

# **MOTIVATION AND SUMMARY**

- Customer churn is one of the most important and challenging problems for businesses today
- Many businesses are utilizing customer churn metrics in order to try and predict churning and improve customer retention.

What factors may or may not be **associated with churning**?

# **QUESTIONS**

What is the profile of someone who is likely to churn?

After determining the profile, which percent of existing customers are now at risk for churning?

# **DATA CLEANUP & EXPLORATION**

- Data Source: BankChurners.csv via Kaggle.com
- Pandas was used to create a dataframe from the csv
- In terms of cleaned data, the most significant edit to the data was that we eliminated all customers with a utilization ratio of 0 (aka they never used the card)
- Keeping zero utilization customer data led to misleading representations
- Two extraneous columns were deleted as they did not contribute to the analysis

# **DATA ANALYSIS**

 Each variable (or column in the datasheet) was investigated whether it did or did not have a statistically significant effect in predicting those at risk for churning via using Matplotlib to create various diversified plots

 After plots were created by using the independent t-test on all factors, we determined which factors were statistically significant and came up with a basic profile of a customer that we believe is at risk for churning

# VARIABLES EXAMINED FOR INVESTIGATION

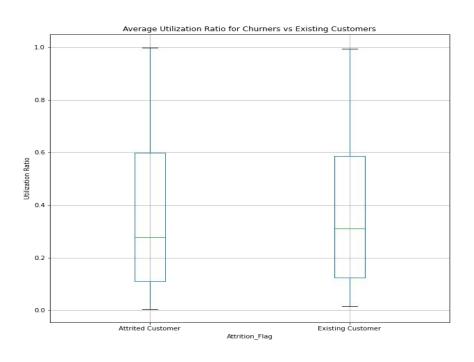
- Age
- Income
- Utilization Ratio
- Transaction Amount
- Transaction Count
- Months Inactive

- Gender
- Marital Status
- Dependents
- Monthly Credit Limit
- Months with the Company

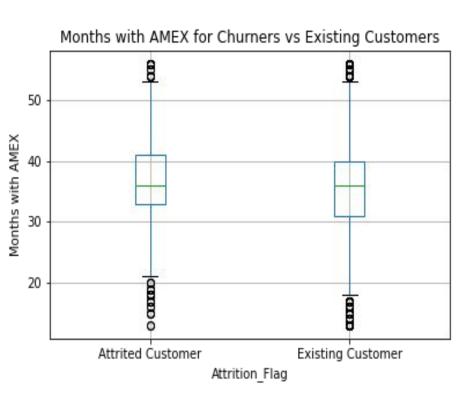
# **QUANTITATIVE DATA**

- Utilization Ratio
- Months Spent
- Monthly Credit Limit
- Total Revolving Balance

