ISSN: 2454-4248
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B2C E-Commerce Customer Churn Management: Churn Detection using Support Vector Machine and Personalized Retention using Hybrid Recommendations

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Abstract - E-Commerce industry, especially the players in Business-to-Consumer (B2C) sector is witnessing immense competition for survival - by means of trying to penetrate to the customer base of their peers and at the same time not letting their existing customers to churn. Avoiding customer attrition is critical for these firms as the cost of acquiring new customers are going high with more and more players entering into the market with huge capital investments and new penetration strategies. Identifying potential parting away customers and preventing the churn with quick retention actions is the best solution in this scenario. It is also important to understand that what the customer is trying to achieve by opting for a move out so that personalized win back strategies can be applied. E-Commerce industry always possess huge amount of customer data which include information on searches performed, transactions carried out, periodicity of purchases, reviews contributed, feedback shared, etc. for every customers they possess. Data mining and machine learning can help in analyzing this huge volume of data, understanding the customer behavior and detecting possible attrition candidates. This paper proposes a framework based on support vector machine to predict E-Commerce customer churn and a hybrid recommendation strategy to suggest personalized retention actions.

Keywords - *E-Commerce; Customer Churn; Support Vector Machine; Hybrid Algorithm; Personalized Retention Recommendation*

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I. INTRODUCTION

B2C E-Commerce is growing exponentially in terms of its contribution to the global retail market. As per details published by eMarketer, a leading market research company, E-Commerce is contributing 8.7% of the overall retail revenue amounting to $1.915 trillion as on 2016. It is expected to grow to $4 trillion with in next four years which will be 14.6% of the total estimated retail spend in 2020. While the growth of the sector is clearly evident and not foreseeing any challenges in near future, peer competition is becoming intense for the existing players in this area. The direct result of the competition is a churn in the customer base for any organization who is not taking necessary measures to prevent such an attrition.

Customer churn or attrition is the scenario where an existing customer ceases the relationship with an organization by no longer availing its service or consuming its products. In the E-Commerce scenario there are four possible states for its customers – new, active, inactive and churned [Fig.1]. The success of the industry is fully dependent on its ability to keep the customers active for long. The cost of acquiring a new customer is quite high due to the immense competition exists in the market. In the case of a new customer, firms could normally reach its financial breakeven (return of investment) only after the customer performs a few transactions which may span over a period of time. Active customers are the back bone for E-Commerce business and organizations should give high attention towards their active customers who may turn inactive and churn afterwards. As Fig. 1 indicates, an inactive customer can either transform to a churned customer or return as an active customer.

A survey conducted by the Rockefeller Foundation revealed that customers move away from one E-Commerce firm to another as they think they are not being cared. Identification of inactive customers and understanding the chances of them parting away is a critical activity for the sustainability of E-Commerce business. There are various approaches that can be adopted to predict potential customer churn which include statistical techniques and machine learning strategies. Customer data available with B2C E-Commerce firms is a rich source of information as purchasing patterns of different customers can be mined out of it. Further, if any customer deviates from the regular purchase pattern and/or the cumulative volume of his/her transactions comes down, there is a potential attrition

Figure 1. E-Commerce Customer States

scenario.

Identification of appropriate retention strategies and personalizing it is the next stage. Here machine learning can help organizations to perform a deep dive into customer preferences and pattern of transactions in the past and also by looking at societal and demographic preferences the customer inherits by participation. Personalization can be at different levels like affinity or aversion towards specific products and/or brands, interest towards competitive discounts and offers, need for specific delivery and payment options, etc.

This paper proposes a solution for proactive detection of B2C E-Commerce customer churn as well as recommendation of personalized retention actions. The next section details on some of the relevant works conducted in related areas by multiple scholars. Subsequently the proposed solution is discussed in detail.

