### SC 1015 Mini Project Z139\_Team8

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Predicting Credit Card Approvals



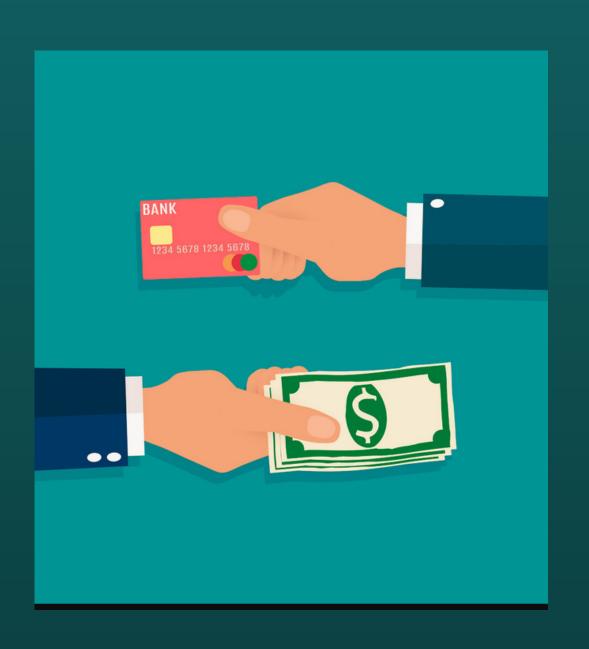


O3 Decision-Tree -> Random-Forest + CV
Importance of predictors
Logistic Regression & Random-Forest + CV

O4 Conclusion

## Significance of Credit Cards Ol

- · Role of cash is decreasing
- Important to accurately assess applicants



• Credit card companies can provide better customer services

- Risk assessment of high-risk applicants
- Help to automate approval process
  - increase efficiency



#### DataSet Overview

	Gender	Age	Debt	Married	BankCustomer	EducationLevel	Ethnicity	YearsEmployed	PriorDefault	Employed	CreditScore	DriversLicense	Citizen	Income	Approved	Approved_Status
0	b	30.83	0.000	u	g	W	V	1.250	t	t	1	f	g	0	+	Approved
1	а	58.67	4.460	u	g	q	h	3.040	t	t	6	f	g	560	+	Approved
2	а	24.50	0.500	u	g	q	h	1.500	t	f	0	f	g	824	+	Approved
3	b	27.83	1.540	u	g	W	V	3.750	t	t	5	t	g	3	+	Approved
4	b	20.17	5.625	u	g	W	V	1.710	t	f	0	f	S	0	+	Approved
5	b	32.08	4.000	u	g	m	V	2.500	t	f	0	t	g	0	+	Approved
6	b	33.17	1.040	u	g	r	h	6.500	t	f	0	t	g	31285	+	Approved
7	а	22.92	11.585	u	g	СС	v	0.040	t	f	0	f	g	1349	+	Approved
8	b	54.42	0.500	у	р	k	h	3.960	t	f	0	f	g	314	+	Approved
9	b	42.50	4.915	у	р	W	v	3.165	t	f	0	t	g	1442	+	Approved

## Data Cleaning

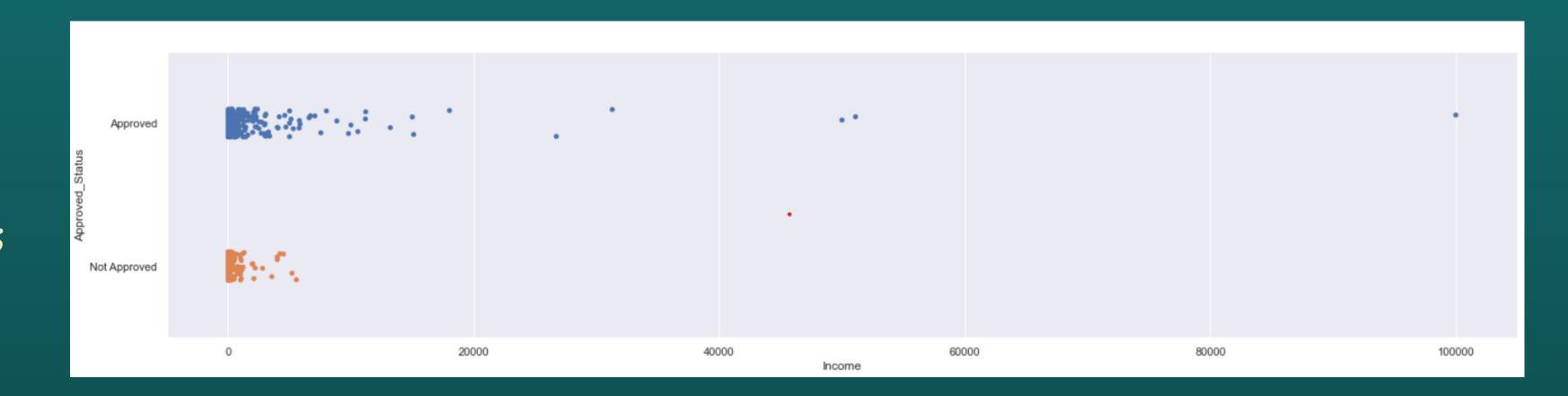
#### Handling with:

