

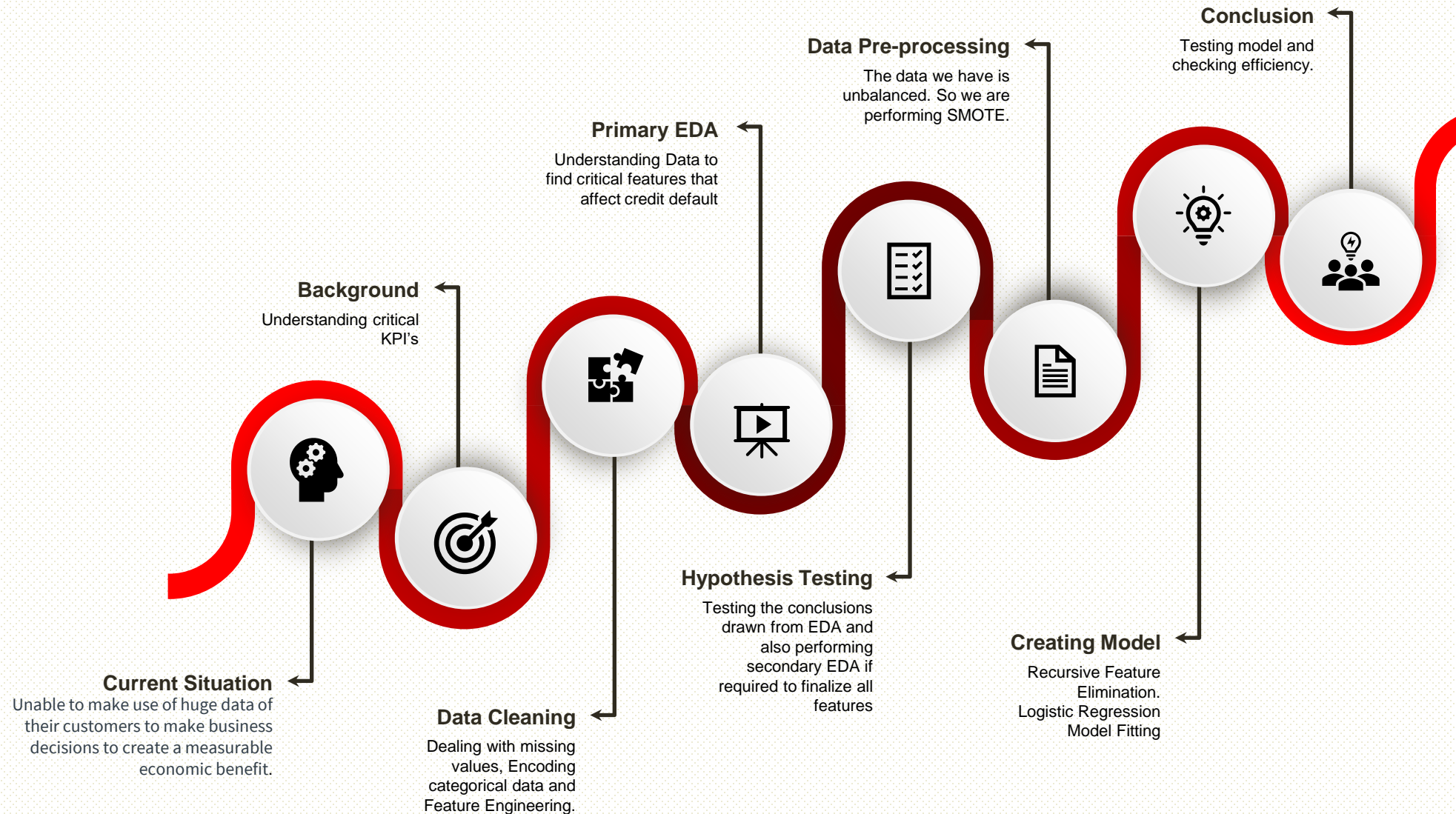


# Credit Default Risk Analysis



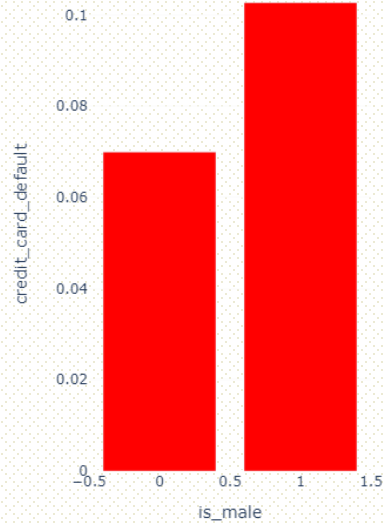
**Team: TISSians**  
**Soumyadeep Pal**  
**Mayuri Jape**

# Methodology

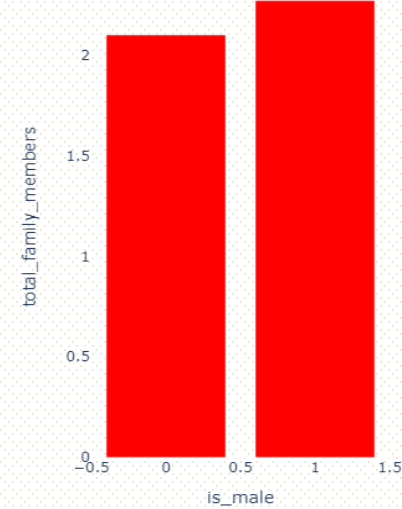


