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2 authors:

Giridhar Maji
Asansol Polytechnic

Soumya Sen
University of Calcutta

Data Warehouse Based Analysis on CDR to Retain and Acquire Customers by Targeted Marketing

Giridhar Maji[1], Soumya Sen[2]

[1]*Department of Electrical Engineering, Asansol Govt. Polytechnic*
[2]*A.K.Choudhury School of Information Technology, University of Calcutta*
[1]*giridhar.maji@gmail.com,* [2]*iamsoumyasen@gmail.com*

***Abstract*: Retaining an existing customer than acquiring a new one is less expensive in terms of marketing cost, bonus, and incentives offered etc. Telecommunication industry across the globe is stiff competitive environment where market is almost saturated and main focus of customer service becomes retaining existing customers and snatching others' customers to increase market share as well as profit. At the same time telecom industry facing the problem of churn or attrition more than anything especially for prepaid customers as the customers could switch the service providers easily. Telecom operators generate huge volume of call detail records every day for every call, SMS or internet access made by its customers. Telecom operators use these huge operational data for business processing to understand customer behavior. In this paper a mechanism is developed to store CDR data in a suitable Data Warehouse (DW) schema and analytically process these using OLAP tools to understand the prepaid customers usage, spending and propensity to marketing offers. Depending on the usage pattern proper segmentation of the customers has been done and they have been categorized for different types of targeted marketing offers and benefits to retain as well as acquire new customers.**

***Keywords*: Telecom CDR; Analytical Processing; Data Warehouse;Telecom Churn Prediction; Customer Retention.**

I. INTRODUCTION

Retaining an existing customer than acquiring a new one is much less expensive. Acquiring [8] and retaining a subscriber is the biggest challenge for every telecom operators in modern days of fierce competition. Identifying those customers who are going to churn (i.e. opt out from the service of the telecom service provider) beforehand and retaining them with some attractive offers and discounts is one of the major business objectives of telecom operators. Again in the same way acquiring new customer from the competitors with targeted marketing offers is also another business goal. For example identifying high yielding subscribers of competitors and sending them targeted teasers for MNP (Mobile Number Portability, where a subscriber can change operator without changing MISDN number i.e. mobile number) offers like "Port out to our network and get 3 months data recharge free of cost", or "Port out to our network and get free rate cutter promo for 3 months" etc. could be used to acquire new customers. Also to ensure that volatile customers do not leave the current telecom operators, they are directly communicated through call or SMS to inform about the benefits or bonus that will make those customers happy and allure them to recharge. Now if the telecom operator knows which customer will be happy to have a data offer (use internet in smart phone very frequently) or rate cutter offer (use to call frequently) then instead of blindly offering benefits to all port out subscribers telecom operator can selectively send targeted offers to the concerned potential customers as per their predicted usage patterns and behavior. In order to leverage technology and business intelligence telecom companies are trying to use their huge amount of day to day transactional data for purposes like understanding customer usage/spending pattern and predicting their future behavior. A lot of different data is continuously stored in many different operational data stores like Customer Relationship Management (CRM), Call Detail Record (CDR) databases, billing system databases etc. Data from all these OLTP (Online Transaction Processing) databases could be properly aggregated and stored in a data warehouse for analytical processing. Some research works have been carried out for customer churn of postpaid mobile subscribers. However there are very few studies for prepaid section. The availability of data for prepaid customers is limited compared to postpaid services. Value recharge pattern is generally irregular and uncertain for prepaid customers.

There are some prepaid data like call detail records (CDR) that can be effectively used for analytical processing by storing them in a suitable Data warehouse schema after aggregation. Using these warehouse data OLAP processing could be done to understand prepaid segment customer behaviors. These data have huge potential in predicting customer behavior, customer mobility and many other business applications such as market share analysis of different mobile brands [9], telecom pricing strategy analysis [11], churn prediction[1], social network analysis[5] etc. In this paper we will discuss how CDR data can be used after proper aggregation and storing in a DW schema for achieving business goals like identifying potential new customers in prepaid segment and also grouping out those segment of subscribers who needs special attention otherwise they might left service. In a nutshell results of our analysis may be utilized for targeted marketing and offering special rates and packages to selected group of prepaid customers who might otherwise have left the service.

