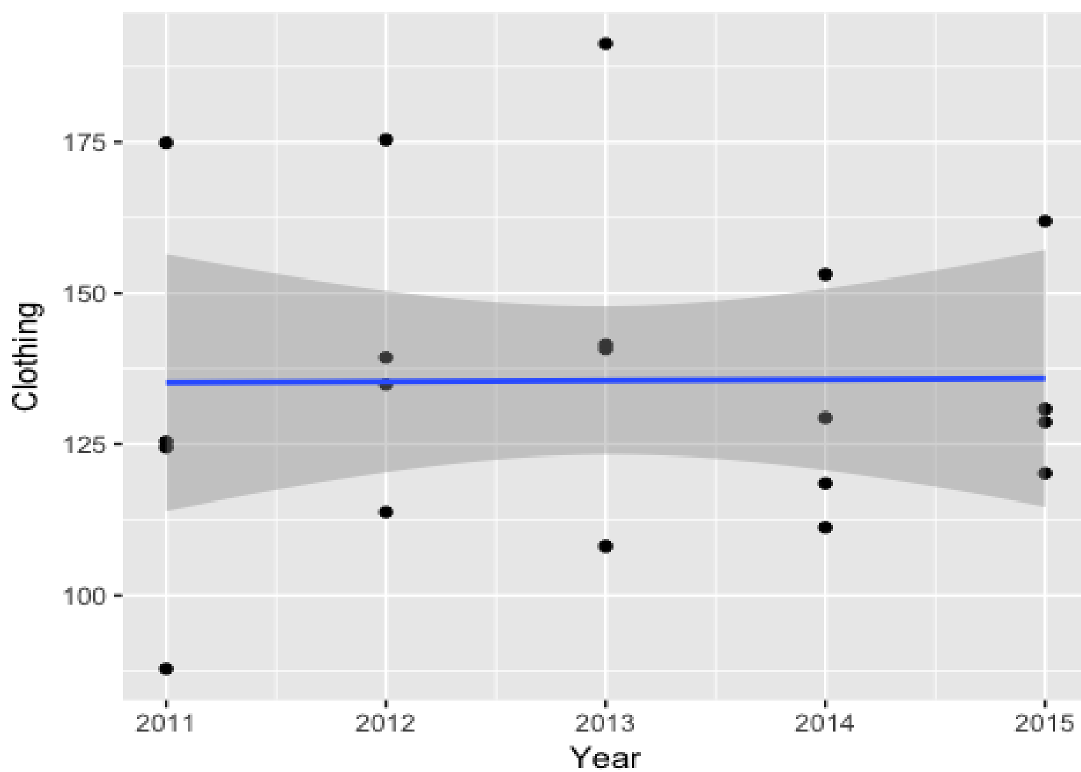

Figure 4. Simple linear regression of Clothing product. The simple linear regression of Clothing product is a straight line over five years by using the R programming language

```
cor(data1$Clothing, data1$Year)

## [1] 0.009986247

#### Fitting the model
lm3<- lm(Clothing~Year, data = data1)
lm3
## Call:
## lm(formula = Clothing ~ Year, data = data1)
##
## Coefficients:
## (Intercept)         Year
##    -216.710        0.175

summary(lm3)
## Call:
## lm(formula = Clothing ~ Year, data = data1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -47.415 -16.096  -5.728   8.791  55.735
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -216.710   8314.224  -0.026    0.979
## Year           0.175      4.130   0.042    0.967
##
## Residual standard error: 26.12 on 18 degrees of freedom
## Multiple R-squared:  9.973e-05,  Adjusted R-squared:  -0.05545
## F-statistic: 0.001795 on 1 and 18 DF,  p-value: 0.9667
```

Correlation = r = 0.009986247. There is no relationship between Clothing and Year; it is increasing in clothing performance about 0 over the five years. So, it is very week correlation; and, a flat line is plotted (look at Figure 4).

Based on the scatterplot in Figure 4, the slope is positive: 0.175. It is close to zero. When Year increases, Clothing neither increases nor decreases. The y-intercept is -216.710. R-square = 9.973e-05 (0.00937%). Here R-squared is close to zero. That means the regression line is not a good fit at all. The P-value is 0.9667, and it is greater than α=0.05. So, we fail to reject the null hypothesis and it is obvious that the slope is equal zero.

```
#### Confidence intervals on the regression analysis
confint(lm3, level = 0.95)

##                      2.5 %       97.5 %
## (Intercept) -17684.247063 17250.827063
## Year             -8.502364     8.852364

#### Preduction (defind=95% confidence)
predict(lm3,data.frame(Year=2016), interval = "confidence")

##      fit      lwr      upr
## 1 136.09 107.3104 164.8696
```

The 95% confidence of interval for the 1st quarter in 2016 is from 107.3104 to 164.8696. We are 95% confident that the predicted value for the 1st quarter in the year 2016 is 136.09.

