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Credit EDA Case Study

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Introduction

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This assignment aims to give you an idea of applying EDA in a real business scenario. In this assignment, apart from applying the techniques that you have learnt in the EDA module, you will also develop a basic understanding of risk analytics in banking and financial services and understand how data is used to minimise the risk of losing money while lending to customers.

Objective

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Use EDA to analyze loan application data and identify patterns to help decide loan approvals.

Actions:

- ✓ Deny the loan
- ✓ Reduce the loan amount
- ✓ Offer higher interest rates to risky applicants

Goals

- ✓ Ensure capable consumers are approved
- ✓ Identify strong indicators of loan default (driver variables)
- ✓ Utilize findings for portfolio and risk assessment
- ✓ Recommendation: Research risk analytics to understand variable types and their significance.

Overview

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Context

- ✓ Loan companies struggle to approve loans due to applicants' insufficient or non-existent credit history.
- ✓ Some consumers exploit this by defaulting on loans.
- ✓ Your task is to help a consumer finance company specializing in urban loans analyze data to ensure capable applicants are approved.

Risks

False Rejection

Not approving a loan for an applicant likely to repay results in lost business.

False Approval

Approving a loan for an applicant likely to default results in financial loss.

Data Scenarios

Clients with Payment Difficulties

Late payment more than X days on at least one of the first Y installments.

Clients with Timely Payments

Payments made on time in all other cases.

Imbalance

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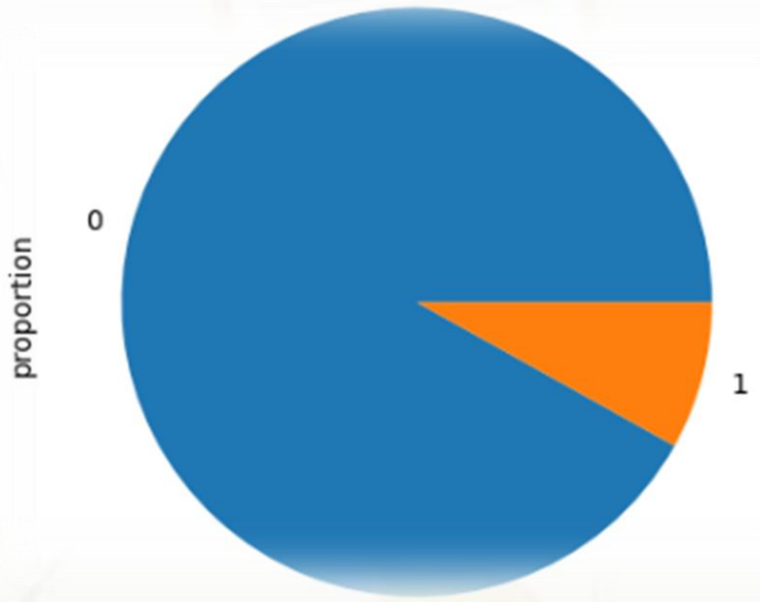

Data imbalance ratio is approximately 20:1 which means we have 20 sample of customer doing payment on time in comparison of 1 sample of customer facing payment difficulty.

Univariate Analysis

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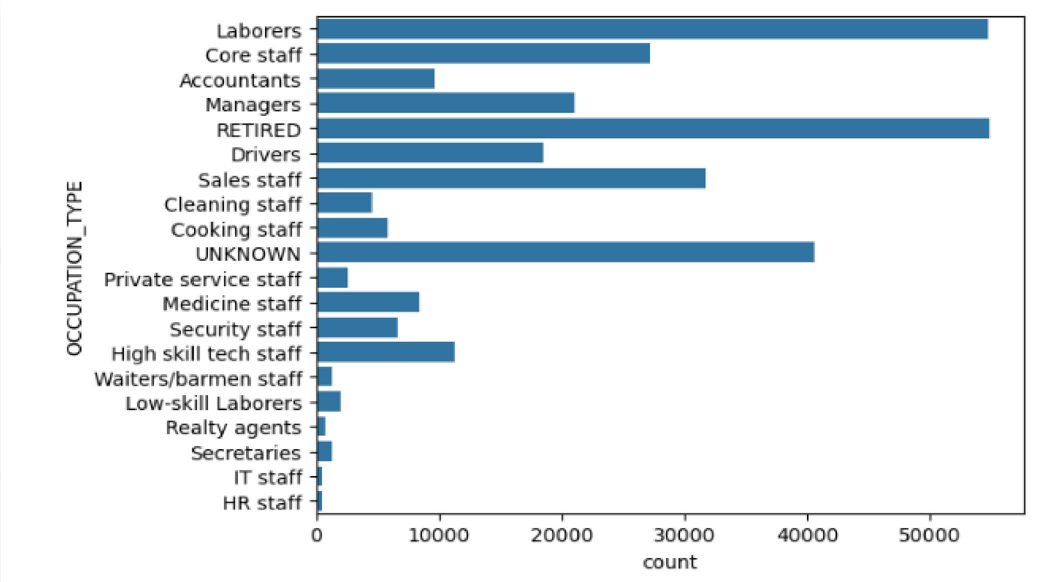
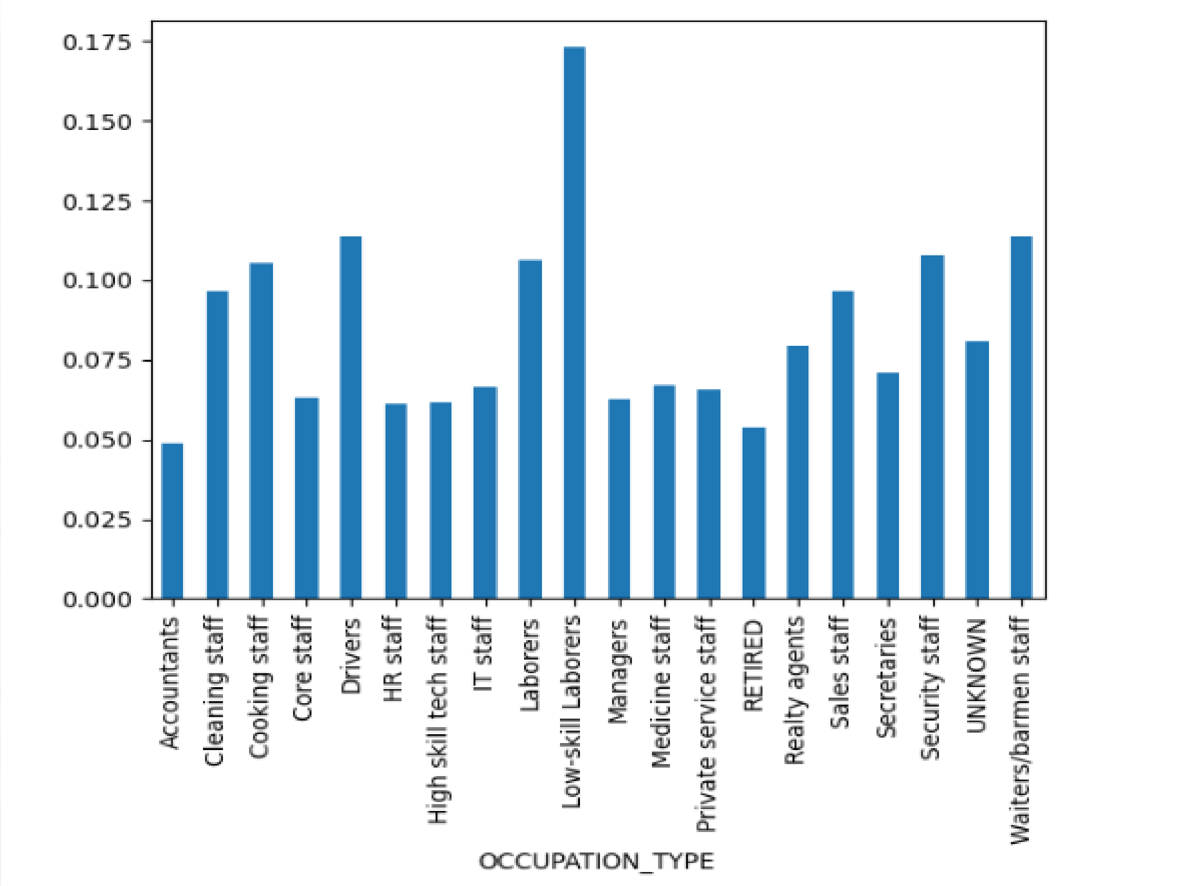