## **UTILIZATION RATIO**



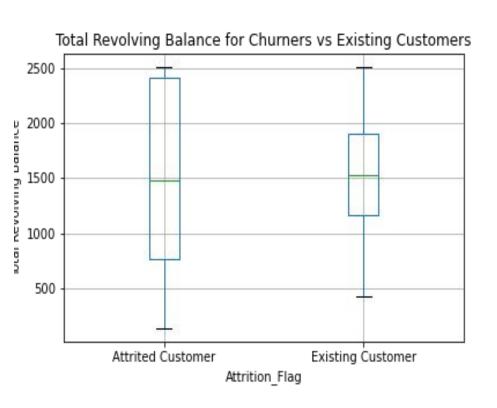
## **MONTHS SPENT**



## **MONTHLY CREDIT LIMIT**



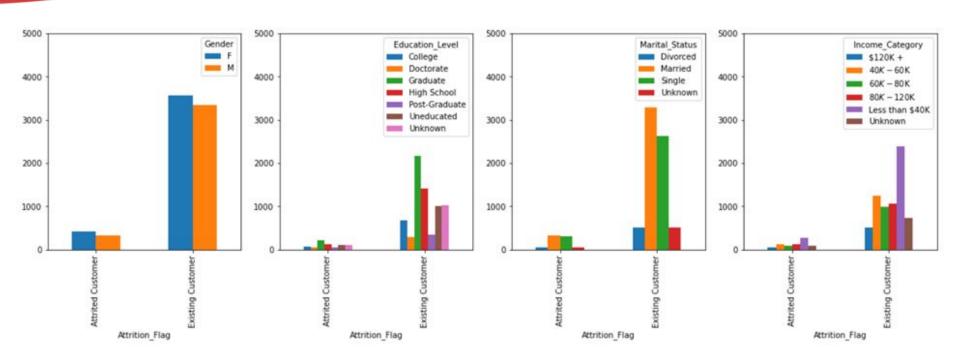
## TOTAL REVOLVING BALANCE



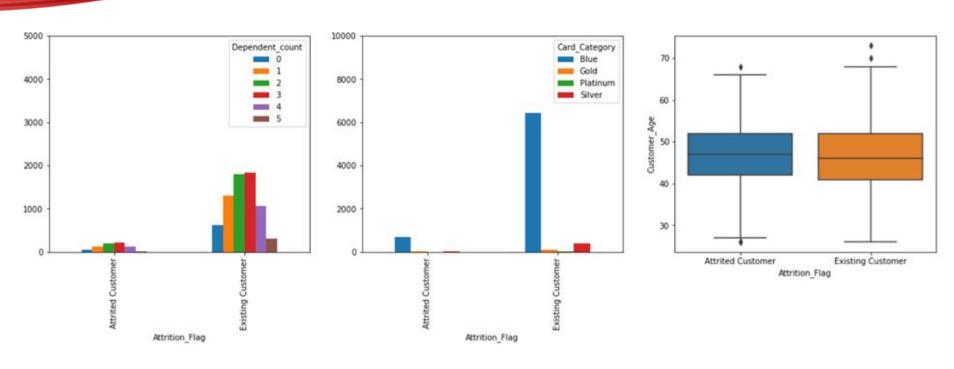
# CATEGORICAL DATA

- Gender
- Education Level
- Marital Status
- Income\_Category
- Dependent Count
- Card Category
- Customer Age

## GENDER, EDUCATION LEVEL, MARITAL STATUS & INCOME



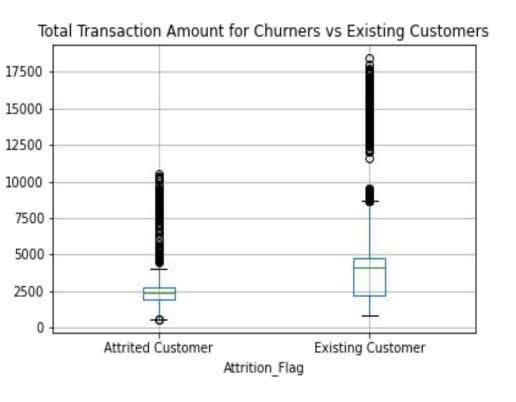
## **DEPENDENT COUNT, CARD CATEGORY & AGE**



# STATISTICALLY SIGNIFICANT AREAS

- Total Transaction Amount
- Total Transaction Count
- Months Inactive Out of 12 Months

### TOTAL TRANSACTION AMOUNT



## <u>Churners</u>

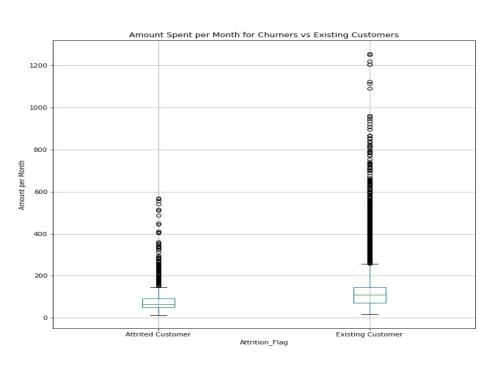
Mean= \$3,148.97 Median= \$2,361.00 Std = \$2,357

