

# Predicting Churn Credit Card Customers

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**Bank Unity**

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# About the Company

*Bank Unity* is a financial institution licensed to receive deposits and make loans. It also provides financial services such as wealth management, currency exchange, and safe deposit boxes.

# Problem

A manager at *Bank Unity* is disturbed by more and more customers leaving their credit card services. They would appreciate it if one could predict who is going to get churn, so they can proactively go to the customer to provide them better services and turn customers' decisions in the opposite direction.



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# Dataset

Source

## Credit Card Customers Dataset

It was uploaded to Kaggle.com.

Records

**10,127 Customer Records**

Features

**21 Features**

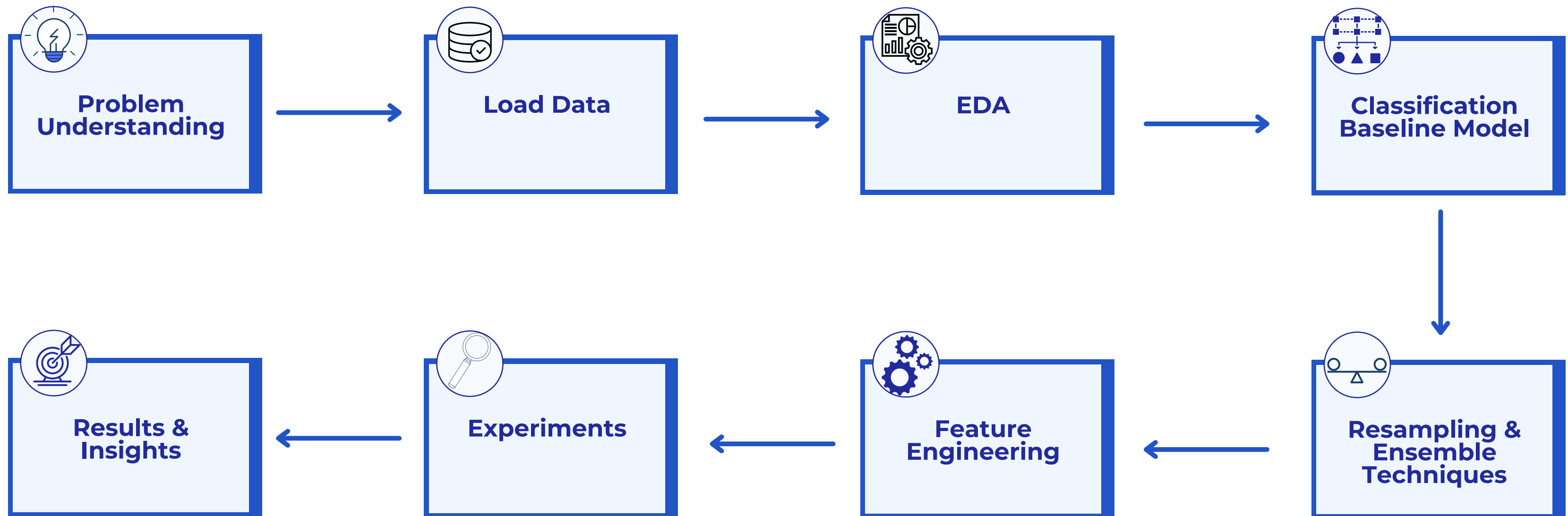
Such as customers' age, salary, marital status, credit card limit, credit card category, etc.

Target

**Attrition\_Flag**

Positive if a customer is attrited, Negative if not.

