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HOW PREDICTIVE ANALYTICS CAN CHANGE RULES OF THE GAME IN TELECOMMUNICATIONS INDUSTRY

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***Abstract* - Telecommunications industry more often than not works in reactive mode with few minor exceptions related to marketing. Most telecom providers' work with their customers in "reactive" mode; that is after the customer complains about the quality of product the vendor would investigate into it.**

However with the fast changing technological advancements like uprising of social platforms and changing business models there is a need for telecom providers to change their operating model to stay ahead in the game.

This white paper discusses the current scenario of operation model in telecom industry and how a combination of predictive analytics along with data mining techniques can revolutionize the telecom industry. The paper also discusses high level framework based on predictive analytics that can be adopted by the telecom industry. The framework would help the telecom players to pro-actively predict the behavior of its customers based on models created from their past behavior and transactions. The model would provide key indications to understand aspects like customer churn probability, cross-sell/up-sell opportunities, best offers for a given customer, customer's loyalty score, customer satisfaction score etc.

I. INTRODUCTION

Telecom industry is mainly involved in the business of selling telecom products like call plans, offers & promotions etc. The business is highly competitive especially in geographies like India due to number of players and the purchasing power of the people. As the margins per call and margin per user improve the continued sustainability of the business depends primarily on expanding customer base and penetrating new geographies.

In order to penetrate new customer base and geographies customer service plays a vital role. Quality of customer service can be drastically increased based on identifying past customer behavior in or to give the most innovative promotional scheme for the customer and market intelligence. Naturally customer satisfaction and market intelligence form the key decision drivers for the business. Some of these key performances Indicators (KPI) include Average Revenue per User, Average Revenue per Call, and Average Margin per User

II. PROBLEM STATEMENT: CURRENT CHALLENGES IN TELECOM INDUSTRY

The industry is mainly facing in following areas:

- Retaining the loyalty of existing customer
- Cross-selling and up-selling the products to the existing customers in most effective fashion
- Create new customer base by providing attractive offers and expanding to new territories.
- Effectively responding to market and seasonal trends.

The above aspects would translate into some of the KPIs Average revenue per user, Churn per month, Subscriber per employee and others.

The key aspect to above points is the "loyalty" which would help other aspects like cross selling, up-selling. The loyalty will also generally translate into good will about the grand and a loyal and satisfied customer would also provide a "word-of-mouth" publicity about the product in social media platforms by expressing sentiments.

The positive sentiment would also translate into addition of new customer as an informed customer would run sentiment analysis tools to see how people are talking about a brand or product in various social platforms. This helps the company's interest in expanding customer base and venturing into new geographies.

III. PROBLEM STATEMENT IN DETAIL

In the current scenario most of the telecom providers are in nascent stage in adopting analytics platform in addressing the loyalty of a customer. Most of the times the providers are not even aware of their most efficient brand ambassador – a loyal customer who is using various services of the company. There are broadly two areas of challenges in the current scenario:

- Challenges in predicting user behavior, market trends and thus effectively responding to them
- Pro-active identification and mitigation of problems like customer churn probability, effectiveness of a campaign or promotion

These challenges would manifest into various problems; some of the key ones given below:

- It will not be possible to provide targeted marketing with tailor-made products/services for customers.
- No incentives for rewarding the loyalty of a customer
- Not able to pro-actively identify the issues customers are facing and actively engage with them to address it.
- It would not be possible to effectively predict the seasonal changes in market trends and effectively respond to them
- CSRs would not able to predict the churn of a customer
- Not able to devise a best plan suited for a customer based on his/her purchase and usage patterns in the past
- Challenges faced by Customer Service Representative (CSR) in understanding the probability of selling a new product to the customer.
- Challenges in getting a single/holistic view of all customer activities and behavior patterns including the purchase patterns, call patterns, support calls, complaints etc.
- Challenges in customer segmentation for predicting revenue

Rest of the white paper discuss on few strategies on how these gaps can be addressed and elaborates how telecom providers can pro-actively engage their customers leveraging predictive analytics and other technologies.

IV. ROLE OF PREDICTIVE ANALYTICS IN ADDRESSING THESE CHALLENGES

With the emergence of various predictive analytics modeling techniques it became easier for the organizations to use the past customer data which they already have to predict the future with good amount of confidence. Predictive analytics provide the necessary tools in effectively modeling things like customer behavior, usage patterns, market trends, probability of customer churn by combining data across various channels of the organization.

Predictive analytics is a fairly new technology which starting gaining more traction after 2009 9. The technology was mainly developed by credit scoring purposes. Prior to the predictive analytics organizations were relying on statistical models to understand the patterns; however those patterns were not effective in providing insights into future behavior.

