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T9 Outliers – Final Project

# Telecom Churn Prediction


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# Problem Statement

A telecom company's postpaid business of voice-only plans is struggling to maintain its strong foothold in the local market due to:

- High churn rate amongst customers leading to a revenue decline of ~500k USD every month.
- The decline in overall customer base (high churn rate combined with low acquisition rate), leading to a decline in total market share.

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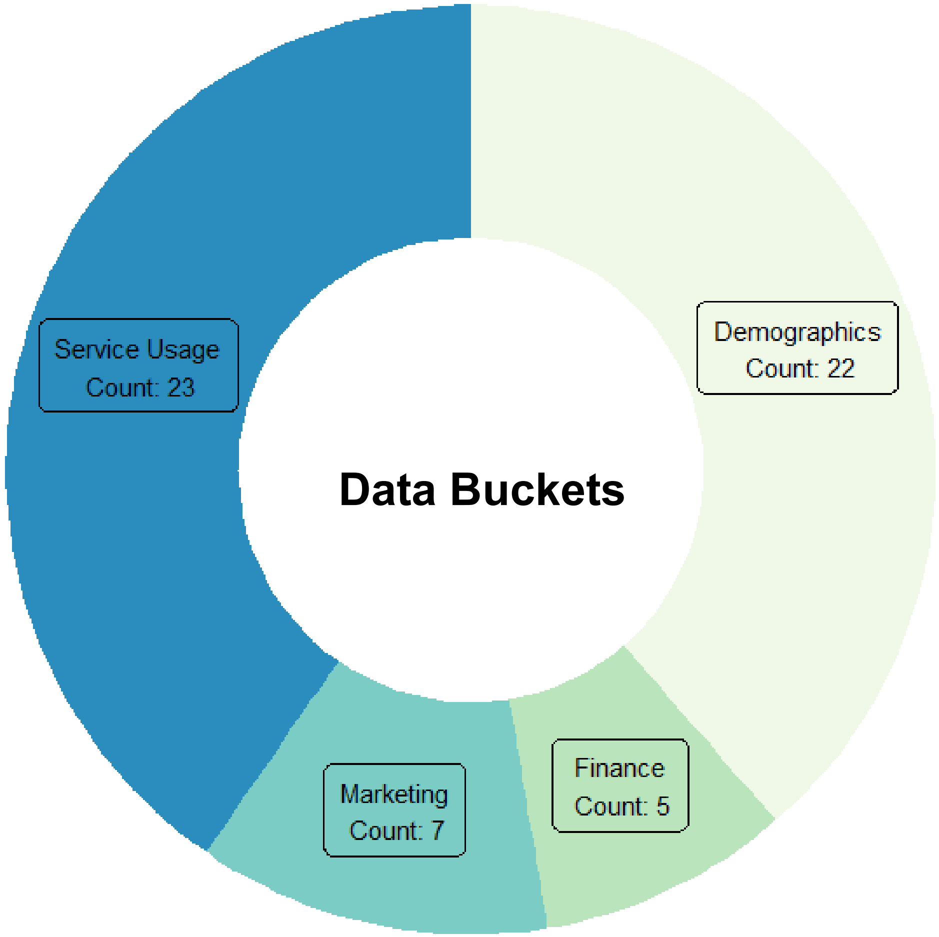
# About the Dataset

Our data is majorly classified into the following categories:

| Data Types | Examples |
|---|---|
| Demographics | occupation, age |
| Service Usage | monthly call minutes, roaming calls |
| Finance | credit rating, monthly revenue |
| Marketing | retention calls, referrals made by customer |