# Methodology



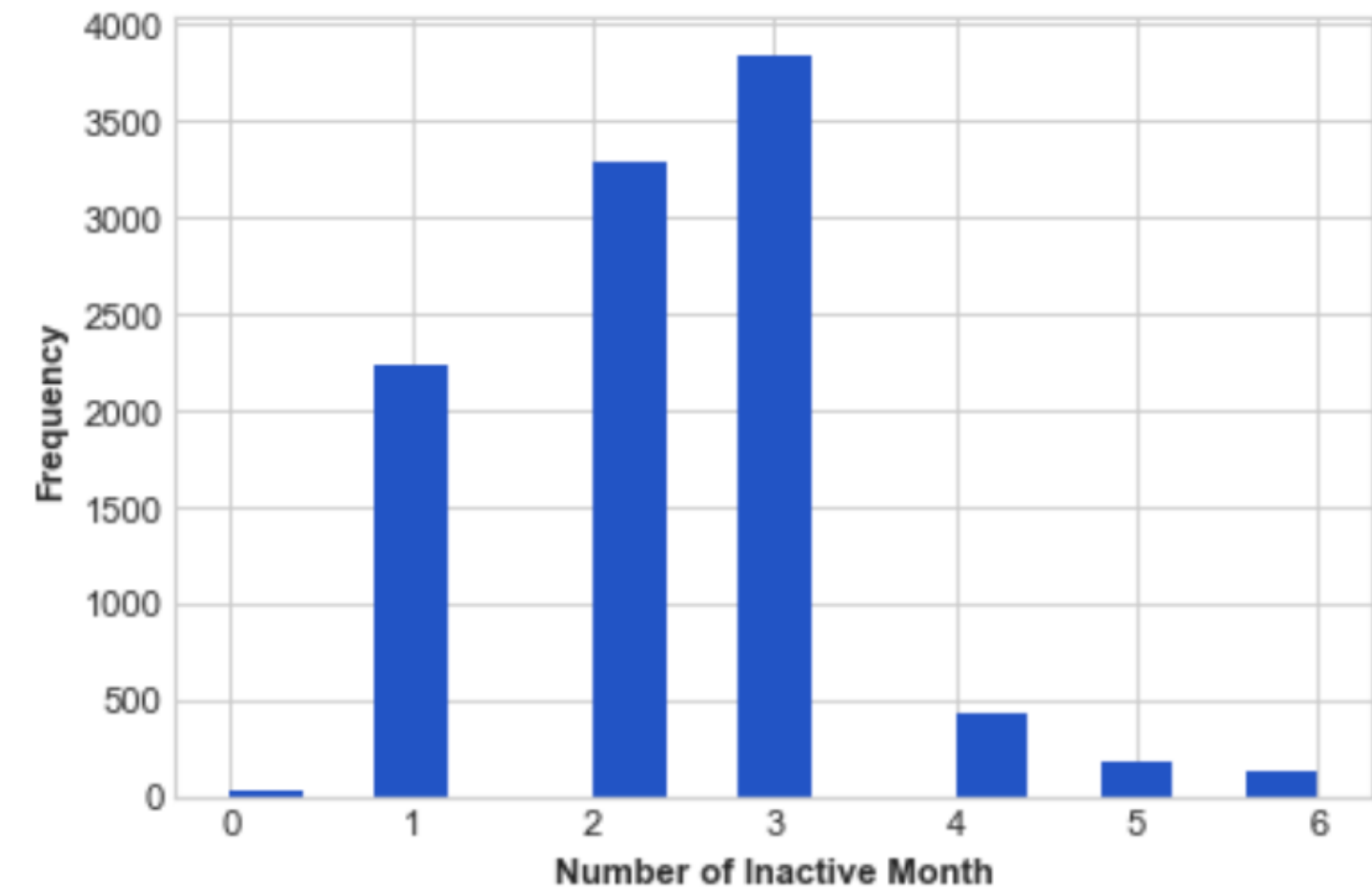
# Exploratory Data Analysis

Propotion of Months on book



The highest number of months on book is about 36, we cannot assume normality of the feature.

Propotion of Inactive Months



The highest number of inactive months is 3, followed by 2 and 1.

# Baseline Model

Actual Values	Existing	Attrited
	Existing	Attrited
Existing	1222	45
Attrited	135	116

