Forecasting of Customer Behavior Using Time Series Analysis

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Abstract. Forecasting future behavior of customers has significant importance in businesses. Consequently, data mining and prediction tools are increasingly utilized by firms to predict customer behavior and to devise effective marketing programs. When dealing with multiple time series data, we encounter with the problem that how to use those time series to forecast the behavior of all customers more accurately. In this study we proposed a methodology to create customer segments based on past data, create Segment-Wise forecasts and then discover the future behavior of each segment. The proposed methodology utilizes existing data mining and prediction tools including time series clustering and forecasting, but combines them in a unique way that results in higher level models in terms of accuracy than baseline model. The proposed methodology has substantial application in marketing for any firm in any domain where there is a need to forecast future behavior of different customer group in an effective manner.

Keywords: Time series analysis · ARIMA forecasting · Clustering · Customer behavior

1 Introduction

Data mining and machine learning tools and techniques have gained growing attention during recent years in all area applications such as marketing and business intelligence (BI) [1–4]. On the other hand, due to the advancements in information systems the huge amount of data is produced by businesses. In order to gain a deep understanding about their business and especially about their customers, many firms exploit BI tools [5, 6]. One of the area in which businesses uses BI techniques is customer behavior forecasting. Although customer behavior has various dimensions, modelling customer behavior in terms of their profitability is an attractive task that many firms attempt to accomplish it perfectly. It is important for a business to predict the future behavior of its customers to formulate proactive actions to respond to the threats and opportunities in an appropriate manner. Therefore, accuracy in forecasting of customer behavior is an important issue that a firm should deal with it.

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In this study, we consider the attributes of the recency, frequency, and monetary (RFM) model [7] as customer behavior dimensions. To forecast customer activity in terms of RFM attribute values, the first requirement is to obtain appropriate data of past transactions. After obtaining the required data, data must be represented in a way to effectively tackle the problem at hand (e.g. forecasting). As we model data of customers as time series, so data analysis task will be faced with some challenges including the need for determining and specifying seasonality of data, noise and outlier management. The second requirement is that how to manage large population of customers and forecast the behavior and finally to construct a representative future time series that reflects the total behavior of customers. To deal with this requirements, we propose a methodology consisting of three approaches and implement them using data of a bank. The first approach which we called it as aggregate approach is a simple approach which firstly compute the mean of all customers' time series and uses it to forecast customers' behavior. The second approach that we named it as Segment-Wise forecasting divided into two sub-approaches including Segment-Wise-Aggregate (SWA) approach and Segment-Wise-Customer-Wise (SWCW) approach. The main characteristic of Segment-Wise methods is that they firstly perform clustering analysis on customer data which are represented in the form of time series data. Clustering step is accomplished by employing time series clustering techniques. An extensive set of experiments is conducted in order to find the best clustering results. Afterward, similar to baseline approach, the autoregressive integrated moving average model (ARIMA) [8, 9] method as a standard and widely-used method is used to time series forecasting. The accuracy of forecasting is evaluated using some accuracy measures (e.g. root mean square error). The results of this study on grocery guild indicates that the SWCW approach obtains a superior performance in terms of accuracy measures.

The reminder of the paper is organized as follows: Sect. 2 give some background on concepts and techniques utilized throughout of the paper. In Sect. 3, we describe the proposed methodology. Section 4 portrays the empirical study and the obtained results. In Sect. 5, we draw the conclusion.

2 Literature Review

2.1 RFM Model

RFM model is a popular model introduced by Hughes [7] which has been employed to measure customer life time value in various area of applications, for example, in retail banking [10, 11] in hygienic industry [12, 13] in retailing [14–18] in telecommunication [19, 20] in tourism [21]. Due to the significant importance of the monetary attribute (M) from banking viewpoint, in this study we interested in forecasting this attribute.

2.2 Time Series Clustering

A time series is defined as a sequence of data points ordered in time, typically in equal-length time intervals [22]. For example, suppose that a variable M is measured over n

time points then the time series M is denoted as $M = (m_1, m_2, \cdots m_{n-1}, m_n)$ where each m_i is the observation of M in time point i.