Rows : 51,047 Columns : 58

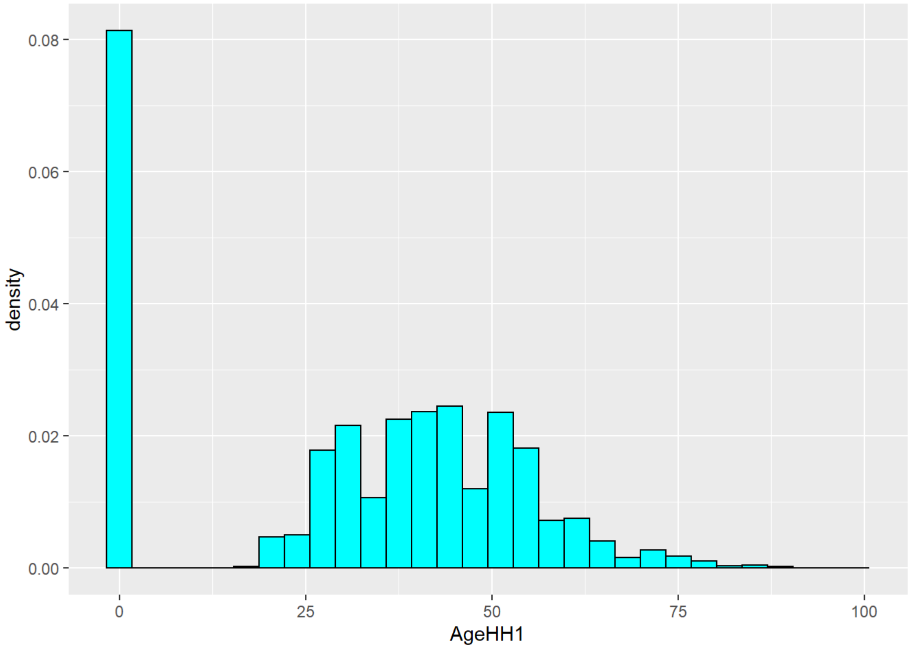
# Key takeaways from EDA

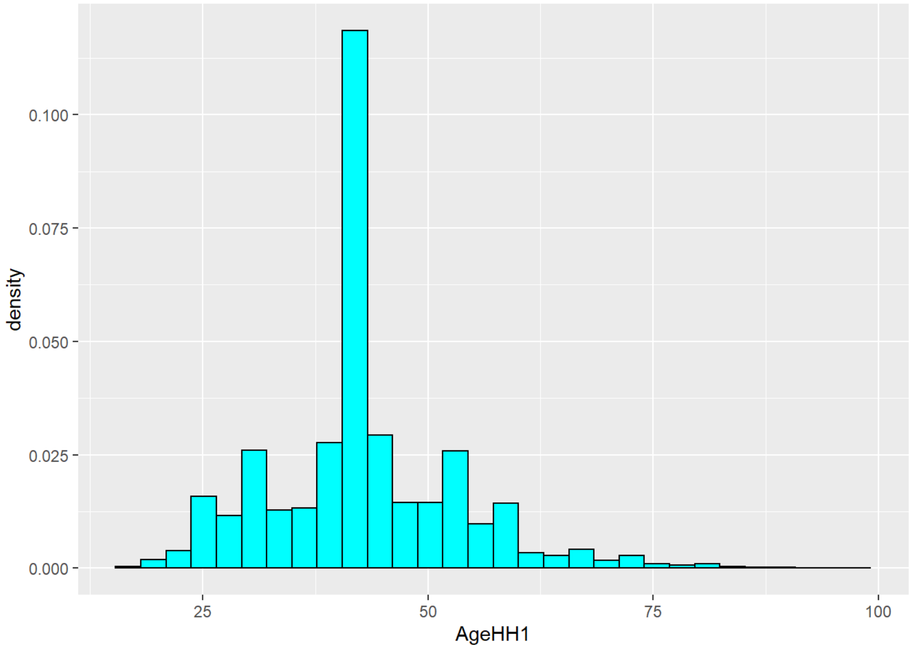
- We observed null values in few columns but it was less than 2%.
- Few customers have incorrect age as 0 which could be interpreted as null values. Hence imputation is necessary.
- There are too many features (57), hence feature selection is required.
- Few customers had < = 0 monthly revenue . These can be considered as outliers and it also shows that few customers are inactive.
- Target class is imbalanced.

