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Modelling Customer Churn Using Segmentation and Data Mining

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Abstract. Customer churn management has drawn much attention from many researchers and practitioners to improve customer retention. The term churn is related to predictions on when a customer abandons his relationship with a company; therefore it has become mandatory for most organizations seeking sustainable and profitable growth. Also increasing in churn rates make companies confront the inevitable heavy marketing campaigns to retain or acquiring new customers. Current churn literature reveals the fact that acquiring new customers costs more than keeping existing ones. However, studies related to churn management mainly focused on methodological improvements regarding the predictive ability, which failed to illustrate a dynamic process in the change of customers' churning behaviour. This paper proposes a model with multi-dimensions of customer churning level via combining segmentation concept within data mining framework to expand the prediction of customer churn. Additionally, comparison to other prediction models, proposed model provides more accurate predictions on customer behaviour and better understanding of relationship between customer and company, mostly applicable in service providing sectors. The potential implications of the model for managers and practitioners are also provided within the paper.

Keywords. Customer Churn, Churn Management, Segmentation, Churn Prediction, Data Mining

Introduction

Customers churn as newly developed concept has been widely employed in telecommunication (e.g., Au et al. 2003), e-Retailing (e.g., Song et al. 2004), and banking (e.g., Hu 2005) industries in recent years. As Engel et al. (1995) coined that understanding and adapting to consumer motivation and behaviour is not optional anymore, it is an absolute necessity for competitive survival. Due to saturated markets and intensive competition under the current circumstances, companies have to start focusing on its Customer Relationship Management (CRM) in order to retain existing customer base. Within the context of CRM, it is a common knowledge that the longer the customer stays with a company, the longer the profit can be made out of them. Hence, retaining its existing customer or preventing them from leaving or switching service providers is one of the key areas in CRM.

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Under the pressure of obtaining better understanding of what factors will affect the customers' behaviour in terms of their decision process whilst considering leaving from a company, theory of churn management has been developed. Customers churn, also aka. customer attrition, is a term that describes the situation that a customer's movement from one company/ service provider to another, and churn management is a term that describes a company or service provider provides various strategies to retain profitable customers (Berson et al. 2000).

There have been several studies that provided promising results on the determination of the likelihood of customers churn and offered important managerial implications. Most of these work, however, had only two dimensions of customer churn, the churners and non-churners, which failed to illustrate the customers' changing of attitudes in a dynamic context. Also, as an important concept in consumer behaviour and decision-making process, customer churn was isolated and not combined within the context of segmentation. Hence, the aim of this paper is to propose a model with multi-dimensions of customer churning level via utilizing segmentation concept, within data mining framework. Segmentation is a key application of data mining in CRM. With grouping the customers according to their attributes or behavioural preferences, segmentation reveals different customer groups that behave similar. Thus information gives company the chance to detect profitable or churn customers. Also segmentation leads company to understand what customers really need and to allocate the marketing campaign resources properly.

The rest of the paper is organized as the followings. Section 1 includes some key terminologies related to churn management and summarizes the empirical studies that have been conducted in the current body of the literature. Section 2 provides information on the proposed model in a detailed manner. Section 3 highlights the potential implications of the model from both academic and practical points of views and concludes the paper with future suggestions.

1. Literature Review

The definition for churn may vary for each organization with regards to the duration that a customer is apart from a company. However, one common agreement is that customer churning can be observed in two groups, the voluntary churning and non-voluntary churning. Non-voluntary churning customer does not attract much attention since those customers are forcefully leaving a company due to issues like failure of keeping up the payments or violation of the terms of conditions. The proportion of these customers is relatively small. Voluntary churning customers, on the other hand, are the ones that companies want to retain. However, voluntary churning customers are very difficult to identify as these customers are making a decision consciously to leave a company (Hadden et al. 2006).

Amongst these voluntary churning customers, two groups of customers can be observed, the incidental churning customers and deliberate churners (Hadden et al. 2006). For customers who incidentally leave a company, churning happens beyond their behavioural attitudes. Companies do not have any control over this type of churning as a customer may move to another location. In our study, we focus primarily on the deliberate churners since they account for the great majority of the voluntary churners and determination of their behavioural change is the problem that most management solutions are trying to resolve.

