A FUZZY LOGIC APPROACH FOR SALES FORECASTING

ABSTRACT

Sales forecasting proved to be very important in marketing where managers need to learn from historical data. Many methods have become available for forecasting, generally used statistical methods, such as exponential smoothing, moving average, autoregressive moving average (ARMA), or the autoregressive integrated moving average (ARIMA). These methods model sales only on previous sales data and tend to be linear in nature and don't take into account both internal and external factors that may directly influence sales. In this paper, a model based on fuzzy logic theory has been investigated and applied to an actual sales forecasting situation faced by marketing managers involving human judgment. To illustrate the model, we simulated sales forecast based on an exponential smoothing model that minimize the Mean Squared Error (MSE) and inferred the result with the Fuzzy Logic System (FLS) developed.

INTRODUCTION

Sales forecast have been of interest for a number of marketing researchers. In fact, West [17] conducted a survey mailed to 900 senior Canadian marketing executive and top managers responsible for marketing in smaller companies. West targeted marketers because they are responsible for sales forecasting. He found that only 10% of of the companies surveyed used one method. This means that 90% of them used more than one method, generally combining quantitative forecasting methods with qualitative ones.

Qualitative forecasting is based on human reasoning that is complex, tainted of reasonable amount of imprecision, vagueness and uncertainty. Known conventional quantitative techniques to represent humanistic systems failed, because revealed to be to unable handle fuzziness and lack or a low level of precision to mimic human reasoning in solving real world problems. There are many mathematical models used to deal with such problems, including stochastic models, mathematical models that follow the laws of physics and models which have emerged from mathematical logic. However, these models face a general difficulty on how to build an appropriate mathematical model from a given problem? Obviously, the evolution of Technology and advanced computer systems makes it possible; but, managing such systems remains a real challenge to cope with randomness ambiguity and uncertainty and are very hard to implement. This type of problems involving such vagueness and ambiguity, are often related to the process of human thinking, are better represented by Fuzzy Logic Theory, developed initially by Zadeh [19].

In this paper, we will first, present forecasting sales methods used by business. Second, Fuzzy Logic Theory is introduced along with Fuzzy Logic System (FLS) structure. The next section is reserved for the Sales Forecast FLS and a numerical illustration. Finally, we conclude.

FORECASTING SALES METHODS

Forecasting sales methods are interesting and difficult. It involves predicting the amount of products that people will purchase given the products features and condition of sales. Two types of forecasting methods are known, namely the quantitative ones and the qualitative ones. In this section, we don't aim to develop and present the different forecasting technique used in sales forecasting. We only list some of these techniques and the reader who is interested in them can consult the references listed at the end of this paper.

Quantitative sales forecasting methods

Quantitative methods make no use of marketing managers' knowledge of series. They assume that the casual forces that have affected a historical series will continue over the forecast horizon [8][10]. Among the multiple methods used, one can use the direct extrapolation of the trend [11], the exponential smoothing [5], the seasonal adjustment known as moving average, used in short term forecasting [4][9], or the naïve forecast appropriate in situation of large uncertainty [2][14]. More complication forecasting methods can be used such as the autoregressive moving average (ARMA) [18] model and the autoregressive integrated moving average (ARIMA) [18] model, among others.

The casual approaches to sales forecasting approach suppose that the marketing manager can forecast the factors that cause sales to vary. This begins environmental factors such as population, Gross National Product (GNP) and legal system. These factors affect the behavior of customers, competitors, suppliers, distributors and partners. Their actions lead to a market forecast and provide inputs for the market share forecast. The of the market forecast and the market share forecast determines the sales forecast. Econometrics models are used in this case to determine the sales forecast [1][12][15][16].