A. Churn definition

Churn, in general, is defined as the loss of customers. In India a prepaid customer makes a recharge of certain amount (depending on the service provider recharge denomination varies) and he get some talk value, data value as well as a fixed validity period. During that period he can make outgoing calls, receive calls and can use messaging service. After that period, a customer is able only to receive calls, also during certain period of time. After that period, the SIM card is deactivated. Of course, until the deactivation, a customer can make a recharge and validity period gets extended. Let us analyze the following example [1]: A customer recharges some balance, spends its value during the same day and throws the SIM card away. As per the above rules, the telecom operator deactivates the SIM card only after validity period. Retention actions are usually addressed short before the expected date of churn, so relying on the date of expiration can be very ineffective.

B. Call Detail Record

A CDR is a call detail record that is generated for every user event on the network and contains a broad spectrum of relevant information, including the phone numbers and IMEIs of both the calling and receiving parties, the cell tower location, the start time of a call, and its duration etc [2]. CDRs are a subtype of event detail records (EDRs), which contain information about calls, SMS, value-added services, data usage, and all other services subscribers use. CDR is stored by all telecom operators though data semantics varies a bit among them. CDR contains sufficient information to identify the compelling features of each telecom event including calls, SMS, data services etc. CDRs are generated in real-time so it can be made available almost immediately for mining. Whereas billing data is available only monthly. A typical CDR data fields are shown in Figure 1.

Calling Party mobile Number	Called Party Mobile Number	Caller Cell ID	Location Area Code	Call Time	Call Duration	Served IMSI
919832747948	919434346553	6182	41708	2012-12-06 14:24:32	00:12:34	4600013511068690

Fig. 1. Example Set of CDR Fields

CDRs cannot be used in its raw form as the goal is to gain insight into customer usage behavior not at the particular call event details. As suggested in [7] all telecom events of a customer need to be summarized into a single entry that will depict the customer's usage behavior. Choosing the features for any business analysis is the most important part to extract useful business knowledge about the customers. Author of [7] has given a list of such characteristics that can be used to generate a summary description of a customer based on the calls they made and receive over some time period. Some of them are: average call duration, number of calls made, number of calls received, average number of week day calls, average number of week end calls etc.

C. Datawarehouse and OLAP

A **data warehouse** is a subject-oriented, integrated, nonvolatile, and time-variant collection of data in support of management's decisions [3]. The information stored in a DW is usually exploited by OLAP tools. OLAP tools conceptually model the information as multidimensional data cubes where data is divided into facts and dimensions.

Dimensions are the business users' perspectives on which analytical trend or pattern analysis is based. **Facts** are the main events or transactions where as dimensions provide the context to the facts. **Measures** usually represent the properties of the fact that the user wants to analyze. In case of CDR DW measures can be like average call duration, total numbers of received calls, average spending per month, ratio of in network calls and out network calls etc.

A data cube or cuboid is the most granular representation of data in OLAP and it allows data to be modeled and viewed in multiple dimensions at the logical level. The cuboid that corresponds to the fact table is called the base cuboid. All possible combination of the cuboids could be generated from base cuboid using consecutive roll-up operations and it results in a lattice structure.

The cubes in a DW can be stored in a multidimensional database by following either a Relational OLAP (ROLAP) and/or a so-called Multidimensional OLAP (MOLAP) approach. ROLAP systems use relational database technology for storing data to achieve good query performance, better scalability and good support for frequent updates. ROLAP implementations typically employ star or snowflake schemas, both of which store data in fact tables and dimension tables.

II. RELATED WORK

Telecommunication data such as Call details, network data, and customer's data has been used for data mining to understand customer behavior. The author in [7] discusses the main 4 issues with mining telecom data and possible solutions to them. Some of the issues that telecom data mining are facing: a) huge volume of data, b) raw data cannot be used readily, and it needs proper transformation and aggregations before being used for analysis, c) for real time data mining performance is not good. Author [7] also identifies some of the aggregating features that are beneficial to create a customer profile based on telecom CDR data. Some of the aggregating features that can be useful are: number of calls received by a customer in a month, number of calls placed, number of SMS sent, amount of data access, number of balance recharges made etc.

