

# Predictive Modeling in Campaign Management

Shruti Mahajan, Devika Antarkar, Ryan Roy, Manish Nagare, Rakhi Kalantri, Vijay Tiwari

**Abstract**— Every service provider in telecom industry aims at reducing the gap between the consumer and the service provider by providing effective means of communication. This is done to generate revenues and keep the consumer active on its network by providing customer satisfaction.. This goal is well achieved through Campaign Management. It deals with forwarding various campaigns to the consumer, by analyzing the usage pattern and the behavioral profile of the consumer. These can be sent through various channels. For such requirements, predictive analysis plays a major role in understanding the consumers behavior based on the previous usage pattern and recorded data for the particular consumer. This helps service providers in effective and strategic campaign generation, forwarding and designing.

**Index Terms**— campaign, churning, profiling, segmentation, tactic.

## I. INTRODUCTION

The term customer segmentation and customer predictive modeling are often used interchangeably, however these are different and support different business objectives. Customer segmentation is the practice of dividing the customer base into distinct groups, also known as tactics. The separation of customers into different groups is often based on multiple parameters such as type of customer, age, circle, usage, etc. However, predictive modeling is forecasting consumers behavior and propensities and assigning score or ranking to each customer that depicts their anticipated actions. Thus, it is important to understand the need of predictive modeling and what it conforms to.

A predictive model

- Identify targets for marketing campaigns
- Forecasts customer behavior
- Optimize effectiveness of marketing objective and helps understand various constraints
- Measures impact of specific marketing elements and campaign strategy

Customer segmentation helps guide predictive modeling

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in short term and long term allocation decisions and tailoring campaign configurations. It involves testing and analysing various combination of variables and seeing which has more impact. It makes use of statistical and OLAP(Online Analytical Processing) tools to understand data trends and previous analysis.

## II. LITERATURE SURVEY

The traditional marketing process involved using various advertisement channels such as newspaper advertising, ad-making, etc. This has a possible drawback ,as we cannot keep track of the consumers and their behavior towards the given product or service provided by the organization. With the help of various databases, data analytic tools and techniques the consumer information is stored and consolidated in a structured manner.

If a customer responses only to a marketing message or information sent through particular channel such as Email or SMS, then through data analytics the tactics can be performed accordingly. For example, if the consumer responds more towards campaigns sent through Email, then the organization will forward campaigns through Email in order to achieve to receive responses and feedbacks. This has a many other advantages:

The organization understands the customer behavior toward various services and products provided through the use of various data analysis methods applied on a given set of data.

The consumer response towards a particular channel can be well received and further campaigns would be sent through that channel.

The organization can also perform Churning ,i.e the inactive consumers can be ranked according to their response or activity. This helps in analyzing the inconsistencies and inadequacy from organization's side.

The organization can hence backtrack and check for the faults ,e.g. If the consumer was added into a wrong tactic. If so, then the consumer won't respond to the campaign sent.[3]

Predictive analytics involve methods and technologies enabling organizations to spot patterns and trends in data, test large numbers of variables, develop and score models and mine data for unexpected insights. As predictive models become mainstream, 71% of organizations are planning to leverage real time data. Our focus is on predictive analytics-driven campaigns where analytics either support or are real-time in the algorithms, decision rules, applications and scoring mechanisms that are relied upon to inform or carry out campaign decisions and/or actions. Most organizations now view data and analytics as important

corporate assets. Advancement in design principles and algorithms has improved model precision, accuracy and recall, and they have enabled companies to build better and faster predictive models. In addition, advancements in data warehouses and tool-suite workbenches are taking advantage of technological breakthroughs like in-database and in-memory analytics to provide new possibilities. In this context, there is a significant opportunity to more closely link customer demand management with supply chain management in what is now commonly referred to as 'Demand Chain Management' (DCM). DCM requires strong marketing and supply chain functional area collaboration in order to minimize sub-optimization. To address the role of campaign management in DCM, we adapt a purposefully broad definition for the term 'campaign' to refer to, "... a series of simultaneous or sequential operations, within a given time and space, designed to achieve a strategic aim". This definition is not unique; Gartner defines multichannel campaign management (MCCM) as a process that enables companies to define, orchestrate and communicate offers to customer segments across multichannel environments, such as websites, mobile, social, direct mail, call centers and email.[4]

### III. GENERATION OF PREDICTIVE MODEL

#### A. Campaign Management Process

Figure 1 illustrates the closed loop Campaign Management Process. The various steps involved in Campaign Management are:-

The data is collected from various sources and stored in a common system using different data warehousing techniques.

This data is accessed for different purposes and for various other processes other than campaign management.

For the purpose of campaign management the data is loaded to perform aggregations, functions, procedures, etc to meet the campaign requirements.

This data is processed using R Model. R Model provides predictive analysis for the customers by assigning each customer a score.

The campaign manager then takes decision based on leads from R model and the analytics performed based on campaign requirements.

Now, a campaign tactics are generated and accordingly it is forwarded to customers which are grouped under the tactic.

