



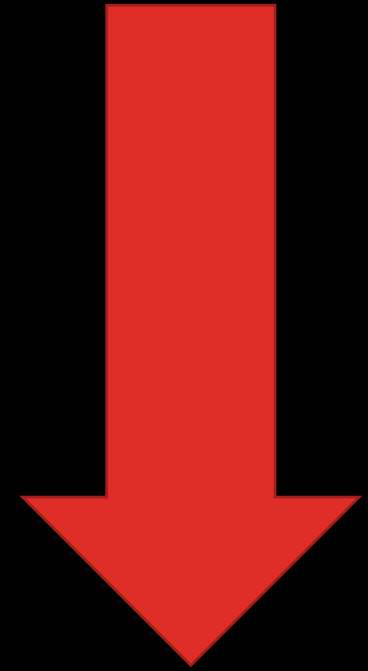
# ANALYSES AND PREDICTION ON LOAN DEFAULTS

Beverly Yang

05MAR23

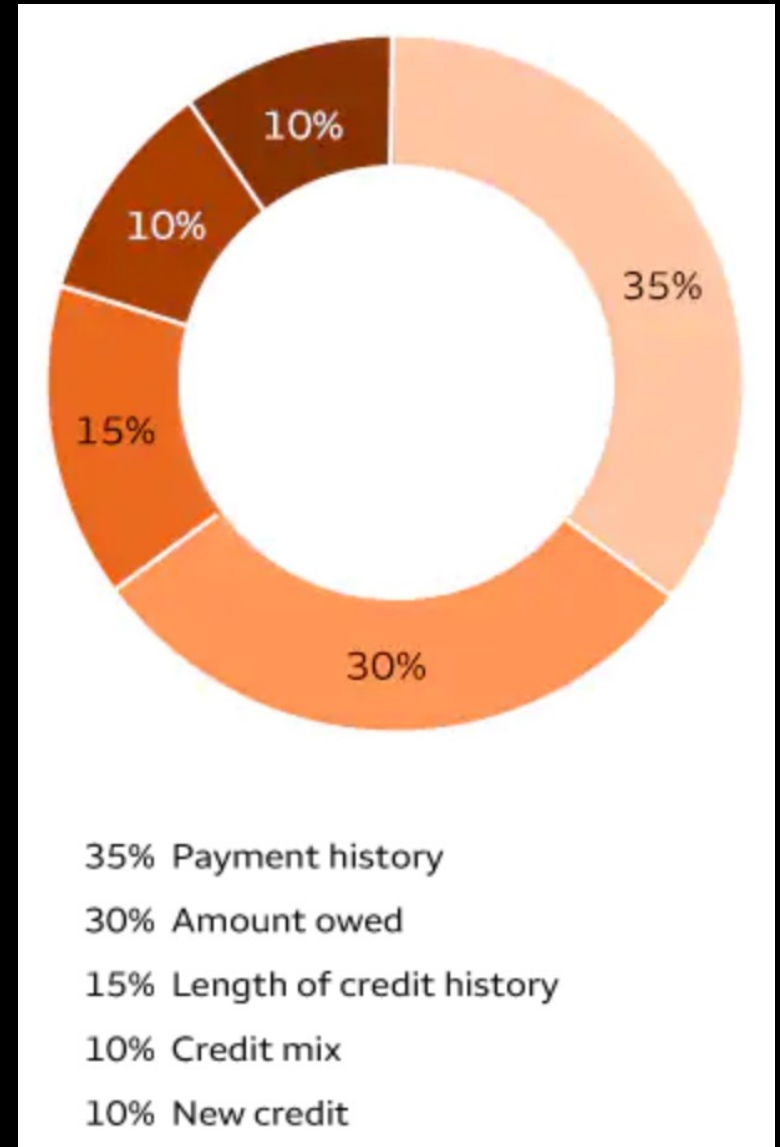
