

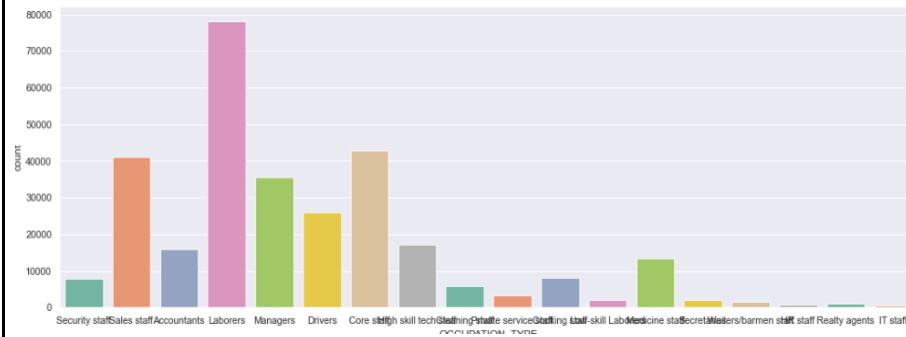
Data Collection and Preprocessing Phase

Date	10 July 2024
Team ID	739835
Project Title	Credit card approval prediction using ML
Maximum Marks	6 Marks

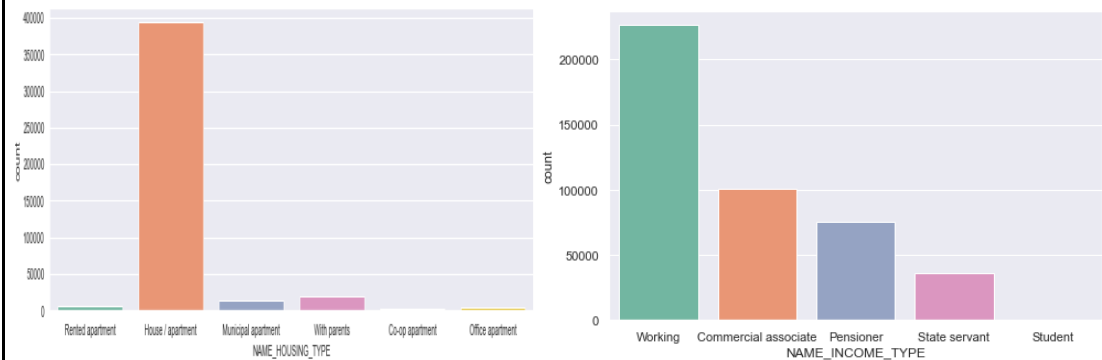
Data Exploration and Preprocessing Report

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.

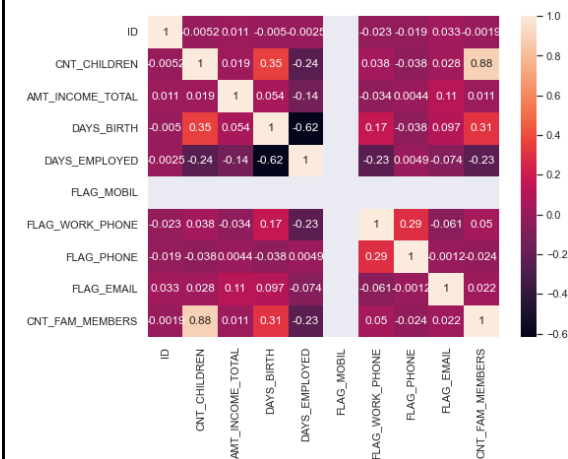
Section	Description																																																																																	
Data Overview	<u>Dimension:</u> 614 rows × 13 columns <u>Descriptive statistics:</u>																																																																																	
	<table><tr><th>Feature</th><th>Count</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																																																																															
Loading Data	<table><thead><tr><th></th><th>ID</th><th>CODE</th><th>GENDER</th><th>FLAG_OWN_CAR</th><th>FLAG_OWN_REALTY</th><th>CNT_CHILDREN</th><th>AMT_INCOME_TOTAL</th><th>NAME_INCOME_TYPE</th><th>NAME_EDUCATION_TYPE</th><th>NAME_FAMILY_STATUS</th><th>NAME_HOUSING_TYPE</th><th>DAYS_BIRTH</th></tr></thead><tbody><tr><td>0</td><td>5008804</td><td></td><td>M</td><td>Y</td><td>Y</td><td>0</td><td>427500.0</td><td>Working</td><td>Higher education</td><td>Civil marriage</td><td>Rented apartment</td><td>-12005</td></tr><tr><td>1</td><td>5008805</td><td></td><td>M</td><td>Y</td><td>Y</td><td>0</td><td>427500.0</td><td>Working</td><td>Higher education</td><td>Civil marriage</td><td>Rented apartment</td><td>-12005</td></tr><tr><td>2</td><td>5008806</td><td></td><td>M</td><td>Y</td><td>Y</td><td>0</td><td>112500.0</td><td>Working</td><td>Secondary / secondary special</td><td>Married</td><td>House / apartment</td><td>-21474</td></tr><tr><td>3</td><td>5008808</td><td></td><td>F</td><td>N</td><td>Y</td><td>0</td><td>270000.0</td><td>Commercial associate</td><td>Secondary / secondary special</td><td>Single / not married</td><td>House / apartment</td><td>-19110</td></tr><tr><td>4</td><td>5008809</td><td></td><td>F</td><td>N</td><td>Y</td><td>0</td><td>270000.0</td><td>Commercial associate</td><td>Secondary / secondary special</td><td>Single / not married</td><td>House / apartment</td><td>-19110</td></tr></tbody></table>		ID	CODE	GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSING_TYPE	DAYS_BIRTH	0	5008804		M	Y	Y	0	427500.0	Working	Higher education	Civil marriage	Rented apartment	-12005	1	5008805		M	Y	Y	0	427500.0	Working	Higher education	Civil marriage	Rented apartment	-12005	2	5008806		M	Y	Y	0	112500.0	Working	Secondary / secondary special	Married	House / apartment	-21474	3	5008808		F	N	Y	0	270000.0	Commercial associate	Secondary / secondary special	Single / not married	House / apartment	-19110	4	5008809		F	N	Y	0	270000.0	Commercial associate	Secondary / secondary special	Single / not married	House / apartment	-19110
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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	-																																																																														