✓Laborers are highest in the applicants list followed by Retired applicants.

✓Graph shows mean payment difficulty by occupation type

✓Low-skill laborers face the highest payment difficulty (~17.5%).

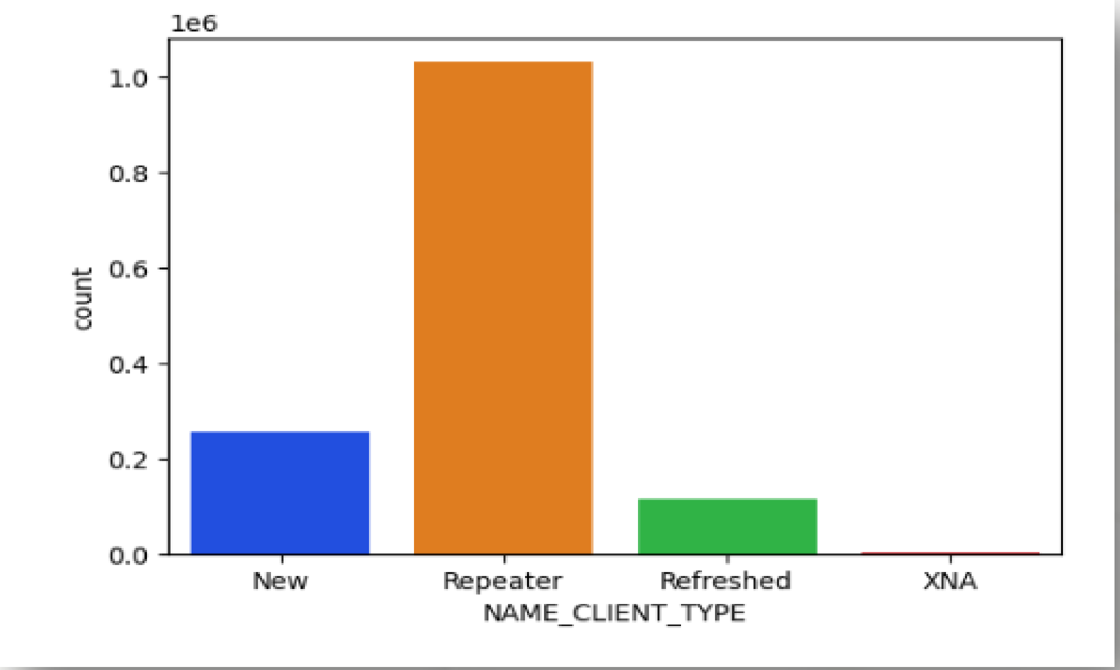
✓Accountants and retired people mostly pay on time.

OCCUPATION_TYPE

Univariate Analysis

NAME_CLIENT_TYPE

✓Repeater are more as compared to the new customers



FLAG_OWN_CAR	FLAG_OWN_REALTY	TARGET	
0	0	0	90.946859
		1	9.053141
	1	0	91.702857
		1	8.297143
1	0	0	92.923058
		1	7.076942
	1	0	92.642271
		1	7.357729

Name: proportion, dtype: float64

✓Image shows payment difficulty percentages based on car or house ownership.

✓Having a car or house does not significantly affect payment difficulties.

✓In all cases, the percentage is around 8%.