# Gender and Credit Default Risk

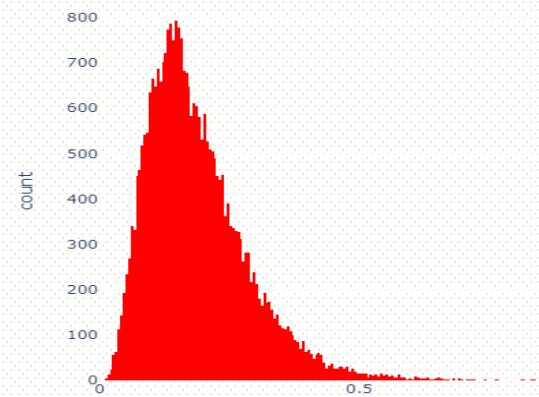
is\_male VS. credit\_card\_default



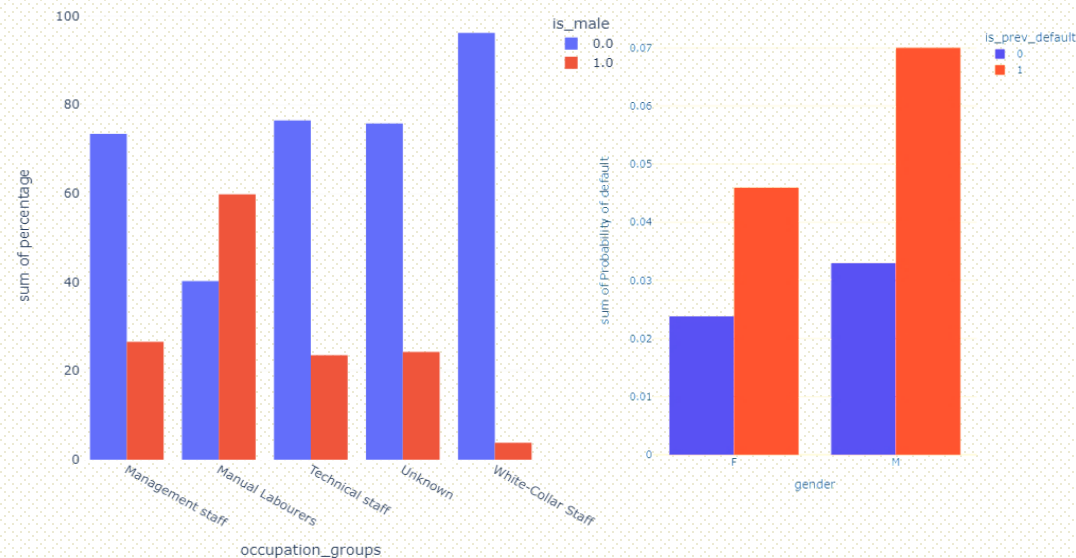
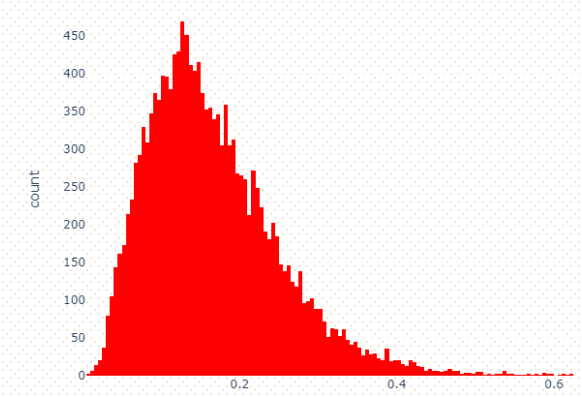
is\_male VS. total\_family\_members



