Predicting Credit Card Default Using Machine Learning

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Introduction

In this project, I aim to solve the following problems:

- Which features are the best predictor of default?
- What is the relationship between default and other features?
 - Marital status, education level, gender, etc...

Dataset

Credit Card Default

- Demographic data: sex, marital status, education level, age
- * Payment data: credit limit, bill amount, payment amount, payment delay
- April September, 2005
- * 30,000 Taiwanese credit card customers.

Source: UCI Machine Learning Repository

Data Wrangling

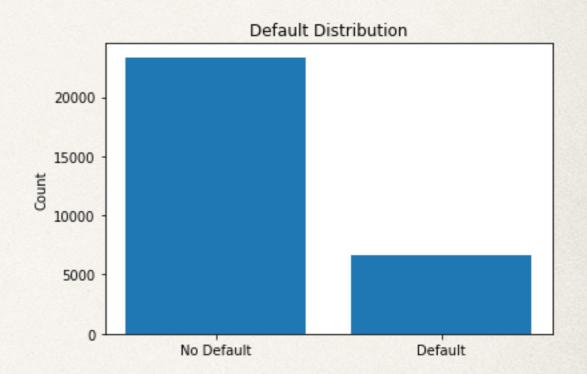
- Change SEX to 0 & 1
- Change unlabeled EDUCATION values to 'other'
- Change unlabeled MARRIAGE values to 'other'
- Binarize PAY_0 PAY_6

Data Analysis

- Investigate each variable in relation to default
- Look for trends and outliers

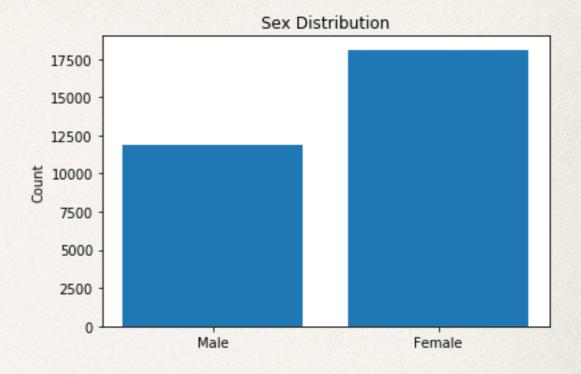
Default

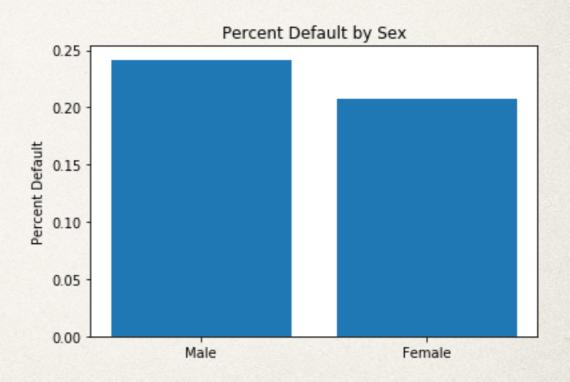
- Unbalanced dataset
- * 22.12% default percentage



Sex

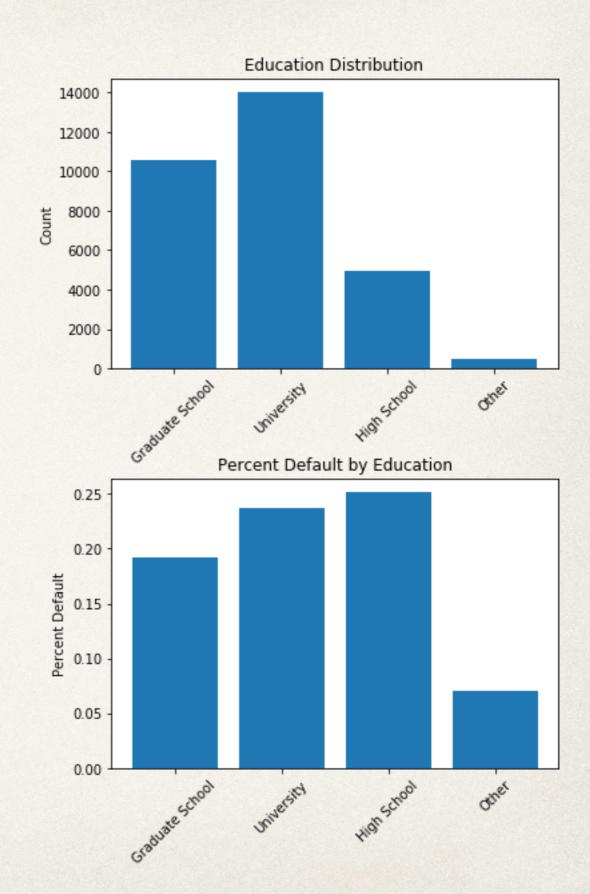
- More female clients than male clients
- Male clients have higher chance of default
- Chi-squared test results:
 - -Test statistic 47.71
 - -P-value 4.94e-12





