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New Product Demand Forecasting

A literature study

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Abstract
With new machine learning techniques and statistical methods, the field of sales forecasting has evolved over recent years. However, when little historical data is available, most of these methods are not usable or less reliable. In case of introducing a new product, the challenge is to determine how the product will be received by the customers. To achieve better understanding, this paper outlines different types of product introductions, a variation of techniques and a handle on which techniques to use in which situation.

Keywords: Sales forecasting, Bass-model, Product Introduction, New product forecasting

Preface

This research paper is written as part of the Master Business Analytics at the Vrije Universiteit Amsterdam. During my dual work period, which is also part of the Master curriculum, one of the projects I worked on was about demand forecasting. Over the past years many algorithms and tools have been created to predict customer demand as accurate as possible. Most techniques are based on a long history of sales in which (seasonal) patterns and irregularities can be discovered. Unfortunately, with new product introductions there is little or no data available. My interest in this field was triggered, because especially these sales forecasts are of great importance for the company involved. This research paper will outline different techniques for product introductions and will give an advice on which models and techniques can be used in a particular situation.

I would like to thank my supervisor Ger Koole for the guidance in writing this research paper.

Contents

1 Introduction

This paper discusses a variation of methods which can be utilized when making a demand forecast for a new product. The field of demand forecasting bloomed with the increase in computer power and the upcoming of more machine learning techniques and statistical forecasting methods. The forecasting methods mainly look for a trend or (seasonal) pattern in the historical sales data and sometimes relates this to events of other sources. However, when a new product is introduced, little or no historical data is available. Most of the machine learning and statistical methods need a certain amount of history to make a (reliable) forecast. Hyndman et al. states when considering monthly data, the ARIMA method and Holt Winters' method need a minimum of respectively 16 and 17 months of data to produce normal forecast [9]. When the historical sales data of the product has a lot of variation, even more months of sales history is needed.
When introducing a new product, the company is in a lot of uncertainty and risk. Especially with completely new (also called new-to-the-world) products, since it is hard to examine whether this new product is going to be a success. When introducing a new product, investments need to be made. A forecast needs to be made to determine what the sales are going to be during the introduction period. If the forecast is too ambitious, this can result in overstock and not earning back the investments. If the sales are underestimated, this leads to turning customers away, resulting in lost sales. The accurateness of the forecast can make a real difference in the success and adoption of the product by the customer.

The problem this paper addresses is how a forecast should be made when no historical sales data of the product is available. The research goal is formulated as follows:

Which demand forecasting technique can be used when introducing a new product?

The paper has been organised in the following way. It starts by discussing the different types of new product introductions are described. It will then go on to give an overview of the literature related to this type of forecast techniques. After this some additions to current techniques are proposed. The following chapter introduces guidelines and oversight which methods can be utilized in what situation. This chapter is followed by some real-world examples of how to use the decision tree and the different tables. The final chapter is the conclusion and discussion.

2 Types of new product introductions

Not every new product introduction is the same. There is a big difference between a really new product, which is the result of innovation and has never been on the market, and an improvement of an existing product. The amount and existence of sales data differs per introduction. Additionally, information about the market may or may not be available. Furthermore, producing a new-to-the-world product will involve more risk than adding a product to an existing product line. The risk of introducing a new article decreases when more data is available. The goal is to collect as much relevant data as possible, to decrease uncertainty. Ismail et al [11] stated that there are six categories of new product introductions.

- New-to-the-world products
- New-to-the-firm products
- Additions to existing product lines
- Improvements and revisions of existing products
- Repositioning of products
- Cost reduction

Kahn [12] states that there are seven categories of new products. He identifies all the categories that Ismael stated, but adds a seventh category; New-market product introductions. Kahn also provided a clear oversight in the form of a matrix, which outlines where the new product can be placed in terms of Market and Technology. This matrix is shown in figure 1.

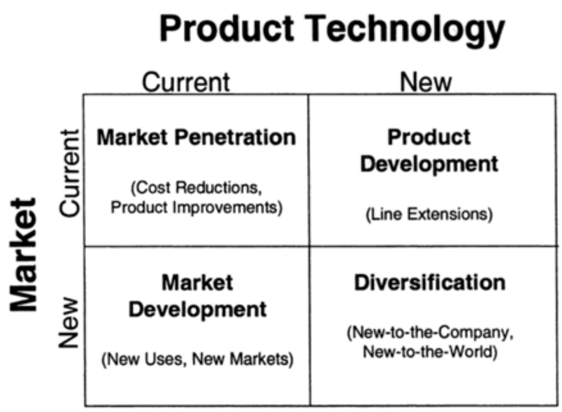

Figure 1: Kahn Marketing Mix Matrix

Different kinds of product introductions need a distinct approach to create a trustworthy sales prediction. Some types of introductions can utilize historical sales data from other products to create predictions. When products are too different from products already in circulation, historical sales of other products add no value to the new product prediction. The realization must be there that more data is not always better. In this section the different types of product introductions are described.

2.1 New-to-the-world products

New-to-the-world products are also called really new products. This product introduction creates a new market, and is not part of another market. New-to-the-world products are the most difficult category to predict. Most of the time these products include technological features from which it is not clear whether there is a large adoptive group. Therefore, whether there is a large adoptive group needs to be examined extensively before making the decision of taking the product in production. Additionally, the chance of acceptance is a feature that is likely to be used in this kind of forecasts. Because no historical sales data is available about this new product, data needs to be generated. This can be executed in different ways, for example by using external data sources or conducting surveys with potential customers.

2.2 New-to-the-firm products

With new-to-the-firm products there is already a market for the product. The product is not new for customers, but only for the firm. In this case historical data about sales of this product does exist, but is most likely not available for the competitor firms. It is possible to investigate the growth of the industry in which the product is located, which is most likely made available by the government. For the Netherlands this information is made available by the 'Centraal Bureau Statistiek' (CBS), and for Europe this information can be found by using the data bank of Eurostat. New-to-the-firm products can be a part of horizontal integration, also known as parallelization. In this case the firm is already active in another sector, but is broadening their assortment. Next to this it is also possible that a new business is constructed on the development of this product. In the first case there is data available of other products, which potentially can be used in the demand forecast of the new product. In the second case no internal data is available, which can complicate the process.

2.3 Additions to existing product lines

If there is a new product added to an existing product line, it means that internal sales data about the currently sold product is available. There is an idea how big the market is for the existing product(s) and this data can be used to potentially determine the order of magnitude or the seasonality of the new introduction. Next to this, it must also be taken into consideration that by this addition to the product line, the sales of the existing products potentially will be influenced.

2.4 Improvements and revisions of existing products

Next to additions to a certain product line, it is also possible to revise or improve a product. This revision can be of great impact or can have almost no effect on the sales of a product. Whether or not a revision of a product will have an effect on the sales needs to be determined and quantified.

2.5 Re-positioning of existing products

A product can have multiple purposes. when re-positioning existing products the actual product is not new, but the way it is used is different. For this new purpose, the product is new. In this situation it is complex whether or not the sales history can be used by determining the forecast for the new position of the product. It is wise to take along this historical data in the forecasting process of the new position, but not to base the whole forecast solely on this data.

2.6 Cost reduction of existing products

When a product undergoes a cost reduction, the actual product will stay the same, but will be produced and sold for a lower price. It can be seen as a new introduction, because the product possibly attracts a different customer. With this kind of product introduction the seasonality of the product can most likely be adjusted from the existing product, assuming that this will not drastically change with a cost reduction. The level, or average, value around which the seasonal pattern moves needs to be comprehensively reexamined. For example, the average value of the sales increases, because the product is now affordable for a larger group of customers.

2.7 New-market product introduction

The last category, which was introduced by Kahn [12] is the new-market product introduction. In this product introduction, the product is not new to the firm or the world, but it is new to the market that it is introduced to. This can be a new country, in which the company did not sell the product before. In this case, data from other markets is present and can be used for the forecast of this new market.

3 Literature review of existing methods

In this section a literature review will be conducted on the different already existing forecast methods when little or no data is available. Per method a description and requisite data will be specified. Next to this it will be discussed whether or not this method is applicable to all the different types of product introductions. Whether a product introduction is successful, is for a great part dependent on the level of acceptance. Acceptance of a product introductions depends on different scenario's of several variables, which are all hard to forecast. Examples of these variables are the level of infrastructure, technology, taxes and environmental awareness of the customers [28]. To forecast all the variables and eventually conduct the demand forecast, data about these variables and forecast methods are needed. In this section, both qualitative and quantitative models are considered. Qualitative methods are non-data based methods, an example is a grounded expert opinion. All these qualitative methods are subjective, but can be used when no relevant sales data is available or as an adjustment to a statistic model. Quantitative methods are methods based on numerical analysis. This analysis is more objective and based on measures and most of the times historical data is used. The first section of this chapter is also of quantitative nature, the simple forecast methods.

3.1 Simple forecast models

When there are a few historical sales points available, or the product which is introduced can be compared to an already existing product, the most standard is implementing a simple model. The simple models are mostly used as benchmark, but in the situation of a new product these techniques might give insight. Next to this, Fader et al. states that simpler forecast also have upsides. When a model is simple and can be explained, the managers and stakeholders of a company can also understand the model. If the stakeholders can understand the model, this will increase confidence in the forecast [4]. Additionally, these kind of models can be produced against low costs and in a fast way. This section assumes that the sales data is aggregated per time period. The time periods can be aggregated in the form that is needed, for example per day, week or month. In this section different simple forecast methods are discussed, based on the notation of Hyndman et al.[10]. y_T is stated as the realisation at time T. $\hat{y}_{T+h|T}$ is stated as the forecast with h time steps forward, with history until time T.

