HYBRID FEATURES FOR CHURN PREDICTION IN MOBILE TELECOM NETWORKS WITH DATA CONSTRAINTS

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INTRODUCTION

What is churn?

Churn, also known as customer attrition, is a phenomenon where a customer switches a service provider due to factors such as pricing, location, service quality and so on.

What is churn prediction?

The process of predicting which customer in a network is likely to leave that network is known as churn prediction.

This requires to build an accurate churn prediction model for identifying customers most prone to churn.

Applications of behavioural models have assumed significance in the area of information security, spanning from malware detection to network and IoT security. In this work, its application to churn prediction is described.

DATA DESCRIPTION

We analysed the CDRs (Call Data Records) provided by one of the largest mobile operator in India.
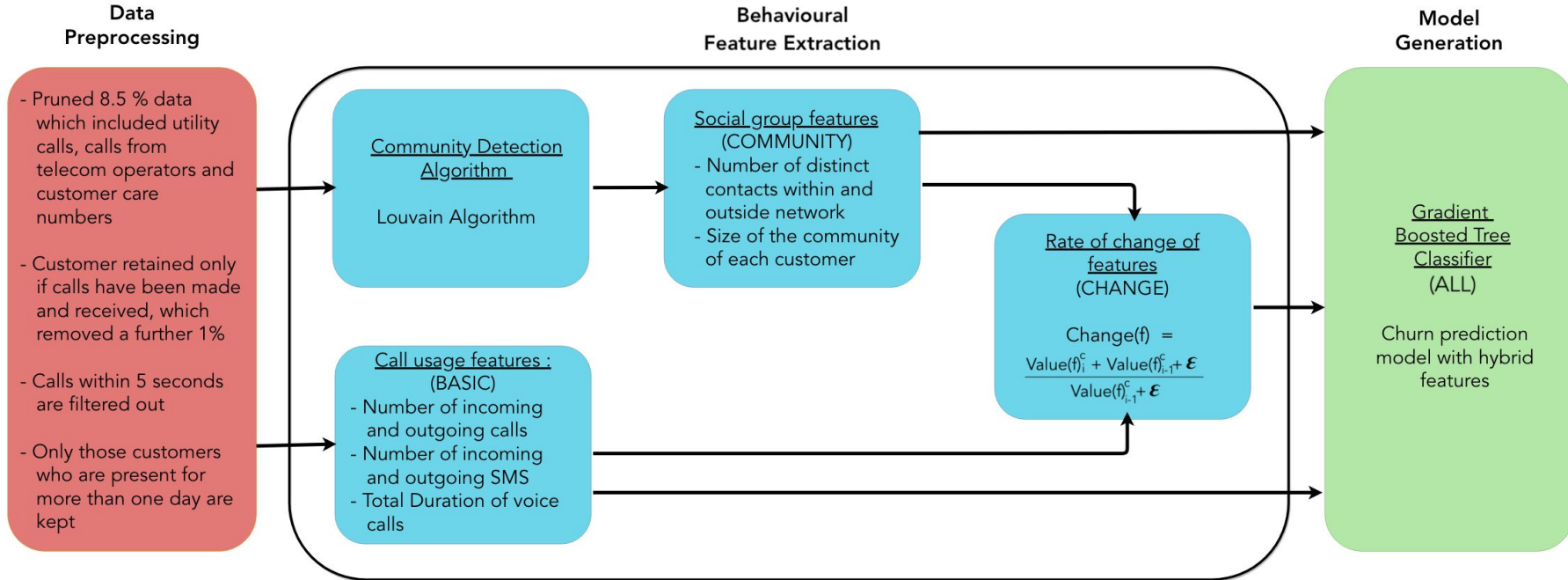
The data contains detailed record of calls made by a segment of customers active during a period of one month in a large metropolitan city in India.

The original dataset consists of 400+ million CDR entries with details pertaining to a call such as the time, duration, call type, originating number, destination number etc. as maintained by the mobile operator for billing purposes.

No demographic and contractual information were used.

The novel hybrid behavioural features proposed here are purely based on those that can be extracted from CDRs alone.

