

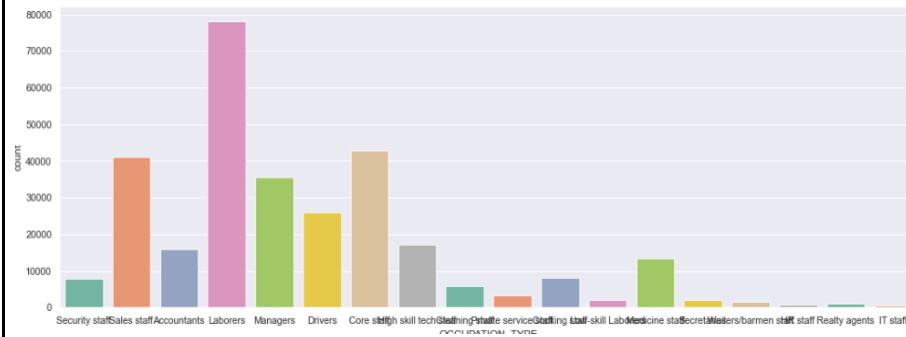
Data Collection and Preprocessing Phase

Date	10 July 2024
Team ID	739722
Project Title	Credit card approval prediction using ML
Maximum Marks	6 Marks

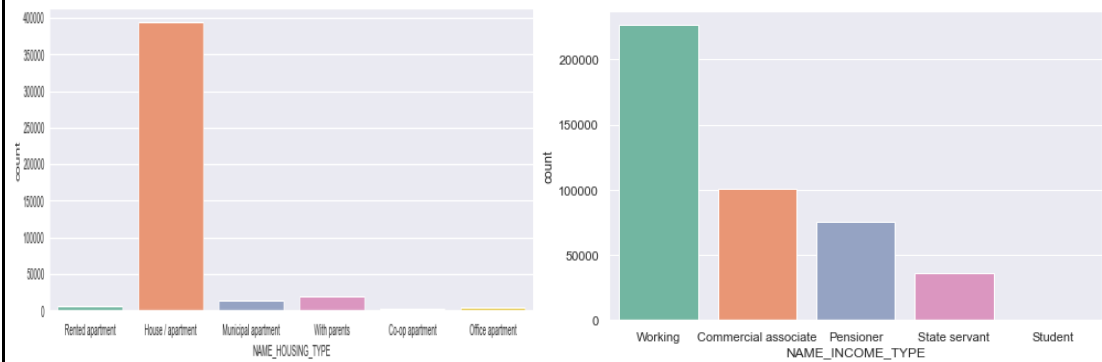
Data Exploration and Preprocessing Report

Dataset variables will be statistically analyzed to identify patterns and outliers, with Python employed for preprocessing tasks like normalization and feature engineering. Data cleaning will address missing values and outliers, ensuring quality for subsequent analysis and modelling, and forming a strong foundation for insights and predictions.