- NULL values 1.7%
- ambiguous features due to confidentiality (Education level & Ethnicity)

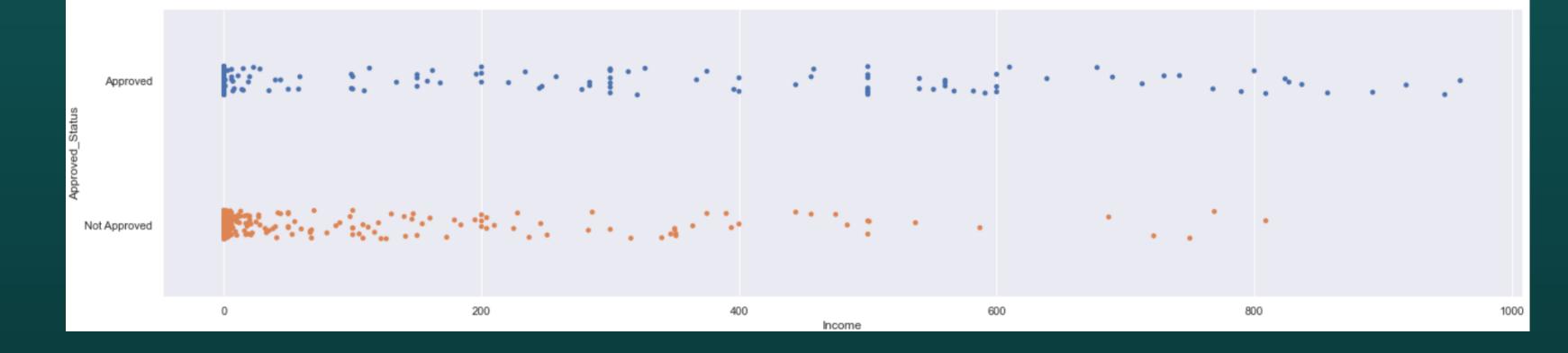
## Exploratory Analysis

## Numerical Data

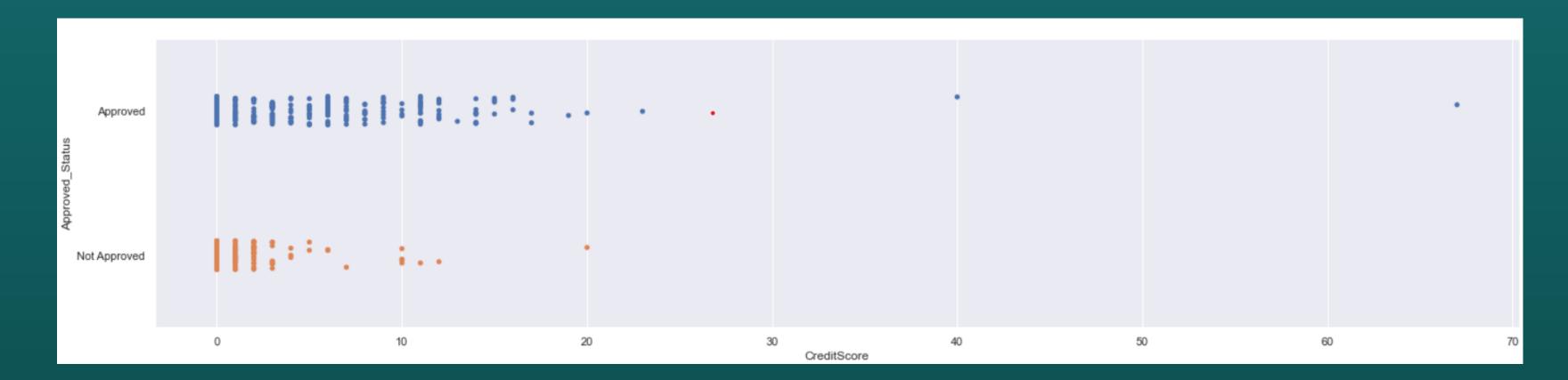
#### Income With Outliers



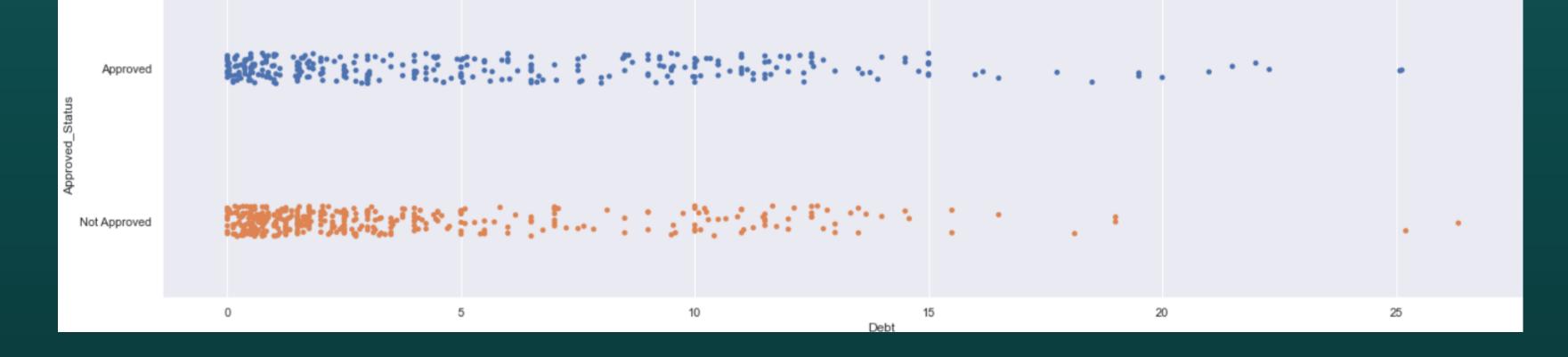