debt-to-income of F



debt-to-income of M



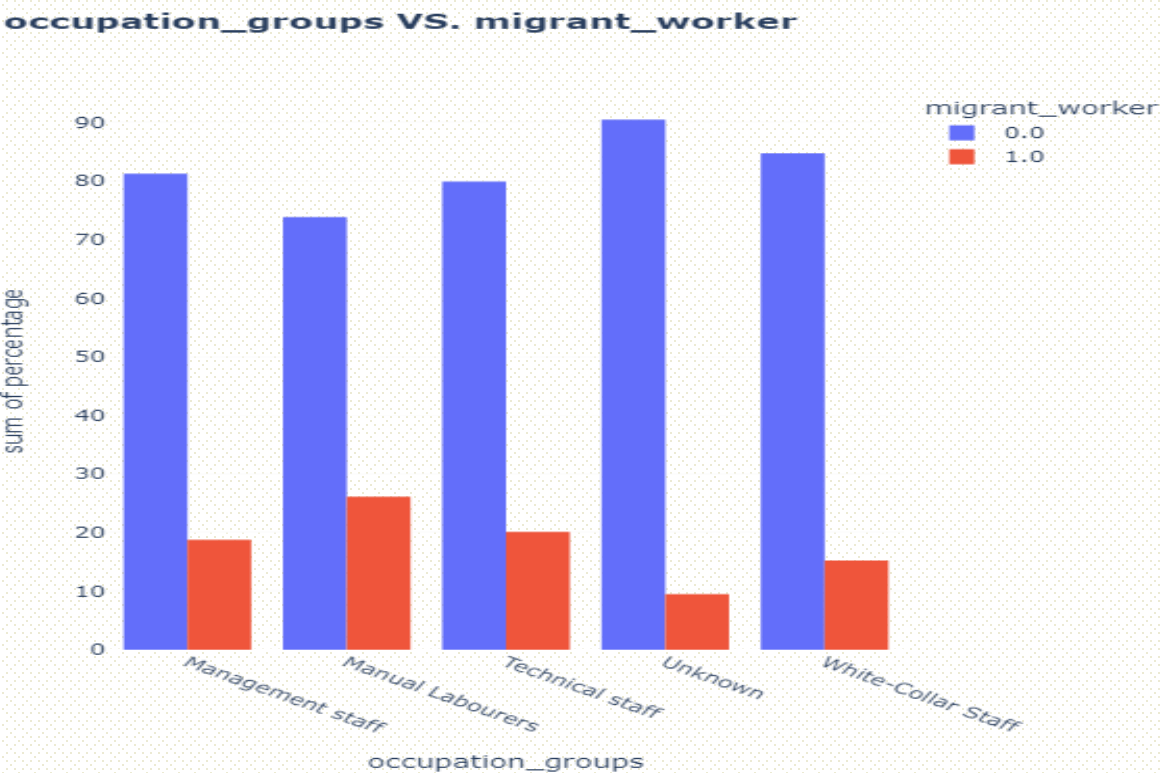