3.1.1 Average Approach

The average approach can be expressed by the following formula:

$$\hat{y}_{T+h|T} = \frac{\sum_{i \leq T} y_i}{T}$$

with h an integer as the number of time periods forecasting forward, T the current time and y_t the demand forecast for time t. The idea of the average approach is that the forecast equals the mean of the historical sales data. The average approach can be conducted if the product is expected not to have a great variation or seasonal fluctuation. This method can be utilized when there is already some sales data available about the new product or sales data of a similar product is available.

3.1.2 (Seasonal) Naive Approach

The naive approach and seasonal Naive approach can be expressed by the following formulas respectively:

$$\hat{y}_{T+h|T} = y_T$$
$$\hat{y}_{T+h|T} = y_{T+h-m(k+1)}$$

with m the number of seasonal periods and k the integer part of $\frac{h-1}{m}$. The integer part is taken because you only want to take a complete period of time into account. The seasonal naive approach needs a minimum of m periods of history, this means that this model is most of the times not suited for a new introduction. The approach can be altered to $y_{t+1} = x_{t+1-m}$ where x is a similar product with a longer history. For the Naive Approach only one data point is needed, which makes it possible to use this method directly when the product is introduced. This method is not a very complicated, but can give a direction if little history is present. The approach builds on the reasoning that the forecast is equal to the last (seasonal) data point. The method can be utilized in similar situations to the average approach.

3.1.3 Drift method

The Drift method is an addition to the Naive model. The difference in y between the first data point and the last data point is the change over time, also called the drift. The idea is that this difference, so increase or decrease, will continue in the next time unit. This leads to the following formula:

$$\hat{y}_{T+h|T} = y_T + \frac{h}{T-1}\sum_{t=2}^{T}(y_t - y_{t-1})$$

This method can be used if the data shows a trend and does not have a seasonal pattern. For this method, only two data points are needed, so still with a small history, this method can be used. Just as the other simple methods, this method can be used with little sales data or data of a similar product.

3.2 Market Research

Market research is one of the most well-known tools to collect data about an unknown or new market. This market research can be used to discover different aspects of the market, for example the size of the market, or to quantify the competition or the need for a new product in this market. This market research can again be conducted with two types of methods, quantitative and qualitative methods. This section outlines two types of product introductions, Economic choice theory and Conjoint analysis.

3.2.1 Conjoint analysis

Conjoint analysis is a popular form of market research. The goal of conjoint analysis is to determine how potential customers value different attributes of the product. This is a survey-based model and was introduced in the 1970's. Green et al. states that every decompositional method which estimates the structure of of a customers preference is conjoint analysis. The customer gives weights of importance, or his or her preference to different combinations of attributes that are specified [8]. Examples of attributes are the price, size or brand of a product. For this research, a panel of potential customers is needed. The panel members will receive a survey with different hypothetical situations, on which they have to give their preference, or rank the situation to their preference. The survey is conducted individually. The design of the conjoint analysis approach is as displayed in figure 2.

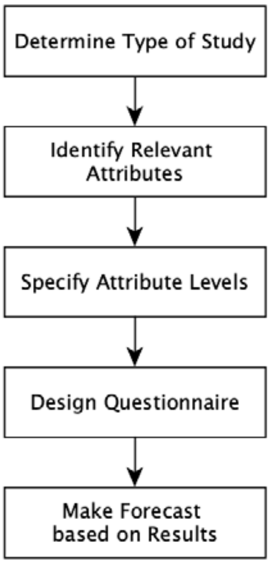

Figure 2: Conjoint Analysis Workflow

The first step is to determine the type of study. There are three ordinary options for this. The first option is the choice-based conjoint. With this study all individuals of the panel need to choose one of the hypothetical situations that are set per question. The second option is ranking-based conjoint. In this situation the panel members have to rank the different situation in order of their preference. The last option is rating-based conjoint in which the panel members are asked to rate the different scenario with a score. The second step is to identify relevant attributes. In this step the different attribute of a product needs to be determined, for example size, brand, price. It is important that the attributes are not directly correlated to each other, in that way it can be determined which attribute is most important for the customer. The next step is to assign the different options to the different attributes. The options need to be realistic, plausible and interesting for the forecasting party. An example is to propose an extensions to an existing product and include the existing product as an attribute, and two different prices. Following, the questionnaire needs to be designed. In this steps the different attributes are combined in hypothetical situations. If the same example is used, choices for the panel members are: Existing product for price A, Existing product for price B, extension to existing product for price A or extension to existing product for price B. This questionnaire is conducted by the individual panel members and the results are analyzed. From this, a demand forecast can be drawn. The best results are produced if the new product is an addition or revision of an already existing product. In that way the sales data of the already existing product can be used to make a forecast for the new product introduction. When this theory is applied to new-to-the-world products, most of the times, the product category is not well understood by the participants and they have limited or no experience with purchasing or using the product. Additionally, the social aspects of a totally new product, for example word-of-mouth referrals, can not be taken into account. [29] When referring back to the types of new products introduced in chapter 2, the conjoint analysis can not be used when introducing a new-to-the-world product and works best with improvements and revisions of existing products and cost reductions.

3.2.2 Economic choice theory

McFadden wrote a paper about economic choice theory, it permits the use of data from psychometric and conjoint experiments to produce market forecasts [19]. This suggests that Economic Choice theory is an addition to the forecast of the conjoint analysis, which was discussed in the previous section. Economic choice theory is based on the behavioral intention of a potential customer to maximize it preferences. McFadden states that Economics often treats customers as a black box. This black box has an input of product attributes, socioeconomic characters, market information, historical experience and market constraint and an output of market behavior. In the case of a product introduction the output would be a purchase decision or adoption of the product. For this black box, he constructed a path diagram for the customer decision process, given in figure 3. The goal is to give a value to the different variables within the black box, which lead to a decision. In this way it is possible to see the probability of purchase of a potential customer.

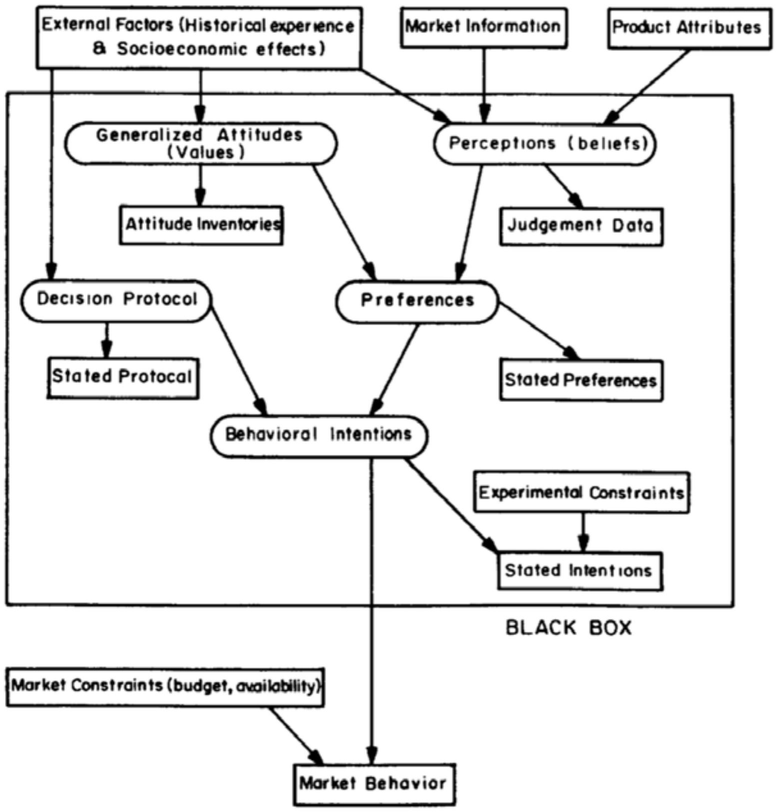

Figure 3: Path Diagram for the Customer Decision Process

Choice models can help quantifying the weight of the different variables within the black box. For example the simple Multinomial Logit Model (MNL). This model gives the probability that a person will choose an article over an alternative at a certain time. The model is given by:

$$\mathbb{P}_C(i) = \frac{e^{V_i}}{\sum_{j \in C} e^{V_j}}$$
$$C = 1, 2, \ldots, M$$
$$V_i = x_{i1}\beta_1 + x_{i2}\beta_2 + \cdots + x_{iK}\beta_K$$
$$\text{For } i \in C$$

With x the product aspects or functions of measured attributes, with β the importance of the weight parameters and with V as the scale functions, which summarizes the desirability of the alternative products. C is the set of product alternatives of size M. Examples of the x variable are the price of the product, how sustainable the product is, the operating costs, the current gross domestic product, etc. The idea of this model is that a potential customer gives a weight β to each product aspect x. For each similar product the "score" V_i is computed and with the formula for $\mathbb{P}_C(i)$ the ratio of demand for the chosen product i against the other products in C are measured. When the size of the total market is available, this can be multiplied with the outcome of $\mathbb{P}_C(i)$, which lead to the expected demand of the sales of the new product. From the different product introductions described in chapter 2, all types of product introductions can use Economic Choice Theory, except for New-to-the-world products and New market product introductions which fall outside of an existing market. This research is also very interesting if the firm is introducing a product in the market in which they are already active. It is in this way possible to measure whether current customers of your "old" product will switch to the newly introduced product.