"Others"

Frist, we plot the simple linear regression line for "Others" product’s performance as it shows in Figure 5 to analyze the performance of "Others. "

```
#### Plot the data in Others
ggplot(data=data1, aes(x=Year, y=Others)) + geom_point() + geom_smooth(
method = "lm")
```

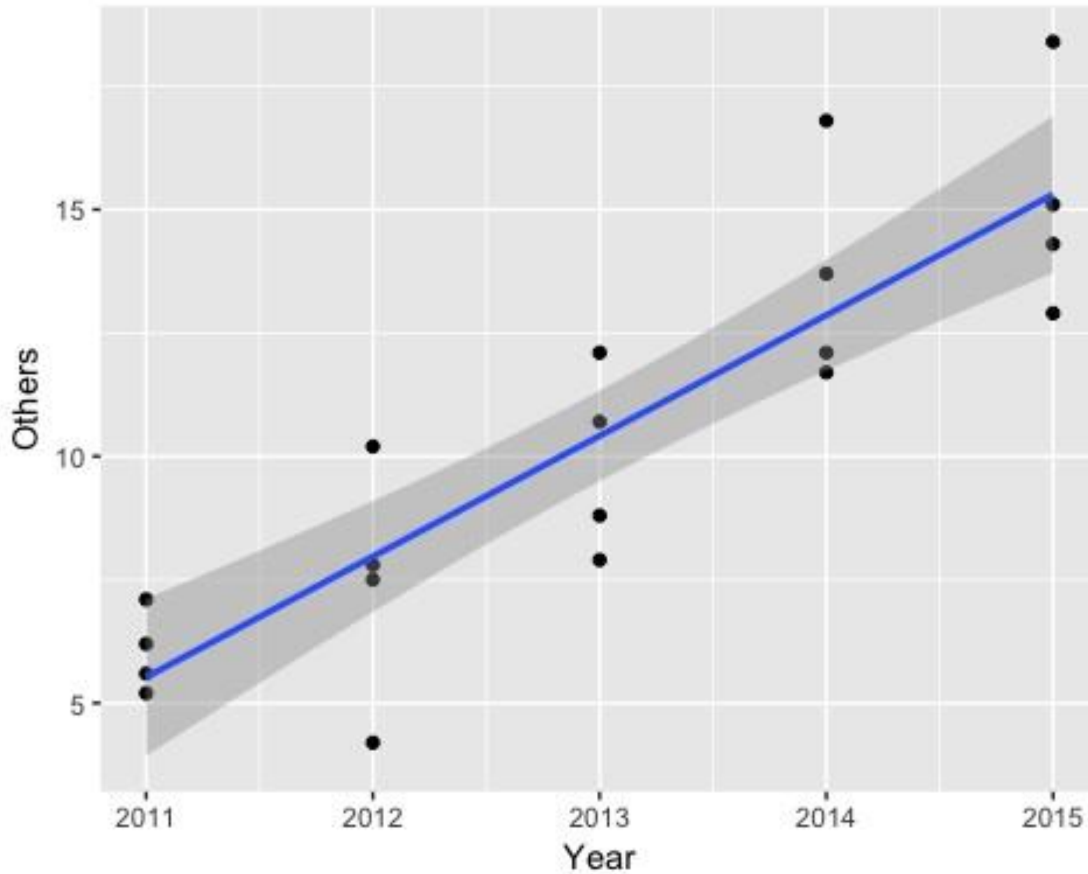

Figure 5. Simple linear regression of "Others" product. The simple linear regression of "Others" product gradually increases over five years by using the R programming language.

```
cor(data1$Others, data1$Year)

## [1] 0.881080

#### Fitting the model
lm4<- lm(Others~Year, data = data1)
lm4
## Call:
## lm(formula = Others ~ Year, data = data1)
## Coefficients:
## (Intercept)         Year
##   -4911.370        2.445
```

```
summary(lm4)
## Call:
## lm(formula = Others ~ Year, data = data1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.7700 -1.0437 -0.1875  1.0237  3.9400
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -4911.3700   622.7323  -7.887 3.00e-07 ***
## Year            2.4450     0.3094   7.904 2.91e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.957 on 18 degrees of freedom
## Multiple R-squared:  0.7763, Adjusted R-squared:  0.7639
## F-statistic: 62.47 on 1 and 18 DF,  p-value: 2.912e-07
```

Correlation = r = 0.8810804. The relationship between "Others" and Year is a relatively strong positive relationship. There is a gradual increase in the "Others" product performance of about 0.8810804 over the five-year period. In Figure 5, a regression line of best fit was plotted.

