# Profit Maximization Using Prediction Model

*Devare Jayvant[1] ,Phalke Vrushali[2],Ajabe Varsha[3],Phalke Ashwini and Chaudhari Sheetal[4]*

Department of Computer Engineering, Sharadchandra Pawar College of Engineering, Dumberwadi (Otur)
Email: jayvant.devare@gmail.com,vphalke26@gmail.com,varsha.ajabe12@gmail.com,ashwini.phalke4@gmail.com.

**Abstract***: -* The objective of this contest is to maximize the profit using metric by which classifier's performance will be tested and applied to customer churn problems which will be driven by classifiers i.e. customer churn prediction model. The public dataset that has customer usage pattern and if the customer has churned or not ,these factors will be applied to our profit maximizing framework. With the explosive growth of data, and the increasing popularity of social network sites, companies will rely more than ever on data mining techniques to support their decision making process. In such cases, the cost-benefit analysis framework provides directions on how to develop performance measures tailored to specific business problems.

***Keywords:-*** Data mining, classification, performance measures

## I.INTRODUCTION

In recent years, Due to the saturated markets and competitive business environment, Customer churn becomes a focal concern of most firms in all industries. Also use of data mining techniques in business application has increased. Therefore the need for adequate performance measures has become very important. Rather than using Receiver operating characteristic (ROC) curve, which is a graphical representation of the classification performance for varying thresholds, it is better to capture the performance of a classification method in a single number. The problem with ROC is that they implicitly make unrealistic assumptions about misclassification costs. The H measure overcomes this problem and focuses on misclassification costs.

The objective of this contest is to maximize the profit using metric by which classifier's performance will be tested and applied to customer churn problems which will be driven by classifiers i.e. customer churn prediction model. The public dataset that has customer usage pattern and if the customer has churned or not, these factors will be applied to our profit maximizing framework.With the explosive growth of data, and the increasing popularity of social network sites, companies will rely more than ever on data mining techniques to support their decision making process. In such cases, the cost-benefit analysis framework provides directions on how to develop performance measures tailored to specific business problems.

There will be frameworks to measure this.

1. A cost-benefit analysis framework will have two types of performance measures.

The first metric is the maximum profit (MP), whereas the second metric is the expected maximum profit (EMP). There are different types of business so for each complex situation in which classification methods are employed, it is difficult to define one single profit driven performance measure.

2. The prediction of customer churn, which has become a very important business

problem.Consider telecom industry, telecommunication markets are getting saturated, and the emphasis is shifting from attraction of new customers to retention of the existing

customer base. In this context, customer churn prediction models play a crucial role

and new approaches such as the use of social network data are explored When investigating and comparing these data mining techniques for customer churn prediction, it is imperative to have an best performance measure. Therefore, with the guidance of the cost-benefit framework, a new performance measure which consistently incorporates the losses and gains will be developed. This metric is that unambiguously identifies the classifier which maximizes the profit and determines the fraction of the customer base which should be targeted to maximize the profit.

## 2. WORKING PROCESS

**The Business Pain**:

Most telecom companies suffer from voluntary churn. Churn rate has strong impact on the life time value of the customer because it affects the length of service and the future revenue of the company. For example if a company has 25% churn rate then the average customer lifetime is 4 years; similarly a company with a churn rate of 50%, has an average customer lifetime of 2 years. It is estimated that 75 percent of the 17 to 20 million subscribers signing up with a new wireless carrier every year are coming from another wireless provider, which means they are churners. Telecom companies spend hundreds of dollars to acquire a new customer and when that customer leaves, the company not only loses the future revenue from that customer but also the resources spend to acquire that customer. Churn erodes profitability.

**Process:**
New customers flow into the customer base by subscribing to a service of an operator, and existing customers flow out of the

customer base by churning. When setting up a churn management campaign, the fraction _ of the customer base with the highest propensity to churn is contacted at a cost f per person and is offered an incentive with cost d. In this fraction, there are true would-be churners and false would be churners. In the latter group everyone accepts the incentive and does not churn, as they never had the intention. From the former group, a fraction _ accepts the offer and thus results in gained customer lifetime value (CLV ), whereas the fraction $1-\alpha$

effectively churns. In the fraction $1-\alpha$, which is not targeted, all would-be churners effectively churn, and all non churners remain with the company.