# Data Preprocessing

# How to deal with incorrect data entries and handle outliers?

- Imputed median for age column as we observed data was skewed
- Removed inactive customers as well (Monthly revenue and minutes  <= 0)

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# What are the important features that are impacting customer churn?

- Our dataset contains a lot of variables, hence it was necessary to select only the important features.
- For this purpose, we have done Chi Square tests on the categorical variables and ANOVA test on the numerical variables.
- We have selected the features based on the p value obtained.

# Feature selection for Categorical Features

| Variables | P-value ( <0.05) | Chi-square (X-squared) |
|---|---|---|
| IncomeGroup | 0.00020 | 32 |
| ChildrenInHH | 0.03163 | 5 |
| Homeownership | 0.00303 | 9 |
| PrizmCode | 0.00026 | 19 |

# Feature selection for Numerical Features

| Variables | P-value ( <0.05) |
|---|---|
| MonthlyMinutes | 0 |
| MonthlyRevenue | 0.0068 |
| TotalRecurringCharge | 0 |
| DirectorAssistedCalls | 0 |
| OverageMinutes | 2e-04 |
| RoamingCalls | 0.0141 |
| DroppedCalls | 5e-04 |
| UnansweredCalls | 0 |
| CustomerCareCalls | 0 |
| MonthsInService | 0 |
| UniqueSubs | 0 |
| ActiveSubs | 5e-04 |
| CurrentEquipmentDays | 0 |
| AgeHH1 | 0 |
| AgeHH2 | 0 |

# How to handle an imbalanced dataset for customer churn?

We have tried the following sampling techniques to balance our data before modelling:

- Under sampling
- SMOTE (Over Sampling)

We have tested our models on both the sampling techniques.

# Which model evaluation metrics should be considered to choose the best fit model?

**Actual**

**Predicted**

| | Churned | Not Churned |
|---|---|---|
| Churned | Well Done (TP) | Not that critical (FP) |
| Not Churned | Danger Zone (FN) | Well Done (TN) |

**Danger Zone** <- Customers who are going to churn but are not detected by the model (Recall)

**Not that Critical** <- Customers who aren't going to churn but model says churn

# Logistic Regression Model

- Logistic regression is one of the commonly used models for classification.
- For our model, we used all the features that we selected and we built a binomial logistic regression model.
- We built the model on pre-processed under sampled and over sampled data.

# Logit Model Evaluation

### Confusion Matrix for SMOTE

| | Prediction | | |
|---|---|---|---|
| Actual | | Not Churned | Churned |
| | Not Churned | 7,074(TN) | 106(FP) |
| | Churned | 5,516(FN) | 120(TP) |

Accuracy: 56.13%    Recall: 53.09%

### Confusion Matrix for Under Sampling

| | Prediction | | |
|---|---|---|---|
| Actual | | Not Churned | Churned |
| | Not Churned | 1,895(TN) | 1,047(FP) |
| | Churned | 1,441(FN) | 1,377(TP) |