As McCann and Gallagher (1990) stated that the key problem that companies currently facing are finding proper ways to enable them to identify possible trends of customers' future churning behaviour by analysing and interpreting the enormous quantity of data obtained on a daily basis, so that actions aiming at retaining profitable customer can be properly implemented. Hence, researchers tend to concentrate on the accuracy of the models they predicted. Hadden (Hadden et al. 2006) pointed out that the accuracy issue is the focal point for the next generation of churn management.

This trend in churn management generated waves of studies focusing on pure methodological improvements. From logistic regressions (Neslin et al. 2006), decision trees (Wei and Chiu. 2002) to different methods have been employed aiming at improving the accuracy of customer churn model. A summary of these methodological key studies in churn management area is presented in Table 1. Should those studies carefully analysed one can easily observe that the majority of those empirical studies utilised data mining and machine learning techniques, which have become rather essential for predictive studies like churn management. According to these studies, some of the methods indeed provided better prediction whilst being tested with a particular dataset. However, the improvements are normally limited to an industry or even a company. We cannot observe any generic improvements from simply employing different methods. It shows the necessity to explore not only methodological improvements but also the conceptual development.

Table 1. Churn management studies.

Authors	**Industry**	**Variables Used**	**Techniques Utilised**
Casabayo, Agell & Aguado, 2004	Food retailing	Demographics and Behavioural characteristics	Fuzzy classification
Song, Kim, Cho & Kim, 2004	Online game	Behavioural characteristics	Self-organising maps (SOM) Association rule mining Multi-layer perceptron neural network
Hung, Yen & Wang, 2006	Telecommunication	Demographics and Behavioural characteristics	Decision tree analysis Multi-layer perceptron neural network
Neslin, Gupta, Kamakura, Lu & Mason 2006	Tournament competition	Demographics and Behavioural characteristics	Logistic regression Decision tree analysis Multi-layer perceptron neural network Cluster analysis Discriminant analysis Bayesian network
Hu, 2005	Retail banking	Behavioural and Product characteristics	Decision tree analysis Selective Bayesian network Multi-layer perceptron neural network Boosted naive Bayesian

Authors	Industry	Variables Used	Techniques Utilised
Au, Chan & Yao, 2003	Telecommunication	Demographics and Behavioural characteristics	Evolutionary learning
Kim, 2006	Telecommunication	Demographics and Behavioural characteristics	Multi-layer perceptron neural network Logistic regression
Coussement and Poel, 2008	Subscription Services	Behavioural characteristics	Support vector machines
Jahanzeb and Jabeen, 2007	Telecommunication	Behavioural characteristics	Linear regression
Burez and Poel, 2007	Digital entertainment	Behavioural characteristics	Logistic regression
Xevelonakis, 2004	Telecommunication	Behavioural characteristics	Decision tree analysis
Burez and Poel, 2009	Banking, subscription services, Pay-Tv	Behavioural characteristics	Logistic regression, random forests, Gradient boosting
Tsai and Yu, 2009	Telecommunication	Behavioural characteristics	Multi-layer perceptron neural network, SOM
Coussement and Bock, 2013	Gambling	Behavioural characteristics	CART decision trees, random forests
Huang and Kechadi, 2013	Telecommunication	Demographics and Behavioural characteristics	Decision tree analysis, SOM

In the recent studies, some of the scholars have noticed this necessity and introduced various conceptual improvements, such as creating a customer value score (e.g., Jahanzeb and Jabeen 2007), and combining customer life value into the context of customer churn (e.g., Kim et al. 2006; Neslin et al. 2006). All of them tried to integrate the concept of customer churn with other theories but failed to identify the problems or gaps within the customer churn.