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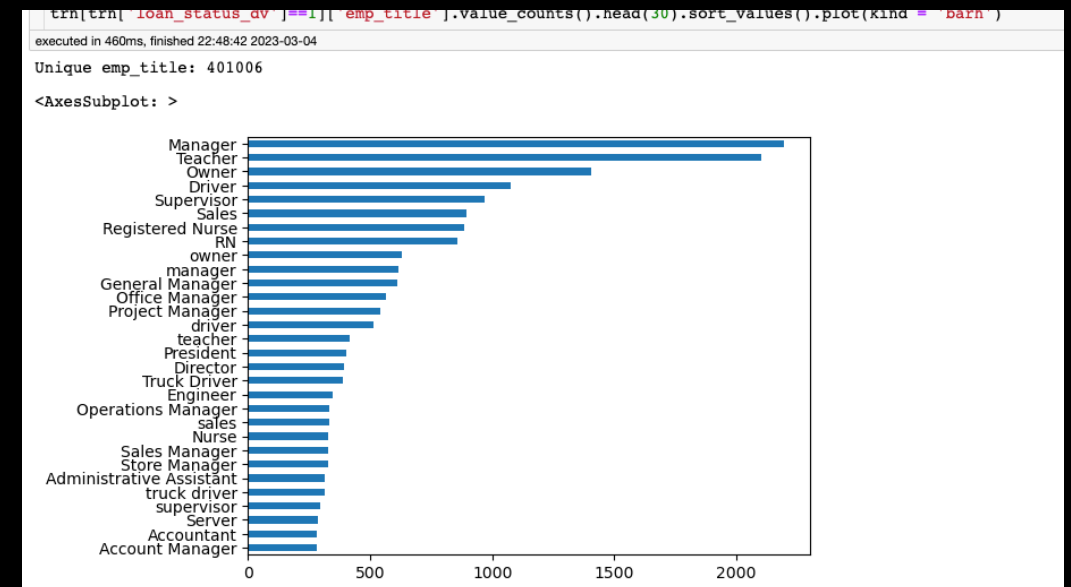
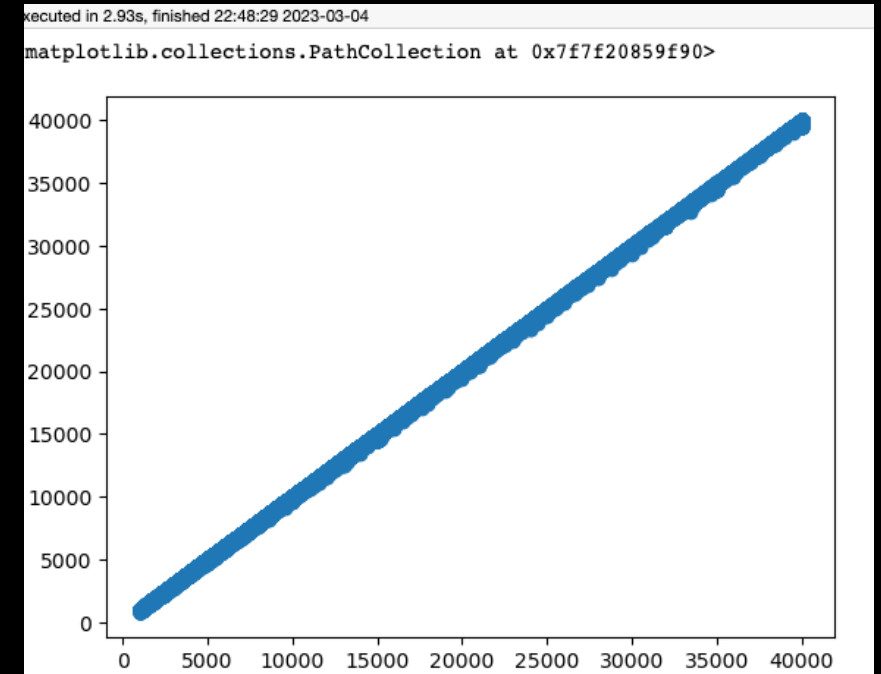
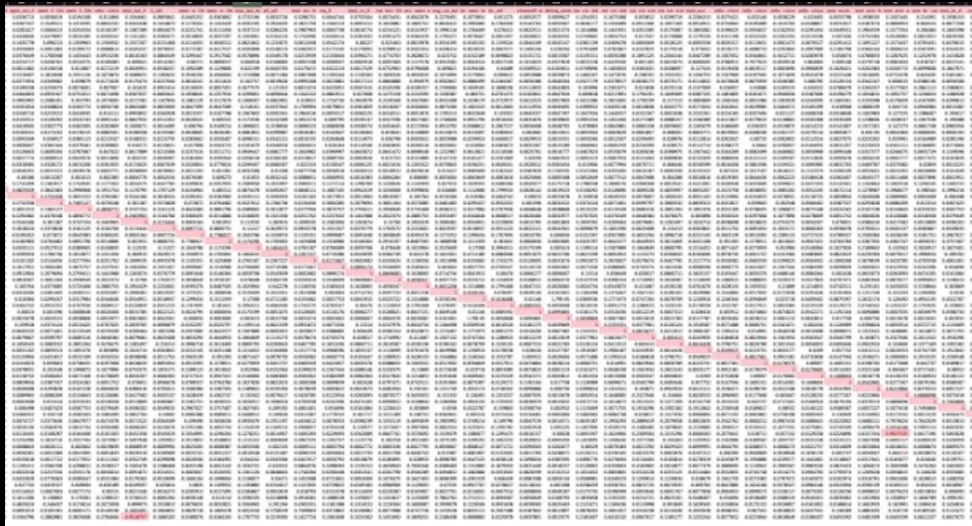
# SUMMARY AND GOAL