## Training Scores



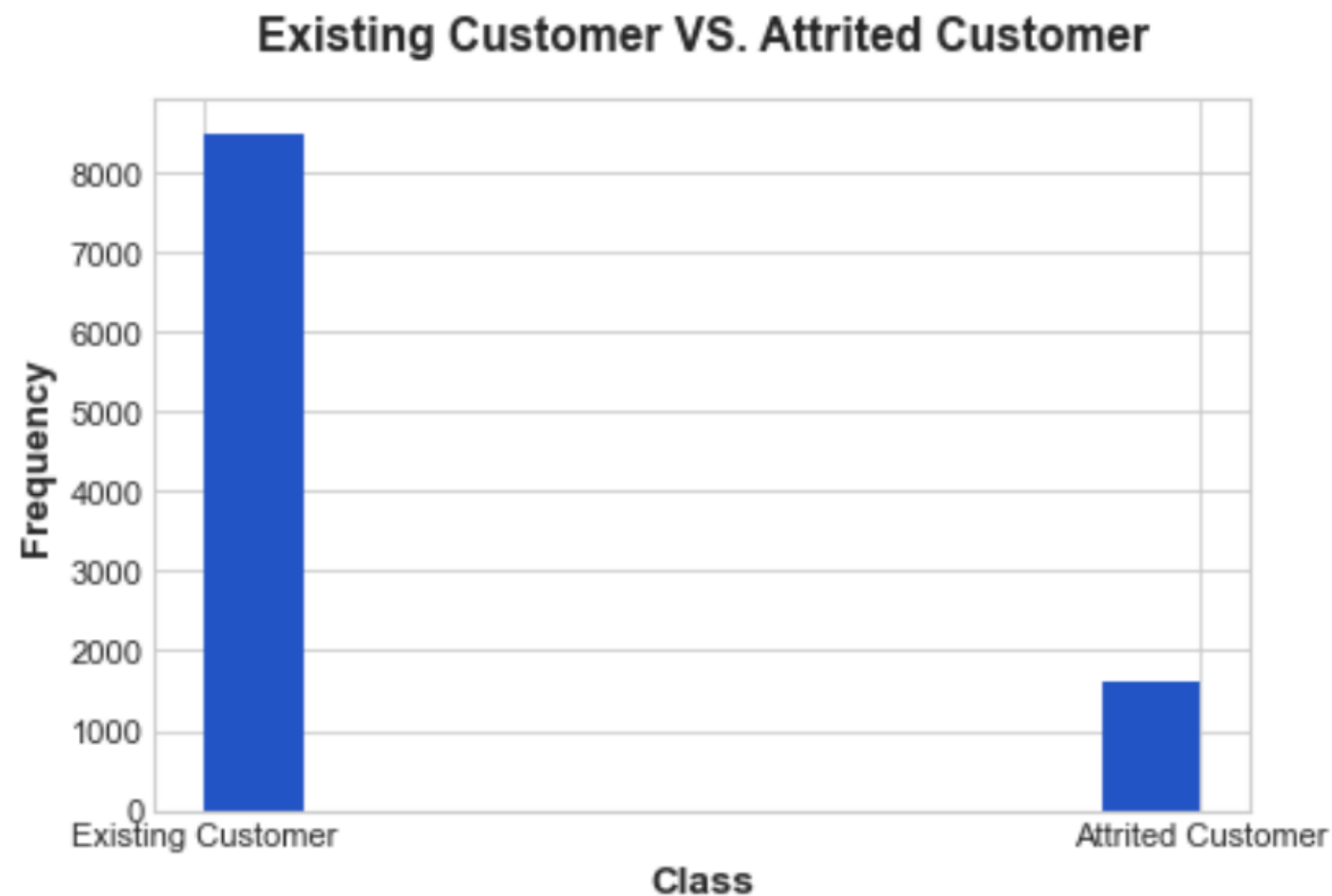
Accuracy = 0.889  
Precision = 0.728  
Recall = 0.494  
F-1 = 0.588  
F-beta of 2 = 0.528

## Validation Scores



Accuracy = 0.881  
Precision = 0.72  
Recall = 0.462  
F-1 = 0.563  
F-beta of 2 = 0.498