In fact, when we look at the efforts have been made in the area of churn management we could argue that in terms of understanding the scope of churn management it has been narrowed to a binary problem. Either a company loses its customers or keeps them. This may seem quite right in terms of the result of the churn management efforts, however, when modelling the problem this point of view restricts the researchers to be able to see the trend behind the churn action. Therefore, we need a different angle to model the problem. In order to achieve this, we will propose a conceptual framework through making an analogy using segmentation concept and a methodology to perform the proposed idea by making use of data mining.

2. The Proposed Model

2.1. RFM Model

In Customer Relationship Management context, RFM (Recency, Frequency, Monetary) is a commonly used model for interpreting customers' prior behavioural actions and applied for organizations. Recency refers to the time interval between latest purchase and time the determined time period. A loyal customer has shorter time intervals and this means that customer tend to purchase again. According to others, low recency means more loyal. Frequency refers to number of purchases in a particular time period. Bigger numbers show the loyalty of customers and willingness to purchase again. Monetary refers to amount of total spendings in a particular time. Bigger spendings shows customer's loyalty and commitment to company. Customer with a high frequency, high monetary and low recency means can be defined as valuable customer (Hu et al., 2013).

For large datasets RFM is a good, fast and practical method which helps to understand most valuable or less valuable customers. Two studies were proposed to group customers for each RFM variables by adding weighting into calculation. Hughes (Hughes, 1994) suggest three RFM variables have equal importance so weights should be equal, when Stone (Stone,1995) suggests RFM variables' importance vary due to sector. Stone's suggestion have been approved in some studies (Chuang and Shen. 2008; Bin et al. 2008; Hiziroglu. 2009) These weights which sum of total is 1, are multiplied with each RFM variable to create a score for each customer. Regarding our study in retailer sector, we use weights where Recency is more important and frequency and monetary are equal, 0.50, 0.25, and 0.25 respectively (Hiziroglu. 2009). The score stands for value of each customer where biggest score means loyal and lowest score means disloyal. The scores will be used for predicting with techniques which will be stated later.

2.2. Segmentation

In this study, we will try to unveil a key limitation within the context of customer churn. Under the current customer churn theory there are only two dimensions, the churner and non-churners (Hadden et al. 2005), which cannot explain customers behaviour and their decision processes, as they might tend to gradually change from non-churners to churners or possibly the other way around (Song et al. 2004). This limitation, we believe, is the one of the fundamental causes of the weak predictive power of many existing models. Instead of having only two dimensions, we introduce a model with the capability of handling multi-dimensions.

The multi-dimensionality can be achieved by means of the concept of segmentation, particularly segmenting individual customers. Segmentation, from a technical point of view, is the process of homogenously grouping individuals into groups that have similar characteristics. Should we consider those characteristics are the ones related to churning tendency of the customers then any attributes associated with this can be used as a basis for segmentation, such as demographics and behavioural characteristics. When the number of segments is set to two then nature of the problem is no different than customer churn modelling as the customers will be assigned to one of those categories similar to the example of churners and non-churners. However, in a typical segmentation result one possibly would get more than two classes. Our suggestion is that if we classify customers into more than two categories based on customer behavioural characteristics then we would obtain classes which could represent different churning levels, e.g. strictly non-churners (very loyal or high value customers), non-churners (loyal), possible churners (low loyal), and churners (non-loyal). If we consider those categories as customer segments, then here at this point the transition between those segments over time or the stability of those segments would indicate the tendency towards the real churn.

Determining a customer as churn or loyal in retail context, based on the simple equation: When a customer doesn't buy or buy less than a money limit in consecutive three months, considered as churner, otherwise non-churner. We consider a customer defines as churner who doesn't buy in consecutive three months. This churning time varies due to different sectors. In newspaper subscription, churning time is consecutive four weeks (Coussement and Poel. 2008), in retailer sector churning is consecutive three months (Migueis et al. 2012), in banking sector churning time is consecutive six months (Popovic and Basic. 2009) etc.