CHURN PREDICTION MODELLING

Data Preprocessing

Behavioural Feature Extraction

Model Generation

- Pruned 8.5 % data which included utility calls, calls from telecom operators and customer care numbers

- Customer retained only if calls have been made and received, which removed a further 1%

- Calls within 5 seconds are filtered out

- Only those customers who are present for more than one day are kept

Community Detection Algorithm

Louvain Algorithm

Social group features (COMMUNITY)
- Number of distinct contacts within and outside network
- Size of the community of each customer

Rate of change of features (CHANGE)

$$\text{Change(f)} = \frac{\text{Value(f)}_i^c + \text{Value(f)}_{i-1}^c + \varepsilon}{\text{Value(f)}_{i-1}^c + \varepsilon}$$

Call usage features :
(BASIC)
- Number of incoming and outgoing calls
- Number of incoming and outgoing SMS
- Total Duration of voice calls

Gradient Boosted Tree Classifier (ALL)

Churn prediction model with hybrid features

EXPERIMENT AND RESULTS

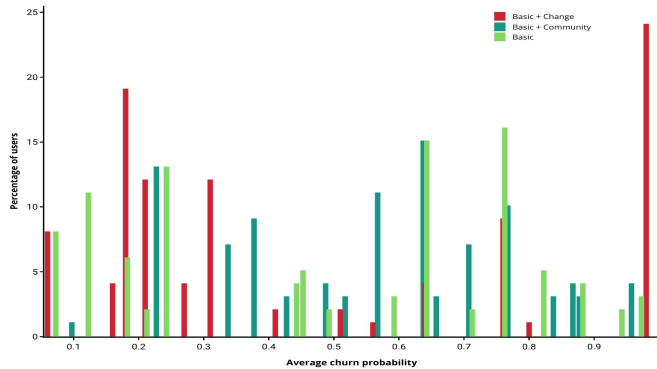For training and testing, we have considered 2 cases:

CASE 1 -
1. Churners inactive after first 2 weeks
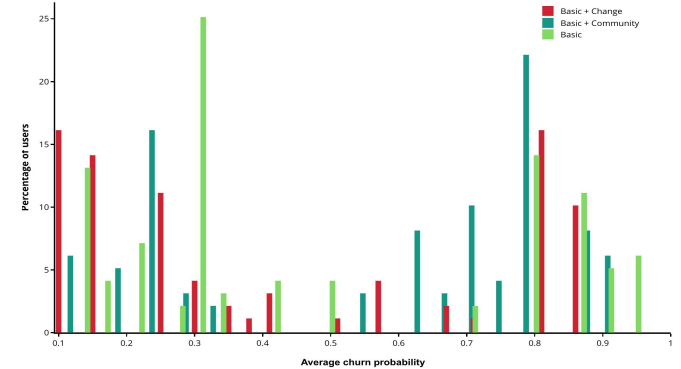2. Churners : 89,745
3. Non-churners :106,002

CASE 2 -
1. Churners inactive after first 3 weeks
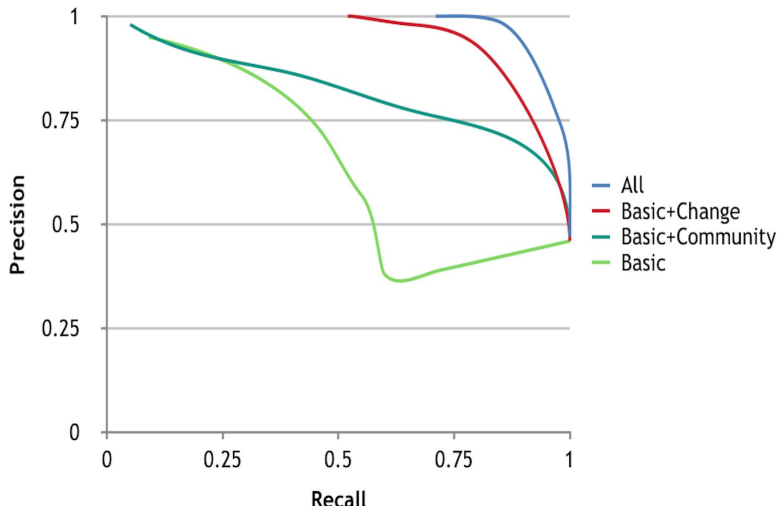2. Churners : 97,859
3. Non-churners :106,002

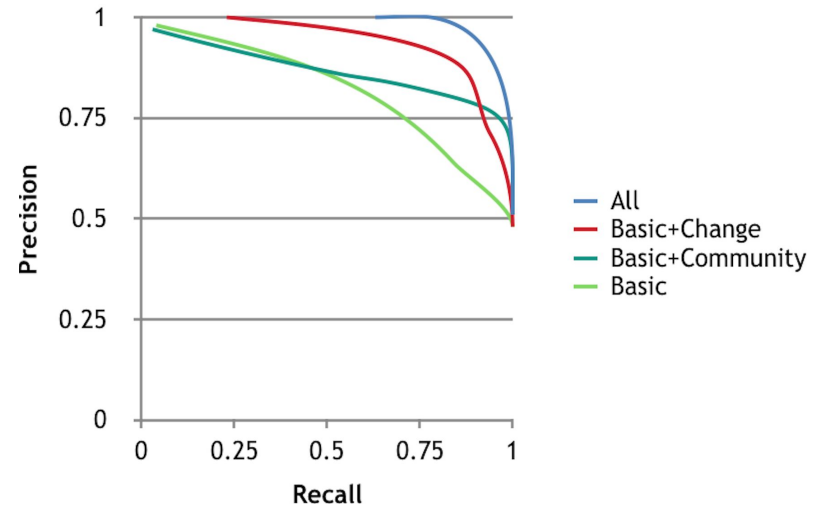# Improved class separation in the learned model when the novel hybrid features are considered