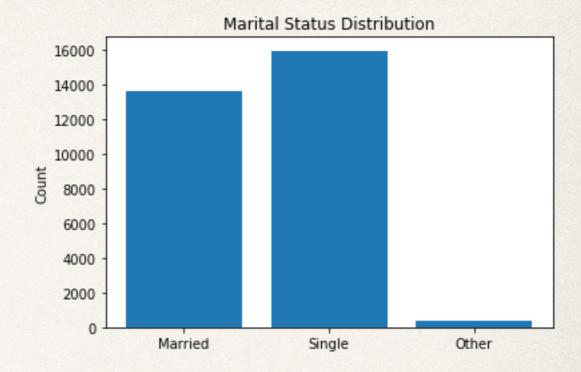
Education

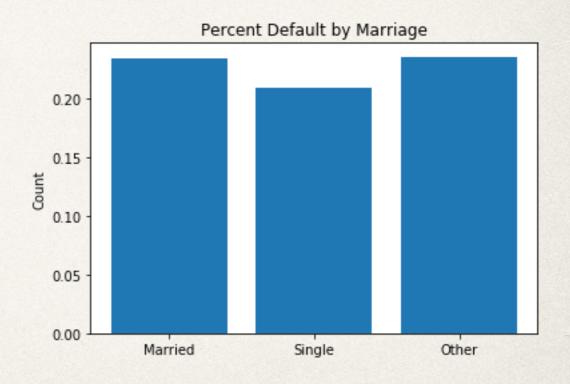
- Negative correlation between education level and default
- Low sample size Other
- Chi-squared test results:
 - -Test statistic 160.41
 - -P-value 1.50e-34



Marriage

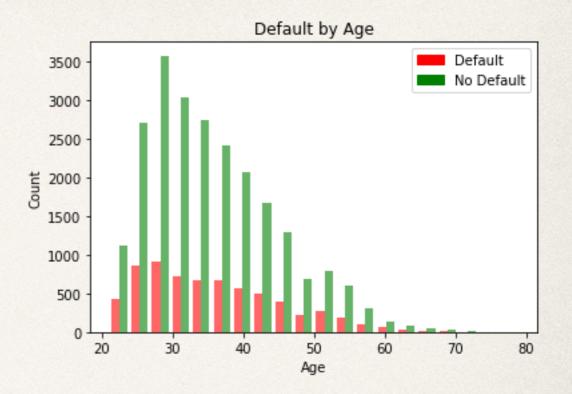
- Single has lower percent default than married
- Low sample size Other
 - Other = divorced?
- Chi-squared test results:
 - -Test statistic 28.13
 - -P-value 7.79e-7