- Better assess the risk of potential borrowers
- Assumption:
  - Revolving credit features more important than installment features
  - Derogatory and delinquency remarks are considered
  - Select model based on highest ROCAUC score
- Most of categorical features removed
- Saga-lasso logistic regression model is the best at detecting loan default



# EXPLORATORY DATA ANALYSIS

- Data Cleaning and Preprocessing
  - Charged off event rate is: 7.31%
- Numeric: Pearson's correlation
- Categorical: Chi-square, and Cramer V score
- Most numerical data skew to the right



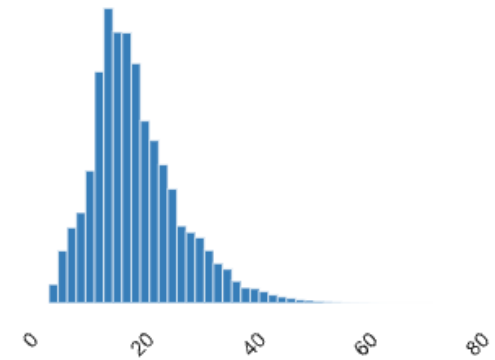


cr\_dur\_yr

Real number (R)

Distinct	2775
Distinct (%)	0.2%
Missing	0
Missing (%)	0.0%
Infinite	0
Infinite (%)	0.0%
Mean	18.68857259