# Data Imbalance



Number of Observations

10127

Number of Attrited Customer

1627

Number of Existing Customer

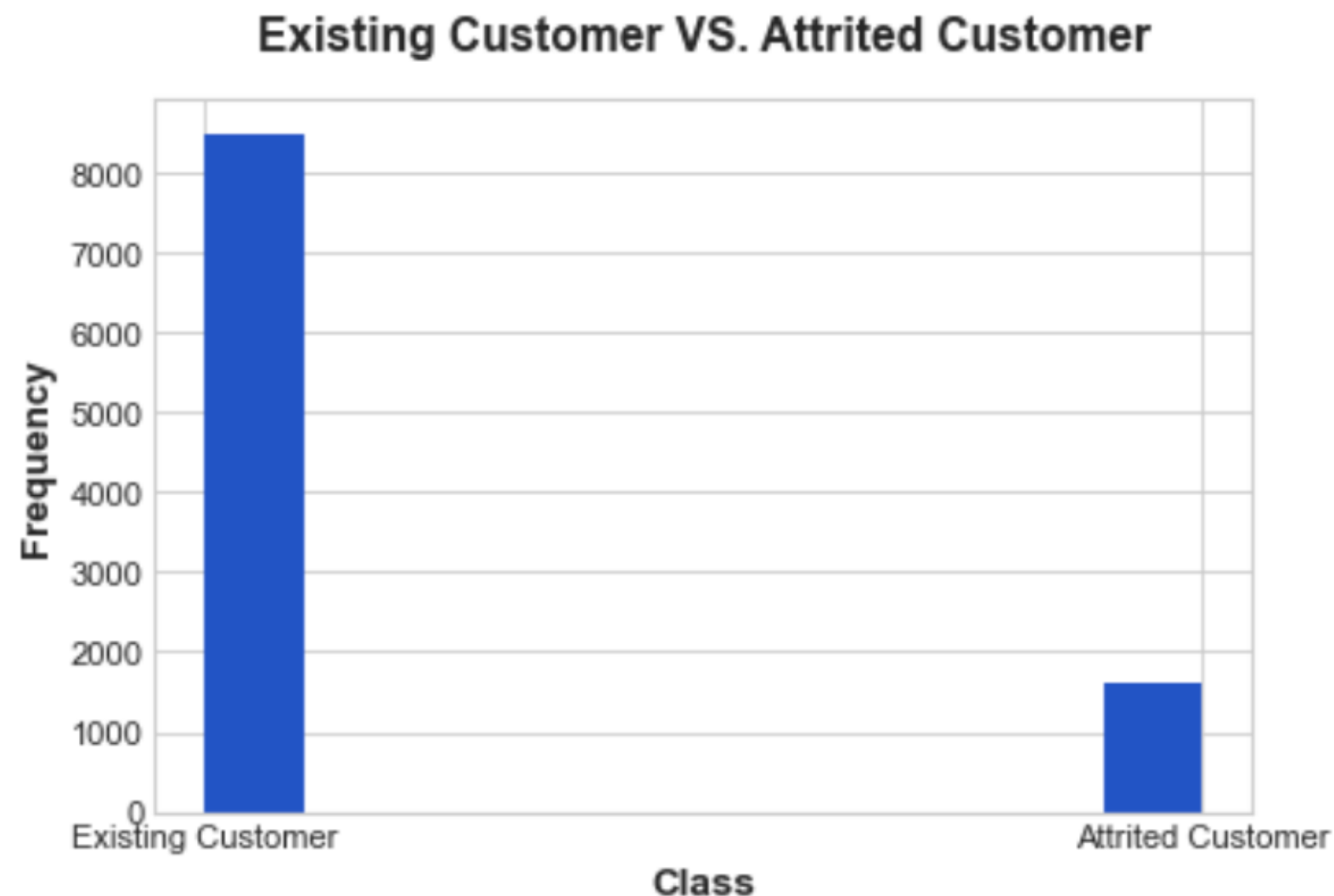
8500

Event Rate

16.1%



# Data Imbalance



## Approaches for Imbalanced Data

### Resampling Techniques

- Random Under-Sampling
- Random Over-Sampling
- ✓ ○ SMOTE

### Bagging Based techniques

- Random Forest

### Boosting-Based techniques

- Ada Boost

# Feature Engineering

## Convert Categorical Columns to Dummy Variables

Resulted in decreasing the models' scores.

## Factorize Categorical Columns

Resulted in increasing the models' scores.

## Scale Numerical Columns

Using `StandardScaler()` on numerical columns.

# Experiments

Classifier		Recall	Precision	F-1	F-2
Logistic Regression	train	0.813	0.82	0.817	0.815
	val	0.776	0.450	0.57	0.678
Decision Tree	train	1.0	1.0	1.0	1.0
	val	0.84	0.70	0.768	0.810
Random Forest	train	1.0	1.0	1.0	1.0
	val	0.90	0.83	0.865	0.886
Ada	train	0.967	0.959	0.963	0.965
	val	0.912	0.760	0.829	0.877