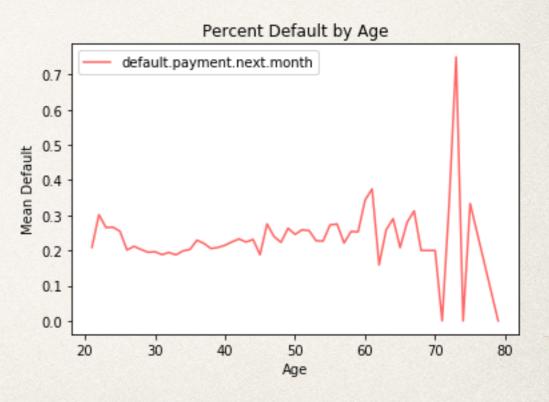




Age

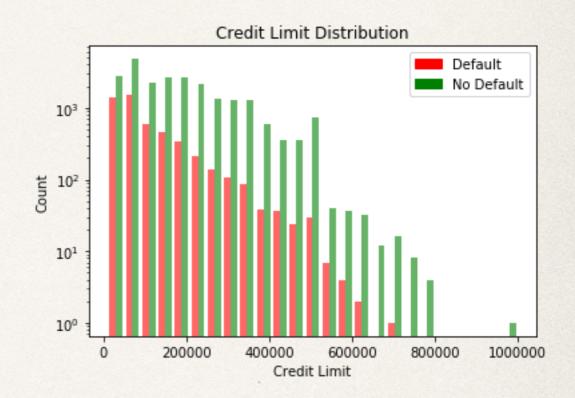
- Default highest in ages 20-25
 - Decreases after 25
 - Increases after 35
- Low sample size for ages 50+
- T-test results:
 - -Test statistic -2.41
 - -P-value 0.016





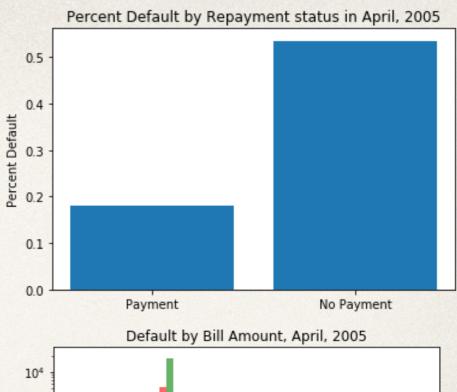
Credit Limit

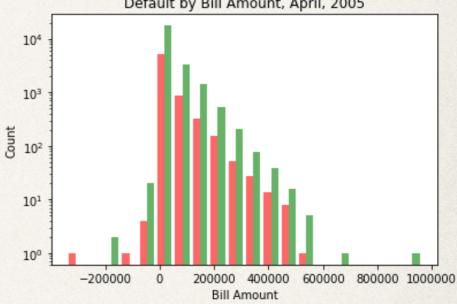
- Mean credit limit for defaulting clients is NT\$47990 lower than non-defaulting clients
- * T-test results:
 - -Test statistic 26.91
 - -P-value 1.30e-157

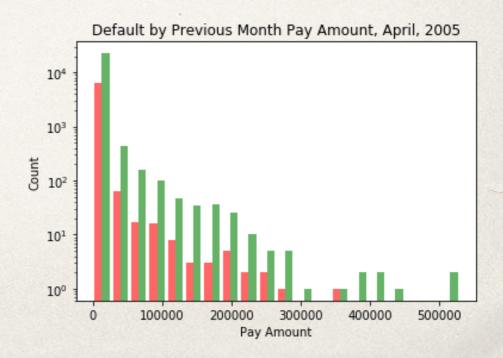


Pay Data April, 2005

- * 18.67% of paying clients defaulted
- Clients with bill amount 0 or less defaulted (?)
- Negative correlation between pay amount and default
- T-test results (bill amount):
 - -Test statistic 0.930
 - -P-value 0.352
- T-test results (pay amount):
 - -Test statistic 9.22
 - -P-value 3.03e-20