3.3 Diffusion models

Rogers described diffusion in 1962 as the process by which an innovation is communicated over a specific channel to members of a social system, over time. This communication differs from standard communication, because the message is concerned with a new innovation [25]. After all this time and with the introduction of more complex systems and computer power, diffusion is still widely used to forecast new-to-the-world products. One of the most well-known diffusion models is the Bass model. In this section the Bass model and important expansions of this model will be discussed. Next to this the simpler Life-Cycle approach will be considered.

3.3.1 Basic Bass Model (1969)

The Bass model was first introduced in 1969 by Bass. The Bass model is a model for timing of initial purchase of new consumer products. The Bass model is created to offer a starting point for long-term forecasts of really-new and durable products. There are restrictions whether the Bass model can or cannot be used. To use the Bass model, the firm must have recently introduced the product and retrieved sales data from these periods. Or the product is not yet introduced, but similar products or technology can be used by looking at the sales history [2]. The Bass model recognizes two groups of customers; innovators and imitators. When a new product or technology is introduced, this is communicated to members of a social system [25], where a little group of this social system is interested and will purchase the product, these are the first adopters. The others will form second group, the imitators, this group is influenced by the word-of-mouth of the innovators. Slowly all imitators will become adopters. The Bass model is best described using the conceptual structure, given in figure 4 [11].

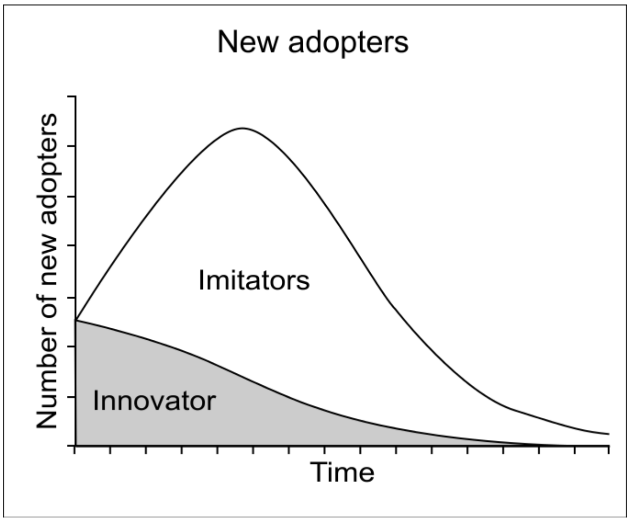

Figure 4: Bass model: Number of new adopters over time

The Bass model is based on the hazard function. The hazard function is the conditional probability that an event will occur at time t given that the event has not yet occurred. In this case the event is the adoption of the product. We define $f(t)$ as the the probability of adoption at time t. $F(t)$ is introduced as the fraction of the potential customers that are adopted at time t. This leads to the following formulation, with p the coefficient for innovation and q the coefficient of imitation.

$$\frac{f(t)}{1-F(t)} = p + qF(t)$$
$$f(t) = p + (q-p)F(t) - q[F(t)]^2$$

Note that $F(0) = 0$ because at time 0, the fraction of adopted customers is equal to zero. If we rewrite the second equation, this results in the following [2].

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + (\frac{q}{p})e^{-(p+q)t}}$$

$$f(t) = \frac{(p+q)^2}{p} \frac{e^{-(p+q)t}}{(1 + (\frac{q}{p}e^{-(p+q)t})^2}$$

If $f(t)$ is differentiated, this leads to to the time of the peak sales (t^*).

$$t^* = \frac{1}{p+q} \ln(\frac{q}{p})$$

We introduce m as the upper limit on sales per time period. The number of sales at time t ($S(t)$), and corresponding the number of sales at the peak (S^*) can now be formulated respectively as:

$$\begin{aligned} S(t) &= mF(t) \\ &= m\frac{(p+q)^2}{p} \frac{e^{-(p+q)t}}{(1 + \frac{q}{p}e^{-(p+q)t})^2} \\ S^* &= \frac{m(p+q)^2}{4q} \end{aligned}$$

To make an accurate forecast, the parameters p, q and m need to be estimated. This can be done in different ways, for example by using historical data of similar products. When the product is recently introduced, information about the parameters can be extracted from the product its own historical data. Bass estimates the parameters from discrete time series data. Bass also suggests that m, the total number of initial purchases over the total period, is decided by an expert in the organization. The Bass model can only be used for forecasting durable, new-to-the-world products. This is one of the assumptions of the Bass model.

3.3.2 Additions to basic Bass: Successive Generations of High-Technology Products

In 1987 Bass wrote a follow up paper on the basic Bass model together with Norton [23]. The Bass model was extended for adoption and substitution for successive generations of high-technology products. The idea is that every generation is introduced before the previous model is taken out of the market. The sales of the newly introduced products can be customers that bought the previous product, or new acquired customers. The same parameters are used as in the basic Bass model. $F(t)$ is again the fraction of the potential customers that are adopted at time t and given by:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + (\frac{q}{p})e^{-(p+q)t}}$$

The coefficient for innovation is denotes by p, q is the coefficient of imitation. The m_i is denoted as the upper limit on sales per time period for generation i. Additionally the A is added as the upper limit of applications for which the innovation can be used. The r is the rate at which an average application consumes the product. The index i is introduced as the indication of the generation. S_i is the sales of generation i. When considering a case of three generations, the sales are denoted as follows:

$$\begin{aligned} S_1(t) &= F_1(t)m_1 - F_2(t-\tau_2)F_1(t)m_1 \\ &= F_1(t)m_1[1 - F_2(t-\tau_2)] \\ &\text{for } t > 0 \\ S_2(t) &= F_2(t-\tau_2)[m_2 + F_1(t)m_1] \\ &\text{for } t > \tau_2 \\ S_3(t) &= F_3(t-\tau_3)[m_3 + F_2(t-\tau_2)[m_2 + F_1(t)m_1]] \\ &\text{for } t > \tau_3 > \tau_2 \end{aligned}$$

One assumption that is made is that two generations can exist next to each other, but the earlier generation will always fade out first. Additionally, the sales of a certain generation are only influenced by the previous and the next generation. This addition to the Bass method is only suitable when introducing a new product and a successive generation of high-technology products. This means that this method can be used for new-to-the-world product introductions and with additions, revisions and improvements to existing product lines.

3.3.3 Additions to basic Bass: Statistical and Machine Learning

Over the years, a lot of suggestions are made as an addition to the basic Bass model. Nearly all additions or revisions are made in the way the parameters p and q are determined. The methods for determining the parameters can be split into three categories. [14] First of all, the Bayesian approach. The Bayesian approach is to first determine the parameters first with a pre-launch forecast and update the parameters when data about the sales becomes available. Secondly, there is a subjective approach. This approach uses the managerial judgments of tangible information to estimate the parameters through an algebraic estimation [17]. Lastly, the analogical approach. This approach assumes that new products have the same diffusion pattern as analogous products. The parameters of the new product are constructed by weighted similarity of the parameters of analogous products.
Lee et al. uses a Machine Learning method to estimate the parameters of the Bass model. This method falls in the category of the analogical approach. Setting up the model structure of a Machine Learning model exists of multiple layers. The structure of the Machine Learning model of Lee et al is displayed in table 3.3.3.

Model structure	**Lee et al.**
Learning task	Predicting Bass model parameters prior to the launch of the new product
Input variable	Product attributes
Output variable	Diffusion characteristics
Appropriate algorithms	- Multivariate Linear Regression (MLR) - Support Vector Regression (SVR) - Gaussian Process Regression (GPR) - K-Nearest Neighbor Regression (k-NN) - Artificial Neural Networks (ANN) - Classification and Regression Tree (CART) - Ensemble models
Performance criteria	- Mean Absolute Error (MAE) - Root Mean Square Error (RMSE)

Table 1: Table: Structure Machine Learning model Lee et al.

To correctly estimate the parameters of the Bass model, two types of data sources are used by Lee. Firstly, the sales data from already existing products, from which the Bass parameters are estimated on using the non-linear least squares. The second data source comes from expert judgment and includes attributes of the products, including the attributes of the newly introduced product. After the data is constructed, the development of the different regression models can start. Lee tests the six different regression models listed in table 3.3.3 and also uses the outcomes of the models to construct an ensemble model. At the end the validation of the different models is done by using the MAE and the RMSE. By using the example data set of Lee, the best model is the ensemble model. The best performing single model is the Multivariate Linear Regression model. The estimated parameters p and q differ minimal between the MLR and the ensemble model. Since this is an addition to the Bass model, the method can still only be used to forecast durable, new-to-the-world products.