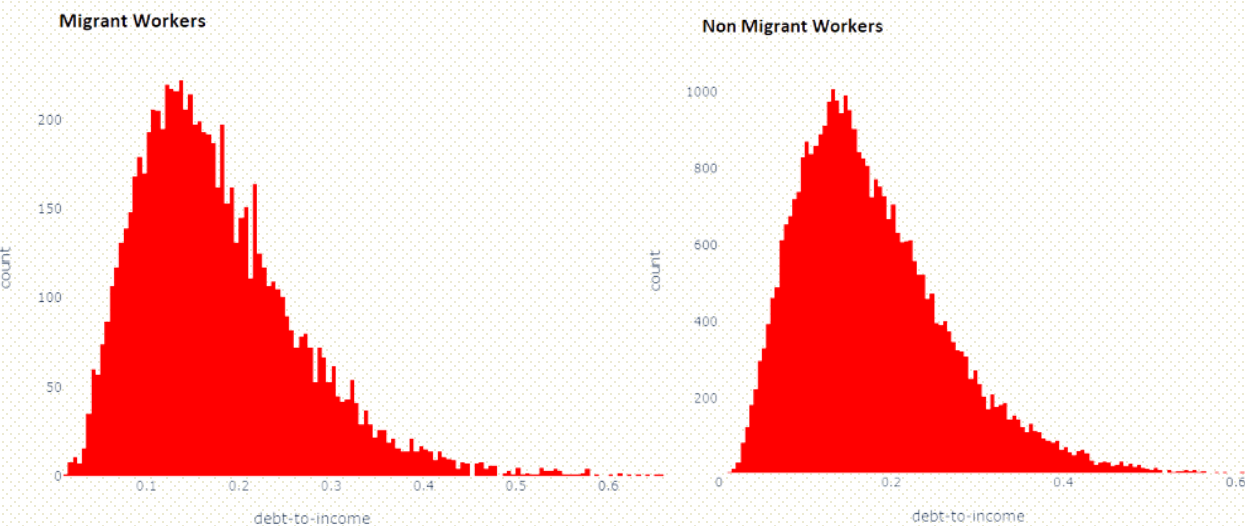
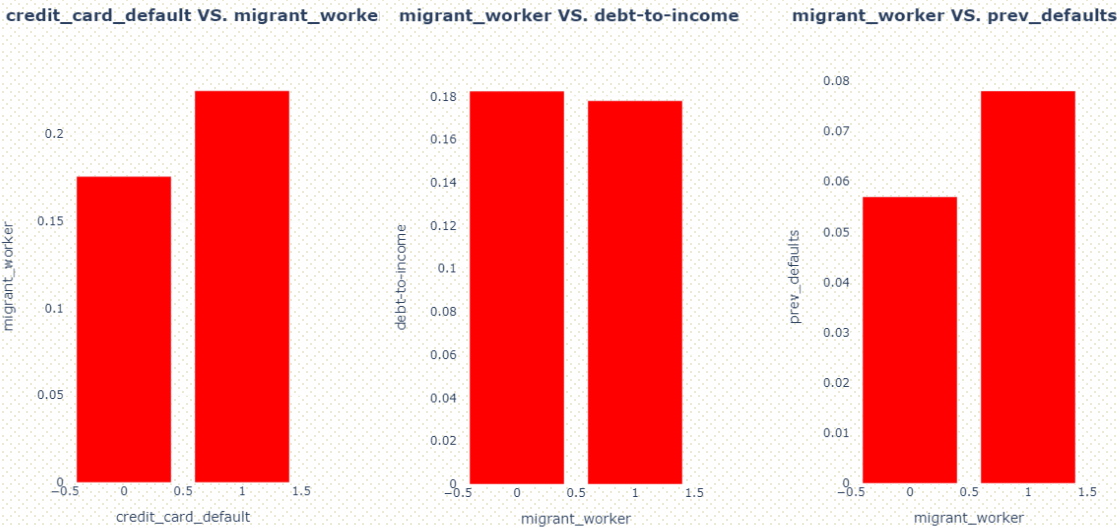
## Insight