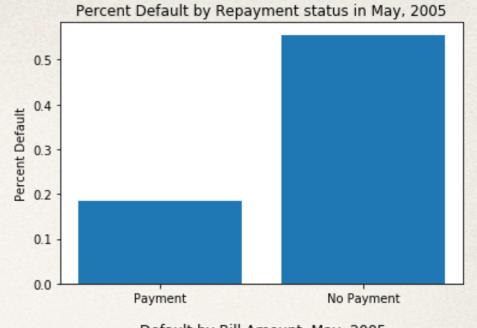


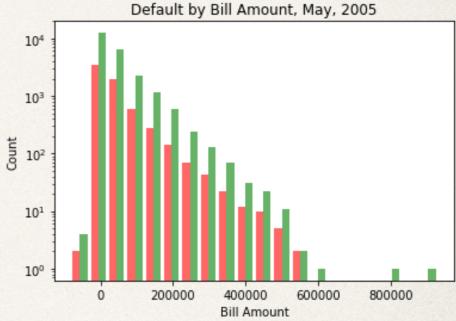


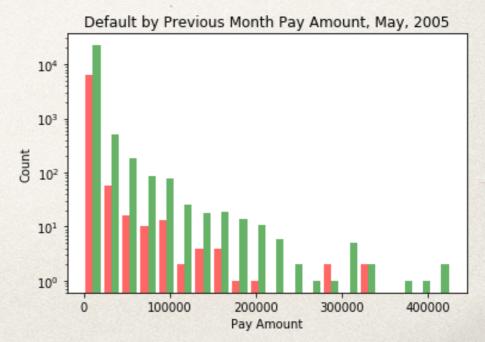


Pay Data May, 2005

- * 18.45% of paying clients defaulted
- Clients with bill amount 0 or less defaulted (?)
- Negative correlation between pay amount and default
- T-test results (bill amount):
 - -Test statistic 1.17
 - -P-value 0.241
- T-test results (pay amount):
 - -Test statistic 9.56
 - -P-value 1.24e-21

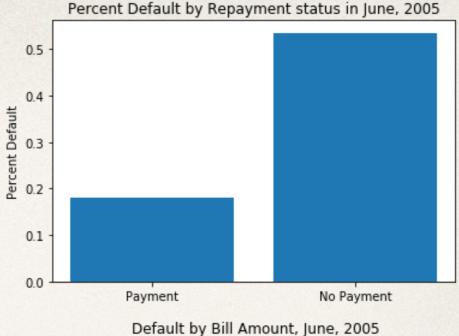


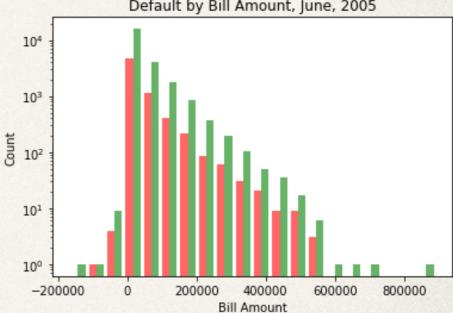


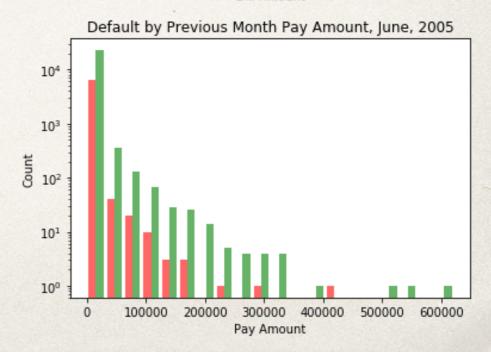


Pay Data June, 2005

- 17.95% of paying clients defaulted
- Clients with bill amount 0 or less defaulted (?)
- Negative correlation between pay amount and default
- T-test results (bill amount):
 - -Test statistic 1.75
 - -P-value 0.079
- T-test results (pay amount):
 - -Test statistic 9.85
 - -P-value 6.83e-23

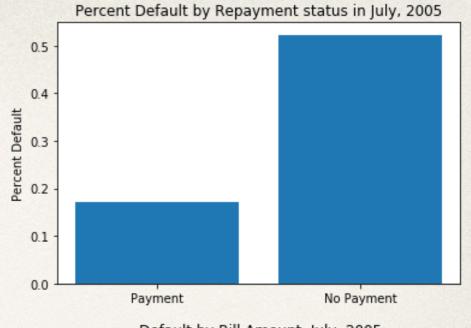


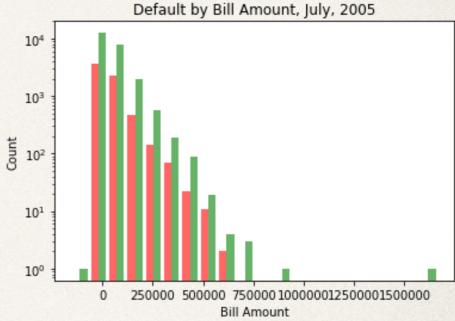


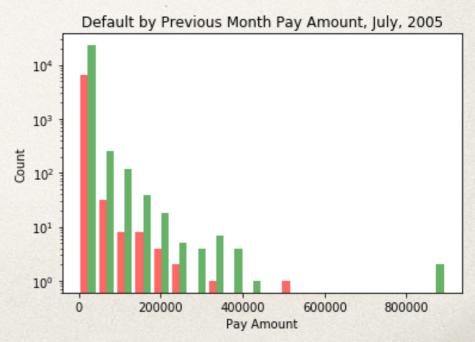


Pay Data July, 2005

- * 17.19% of paying clients defaulted
- Clients with bill amount 0 or less defaulted (?)
- Negative correlation between pay amount and default
- T-test results (bill amount):
 - -Test statistic 2.43
 - -P-value 0.015
- T-test results (pay amount):
 - -Test statistic 9.75
 - -P-value 1.84e-22