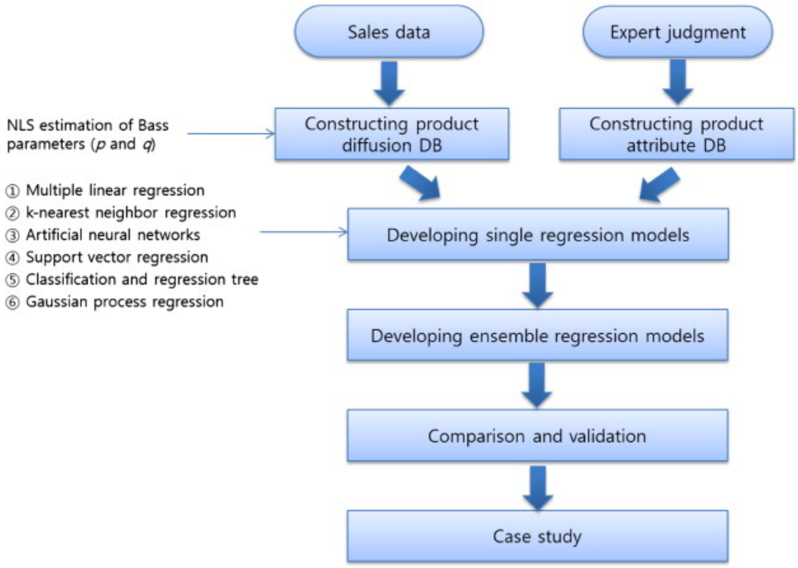

Figure 5: Addition to Bass: Lee's Overall Procedure

3.3.4 Life Cycle approach

When there is an introduction of a new-to-the-world product, no historical data is available. Morrison [22] states that forecast can still be prepared when using the life-cycle approach. Morrison distinguishes three phases of product life, the Introduction phase, the Growth phase and the Maturity phase.
The introduction phase represents the very first period of the product. In this phase there is a slower growth and most of the times the marketing department is still experimenting with finding the right channels to communicate with the members of a social system. In the Growth phase the highest rate of customer acceptance is reached. In this period the product is purchased at the highest pace. Morrison states that the forecast can be established by answering three basic questions:

- What is the maximum level of saturation? (S)
- What is the inflection point or half life of the product? (I)
- What is the delay factor? (A)

The maximum level of saturation is the maximum number of units that a firm can sell until some distant point in the future. By performing a primary market research and/or conducting purchase surveys, the maximum level of saturation can be found. The inflection point is the point where the product is sold at highest rate. It is assumed that this is at one-half of the long run saturation level. The Delay factor represents the delay which is caused by time spend in the Introduction phase. This Delay factor is a number between zero and one. When the delay factor is close to zero, almost no delay is observed and sales are from the start rapidly increasing.
When the S (saturation level), I (inflection point) and A (delay factor) are determined, a forecast can be made. The New Product Sales Forecast are computed by the following formula:

$$F(T) = \frac{S}{1 + e^{IA}e^{-AT}}$$

with T as the time index. So if $T = 1$, this will result in the forecast for the first month. For this forecast, no historical data is needed, but it is important to spend time on estimating the three parameters. The Delay factor is the hardest parameter to predict and also the most subjective. It may be suggested that an additional analysis of similar product introductions is analyzed to estimate this parameter well. Morrison states that the Life Cycle approach is only applicable to new-to-the-world product [22].

3.3.5 Diffusion Techniques for Advance Purchase Orders

The last years, ordering items before they are released becomes more popular. The main reason is the upcoming of the internet. But also before the Internet it was often possible to make an advance purchase order. This data can be of great value when introducing a new product, because it can possibly be an indicator about how well the new product will sell. Moe and Fader developed a model that uses the advance purchase orders to predict the demand for the new product [21]. The model of Moe and Fader considers, just as the Bass model, two groups of customers, the innovators and the imitators or followers. The parameters for the imitators are correlated with the parameters for the innovators. The assumption is made that followers will not make advance purchase orders, this is only done by the group innovators. The data which is used in this model is solely data of past sales of new products and the advanced purchase orders of the corresponding products. It is still possible that the innovators influence each other, this is modeled by the following cumulative distribution:

$$F_1(t) = 1 - e^{-\lambda_1 t^{c_1}}$$

With F_1 the number of innovators that (pre-)ordered the product, t as the time and λ_1 and c_1 as the model parameters. The number of imitators or followers are modelled by:

$$F_2(t) = 1 - e^{-\lambda_2 (t-t^*)^{c_2}} \text{for } t \geq t^*$$

With F_2 the number of imitators that ordered the product, t as the time, t^* as the release date and λ_2 and c_2 as the model parameters. The two cumulative distributions are Weibull distributions. To combine the two groups of customers, a mixed-Weibul model is used, with the following cumulative distribution function (cdf):

$$F(t) = \begin{cases} \phi[1 - e^{-\lambda_1 t^{c_1}}] & \text{for } t < t^* \\ \phi[1 - e^{-\lambda_1 t^{c_1}}] + (1-\phi)[1 - e^{-\lambda_2 (t-t^*)^{c_2}}] & \text{for } t \geq t^* \end{cases}$$

With ϕ ($0 \leq \phi \leq 1$) the fraction of innovators and λ_1, λ_2, c_1 and c_2 all > 0. This function is rewritten to account for implementation issues as discrete time, right truncation, hierarchical Bayes method and product-specific covariates. These issues need to be handled to deal with the data set. In this model discrete time scale is used, because the sales and pre-order information was aggregated per week. When using the model it is also possible to aggregate the data on another level (day, month, year, etc). The right truncation is needed because the number of customers after the pre-order period is unknown. Hierarchical Bayes methods are used over a number of different product introductions to estimate the prelaunch model. Lastly, product-specific covariates are used, because the different behavior of products in the data set can be explained by the covariates of the products.

When the proposed model was tested against two benchmark models: the Bass diffusion model and the Weibull-gamma mixture, the proposed model outperformed both of the benchmarks. The parameters of the different parameters (λ_1, λ_2, ϕ, c_1 and c_2) are very dependent on the number of prelaunch weeks. For this analysis it is necessary that there is (prelaunch and sales) data available about similar products to correctly determine the different parameters for the model. When a new-to-the-world product is introduced and the firm has data about other new-to-the-world products in their introduction period, this approach can be used. The same accounts for the New-to-the-firm products, the additions to existing product lines, re-positioning, improvements and revisions of existing products. With cost reductions the technique is mostly not applicable, because regularly there is not a new product introduced where pre-ordering is possible. New-market product introductions are also only relevant if there is data available about product introductions in the new market.

3.4 Judgmental forecasting

Forecasts are barely a result of solely statistical forecast methods. Judgment of for example managers need to be taken into account, just as special events or a change in national policy. Additionally, when no or little data is available at all, judgment forecast is the only option. When using judgmental forecasts, it needs to be taken into account that the person making this forecast has certain domain knowledge about the product. Additionally, how more up-to-date the information on which the judgmental forecast is based, the more accurate the forecast [13]. When using a judgmental forecast, it should be taken into account that this forecast is always subjective. The judgment forecast is a result of a person his vision. The vision of a person can change rapidly and can be influenced by the role that this person plays in the launch of the new product. If the judgmental forecast is made by, for example, the designer of the product, the judgmental forecast will most likely not predict a failure of the product.
On the other hand is the field of judgmental forecasting matured and the approaches and methods are more structured and systematic [10]. If it is possible to use statistical forecasting methods, this should be preferred to solely make use of judgmental forecasting methods. Hyndman et al. states that there are three situations in which judgmental forecasting is used. Firstly, when there is no data available and thus statistical methods and other approaches can not be applied. Secondly, if judgmental forecasts are used to adjust the statistical forecast. Lastly, judgmental forecasts can be used when produced independently from the statistical forecast and merged to one final forecast [10]. In this section the different approaches and methods are outlined when performing a judgmental forecast.

3.4.1 Scenario building

The future is uncertain. To account for uncertainty, one can create different scenarios. This can be performed in a simple way, by producing a best-, worst- and average-case-scenario with corresponding forecasts. Another option is to take a more structured approach as introduced by Mercer [20]. Mercer constructed an approach consisting of six steps, leading to two or three different scenarios. All scenarios include a different turn of events and an adjusted forecast to these events. The scenarios and forecasts are presented to the management, they decide which scenario or combination of scenario is most likely or has the lowest risk. The six steps approach of Mercer is visualized in figure 6. This process can be conducted by individuals independently or as a group of individuals. In the first case the different opinions of the individuals can be compared which can be practical since the individuals do not have to be at the same place at the same time. Meanwhile, the group approach can lead to an comprehensive brainstorm and unforeseen drivers or connections between drivers. The steps of this scenario building are described in six bullet points.

- The first step in this process is to decide which are the drivers for change. For this a brainstorm and thinking out-of-the-box can be of great value. These factors, also called variables, can be related to internal or external context.
- Secondly, these drivers need to be connected in a framework. In this way we can map which factors are related and have an effect on one another.
- Once the mapping is set, the third step is to produce the first scenarios. The initial scenarios are created by grouping drivers which in the prior step were close to each other in the created framework. The scenarios can just be drafts and the goal is to produce between seven and nine small scenarios.
- After specifying the seven to nine different scenarios, the scenarios have to be rewritten to the two or three final scenarios. This is only for practical reasons and because the presented scenarios should be clear and concise. Additionally, one can, most of the times, not presents nine different scenarios to a group of managers with all keeping their full attention.
- The fifth step is writing down the scenarios. This can be done in a text format, with graphs or diagrams. In this case the scenario should include a demand forecast for the product.
- The last step is to identify the issues arising. In this step all the scenarios are reviewed and one lists the most critical outcomes. This list should be include all points which can have a great impact on the organization.

