A Conceptual Model to Cross Sell Value Added Services in Telecom Industry

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Abstract—Value added services have become an important aspect of telecom operator’s profitability. However, while selling value added services, operator’s need to match promotions to specific consumers based on their individual preferences. Pattern association has emerged as one of the powerful tool that can help in identifying consumer preferences based on their historical services usage data. Based on the application of neural networks, this study proposes the use of pattern association rules to develop a technique for identifying profitable value added services and campaigns for specific consumers and thus increase revenue from the existing customer base. This technique has its advantage in its computational efficiency as well as simplicity in usage.

Keywords: mobile value added services, pattern association rules, neural networks, consumer preference.

I. INTRODUCTION

With liberalization, there has been a sharp increase in the number of telecom operators in the Indian context. Increased competition has ensured that the telecom operators increase their customer base by attracting new consumers as well as retaining the old ones. However in the recent scenario because of lower tariff rates and comparatively low switching costs it has become easier for customers to switch. In such a scenario where it is difficult to differentiate between operators, customer service and value added services become very important in maintaining customer loyalty. Also since now the new subscriptions will largely happen at the bottom of the pyramid therefore the new subscriptions will further lower the average revenue per user. In such a scenario mobile value added services sector is a potential long-term revenue stream as it will be easier to sell more to the existing customers [11].

Also with the availability of large customer data, companies can engage in selective promotion of value added services to its customer in order to increase the revenue as well as satisfy the customer. Value Added Services (VAS) can be used to increase customer loyalty, particularly if services are priced to encourage usage and if they involve some “time investment” from the customer such as backing up personal data or creating personalized content [4]. It was also stressed for the need of different value added services for different markets and quoted that competitive pressures are forcing operators to improve their market segmentation and enhance the value of value added services for their customers [15].

With this context our paper proposes a method to identify the possible services and offers customers might be interested based on their previous transaction data with the operator.

II. LITERATURE REVIEW

Developing customer models (called also profiles in the literature) is an important step for targeted marketing for the huge perceived benefits [16]. In product companies, examples of developing algorithms for customer need identification are found in abundance in literature. Studies proposed approaches wherein they formulated classification algorithms for the identification of customer need patterns and for effective product development [8]. It was also found that content selection through website browsing contributes to the segmentation of online customers and how the current and prospective activities of the individual can be accurately determined and predicted [12]. The Hidden Markov models in the first stage for predicting probabilities of individual customer behaviors from relatively short samples of recent product-purchasing histories [7]. Studies used clustering techniques like K-means and KQV, to cluster customers using knowledge about attributes that are broadly grouped under usage, revenue, services, and user categories [6]. It was also found that by segmenting customers according to the research results and targeting pricing schemes specific to these segments would potentially improve customers’ price perceptions and their intentions to purchase mobile services [14]. Variety of specialized algorithm attempted to use handset-based usage data acquired straight from end-users in established panel study processes to understand customer preferences [18]. Studies have attempted to demonstrate how hybrid data mining techniques (e.g. using classification and genetic algorithm [2]) can create value for telecom companies by cross-selling VAS to generate better average revenue per user (ARPU).
With researchers stressing the need for identifying one to one customer specific product promotion, there isn’t much literature in the telecommunications sector to address to this need. However the often cited poor productivity of new customer acquisition spending is in large part due to methodological neglect, particularly the ineffectiveness of the open offer-centric customer recruitment programs [5]. With this gap, this research paper proposes a data mining technique based on association rules particularly for the telecommunications scenario. This will help in identifying value added services that need to be communicated to the customer based on their previous transaction data.

III. CONTRIBUTION

While there has been few studies attempting to create value for telecom service providers, to cross-sell value added services, none of the significant studies attempted to do the same by generating association rules from historic consumer preferences. While the usage of neural network ensures that there is extensive sensitivity to changes in consumer purchase behavior, the connection with possible profit that may be generated based on the strength of the association rule ensures that only those association rules are chosen which have greater probability to generate profit for the telecom service provider. The sensitivity of the generated association rules and the focus on profitability is an unique contribution in this conceptual paper.

IV. PROPOSED TECHNIQUE

Pattern association rules will be used to develop the proposed technique in this paper. Current pattern association studies in data mining started developing from 1993. Studies [2, 9, 10] on pattern association have demonstrated the high utility of the theory. Many specific algorithms [13,1] were established as having superior performance to previous techniques.

Based on previous research done in the field of pattern association, a methodology is being suggested for the usage of pattern association in the field of purchase of value added services from a telecom service provider by the customer. For the generation of association rules, each purchased service or to be purchased service, be it a ring-tone or a call-alarm, for a provider by the customer. For the generation of profit, the sensitivity to changes in consumer purchase behavior, the connection with possible profit that may be generated based on the strength of the association rule ensures that only those association rules are chosen which have greater probability to generate profit for the telecom service provider. The sensitivity of the generated association rules and the focus on profitability is an unique contribution in this conceptual paper.