II. Related Works

Researchers have approached churn prediction in different dimensions. One of the early research in this area was conducted by Hennig-Thurau et al. [1] by developing a conceptual model to study the impact of customer satisfaction and relationship quality on customer retention process. Bolton et al. [2] studied about the implications of loyalty program memberships and service experiences on customer retention. Neslin et al. [3] carried out a descriptive analysis of the methodological factors contributing towards the accuracy of customer churn prediction models. Jamal et al. [4] came up with a model to study the relationship between customer churn and influencing parameters such as failure recovery and customer service experience. Hadden et al. [5] carried out a comparative analysis of three data mining models - neural networks, regression and regression trees to evaluate their capabilities in predicting customer churn. Scholars have come up with distinctive churn prediction models and studies on multiple industrial domains like telecom where there were quite a lot of work can be observed like [6], [7], [8], [9], [10] and [11]. Other areas include retail banking [12], credit cards [13], mobile social games [14], online gambling [15] and email marketing [16]. In the earlier work on the B2C E-Commerce customer churn detection [17], customer churn prediction was achieved by the use of logistic regression approach.

Generation of automatic retention strategies is a form of offering recommendation services. There are quite a lot of researches can be found in the area of recommender systems. One of the obvious input criteria for recommendation generation is the customer profile and the earlier recommender systems were fully relying on the same along with the behavioral traits of the user [18]. Further researches started covering aspects like trust factor [19], past transaction patterns [20], societal inputs from those who belongs to similar demographic group and/or having similar past transaction traits [21], contextual information [22], etc. When societal inputs are taken into consideration for generation of recommendations, it is considered as a collaborative approach. Normally this approach is used in combination with demography based approach. The key parameter in consideration in such models is the similarity among customer profile which is determined based on algorithmic approaches [23] [24].

III. Methodology

Figure 2. Churn Management Model

The model proposed in this paper cover a twofold approach [Fig.2] to deal with B2C E-Commerce customer churn. The first part is the proactive detection of potential churn scenarios leveraging support vector machine technique. The second part cover generation of personalized retention strategies by adopting a hybrid approach which is a combination of content-based, collaborative, demographic and knowledge-based approaches.

A. Churn Detection

Proactive churn detection can achieved by populating risk scores for each customer by applying predictive analytics techniques like statistical models and/or machine learning algorithms. The various input parameters which cater to this process include customer demography, purchase pattern, usage metrics, customer reviews, net promoter score, etc. All these information is already available with the B2C E-Commerce firms for every customer since the date on which they register with the firm. So, what is required now is to finalize a mechanism to process this data. One option is to use regression techniques like logistic regression as a statistical models to predict potential churners [13] [17]. Alternate option is to leverage machine learning tools like support vector machine.

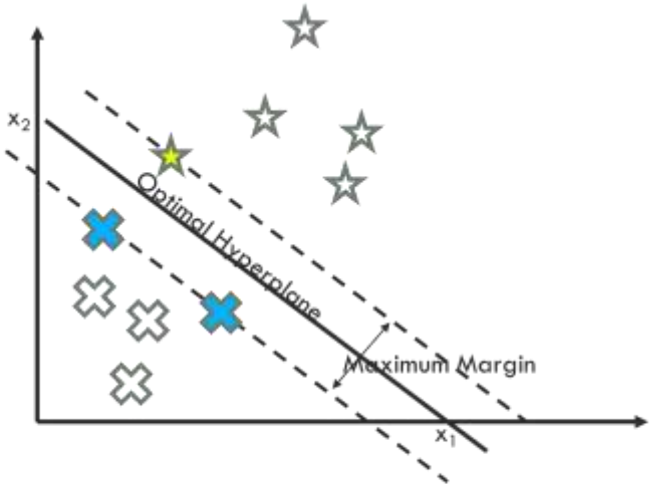

Figure 3. Maximum Margin Hyperplane of SVM

Support Vector Machine (SVM) is a supervised learning technique widely used in machine learning scenarios to deal with both classification and regression problems [25]. SVM is based on the concept of decision planes which separates a set of entities into different class memberships. SVM does the learning from a training set where each element is marked as the member of one of the two possible classes. From this accrued learning, SVM builds a model which can allocate any new element into one of the two categories. In order to achieve this, an optimal hyper-plane is algorithmically defined in the feature space which acts as a decision boundary [Fig.3] for the classification problem in consideration. In this case, SVM can be considered as a non-probabilistic binary linear classifier.