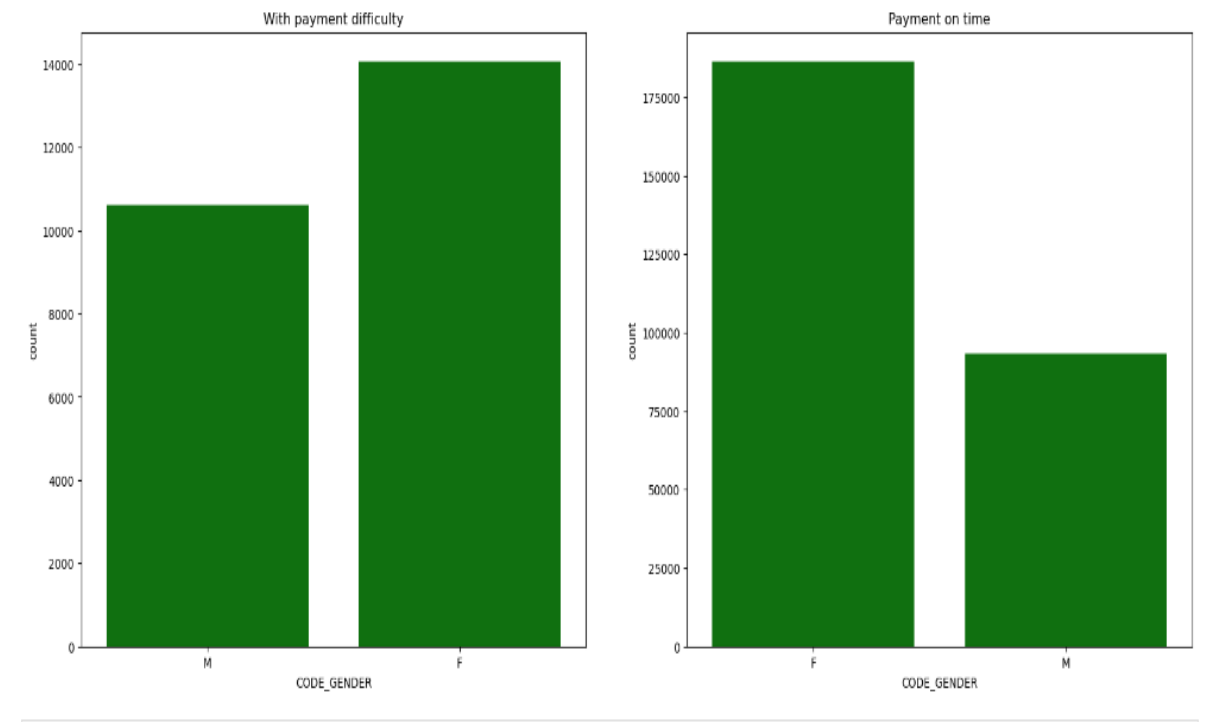
FLAG_OWN_CAR

FLAG_OWN_R EALTY

Univariate Analysis

CODE_GENDER

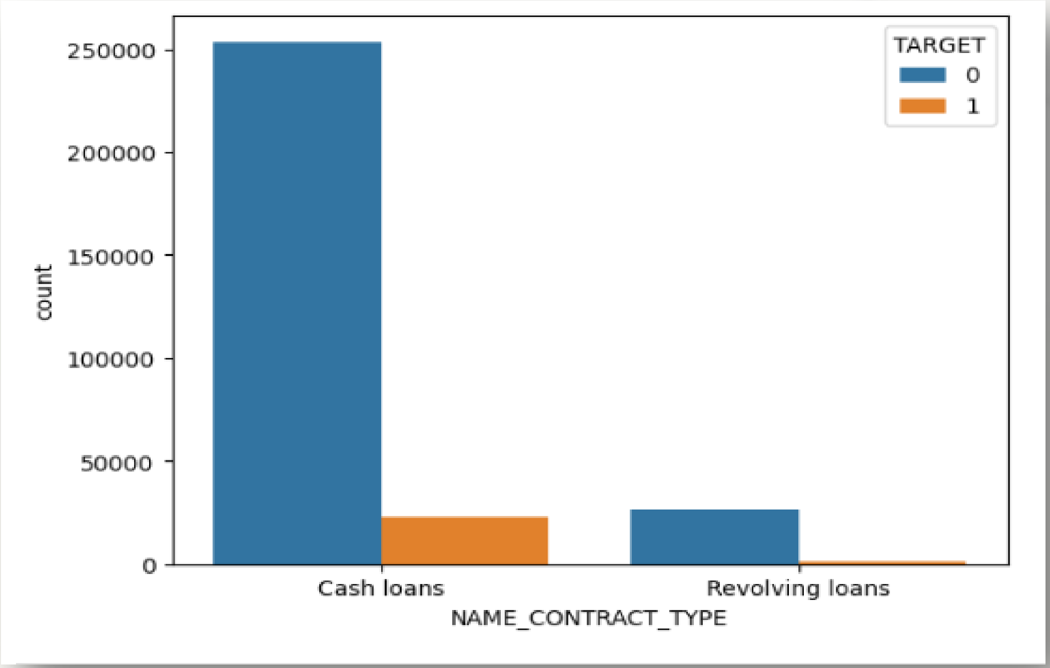
CODE_GENDER	TARGET	
F	0	92.985545
	1	7.014455
M	0	89.808256
	1	10.191744



✓Female applicants outnumber male applicants.

✓Payment difficulty: ~10% for males, ~7% for females.

✓Payment difficulties are similar across genders, with minimal difference.



✓There is not much percentage difference between cash loans and revolving loans regarding payment difficulties.

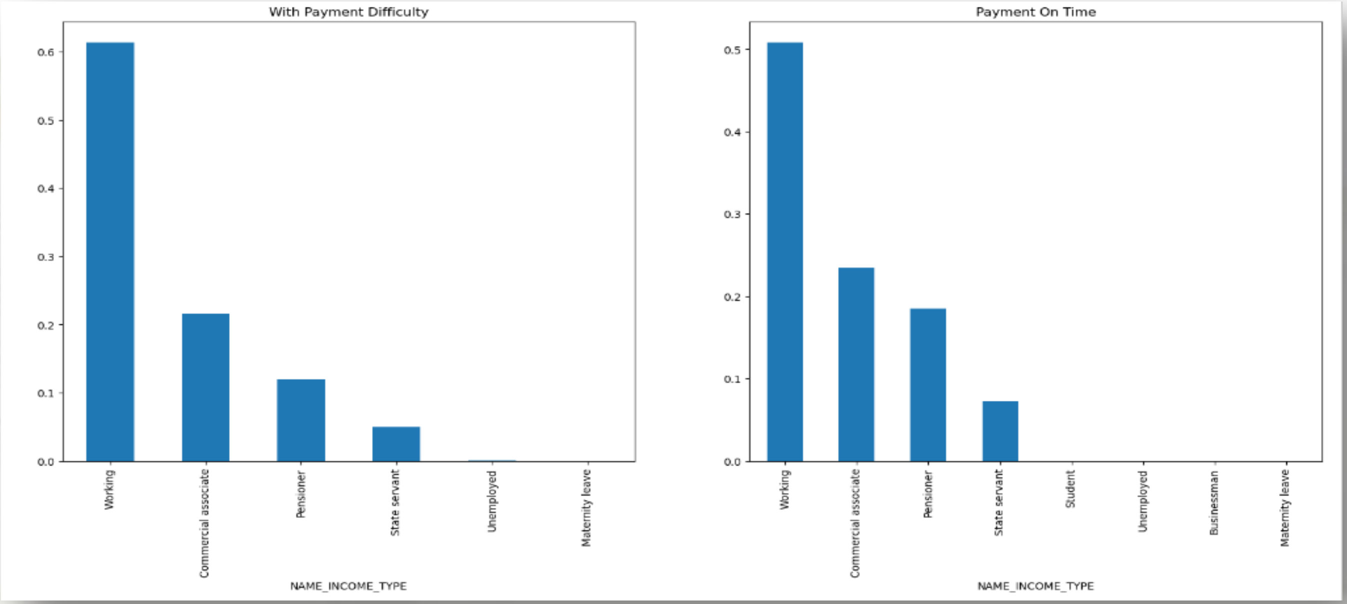
✓In cash loans, 8% of customers experience payment difficulties, while in revolving loans, there are 5%.

