

# BDM 2053 Project

Model for Predicting Credit Card Customer Attrition

**Presented by: Group 1**

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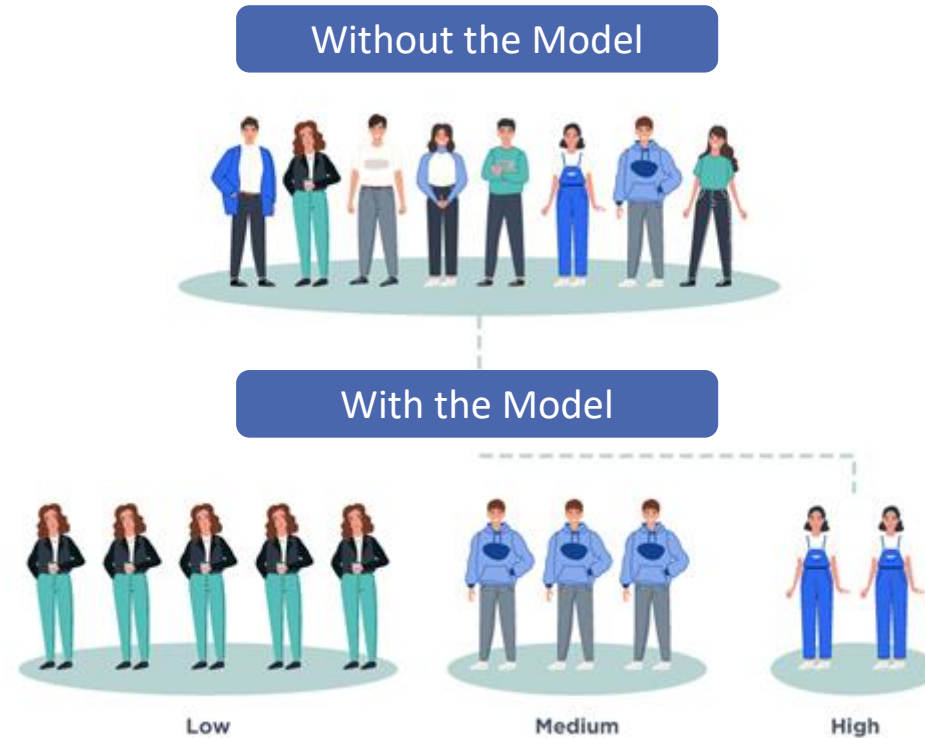
Luz Zapanta

# Agenda

- ▶ Objectives
- ▶ Methodology
- ▶ Data Pre-Processing and Exploratory Data Analysis
- ▶ Modeling Techniques and Results

# Objectives

- ▶ Identify early indicators of credit card attrition based on customer profile and spend behavior
- ▶ Build a predictive model to identify and segment customers based on attrition risk