Qualitative sales forecasting methods

Several companies use traditional sales forecast stage to generate their sales forecast. In this methods, sales representatives and managers are asked to make a qualitative assessment of their opportunity. This forecast is based on the sales representatives and managers' intuition rather than metrics. The accuracy of their forecast can be improved by the use of structured qualitative methods such as the the Delphi [13] method. Among newly developed methods is the Data–Driven sales forecasting method. This method uses opportunity stages. In fact, in Customer relationship management (CRM) systems, such as Microsoft Dynamics, each opportunity has a status or stage. Each stage represents a milestone that one works towards to take a validated sales opportunity across the finish line. In the CRM, these stages might be steps like prospecting, qualifying needs, assessment, presentation, negotiation and closure (sales finalized or closed). Each of these stages will have a "probability of closing" associated with them. In early stages, the "probability of closing" can be for example 10% while in a later stage, for example in the negotiation stage, it can be 90%. Using this method, sales forecast can be determined as follow:

$$S_f = \sum_{1}^{i} \sum_{1}^{j} p_j s_j \qquad (1)$$

where,

p_j is the "probability of closing" for client j
s_j is the sales amount for client j
i is the i-th sales representative

Baker [3] stated forecasting methods based on extrapolation are inexpensive and often adequate for forecasting decisions that need to be made. However, in situations where large changes are expected, casual approaches are recommended. Combining quantitative and qualitative forecasting methods take into account both the historical data and trend as well as sales representatives and marketing managers opinions as expert of the field. In the next section, we will introduce the Fuzzy Logic Theory as a method to integrate sales representatives and marketing managers' opinions and judgments for sales forecasting.

FUZZY LOGIC THEORY

Fuzzy logic, used to formalize human reasoning, is an extension of Boolean logic developed by Zadeh [20] based on fuzzy sets theory, which is a generalization of the classical set theory. Fuzzy logic aims to decrease complexity by allowing the use of imperfect information in sensible way. One major advantage of fuzzy logic is that the rules are set in natural language with many inputs and output variables to allow solving complex problems and is able to give results in the form of recommendation for a specific interval of output. In classical set theory, elements follow the law of the excluded middle, either belong to or do not belong to a set. A function $f_A(x)$ describing the classical set A (non-fuzzy) is presented as follow:

$$f_A(x) : X \rightarrow \{0,1\} \quad \begin{cases} f_A(x) = 1 \; if \; x \in A \\ f_A(x) = 1 \; if \; x \notin A \end{cases} \tag{2}$$

Whereas in fuzzy logic theory, a fuzzy subset A of a universal set X is characterized by the following membership function:

$$\mu_A : X \rightarrow [0, 1] \tag{3}$$

which assign a real number $\mu_A(x)$ in the interval $[0, 1]$, to each element $x \in X$ t, where the value of $\mu_A(x)$ at x shows the grade of membership of x in A.

The degree of membership function is determined by placing a chosen input variable on the horizontal axis, while vertical axis shows quantification of grade of membership of the input variable. The membership function varies between zero and one; zero means that input variable is not a member of the fuzzy set, one means that input variable is a member of the fuzzy set. These membership functions can be represented by using graphical representations. This graphical representation can be based on a fuzzy association pairs, matrices, or mathematical equations that can have different shapes (triangular most common one, bell, trapezoidal, Gaussian, Bell, and Sigmoid, sinusoidal and exponential). Each linguistic term is a fuzzy set and has its own membership function. In this case, $\mu_A(x) \in [0, 1]$, representing the degree of membership of x in A. $\mu_A(x)$ maps each point in X into the real interval $[0.0, 1.0]$. As $\mu_A(x)$ approaches 1.0, the "grade of membership" of x in A increases. The most used membership functions are either the triangular shape or the trapezoidal shape.
A triangular membership function, expressed by (a, b, c) is defined as:

$$\mu(x) = \begin{cases} \dfrac{x-a}{b-a}, a \le x \le b \\ \dfrac{c-x}{c-b}, b \le x \le c \end{cases} \tag{4}$$

A trapezoidal membership function, expressed by (a, b, c, d) is defined as:

$$\mu(x) = \begin{cases} \dfrac{x-a}{b-a}, a \le x \le b \\ 1, b \le x \le c \\ \dfrac{d-x}{d-c}, c \le x \le d \end{cases} \tag{5}$$

Fuzzy Logic Theory is based on the theory of fuzzy sets, which is a generalization of the classical set theory. Fuzzy Logic Theory is used, in the narrow sense, to describe a formal logic following the principles of fuzzy logic.