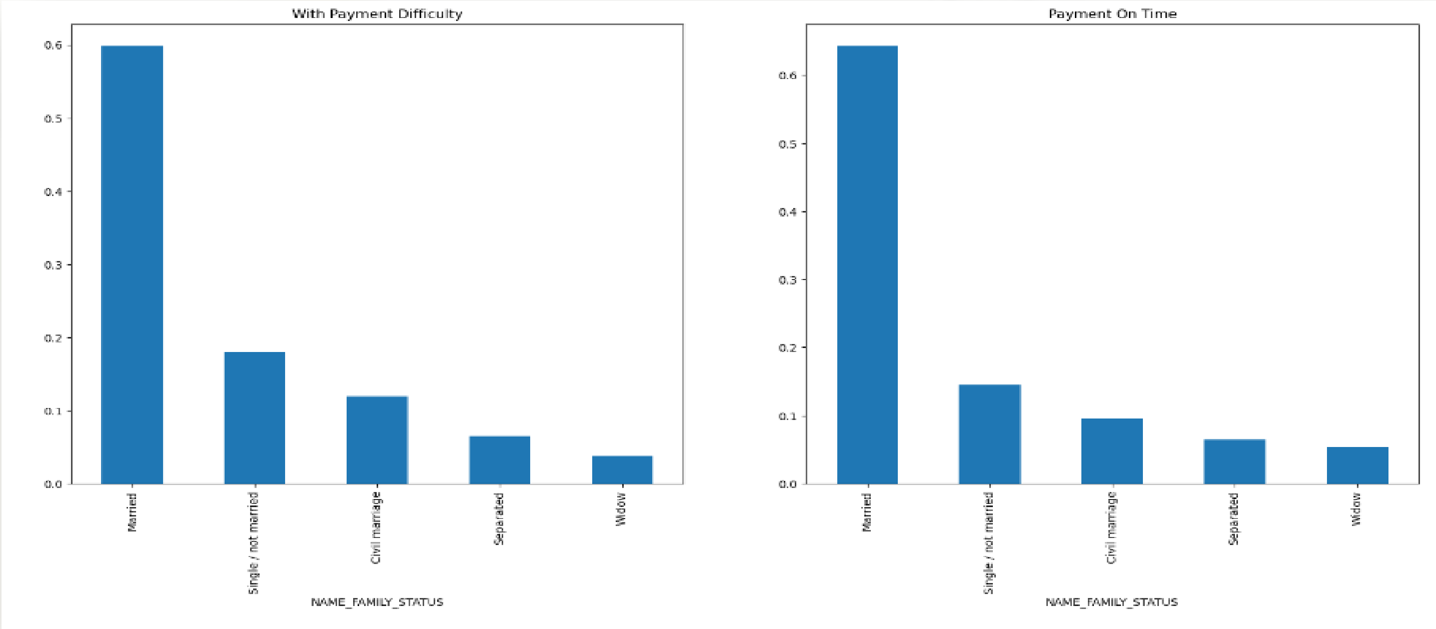
NAME_CONTRACT_TYPE

Bivariate Analysis

NAME_INCOME_TYPE

- ✓ Pensioners and commercial associates mostly make payments on time.
- ✓ Working class customers face the highest payment difficulties.
- ✓ Businessmen, unemployed individuals, students, and those on maternity leave have zero instances of timely payments, but their numbers are few, showing weak correlation.



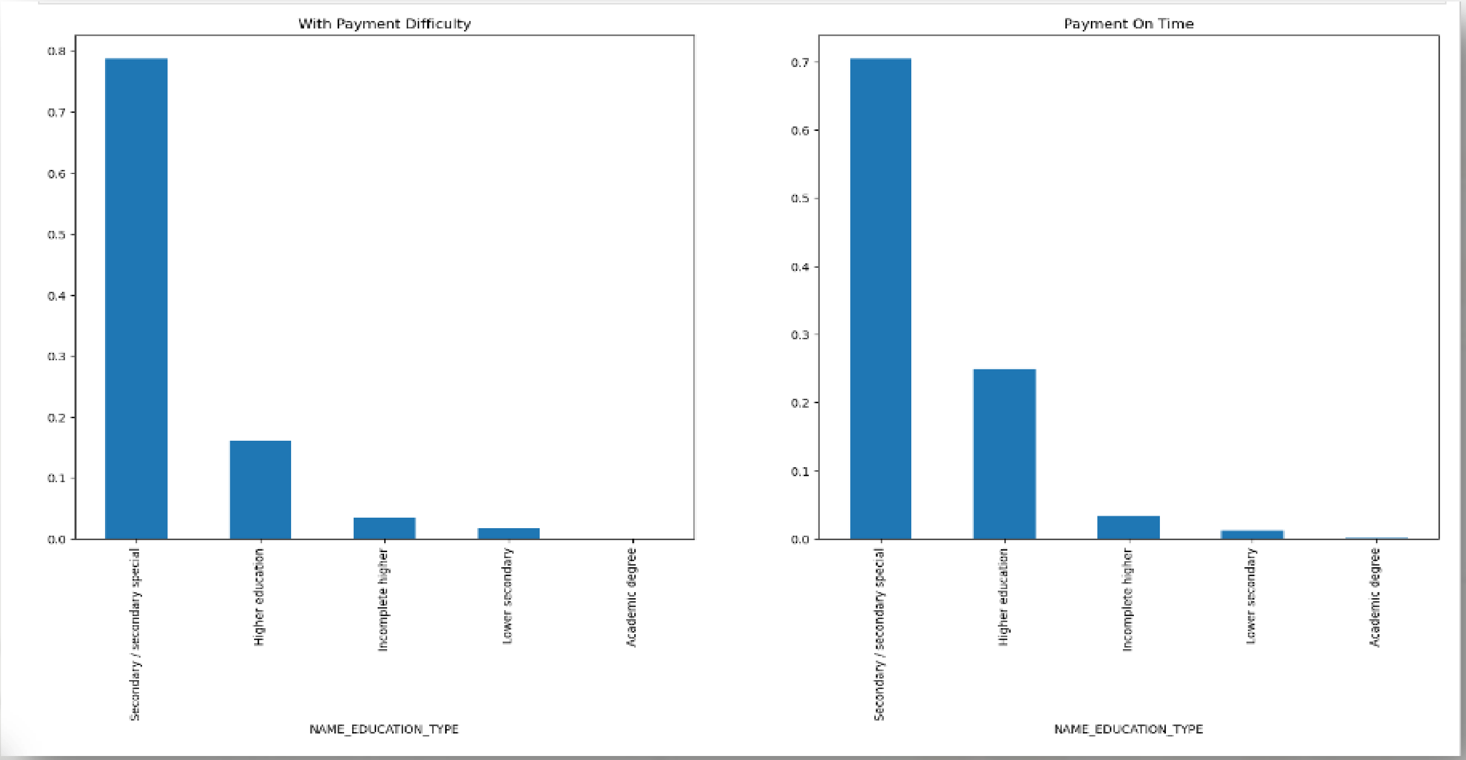


- ✓ Singles or those not married are facing payment difficulties.
- ✓ Among married individuals:
  - 59% are facing payment difficulties.
  - 63% are making payments on time.