Time series clustering is considered as an especial kind of clustering [23, 24] which can be employed for various purposes including: discovering hidden patterns from data, exploratory analysis of data, sampling data and so on [26]. Given a set of time series data $D = \{M_1, M_2, \cdots, M_n\}$, time series clustering is the task of dividing of D into k partitions $C = \{c_1, c_2, \cdots, c_k\}$ such that similar time-series are grouped together based on a certain similarity measure. Then, c_i is denoted as a cluster where $D = \bigcup_{i=1}^{k} c_i$ and $c_i \cap c_j = \emptyset$ for $i \neq j$.

There are two key decisions in time series clustering including determining an appropriate dissimilarity measure between two time series data, and selecting a proper clustering algorithm.

Many dissimilarity measures have been proposed in the literature including Euclidean distance, dynamic time warping (DTW), temporal correlation coefficient (CORT), complexity-invariant distance measure (CID), discrete wavelet transform (DWT) and so on [27]. In the following subsection, we describe some of well-known dissimilarity criteria.

Regarding clustering algorithms, there have been many algorithms proposed which generally divided into four types comprising: partitioning-based, hierarchical, grid-based and density-based [23]. In this study, we use agglomerative hierarchical clustering algorithm for time series clustering as they have shown successful results in this context. Specifically, we employed the Ward method which is based on a sum-of-squares criterion. This method produces clusters that minimize within-cluster variance [28].

Dissimilarity Measures

To describe the following dissimilarity criteria, let us to define the two time series $X = (x_1, x_2, \cdots x_n)$ and $Y = (y_1, y_2, \cdots y_n)$ where n is the number of time-points.

Euclidean Distance

The Euclidean distance between the two time series X and Y is defined as [27]:

$$d_{L2}(X, Y) = \left(\sum\nolimits_{t=1}^{n} (x_t - y_t)^2\right)^2 \tag{1}$$

Dynamic Time Warping

DTW [29] is a popular dissimilarity measure which is calculated based on finding the optimal alignment between two time series. The optimal path is searched using a dynamic programming approach [30, 31].

Considering two time series of X and Y, DTW distance can be described by equation

$$DTW(X, Y) = \min_{r \in M}\left(\sum\nolimits_{m=1}^{M} \left|x_{im} - y_{jm}\right|\right) \tag{2}$$

Where the path element $r = (i, j)$ describes the association between two series. Since DTW is computed employing dynamic programming paradigm, this technique is expensive in computation [26].

Temporal Correlation Coefficient (CORT)
CORT takes into account both proximity on raw values and dissimilarity on temporal correlation behaviors when computing the similarity between two time series [27, 32]. It is defined as equation [27]

$$CORT(X,Y) = \frac{\sum_{t=1}^{n-1}(X_{t+1}-X_t)(Y_{t+1}-Y_t)}{\sqrt{\sum_{t=1}^{n-1}(X_{t+1}-X_t)^2}\sqrt{\sum_{t=1}^{n-1}(Y_{t+1}-Y_t)^2}} \tag{3}$$

Complexity-Invariant Distance Measure
CID which was developed by Batista, Keogh [33] computes the dissimilarity between two time series by estimating the complexity correction factor of the series [34]. A general CID measure is defined as [33]:

$$d_{CID}(X,Y) = CF(X,Y) \cdot d(X,Y) \tag{4}$$

Where $d(X,Y)$ corresponds to an existing distance measure, for example, Euclidean distance and CF is a complexity correction factor given by:

$$CF(X,Y) = \frac{max(CE(X),CE(Y))}{min(CE(X),CE(Y))}, \tag{5}$$

Where $CF(X)$ and $CF(Y)$ are complexity estimator of X and Y, respectively. For time series, $CF(X)$ can be computed as follows:

$$\mathrm{CE(X)} = \sqrt{\sum_{\mathrm{i}=1}^{\mathrm{n}-1}(\mathrm{x_i}-\mathrm{x_{i+1}})^2} \tag{6}$$

Discrete Wavelet Transform
Discrete wavelet transform (DWT) is another popular technique employed to measure similarity between time series [27]. DWT substitutes the original time series by their wavelet approximation coefficient in a proper scale, and then measure dissimilarity based on the wavelet approximations [27]. More information on wavelet methods in the context of time series clustering can be seen in Percival and Walden [35].