In this paper, both purchases would be represented as separate transactions and each transaction would be encoded as a vector. Let \( x \) be the vector for the purchase of the original item, \( ABC-123 \), in this case. Then \( t \) would be the vector for the purchase of the associative product, \( XYZ-123 \), in this case.

Thus each associative purchase pair can be represented as an input-output vector pair, say \( x-t \). If each vector \( t \) is the same as the vector \( x \) with which it is associated, then the net is called an auto-associative memory. If the \( t \)’s are different from the \( x \)’s, the net is called a hetero-associative memory. In both types, the ANN not only learns from the specific pattern pairs that were used for training, but also is able to recall the desired response pattern when given an input stimulus that is similar, but not identical, to the training input. This is the part that gives it the pattern recognition capability.

For training the system for pattern association, we use the extended form of the Delta rule, as proposed by Widrow and Hoff (1960), for pattern association since this rule may be used for input patterns that are linearly independent but not orthogonal. We denote our training vector pairs as \( x-t \) and then denote our testing input vector as \( x \). Let \( \alpha \) be the learning rate, \( x \) be the training input vector and \( t \) be the target output for input vector \( x \).

The original Delta rule assumes that the activation function for the output units is the identity function; or, equivalently, it minimizes the square of the difference between the net input to the output units and the target values. An analogy can be drawn from this as the minimization of RMS error. That the delta rule will produce the least squares solution when input patterns are not linear [17]. Using this process, the initial output node values is being computed, being referred here as \( y \).

Using \( y \) as the computed output for the input vector \( x \), \( y \) is calculated as follows:

\[
y_j = \sum (x_i * w_{ij}) \quad \text{for all } i.
\]

and the weight updates are:

\[
w_{ij}(\text{new}) = w_{ij}(\text{old}) + \alpha(t_j - y_j)x_i \quad \text{for all } (i = 1, ..., n; j = 1, ..., m)
\]

Or we can denote the same in terms of weight change as \( \Delta w_{ij} = \alpha(t_j - y_j)x_i \).

Now, we use the extended Delta rule, which allows for an arbitrary, differentiable activation function to be applied to the output units. The update for the weight from the I-th input unit to the J-th output unit is as follows:

\[
\Delta W_{ij} = \alpha(t_j - y_j)x_i \Gamma(y_{in})
\]

Now a hetero-associative memory neural network is being used for the next step. Associative memory neural networks are nets in which the weights are determined in such a way that the net can store a set of \( P \) pattern associations. Each association is a pair of vectors \( (x(p), t(p)) \), with \( p = 1, 2, ..., P \). Each vector \( x(p) \) is an \( n \)-tuple (has \( n \) components), and each \( t(p) \) is an m-
tuple. The weights of the network are determined by the extended Delta rule as mentioned earlier in the paper.

The algorithm to find out the association between the vectors is as follows:

**Step 1:** For each input vector \( X_i \), do Steps 2 to 4.

**Step 2:** Set activations for input layer units equal to the current input vector \( X_i \).

**Step 3:** Compute net input to the output units:

\[
y_{in} = \sum X_i W_{ij}
\]

**Step 4:** Determine the activation of the output units:

\[
Y_j = 1 \text{ if } y_{in} > 0 \\
Y_j = 0 \text{ if } y_{in} \leq 0
\]

Here, \( X_i \) denotes the inputs to the neural network mesh, \( Y_j \) denotes the output of the neural network mesh, and would provide the final association rules, that would indicate whether association exists between the products. \( W_{ij} \) denotes the weights of the interconnecting network branches of the neural network mesh, and would be initialized in the beginning with the extended Delta rule, as indicated earlier.

![Fig. 1: ANN-Pattern Association](image)

The network is denoted along with its symbols in the following diagram [Figure 1: ANN-Pattern Association].

A threshold function has been used here to generate the final association rules by the proposed methodology. The utility of the threshold function would be to minimize the implications of cross-talk, unless the same is not too high. The output unit \( Y_j \) denotes a positive association if \( Y_j = 1 \), which would indicate, for the concerned pair of vectors, \( X_i \) and \( Y_j \). This means that if transaction \( X_i \) happens, \( Y_j \) can be inferred to happen by the rules of association. Thus in such a scenario, a purchase of the value added service corresponding to \( X_i \) would infer a strong probability of purchase of the value added service corresponding to \( Y_j \), following the rules of association. The output unit \( Y_j \) denotes a negative association if \( Y_j = 0 \), which would indicate, for the concerned pair of vectors, \( X_i \) and \( Y_j \). This means that if transaction \( X_i \) happens, the probability of the transaction \( Y_j \) happening can be inferred to be low, or if value added service corresponding to \( X_i \) is purchased, the probability that the buyer would also be interested to purchase the value added service corresponding to \( Y_j \) is rather low, following similar rules of association.