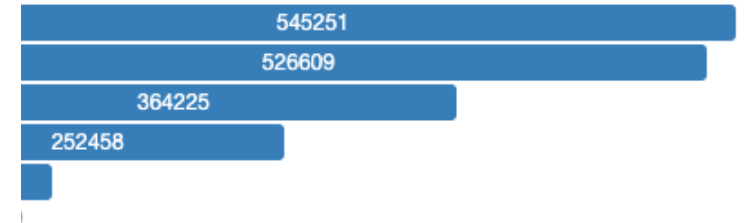
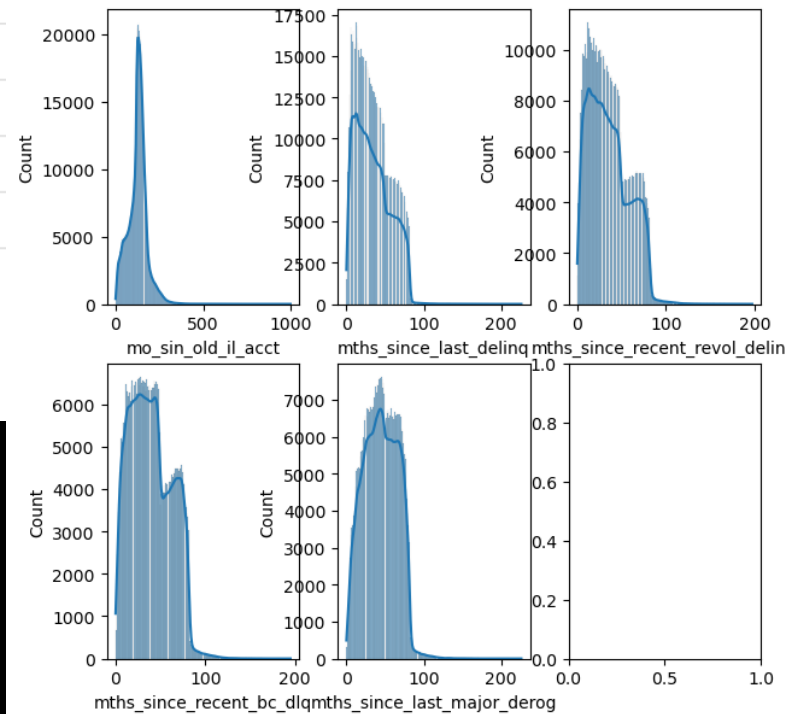
Minimum	3.079452055
Maximum	84.89589041
Zeros	0
Zeros (%)	0.0%
Negative	0
Negative (%)	0.0%
Memory size	13.9 MiB



gi

Categorical

Distinct
Distinct (%)
Missing
Missing (%)
Memory size



More details

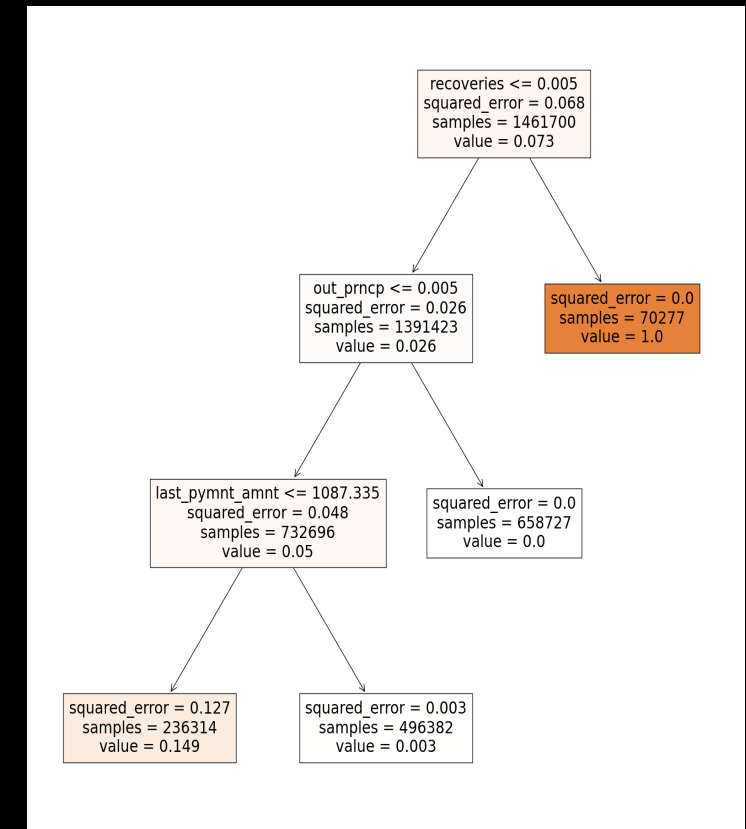
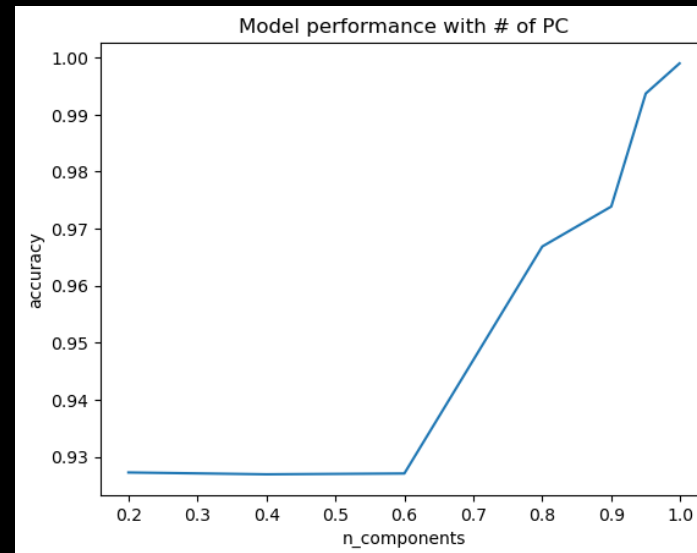
# FEATURE SELECTION AND ENGINEERING