Male consumers are seen to have higher probability to default, due to probable reasons like manual labor has greater percentage of men working in it implying lesser income. Men have less skewed debt-to-income ratio distribution that might be the case because men have on an average higher number of family members. Male individuals also have the higher probability to default the bill provided, they have already defaulted in the past.

# Migrant workers

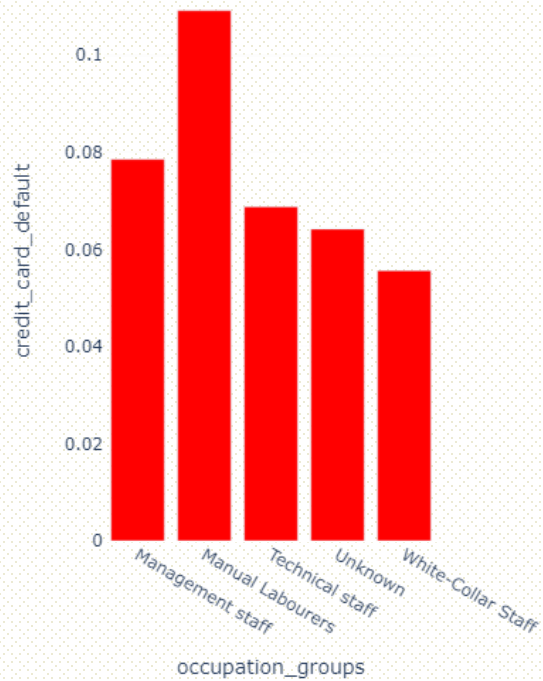
## Insight

Migrant workers have a significantly high probability to default, owing to their occupation type where in manual laborer occupation type have the higher percentage of migrant workers. It is also evident from the graphs that non migrant workers on an average, have a lower debt to income ratio but the distribution of migrant workers is less skewed showing there are relatively more number of migrant workers with high debt to income ratio.

