Credit Card Payments

Presented by Deautaun Ross, Marci Morrell, and Jasmine Castañeda

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Outline

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Data Overview

Data from Kaggle about credit card payments

Original Dataset	777,715 Rows	36,457 Rows	Model Dataset
	20 Columns	8 Columns	

Median percent of payments missed: 45%

Overall Mode Card Status: 0

Data Cleaning

- Renamed columns
- Dropped occupation
- Converted data to the proper types
- Label encoded the objects
- Used clients who have been a client for 6 months or longer

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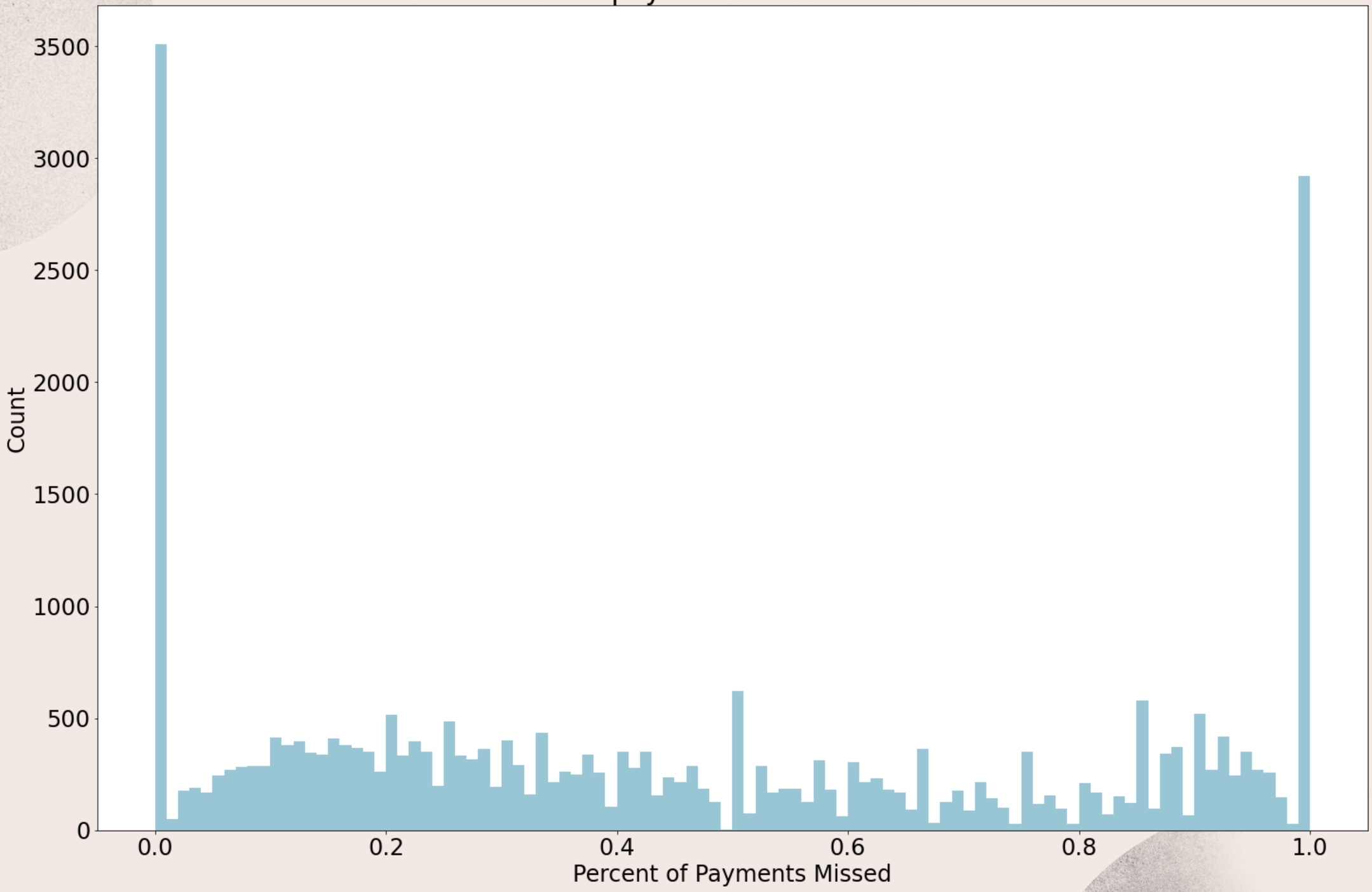
Feature Engineering