For a given data set (x_1, y_1), (x_2, y_2), (x_3, y_3), …, (x_m, y_m), where $y_i = -1$ for inputs x_i in class 0 and $y_i = 1$ for inputs x_i in class 1. Mathematically the decision boundary can be defined as a vector representing a line in two dimension.

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$$\overline{\vec{w}}.\vec{x} + b = 0 \qquad (1)$$

where $\vec{w}$ and $\vec{x}$ are two dimensional vectors and b is a constant representing the bias.

In this manner, the input vector from class 0 can be defined as the negative support vector $\vec{x}_n$ and the input vector from class 1 can be defined as the positive support vector $\vec{x}_p$. Hence the decision boundary on negative side can be defined as

$$\overline{\vec{w}}.\vec{x}_n + b = -1 \qquad (2)$$

and the decision boundary on positive side can be defined as

$$\overline{\vec{w}}.\vec{x}_p + b = 1 \qquad (3)$$

So, the distance between the negative and positive decision boundaries will be $2/||\overline{w}||$ and the size of the margin M will be $1/||\overline{w}||$. Hence, in order to maximize the value of M, the value of $\overline{w}$ need to be minimized. Since all points need to belong to one of the two classes, following constraints can be introduced.

$$\overline{\vec{w}}.\vec{x}_i + b \leq -1 \text{ for all } \vec{x}_i \text{ in class 0} \qquad (4)$$

and

$$\overline{\vec{w}}.\vec{x}_i + b \geq 1 \text{ for all } \vec{x}_i \text{ in class 1} \qquad (5)$$

So, the SVM can be represented as the following optimization problem

$$\text{Minimize } ||\overline{w}|| \text{ subject to } y_i\,(w.x_i - b) \geq 1 \; \textit{for } i = 1, \ldots, n \qquad (6)$$

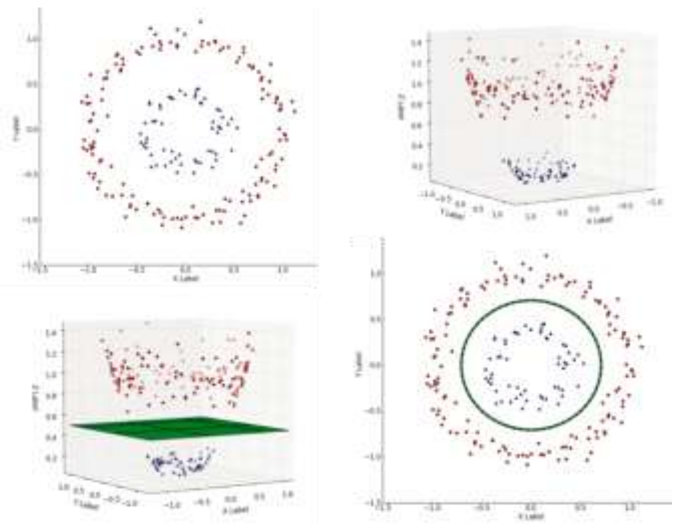

Figure 4. Kernel Trick: Non-separable dataset at lower dimension is converted to higher dimension to make it separable

Support Vector Machines adopt a strategy called kernel trick to perform non-linear classification. In kernel trick, the input elements are mapped into a high-dimensional feature space and classification task is performed. This will result in a similar algorithm comparable to the linear scenario with one exception of every dot product being replaced by the nonlinear kernel function. This enables the algorithm to fit the decision boundary (aka maximum-margin hyper plane) in the higher dimensional transformed feature space. When the hyper plane in the transformed feature space is remapped to the original input space, it may get mapped to nonlinear [Fig.4].