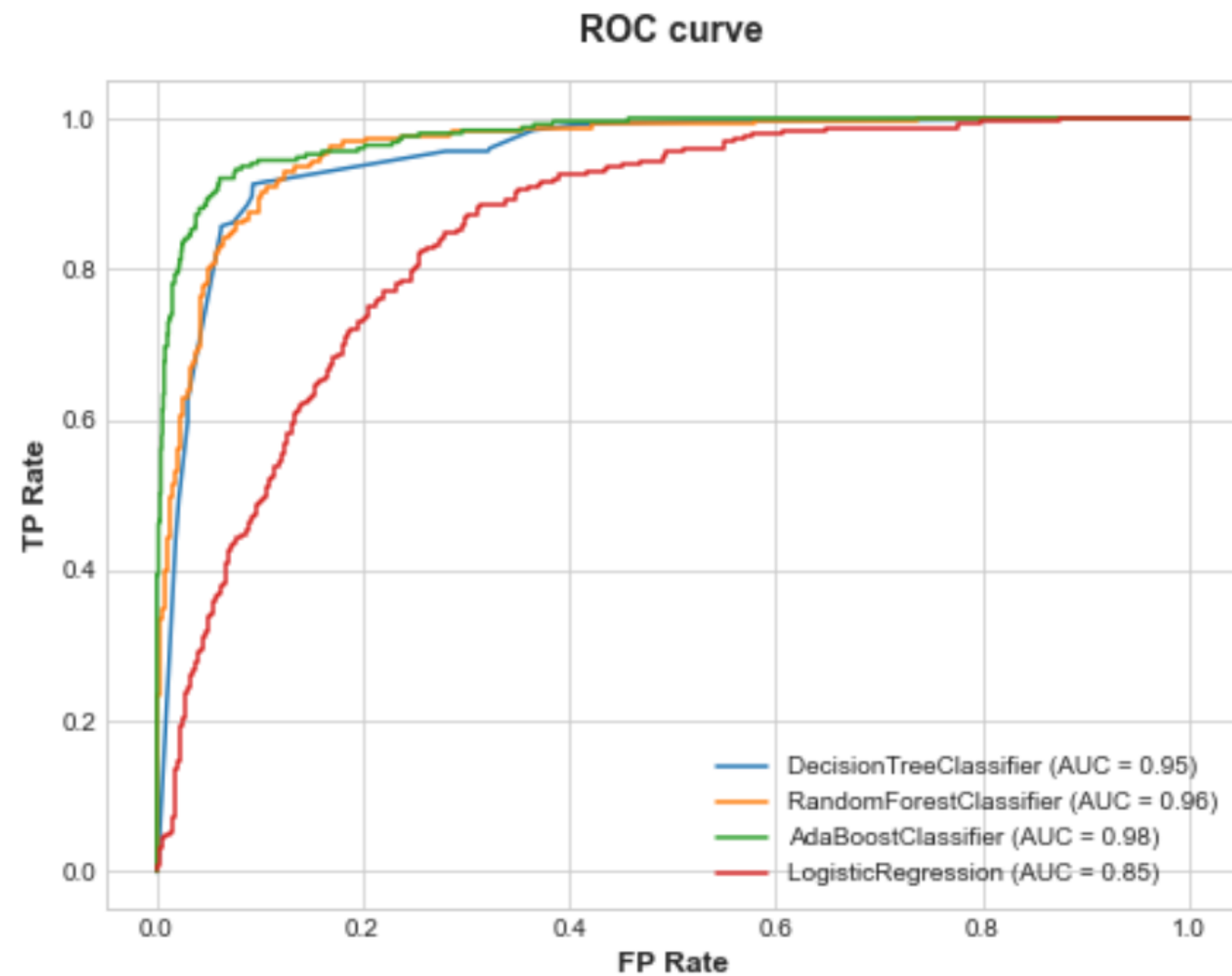
## Split Data

%75 train,  
%15 validation  
%10 test

## Resampling Technique

SMOTE

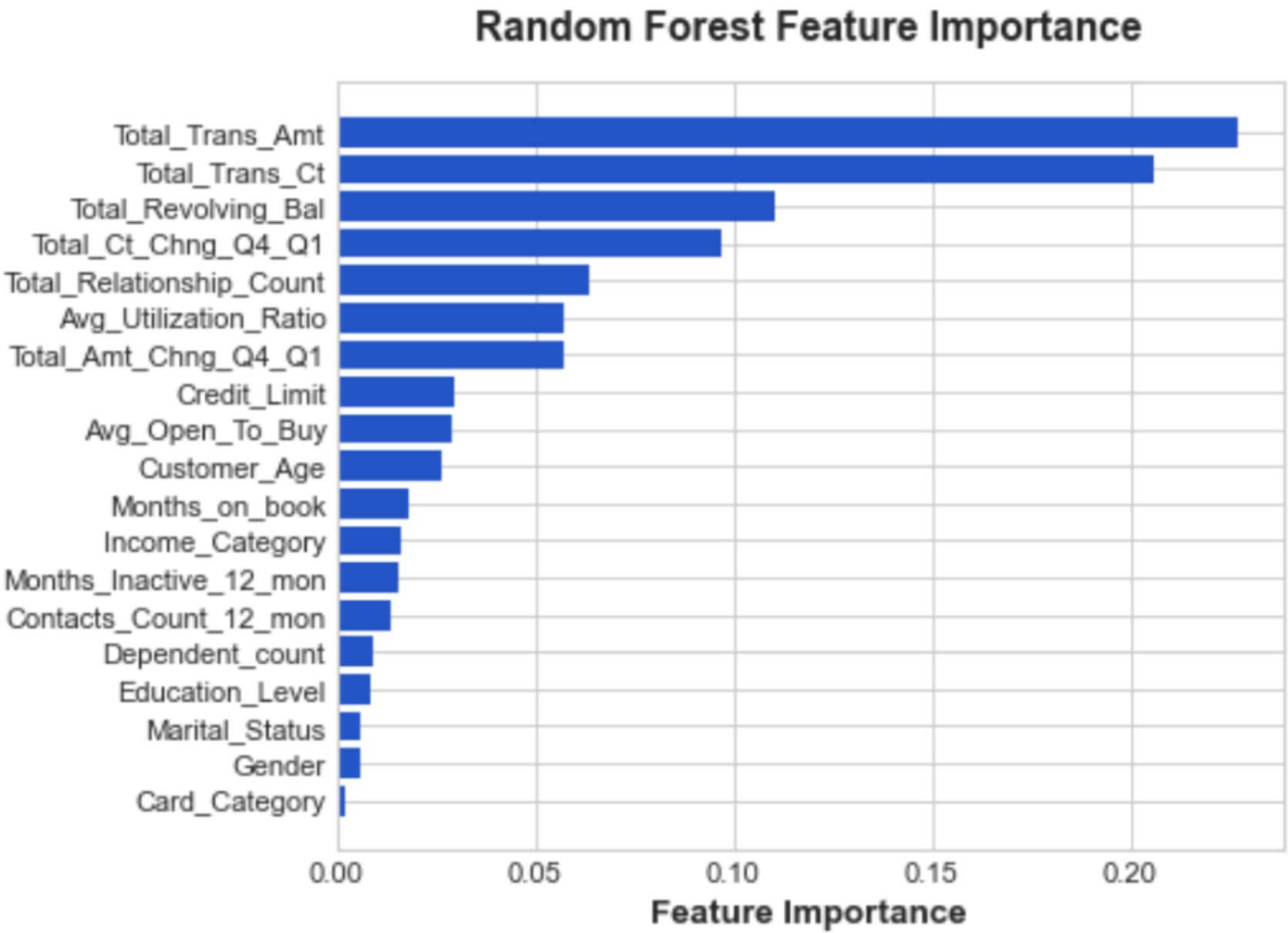
# Experiments



Ada Boost Classifier has best results with 98% AUC, followed by Random Forest and Decision Tree Classifiers with 96%, 95% AUC respectively.

# Feature Importance

For Random Forest



## Low Feature Importance

Gender  
Card\_Category  
Marital\_Status

Were removed.

## Validation Scores

Accuracy = 0.956  
Precision = 0.841  
Recall = 0.904  
F-1 = 0.871  
F-beta of 2 = 0.891

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# Conclusion

## 1 Classifier Performance Metrics of interest

Recall, Precision, F-1, and F-beta

## 2 SMOTE for Handling Imbalance Data

## 3 AdaBoost is the Best Classifier

With precision = 0.88, recall = 0.82, F-1 = 0.85, F-2 = 0.85 and it is consistent with the AUC metric 0.98 in the ROC.

## Future Work

- 1 Try solving the imbalance data with Anomaly Detection Algorithm
- 2 Work on tuning the classifiers more, and try other classifiers.
- 3 Investigate more on why are customers churning

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# Thank You

Any Questions?