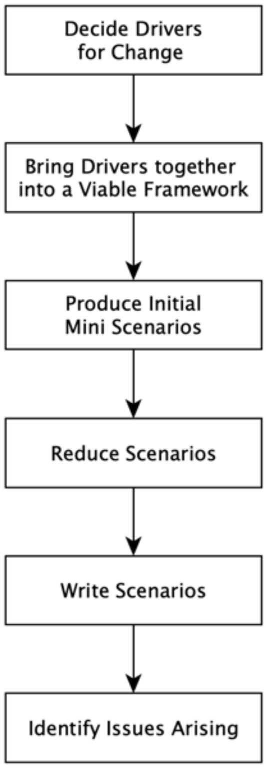

Figure 6: Scenario Forecast Workflow

The scenario building approach can be used with all the different product introductions. Furthermore, scenario building is stated a judgmental forecast, but if it is possible to quantify the drivers for change, forecasts can be made on the base of the these drivers. This approach can be used for all type of product introductions initiated in chapter 2.

3.4.2 Delphi's method

When no data is available about the history of a product, one of the easiest way to create data is to conduct a survey. This survey can be for example be spread under potential customers. Delphi's method takes a similar approach. Delphi's method consists of several steps, which are also displayed in figure 7. The first step is to find a researcher, or in the case of launching a new product, the person which is responsible for the forecasting task. The researcher now defines research questions or goals, which can be part of the survey. Examples of possible questions in the field of product introductions can be; "With what probability will the product succeed?", "Is there a strong seasonal pattern?" or "What will be the average sales after one year?". It is profitable if the researcher is assisted by composing this questionnaire. The next step is to select a panel of experts. All the participants in the panel should be independent. The participants can not meet or communicate. Additionally, the participants can not be part of the research group which defined the questions. The size of the panel is not set, Hyndman et al. advises a group of 5 to 20 experts [10], Archer instructs a group of 10 to 15 experts [1]. After critically selecting the panel, the panel fills in the questionnaire. The researcher receives the responses and makes a statistical report about the findings, outliers and averages per questions. This report is analyzed by the research group, if the group decides that there is a consensus under the panel about the questionnaire, the process can be finished of by summarizing the conclusion. More likely in the first round is that no consensus is achieved already. Potentially the questionnaire is edited or redesigned. Succeeding, the questionnaire is conducted to the panel individually for the second time, but this time including a summary of the answers of the last survey. After repeating this process a number of times, most likely a group consensus is formed and the research results can be prepared [15]. This method can be used with every type of new product. Nevertheless, if data is available it is recommended to also look into statistical forecast methods.

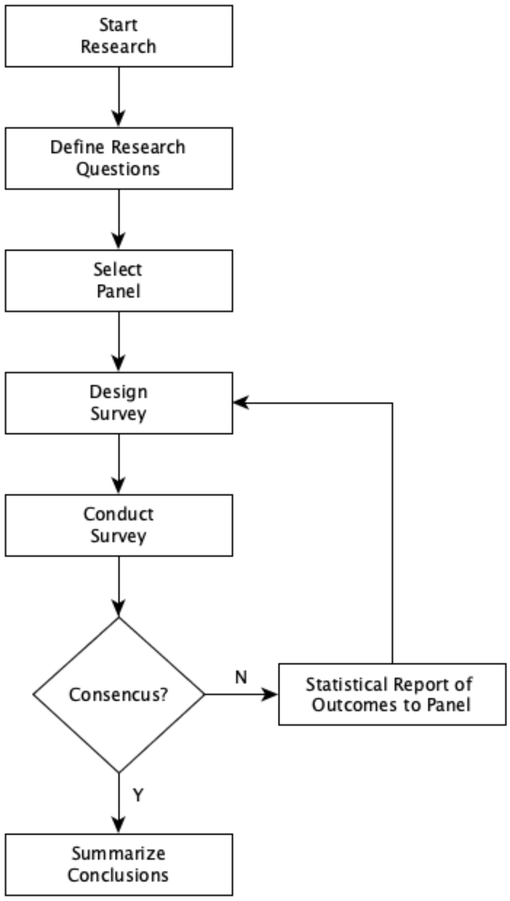

Figure 7: Delphi Process Workflow

3.4.3 Jury of Executive opinion

The Jury of Executive is a top-down approach. For this approach, just as with the Delphi method, a group of experts is needed in the form of a panel. While it was necessary for the Delphi method that the panels formed their own forecast, with this method they need to come to a consensus together. The experts are preferably very diverse and have knowledge about the internal and external terrain of the company. The experts are all from management, or higher, functions within the company. This meeting needs to be set up in a prudent way, to let every individual give their opinion and to minimize the bias. At the end of the meeting, there should be a consensus about the forecast. Furthermore, the leader of the discussion needs to take care of a structured discussion, and make sure that every expert can give their opinion. This approach can be used for all the types of introductions, and should also be considered as an adjustment on top of a statistical forecast, which will be discussed in section 3.4.7.

3.4.4 Forecast by analogy

Forecasting by analogy can be used in three different situations. Firstly, if historical sales of the product are available. Secondly, if no historical data is available, but there is of similar products. Lastly, if no historical sales data is available and also not of similar products. The goal of this approach is to have a less biased forecast. Green et al. introduced a structured approach of this process, consisting of five steps [7]. The steps are also displayed in figure 8.
Before starting the process a researcher is needed who guides the process. Sequentially, the five following steps can be executed.

- The first step is that the target situation needs to be described. This is very important, the success of the forecast depends to a great degree whether the target situation and in this case

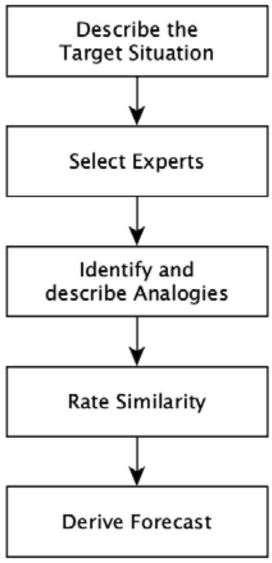

Figure 8: Forecast by Analogy Workflow

the product, is described well. The situation and product should be as unbiased as possible, to achieve this (objective) experts can be consulted.

- Secondly, a group of experts need to be selected, which are familiar with product introductions similar to the described target in the first step. Important is that the experts have different perspectives on the situation, which presumably leads to a variety of analogies.
- This ties with the third step, where the experts identify and describe different analogies as much as possible. Next to this, the possible outcomes of the analogies need to be stated.
- When the analogies are settled, the fourth step is to measure the similarity to the target situation. This can be done, for example by giving each analogy a similarity score between 0 and 1.
- Lastly, a forecast needs to be extracted from the analogies. There are multiple options for this step. The most common options for the researcher are to use the sales of the product with the highest similarity to the target or weight all different analogies with their similarity score [10].

The steps of this approach can be utilized in all different situations described and with all the different product introductions, yet the less data available, the more guesswork and assumptions need to be made. With the note that some kind of similar product data need to be available when introducing the product.

3.4.5 Sales Force Composite

In the 1980's the sales force composite method, together with the jury of executing opinion method were the most used forecasting models, stated by Dalrymple [5]. The sales force composite method is a bottom-down-approach. Instead of the sales representative of the company deciding what the sales of the new product are going to be, the sales managers in the store give their expectations. This prediction is made individually by every store's sales manager and aggregated by the company to get a market-wide prediction. This forecasting technique is very subjective. It is possible that the sales manager is too positive or too negative about a certain product. On the other hand, the sales manager of a store has direct contact with customers and presumably has a good idea of what their customers desire. This method can be used for almost all new product types specified, except in some cases when there is a new market product introduction. If a new product is introduced, but there are no stores which are selling products in the region at the moment it is impossible for store managers to make a regional based forecast. For all the other product introductions a manager of a store can probably make a forecast based on his historical findings or by questioning customers.

3.4.6 Customer intentions

This section "Customer intentions" can be classified under this Judgmental Forecast topic or under the title of "Market Research". The idea behind this approach is, that if no data is available, one can create their own by conducting a questionnaire. In this survey the potential customers can indicate how likely it is for them to purchase the newly introduced product. The interesting part is to compute the conversion of potential customers which uttered to buy the product to the number of customers that actually buy the product. If available, the conversion can be extracted from earlier Customer Surveys of already launched products. Randall et al. states that behavioral theory works better if researched just before the behavior is taken place and works better for already existing products. [24] This is why this approach can be used best when it is a new-to-the-firm product, an addition to an existing product line, when it is an re-positioning or a cost reduction. If the product is introduced to a new market, it depends on whether this item is already known by the inhabitants.

3.4.7 Judgmental Forecast on top of Statistical Forecast

When historical data is available, it is still possible to adjust the Statistical Forecast made. In practice this is done regularly, with good intentions, but not always with a good outcome. The only good reason to adjust a statistical forecast is if extra important information could not be incorporated in the statistical model and will influence the sales forecast. Additionally, it is never profitable to adjust the statistical forecast, if an expert or another stakeholder sees a pattern in the historical data. One should be confident that the seasonal patterns are learned by the statistical model. When a person adds extra seasonal influences, this generally results in a less accurate forecast [10]. On the other hand, when adjustments are made with a reasonable explanation, based on information unknown to the model, the accuracy of the forecast can increase. It is advised to always make adjustments with a group of experts, just as the Jury of Executive opinion, as described in subsection 3.4.3. Another option is to use an adjusted version of the Delphi Method for the revision of the statistical forecast. In this way, all selected experts can make their own adjustments on the forecast and come to a consensus with a structured process. This process is also described in subsection 3.4.2. This model can be used on top of all statistical forecasts and with all the different product introductions.