2.3 Time Series Forecasting

ARIMA
ARIMA modeling [8] is one of the popular and widely-used techniques to time series forecasting. For modeling, the ARIMA can represent various modeling types of stochastic seasonal and nonseasonal time series such as pure autoregressive (AR), pure moving average (MA) and mixed AR and MA models [36].

The multiplicative seasonal ARIMA model, represented as ARMIA $(p, d, q) \times (P, Q, D)_m$ has the following form [9]:

$$\phi_p(B)\Phi_P(B^m)(1-B)^d(1-B^m)^D y_t = c + \theta_q(B)\Theta_Q(B^m)\varepsilon_t \tag{7}$$

Where

$$\phi_p(B) = 1 - \phi_1 B - \cdots - \phi_p B^p,\ \Phi_P(B^m) = 1 - \Phi_1 B - \cdots - \Phi_P B^P \tag{8}$$

$$\theta_q(B) = 1 + \theta_1 B + \cdots + \theta_q B^q,\ \Theta_Q(B^m) = 1 + \Theta_1 B + \cdots + \Theta_Q B^Q \tag{9}$$

And m is the seasonality frequency,B is the backward shift operator,d is the degree of ordinary differencing, and D is the degree of seasonal differencing, $\phi_p(B)$ and $\theta_q(B)$ are the regular autoregressive and moving average polynomials of orders p and q, respectively, $\phi_p(B)$ and $\Theta_Q(B^m)$ are the seasonal autoregressive and moving average polynomials of orders P and Q, respectively, $c = \mu\left(1 - \phi_1 - \cdots - \phi_p\right)(1 - \Phi_1 - \cdots - \Phi_p)$ where μ is the mean of $(1-B)^d(1-B^m)^D y_t$ process and ε_t is zero mean Gaussian white noise process with variance σ^2. The roots of the polynomials.

3 Proposed Methodology

The proposed methodology for customer behavior forecasting is portrayed in Fig. 1. The methodology is divided into three main steps including Preprocessing, Modelling and Evaluation. In the following, we describe each step briefly.