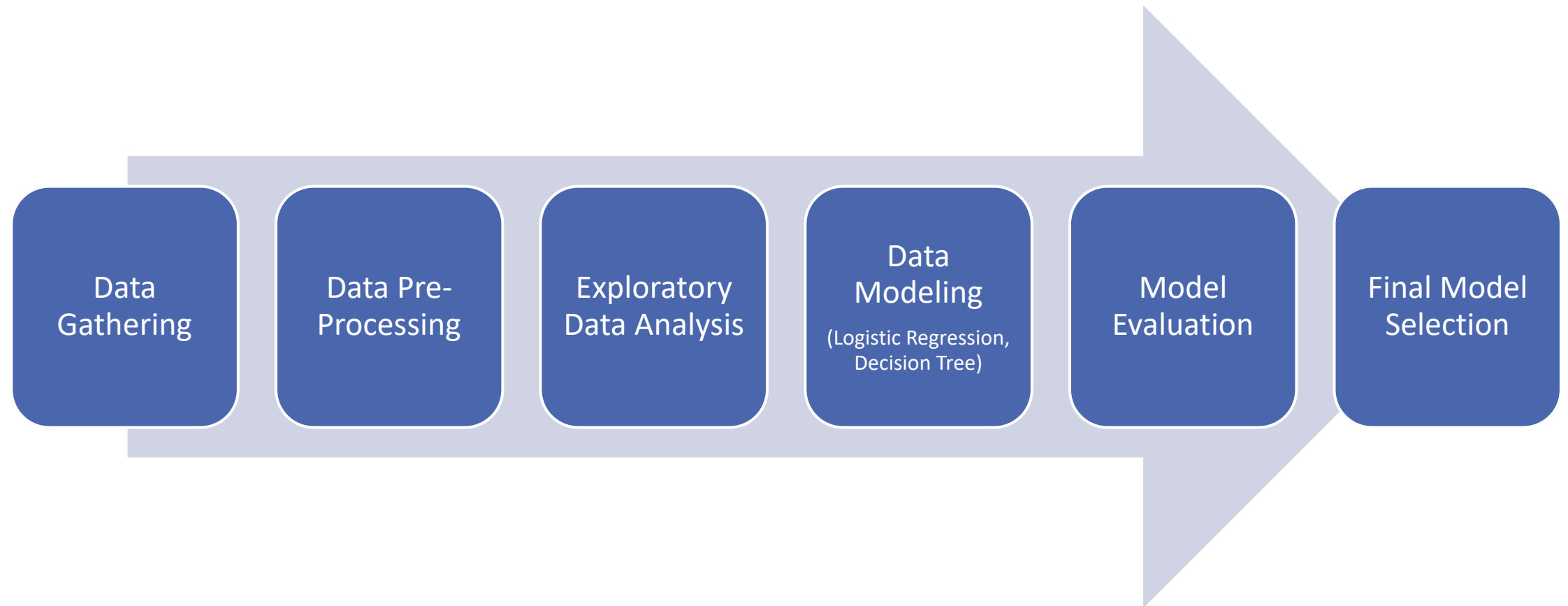


Source: <https://jelvix.com/wp-content/uploads/2022/02/what-is-a-propensity-model.png>

# Methodology

# Methodology

## ► Phases



# Data Gathering

## ► Data

- The raw data has 10,127 rows and 23 columns
- Source: <https://zenodo.org/record/4322342#.ZCM4hXbMI2x>

## ► Dependent Variable: Attrition Flag

## ► Independent Variables (20)



### Demographic Profile

- Age
- Gender
- Number of dependents
- Education level
- Marital status
- Income category



### Customer Relationship

- Months on books
- Number of relationships with the card issuer
- Number of inactive months
- Number of contact numbers
- Type of card
- Credit limit



### Spend Behavior

- Revolving balance
- Average open to buy ratio
- Transaction amount (total and Q4 to Q1 change)
- Transaction count (total and Q4 to Q1 change)
- Average utilization rate