Assume that the segments are formed through some behavioural characteristics of customers, for example Recency, Frequency, Monetary (RFM) values as being an indication of customer loyalty and value. Using RFM data available at a certain period of time, say time *t*, three segments are obtained. Let us label those segments as high loyal, loyal, and low loyal segments. When we reach to a certain time zone, say time *t+1*, we will update our segments using the existing customer database. In terms of the RFM values of the customers there will be movements between those segments and some of the customers will churn and not become a customer anymore. Let us say that the churners also labelled as voluntary churners and non-voluntary churners. If we consider the ones churned from the company we will have five segments including the segments that represent the churners. From time *t* to time *t+1* if we can identify the movements of the customers from one segment to another then we will have a clear idea of the customers who might show a pattern before actually leaving the company.

Determining segments of RFM values based on Ha's (Ha, 2007) High-Low method. First, averages of RFM variables for all customers for a specific period determined by Kohonen network. Secondly, each customer's RFM values compared to average RFM values to determine whether customer's RFM high or low for each variable.

For example; if Recency average of period 1 is lower than recency for customer A, then customer A recency will be R_{low}. From this point of view customer A's frequency and monetary values will be determined with same method. After calculation completes for all periods for all customers, Table 2 shows the sample segments of customers for each *t* period.

Table 2. Sample RFM segments with High-Low method.

Customer	Period 1	Period 2	Period 3	…	Period n
Customer A	RLFHMH	RLFHMH	RLFHMH	…	RHFLML
Customer B	RHFLML	RHFLML	RHFLML	…	RHFHMH
…	…	…	…	…	…
Customer N	RHFLML	RHFLML	RLFLMH	…	RLFHML

According to values of RFM segments $R_LF_HM_H$ segment is the loyal customer for company due the recent visit, lots of visits and above average spendings. On the contrary, $R_HF_LM_L$ segment is the less loyal customer with long duration between time periods, less visits than average and inadequate spendings for a loyal customer. Thus, the new 8 different RFM values will use in transition matrix to determine the paths of each customer who ensued voluntary churn or non-churn. For simplification A,B,C,D,E,F,G,H letters will be used instead of these 8 RFM segments in matrix. For a quick peek for transition paths, Figure 1 reveals a customer's RFM segments in a time periods.