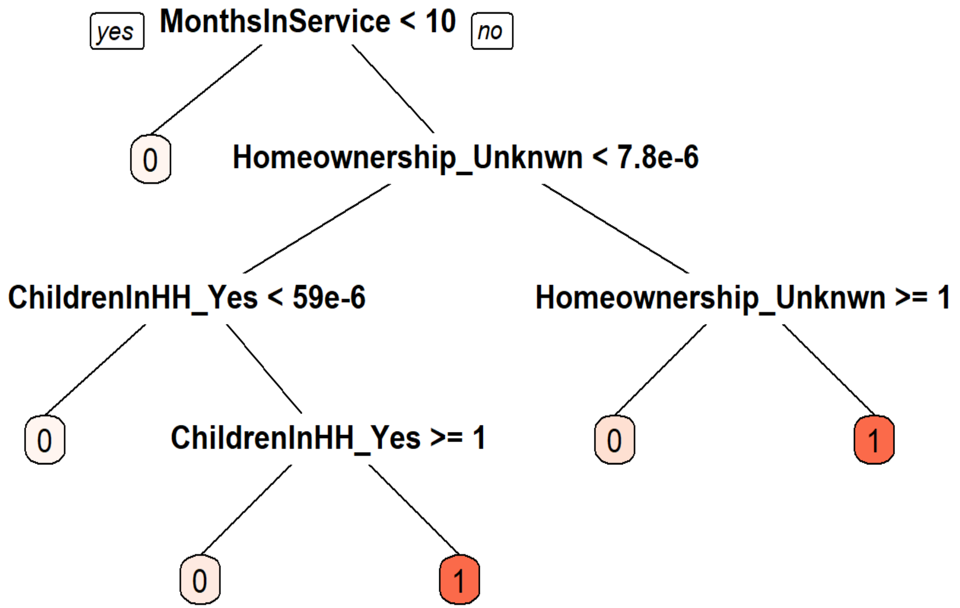
Accuracy: 56.8%   Recall: 56.8%

# Decision Tree Model

- A decision tree is a **decision support tool** that uses a tree-like model to make decisions and their possible consequences.
- We have taken the pre-processed under sampled data to fit in to the decision tree model.
- In our model we are trying to find the variables that is affecting the churn.

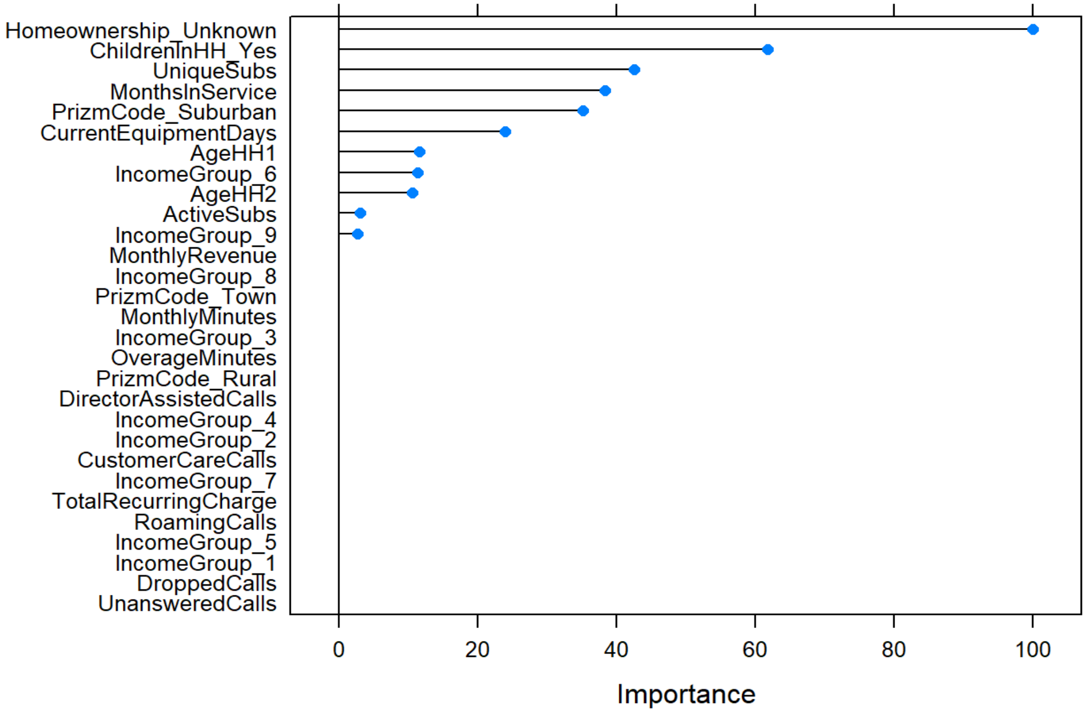
# Decision Tree Model Evaluation

- Figure shows the final decision tree.
- If the customer has less than 10 months in service then the customer is unlikely to be churned.
- If primary holders have no children, then the customer is unlikely to be churned.
- Customers unknown of owning a home are likely to be not churned.