Now, the rules generated needs to be further tested before actual implementation to see whether they create economic profit for the firm where economic profit is defined as the increase in wealth that the seller has from making a transaction, taking into consideration the revenue generated from the transaction and all the costs associated with that transaction. For the same, the strength “\( \alpha \)” of each generated rule would need to be tested on a continual basis. For doing so, the ratio of the transactions that lead to a success of the association rule generated, to the total number of transactions involving the 1st product which may or may not have led to the purchase of the secondary product (as predicted by the association rule) needs to be calculated. This would be used to determine which rules would finally be used on a regular basis, and which would need to be rejected, based on the profit that may be generated by the association rule to the business.

Now, in this study, the economical value of each generated association rule is evaluated using the mentioned algorithm.

**Step 1:** Do step 2 to 4 until all association rules \( (X_i-Y_j) \) have been evaluated.

**Step 2:** Calculate the profit that may be generated on successful completion of the transaction, i.e.

\[
\text{profit} = Y_{j-\text{Val}} \ast \alpha(X_i - Y_j) - C(X_i-Y_j)
\]

**Step 3:** If \( (Y_{j-\text{Val}} \ast \alpha(X_i - Y_j) - C_a) > 0 \), keep the association rule

**Step 4:** If \( (Y_{j-\text{Val}} \ast \alpha(X_i - Y_j) - C_a) \leq 0 \), reject the association rule

Here, in this algorithm, every association rule is referred as \( (X_i-Y_j) \). \( Y_{j-\text{Val}} \) is the revenue generated on completion of the transaction \( Y_j \). The strength of the association rule \( (X_i-Y_j) \) is depicted as \( \alpha(X_i - Y_j) \). \( C_a \) is the cost of converting a customer through targeted advertising into buying incurring transaction \( Y_j \) and in this scenario, would involve the cost of advertising. Finally only those rules are finally kept which propose economical value to the business.

Now, on the actual purchase of product \( X_i \), a profit maximization algorithm is being proposed where the objective function represents the goal of a profit maximization problem and therefore reflects the microeconomic framework of the marketer.

**Step 1:** For transaction \( Y_j \), do steps 2 to 3 for all values of \( Y_j \).

**Step 2:** For each \( Y_j \), calculate \( CY_j \).

**Step 3:** For all \( Y_j \), find maximum \( (Y_{j-\text{Val}} - CY_j) \ast \alpha(X_i-Y_j) \)

**Step 4:** Choose \( Y_j \) for which \( (Y_{j-\text{Val}} - CY_j) \ast \alpha(X_i-Y_j) \) has the maximum value.

Here, \( CY_j \) represents the cost of sales of \( Y_j \) which would include the sum of the cost of selling for the
VAS as is incurred by the telecom company for the transaction. \( Y_{i \text{val}} \) represents the monetary value of the transaction \( Y_j \). The strength of the association rule \((X_i - Y_j)\) is again depicted as \( \alpha(X_i - Y_j) \).

With this algorithm, the associated rule which will generate the maximum expected profit for the marketer for the transaction \( Y_j \) after \( X_i \) has taken place, will be generated eventually, and thus will address the profit maximization objective of the telecom firm. Thus, with this approach, the telecom company will be able to predict after a customer makes a transaction, which purchase would he be interested in, next, and whether attempting to convert such a purchase would create economic value for the business.

V. LIMITATION

The major limitation of this study is that the model has been conceptualized theoretically for application in the telecom domain. It needs to be further tested in a business problem situation to check whether it can actually generate association rules profitably for the telecom service provider.

Also, training for the neural network should be done only in the targeted segment, since demographics and VAS preferences are often purchased based on contextually, culturally and socially relevant factors. So a model trained on a customer segment in a certain telecom circle may not be able to predict quality association rules for another set of customers in a very different telecom circles.

VI. CONCLUSION

This paper has addressed a very important problem of identifying value added services in mobile telecommunication context in order to better target the existing customers. This would enable tele-marketers to cross-sell and up-sell new VAS to their existing customers. It increases revenue by pushing more services to an existing customer base and thus revenue generation is increased without incurring the high cost of acquisition of targeting new customers. It increases the retention as well as helps in increasing the effectiveness of the marketing campaign by reaching to the customers with the relevant promotions.

Further the use of these complex association rules make it computationally simpler with the increase in computational power. Being a data mining technique it relies on data to generate predictions and lacks the explanatory power for explaining the reasons for difference amongst customer segments. However if combined with customer relationship management applications, the proposed technique can be used to better manage the revenues generated from the customers.

REFERENCES