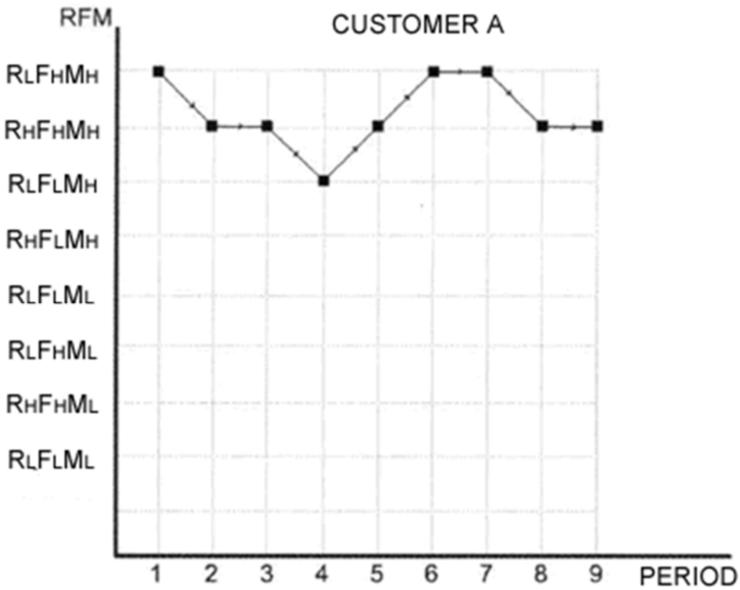

Figure 1. Transition **p**aths for customer A in 9-months period

2.3. Data Procurement, Analysis and Reliability and Validity

For our paper, an English supermarket provided the required data. The data which obtained from customers' loyalty cards consists of eight million transactions of over 100,000 customers during nine months period. For a representative sample, 10% of total customers randomly sampled by using SQL(Structural Query Language) coding. The sample data then processed with cleaning, normalisation and transformation. Next, using RFM high-low rule, 8 different customer segments are determined. With cross-fold validation (Hwang et al.2004), data will divided by 70% -30% ratio of training-test set for validation. Then using data mining technique of Clementine program tool, C5.0, which is powerful predictor in time-variant predictions, the transition possibilities and routes for each segment are calculated. The transition paths of trained data then applied on test data for validation. Thus, same data performed with other predicting techniques which applied in churn prediction, such as logistic regression and decision trees. Then the classification of RFM segments evaluated by PCC (Percentage Correctly Classified-Accuracy) and AUC (area under curve) analysis. The PCC compares probability of being a churner with the actual position of that customer in the confusion matrix. So PCC, shows the ratio of accurate predicting for a classifier. AUC, is well-known performance criterion for the comparison of classification models. Also RFM scores which calculated with weights, will be taken into model. Then results of predicting which regarding RFM scores and our new suggested model RFM segments will compared to comparative analysis.

In order to describe the aforementioned conceptual explanation a schematically representation of the proposed model is presented in Figure 2. Our proposed model involves multi-dimensions of customer churning level using segmentation within data mining framework. This multi-dimensional structure allows to expand the potential usage of customer churn and also to provide more accurate predictions on customer actual behaviour.

As in the majority of the existing churn management studies, organisations are now able to access actual customer behaviour data. The model considers the behavioural characteristics of customers (particularly weighted RFM values) for stability and churn analyses. However, it should be noted that the variables selected may not necessarily have be to RFM values but they could be any type numerical information related to churn behaviour that also allow us to perform customer segmentation. In the weighted RFM method, different weights (w_R, w_F, w_M) are given to each variable as an indication of their importance. The total value of these weights is equal to one. To obtain the weighted RFM values some pre-processing operations including cleaning, transformation, and normalisation must have been done. Since the proposed model suggests making use of select clustering and classification methods, these values should also be normalised to the range of 0-1. Within the model framework two main modules take place: (1) Module 1- RFM segmentation, (2) Module 2- Transition Paths Calculation. A brief explanation of these modules is provided in Figure 2.

Once the customer data is ready to establish the segments at the time period *t*, we therefore need a technique to perform segmentation. Having considered the nature of the problem the segmentation technique should allow us to see more than the assignments of customers to the segments. Also, since the question of how many segments can be obtained is determined as eight different segments, the high-low technique is used to create the segments. Customer segmentation basically could be determined with two ways, statistical or machine learning technique(Ha, 2007) In practice, machine learning techniques do more accurate segments than statistical techniques.(Fish et al, West et al). In Module 1 segmentation operation which will be implemented to segment customers based on the high-low RFM variables extracted in period *t*.

When we reach to the time period *t+1*, should we want to update available segment structure, by using same high-low RFM values of the customers we will be able to reclassify the customers into the existing segments. Module 2 is the process of revealing transition paths for customers' non-churn or churn status. At this point a decision tree technique, C5.0, used for training the data set. The module includes the calculation of customer migration from one segment to another during the time from period *t* to period *t+1* assuming that there is no new customer entry to the company database. In other words, based on the available segment information at time period *t* and *t+1*, a segment transition probability calculation obtained by using techniques.

C5.0 performance results for Churn and Loyal segments' transition path as following. (Figure 3)