Predictive analytics is more important now than ever as the entire business model has changed from a "reactive mode" in the past to "pro-active mode". The more accurately you are able to predict the customer more likely you are going to retain him/her and it is more likely to make an effective sell to him/her. If the business predicts the market trends/seasonal patterns more effectively it can respond to them more effectively to increase the revenue. Predictive analytics has potential to open up and use all these opportunities.

V. CURRENT SOLUTIONS

Telecom providers currently address these challenges in either:

- Building a custom home-grown solution using predictive analytics techniques
- Buying a COTS product to address the challenges. For example predictive analytics product from RedGiant

Custom home grown solution often lacks the necessary feature set to effectively address all dimensions of the problem and is seldom extensible to address future challenges. This white paper provides a comprehensive framework of components based on predictive analytics technology to aid the organizations.

VI. PREDICTIVE ANALYTICS FRAMEWORK

Predictive analytics framework diagram given in next page talks about few essential components which can be adopted and implemented by telecom industries.

The framework essentially consists of these main modules: Analytics engine, Sentiment analysis engine, Heterogeneous source consolidator and profiling engine.

Analytics engine has components to basically do the predictive analytics for the user behavior. The primary component is the user history analyzer which analyzes all the recorded user history and uses "Pattern analyzer" to derive the patterns. The patterns could be something like increased use of service, decreased use of service, increased number of complaints etc. Training module is used for supervised learning. "Data Modeller" components contain the core predictive models which help in creating the predictive score.

Heterogeneous Data consolidator and data mining component is mainly responsible to aggregate the data from variety of internal and external data sources and "cleanse" it into a structured format. A key component in this module is "Data mining engine" which along with "Natural language processor" and "Text analytics" can interpret huge amount of unstructured data to understand user's behavior. For instance an analysis of all recent emails from the customer could reveal that customer is increasingly getting dissatisfied by the service of the company. Text analytics component can look for keywords related to mood/sentiment expressed of the user to come up with positivity/negativity score. "Data transformer" component would transform the discrete set of data gathered from variety of enterprise sources by data mining engine into a structured format so that it can be easily analyzed and interpreted. Various data models will be built on the structured data which can be used for coming up with predictions with greater degree of certainty. "User Identifier" component would help in identifying the feeds/posts in social and online platforms. This component mainly uses the profile information like twitter handle, Facebook personal URL etc. explicitly given by user to the identify the social media posts and feeds related for a specific user.

If the company collects the social data for the user (with user's consent) then social analytics tools can be used to understand the sentiment expressed by user in social platforms.

The next key engine is the "Sentiment analysis engine" which mainly analyzes the user's sentiment in online and offline platforms. It also analyzes the loyalty of the customer based on customer's purchase patterns. It also does brand analysis and sentiment analysis by analyzing huge amount of unstructured data. This analysis need not be specific for a given user. The component attempts to understand the general public sentiment towards the product/service of the organization by analyzing the unstructured data.

The third component is the profiling engine which analyzes the user's interests, tastes, likes based on user's transaction history (done using Spend analyzer). For instance if the user is repeatedly subscribing to online gaming and music services the engine would increase the score in "entertainment" category for the user. This overall profile score will later be fed into the analytics engine.

Finally the analysis of all three engines is mainly used in human interfacing platforms like IVR, online channels, mobile applications or to the applications used by company on-call support staff.

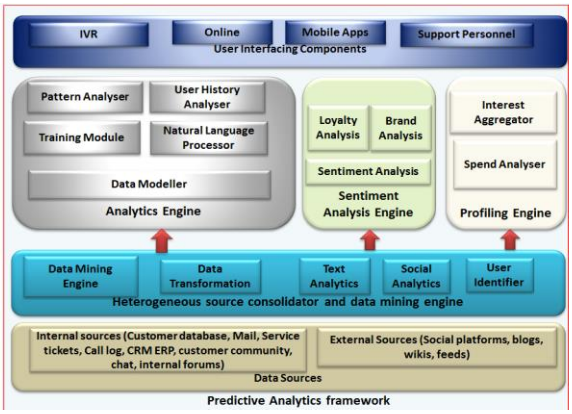

Figure 1: Predictive Analytics Framework

The main component is the analytics engine which creates aggregated overall scores (which is pre-calculated) in various groups. Some of the groups could be:

- Customer churn score
- Customer satisfaction score
- Customer spending score
- Customer loyalty score

Following diagram shows the detailed steps in coming up with a predictive score:

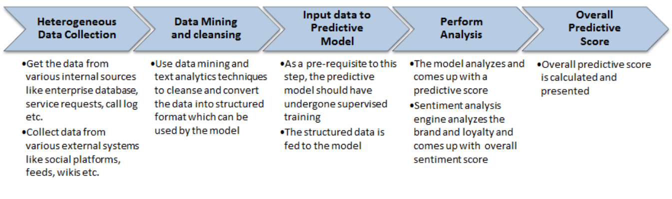

Figure 2: Steps in calculation of prediction score

We will see in the next section on how these scores can be used by telecom providers.