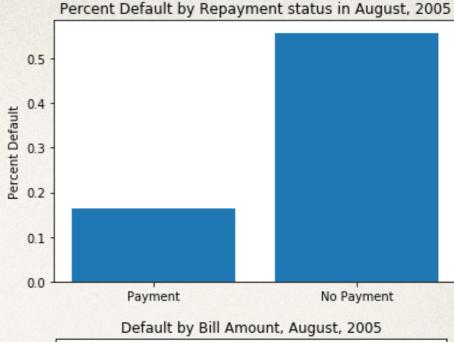


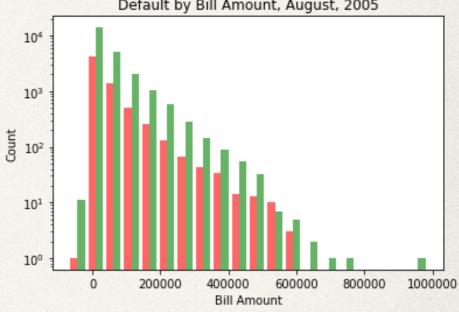


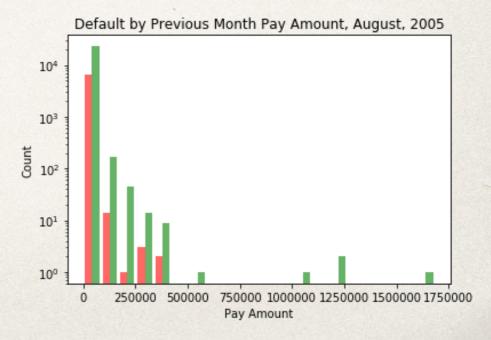


Pay Data August, 2005

- 16.27% of paying clients defaulted
- Clients with bill amount 0 or less defaulted (?)
- Negative correlation between pay amount and default
- T-test results (bill amount):
 - -Test statistic 2.46
 - -P-value 0.014
- T-test results (pay amount):
 - -Test statistic 10.16
 - -P-value 3.17e-24

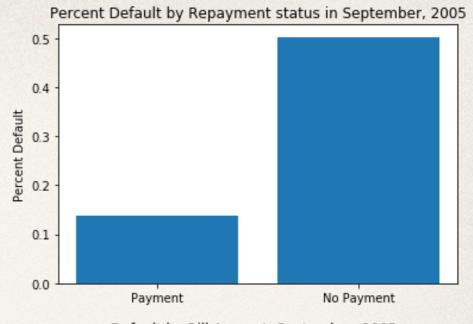


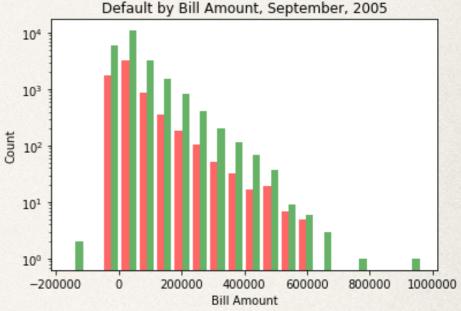


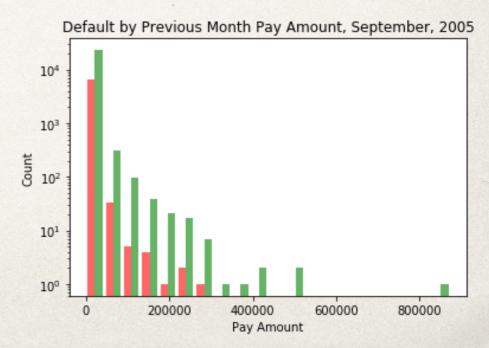


Pay Data September, 2005

- * 13.83% of paying clients defaulted
- Clients with bill amount 0 or less defaulted (?)
- Negative correlation between pay amount and default
- T-test results (bill amount):
 - -Test statistic 3.40
 - -P-value 0.001
- T-test results (pay amount):
 - -Test statistic 12.66
 - -P-value 1.15-36