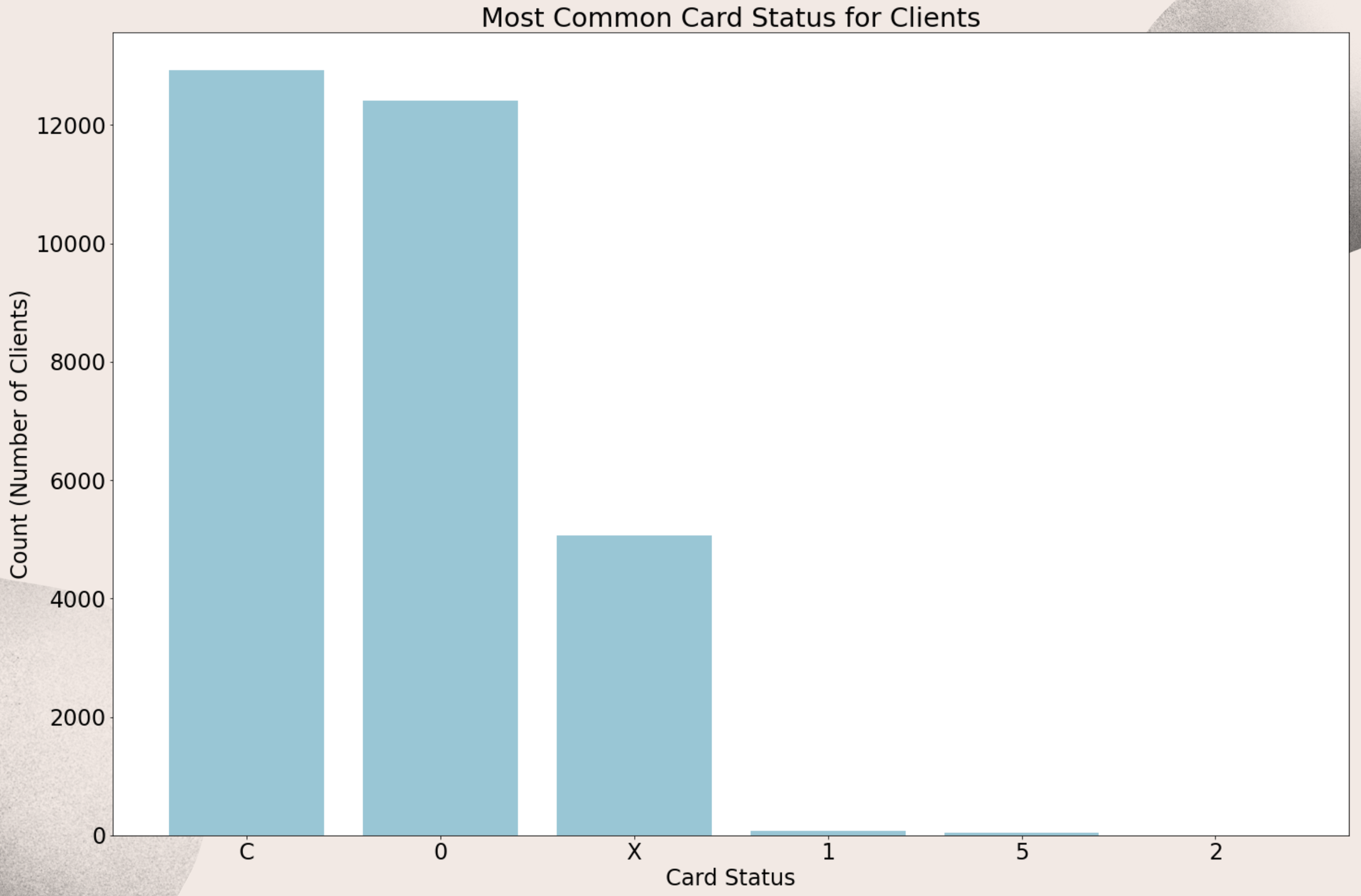
- Total amount of card status entries for a unique card holder
- Percentage of payments they have missed
- Mode card status of unique card holder