There are basically two approaches to customer base management by preventing churn and acquiring new customers. One traditional model considers many different aggregating features to profile a customer calling behavior and based on the result predicting churn. Another approach is based on social network analysis of the customer relationships with other customers. In this model the features or attributes of the links or social ties between customers are examined and outcome is used to predict churn. Expectation is that customers, strongly connected by links will show similar behavior, that is, if one of them churns then others will likely to follow [12]. Kusuma et al [19] analyzed about the value addition in churn prediction models by combining regular tabular data mining and social network mining using communication graph formed by the customers. They have extended classical tabular churn datasets with predictors that are derived from social network neighborhoods of the customers. Authors in [20] has investigated the social network graph built using real life CDR data and examined the resulting network properties of the social graph. They also analyzed the cliques in the network along with dynamics of the network along with possible application and utilization.

As telecom industry is getting saturated and competition to gain new customer as well as retaining existing ones are becoming more difficult, telecom operators are utilizing their operational data for decision making and customer profiling to increase profit margin [13][14]. Profit is again linked with the customer base, which in turn depends on number of active customers, call duration, quality of service, rate plans in comparison to other competitors and as a whole ability to satisfy customers [15]. A quality decision system can be built with the use of proper design of DW, data mining, ETL and OLAP with visualization tools [16]. Authors of [10] investigates into the integration and analysis of data from CRM and CDR using service oriented approach to help the telecom operator in taking real-time decision about the customer rate plan to increase user satisfaction and in return profit gain. Authors in [17][18] considered business decision support system and business intelligence as a strategic information system made to provide actionable information through a centralized DW, collected from many operational sources(like CDR, CRM, Billing Data etc), summarized into meaningful information via data mining and OLAP tools, to facilitate business insights leading to informed decisions and hence profitability. They have used it for global enterprise decision support system and hotel management's performance analysis respectively.

In this paper proper DW schema is proposed along with identified facts and dimensions to store and use data mining to analyze the telecom data (CDR, CRM, Billing), and propose customer profiling criteria based on ON net and OFF net call frequency as well as call volume to classify them for different types of promotional actions. It will assist telecom decision makers to make relevant, precise, timely and smart decision in offering rate plans and offers that match perfectly the requirements of the customers who otherwise would have been left the service and in turn convert the 'would have churned' customer a satisfied loyal customer. Due to 'word of mouth' spread it will lead to increase in customer retention and hence profitability.

III. PROPOSED DW SCHEMA FOR CUSTOMER PROFILING FROM CDR

Our goal of the study is to identify those customers who might leave the service of the telecom providers due to non-compatible rate plans or any other cost sensitive dissatisfaction from Call data and customer details acquired from many different operational databases and transactional systems. It is also possible to identify influential customers who, with proper incentives can bring some new customers to the telecom operator's network. Such campaigns may be named like: *buddyzone*. Sole purpose of such campaigns will be to send promotional offers to those identified group of customers who can bring his close ties into our network due to the given incentives. Incentives can be reduced call rates among *buddyzone* members or surprise data balance per referred peers etc. Now to achieve the said goal it is required to analyze huge amount of operational raw data stored in multiple OLTP systems.

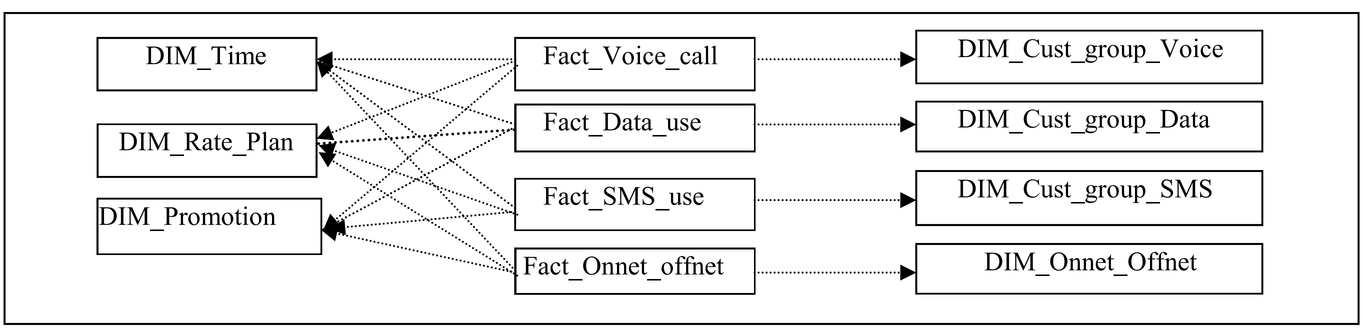

Fig. 2. Logical Fact constellation that can be constructed for both prepaid and postpaid customer segments