As a general rule, any mathematical function that can ratify Mercer's condition [26] can be treated as a kernel function. However, the most frequently adopted kernel functions are based on either Euclidean distance or Euclidean inner products. The key factors impacting the selection of kernels include type of the boundaries between the classes and the data structure being used. SVM is considered as the most reliable classification algorithm in multiple complex real time scenarios. A few examples include Hand-written character recognition [27], Image/face detection [28], pedestrian detection [29], hypertext categorization [30] and fraud detection [31] [32]. The major advantage for SVM in these scenarios is the avoidance of over fitting problem with the help of a proper training phase to create the classification model.

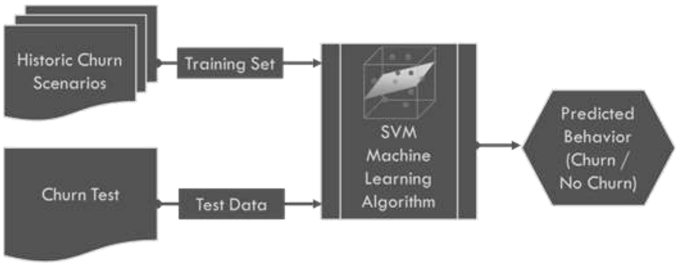

Figure 5. Churn Detection Framework using SVM

In the context of B2C E-Commerce churn detection, a binary classification of the complete customer base is carried out with the help of support vector machine to identify the potential churners [Fig.5]. Every customer is represented in an n-dimensional vector space with each of the customer characteristics forming one of the vector dimensions in the feature space. The SVM Model is trained using historic churn data, customer characteristics and transactions traits. Further periodic churn test is performed for each member in the customer database to detect potential attrition scenarios.

B. Personalized Retention

A hybrid approach [33] is the most reliable strategy to generate a list of optimal personalized retention options in the B2C E-Commerce world [Fig.6]. It is proposed to use the combination of content-based [34], collaborative [35], knowledge-based [36] and demographic [37] approaches to yield the best recommendation result.

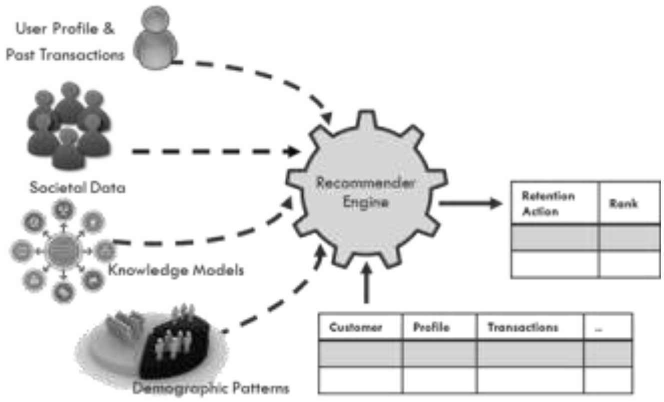

Figure 6. Hybrid Recommendation Strategy for Retention Actions

The profile information and the past transactional traits of the customer contributes the input data for generating content-based recommendations. The demographic information of the customer and the accrued knowledge over a period of time are the inputs for demographic and knowledge based recommendations. Collaborative recommendations are generated by looking at the behavioral patterns of similar users. Similarity based recommendations are generated based on the perceived utility of them to the target customer and it is estimated by using some sort of similarity functions. Recommendations generated in this manner normally possess a high degree of personalization as they are unique for each customer and is influenced by the individual profile and past behavior patterns.