total_rec_int	6.33E-03	num_accts_ever_120_pd	-1.01E-06
loan_amnt	5.67E-03	mort_acc	-6.02E-07
recoveries	3.80E-03	num_tl_op_past_12m	-4.03E-07
total_rec_late_fee	2.67E-05	pub_rec_bankruptcies	-3.22E-07
revol_bal	1.95E-05	pub_rec	-2.99E-07

- Impute numeric values: dti, inq
- Create credit history feature
- 44 features are used for training

## Feature importance:

- Baseline logistic regression model
- PC performance
- Decision Tree Regressor



# MACHINE LEARNING MODELING

Simple logistic regression modeling

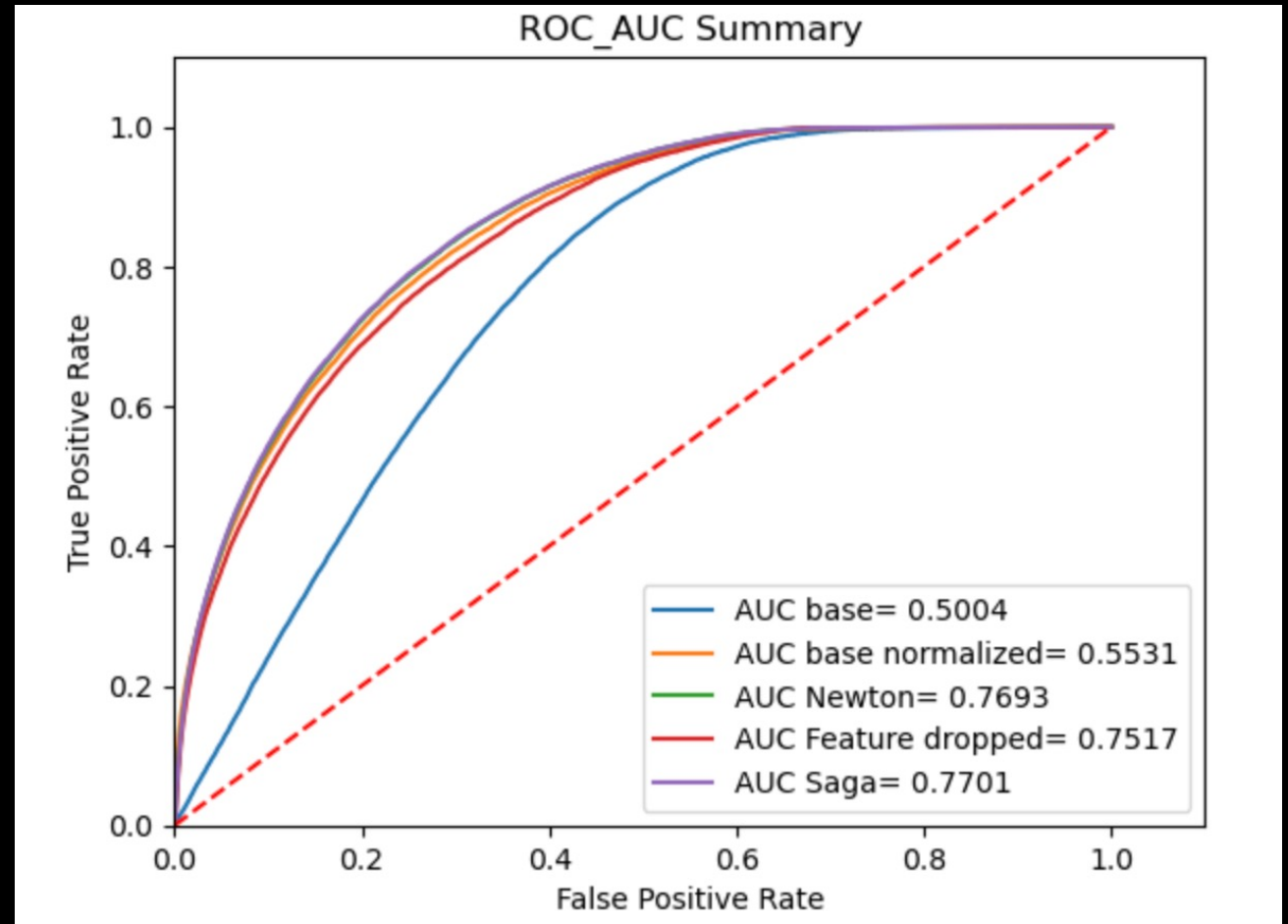
1. Helper functions for one-hot encoding, scoring, plotting ROCAUC
2. Prepare features and target
3. Split training dataset into training and validation set. Use all test data for prediction
4. Normalization
5. Fit various logistic models
6. Predict use trained model