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VII. IMPLEMENTATION OF PREDICTIVE ANALYTICS FRAMEWORK

The key steps in using the predictive analytics framework are depicted in the flow diagram.

Step – 1: Define the key business goals and KPIs. For instance a telecom provider needs to get insights into the probability of successful cross-sell for a customer; others may be interested in understanding the best call plan that can be recommended to maximize revenue.

Step-2: Data aggregation: Collect the historical data from numerous enterprise sources. This could include usage history, purchase history, call duration log, support tickets etc. After data is aggregated it needs to be transformed into a structured format for interpretation.

Step -3: Predictive Modeling: The structured data is used to create analytical models which would help in coming up with predictive score for each of the identified KPIs in the first step. The models are often in the form of a business rule derived from the data mined. A sample rule could be: *If customer has made 10 support calls in last 1 month And 4 of them are still unresolved then customer satisfaction score would be 3 times lesser than the average.*

Step-4: Scenario analysis & selection: Upon receiving predictive score, the business can analyze various scenarios like what-if analysis and choose the optimal one.

Step-5: Actionable insights: Predictive analysis is actionized in this step. The optimal scenario chosen is executed. This would involve various things like offering most suitable promotion to the user, coming up with most competitive pricing for a given season etc. Use the analytics model in defining the organization strategy and in organization decision making process.

Step-6: Monitor and Evaluate: The effectiveness of the predictive analysis is closely monitored and it is feedback into the analytics model for continuous optimization.

VIII. A CASE STUDY TO PREDICT THE CUSTOMER CHURN PROBABILITY

A detailed case study is given below which employs the above framework to predict the churn probability of a customer.

Step-1: KPI definition and model training: As the initial step the key performance indicators (KPIs) for customer churn are identified. In this case study the KPIs are churn probability, customer satisfaction score, retention with incentive probability.

Simultaneously the models employed in the framework undergo supervised training with vast amount of previous customer data. The data includes both explicitly expressed by customer and implicitly obtained by the system:

Explicit customer data:

- customer provided survey ratings,
- explicitly expressed ratings/feedback,
- complaints logged
- Positivity about the product in social platforms/feeds

Implicit customer data:

- income
- failed calls
- order history
- balance
- type of packages subscribed
- Number of customer care calls.

More about the models: The framework employs three models for calculating prediction scores individually. The analytics engine uses the weighted average of the three scores to arrive at the overall prediction score. This is done in order to improve the quality of prediction score. Following are the three models and their high level details:

1. **Regression Model:** This model employs the logistic regression where the churn probability is estimated with following function:

> P (churn) =1/ (1+e-T)
> Where T=a+bX with a as a constant value and b as co-efficient vector and X as directly-related predictor attributes

The regression model is given the rich set of previously churned customer data mentioned before so that T is fine-tuned.

2. **Neural-network model:** This model attached weight for each of the predictor attributes and the weight is continuously updated during the supervised training. Normally neural networks require large data sets for high quality prediction.

Once we input the subject customer's data to the model it uses the weights of the predictor attributes to come up with prediction.

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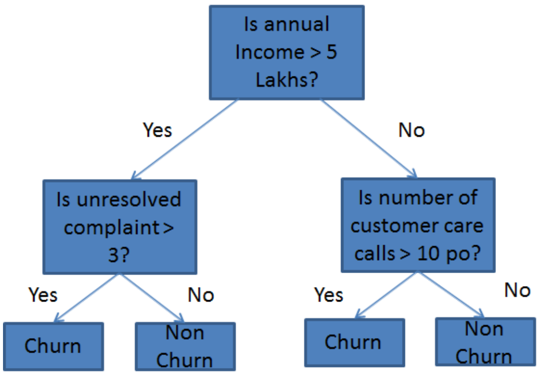
3. **Decision Tree model:** This is the simplest of the models though an effective one. The model uses the set of customer input attributes and works top-down in splitting the set of attributes into a homogenous set. A sample decision tree for churn is given below:



After the training each model has sufficiently tuned predictor function that is ready to perform prediction

Step-2: Data aggregation and cleansing: As a next step we need to get a consolidated view of target customer data for which the framework is going to perform prediction. The data is obtained similar to the predictor input attributes used in step-1. This includes implicit customer data like purchase history, call logs and explicit customer data like number of complaints logged, explicit service rating.

Once the data is aggregated the heterogonous source consolidator cleanses the data and transforms into a structured format which the models can use for prediction.

Step-3: Calculation of overall prediction score: The subject customer's data is fed to each of the three models and a weighted average score is calculated.