This work uses cosine similarity measure [23] to determine the similarity among two customers. Using cosine similarity function, a high value shows that the customers are very much similar and vice versa. Retention recommendations are proposed after identifying the neighborhood for each potential churning customer, detected in the earlier phase. A customer "j" can be considered in the neighborhood for a customer "i", if the tastes and preferences of "j" are matching to that of "i" while applying cosine similarity measure between them. Mathematically

$$sim(i,j) = \cos(i,j) = \frac{i.j}{\|i\| \times \|j\|} \tag{7}$$

$$\cos(i,j) = \frac{\sum_{s \in S_{ij}} r_{i,s} r_{j,s}}{\sqrt{\sum_{s \in S_{ij}} (r_{i,s})^2} \sqrt{\sum_{s \in S_{ij}} (r_{j,s})^2}} \tag{8}$$

where

$r_{i,s}$ is the rating of an item s by user i
$r_{j,s}$ is the rating of an item s by user j
$S_{ij} = \{ s \in Items \mid r_{i,s} \neq \emptyset \wedge r_{j,s} \neq \emptyset \}$, set of all items rated by both user i and user j
$i.j$ is the dot product of vectors i and j

Here customer "i" belongs to the predicted set of potential attrition candidates and customer "j" belongs to the set of loyal customers J, where J is the set of customers with more than 90% loyalty, i.e. having less than 10% probability to churn. This type of neighborhood formation differentiates customer retention framework from traditional recommender systems, where the neighborhood is always formed with fully similar customers to the customer in focus.

Following are the key considerations or hypothesis for proposing personalized retention strategy for potential churn scenario:

- A potential customer churn can be prevented by recommending relevant offers / services.
- Significance of an offer / service may vary with customer
- Customers with similar preferences will behave in similar manner

IV. DISCUSSION

The proposed framework in this paper adopts a two stage approach – proactive detection of potential churners and generation of personalized retention options. In the first stage, support vector machine is chosen as the machine learning technique to detect potential attrition. In the earlier study logistic regression was used as the binary classifier to identify churners and it worked well with lesser number of dimensions in consideration. SVMs can perform better classification with higher dimension vector spaces with the help of kernel trick by using an appropriate kernel function. On the same time, the difficulty to choose the "right" kernel function and longer training time required to deal with large data sets are being considered the disadvantages of SVM.

Once potential attrition scenario is identified during the first stage, it is required to generate appropriate retention recommendations. The proposed framework suggests to use a hybrid approach to finalize the retention strategy. In the earlier work [17], content-based filtering was disregarded as the past transactions do not have much significance in churn and retention context. However in this work, content-based filtering is leveraged in the solution to improve personalization aspects of recommendations. Similarly, earlier study omitted demographic aspects, assuming customer may demonstrate varying purchase patterns during multiple demographic stages. However it is identified that current demographic information (like age, geographic location, etc.) may have an influence on the customer's stickiness to an E-Commerce firm and hence need to consider for finalizing the retention recommendations. Like in the earlier work, collaborative aspects are given key importance in this study as well. An additional aspect of knowledge-based filtering is introduced in this study to strengthen the retention strategies being suggested.

V. CONCLUSION

Multiple studies in marketing domain proved that retention of existing customers is the best option to sustain in the B2C E-Commerce business in comparison with penetrating to the customer base of the competition as the latter is almost five times costlier than retention. Further it requires more time and more number of transactions to consider a new customer as profitable. As per the observations from a study carried out by Bain & Co., 5% improvement in customer retention can result in about 25% increase in profitability. Another statistics shows that active customers does more business in B2C E-Commerce in comparison with new customers – probability of business from active customers is 60-70% whereas it is only 5-20% with new customers. All these observations, emphasize on the importance of customer retention and avoidance of churn.

This paper proposes a framework that helps to detect potential customer attrition by leveraging the power of machine learning algorithms, specifically support vector machine. The huge volume of data available with E-Commerce firms can be mined to reveal hidden customer characteristics and behavior patterns and any change in the anticipated trends or patterns can be treated as a possible customer churn. Further, hybrid recommendation strategies are leveraged to come up with personalized retention strategies. As a next step, evaluation of recommendation effectiveness and automatic feedback to improve the SVM model is planned. Also checking on whether ensemble algorithms can be adopted to improve the effectiveness of churn detection process in comparison with SVM model.

ACKNOWLEDGMENT

I acknowledge and would like to thank Mr. Renjith Ranganadhan for the support, guidance, reviews, valuable suggestions and very useful discussions in the domain of retail marketing.

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