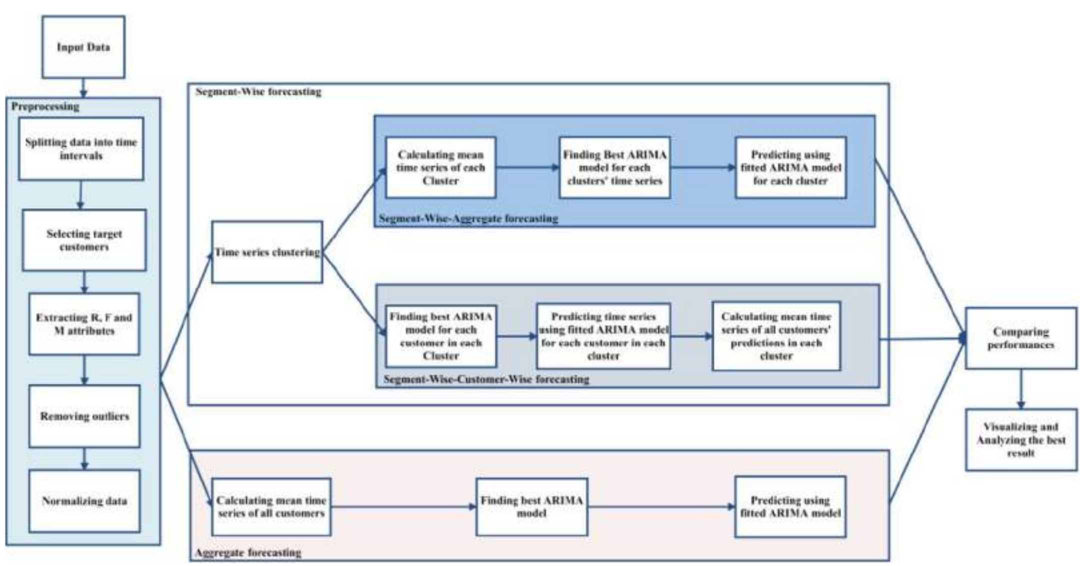

Fig. 1. The steps of proposed methodology

3.1 Input Data

The input of this methodology is the customers' past purchases data

3.2 Preprocessing

In this step, cleaning and transforming data into RFM model attributes are performed using the following steps.

Splitting Data into Proper Time Intervals
As the time series data is used in this model. The data must be divided into time intervals. So, the customers' data are aggregated at each time points.

Selecting Target Customers
In this step, based on attributes for each customers and the resulted data from previous step, the customers who have value in all time points are filtered.

Extracting R, F and M Attributes
The proposed methodology is based on RFM model, so the data for a time point must be transformed into R, F and M attributes of RFM model. The R attribute is the days between the date of last purchase and the date of end of the time point. F attribute is the frequency of purchases in a time point. M attribute is the total amount of purchases in a time point.

Removing Outliers
The incorrect data or data with anomaly values are removed. In this step each attribute of RFM model for each time point are evaluated under an anomaly detection algorithm [23] and the outliers are removed.

Normalizing Data
Each time point is analyzed independently so the data for each time point normalized separately. The Min-Max normalization algorithm is used in this model.

3.3 Modelling

In this step, we proposed three approaches for time series forecasting that are as follows:

Aggregate Forecasting
Aggregate forecasting is the baseline approach of forecasting which is based on aggregating all customers' RFM model attributes. The steps in this phase are as following:

Calculating Mean Time Series of all Customers
In this step for each attribute of RFM model the mean value of all customers is calculated. These values are used for time series prediction in the next steps.

Finding the Best ARIMA Model
Using the mean time series of all customers, the best ARIMA model is built.

Predicting Using the Fitted ARIMA Model
In this step, the fitted model is used to predict future values. The performance of the model is evaluated using evaluation measures.

Segment-Wise Forecasting
In this subsection, we describe the Segment-Wise forecasting methods.

Time Series Clustering
This phase is based on the idea that the time series forecasting of customer segments with the same behaviors over time can be more accurate than forecasting of all customers without any behavioral segmentation. For this purpose, in this step the best time series similarity measures are selected and hierarchical clustering with the best linkage methods is implemented. The outcome of this step is the customer segments with the same behavior over time.

Segment-Wise-Aggregate (SWA) Forecasting
In this strategy of customer time series forecasting, mean values of RFM model attributes for each cluster are calculated. Forecasting model based on ARIMA model for each cluster is built and prediction based on constructed model is generated.

Calculating Mean Time Series of Each Cluster
Using the resulted segments of customers from the clustering step, the mean time series for each attributes of RFM model are calculated.

Finding the Best ARIMA Model for Each Customer Segment
For each segment, the best ARIMA model is built.

Predicting Using Fitted ARIMA Model for Each Cluster
Time series prediction using fitted model is generated in this step and evaluating parameters generated for the next phase.

Segment-Wise-Customer-Wise (SWCW) Forecasting
This strategy of forecasting is based on forecasting the future values for each customer separately. Calculate mean time series of all customers' predictions. The steps in this strategy are as following:

Finding the Best ARIMA Model for Each Customer in Each Cluster
For each customer, the best ARIMA model is obtained.

Predicting Time Series Using Fitted ARIMA Model for Each Customer in Each Cluster
By using the fitted models for each customer in each cluster the future values are predicted.

Calculating Mean Time Series of all Customers' Prediction in Each Cluster
As all customers' prediction time series for each cluster are generated, mean value of all prediction in each cluster is used as the predicted time series for each cluster.

3.4 Evaluation

To test the performance of built models, we utilized the root mean square error (RMSE), and symmetric mean absolute percentage error (SMAPE) [37] to measure the performance of the ARIMA models.