Card Status

0	<1 month overdue
1	1-2 months overdue
2	2-3 months overdue
3	3-4 months overdue
4	4-5 months overdue
5	>5 months overdue
C	Paid off that month
X	No loan for the month

Distribution of Target Columns


Distribution of payments missed for each client
Count
3500
3000
2500
2000
1500
1000
500
0
0.0
0.2
0.4
0.6
0.8
1.0
Percent of Payments Missed


Most Common Card Status for Clients
Count (Number of Clients)
0
2000
4000
6000
8000
10000
12000
C
0
X
1
5
2
Card Status

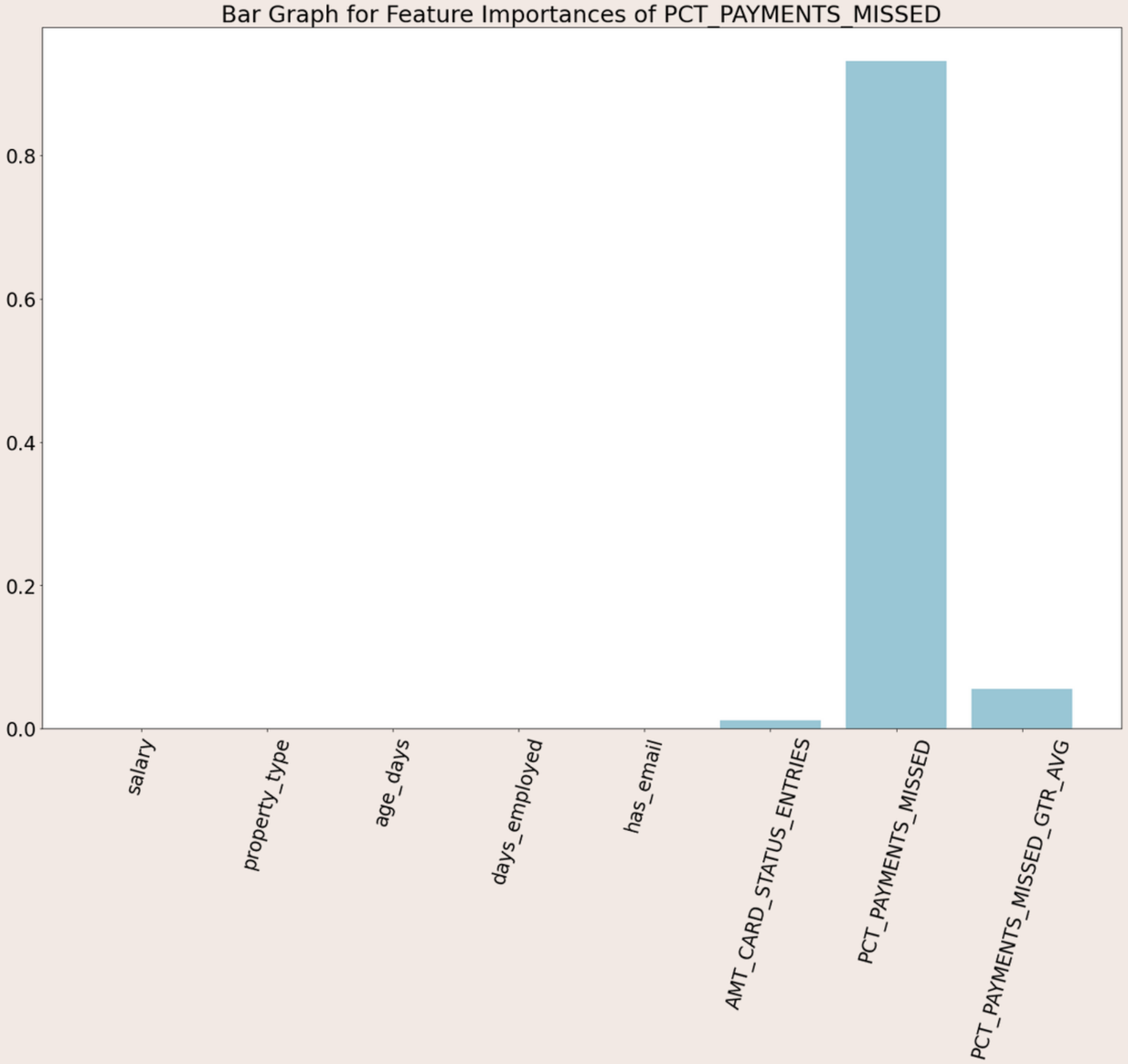
Model Building

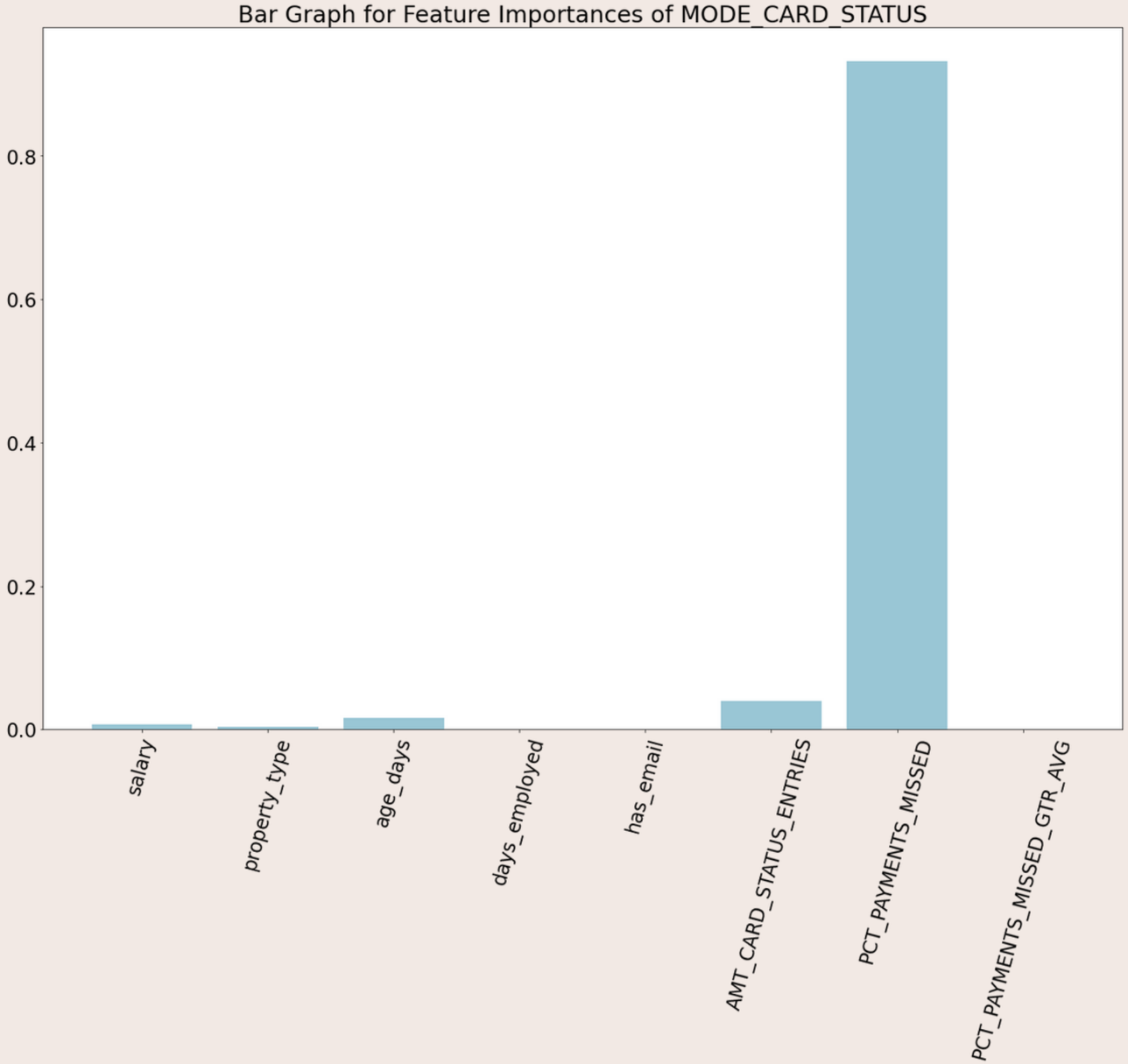
Percent of Missed Payments

- Regression Model
- Gradient Boost Regressor

Mode of Card Status

- Classification Model
- Gradient Boost Classifier


Bar Graph for Feature Importances of PCT_PAYMENTS_MISSED
0.0
0.2
0.4
0.6
0.8
salary
property_type
age_days
days_employed
has_email
AMT_CARD_STATUS_ENTRIES
PCT_PAYMENTS_MISSED
PCT_PAYMENTS_MISSED_GTR_AVG


Bar Graph for Feature Importances of MODE_CARD_STATUS
0.0
0.2
0.4
0.6
0.8
salary
property_type
age_days
days_employed
has_email
AMT_CARD_STATUS_ENTRIES
PCT_PAYMENTS_MISSED
PCT_PAYMENTS_MISSED_GTR_AVG

Features Used in Models

Salary

Property Type

Age

Days Employed

Has E-mail

Length of Card Holding

Mode Card Status

Is the Percent of Missed Payments Greater than the Median (Boolean)