2.2. Applications:

1. Banking
2. Mobile telecommunication
3. Life insurances

## II. OPEN DESIGN
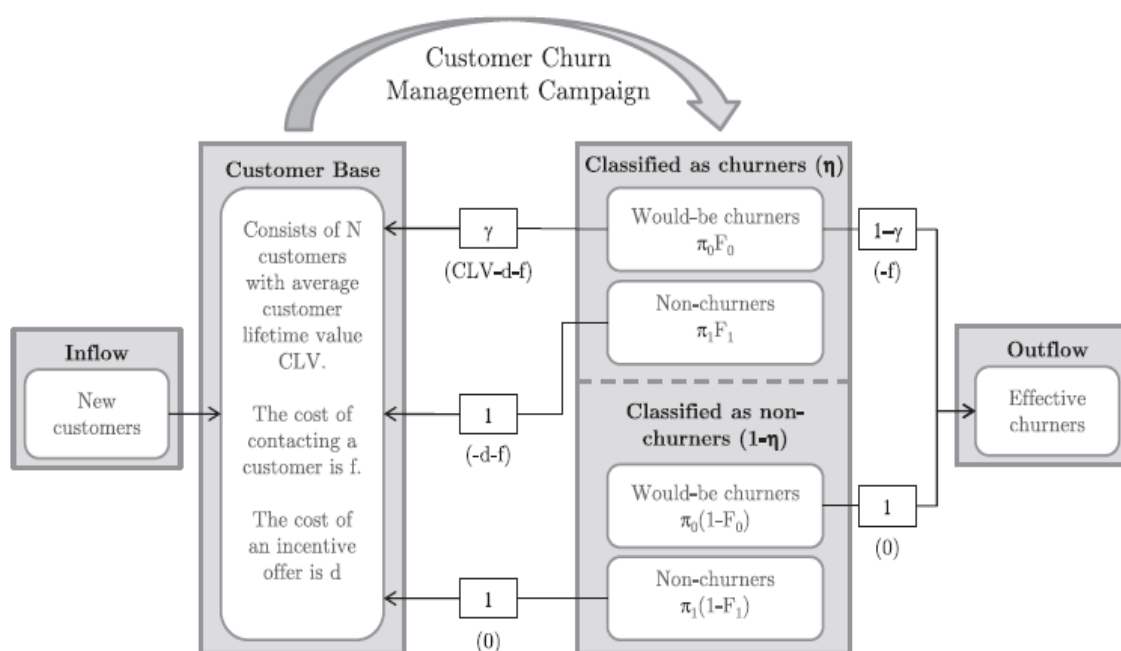


**Fig.1. Architecture.**

## CONCLUSION

This module's proactive retention approach is based on combining customer churn prediction and marketing action optimization. This module thus goes beyond "actionable customer analytics" to automatically determine exactly what marketing action should be run for each at-risk customer to achieve the maximum degree of retention possible.

Customer churn and its role in developing customer lifetime value models have been previously discussed. Churn rate - or its complement, **retention rate** is one of the key factors that modifies the customer lifetime value formula to properly account for future cash flows.

## REFERENCES

[1] 1] T. Fawcett, "An Introduction to ROC Analysis," Pattern Recognition Letters, vol. 27, no. 8, pp. 861-874, 2006.

[2] D. Hand, "Measuring Classifier Performance: A Coherent Alternative to the Area under the ROC Curve," Machine Learning,vol. 77, no. 1, pp. 103-123, 2009.

[3] W. Verbeke, D. Martens, C. Mues, and B. Baesens, "Building Comprehensible Customer Churn Prediction Models with Advanced Rule Induction Techniques," Expert Systems with Applications,vol. 38, pp. 2354-2364, 2011.

[4] A.A. Nanavati, R. Singh, D. Chakraborty, K. Dasgupta, S.Mukherjea, G. Das, S. Gurumurthy, and A. Joshi, "Analyzing the Structure and Evolution of Massive Telecom Graphs," IEEE Trans. Knowledge and Data Eng., vol. 20, no. 5, pp. 703-718, May 2008.

[5] S. Ali and K. Smith, "On Learning Algorithm Selection for Classification," Applied Soft Computing, vol. 6, no. 2, pp. 119-138,2006.

[6] P. Baldi, S. Brunak, Y. Chauvin, C. Andersen, and H. Nielsen,"Assessing the Accuracy of Prediction Algorithms for Classification:An Overview," Bioinformatics, vol. 16, no. 5, pp. 412-424, 2000.

[7] P. Domingos, "Metacost: A General Method for Making Classifiers Cost-Sensitive,"
Proc. Fifth ACM SIGKDD Int'l Conf. Knowledge Discovery and Data Mining, pp. 155-164, 1999.

[8] W. Verbeke, K. Dejaeger, D. Martens, J. Hur, and B. Baesens,"New Insights into Churn Prediction in the Telecommunication Sector: A Profit Driven Data Mining Approach," European J.Operational Research, vol. 218, no. 1, pp. 211-229, 2012.