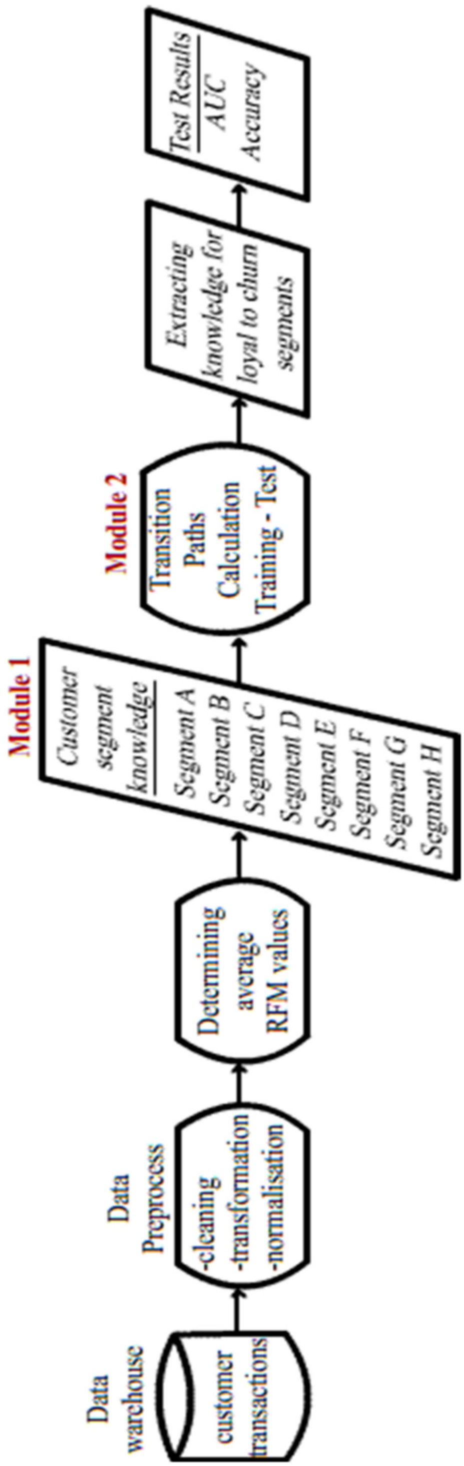

Figure 2. The proposed model

Rule 1 for **L** (21; 0,957)

if D3 = B

and D4 = D

and D5 = D

then **L**

Rule 2 for **L** (42; 0,955)

if D5 = F

and D6 = A

then **L**

Rule 3 for **L** (21,042; 0,868)

if D2 = B

and D3 = B

and D6 = D

then **L**

Rule 6 for **C** (120; 0,902)

if D4 = H

and D5 = F

and D6 = H

then **C**

Rule 7 for **C** (98; 0,84)

if D4 = F

and D5 = H

and D6 = H

then **C**

Rule 8 for **C** (62,94; 0,847)

if D4 = G

and D5 = H

and D6 = G

then **C**

Figure 3. C5.0 transition rules for churn and loyal segments

3. Results and Analysis

3.1. Classification Performance

The results in Table 3 and 4 show the classification performance of weighted RFM scores and RFM High-Low segmentation by using AUC and PCC evaluation. Table 3 provides classification performances for two models in terms of AUC. Table 4 shows the PCC which is the performance of accuracy of correct predicting for whole data. As seen on Table 3 and 4, new RFM high-low segmentation model has better performance than standard weighted RFM scores, where C5.0 showed best ratios to others.

Table 3. AUC Performance comparison.

Techniques	**RFM High-Low segmentation (%)**	**Weighted RFM scores (%)**
Logistic regression	85	82,6
Decision Trees	87,3	85,1
C5.0	89,20	86,7

Table 4. PCC(Accuracy) Performance comparison.

Techniques	RFM High-Low segmentation (%)	Weighted RFM scores (%)
Logistic regression	89,5	88,84
Decision Trees	91,34	81,9
C5.0	91,87	89,40

3.2. Comparison of Models

The comparison of tables in Table 5 and 6 show the hit ratio and capture rate of each models according to confusion matrix. In confusion matrix, hit ratio refers to ratio of correctly labelled (churn or non-churn) data to total labelled (churn or non-churn) data, where capture rate refers to correctly predicted data to total data. As seen on Table 5 and 6, RFM high-low segmentation has better ratios than to other, where C5.0 has given best ratios among other techniques.

Table 5. Hit ratio comparison.

Techniques	RFM High-Low segmentation (%)	Weighted RFM scores (%)
Logistic regression	81,28	80,90
Decision Trees	84,23	85,60
C5.0	89,40	87,83

Table 6. Capture rate comparison.