RMSE is defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum\nolimits_{t=1}^{n} (\hat{y}_t - y_t)^2} \tag{10}$$

Where y_t and $\hat{y}_t$ are the actual and forecast values of the series in time point t respectively.

In addition, SMAPE is represented by:

$$SMAPE = \frac{1}{n}\sum\nolimits_{t=1}^{n} \frac{|\hat{y}_t - y_t|}{\frac{|\hat{y}_t| + |y_t|}{2}} \tag{11}$$

Where y_t and $\hat{y}_t$ are the actual and forecast values of the series in time point t respectively.

4 Empirical Study and Analysis

4.1 Input Data

In this study we used transactions of POS customers, total transactions are 1,200,000. A sample of data with the features are shown in Table 1. Terminal ID is the ID of POS device that a customer used; Transaction Date field indicates the date of a transaction; Transaction Amount is the value of a transaction in IRI currency; and finally Terminal Guild field shows the guild in which each customer belongs to it.

Table 1. A sample of data for illustration of the input data

Terminal ID	Transaction Date	Transaction Amount (IRI)	Terminal Guild
3128803	01052018	344002	11
3129948	01052018	982000	11
3136664	01052018	2700000	3
3143083	01052018	542201	8
3166247	01052018	1200000	1
3166657	01052018	1800000	11

Since the ultimate goal of any firm often is reaching the desired profitability, hence, we only use the Monetary attribute as a representation of customer behavior. Therefore, in this study, we consider the problem of the prediction of the future behavior of customers in terms of Monetary.

4.2 Preprocessing

Splitting Data into Proper Time Intervals

We divided our daily data to weekly data to make it more manageable. As the gathered data is for 11 months, the resulted data consists of 44 time points.

Selecting Target Customers

In our experiment, we concentrated on analyzing active customers which are defined as customers who have transactions in all time points. Total active customers are 123000 customers. As in our data we have guild field, we chose a specific guild for analysis.

Extracting R, F and M Attributes

As the model is based on the RFM model, RFM model attributes were derived from the data.

Removing Outliers

To reduce the effect of outliers, we carried out outlier detection using standard deviation.

Normalizing Attributes

The Min-Max normalization algorithm [23] was used in this step.

4.3 Modelling

In this step, for each approach, we used auto.arima function in the forecast package for R [38] to find the best ARIMA model.

Aggregate Forecasting

Based on the definition of this approach in Sect. 3, this is the baseline method which doesn't consider the clustering step. It works based on forecasting the mean time series of all customers using ARIMA model. The results and evaluation of this strategy is presented in next subsection.

Segment-Wise Forecasting

As described in proposed model section, to implement this approach, time series clustering was accomplished and the outcome results used for forecasting. The best time series clustering based on the silhouette validity index [39] as can be seen in Table 2 is clustering with CID and k = 4.

Table 2. The silhouette index for each combination of cluster numbers (K) and distance measures

Distance measure	K = 4	K = 5	K = 6	K = 7	K = 8
Euclidean	0.13	0.13	0.13	0.14	0.14
CORT	0.17	0.17	0.16	0.16	0.17
DTW	0.21	0.21	0.22	0.15	0.15
CID	**0.4**	0.28	0.28	0.24	0.28
DWT	0.37	0.38	0.38	0.39	0.39

Table 3. Size of the obtained clusters

Cluster number	Size
Cluster 1	99
Cluster 2	88
Cluster 3	40
Cluster 4	30

The population of each customer segment using CID algorithm with 4 clusters is illustrated in Table 3.

Our analysis is concentrated on M attribute of RFM model. For the SWA forecasting, the mean value of M attribute for each cluster is calculated and ARIMA model built based on that time series. The forecasting for each cluster conducted using proper fitted model.

In the SWCW forecasting, time series forecasting for each customer using ARIMA model is performed and the mean value of all forecast data is the forecast time series for each cluster.

The results and evaluation of these strategies are presented in next subsection.