# Data Pre-Processing and Exploratory Data Analysis

# Data Pre-Processing

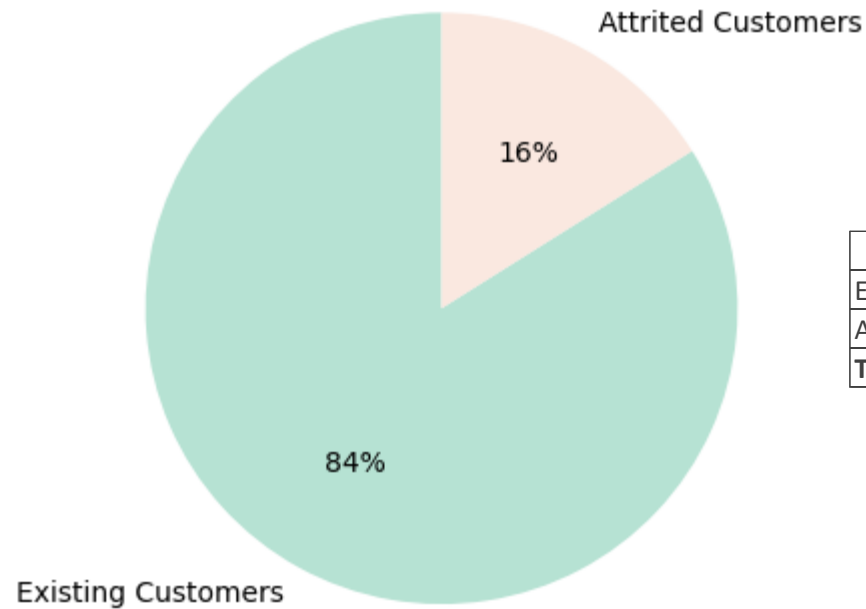
- ▶ Data quality checks
  - No feature has null or nan values
  - No duplicate records
  - Education\_Level, Marital\_Status and Income\_Category have 'Unknown' data as value
- ▶ Dropped unnecessary features
- ▶ Transformed Target Variable (Attrition\_Flag) to numerical value (1/0)

	column_name	data_type	count_unique_values	count_unknown	count_null	count_nan
	Client_Num	int64	10127	0	0	0
	Attrition_Flag	object	2	0	0	0
	Customer_Age	int64	45	0	0	0
	Gender	object	2	0	0	0
	Dependent_Count	int64	6	0	0	0
	Education_Level	object	7	1519	0	0
	Marital_Status	object	4	749	0	0
	Income_Category	object	6	1112	0	0
	Card_Category	object	4	0	0	0
	Months_on_Book	int64	44	0	0	0
	Total_Relationship_Count	int64	6	0	0	0
	Months_Inactive_12_mon	int64	7	0	0	0
	Contacts_Count_12_mon	int64	7	0	0	0
	Credit_Limit	float64	6205	0	0	0
	Total_Revolving_Bal	int64	1974	0	0	0
	Avg_Open_To_Buy	float64	6813	0	0	0
	Total_Amt_Chng_Q4_Q1	float64	1158	0	0	0
	Total_Trans_Amt	int64	5033	0	0	0
	Total_Trans_Ct	int64	126	0	0	0
	Total_Ct_Chng_Q4_Q1	float64	830	0	0	0
	Avg_Utilization_Ratio	float64	964	0	0	0
	Naive_Bayes_Classifier_1	float64	1704	0	0	0
	Naive_Bayes_Classifier_2	float64	640	0	0	0



# Exploratory Data Analysis

- ▶ Overall attrition rate is **16%**.
- ▶ Majority of the customers did not attrite (84%), therefore, we have an imbalanced class.

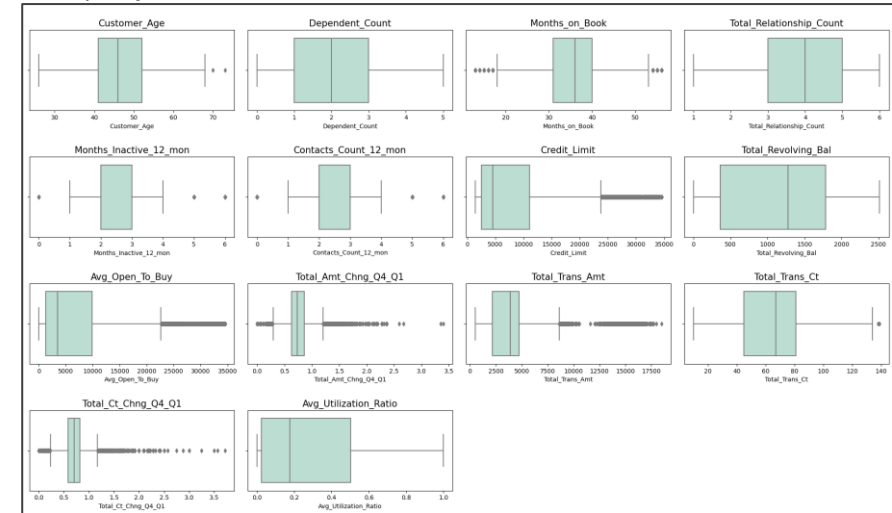


Attrition Flag	Count	%
Existing Customers: 0	8,500	84%
Attrited Customers: 1	1,627	16%
Total	10,127	100%