Techniques	RFM High-Low segmentation (%)	Weighted RFM scores (%)
Logistic regression	89,13	83,86
Decision Trees	89,32	84,13
C5.0	89,56	84,7

4. Implications and Conclusion

The model we proposed in this paper has better results than the standard weighted RFM score model. The minor difference between techniques which shown in Table 3, 4, 5 and 6 should be considered with the retailer database of hundreds of thousand customers. For example, extra %1 correctly detected possible churners would mean more than a thousand customers which could lead a company more profitable than before.

From a managerial point of view it is crucial to find out whether the loyal customer segments will shrink or not. Through employing the aforementioned model, not only we will be able to see the movements between segments (which customers switched to which segment) but also it will be possible to observe the extent of the degree of those movements by carefully analysing the changes in possibilities of churning or nonchurning. The benefits of acquiring possibilities for the same customers at two different stages will be as follows:

(1) The changes in possibility values before and after movement will represent the stability of the segments and this information can also be interpreted as the retention rate of each customer segment. Therefore, before the next period for a company the customers who are at risk can be spotted by just looking at the changes in possibility values and a preventive action can be taken towards retaining those customers before it is too late for the company.

(2) The effectiveness of current marketing strategies and the total segment equity can be calculated and evaluated by using this procedure. Should a company wants to implement a retention strategy to keep the customers who are in danger zone then the actual results of those actions can be measured in order to see how much the strategies were effective.

By using the segmentation model to detect possible churner customers which proposed in this paper, companies can define the target of future retention marketing campaigns by taking into account future churners.

The main conclusion of proposed model that with easy-to-use RFM segmentation, possible churn customers would be detected with a high correct possibility by using simple collectible variables of a customer.

Although the proposed idea may not be extensively applicable in all industries due to the lack of the ability to collect such customer information and yet it has not been tested on an empirical study, we could argue that it is promising in terms of its potential implications. Also, there are still other issues need to be considered for future studies in order to minimise the model's limitations. Those considerations could be the following: (a) enabling the model to take into account new customer acquisition, (b) having the model to adapt real time dynamic changes in customer database so that it can automatically decide when to recreate the segmentation structure, (c) new variables could be added to RFM, such as Length (Length of relationship), Complaints, D (distance between home and company for retailer sector) and (d) demographics variables also a good predictor for loyalty for customers, so for future churn segmentation, adding demographic variables to the RFM model could be considered.

References

[1] Au, W., Chan, K. C. C., and Yao, X., A novel evolutionary data mining algorithm with applications to churn prediction. *IEEE Transactions on Evolutionary Computation,* 7(6) (2003), 532–545.

[2] Berson A., Smith, S. and Thearling, K., *Customer retention building data mining applications for CRM*, McGraw-Hill, New York, 2000.

[3] Burez, J. and Poel, D. V., CRM at a pay-TV company: Using analytical models to reduce customer attrition by targeted marketing for subscription services. *Expert Systems with Applications*, 32(2) (2007), 277–288.

[4] Burez, J. and Van den Poel, D., Handling class imbalance in customer churn prediction, *Expert Systems with Applications*, 36(3) 2009, 4626-4636

[5] Casabayo', M., Agell, N. and Aguado, J. C., Using AI techniques in the grocery industry: Identifying the customers most likely to defect. *The International Review of Retail, Distribution and Consumer Research*, 14(3) (2004), 295–308.

[6] Coussement, K. and Poel, D. V., Churn prediction in subscription services: An application of support vector machines while comparing two parameter-selection techniques. *Expert Systems with Applications*, 34(1) (2008), 313–327.

[7] Coussement, K. and De Bock, K. W., Customer churn prediction in the online gambling industry: The beneficial effect of ensemble learning, *Journal of Business Research*, 66(9) 2013, 1629-1636

[8] Engel, J. F., Blackwell, R. D. and Miniard, P. W., *Consumer Behaviour, 8th edition*, Fort Worth : Dryden Press, TX, USA, 1995.

