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ATM REPLENISHMENT FORECASTING WITH SUPPORT VECTOR MACHINE – A CASE STUDY

[1]EVRIM GENCALP, [2]MUJDE EROL GENEVOIS, [3]MICHELE CEDOLIN

[1,2,3]Industrial Engineering Department, Galatasaray University,Turkey
E-mail: [1]evrimgencalp@gmail.com, [2]merol@gsu.edu.tr, [3]mcedolin@gsu.edu.tr

Abstract - In the cash management process of banks, Automated Teller Machine (ATM) hold an important role. The correct ATM replenishment policies is directly dependent to the correct forecasting of the cash transactions such as withdrawal and deposits. The money in the ATMs are deprived from interest, however the lack of necessary amount of money might yield to the client loss. Therefore, the forecasting studies concerning the ATMs is an important topic that investigated in the literature. In this study, a machine learning model by using Support Vector Regressor (SVR) algorithm is applied to predict daily cash withdrawals of 5 ATMs considering different factors.

Keywords - Cash Management, Time Series Prediction, Machine Learning, SVM

I. INTRODUCTION

Supply Chain Management researches and as a part of SCM forecasting studies are ignored areas in services industries rather than manufacturing industries [1]. Although the main objectives of these two kinds of industries are similar, like revenue maximization or resource minimization, their environment and the methods should be used are widely varies between them.

While inventory cost is one of the main concerns of product based companies, service based companies does not have this concern. Essential affairs of a service based company are quality and availability of the service.

There are fundamental differences between product based and service based organizations which cause the forecasting methods used for these kinds of organizations differ from each other [2]. Intangibility of service based products is one of these differences. While this feature gives an advantage to service based companies by eliminating constraints of logistics processes, decreases measurability of amount of demand of the service. Another difference is need for simultaneity. Demand of a product may be deferrable a fair amount of time but demand of a service is lost in a case of inability to meet demand. Heterogeneity is one another difference between service based and product based companies. Services cannot be easily standardized. Every customer experiences a different service each time and quality of a service cannot be measured easily.

Eventually, because of characteristic fluctuations in the demand for services and the fact that services are produced and consumed simultaneously, service based businesses face the problem of matching capacity and demand continuously [3].

In the remainder of this paper, first we give a literature review of cash management of banks and time series prediction models in section II. Then we mention the methodology used in section III. Afterwards we perform an application and give results in section IV. Finally, conclusions and suggestions for the next steps to the research are presented in section V.

II. LITERATURE REVIEW

2.1. ATM Cash Replenishment Prediction

In ATM cash replenishment, banks want to use less resources, like cash kept in ATMs, trucks for transport money, while meeting customer demand. According to Simutis (2008), generally banks keep %40 more money than they need while %15 is efficient as safety stock [4]. As well as surplus is an undesirable and costly situation [5], stock-out also an unwelcomed case and generally its cost is an inestimable cost [6]. Traditional forecasting methods which are smoothing and regression methods such as exponential smoothing and weighted moving average are applied to daily cash withdraws for individual ATMs [7]. These methods use only cash withdraw data and try to catch a trend or seasonality in the historic data [8].

An alternative and precise way predicting ATM cash demand is Time Series Forecasting with advanced statistical models like ARIMA or Machine Learning Algorithms and Neural Networks [9]. ARIMA models are the most generic and basic time series forecasting models. The fact that these models are easy to implement and can be solved with shorter run times, increases their preferability. One disadvantage of ARIMA models is that these models predict future demand by using only demand data and does not use features to correlate sudden changes and fluctuations with them [10]. Machine Learning Algorithms are another way to make Time Series Prediction. There are various models like K'th Nearest Neighbor (KNN), Support Vector Machine, Tree Search, Random Forest and Boosting Algorithms. The right model to be used for prediction is determined according to features and structure of data. Exploratory Data Analysis and visualization tools should be used as assistants to determine right model.

2.1. Machine Learning Algorithms

Machine Learning algorithms, basically grouped as supervised, unsupervised and reinforcement algorithms. Supervised machine learning algorithms are classification and regression algorithms. They are taught by example data set. This dataset includes the desired inputs and outputs. Unsupervised machine learning algorithms are usually called as clustering algorithms and they are trained only input datasets to identify patterns. Reinforcement learning algorithms are not trained like supervised and unsupervised algorithms. They learn from mistakes. Decision Tree, Support Vector Machine, K'th Nearest Neighbor and Logistic Regression are types of supervised learning algorithms.