# Variable Importance in Decision Tree

- Figure shows the variable importance in the decision tree model.
- Customers unknown of owning a home is given high importance while plotting the decision tree followed by chances of children being primary holder, unique subscribers, months in service of the customers.

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# Confusion Matrix

- Confusion matrix shows the performance of the classification algorithm.
- There are 7180 True negatives, 4557 false positives , 0 false positives and 1079 true positives.
- Model gave the accuracy of 64.4%.

| | | Prediction | |
|---|---|---|---|
| | | Not Churned | Churned |
| Actual | Not Churned | 7,180(TN) | 4,557(FP) |
| | Churned | 0(FN) | 1,079(TP) |

# Naïve Bayes Model

- The Naive Bayesian classifier is based on Bayes' theorem with independent assumptions between predictors.
- Naive Bayes classifier assume that the effect of the value of a predictor (x) on a given class (c) is independent of the values of other predictors.
- Naïve Bayesian model is easy to build and fast to predict class of test data set, requires less training and performs well in case of categorical input variables.
- We have taken pre-processed under sampled and smote data for our model building.

# Naïve Bayes Model Evaluation

**Confusion Matrix for SMOTE**

| Prediction | | | |
|---|---|---|---|
| | | Not Churned | Churned |
| Actual | Not Churned | 754(TN) | 330(FP) |
| | Churned | 6426(FN) | 5306(TP) |

Accuracy: 47.3%    Recall: 30.05%

**Confusion Matrix for Under Sampling**

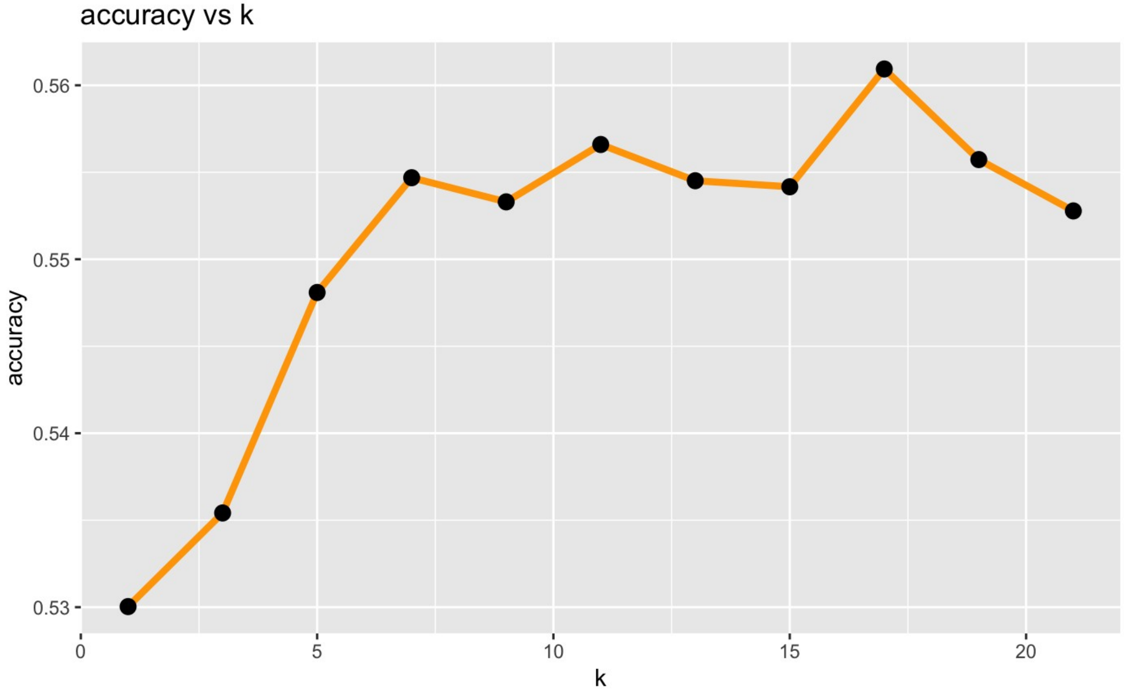
| Prediction | | | |
|---|---|---|---|
| | | Not Churned | Churned |
| Actual | Not Churned | 1528(TN) | 1089(FP) |
| | Churned | 6426(FN) | 1729(TP) |