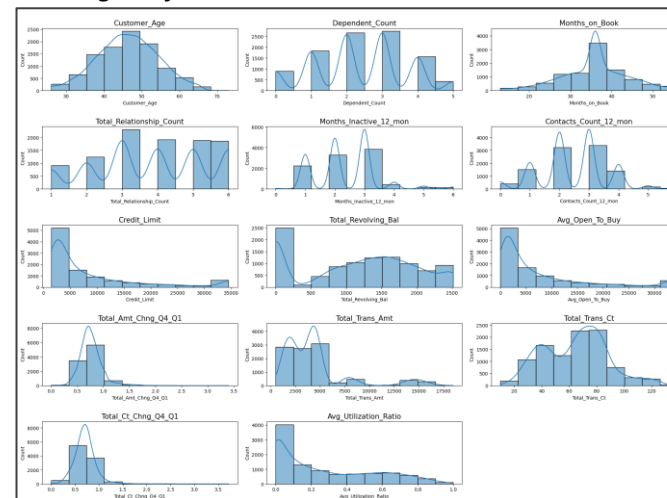
# Exploratory Data Analysis

- ▶ **Gender:** Attrition is more prevalent in female customers vs male customers.
- ▶ **Education Level:** There are more Doctorate and Post-Grads customers who attrited.
- ▶ **Marital Status:** Those with relationship status = "Single" or "Unknown" recorded more attrition than those who are married or divorced.
- ▶ **Income Category:** Customers in the 60K-80K income bracket have the lowest attrition rate.
- ▶ **Card Category:** Those with premium and gold cards have more attrition than blue and silver cardholders
- ▶ Dummy variables were created based on the results of EDA