<b>solver</b>	<b>'liblinear'</b>	<b>'lbfgs'</b>	<b>'newton-cg'</b>	<b>'sag'</b>	<b>'saga'</b>
Multinomial + L2 penalty	no	yes	yes	yes	yes
OVR + L2 penalty	yes	yes	yes	yes	yes
Multinomial + L1 penalty	no	no	no	no	yes
OVR + L1 penalty	yes	no	no	no	yes

[Source](#)

# MODEL PERFORMANCE USING TRAINING SET

- Most accurate and precise:
  - base normalized
    - 93% accuracy
    - 70% Precision
- Best recall:
  - newton-Cholesky: 83%





# MODEL SELECTION

- Saga for detection
- 42.9% default predicted in test
- Low Precision & High Recall

	Prediction	
Actual	0	1
0	240782	98072
1	4529	22042

None

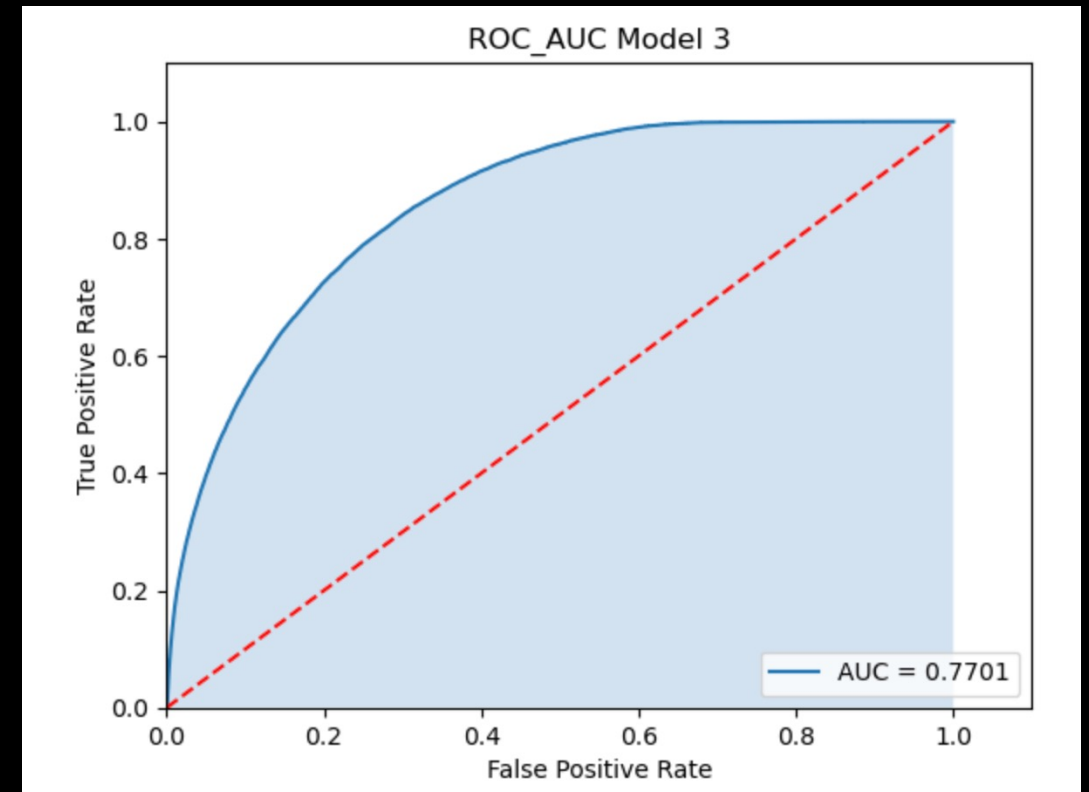
Accuracy: 0.7192282958199356

Precision: 0.18350899978353896

Recall: 0.829551014263671

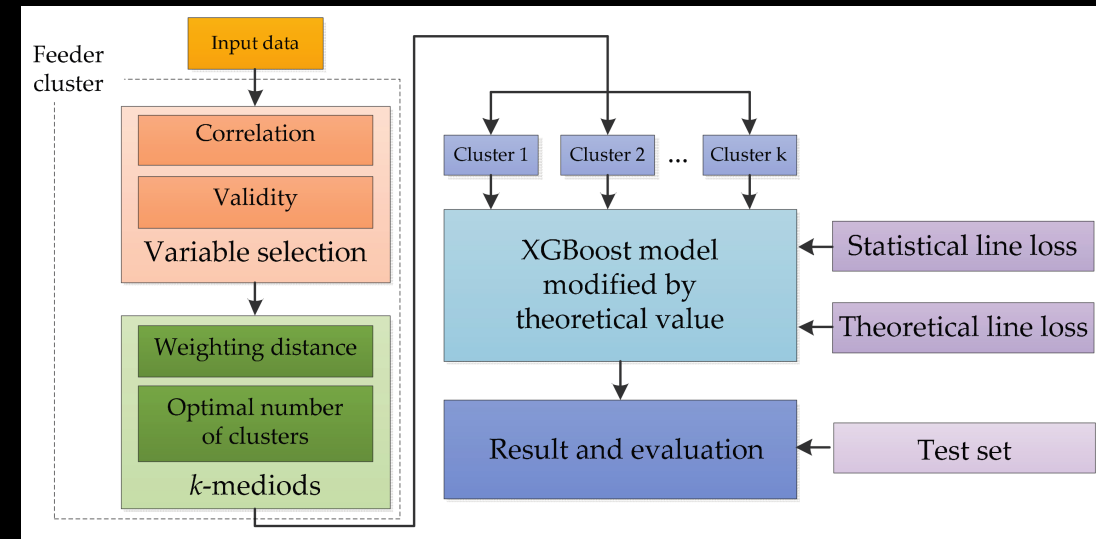
Specificity: 0.7105774168225844

F1 SCORE for Default: 0.30053516037768



# IMPROVEMENTS

- Under-sampling
- EDA:
  - Text mining and refining emp\_title columns
  - Remove all rows with NaNs
  - Investigate geographic implications
- Feature Engineering
  - Assign class weight
  - Advanced imputations
- Narrow down more features (GridSearch)
- XGBoost Tree
- Business understanding



Source



THANK YOU!