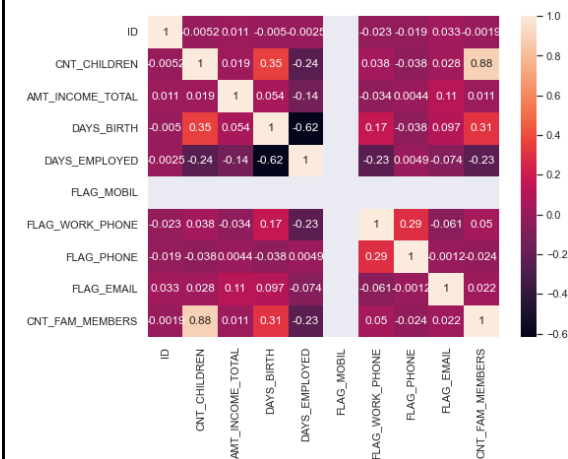
Section	Description																																																																																	
Data Overview	<u>Dimension:</u> 614 rows × 13 columns																																																																																	
	<u>Descriptive statistics:</u>																																																																																	
	<table><tr><th>Feature</th><th>Count</th><th>Mean</th><th>Std</th><th>Min</th><th>25%</th><th>50%</th><th>75%</th><th>Max</th></tr><tr><td>ApplicantIncome</td><td>614</td><td>5403.46</td><td>6109.04</td><td>150</td><td>2877.50</td><td>3812.50</td><td>5795.00</td><td>81000</td></tr><tr><td>CoapplicantIncome</td><td>614</td><td>1621.25</td><td>2926.25</td><td>0</td><td>0.00</td><td>1186.50</td><td>2297.25</td><td>41667</td></tr><tr><td>LoanAmount</td><td>592</td><td>146.41</td><td>85.59</td><td>9</td><td>100.00</td><td>128.00</td><td>168.00</td><td>700</td></tr><tr><td>Loan_Amount_Term</td><td>600</td><td>342.00</td><td>65.12</td><td>12</td><td>360.00</td><td>360.00</td><td>360.00</td><td>480</td></tr><tr><td>Credit_History</td><td>564</td><td>0.842</td><td>0.365</td><td>0</td><td>1.00</td><td>1.00</td><td>1.00</td><td>1</td></tr><tr><td>Age</td><td>614</td><td>35.5</td><td>8.7</td><td>18</td><td>28.0</td><td>35.0</td><td>43.0</td><td>60</td></tr><tr><td>Dependents</td><td>614</td><td>0.5</td><td>0.7</td><td>0</td><td>0.0</td><td>0.0</td><td>1.0</td><td>3</td></tr><tr><td>Approval_Status</td><td>614</td><td>0.69</td><td>0.46</td><td>0</td><td>0.00</td><td>1.00</td><td>1.00</td><td>1</td></tr></table>	Feature	Count	Mean	Std	Min	25%	50%	75%	Max	ApplicantIncome	614	5403.46	6109.04	150	2877.50	3812.50	5795.00	81000	CoapplicantIncome	614	1621.25	2926.25	0	0.00	1186.50	2297.25	41667	LoanAmount	592	146.41	85.59	9	100.00	128.00	168.00	700	Loan_Amount_Term	600	342.00	65.12	12	360.00	360.00	360.00	480	Credit_History	564	0.842	0.365	0	1.00	1.00	1.00	1	Age	614	35.5	8.7	18	28.0	35.0	43.0	60	Dependents	614	0.5	0.7	0	0.0	0.0	1.0	3	Approval_Status	614	0.69	0.46	0	0.00	1.00	1.00	1
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Bivariate Analysis



Multivariate Analysis



Outliers and Anomalies	-																																																																														
Data Preprocessing Code Screenshots																																																																															
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Handling Missing Data	<pre>data['Gender'] = data['Gender'].fillna(data['Gender'].mode()[0]) data['Marital_Status'] = data['Marital_Status'].fillna(data['Marital_Status'].mode()[0]) # Replacing + with space for filling the NaN values data['Dependents'] = data['Dependents'].str.replace('+', ' ') data['Dependents'] = data['Dependents'].fillna(data['Dependents'].mode()[0]) data['Dependents'] = data['Dependents'].fillna(data['Dependents'].mode()[0]) data['Self_Employed'] = data['Self_Employed'].fillna(data['Self_Employed'].mode()[0]) data['ApplicantIncome'] = data['ApplicantIncome'].fillna(data['ApplicantIncome'].mean()) data['LoanAmount'] = data['LoanAmount'].fillna(data['LoanAmount'].mean()) data['Credit_History'] = data['Credit_History'].fillna(data['Credit_History'].mode()[0])</pre>																																																																														
Data Transformation	<pre>data['Gender'] = data['Gender'].map({'Female': 1, 'Male': 0}) data['Married'] = data['Married'].map({'Yes': 1, 'No': 0}) data['Dependents'] = data['Dependents'].map({'0': 0, '1': 1, '2': 2, '3+': 3}) data['Education'] = data['Education'].map({'Graduate': 1, 'Not Graduate': 0}) data['Self_Employed'] = data['Self_Employed'].map({'Yes': 1, 'No': 0}) data['Property_Area'] = data['Property_Area'].map({'Urban': 2, 'Semiurban': 1, 'Rural': 0}) data['Loan_Status'] = data['Loan_Status'].map({'Y': 1, 'N': 0}) # Performing feature scaling using StandardScaler scaler = StandardScaler() X_scaled = scaler.fit_transform(X)</pre>																																																																														
Feature Engineering	Attached the codes in final submission.																																																																														
Save Processed Data	-																																																																														