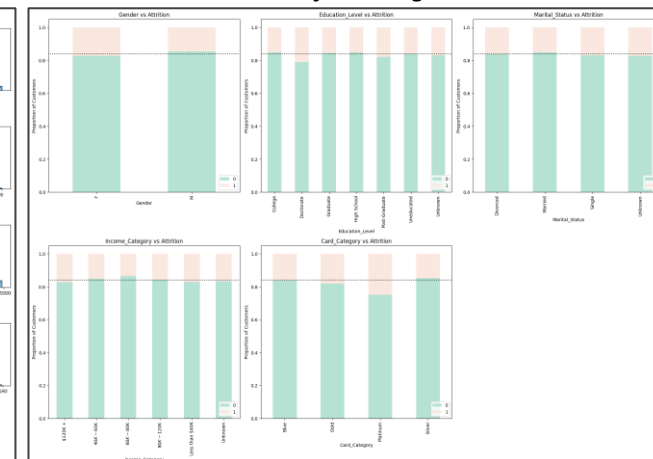
Boxplot for Numerical Features



Histogram for Numerical Features



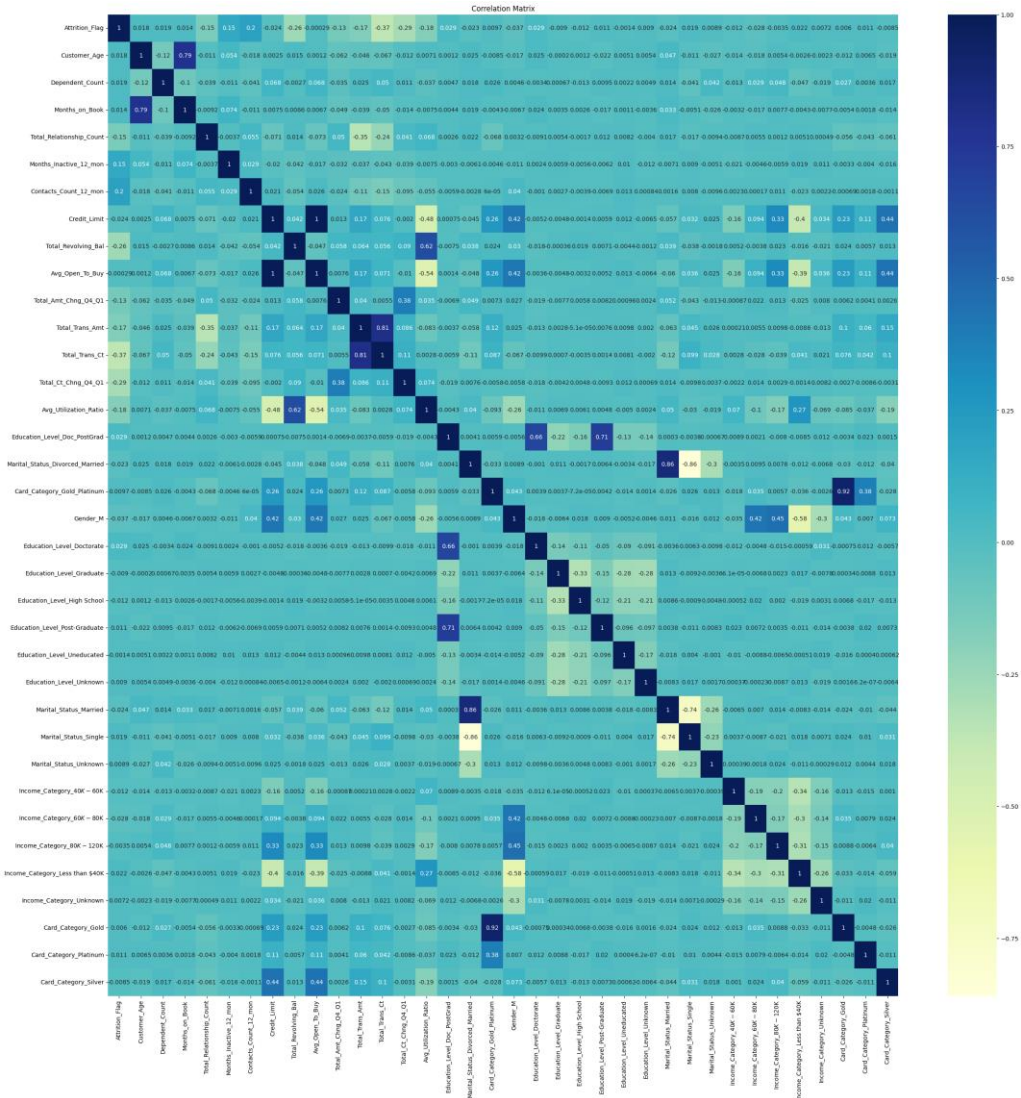
Stacked Column Chart for Categorical Features