4 Additions to existing forecast models

While constructing this paper, I was missing different types of forecast methods or points of view. I collected the different cases and brought them together in this chapter. This chapter exists of additions to previously discussed methods, suggested new forecast models and new types of data sources.

4.1 Contigent products

This addition is a suggestion for a new type of data source. Bayus had the idea to use sales of contigent products for the forecast of the new product. The idea was based on the fact that some products are contigent on the purchase of another purchase. Contigent means that the secondary product is a part or extension on the primary product [3]. An example of this is an option of luxurious tires on a car or blades on a razor. The secondary product is not going to be sold, when the customer does not have the primary product. This approach can be used when introducing a new contigent product. The first step is to determine whether the product is a contigent product. This can be clear like the previous examples, but it can also be harder to determine. For example we take the new Apple Earphones, this item has a new lighting connector. The connector in the new earphones only fit in the newest iPhone models. The previous earphones had a regular AUX cable, which can be used in older iPhones and most devices of other brands. The sales of the older version of the earphones can be used in creating the forecast for this new product, but this can give a wrong view because the new connector excludes a big group of customers. In this case it can be helpful to include the sales of the contigent product. While also analyzing the sales of the newest iPhone, the sales forecast accuracy of the new Apple Earphones with lighting connector can be increased. In this way the sales of a primary item can be an important feature in the sales of the secondary item. This example shows that it is important to identify possible contigent products and identify whether the sales of this product can help by making a forecast for the new product introduction.

4.2 Application of the Bass model

As discussed in section 3.3.1 Bass states that the basic Bass model is only applicable when introducing a durable new-to-the-world product. I state that this Bass model can also be used with introductions into new markets, introducing a product as a new purpose, or when introducing limited editions of durable existing products. We consider the introduction of a new model of a durable product, a new model of a car. A new model release is most of the time a lighter, better looking, less fuel consuming or more technical advanced car. When this new introduction is announced, a great group of customers will not buy the older edition if a new model is introduced in a few months. This situation can be compared to a new-to-the-world product. Just as with the release of a new-to-the-world product, there are innovators and imitators. Imitators will only buy the new car when they are influenced by the group of innovators. Next to this, the Bass model assumes that the innovators must influence the imitators with word of mouth advertisement, which is also the case with this example. The parameter m of the Bass model, which stands for the the upper limit of sales in the time period of forecast, can in this case be determined in a different way. Bass suggest to let this number be decided by an expert in the organization, but when past sales of similar product introductions are available, the m can be determined by using statistical methods. The same comments can be made with introductions into new markets. If for example this new car is already available in America, but not yet in Europe. I argue that the Bass model is still applicable in this situation. The product is not new-to-the-world, but new-to-Europe, expected is that imitators wait until they are influenced by the group of local innovators. The group of imitators is described as the group that is influenced by the word of mouth of the group of innovators. It must be stated that with the upcoming of social media and the internet, that the world has become smaller. The imitators and innovators in this example from Europe are possibly also influenced by the innovators in America. Logically, this will result in earlier peek sales. Visually, considering figure 3.3.1, the peak will be steeper and the peak sales will lie more towards the y-axis. It is wise in this situation, to also look into section 3.3.5, which also is a diffusion technique, but works with advanced purchase orders. Concluding, I suggest that the Bass model can also be used when introducing a product in a new market or when it differs enough from similar products.

4.3 Decomposition

In literature about new product forecasting, decomposition is rarely used when predicting the sales of a new product. Most papers which involve decomposition are based on a longer history. My opinion is that decomposition can be used in new product demand forecasting. There are two types of decomposition, judgemental decomposition and based on time-series. The methods are both "deconstructing" the data points which are known and try to create a forecast on the different elements.

Firstly, the judgemental decomposition. This decomposition method tries to split the forecasting question in multiple questions. The questions are for example about the current market of the product or about the number of products sold on an average day. In this way the different components of influence can be described and calculated [16]. This method can be used with the forecast of all different product introductions.

When considering decomposition in time-series forecasting, we state that a time-series exists of four different components. Firstly, the level of the series (ℓ), which is the average of the series considering all data available. Secondly, the trend (b), which stands for an overall increase or decrease of the series. Additionally, the seasonality (s), which stands for the repeating pattern in the series. Lastly, the noise, this is the residue when extracting the other components, also called the randomness of the series. All of the components can vary per time unit, denoted with a subscript with the time t. With time series models, most of the times the Holt Winters' additive and multiplicative model are used. When the seasonal component of the time series is constant in variation through the periods of the historical data, the Holt Winters' additive method is preferred over the multiplicative method. When seasonal variations increase with the level component of the series, the multiplicative method is preferred [10].
The Holt Winters' additive method is given by the following equations:

$$\begin{aligned}
\hat{y}_{t+h|t} &= \ell_t + hb_t + s_{t+h-m(k+1)} \\
\ell_t &= \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\
b_t &= \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \\
s_t &= \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1-\gamma)s_{t-m},
\end{aligned}$$

With ℓ, b and s as defined before. With m the frequency of the seasonality and α, β^* and γ as the smoothing parameters. With $k = \frac{h-1}{m}$, the integer part is extracted to take a complete period of time into account.
The Holt Winters' multiplicative method is given by the following equations:

$$\begin{aligned}
\hat{y}_{t+h|t} &= (\ell_t + hb_t)s_{t+h-m(k+1)} \\
\ell_t &= \alpha\frac{y_t}{s_{t-m}} + (1-\alpha)(\ell_{t-1} + b_{t-1}) \\
b_t &= \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1} \\
s_t &= \gamma\frac{y_t}{(\ell_{t-1} + b_{t-1})} + (1-\gamma)s_{t-m}
\end{aligned}$$

For Holt Winters' and other time-series models a lot of historical data is needed. When producing a forecast for monthly aggregated data a minimum of 17 months are needed to make a forecast on data without a lot of noise [9]. This means that this method can only be used when 1.5 years of data is available. The reason that this section is in this new product forecasting paper, is because decomposed series of similar or contigent products can give extra insight to the behavior of a product in the market. With both of the Holt Winters' methods a forecast $\hat{y}_{t+h|t}$ is constructed, but more interesting for this purpose, the deconstructed parts of the series are extracted. The decomposition of similar products can be an addition to, for example, the judgemental forecasting by analogy, which was discussed in section 3.4.4. By deconstructing different products that the company is already producing, patterns can be found, which can be of great value for new product forecasts where no data is available. This method can be used when the product introductions are a an addition to an existing product line, with improvements, revisions or cost reductions of existing products and when introducing a product into a new market. In the other situations it is less likely that similar product data is available or whether it will add value, but this can differ per situation.

4.4 Triangulation

Triangulation is used in social sciences, the idea is that the confidence in a certain solution is greater if multiple methods give the same result [27]. The idea is formed upon the idea of land surveying techniques where one point must be approximated, starting from two distinctive points. When the two starting points approximate the same point, the point is determined as trustworthy [26]. I suggest that this method can also be used when forecasting a product introduction. The two methods are executed separately and the results are compared. When the two forecasts lie close to each other, the forecast can be used. When the forecasts show different patterns or trends, the forecast needs to be examined further. The forecast methods used can be qualitative, quantitative or a combination of the two. To determine whether the forecasts are similar, for example a jury of executive opinion can be used, which was described in section 3.4.3.

4.5 Ensemble Forecast

Related to triangulation, using multiple forecasts methods independently from each other to come to a prediction can be expanded. The model that I have in mind can best be described in the form of a diagram, which is displayed in figure 9 and will be described step wise in this section.