A customer feedback can be generated through surveys. These surveys again works as a source for more refined analysis of customer data and consumer profiling.

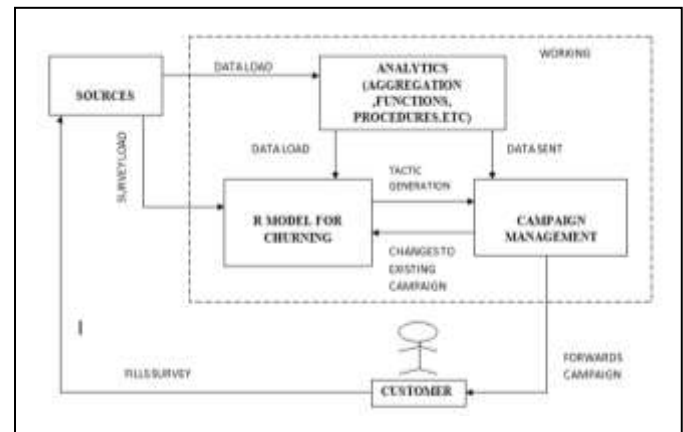


Fig. 1. Campaign management Process

#### B. Data exploration and preparation

The predictive models need data to execute upon, they do not operate on their own. In a telecom organization, data is received from various sources. Sources of data have sufficient number of records, history and fields (i.e. variables), providing a good chance for patterns and relationships of data to have a significant business value. Data exploration and preparation can be done with the help of analytics tools. It enables analysts to compile descriptive statistics of various fields (min/max or standard deviation) and identifying relationships between columns of single tables and across tables. Once the data is selected and examined, it is transformed to a different format so that it can be read by an analytical tool. Preparing data means cleaning data from many errors and then converging into a single table with huge volume of records and the columns that they reside in. [1] Usually, here additional transformations are applied to optimize data for specific types of algorithms. For example, they can aggregate data in one or more fields, such as changing daily usage to monthly usage.

#### C. Building predictive Model

The basic process involves running one or more algorithms against a data set with known values for dependent variables. Then, split the data set in half and use one half for creating a training model and the other for testing the training model. Here, we wish to predict which customers will churn, we use an algorithm to a database of customers who have churned in the past 12 months to 'train' the model. Then, run the resulting training model against the other part of the database to see how well it predicts which customers actually churned. Lastly, we validate the model in real life by testing it against live data.

Selection of variables is the most challenging task for modeling. Often, analysts start with utilizing various variables and at the end number of variables decrease significantly. Most analysts deploy the predictive model by scoring it. Here, we transform the predictive model into SQL statements or programming code and then apply the statement or code to every single record in the database pertaining to the subject area of the model. The result is a 'score', usually a value between 0 and 1, that gets inserted into

database record as an additional field. for example, for churn if the score for a consumer is greater than 0.65, then the costumer can be considered an active customer, else it is a passive customer. This involves exposing the entire customer base to churn. Instead, we can highlight one variable in the model that can cause the customer to churn. These variables are known as 'tripwires'. To operate a predictive model, we need to embed the model results or scores into a set of rules. These rules usually create an 'if, then else' statement across the score.

#### IV. PURPOSE OF PREDICTIVE MODEL

Campaign Management is integral process in determining the various aspects of customer behavior .It determines the amount of expected execution of campaign with respect to the requirements, constraints of a given campaign towards a particular customer base. It helps us to achieve the following goals with the help of analysis toll such as R.

##### A. Identify Customer Targets

This can be classified as modeling for selection of customers for programs or campaigns (Response Modeling). Response model attempts on leveraging subscriber's collective knowledge on each individual customer to determine if they are fit or satisfy the requirements for particular campaign. The initial development of these models often require real-time testing to accumulate valuable customer response data and insights. Once collected, each customer can be assigned a precise score representing their likelihood to respond to particular campaign sent.

##### B. Forecasting customer behavior

Predictive modeling techniques can be used to estimate lifetime customer value, with other key impact behavior features like recharge propensities, expected recharge amount, aggregate data usage levels, customer loyalty levels and service usage. Behavioral forecasting models are used to support broad range of applications including: campaign targeting, financial and operational forecasting, customer investment allocation and inventory planning.

##### C. "Return on Investment" optimization

Predictive models also play an important role as subscribers optimize usage of some of their primary marketing levers such as, value proposition, price, channel and data usage. For example, predictive modeling and optimization techniques are often leveraged to help subscribers get greatest return on their campaign offer and promotion budgets. The more sophisticated model-driven, optimization tools are generally designed to allow companies to forecast expected lift in sales under different types of scenario's. The multivariate nature of predictive modeling provides the means to measure the impact of individual campaigns on customer behavior in a controlled manner.

##### D. Analysis Tool Used- "R"

In the past few years, R has become popular in field of data science and important in Finance and analytics- driven

companies. R virtually consists all the possible statistical models, data manipulation and charts that could ever be required by a modern day analysis. It provides a large collection of graphical and statistical techniques, consisting of modeling (linear and non-linear), statistical tests, time-series, classification, clustering, etc.