[9] Etzion, O., Fisher, A. and Wassergruk, S., e-CLV: A modeling approach for customer lifetime evaluation in e-commerce domains, with an application and case study for online auction. *Information Systems Frontiers*, 7(4) 2005, 421–434.

[10] Ha, S. H., Bae, S. M. and Park, S. C., Customers time-variant purchase behavior and corresponding marketing strategies: An online retailer's case. *Computers and Industrial Engineering*, 43(4) 2002, 801–820.

[11] Hadden, J., Tiwari, A., Roya, R. and Ruta, D., Churn prediction: Does technology matter? *International Journal of Intelligent Technology*, 1(1) 2006, 104–110.

[12] Hadden, J., Tiwari, A., Roya, R. and Ruta, D., Computer assisted customer churn management: State-of-the-art and future trends. *Computers and Operations Research*, 34(10) 2005, 2902–2917.

[13] Hiziroglu, A. A Soft Computing Approach to Customer Segmentation. Manchester, University of Manchester, 2009, 183 p.

[14] Hu, X., A data mining approach for retailing bank customer attrition analysis. *Applied Intelligence*, 22(1) 2005, 47–60.

[15] Huang, Y. and Kechadi, T., An effective hybrid learning system for telecommunication churn prediction, *Expert Systems with Applications*, 40(14) 2013, 5635-5647

[16] Hung, S., Yen, D. C., and Wang, H., Applying data mining to telecom churn management. *Expert Systems with Applications*, 31(3) 2006, 515–524.

[17] Jahanzeb, S. and Jabeen, S., Churn management in the telecom industry of Pakistan: A comparative study of Ufone and Telenor. *Journal of Database Marketing and Customer Strategy Management*, 14(2) 2007, 120–129.

[18] Kim, Y., Toward a successful CRM: Variable selection, sampling, and ensemble. *Decision Support Systems*, 41(2) 2006, 542–553.

[19] Kim, S. Jung, T., Suh, E. and Hwang. H., Customer segmentation and strategy development based on customer lifetime value: A case study. *Expert Systems with Applications*, 31(1) 2006, 101–107.

[20] Lejeune, M.A.P.M., Measuring the impact of data mining on churn management. *Internet Research: Electronic Networking Applications and Policy*, 11(5) 2001, 375–387.

[21] Libai B., Narayandas D. and Humby C., Toward an Individual Customer Profitability Model: A Segment-Based Approach, *Journal of Service Research*, 5(1) 2002, 69-76.

[22] McCann, J. M. and Gallagher, J. P., *Expert systems for a scanner data environment: The marketing workbench experience*. Kluwer Academic Publishers, Norwell, MA,USA, 1990

[23] Migueis, V., Poel, D., Camanho, A.S. and Cunha, J., Modeling partial customer churn: On the value of first product-category purchase sequence. *Expert Systems with Applications,* 39 2012, 11250-11256.

[24] Neslin, S. A., Gupta, S., Kamakura, W. Lu, J. and Mason, C. H., Defection detection: Measuring and understanding the predictive accuracy of customer churn models. *Journal of Marketing Research*, May, 43(2) 2006, 204–211.

[25] Popovic, D. and Basic, B.D., Churn Prediction Model in Retail Banking Using Fuzzy C-Means Algorithm, *Informatica*, 33 2009, 243-247

[26] Song, H. S., Kim, J.K., Cho, Y. B., and Kim S. H., A personalized defection detection and prevention procedure based on the self-organizing map and association rule mining: applied to online game site. *Artificial Intelligence Review*, 21(2) 2004, 161–184.

[27] Tsai, C. and Lu, Y., Customer churn prediction by hybrid neural networks, *Expert Systems with Applications*, 36(10) 2009, 12547-12553

[28] Wei, C. and Chiu, I., Turning telecommunications call details to churn prediction: A data mining approach. *Expert Systems with Applications*, 23(2) 2002, 103–112.

[29] Xevelonakis, E., Developing retention strategies based on customer profitability in telecommunications: An empirical study. *Database Marketing and Customer Strategy Management*, 12(3) 2004, 226–242.