Our required business questions will be complex in nature requiring aggregation of raw data as well as joining many different tables from multiple operational systems. Data warehouse is best suited for such purposes as it stores aggregated data in summary form for faster performance and quick resolve of adhoc business queries. Once it is decided that DW will be used for analysis, then it is important to identify the customer grouping features and criteria i.e. dimensions and facts of the DW schema. Raw data will be summarized based on identified dimensions to make it easily understandable and analyze for management decision makers. In our analysis we find our business subjects or facts (we need to work with multiple facts at a time such as voice call, data call etc.) are sharing numbers of common parameters or dimensions. Thus the entire business process needs to be organized in the form of fact constellation which is depicted in figure 2. However each of the fact would follow star schema or snowflake schema, which is depicted in figure 3. Time, rate plan and promotion are common dimensions for all fact constellations, but the fact table as well as customer group dimension will change depending on the segment of customer we are focusing. As an example the schema has been drawn for prepaid segment for voice call analysis in figure 3.

Here our target is to identify different groups of customers within own network (ON net customers) and outside own network (OFF net customers) who make calls or receive calls from our network. We only have CDR data related to ON net customers but for OFF net customers we know only the MSISDN number or simply the phone number with may be cell tower location and call related details but not customer profile data. Next grouping will be among the ON net customers based on total spending on call, sms, internet data etc. Again within high spending group there can be a few patterns like Total ON net calls (Calling frequency) are more than OFF net calls and vice versa. Also call usage and spending are different among 'prepaid' and 'postpaid' customer groups. So "Customer Group" becomes an important dimension in our proposed schema. Depending on the rate plans also customers can be grouped as customer group with 'pay-per second' or customer group with 'pay per minute' plans. This dimension will enable us to consolidate all call, sms, internet data, value added services and activities at the customer group level instead of individual customer or call event level (raw data contains call event level granularity). We will be able to identify monthly average call volume as well as spending of a customer group, ON net call volume, OFF net call volume, frequency of ON net call etc.