Accuracy: 56.5%   Recall: 51.9%

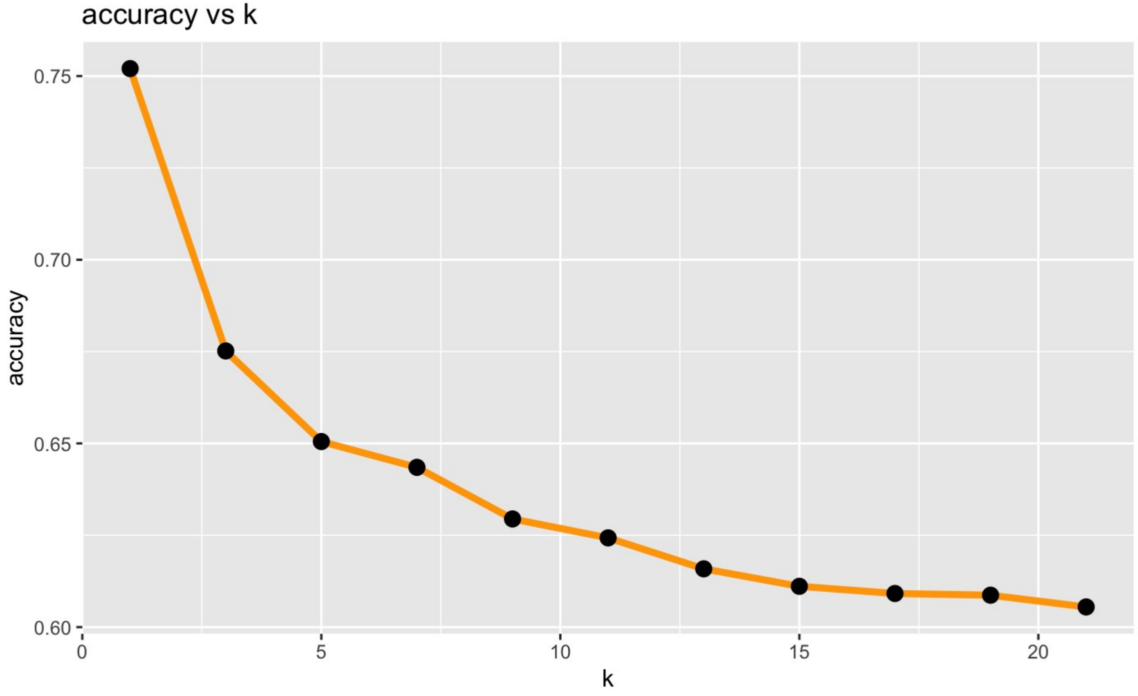
# KNN Model

- Churn variable will be used as the dependent variable. All other selected features will be used as predictor variables.
- Categorical data fields have been converted from Yes or No to either 0 or 1.
- We found out optimal K value by finding accuracy for each K value and selected the best one.