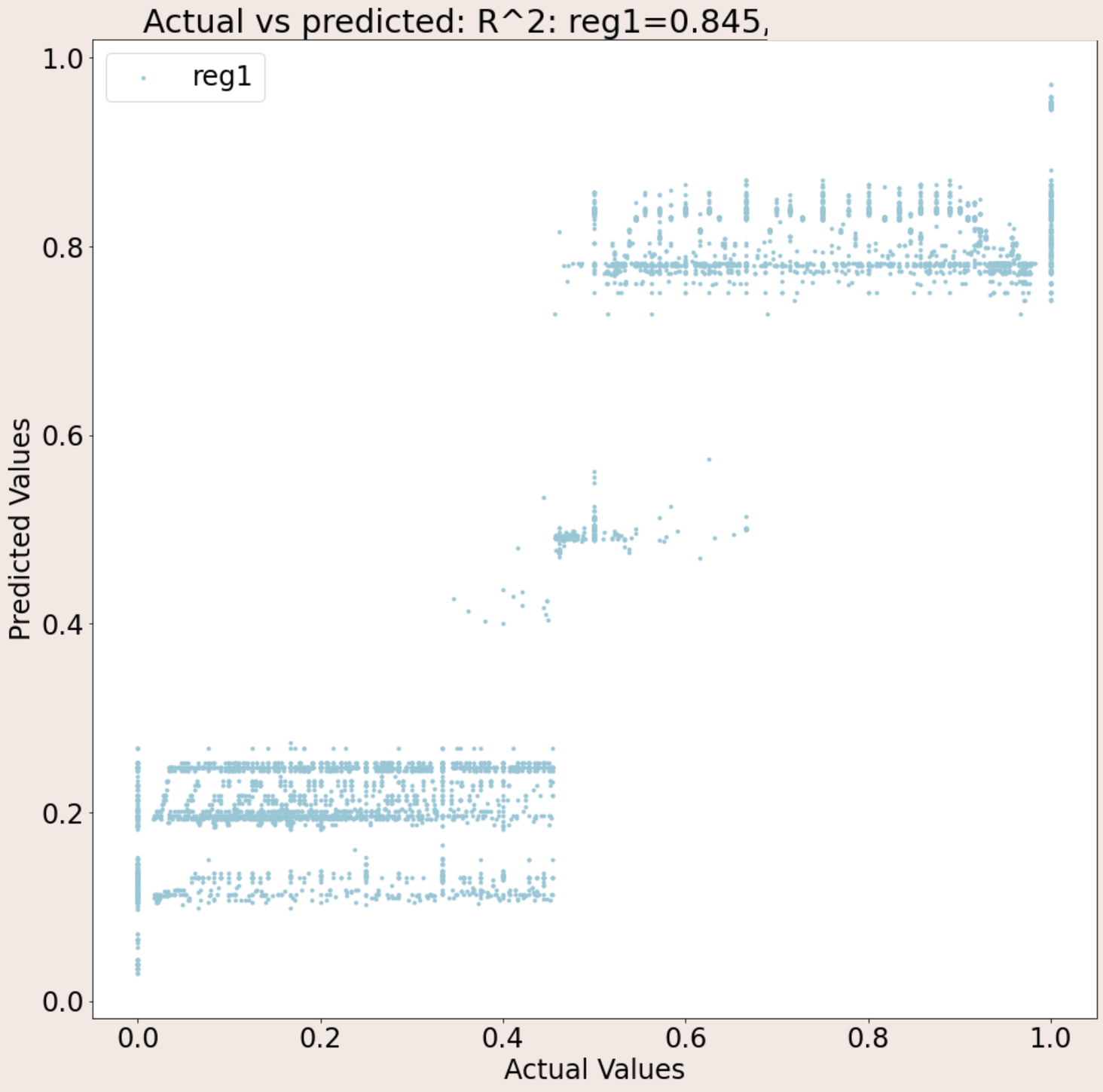
Percent of Payments Missed

Percent of Payments Missed

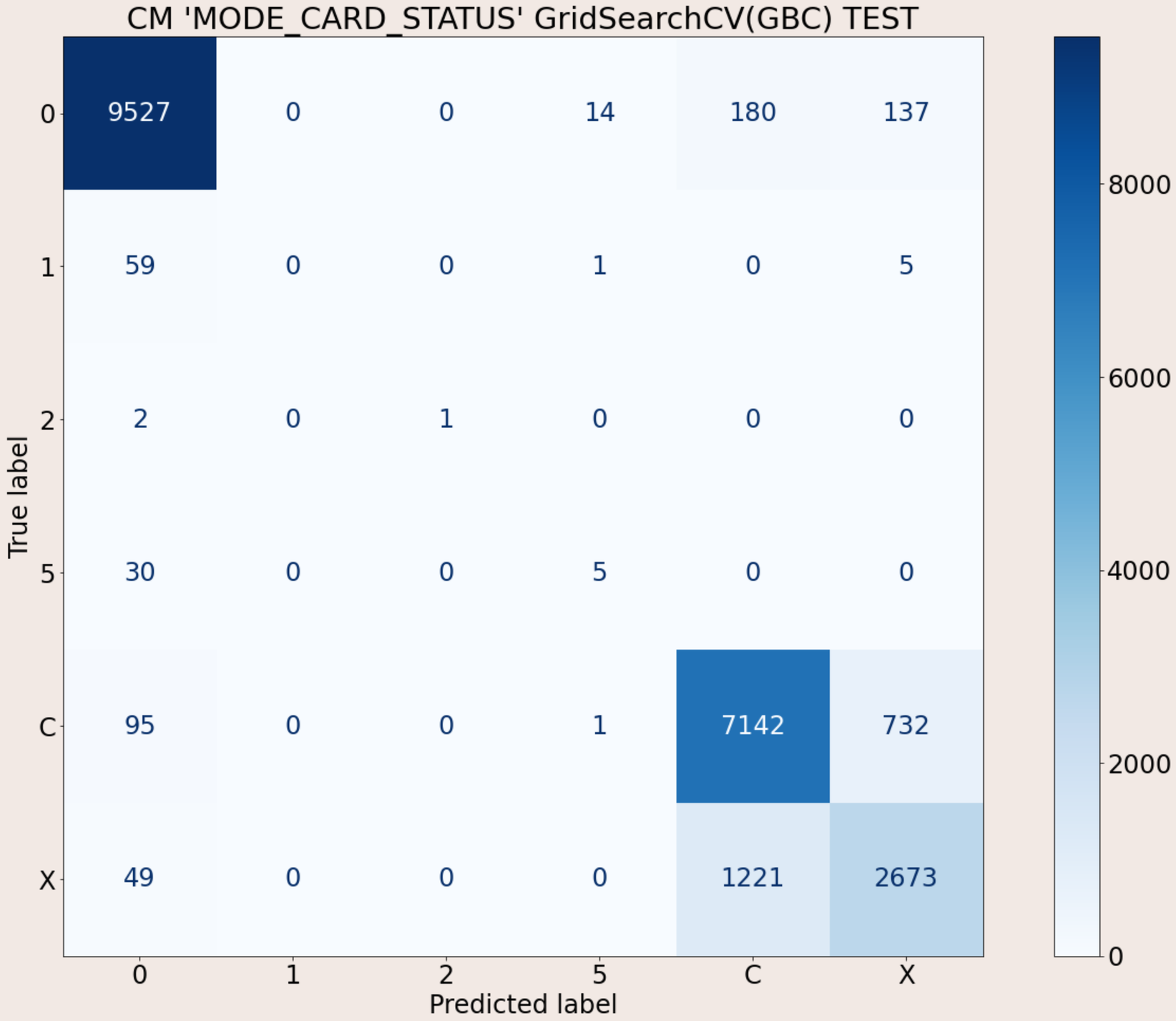
-Gradient Boosting Regressor

-Used GridSearchCV for hyperparameter tuning

- Hyperparameters:
  - min_samples_split (5)
  - min_samples_leaf (6)
  - max_depth (4)
  - loss (Squared Error)
  - learning_rate (.3)
  - n_estimators (150)
  - criterion (Squared Error)
  - tol (1e-3)
  - validation_fraction (.1)
  - n_iter_no_change (2)



Mode Card Status



Mode Card Status

-Gradient Boosting Classifier

- Used GridSearchCV for hyperparameter tuning

- 88% accuracy

- Hyperparameters:

  - min_samples_split (7)
  - min_samples_leaf (7)
  - max_depth (3)
  - loss (Squared Error)
  - learning_rate (.3)
  - n_estimators (150)
  - criterion (Squared Error)
  - tol (1e-3)
  - validation_fraction (.1)
  - n_iter_no_change (2)

Problems and Limitations

- Our model had a hard time predicting values between 30-70 for percent missing

- Data may not be able to tell us the values we were looking for, the featured engineered columns

- Data is unbalanced for classification but we are able to get clear predictions. There is an absence of data from the card status 1-5

Conclusions

-Majority of card holders miss all or none of their payments

-Salary, Property Type, Age, Days Employed, Has E-mail, Length of Card Holding, and Mode Card Status are important when analyzing cardholders

Thank you

Any Questions?