# Exploratory Data Analysis

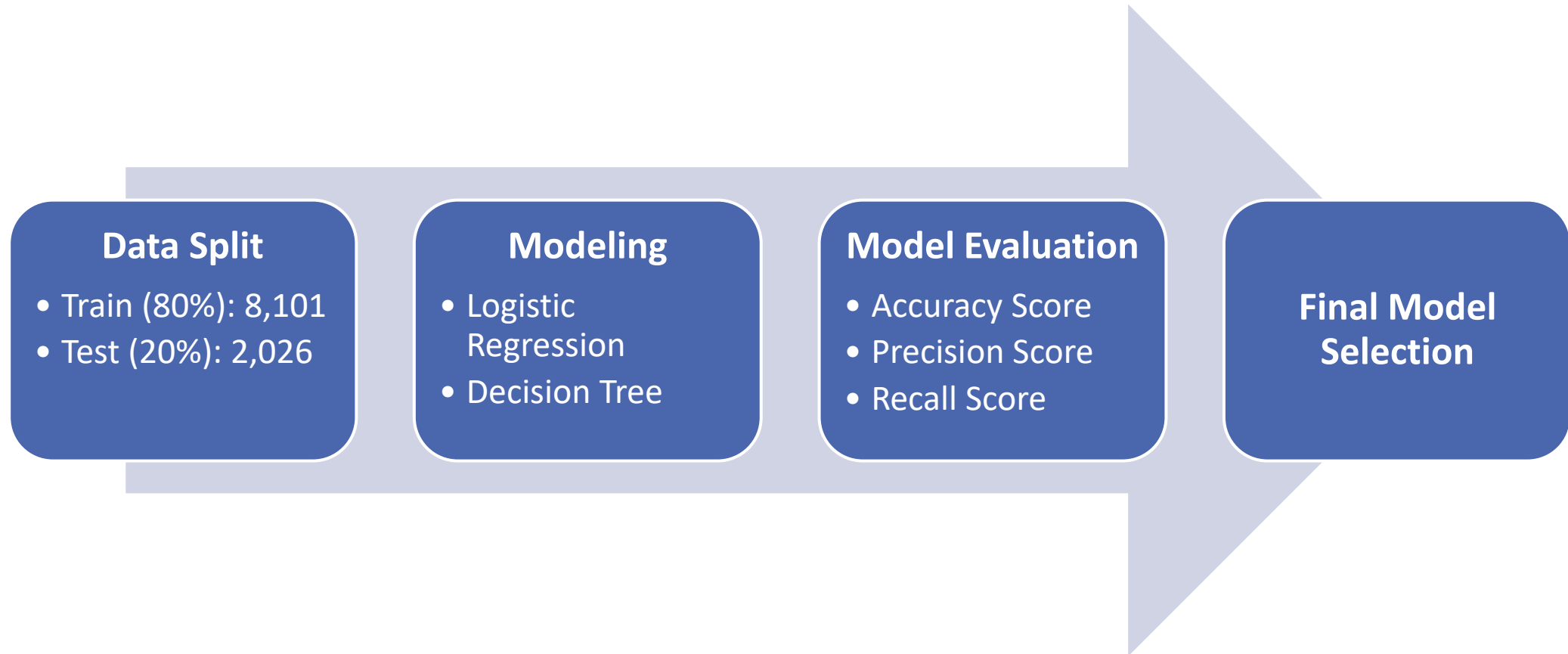
- **Correlation Heat Map:** Some of the variables with strong correlation with Attrition are:

- Total\_Trans\_Ct: total transaction count
- Total\_Ct\_Chng\_Q4\_Q1: change in total transaction count from Q4 to Q1
- Total\_Revolving\_Bal: total revolving balance



# Modeling Techniques and Results

# Modeling Techniques



# Modeling Techniques

## Logistic Regression

1. Standardize/Scale numeric features
2. Oversampling using SMOTE (Synthetic Minority Oversampling Technique) algorithm
3. Fit Logistic Regression
  - Recursive Feature Elimination (30 features)
  - Manual feature selection
4. Model Assumption Checks
  - p-value of predictors
  - Signs of coefficients
  - Test for multicollinearity using Variance Inflation Factor (VIF)
5. Model Evaluation

## Decision Tree

1. K-Fold cross validation to select optimal max\_depth (result = 4)
  - Repeated stratified k-fold (10 folds, 3 repeats)
  - Oversampling using SMOTE (Synthetic Minority Oversampling Technique) algorithm
2. Fit Decision Tree
  - max depth = 4
  - min leaf size = 500
3. Model Evaluation

# Logistic Regression Results

## ► Significant Features

↓ Gender (if customer is Male)