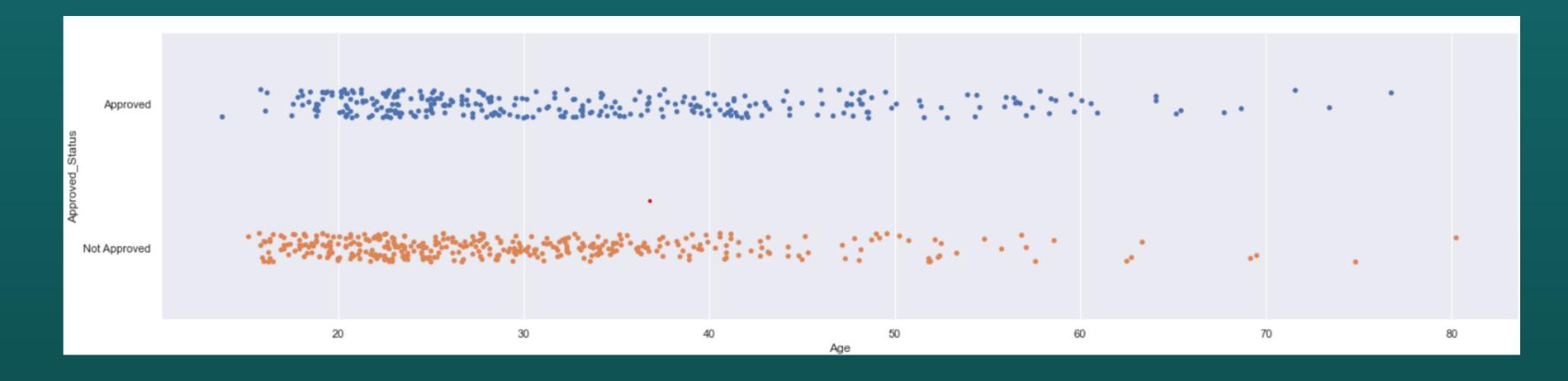
#### Credit



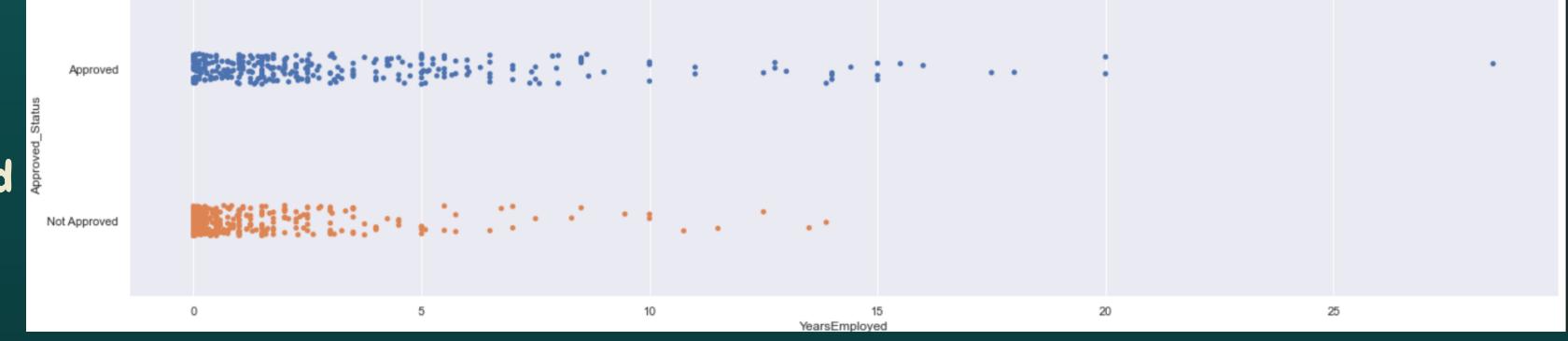




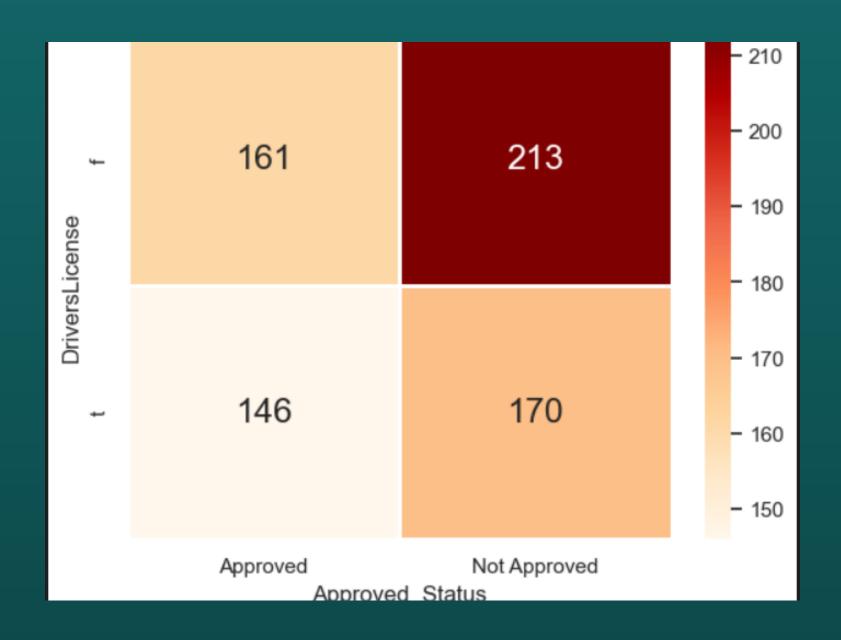


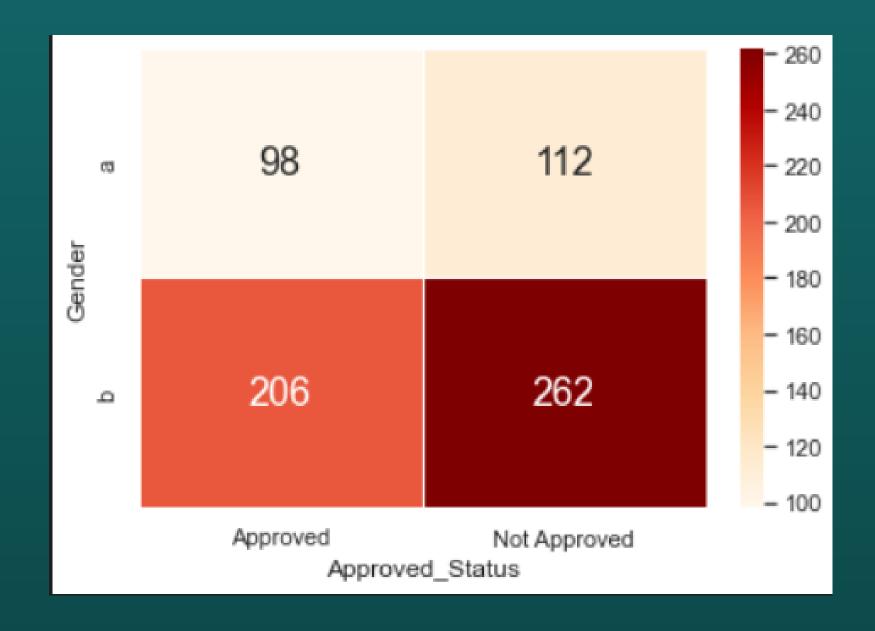