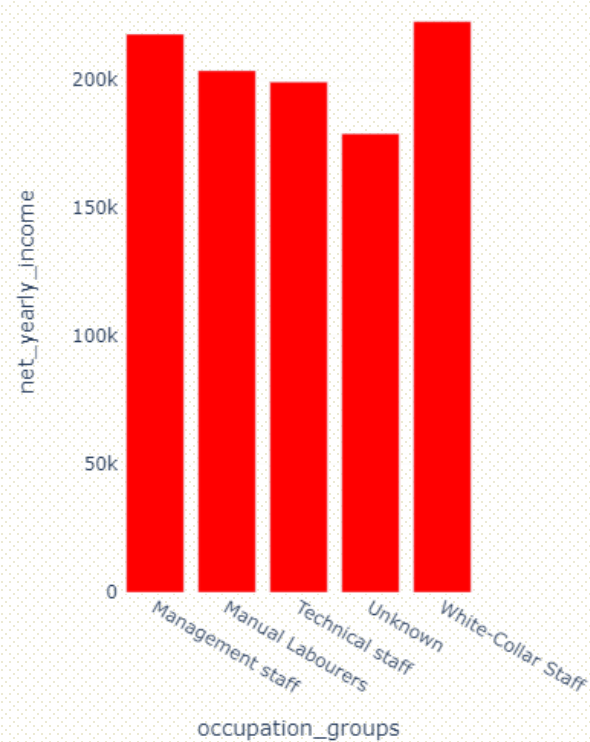


# Occupation Type

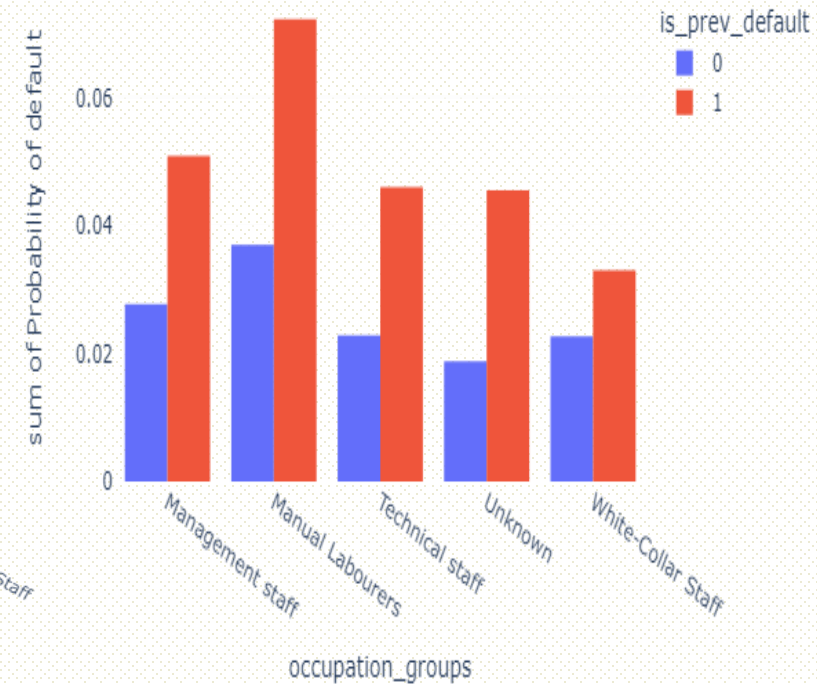
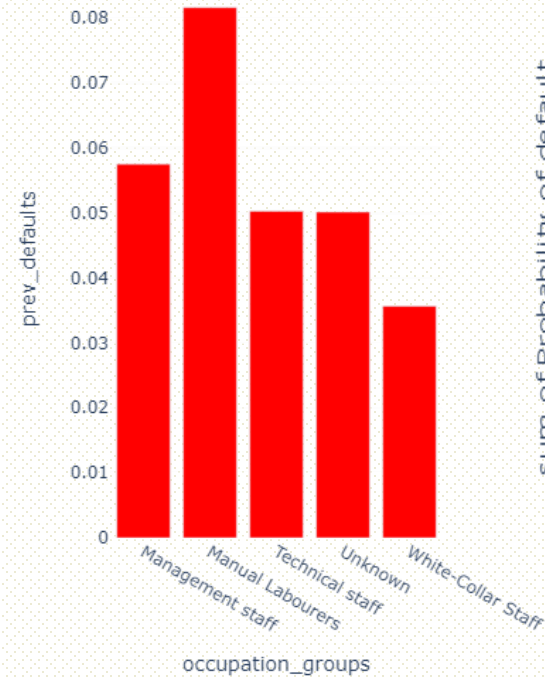
occupation\_groups VS. credit\_card\_defi



occupation\_groups VS. net\_yearly\_inco



occupation\_groups VS. prev\_defaults



## Insight

Manual Laborers have significantly higher probability of default as compared to other occupation types owing to higher proportion of previous defaults, lower income. This could be because most manual labors have lower income and job security and are daily earners hence their chances of defaulting increases.