↑ Number of Dependents

↓ Total Relationship Count

↑ Number of Inactive Months

↑ Credit Limit

↓ Total Revolving Balance

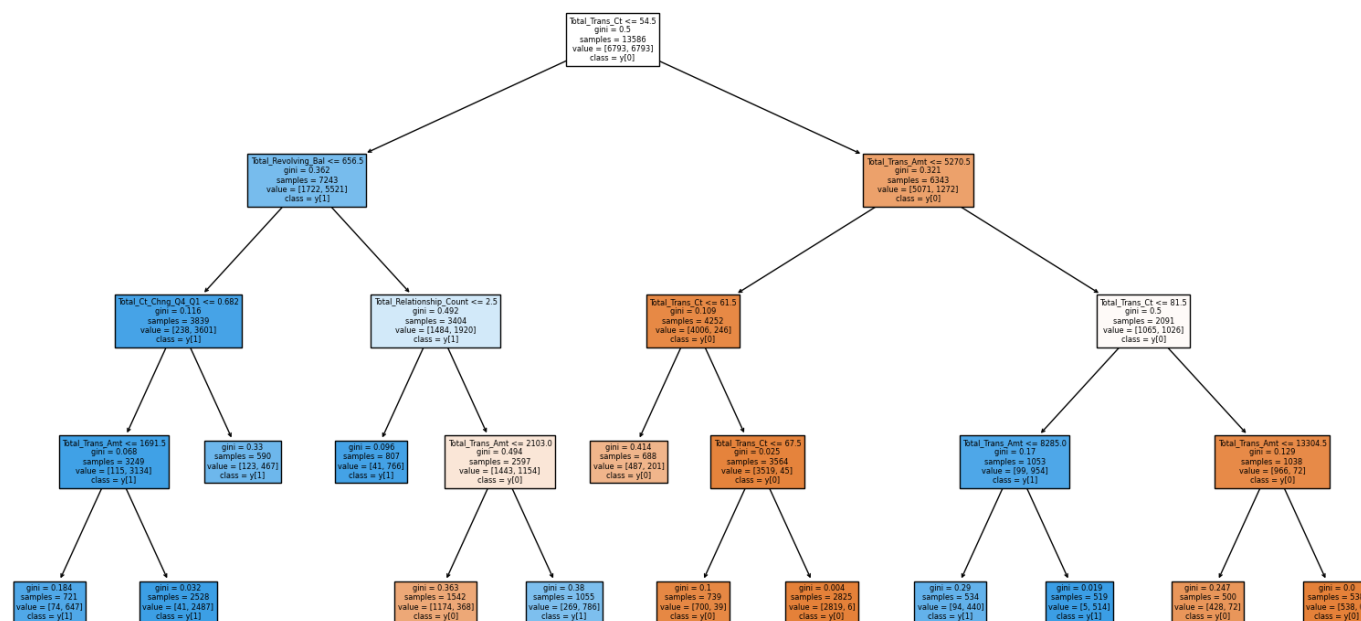
↓ Total Transaction Count

Predictors	Coefficient	P-value	VIF Factor	P-value Check	VIF Check
const	-0.6303	0.0	2.141598	Passed	Passed
Gender_M	-1.0810	0.0	1.279530	Passed	Passed
Std_Dependent_Count	0.1329	0.0	1.006042	Passed	Passed
Std_Total_Relationship_Count	-0.7370	0.0	1.019864	Passed	Passed
Std_Months_Inactive_12_mon	0.5400	0.0	1.021152	Passed	Passed
Std_Credit_Limit	0.3237	0.0	1.302371	Passed	Passed
Std_Total_Revolving_Bal	-0.7454	0.0	1.035719	Passed	Passed
Std_Total_Trans_Ct	-1.8669	0.0	1.061784	Passed	Passed

# Decision Tree Results

## ► Important Features (Highest to Lowest)

- Total Transaction Count
- Total Transaction Amount
- Total Revolving Balance
- Total Relationship Count
- Change in Total Transaction Count from Q4 to Q1