# Categorical Data





#### Drivers License

#### Gender

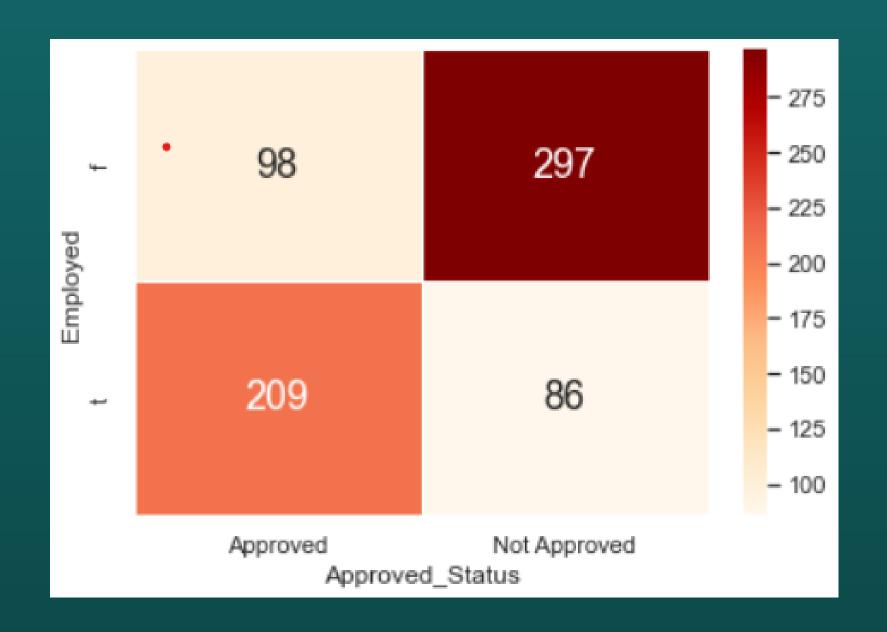




Citizen

## Marital Status





#### PriorDefault

## Employed

- From a data set with a balanced number of values in the response variable, we tried to train some classification models to get better predictions.
- After a few attempts of model training using different approaches, we managed to improve the accuracy from about 0.81 to 0.89 on average.
- The highest attempt is with an accuracy of 0.91, with low false positive and low false negative rate.