Applications of Decision Tree Machine Learning algorithm are generally pattern recognition and identifying disease and risk trends. Support Vector Machine Algorithm is used for classification problems that require high accuracy and efficiency of data [11]. KNN algorithm is used for handwriting detection applications and image and video recognition. Logistic Regression which is the simplest supervised machine learning algorithm is applied to classifying words as nouns, pronouns, and verbs and weather forecasting and voting prediction problems [12].

In time series prediction with machine learning algorithms, feature selection is an important success factor. There are various feature selection methods. Measuring correlation ratio between features and cash withdraw amount is a widely used method. In ATM cash withdraw forecasts mostly used features are ATM location, seasonal factor, holidays and daily historic data [13]. To simplify forecasting model, aggregating daily withdraw data can be a beneficial method [14]. To move on to the next step, forecasting results can be used as initial results of a linear programming model to optimally allocating resources [15].

To measure accuracy of prediction model there are diverse range of error metrics. In time series prediction models, Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) are commonly used metrics due to lack or surplus amount of predicted withdrawals does not neutralize each other in these metrics [16].A general overview of time series forecasting methods can be seen in Figure 1 [17].

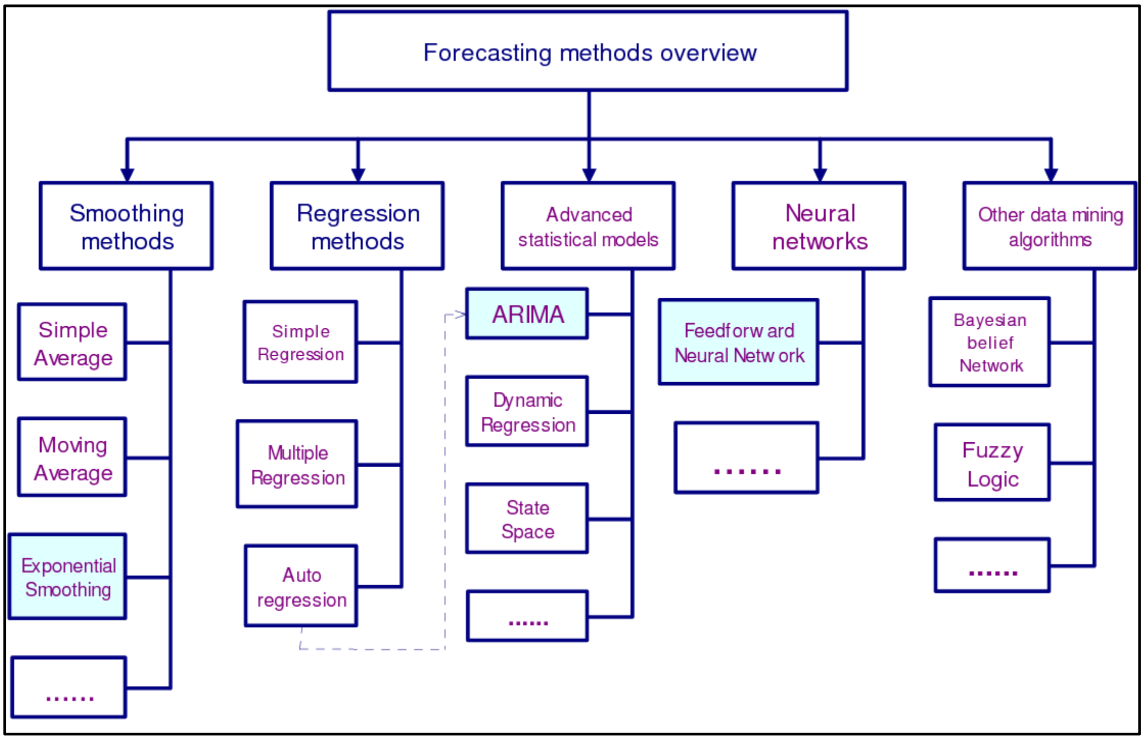

Fig.1.Time Series Forecasting Methods

III. METHODOLOGY

Differently from classification or clustering models, in time series prediction models, seasonality is a complicating agent. Machine learning algorithms are effective methods in time series prediction due to easiness in introducing time effect to model. Support Vector Machines, firstly have been proposed to solve pattern recognition problem as a binary classification problem which is named as Support Vector Classifier (SVC) [18]. Recently, due to its successful implementation, SVM has been came in a widely used method in time series prediction (SVR) [19].

Basic idea of support vector machines is to find hyperplane for linearly separable patterns. Support vectors are the data points that lie closest to the hyperplane (SVC) or regression line (SVR). SVMs aim to maximize the margin around the separating hyperplane.