# Accuracy vs k value plot




**For Under Sampling**




**For SMOTE**

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# KNN Model Evaluation

**SMOTE**

| Prediction | | | |
|---|---|---|---|
| Actual | | Not Churned | Churned |
| | Not Churned | 4427(TN) | 1,393(FP) |
| | Churned | 2,753(FN) | 4,243(TN) |

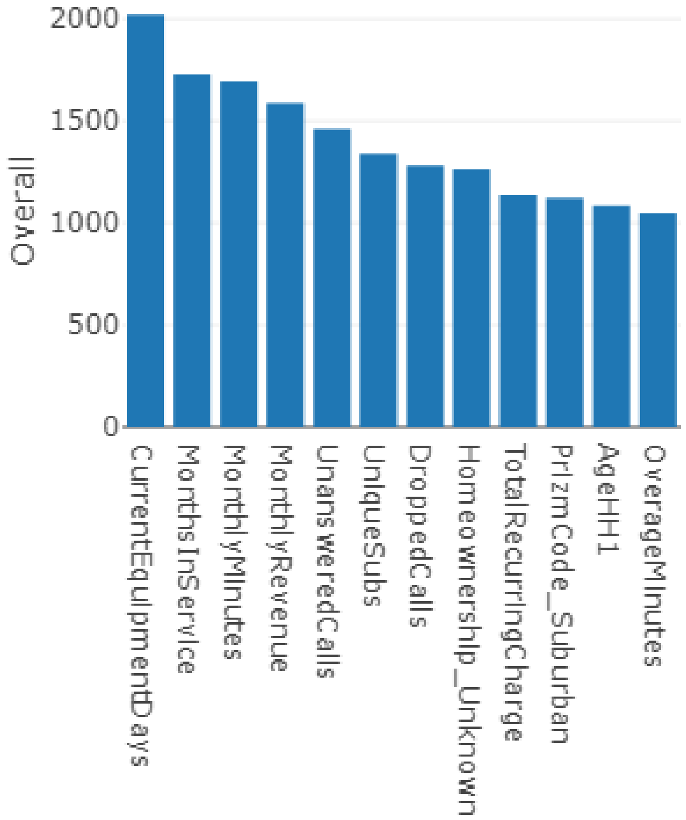
Accuracy: 67.6% Recall: 61.7%

**Under Sampling**

| Prediction | | | |
|---|---|---|---|
| Actual | | Not Churned | Churned |
| | Not Churned | 4818(TN) | 1653(FP) |
| | Churned | 2362(FN) | 1165(TN) |

Accuracy: 56.1% Recall: 59.7%

# Random Forest Model




- Figure shows the Feature importance for the Random Forest model.
- Current Equipment , months in service, Monthly minutes and Unanswered calls are important features in predicting churn.

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# Random Forest Model Evaluation

**SMOTE**

| Prediction | | | |
|---|---|---|---|
| Actual | | Not Churned | Churned |
| | Not Churned | 5,026(TN) | 1,328(FP) |
| | Churned | 2,154(FN) | 4,254(TP) |

Accuracy: 72.7% Recall: 66.3%

**Under Sampling**

| Prediction | | | |
|---|---|---|---|
| Actual | | Not Churned | Churned |
| | Not Churned | 1,786(TN) | 1,328(FP) |
| | Churned | 1,127(FN) | 1,691(TP) |