#### Attempt 1: Decision Tree

Test Data

Accuracy: 0.8382352941176471

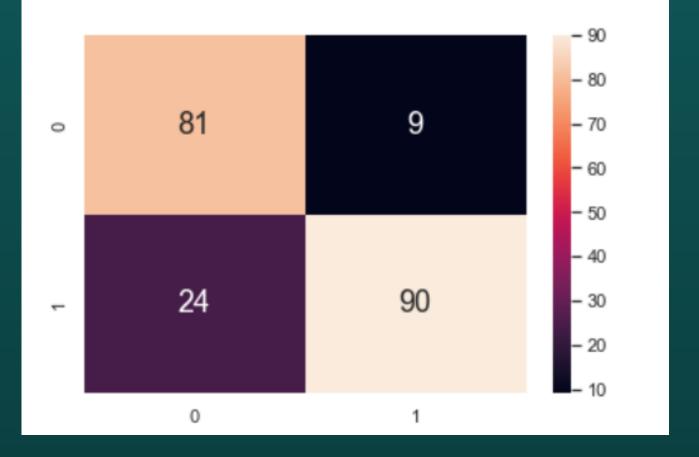
TPR Test: 0.7894736842105263

TNR Test: 0.9

FPR Test: 0.1

FNR Test: 0.21052631578947367

Precision: 0.7714 Recall: 0.9000 F-score: 0.8308



#### Attempt 2: Random Forest Classifier (Cross-Validation)

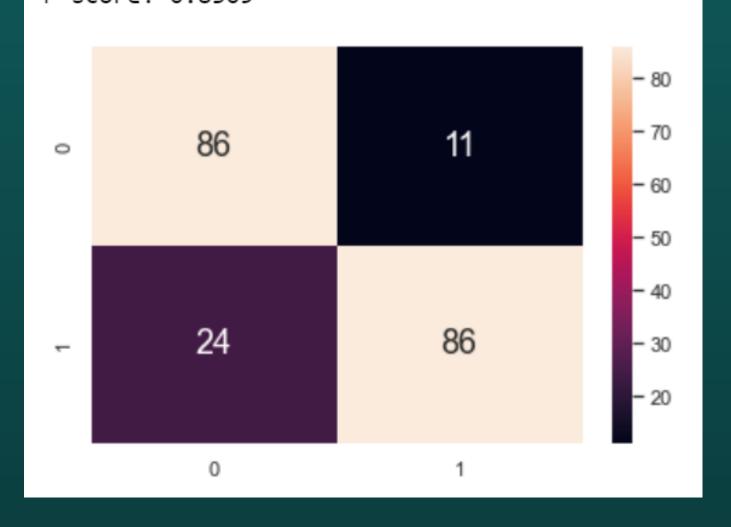
Train Accuracy: 0.865424430641822

Test Accuracy: 0.8309178743961353

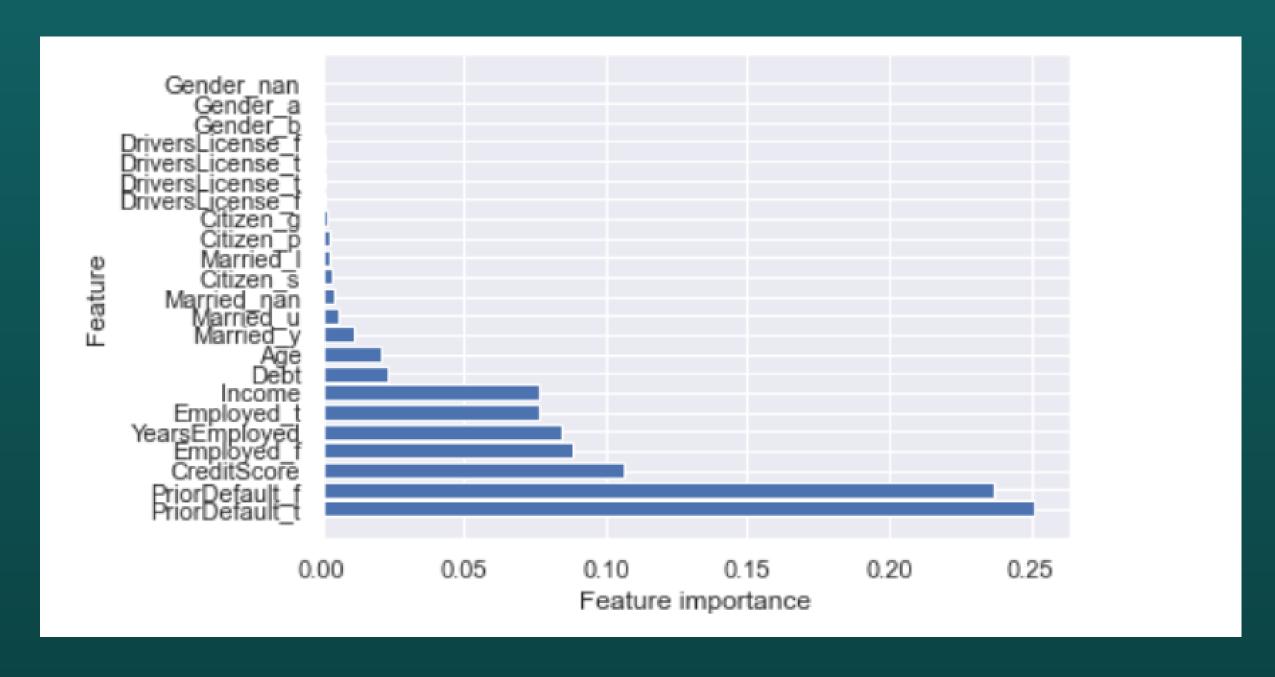
Current accuracy on the test set = 0.83 We try to improve this! TPR Test: 0.7818181818181819
TNR Test: 0.8865979381443299