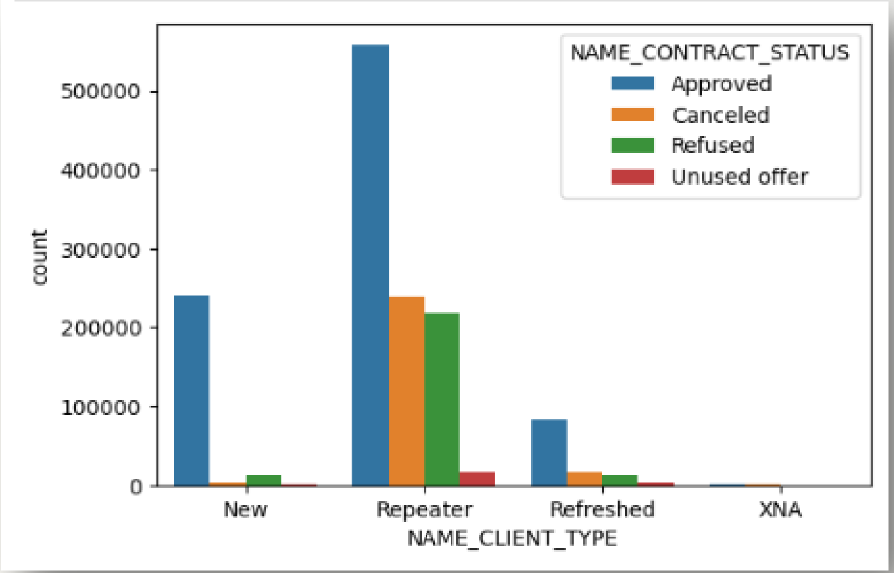
NAME_FAMILY_STATUS

Bivariate Analysis

NAME_EDUCATION_TYPE



✓ Applicants with the Higher education have done their payments mostly on time



✓ Repeaters got maximum number of approvals followed by new customers

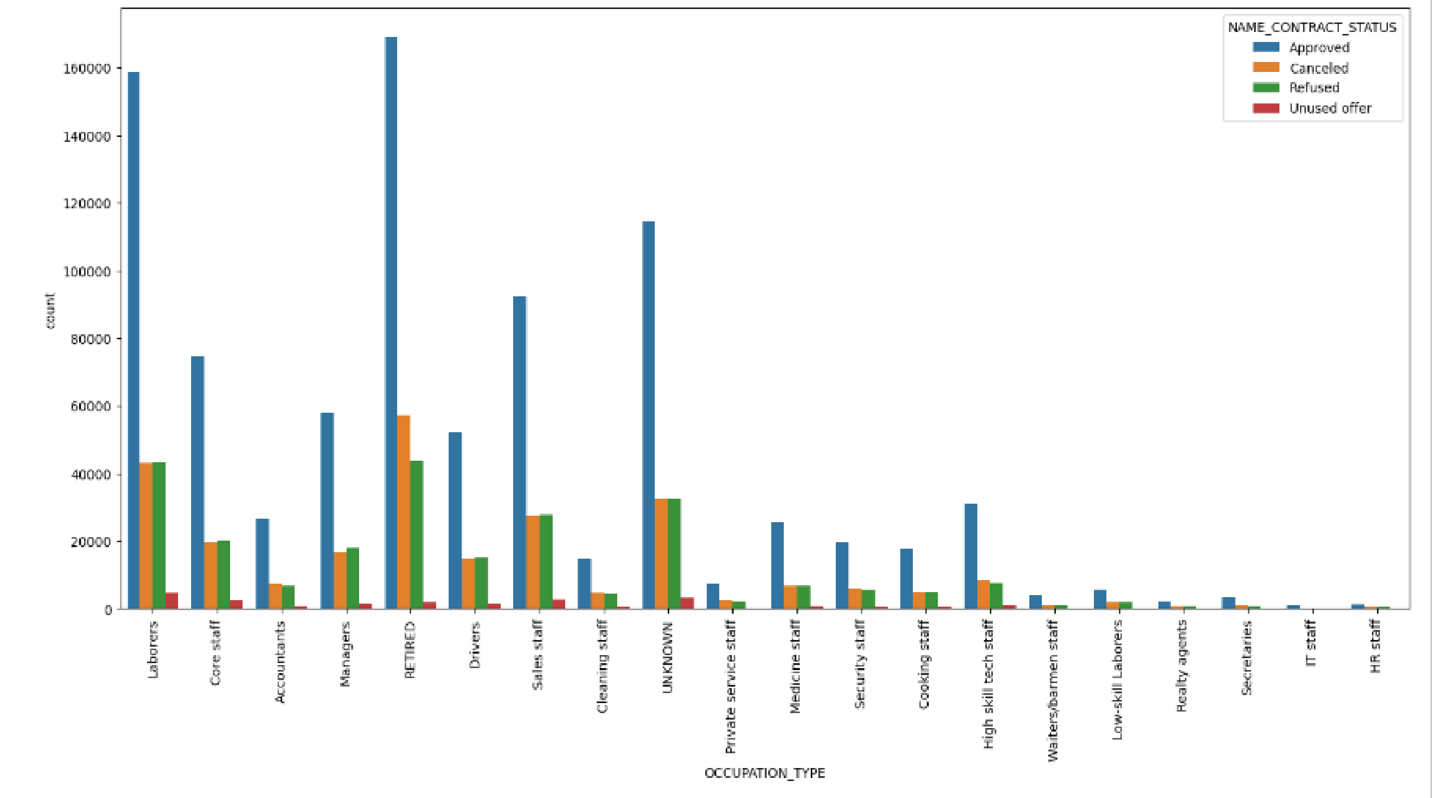
NAME_CLIENT_TYPE

vs

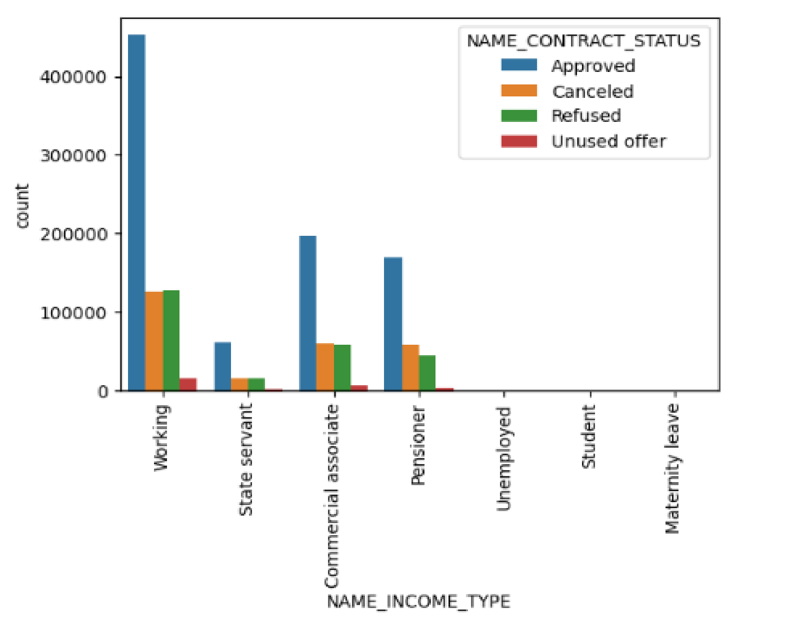
NAME_CONTRACT_STATUS

Bivariate Analysis

OCCUPATION_TYPE vs NAME_CONTRACT_STATUS



- ✓ Retired customers have got maximum number of approvals followed by labourers