The mathematical notation for a fuzzy set A given the finite domain $\{x_1, x_2, \cdots, x_n\}$ and membership function μ_A is:

$$\mu_A(x_1) \,/\, x_1 + \mu_A(x_2) \,/\, x_2 + \cdots + \mu_A(x_n) \,/\, x_n \qquad (6)$$

where

$\mu_A(x_i) \,/\, x_i$ (a singleton) is a pair "grade of membership element"

In fuzzy logic, the intersection of two fuzzy sets (AND operator), A with a membership function μ_A, and B with a membership function μ_B, written $A \cap B$, is a new fuzzy set defined as $\mu_{A \cap B} = min(\mu_A, \mu_B)$. The union of two fuzzy sets (OR operator), A with a membership function μ_A, and B with a membership function μ_B, written $A \cup B$, is a new fuzzy set defined as $\mu_{A \cup B} = max(\mu_A, \mu_B)$. The complement is defined as the negation of the specified membership function and defined as $\mu_{\bar{A}} = 1 - \mu_A$.

Zadeh [20] had classified computing into two separate categories; hard computing and soft computing. The hard computing relates to computations based on Boolean algebra and other crispy numerical computations, then it is tolerant of imprecision, uncertainty and partial truth. Whereas soft computing encompasses fuzzy logic, neural network and probabilistic reasoning techniques, such as genetic algorithm, and parts of learning theory. Unlike hard computing, Soft computing is more analogous to thinking of human mind [6][7].

Figure 1 presents a Fuzzy Logic System (FLS) and its four major units, namely, a fuzzification unit, a fuzzy knowledge-base unit, a fuzzy inference engine unit and a defuzzification unit.

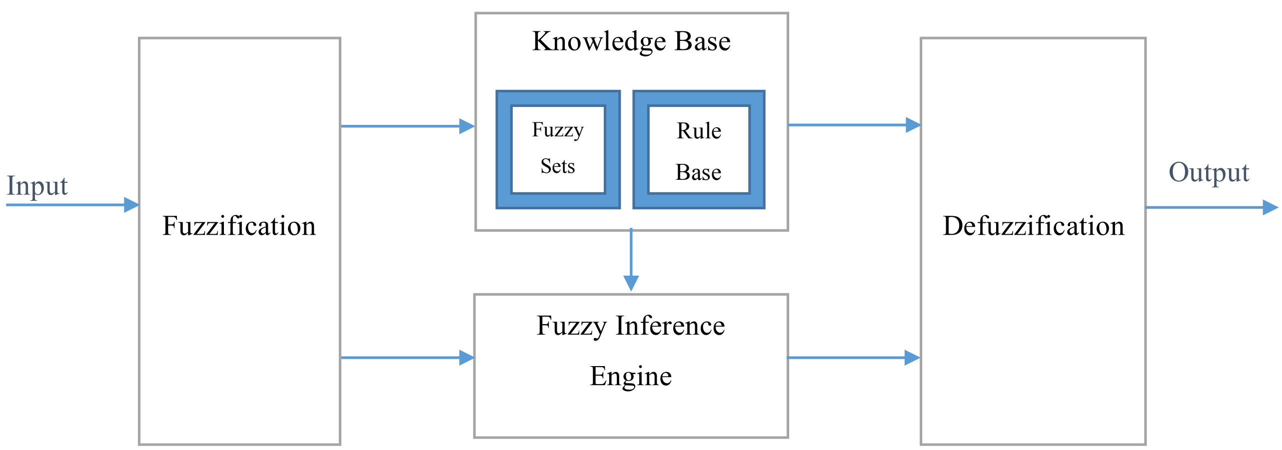

Figure 1. Fuzzy Logic System (FLS) Structure

Fuzzification unit

Fuzzification is the process of making a crisp vakue fuzzy. This step delivers input parameters for the fuzzy system based on which the output result will be calculated. Then, the parameters are fuzzified, mapped into suitable linguistic values that may be viewed as labels of fuzzy sets, with use of pre-defined input membership functions. The membership functions associate a weighting factor that determine the degree of influence or degree of membership for each active rule. Then a set of fuzzy output response are produced by computing the logical product of the membership weights for each active rule.