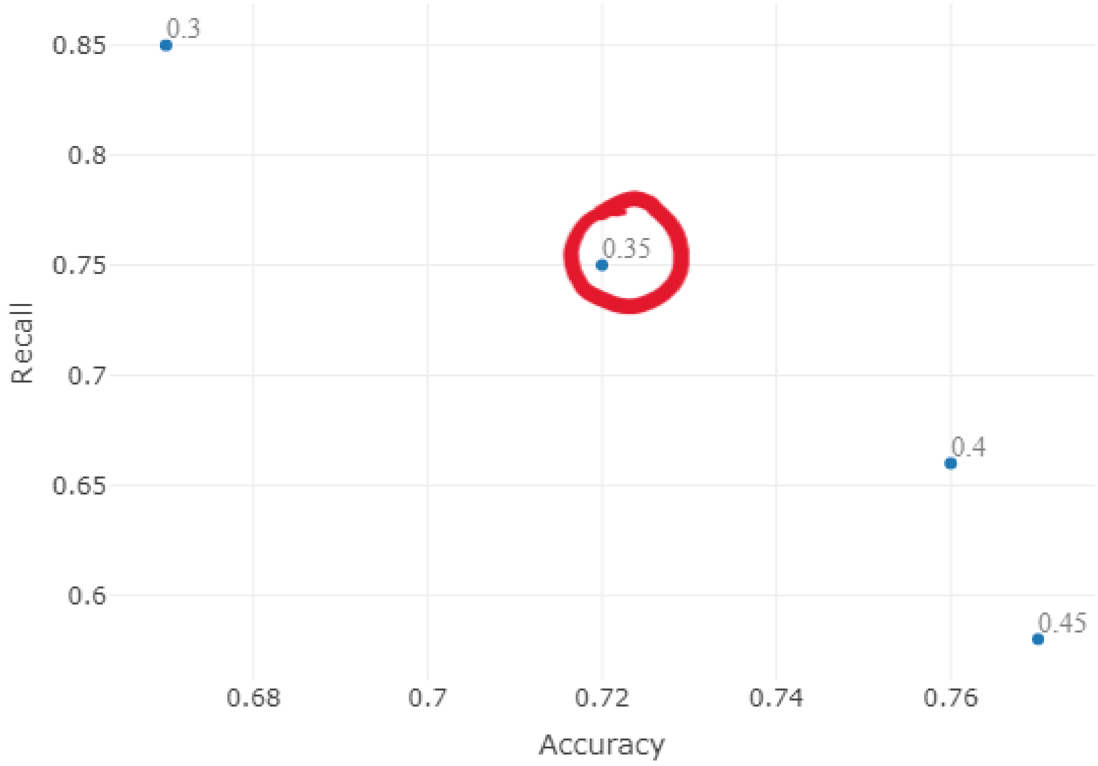
Accuracy: 58.61% Recall: 60.00%

# Model Evaluation

| | SMOTE | | UNDER SAMPLING | |
|---|---|---|---|---|
| **Model** | **Recall** | **Accuracy** | **Recall** | **Accuracy** |
| **Logistic Regression** | 0.53 | 0.56 | 0.56 | 0.56 |
| **Decision Tree** | 0.61 | 0.64 | 0.54 | 0.56 |
| **Naïve Bayes** | 0.10 | 0.47 | 0.51 | 0.56 |
| **KNN** | 0.61 | 0.67 | 0.59 | 0.56 |
| **Random Forest** | 0.66 | 0.72 | 0.60 | 0.58 |

# Improving Random Forest for better Recall

Trying out different threshold cut-off values for better recall and accuracy
Threshold values : 0.30,0.35,0.40,0.45




| | | Prediction | |
|---|---|---|---|
| | | Not Churned | Churned |
| Actual | Not Churned | 5,026(TN) | 1,328(FP) |
| | Churned | 2,154(FN) | 4,254(TP) |

**Best Fit Model**

| Accuracy | Recall |
|---|---|
| 0.72 | 0.75 |

# Model Interpretation

| Customer types | Counts | % |
|---|---|---|
| High risky customers<br>Churn Probability > 0.80 | 2379 | 73% |
| Moderate risky customers<br>Churn Probability  > 0.60 | 864 | 23% |

# Conclusion

- Logistic regression and Naïve Bayes didn’t perform well due to the complexity of the relation between the target and features.
- Reduced 57 features to around 20 by using Chi square and ANOVA test
- Data Imbalance technique **SMOTE** worked well.
- All the models had a low recall, it's difficult to detect customer which are going to churn.
- Random forest performed well hence the model was tuned for better Recall.
- We further divided the outcome of the model into high-risky customers and moderately risky customers for a better interpretation of the model.

# Thank you