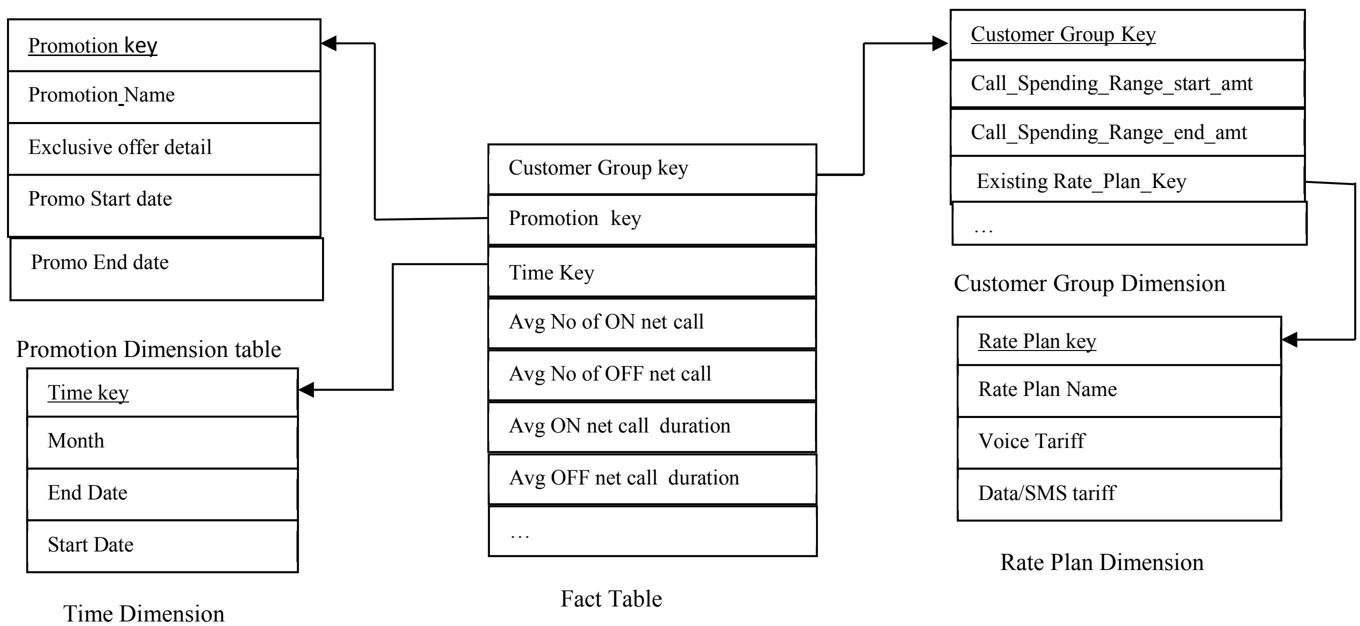

Fig. 3. Proposed DW schema for voice call spending analysis

Different categories of customer will be clustered differently while we consider promotional offers that are given from time to time. 'Pay per second' and 'pay per minute' are two popular rate plans among Indian telecom operators. Again there are different rates for 'local' and 'STD' calls. Also promotional rate varies depending on called numbers belonged to same network (of the subscribed telecom operator) or to other networks. Generally same network calls are given cheap promotional offers to attract more close neighbors of a subscriber into the network. So keeping Promotion as a dimension will add another perspective to look at the data. Analyzing the impact of promotional offers on existing different customers segments can be accomplished easily with the incorporation of this dimension. Promotion dimension contains the details of the marketing campaigns like offer details, offer criteria, offer start date, offer end date etc. There can be dimension hierarchies like regular promotions and seasonal promotions, offered to new and existing customers. "Exclusive Offer detail" is a multi-valued attribute. It could be designed according to the service providers business planning and marketing strategy. Other sub categories of promotion can be based on concerned telecom region and demand of some particular type of value added service. Teaser promotions based on the customer age and income becomes a sub category.

Any DW always contains time stamped data. So here also time series data will be stored. So time becomes an important dimension for the analysis. Time-stamped data is converted to suitable time format during extract, transform and loading process. Time dimension will have key and other fields like start date and end date for different important customer events. Also data may be stored by aggregating weekly, monthly or even quarterly, yearly. Analysis based on this dimension will allow us to interpret the dynamics of the customer calling activities and evolving patterns with time. It also allows comparing and contrasting effects of targeted marketing with the historical data. It helps in evaluating changing trends due to different marketing campaigns.

Our proposed DW schema with possible fact and dimension table entries has been shown in figure 3. It has three main dimensions that we already discussed for our analysis; such as customer_group, time and promotional offers.

Fact table contains the keys to all the dimension tables identified. Some of the important measures that summarize important call data features per consumers groups are like number of ON net calls, Number of OFF net calls, average ON net call volume, and average OFF net call volume. Same kind of data related to SMS and internet use can also be included but not shown in the schema for simplicity. Here we have proposed a relational database based (ROLAP) DW schema of snowflake type as dimension tables contain keys to other more detailed sub-dimension tables. Only two such relationships have been shown in the schema. Customer_group dimension table contains primary key to Rate plan table where all other rate plan related details are stored. Similarly for grouping customers based on their average spending on different type of services can be analyzed using the spend dimension. As an example management might be interested in knowing Total number of customers who spends Rs 200 – Rs 300 in voice call and then find out the average spending of the "Rs-200_to_Rs-300_voice_service" customers. In a similar fashion customers can be grouped based on monthly amount spend on other services like internet data, and sms or voip etc. So it is possible to have customer groups like "Rs-300_to_Rs-500_voice_service", "Rs-100_to_Rs-200_data_service" etc with monthly average spending amount. Next we can analyze those groups which combines one or more services and rank them in order of average amount spend. So those groups of customers that appear in the upper portion of the rank list earns most of the profits. So our aim will be to retain them with suitable offers as well as make proper mix of different service offer so as to increase the number of customers in those groups. It is also possible to try out many such pilot offers among those customer groups with lower ranks and analyze if their ranking improves. For example high voice call users can be offered some amount of data balance with some extra bucks, high data user can be offered some portion of the data in high speed with a little extra amount or high voice call users may be offered some free data balance as a teaser so that they enjoy the benefits of being net connectedness and even after the offer is over they get addicted and recharges for data balance and hence increase their monthly income. Their rank also improves as per our analysis too.