Feature	Feature Importance
Total_Relationship_Count	0.066952
Total_Revolving_Bal	0.107659
Total_Trans_Amt	0.187765
Total_Trans_Ct	0.631242
Total_Ct_Chng_Q4_Q1	0.006382



# Model Evaluation and Final Model Selection

## ► Final Model: **Decision Tree**

- **Classification Accuracy:** 91% were predicted correctly
- **Precision:** Out of all the customers that the model predicted would attrite, 65% actually did.
- **Recall:** Out of all the customers that actually attrited, the model predicted this outcome correctly for 85% of those customers.

Set	Metric	Logistic Regression	Decision Tree
Train	Accuracy Score	82%	90%
	Precision Score	81%	90%
	Recall Score	83%	90%
Test	Accuracy Score	80%	91%
	Precision Score	43%	65%
	Recall Score	80%	85%

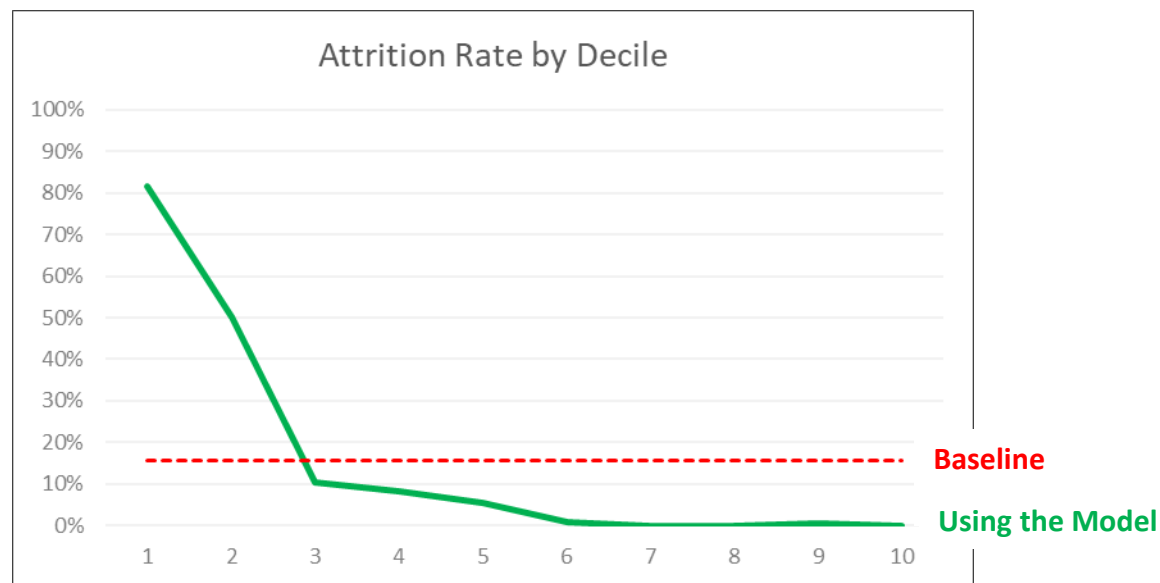
# Model Use Case

## ► Targeting Customers for Anti-Attrition Campaign

If we prioritize the Top 20% customers with highest probability of attrition, we have 66% chance of getting customers who will cancel their credit card account – **50 PPS higher** than our 16% baseline.

Test Set

Decile	No. of Attrited Customer	No. of Customers	% Attrited Customer	Cumulative %
1	165	202	82%	82%
2	102	203	50%	66%
3	21	202	10%	47%
4	17	203	8%	38%
5	11	203	5%	31%
6	2	202	1%	26%
7	0	203	0%	22%
8	0	202	0%	20%
9	1	203	0%	17%
10	0	203	0%	16%
Overall	319	2,026	16%	16%



Thank you.