- ✓ Student approval rate is highest at 83%, followed by civil servants at 65%.
- ✓ The highest refusal rate is among unemployed individuals at 30%.

NAME_INCOME_TYPE vs NAME_CONTRACT_STATUS

Bivariate Analysis

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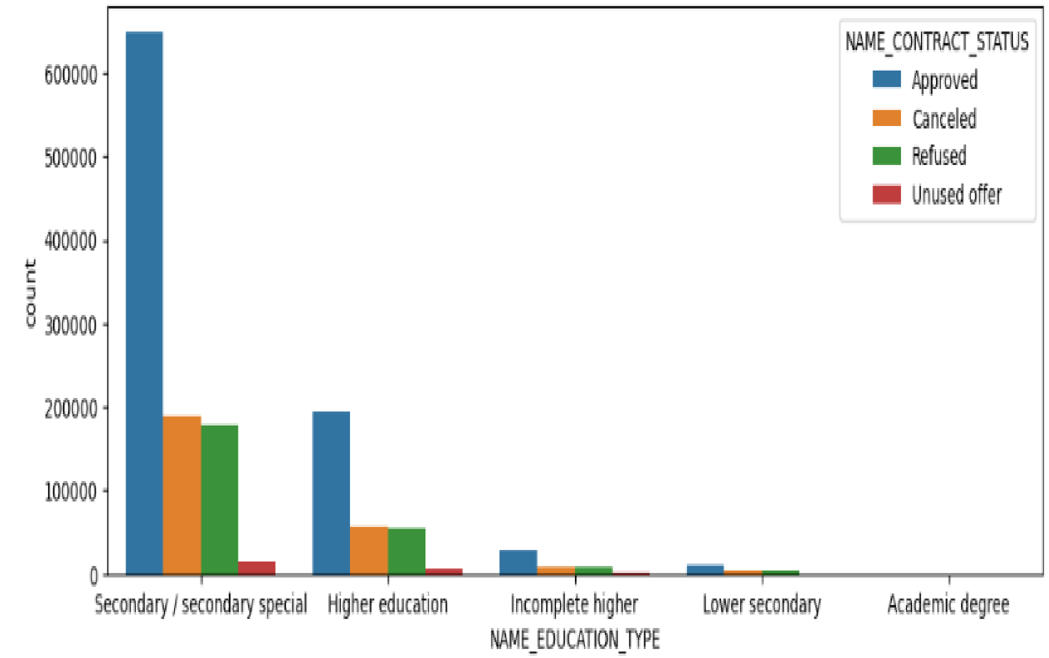
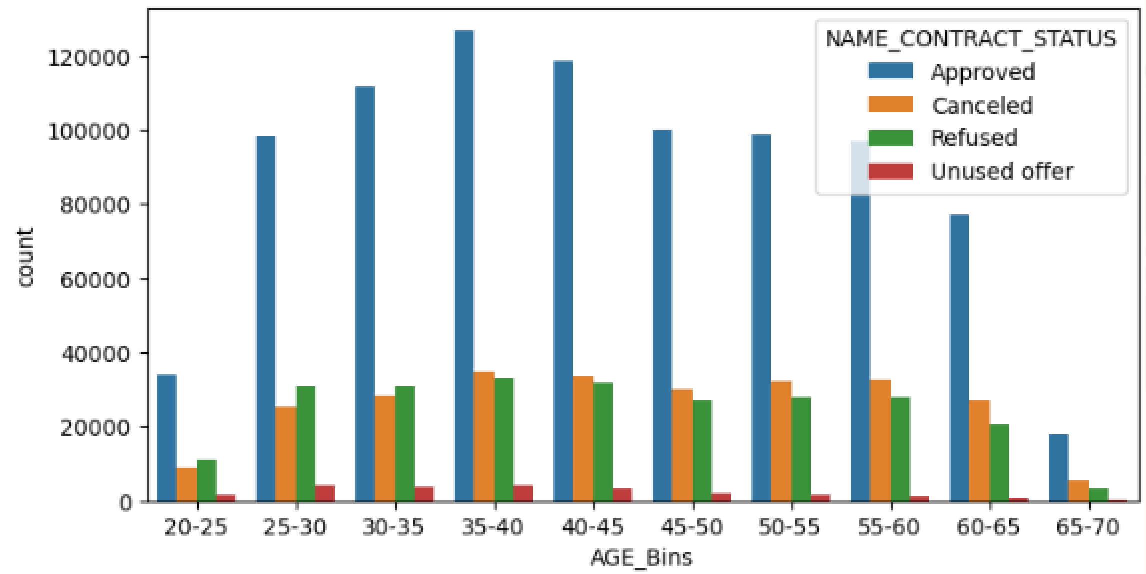
NAME_EDUCATION_TYPE
vs
NAME_CONTRACT_STATUS



- ✓ Applicants with academic degree has maximum percentage of approval.



✓Percentage of approvals are maximum in the age range of between 30-45 and also surprisingly between 65-70 age range.