Knowledge-base
The knowledge base consists of two sub-units; the fuzzy sets database and the rule base. In the knowledge-base 'facts' are represented through linguistic variables and the rules follow fuzzy logic. The concepts associated with fuzzy sets are used to characterize the rules base and how data manipulation is handled in the system. These concepts are subjectively defined and based on experience.

Fuzzy inference engine
The fuzzy engine is the kernel of the FLS, which has capability of simulating human decision–making. It is based on fuzzy concepts and inferring fuzzy control actions using fuzzy implication (fuzzy relation) as well as the rules of inference in fuzzy logic. The fuzzy inference engine handles rules inference where human experience can easily be included through linguistic rules.

Defuzzification
Defuzzification is the process of converting fuzzy output sets to crisp values. The defuzzification process is aimed at producing a non-fuzzy output that best represents the possibility of distribution of an inferred fuzzy input. There are different methods for defuzzification. The mostly-used are the Maximum Criterion (MC), the Center of Gravity (CG) and the Mean of Maximum (MM). Unfortunately, there is no defined procedure for choosing a defuzzification method.

The dynamic behavior of a fuzzy system is characterized by a set of linguistic control rules based on expert knowledge. The fuzzy rule base consists of a set of linguistic control rules written in the form of a rule matrix which is used to describe fuzzy sets and fuzzy operators in form of conditional statements. A single fuzzy if-then rule can be written as follows:

"*IF* A is satisfied (premise), *THEN* R is inferred"

where A is a set of conditions that have to be satisfied and R is a set of consequences that can be inferred. In rule with multiple parts, fuzzy operators are used to combine more than one input using AND (min), OR (max) and NOT operators. Consequently, the success of a fuzzy systems depends on how well this knowledge-base is structured.

SALES FORECAST FLS AND NUMERICAL EXAMPLE

Sales Forecast FLS
We run a monte-carlo simulation in order to obtain 360 historical data (monthly data over 30 years). We used the exponential smoothing method to obtain 12 months forecast. The forecast equation is as follows:

$$\hat{F}_{t+1} = \alpha F_t + (1-\alpha)\hat{F}_t \tag{7}$$

where

$\hat{F}_{t+1}$ is the forecast of the sales for period $t+1$
F_t is the sales for period t
$\hat{F}_t$ is the forecast of the sales for period t
α is the smoothing constant $(0 \le \alpha \le 1)$

We choose a value of α that minimizes the MSE.

The inputs to the FLS are the sales forecast. The triangular membership function was used for all fuzzy sets, and the of overlap for successive sets for a particular model is identical. Our universe of discourse reflects an extension of the range of the historical values of monthly forecasts (12 months). The rule base is populated by marketing experts (managers and sales representatives) estimations. Then, the results are obtained from running the Fuzzy Inference Engine and the defuzzification step.

Numerical Example
(To be completed)

CONCLUSION

Sales forecasting proved to be very important in marketing where managers need to learn from historical data. Many methods have become available for forecasting, generally used statistical methods, such as exponential smoothing, moving average, autoregressive moving average (ARMA), or the autoregressive integrated moving average (ARIMA). These methods model sales only on previous sales data and tend to be linear in nature and don't take into account both internal and external factors that may directly influence sales. However, as discussed in this paper extrapolating patterns and relationships from the past to the future can't provide accurate predictions in a context of high uncertainty and vagueness. The application of fuzzy logic in sales forecasting provide better estimates for marketing managers and sales representatives.

We developed a Fuzzy Logic sales forecast System that integrates into the "traditional" sales forecast the experience and the judgments of the marketing managers and sales representatives. The fuzzy logic is a modeling approach that integrates the fuzziness of real-life information. The results inferred the fuzzy system take into account the ambiguity and the vagueness. Finally, we illustrated the developed system with a numerical example.

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