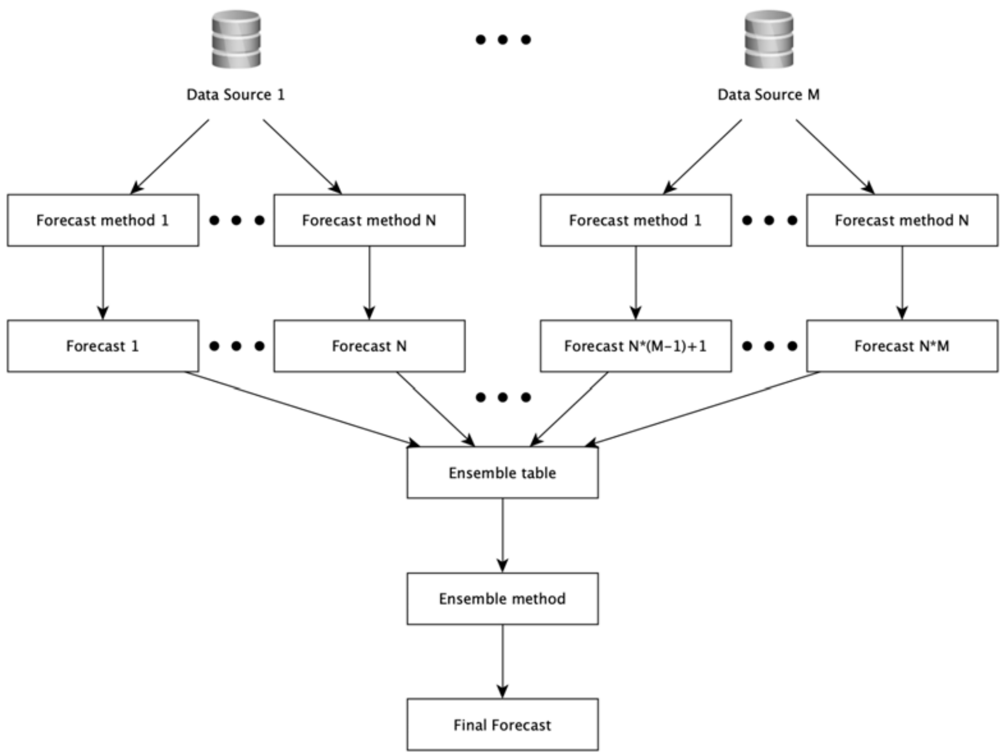

Figure 9: Ensemble method

- The first step is to gather the different data sources which possibly have an effect on the sales behavior of the product.
- The second steps is to use all relevant forecast methods, the tables in chapter 5 can help with choosing the right forecast methods.
- Per data source and forecast model combination, a forecast is created independently.
- Sequentially, all forecasts are gathered in one table and an ensemble method is used to come to one final forecast. An example how this table is constructed is shown in table 4.5. This table has all forecast methods on the horizontal axis, and the last column as the target table. On the vertical axis the different time periods of the train and test set are given. When the time period is part of the train set, the target value is known. When the time period is part of the test set, the target value needs to be determined, this is the forecast value.

- The ensemble forecast method can train on the different forecasts and targets in the train set and create a forecast for the train set. This ensemble forecasting method can be of a quantitative or qualitative nature. When using a qualitative forecasting method, it can be useful to visualize the different forecasts and target values. An example of a qualitative forecast method is the jury of executive opinion. It is also possible to use a quantitative method as an ensemble method. This can be a simple linear model, but also a machine learning method. Examples of machine learning models are the Random Forest model or Neural Networks. When table 4.5 is inserted in the forecasting methods stated, the model will train on the train set and will give weight to the different forecast models. In this way, a forecast based on all individual forecasts is calculated.

	Forecast 1	...	**Forecast N**	...	**Forecast N*(M-1)+1**	...	**Forecast N*M**	**Target**
Train period 1	TR(1,1)	...	TR(N,1)	...	TR(N*(M-1)+1,1)	...	TR(N*M,1)	Sales period 1
...	...		...		...		...	...
Train period X	TR(1,X)	...	TR(N,X)	...	TR(N*(M-1)+1,X)	...	TR(N*M,X)	Sales period X
Test period 1	F(1,1)	...	F(N,1)	...	F(N*(M-1)+1,1)	...	F(N*M,1)	Forecast 1
...	...		...		...		...	...
Test period Y	F(1,Y)	...	F(N,Y)	...	F(N*(M-1)+1,Y)	...	F(N*M,Y)	Forecast Y

Table 2: Ensemble Forecast table

This method can be used in all situations when relevant data is available or can be created. The power of this model is that all the different forecast models that are applicable to the type of product introduction can be used and can be taken into account.

5 Taxonomy

For managers and sales departments it is a challenge to make an accurate prediction for the demand of a new product. This article and especially this chapter can be useful as a starting point of this demand forecast. Firstly, one determines the type of new product that is introduced. This decision can be made by using the decision tree in figure 10.

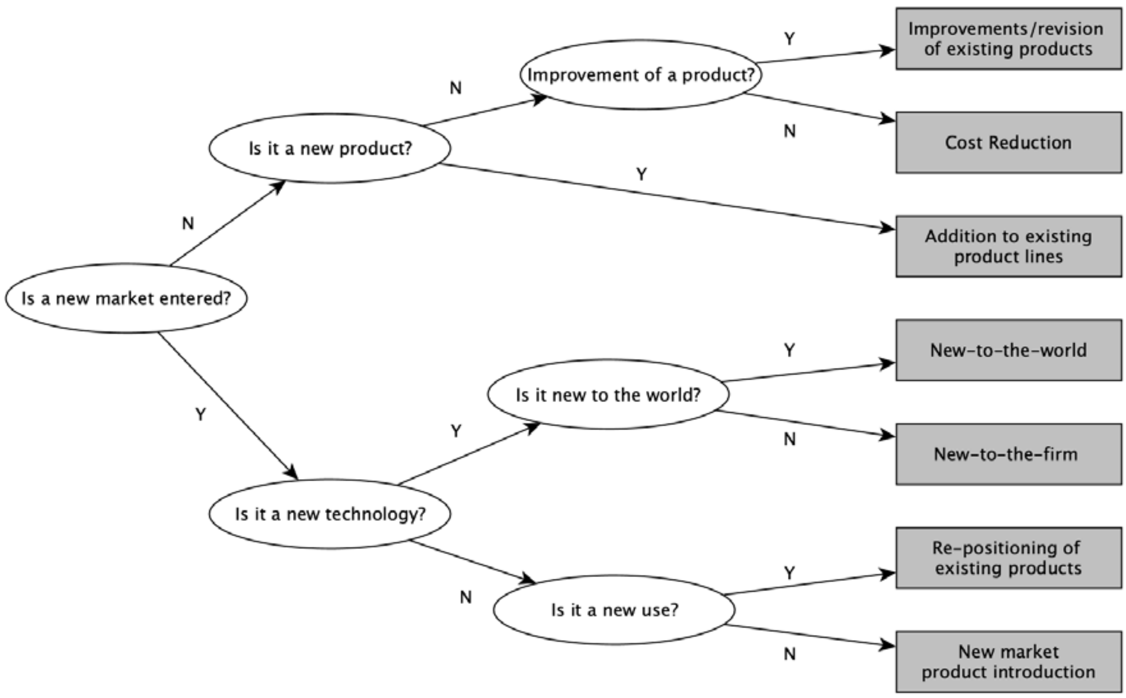

Figure 10: Decision Tree Product Introduction

It is wise to read through all the different types of introductions to make sure the right type of product introduction is chosen. Some of the choices in the decision tree are open to discussion. The different types of introductions can be found in section 2.
When the type of product introduction is stated, the different forecast methods can be looked into. In table 5 the different types of products can be found on the horizontal axis and the methods which were described in the previous chapters on the vertical axis. Per method and product introduction combination, an advise is given whether to use the stated method with this type of product introduction or under which condition. Additionally, a second table is added with all the different forecast methods listed complemented with the data an assets which are needed to conduct this forecast correctly. The last column of this table, in which the section of this method is indicated, is added for convenience. In table 5 this overview can be found.

Methods/ Type of Introductions	**New-to-the-world**	**New-to-the-firm**	**Additions to existing product lines**	**Improvements and revisions**	**Repositioning of existing products**	**Cost Reduction**	**New market product introduction**
Simple forecast methods							
Average Approach	No	If competitor data available	Yes	Yes	Yes	Yes	Yes
(Seasonal) Naive Approach	No	If competitor data available	Yes	Yes	Yes	Yes	Yes
Drift Method	No	If competitor data available	Yes	Yes	Yes	Yes	Yes
Market Research							
Economic choice theory	No	Yes	Yes	Yes	Yes	Yes	No
Conjoint analysis	No	Yes	Yes	Yes	Yes	Yes	Depends
Diffusion models							
Basic Bass model	Yes	No	No	No	No	No	No
Additions to Bass: Successive Generations	Yes	No	Yes	No	No	No	No
Additions to Bass: Statistical and ML	Yes	No	No	No	No	No	No
Life Cycle Approach	Yes	No	No	No	No	No	No
Advance Purchase Orders	Yes	Yes	Yes	Yes	Yes	No	Yes
Judgmental forecasting							
Scenario building	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Delphi's method	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jury of Executive opinion	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Forecast by analogy	Yes, altered version	Yes	Yes	Yes	Yes	Yes	Yes
Sales Force Composite	Yes	Yes	Yes	Yes	Yes	Yes	No
Customer Intentions	No	Yes	Yes	Yes	Yes	Yes	Depends
Judgemental on top of statistical forecast	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Additions to existing models							
Application of Bass	Yes	No	Depends	No	Depends	No	Yes
Decomposition	No	If competitor data available	Yes	Yes	Yes	Yes	Yes
Triangulation	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ensemble Forecast	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Mapping of forecast methods and types of introductions

Methods	**Data needed**	**Assets needed**	**Section**
Simple forecast methods			
Average Approach	Historical sales data of new or similar product	Excel	3.1.1
(Seasonal) Naive Approach	Historical sales data of new or similar product	Excel	3.1.2
Drift Method	Historical sales data of new or similar product	Excel	3.1.3
Market Research			
Economic choice theory	External Factors, Market Information and Product Attributes	Excel	3.2.1
Conjoint analysis	-	Survey makers and customer panel	3.2.2
Diffusion models			
Basic Bass model	Market Information	Excel	3.3.1
Additions to Bass: Successive Generations	Market Information, Historical sales data previous product	Excel	3.3.2
Additions to Bass: Statistical and ML	Historical sales data	Python or R, team of experts	3.3.3
Life Cycle Approach	Historical sales data of new or similar product	Excel, team of experts	3.3.4
Advance Purchase Orders	Data of introductions of similar products	Excel	3.3.5
Judgmental forecasting			
Scenario building	-	Team of scenario makers	3.4.1
Delphi's method	-	Survey makers and customer panel	3.4.2
Jury of Executive opinion	-	Team of experts	3.4.3
Forecast by analogy	Historical sales data of similar products	Excel and a team of experts	3.4.4
Sales Force Composite	-	Sales Managers of stores	3.4.5
Customer Intentions	-	Survey makers and customer panel	3.4.6
Judgemental on top of statistical forecast	Statistical forecast	Team of experts	3.4.7
Additions to existing models			
Application of Bass	Market Information	Excel	4.2
Decomposition	Statistical: Historical sales data of similar products Judgemental: Market Information	Statistical: Excel, R, Python Judgemental: Team of experts	4.3
Triangulation	Multiple forecasts		4.4
Ensemble Forecast	Multiple forecasts	Excel, R, Python	4.5

Table 4: Data and Assets needed per forecast method

7 Conclusion

The aim of the present research was to examine which forecast method could be utilized in which situation. The corresponding research question was stated as follows:

Which demand forecasting technique can be used when introducing a new product?