4.4 Evaluation

In the following, we have given the results of the three approaches in terms RMSE and SMAPE (Table 4). As seen from Table 4, the SWCW approach outperforms other methods. Therefore, in the following we compare the performance of the two approach that are categorized as Segment –Wise approach.

Table 4. Performance of the three forecasting methods in terms of RMSE and SMAPE

Forecasting method	RMSE	SMAPE
Aggregate Forecasting	0.045	0.59
Segment-Wise-Customer-Wise(SWCW)	**0.0344**	**0.3818**
Segment-Wise-Aggregate(SWA)	0.0468	0.8584

Table 5 summarized the results of forecasting using Segment-Wise methods. As indicated in Table 5, the SWCW forecasting approach outperforms the SWA in terms of RMSE and SMAPE. In addition, for better comparison of the results, the results of forecasting of 8 time points (test split) for the Segment-Wise approaches are illustrated in Figs. 2, 3, 4 and 5. These figures show the actual data value (dashed black line), the value predicted by the SWA forecasting method (red color) and the value predicted by SWCW method (green color). As seen from Figs. 2, 3, 4 and 5, the SWCW approach has a higher forecasting power than the SWA method.

Table 5. Results of forecasting using SWA and SWCW methods

Segment	Segment-Wise-Customer-Wise		Segment-Wise-Aggregate	
	RMSE	SMAPE	RMSE	SMAPE
Segment 1	0.017	0.388	0.023	0.8551
Segment 2	0.036	0.398	0.053	0.995
Segment 3	0.049	0.29	0.052	0.265
Segment 4	0.068	0.436	0.1	1.26
Micro-average	**0.0344**	*0.3818*	**0.0468**	*0.8584*

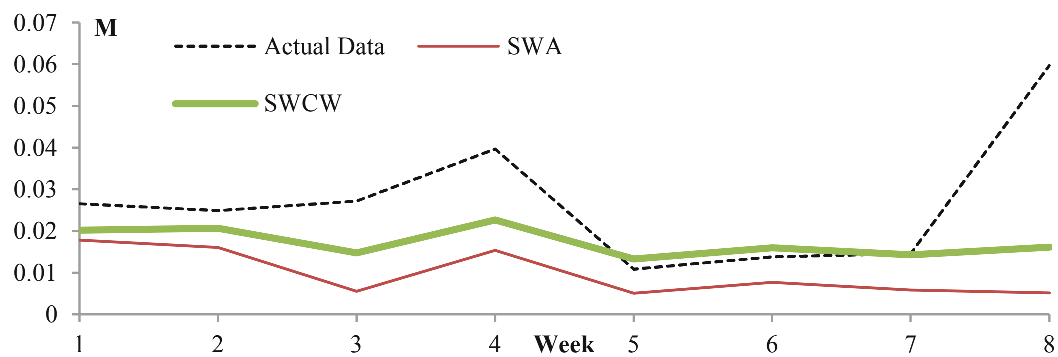

Fig. 2. Forecasting segment 1 future values using SWA and SWCW approaches

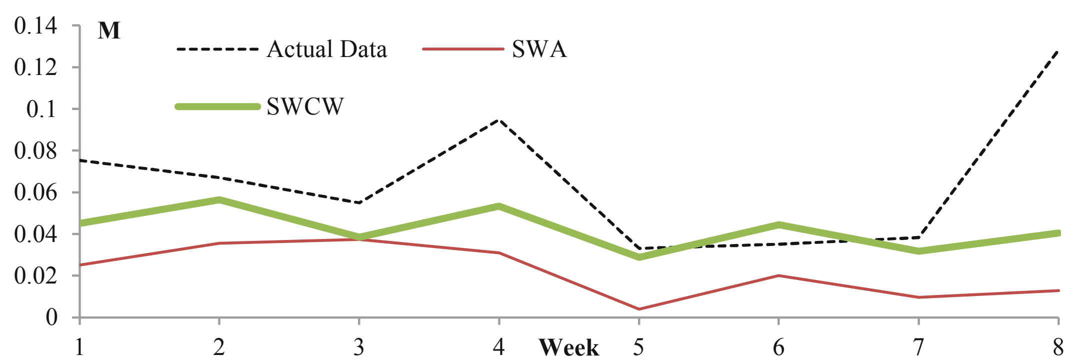

Fig. 3. Forecasting segment 2 future values using SWA and SWCW approaches

The results of this study indicated that SWCW method outperformed the SWA method. It is worth to note, that the results of this research are limited to the available data. Therefore, the results may not generalizable to other time series data. However, the proposed methodology can be employed in other domains to analyze behavior of customers.