AGE_Bins
vs
NAME_CONTRACT_STATUS

Bivariate Analysis

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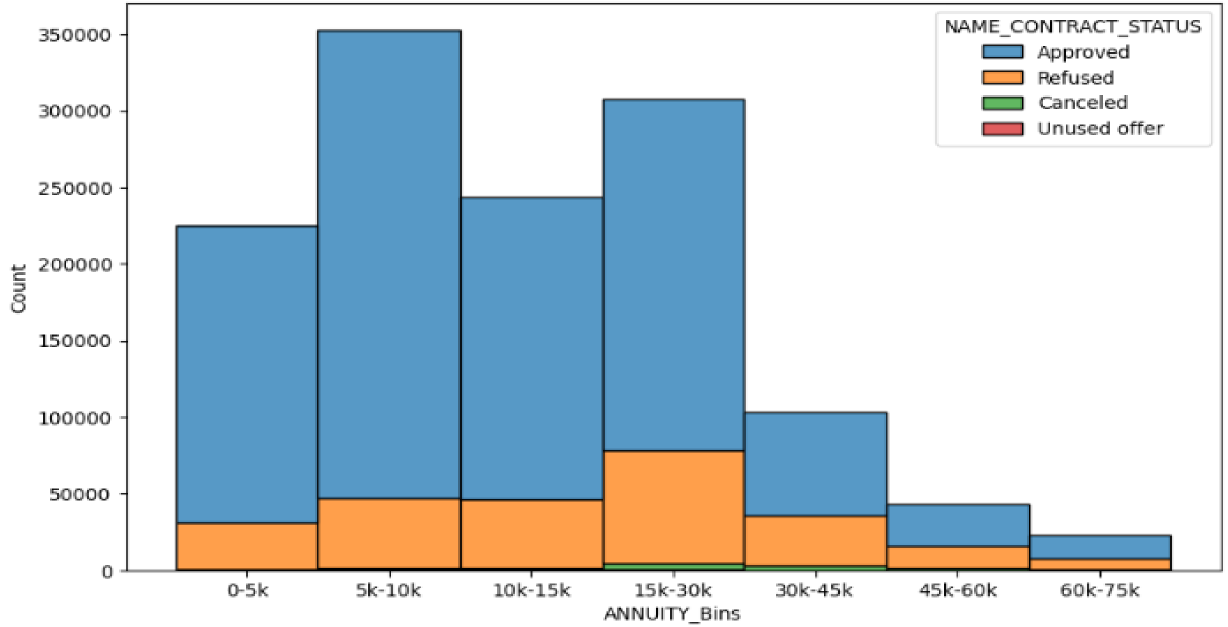
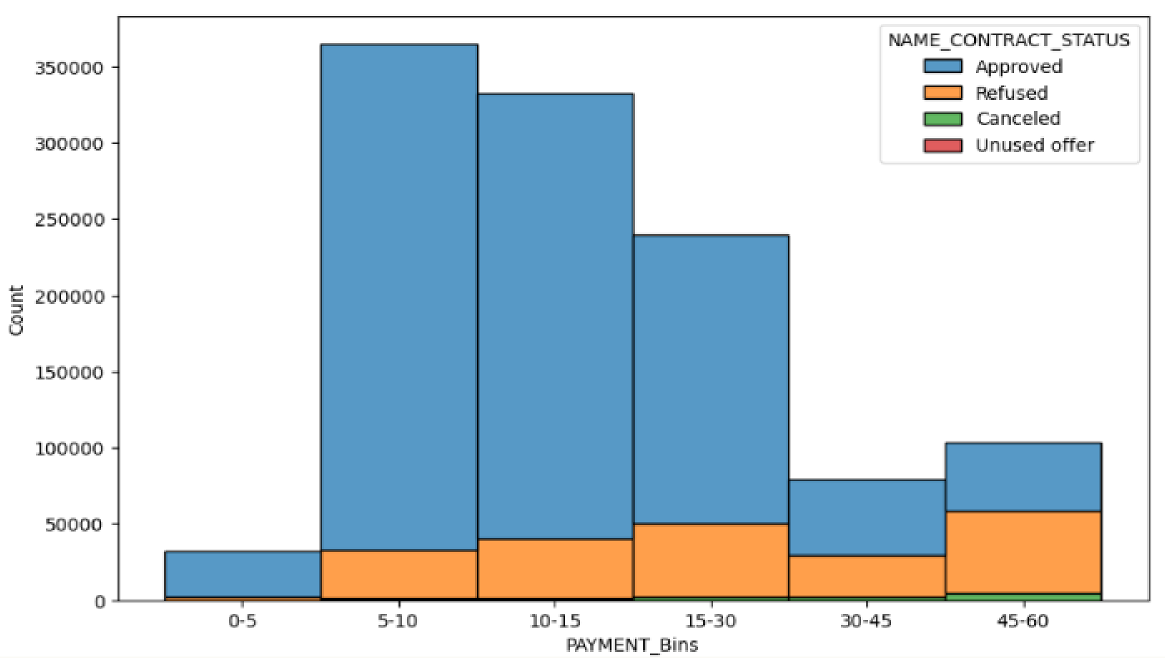
ANNUITY_Bins
vs
NAME_CONTRACT_STATUS



- ✓ **AMT_ANNUITY** represents the monthly EMI for loan repayment.
- ✓ Customers with EMI less than 15,000 receive more loan approvals.
- ✓ Customers with EMI in the range of 15,000-30,000 face the highest number of refusals.



- ✓**CNT_PAYMENT** represents loan repayment duration.
- ✓Longer repayment durations have higher refusal rates.
- ✓Loans with repayment durations less than 10 years have higher approval rates.
- ✓Shorter repayment periods increase the likelihood of loan approval.