Before it was possible to answer this question, the different kinds of introductions needed to be introduced. The seven different types of introductions are introduced in section 2. In chapter 5 a decision tree is introduced which provides assistance in choosing the right type of product introduction. In the same chapter two tables are introduced with guidelines which method can be used in which situation and in which assets are needed to execute this forecast method. In chapter 3 all the different methods can be found. In some situations it is possible that more than one type of product introduction fits the situation. In that case it is possible to use the methods of both of the product introduction types or to choose the best fit for this specific introduction.
The first point that has to be made is that no product introduction is the same. This paper gives guidelines on types of introductions and techniques to use, but there is always room for interpretation and discussion. When the guidelines presented in this paper are followed, a collection of forecasting methods is suggested and the stakeholders can decide which forecast model can be executed with the means available. The second point is that all forecasting techniques need some kind of data. Even when using qualitative forecast methods, data is created to form a forecast. When relevant data is available and added to the forecast, the forecast becomes more trustworthy. Also, when similar or contigent product data is available, it is important that this data is used. Additionally, it is wise to investigate the possibility to include external data. Multiple governments have an open data platform from which data about industries can be extracted. Lastly, when no data is available, data can be created by different judgemental forecasting methods. For example by conducting market research or by consulting with a panel of experts.

To answer the research question, the forecast techniques which can be used when introducing a new product, differ per type of introduction and are depended on the available assets and data available. This paper gives an advise in the form of a decision tree and two tables in section 5, which can be seen as the base when forecasting the demand of a product introduction. In sales forecasting every situation is different and it is wise to scan through the different forecast models, even if they are not directly applicable to your current situation.

8 Further Research

This paper outlines different methods which can be used to conduct a demand forecast. It describes a selection of methods which were proven to work well. This research can always be supplemented with new forecasting methods. One interesting and well bespoken subject in the literature was the tuning of the Bass parameters. In multiple papers this Bass model performed really well when the parameters were tuned in the right way. In this paper I referred to two additions to the basic Bass model. This section can be complemented with more additions and tuning methods for the Bass model.
Additionally, the Economic choice theory is a field on which a lot of literature is written. In this paper only one approach was given. Economic Choice theory really focuses on the “why” question that a lot of companies have. Why is this product selling worse than was expected and how can we adjust to this? I think that when the data of the customer decision process can correctly be quantified, the sales forecast can profit of this a lot. Lastly, more research can be done in the field of ensemble methods. When a company has the resources to perform more than one of the stated forecast models and combine them to one final forecast, it can possibly add a lot of value. As already stated, the more relevant data and forecast methods to execute, the more insight is gained.

References

[1] Brian H. Archer (1980), Forecasting demand, Quantitative and intuitive techniques. International Journal of Tourism Management (March 1980) 5-12.

[2] Frank M. Bass (1969), A New Product Growth for Model Consumer Durables. Management Science, Vol. 15, No. 5, January, 1969, United States of America.

[3] Barry L. Bayus (1987), Forecasting Sales of New Contingent Products: An Application to the Compact Disc Market. The Journal of Product Innovation Management, Volume 4, Issue 4, December 1987, Pages 243-255.

[4] Peter S. Fader and Bruce G. S. Hardie (2005), The value of simple models in new product forecasting and customer-base analysis. Applied Stochastic Models in Business and Industry, 2005; 21:461–473.

[5] Douglas J. Dalrymple (1987), International Journal of Forecasting, Volume 3, Issues 3–4, 1987, Pages 379-391.

[6] Denzil G. Fiebig, Michael P. Keane, Jordan Louviere, Nada Wasi (2010), The Generalized Multinomial Logit Model: Accounting for Scale and Coefficient Heterogeneity. Marketing Science 29(3):393-421.

[7] Kesten C. Green and J. Scott Armstrong (2007), Structured analogies for forecasting. International Journal of Forecasting, Volume 23, Issue 3, July–September 2007, Pages 365-376.

[8] Paul E. Green and V. Srinivasan (1978), Conjoint Analysis in Consumer Research: Issues and Outlook. Journal of Consumer Research, Volume 5, Issue 2, 1 September 1978, Pages 103–123.

[9] Rob J. Hyndman and Andrey V. Kostenko (2007), Minimum sample size requirements for seasonal forecasting methods. Foresight, Issue 6, Spring 2007.

[10] Rob J. Hyndman and George Athanasopoulos (2018), Forecasting: principles and practice. OTexts, second edition (May 6, 2018). Chapters 3, 4 and 7.

[11] Zuhaimy Ismail and Noratikah Abu (2013), New product Demand Forecast based on Bass Diffusion Model. Journal of Mathematics and Statistics, 9 (2): 84-90, 2013.

[12] Kenneth B. Kahn (2006), New Product Forecasting: An Applied Approach, Taylor and Francis Ltd, 2006.

[13] Michael Lawrence, Paul Goodwin, Marcus O'Connor, Dilek Önkal (2016), Judgmental forecasting: A review of progress over the last 25 years. International Journal of Forecasting 22 (2006) 493-518.

[14] Hakyeon Lee, Sang Gook Kim, Hyun-woo Park and Pilsung Kang (2013), Pre-launch new product demand forecasting using the Bass model: A statistical and machine learning-based approach. Technological Forecasting and Social Change, Volume 86, July 2014, Pages 49-64.

[15] Harold A. Linstone and Murray Turoff (2002), The Delphi Method, Techniques and Applications. Digital book, reproduction of the original 1975 book.

[16] Donald G. MacGregor (2001), Decomposition for Judgmental Forecasting and Estimating. Principles of Forecasting. Kluwer Academic Publishers, Pages 107-123.

[17] Vijay Mahajan and Subhash Sharma (1986), A simple algebraic estimation procedure for innovation diffusion models of new product acceptance. Technological Forecasting and Social Change, Volume 30, Issue 4, December 1986, Pages 331-345.

[18] Daniel McFadden, Kenneth Train and William B. Tye (1978), An Application of Diagnostic Tests for the Independence From Irrelevant Alternatives Property of the Multinomial Logit Model. Transportation Research Record Journal of the Transportation Research Board (637):39-45.

[19] Daniel McFadden (1986), The Choice Theory Approach to Market Research. Marketing Science, Vol 5, No. 4, Fall 1986, United States of America.

[20] David Mercer (1995), Scenario's made easy. Long Range Planning, Volume 28, Issue 4, August 1995, Pages 7-8 and 81-86.

[21] Wendy W. Moe, Peter S. Fader (2002), Fast-Track: Article Using Advance Purchase Orders to Forecast New Product Sales. Marketing Science 21(3):347-364.

[22] Jeffrey S. Morrison (1995), Life-Cycle Approach to New Product Forecasting. The Journal of Business Forecasting Methods and Systems, Vol. 14, No. 2.

[23] John A. Norton and Frank M. Bass (1987), A diffusion theory model of adoption and substitution for successive generations of high-technology products. Management Science, Volume 33, Issue 9, September 1987, Pages 1069-1086.

[24] Donna M. Randall and James A. Wolff (1994), The time interval in the intention-behaviour relationship: Meta-analysis. British Journal of Social Psychology, 33, 405–418.

[25] E. M. Rogers (1962), Diffusion of Innovations, New York: The Free Press, 1962.

[26] Paulette Rothbauer (2008), Triangulation. The SAGE Encyclopedia of Qualitative Research Methods. Sage Publications, 892-894.

[27] Triangulation of Data Sources and Research Methods (2018), National Academies of Sciences, Engineering, and Medicine. Changing Sociocultural Dynamics and Implications for National Security: Proceedings of a Workshop. Washington, DC: The National Academies Press. Chapter 3.

[28] Glen L. Urban, Bruce D. Weinberg and John R. Hauser (1996), Premarket Forecasting of Really-New products. Journal of Marketing, Vol. 60, No. 1, January 1996, 47-60.

[29] Dick R. Wittink and Trond Bergestuen (2001), Forecasting with Conjoint Analysis. Armstrong J.S. (eds) Principles of Forecasting. International Series in Operations Research and Management Science, vol 30. Springer, Boston, MA. Chapter 5.