## **Existing**

Mean = \$4,861.27 Median = \$4,081.00 Std = \$3611.78

## P-value 9.9e-51

## TRANSACTION AMOUNT (BY MONTH)



## TOTAL TRANSACTION COUNT



#### **Churners**

Mean: 45

Median: 43

Standard Deviation: 14.38

## **Existing Customers**

Mean: 68

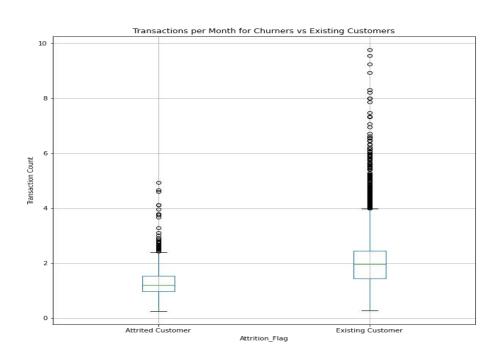
Median: 70

Standard Deviation: 24

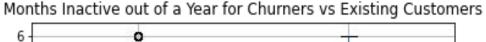
## P-value

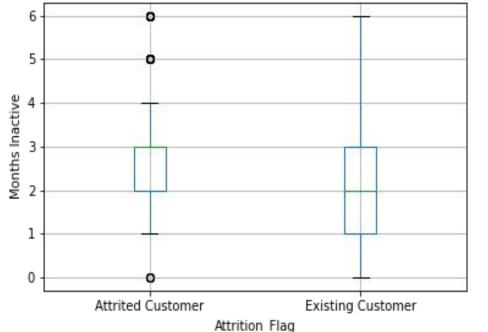
6.9e-212

# TRANSACTION COUNT (BY MONTH)



## **MONTHS INACTIVE**





## **Churners**

Mean: 2.73

Median: 3

Standard Deviation: 0.9

## **Existing Customers**

Mean: 2.27

Median: 2

Standard Deviation: 1.02

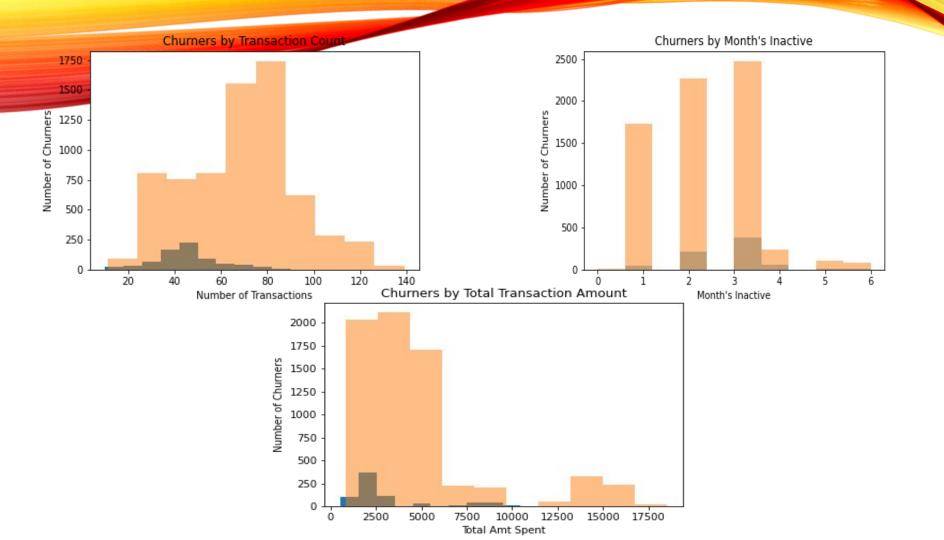
## P-value

2.8e-35

# PROFILE OF A CHURNER

Total Trans Count <= 51

Months Inactive >= 3



# RISK OF EXISTING CUSTOMER CHURN

- Existing customers who meet both conditions - 1%

- Existing customers who meet one of the two conditions - 68%

# **LIMITATIONS**

- The dataset is quite large, containing data from more than 10,000 credit card accounts with 19 variables
- Data may be skewed by card category (revolving balance cards vs monthly pay in full cards)
- The dataset is missing variables that would have been valuable in our analysis

# ADDITIONAL AREAS WORTH EXPLORING

- Some important variables were not included in the dataset but would be worth exploring:
  - Customer credit score
  - Annual percentage rate per card
  - Time period of dataset collection
  - Geographic location of the customer
  - Special offer such as 0% or low APR for a particular time period

# QUESTIONS?