The sentiment expressed by the subject customer in available social platforms and feed is also factored into the overall calculation of KPI

Step-4: Scenario analysis: Based on the overall predictive score various scenarios are analysis. Following are the sample scenarios in this case study:

- What is the price break that can be offered?
- What is the probability that customer would leave without incentive?

Step-5: Actionable insights: The KPIs obtained in step-3 offer valuable actionable insights to actionize the customer retention campaign. For instance the retention with incentive probability obtained from the models can be used to decide which customers can be offered incentives cost-effectively.

Step-6: Continuous monitoring and feedback: The effectiveness of prediction score is continuously monitored for its accuracy. This will again be fed back to the three models as part of continuous training process thus improving the model accuracy.

IX. KEY DIFFERENTIATOR & SMARTNESS OF THE SOLUTION

A predictive analytics based solution is mainly different from the traditional solution approach in following ways:

1. It employs pro-active approach to problem solving which keeps the business ahead in the game.
2. Leverages the collective knowledge of the organization by analyzing all the data and
3. building analytical models based on it
4. Equips the organization to better respond to market dynamics and changing customer behavior

Following are some sample benefits:

1. Predicting the customer churn probability and reducing attrition
2. Identifying cross-sell and up-sell opportunities
3. Effective marketing by identifying opportunities in making the best possible offers

Let's examine each of the above categories in detail:

If the analytics engine has analyzed that customer churn score is high after analyzing user's recent call history, user's mails etc. then it would indicate that the probability that customer would move away is very high to all human interfacing channels. So next time when the customer calls-in or writes a mail the support staff can effectively use the churn score to prioritize the request and offer discounts and promotions to the customer and to ensure that issue is addressed to customer satisfaction.

Similarly if data mining component and spend analyzer component has identified a high "customer spending score" then this information can be used by human interfacing channels for cross-selling and up-selling opportunities.

Customer satisfaction score and loyalty score is a strong indicator of importance of customer which can be used to offer periodic offers and encourage the opportunities to get referrals from the customer. It will be highly likely that customer is going to provide good publicity for the product and provide good number of referrals.

Let's look at the key business and technological problems solved by the solution. Following are the key business problems that can be addressed:

1. Revenue maximization in various aspects: increased ROI, customer retention etc.
2. Effective and targeted marketing campaign
3. Better customer insights
4. Reduced costs by avoiding unnecessary offers
5. Better product recommendations

Following are some of the key technical problems that this solution aims to solve:

1. Consolidating and leveraging entire organization data for creating predictive models.
2. Factoring-in the social media platforms to identify the product and brand sentiment
3. Providing near-real-time customer insights based on models.

This solution can also be used in other industries like:

1. Financial industry while processing applications
2. Credit scoring
3. Ecommerce industry for detecting fraudulent transactions
4. Online subscription services
5. Retail industry for targeted campaign
6. Insurance industry while processing applications and claims

X. CONCLUSION

This paper discussed some of the challenges currently being faced by telecom providers and provided a framework based on predictive analytics to address them. It discussed a pro-active approach towards addressing the key issues and also provided a guideline for defining the analytics strategy for the organization.

XI. REFERENCES

1. McCue, C.,(2007), Data Mining and Predictive Analysis, Butterworth-Heinemann

2. Davenport, T., and Harris, J., (2007),Competing on Analytics: The New Science of Winning, Harward Business School Press

3. Siegel, E., and Davenport, T., (2013), Predictive Analytics: The Power to Predict Who Will Click, Buy, Lie, or Die, John Wiley & Sons, Inc.

4. Coggeshall, S., and Wu, J., (2012),Foundations of Predictive Analytics, Chapman and Hall/CRC

5. Siegel, E., (2004), Driven with Business Expertise, Analytics Produces Actionable Predictions. Available at http://www.destinationcrm.com/Articles/ReadArticle.aspx?ArticleID=44224

6. Siegel, E., (2013), Driven with Business Expertise, Analytics Produces Actionable Predictions. Available at http://www.predictiveanalyticsworld.com/lower-costs-with-predictive-analytics.php

7. Ventana Research, (2011), Predictive Analytics Are on the Rise. Available at http://blog.ventanaresearch.com/2011/04/25/predictive-analytics-are-on-the-rise/

8. Siegel, E., (2013), Predictive Analytics Delivers Value Across Business Applications. Available at http://www.predictiveanalyticsworld.com/businessapplications.php

9. Siegel, E., (2013), Predictive Analytics' Killer App: Retaining New Customers. Available at http://www.predictiveanalyticsworld.com/customer_retention.php

10. Siegel, E., (2005), Predictive Analytics with Data Mining: How It Works. Available at http://www.predictionimpact.com/predictive.analytics.html