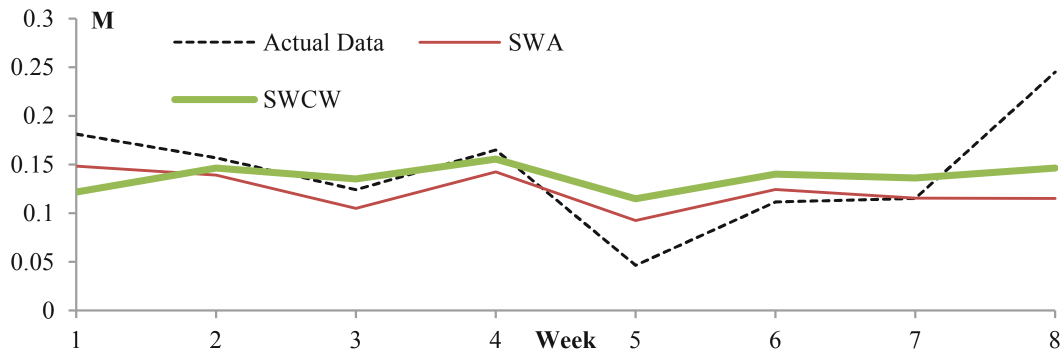

Fig. 4. Forecasting segment 3 future values using SWA and SWCW approaches

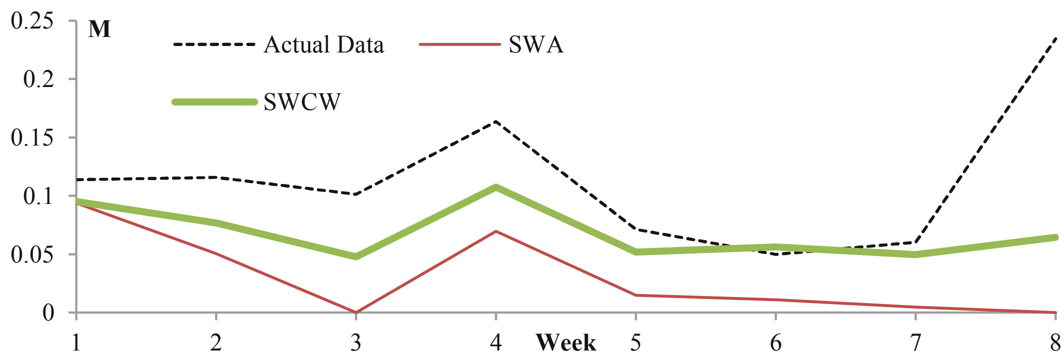

Fig. 5. Forecasting segment 4 future values using SWA and SWCW approaches

5 Conclusion

Forecasting future behavior of customers is one of the main purposes of almost any firm in any domain. In this study, we proposed a combined methodology to forecast customer behavior. This methodology combines the state-of-the-art data mining and time series analysis techniques including time series clustering along with time series forecasting using ARIMA model. the methodology describes the essential steps of fore casting including preprocessing, modelling and evaluation. We considered RFM attributes as customer behavior dimensions. In order to demonstrate the application of the proposed methodology, we have carried out a case study on data of a bank in Iran. Results of case study indicated that Segment-Wise-Customer-Wise (SWCW) method outperforms the other methods in terms of accuracy measures including RMSE and SMAPE. This method, can be able to predict future behavior of different segments of customers effectively. The proposed combined method can be utilized in other domains to predict customers' future behavior.

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