Data Modeling

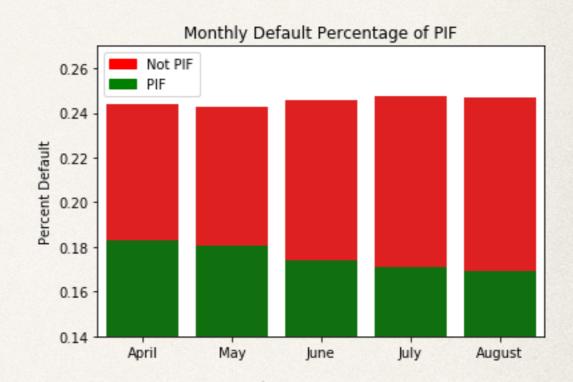
- Engineer 'PIF' feature
- Split categorical columns into dummy variables
- Feature selection
- Model selection
- Metric selection
- Model tuning

Engineering 'PIF'

- * PAY_AMT(N) >= BILL_AMT(N 1)
 - August to April

EDA for PIF Columns

- * 16.92% of clients who paid their August bill in full defaulted
- Negative balances
- Closed accounts labeled as default?



Feature Selection

- Drop clients who closed their accounts
 - ❖ PIF8 = True & default = True
- Exclude bill amount, pay amount columns
 - Described by 'PIF'

Split categorical columns

- Marriage, Education
- Pandas get_dummies

Model Selection

- SciKit Learn
 - Decision Tree
 - Support Vector Machine
 - Random Forest
 - AdaBoost

Metric Selection

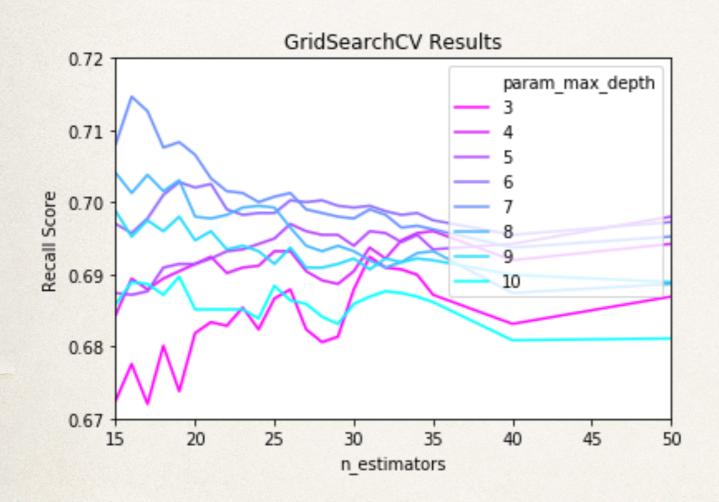
Goal: save the bank money

- ❖ Accuracy: (TP + TN) / (FP + FN)
- Precision: TP / (TP + FP)
- * Recall: TP / (TP + FN)
- * F1: 2 * (precision * recall) / (precision + recall)

Model Tuning

- * SciKit Learn GridSearchCV
- Maximize recall score
- max_depth & n_estimators

Model Tuning



	feature	score
14	PIF_8	0.273711
8	PAY_9	0.225856
9	PAY_8	0.108314
10	PAY_7	0.076283
11	PAY_6	0.067449
0	LIMIT_BAL	0.055806
12	PAY_5	0.045125
15	PIF_7	0.044115
17	PIF_5	0.028379
13	PAY_4	0.025130
16	PIF_6	0.021164
18	PIF_4	0.009774
7	AGE	0.006657
2	GRADUATE_SCHOOL	0.003303
1	SEX	0.002296
3	UNIVERSITY	0.001859
6	SINGLE	0.001832
5	MARRIED	0.001518
4	HIGH_SCHOOL	0.001428

Model Results

Confusion Matrix			
	Predicted No Default	Predicted Default	
No Default	3973	709	
Default	275	705	

Recall Score: 0.7194

Analysis Results

- Payment features best indicator of default
- Demographic features not as clear
 - Married clients are more likely to default than single
 - Males more likely to default than females
 - Default is highest for customers age 20-25

Further Research

- Dive deeper into false negatives data
- Try using only demographic data
- Further analysis on relationship between demographics and default