R helps in representing complex data as unique data visualizations. Evaluation of result in R is simply a programming language designed specifically for data analysis that also has the capability to use mix and match models for best results.

R is easily extensible through functions and extensions. R is an open source and can be extended easily as individuals using it can contribute in its growth. Dynamic and static graphics are available through additional packages. R can easily deal with complex and large datasets.

##### E. Data Set

Above figure lists different attributes used .

SR. NO.	Attribute name
1	State
2	Account Length
3	Phone
4	Intl. Plan
5	Day Mins
6	Day Calls
7	Day Charge
8	Night Mins
9	Night Calls
10	Night Charge
11	Intl. Mins
12	Intl. Calls
13	Intl. Charge
14	CustServ. Calls
15	Churn

Fig. 2. Used Data set

#### V. STEPS IN CHURN ANALYSIS

Predict is a generic function for predictions from the result of model fitting functions. This is explained in points A,B and C through Fig. 3.The steps involved are as follows:

##### A. Read data from .csv file.

```
churn <-- read.csv("C:\\Users\\R\\churn.csv",header=T)
```

The above syntax reads the csv file, "churn.csv" into R module.

##### B. Names of all the attributes

Syntax shown below defines all the attributes present in the given data set.

```
>names(churn)
```

```
"State", "Account Length", "Phone", "Intl.Plan",  
"Day.Mins", "Day.Calls", "Day.Charge", "Nights.Mins", "Nights.Calls", "Night.Charge", "Intl.Calls", "Intl.Charges", "Intl.Mins", "Cust.Serv.Calls", "Churn"
```

### C. Determining complete data set

After determining the entire data set, we split it into two halves, one for creating training model and the other for testing the training model. If both sample and training model have similar target variable distribution, then the training model is validated. This training model conforms to previous analysis and variables present in the data set.

```
> churn <- read.csv("C:/Users/admin/Documents/dp.csv",header=T)
> churn
  PHONE.NUMBER VOICE.USAGE DATA.USAGE DAY.CALLS MONTH.CALLS DAY.MINS
1 -968516412      -60      -120      -12      -34      -120
2 -968542312      -50      -12      -2      -12      -52
3 -968475254      -86      -50      -45      -12      -85
4 -921558321      -89      -85      -42      -3      -15
  NIGHT.CALLS NIGHT.MINS INTL.MINS INTL.CALLS INTL.CHARGE CHURN
1      -10      -89      0      0      0      NA
2      -1      -2      0      0      0      NA
3      -5      -10      -12      -1      -50      NA
4      -1      -10      -85      -2      -220      NA
> names(churn)
 [1] "PHONE.NUMBER" "VOICE.USAGE" "DATA.USAGE" "DAY.CALLS" "MONTH.CALLS"
 [6] "DAY.MINS" "NIGHT.CALLS" "NIGHT.MINS" "INTL.MINS" "INTL.CALLS"
[11] "INTL.CHARGE" "CHURN"
> str(churn)
'data.frame':  4 obs. of  12 variables:
 $ PHONE.NUMBER: int  -968516412 -968542312 -968475254 -921558321
 $ VOICE.USAGE : int  -60 -50 -86 -89
 $ DATA.USAGE : int  -120 -12 -50 -85
 $ DAY.CALLS   : int  -12 -2 -45 -42
 $ MONTH.CALLS: int  -34 -12 -22 -3
 $ DAY.MINS    : int  -120 -52 -85 -15
 $ NIGHT.CALLS: int  -10 -1 -5 -1
 $ NIGHT.MINS  : int  -89 -2 -10 -10
 $ INTL.MINS   : int  0 0 -12 -85
 $ INTL.CALLS  : int  0 0 -1 -2
 $ INTL.CHARGE: int  0 0 -50 -220
 $ CHURN      : int  NA NA NA NA
```

Fig. 3. Example of model-fitting function

Now we split the data set into two parts. One for generating the predictive model and the other for testing it.

```
> sample.ind<-sample(2,nrow(churn),replace=T,prob=c(0.6,0.4))
> churn.dev<-churn[sample.ind==1,]
> churn.val<-churn[sample.ind==1,]
```

Fig. 4. Division of complete data set into two data sets: validation and development

```
> table(churn.dev$VOICE.USAGE)/nrow(churn.dev)
-89 -86 -60 -50
0.25 0.25 0.25 0.25
> table(churn.val$VOICE.USAGE)/nrow(churn.val)
-89 -86 -60 -50
0.25 0.25 0.25 0.25
```

Both validation and development samples have similar target variable distribution as observed in Fig. 5.

## VI. CONCLUSION

Predictive analysis helps to achieve targeted communication with the customers. This is due to the emergence of customer personalization and segmentation. Predictive analysis allows one to leverage information, generating more customer-driven campaigns and processes. This yields unprecedented level of targeting across various

channels of campaign forwarding.

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