Working principle of a linear SVM model is given below and illustrated in Figure 2 [20].

$$w * x_i + b \geq 1 \text{ when } y_i = 1$$
$$w * x_i + b \leq -1 \text{ when } y_i = -1$$
$$H_1 : w * x_i + b = +1$$
$$H_2 : w * x_i + b = -1$$

The points on the planes H_1 and H_2 are first points of different classes. H_0 is the median. d^+ and d^- values are the shortest distances to the closest positive and negative points respectively.

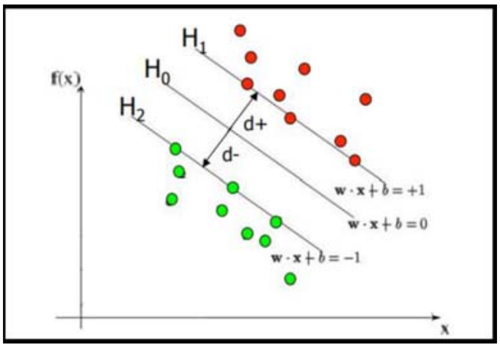

Fig.2.An example of Linear SVM model

In this study, we employed a SVR model to predict cash demand in ATMs. Besides of historic data of cash withdrawals, there will be used some features to help increasing accuracy of the model. These features are days of month, month of year, weekdays and working days, holidays and location of ATM. Detailed information about model will be given in application section.

IV. APPLICATION

As it is mentioned in previous section, Our SVR model consists of ATM cash withdrawal data and year, month, day, working days, weekdays and festival/religion features. We trained our model with 1-year data and tested it with 8 months' data. As error metric mean absolute percentage error is used (MAPE).

MAPE measures the size of the error in percentage. It is calculated as the average of the unsigned percentage error, as shown below:

$$MAPE = \frac{100}{N} * \sum_{i=1}^{N} \left| \frac{x_i - \widetilde{x}_i}{x_i} \right|$$

Where, x_i is the actual observation and $\widetilde{x}_i$ is the estimated value, with a N sample.

The data we used in this application is taken from the online big data platform www.kaggle.com. It is a simulated data with name "data of ATM transaction of xyz bank", consisted of 11590 rows. We used % 70 of the data as training sets and %30 as test data set.A sample of application data is given in the table below.

	ATM name	# of withdrawals	Total Amount	Weekday	Festival Religion	Working Day
1	Big Street	50	123800	Saturday	H	H
2	Mount Road	253	767900	Saturday	C	H
…	…	…	…	…	…	…
…	…	…	…	…	…	…
…	…	…	…	…	…	…
11589	KK Nagar	76	76	Friday	H	H
11590	Christ College	143	143	Friday	H	H

Table 1:The Sample Data Set

While selecting features, first we tried all features one by one and all at once as alternative scenarios.

When measuring the errors, it is seen that scenario which includes all features has higher percentage error than some scenarios with one feature. The scenarios with lowest percentage error are year data scenario and working day data scenario with a percentage error of 44.1%. Weekday data scenario follows them with 44.4% percentage error.

The fact that year and work day data are working well separately, led us to combined them in another scenario. As predicted, percentage error of this new scenario has the lowest value than others. When we add weekday feature which has the second lowest error to the new scenario, percentage error increases.

Mean Absolute Percentage Errors of all alternative scenarios are given in below Table 2.

Feature	Percentage Error (%)
All	44.6
Year	44.1
Month	44.7

Day	44.6
Festival Religion	44.5
Weekday	44.4
Working Day	44.1
Year & Work Day	43.0
Year & Work Day &Weekday	44.0

Table 2: MAPE values of prediction model scenarios

To compare results of our machine learning model, we built an ARIMA model with ATM transaction time series data. As it mentioned before, ARIMA models work with only time series data. Other featured are not needed in this model. In the result of ARIMA model, it is seen that MAPE value is 68%. This outcome shows us machine learning models are mode stronger than regression models like ARIMA with regard to prediction accuracy.

V. CONCLUSION

After we measure mean absolute percentage errors of alternative SVR model scenarios by adding various features, it is seen that the best one is the scenario with cash withdrawal, year and weekday data with a %43 MAPE value. Because of some features are irrelevant, scenario with all features has lower percentage error than this scenario.

In this study, we built a SVR machine learning model by using time series cash withdrawal data. First, we used year, month, day, weekday, working day, festival and religious holiday features one by one. After determining key features from mean absolute percentage error values, we constructed final model with these features.

For a better prediction model, it can be used a larger training data set to learn the patterns of the data. Also, more key features like ATM location, pay days of employed peoples and inflation rate of month can be helpful to improve the prediction model.

As a further research, SVR model can be used as an initial solution to a linear programming model for a resourceutilization or replenishment routing optimization.

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