# Critical Factors

- **Gender:** The analysis showed that male customers have a higher probability of defaulting compared to female customers. This suggests that gender is an important factor to consider when evaluating credit risk.
- **Occupation Type:** Manual laborers were found to have a significantly higher probability of default compared to other occupation types. This implies that occupation type is an important factor to consider when evaluating credit risk.
- **Migrant Status:** Migrant workers were found to have a significantly higher probability of default compared to non-migrant workers. This suggests that migration status is an important factor to consider when evaluating credit risk.
- **Previous Defaults:** Customers who had defaulted on payments in the past were found to have a higher probability of defaulting in the future. This highlights the importance of considering an individual's past credit history when evaluating credit risk.
- **Debt-to-Income Ratio:** The debt-to-income ratio was found to be an important factor in predicting credit default, with customers who have a higher debt-to-income ratio having a higher probability of default.
- **Credit Score:** The credit score was also found to be an important factor in predicting credit default, with customers who have a lower credit score having a higher probability of default.

# Business Recommendations

- **Customized Product Offerings:** The company can customize its product offerings based on the needs and preferences of different customer segments. For example, the company could offer credit products that have flexible repayment options for manual laborers, who may have irregular income. Similarly, the company could offer credit products that have lower interest rates for migrant workers, who may have limited access to credit.
- **Credit Counselling:** The company can offer credit counseling services to help customers manage their debt and avoid default. This could be especially helpful for manual laborers and migrant workers, who may have limited financial literacy and access to financial resources.
- **Risk Mitigation Strategies:** The company can implement risk mitigation strategies to minimize the impact of default. For example, the company could diversify its portfolio by offering credit products to customers in different industries or with different risk profiles. Similarly, the company could implement credit risk scoring models to better assess the creditworthiness of customers and avoid high-risk customers.
- **Customer Retention:** The company can focus on customer retention by offering incentives and rewards to customers who maintain a good credit history and repay their debts on time. This can help to reduce the overall risk of default and increase the lifetime value of customers.

# Model Building

## LOGISITIC REGRESSION

Significant features observed with p-value < 0.05

Net yearly income, number of days employed, yearly debt payments, credit limit, credit limit used, credit score, gender, Is the individual owning a house

	Coef.	Std.Err.	z	P> z	[0.025	0.975]
const	47.8990	0.9158	52.3004	0.0000	46.1040	49.6941
net_yearly_income	-0.0000	0.0000	-3.4056	0.0007	-0.0000	-0.0000
no_of_days_employed	-0.0000	0.0000	-5.5628	0.0000	-0.0000	-0.0000
yearly_debt_payments	0.0000	0.0000	2.7848	0.0054	0.0000	0.0000
credit_limit	0.0000	0.0000	2.1332	0.0329	0.0000	0.0000
credit_limit_used(%)	0.1033	0.0023	44.8675	0.0000	0.0987	0.1078
credit_score	-0.0820	0.0014	-58.5094	0.0000	-0.0847	-0.0792
is_male	0.5941	0.0640	9.2850	0.0000	0.4687	0.7195
is_owns_house	-0.9856	0.0590	-16.6995	0.0000	-1.1013	-0.8700

### 01 MODEL INTERPRETATION

Male individuals have higher Chances of defaulting.

An individual owning house has lower chances of defaulting.

Increased credit limit use

Indicate higher chances of default.

### 02 MODEL METRICS

Recall – 0.92

Precision – 0.99

Overall Accuracy – 0.93

### 03 OPTIMAL THRESHOLD

YODEN's INDEX - 0.918078

Optimal Cut-off - 0.15



# Future Scope



**Incorporate Historical Data:** To test the efficiency of the current model, as compared to what they used to predict before.

- **Expand Feature Set:** The company can consider adding additional variables that may impact the probability of credit default. For example, adding marital status or education level as a feature can help to identify whether these variables impact the likelihood of credit default. The company should incorporate credit amount in the data that will ensure analysis of loss due to default.

**Ongoing Model Monitoring:** The company can implement ongoing monitoring and evaluation of the model's performance to ensure that it remains effective and aligned with the company's overall business goals. This can involve regularly reviewing the model's accuracy and adjusting the feature set as needed to improve its predictive power.



# THANK YOU!