Once call, sms and data events from telecom CDR databases and customer details from billing systems has been processed and aggregated over a time span (may be for a quarter or a year) for each ON network customers and stored in our proposed snowflake schema, we shall be able to view these data from multiple perspectives and also based on the analysis customers are classified and selected; targeted offers are made, then new data is again stored in the same way and effect of the promotional effects can be compared with the earlier data. Effects of each promotion on each categories of customer can be visualized in a multidimensional data cube (MOLAP). However for easy implementation everything has been depicted as ROLAP.

IV. CUSTOMER GROUPING: POSSIBLE SCENARIOS

Customers can be grouped based on a call volume range, number of same network call, and other network call volume as well as data usages.

A) Cust_group_A: All those customers over a selected time period whose ratio of ON network call volume to OFF network call volume is greater than a threshold value.

B) Cust_group_B: Customers who calls mainly OUT network customers i.e ratio of ON network call volume to OFF network call volume is less than a threshold value.

There can be two distinct cases:

1)Cust_group_B(1): This group of customers calls very large number of OUT network customers but only a few times each i.e. Total call volume is high but the frequency of calls is less. Average call duration per distinct OFF network call is low.

2)Cust_group_B(2): Concerned customers calls only a limited number of OFF network customers but call them very frequently i.e. total call volume is large also frequency of calls is high. Average call duration per distinct OFF network call is high.

V. CUSTOMER GROUPING: POSSIBLE APPLICATIONS

It will have many business advantages like it can be utilized for targeted marketing campaigns and helps in predicting acceptance of such marketing offers. Category (A) customers can be termed as loyal group of customers where most of their peers are also in the same network. These are the most profitable customers as they could be retained by offering little benefits and surprised bonuses. Target of any telecom operator should be to maximize these types of customers. For that purpose our proposed data cubes with this category of customer grouping can be analyzed in time series to understand spending patterns of loyal group of customers over time etc. Any customer falling in (A) will love to stay if he is given well 'within the network' rate plan. Similarly (B[1]) category customers will likely to love an offer to a reduced call rate throughout any network. B[1] customers are mainly business minded persons and it is expected most of the calls made for non-family, non-personal purposes as call volume is large but individual call durations are small. Most of the times these are corporate connections or bills are paid by some business organization. Hence this category is not much susceptible to individual offers. These are normally taken in bulk by the corporate agencies. Third category of customers i.e. B[2] are our target for retaining and acquiring new customers. These customers are much prone to shift to other operators if not cared, as they call only limited number of other network customers frequently; expectation is that these are close friend or family members of the customer and most of the calls made are for personal reasons and long duration calls. Normally telecom operator earns profit by utilizing more and more ON net calls during the odd hours so as to maximize infrastructure use. This is mainly possible with personal calls as only that type of calls are of long duration as well as happens in odd hours of the day. B[2] customers may anytime port out to the network of their close friends. In order to retain them and also to bring under close ties proper marketing offers should be given. Once all customers are categorized into above groups then it is easy to offer different targeted promotional benefits depending on the category of the customer.

VI. CONCLUSION AND FUTURE WORK

Telecom customers have been grouped depending on their usage pattern as well as calling behavior based on CDR data. Model DW schema is also defined for creating OLAP cubes for easy visualization and analysis on summarized data from multiple perspectives. For the above purpose different logical fact constellation models with different dimensions as well as customer categorization has been identified. Same kind of study can be used using similar DW schema and telecom data to identify early adopters (i.e. those enthusiast customers who are much more likely to try any new and beta services including value added services). Early adopters are most of the times loyal customers too. So if identified properly then those customers can be offered any pilot or test or experimental promotions to acid test the market. Going forward we are going to implement this scheme with real CDR data and try to understand the impact of targeted offers on churn behavior. One more area to consider in future will be to consider geo location aware context of CDR data. CDR data also contains coarse location of the customer, so relation between customer churn pattern and his spatial location can be analyzed by looking into this from a location perspective. Does churn decision depends on geographical location and varies with different parts of the region even if same promotional offers have been given to retain them? Does churn depends also on the quality of infrastructure present in some region? This correlation analysis is interesting future work which could be resolved utilizing available location data from CDR. Furthermore data mining based approach could be incorporated to figure out exact plan or offer for the customers by analyzing exact billing data. This could help in to design fully customized offers for the customers. This would result in better percentage of retention of the existing customers as well as attract other customers from the competitor's networks.

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