FPR Test: 0.1134020618556701 FNR Test: 0.218181818181817

Precision: 0.7818 Recall: 0.8866 F-score: 0.8309



#### Figure out Features with Higher Importance



From the graph, we extract some of the more important features:

- i. Numerical Predictors: Debt, Income, Credit\_Score, Years\_Employed,
- ii. Categorical Predictors: Employed, Prior\_Default

## Attempt 3: Logistic Regression with the extracted predictors

Train Data

Accuracy: 0.8840579710144928

Test Data

Accuracy: 0.8502415458937198

TPR Train : 0.8754578754578755
TNR Train : 0.8952380952380953

FPR Train : 0.10476190476190476 FNR Train : 0.12454212454212454

Precision: 0.8468 Recall: 0.8952 F-score: 0.8704



## Attempt 4: Random Forest Classifier (cross-validation) using the extracted predictors

Test Data

Accuracy: 0.9135135135135135

TPR Test: 0.8804347826086957

TNR Test: 0.946236559139785

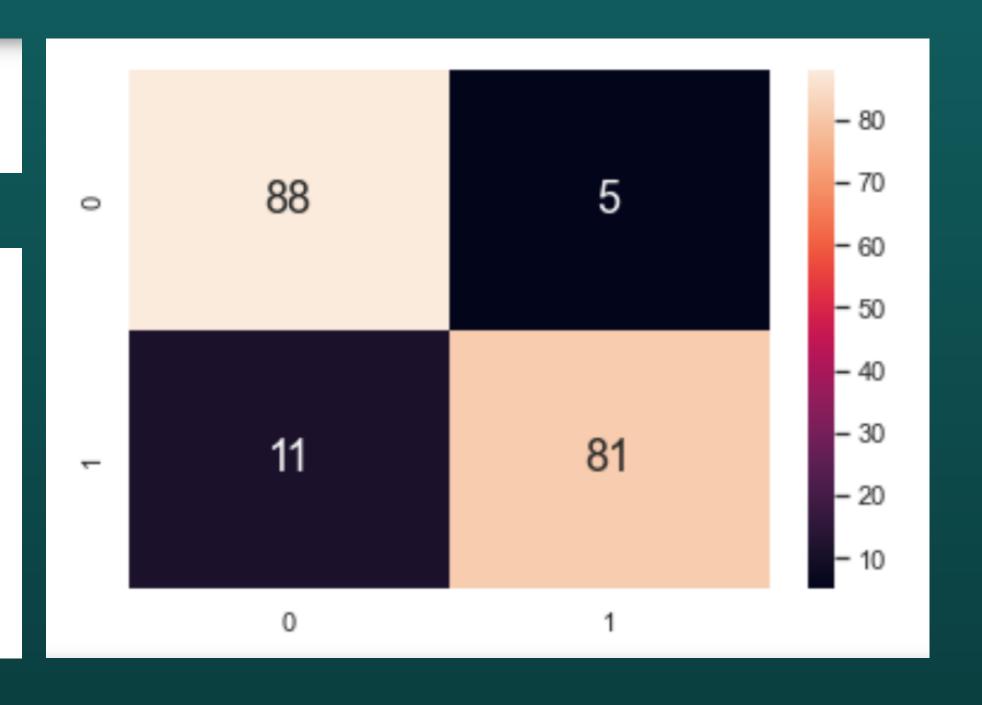
FPR Test: 0.053763440860215055

FNR Test: 0.11956521739130435

Precision: 0.8889

Recall: 0.9462

F-score: 0.9167



#### Conclusion

From our classification model, a credit card application is likely to be approved when:

- debt <= 2.35K,
- income >= 397/month
- being employed
- years of employed of at least 5 years is prefferred,
- no record of prior default (active/passive cancellation of credit card)
- credit score > 2.5