According to Figure 5, the slope is positive: 2.445. When Year increases, "Others" increases. The y-intercept is - 4911.370. R-square = 0.7763, which is a much better fit of the regression line. The P-value is 2.912e-07; and, it’s smaller than α (the level of significance value α=0.05). So, we reject the null hypothesis. Hence, the slope of independent variable is not equal 0. Thus, the relationship between the dependent variable and the independent variable is strong.

```
#### Confidence intervals on the regression analysis
confint(lm4, level = 0.95)
```

```
##                   2.5 %       97.5 %
## (Intercept) -6219.682118 -3603.057882
## Year            1.795069     3.094931

#### Preduction (defind=95% confidence)
predict(lm4,data.frame(Year=2016), interval = "confidence")

##     fit      lwr      upr
## 1 17.75 15.59442 19.90558
```

The 95% confidence of interval for the 1st quarter in the year 2016 is from 15.59442 to 19.90558. We are 95% confident that the predicted value for "Others" in the 1st quarter of 2016 is 17.75.

According to these analyses, the performance of Leather Good, Footwear, and Clothing had a weak relationship with the years from 2011 to 2015. From hypothesis testing, we may accept the null hypothesis for these products, since the slope is equal zero. Furthermore, the "R-square" in these products is a small number, which means the regression line is not a line of best fit. This makes it hard to make predictions for these products; even though, by using some analysis in the R programing, we can estimate the predicted value in the 1st quarter of 2016 year for Leather Goods, Footwear, and Clothing that will be €549.565, €121.6875, and €136.090 respectively, with 95% level of confidence. On the other hand, "Others" has a good performance during the five years period. From the hypothesis test, we reject the null hypothesis. So the slope is not equal zero. Also, R-square is a large number; hence, the regression line is a line of best fit. Based on this, one can easily predict the "Others" product values for the 1st quarter in 2016. This value is €17.75, with 95% level of confidence.

CHAPTER V

CONCLUSION

The ability to predict profits in the fashion industry is dependent on the ability to select the right tools. This thesis outlined some of the models that can be used to predict profits for one of the fashion companies. The company of focus in this case was the Prada Company. Data about the products were collected for a five-year period from Prada's website. These data are for four quarters in each of the five years. We also predicted profits for the 1st quarter in the year 2016 because this was the only available data.

One of the models used to aid in the processing of the predictions was a tool used in game theory. This model required us to assume probabilities for each product. We, then, were able to calculate the expected values for these products (profits). The second tool we used was the Tableau platform. We used this tool to get an overview of the performance of Prada's products. The third tool that we used to predict the profits of the products was the simple linear regression model. To analyze this model, we used chunks of code in the R programing language. This process allowed us to have a closer look at the performance of Prada's products. In the R programing language, we used a simple linear regression function to determine the relationship between the products' performances during the five-year period.

Results from these various models were almost similar. For instance, using the game theory model, the expected values of Prada's products over 5 years, and the actual values of these products for the full year in 2016 are similar. The expected value of Leather Goods was €2,049.57, and the actual value was €1,804.00. In Footwear and Clothing, the expected values were €543.29 and €554.32 respectively; however, the actual values are €679.00 and €600.00 respectively. The expected value of the "Other" was €45.66 while the real value was €56.00.

The game theory model had similar predictions to the simple linear regression model for the first quarter in 2016. Furthermore, the prediction of the two different models (which are the game theory model and the simple linear regression model) yield similar numbers for the prediction of the first quarter in 2016.

For the simple linear regression model, the estimated value of Leather Goods was €549.57, which falls between the lower and the upper values (€454.5809 and €644.5491); while the expected value of Leather Goods was €482.07. The expected value of the Footwear product from the game theory model was €135.16. By analysis, the Footwear product has an estimated value of €121.69, which falls between the lower value (92.57) and upper value (150.80). For Clothing, the expected value is €139.44 while the estimated value is €136.09. Lastly, the expected value for "Other" is €15.46, and the estimated value is €17.75. Based on the above information, the game theory model offers the better model for predicting future performance of a firm’s product. However, it is expected that one uses the correct probabilities for them to get accurate expected values.

At the end of the exercise, it was noted that Leather Goods posted the greatest profit. Profits of Leather Goods showed about a third of the profit of all the products, but its overall performance, according to game theory and the analysis models, is not good. However, "Others" showed a good performance during the targeted five years. To prompt a better performance for Leather Good, Prada can use leather items to create more and more of the “Other” products. In other words, they may make more “Others” products created by leather, since “Others” showed a good performance. This would probably improve the performance of the Leather Goods products in the future.

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