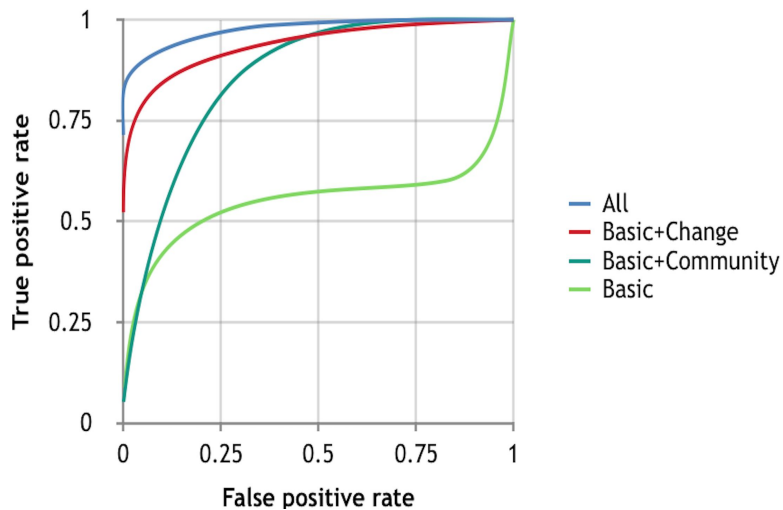Average Churn Probabilities Plot of BASIC, BASIC + COMMUNITY and BASIC+CHANGE for Case 1

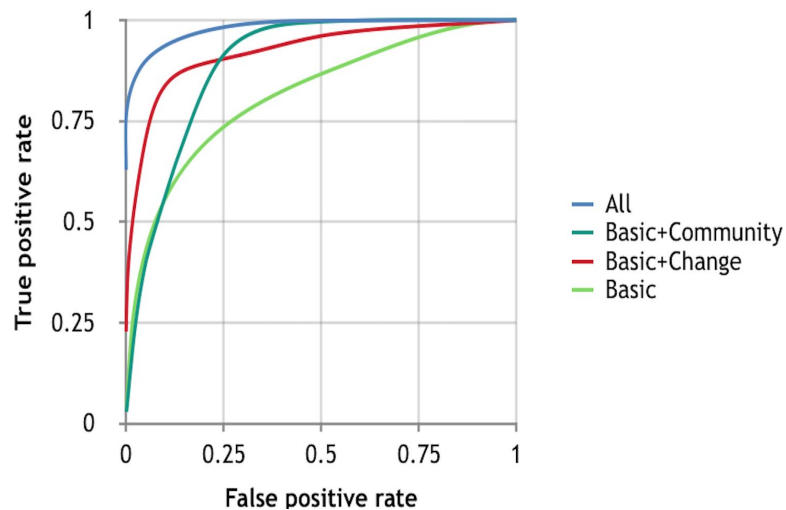Average Churn Probabilities Plot of BASIC, BASIC + COMMUNITY and BASIC+CHANGE for Case 2

Comparison of ROC curves for 4 models - BASIC, BASIC+COMMUNITY, BASIC+CHANGE,ALL for Case 1

Comparison of ROC curves for 4 models - BASIC, BASIC+COMMUNITY, BASIC+CHANGE,ALL for Case 2

Comparison of Precision-Recall curves
for 4 models - BASIC,
BASIC+COMMUNITY,
BASIC+CHANGE,ALL for Case 1

Comparison of Precision-Recall curves
for 4 models - BASIC,
BASIC+COMMUNITY,
BASIC+CHANGE,ALL for Case 2

CONCLUSION AND FUTURE WORK

The predictive power of our hybrid behavioural feature set consisting of features based on changes in call usage patterns and changes in social groups augment the churn prediction model in the face of data constraints.

The work can be extended to handle detection of extreme churn events associated with competitive schemes and also in detecting compromised IoT nodes or nodes in a WSN by identifying similar behavioural features.

THANK YOU