PAYMENT_Bins
vs
NAME_CONTRACT_STATUS

Bivariate Analysis

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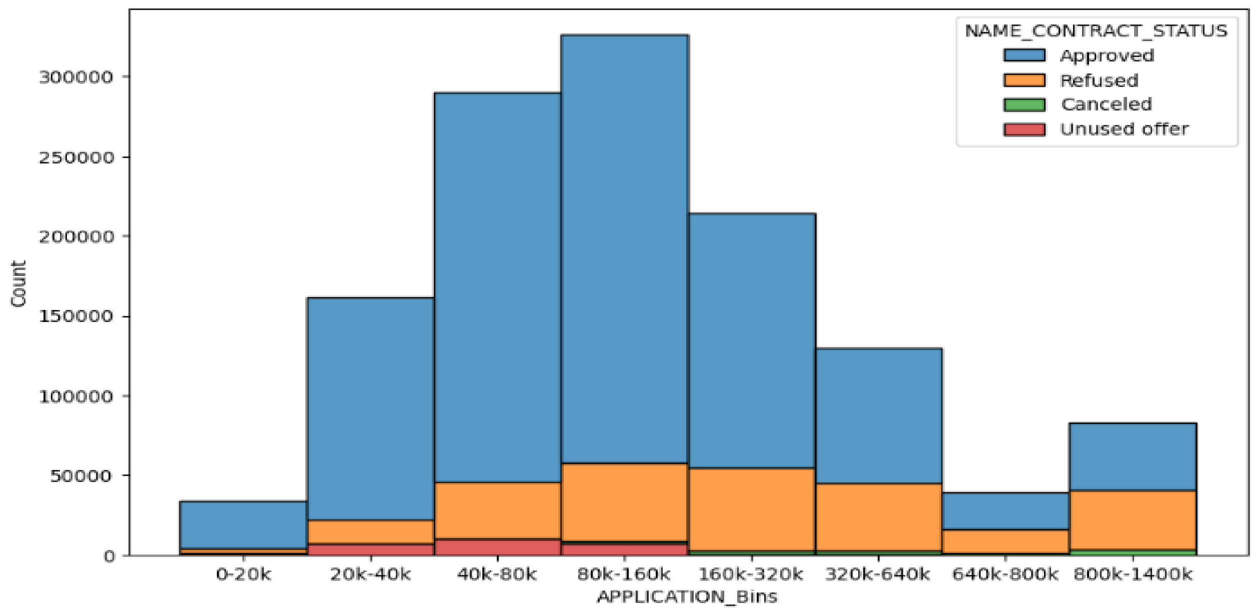
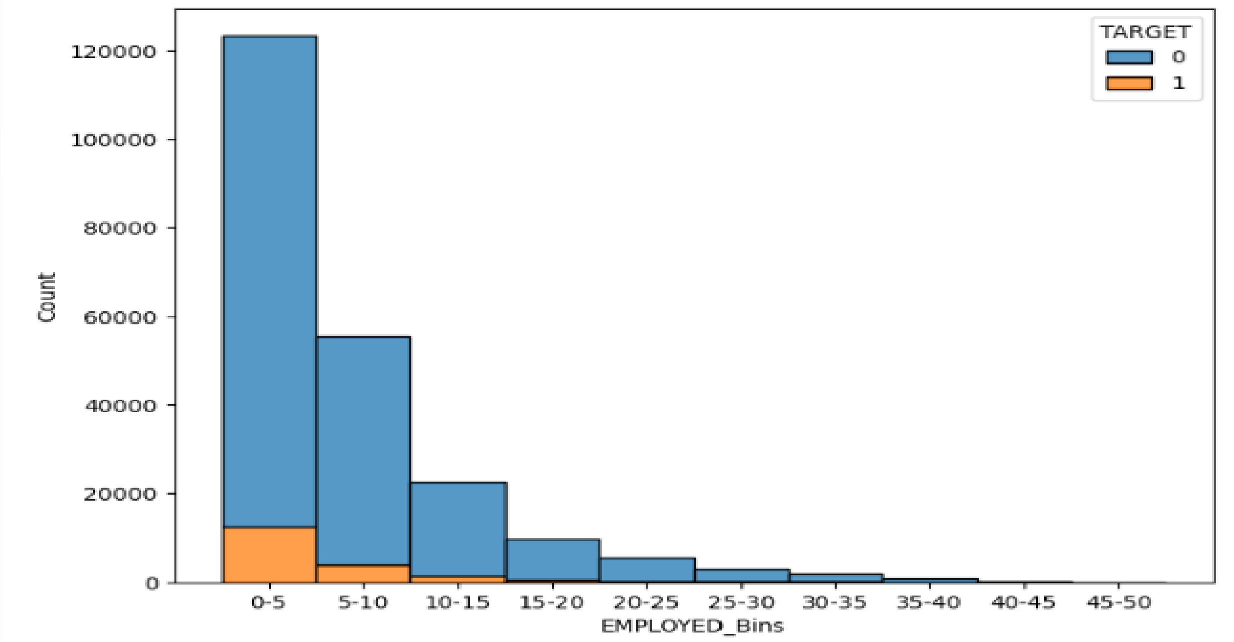
APPLICATION_Bins
vs
NAME_CONTRACT_STATUS



- ✓ AMT_APPLICATION represents the loan amount requested by the customer.
- ✓ Refusals are more common for loan amounts greater than 160k.



✓Customers employed for less than 5 years face the most payment difficulties

✓Customers employed for more than 10 years have a higher chance of repaying loans on time.

EMPOLYED_Bins
vs
NAME_CONTRACT_STATUS

Multivariate Analysis

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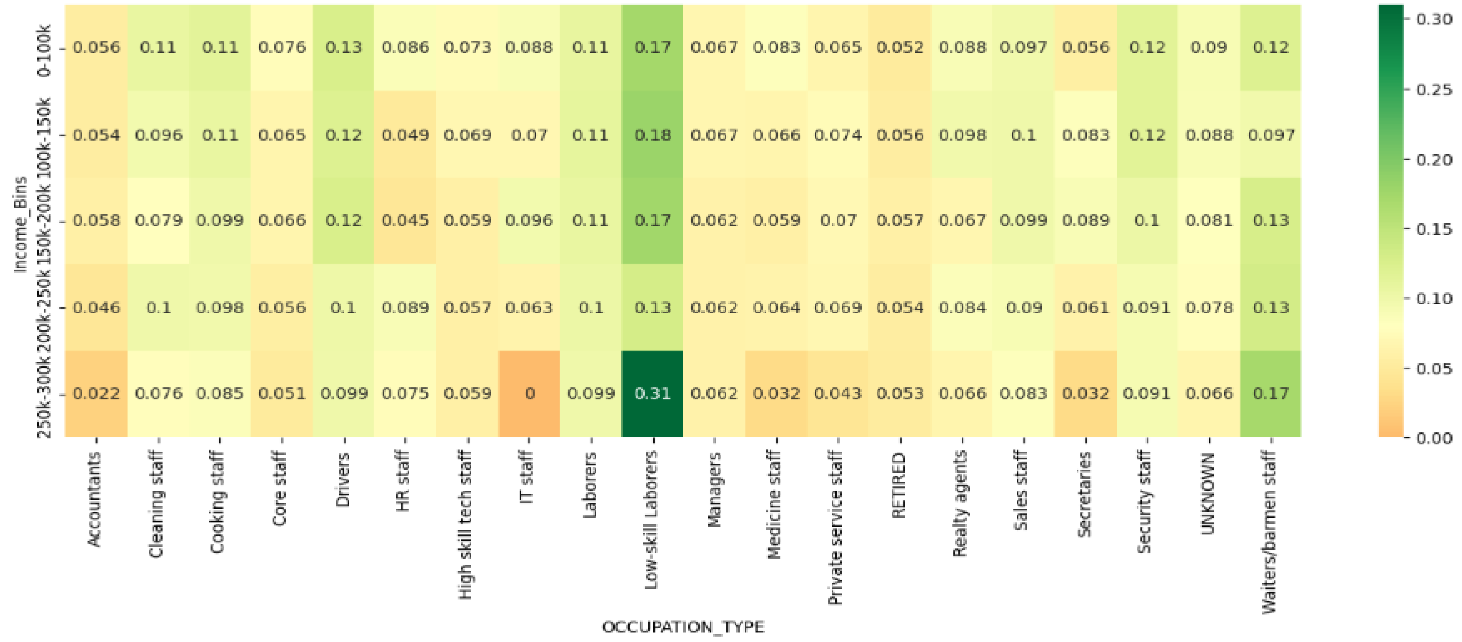
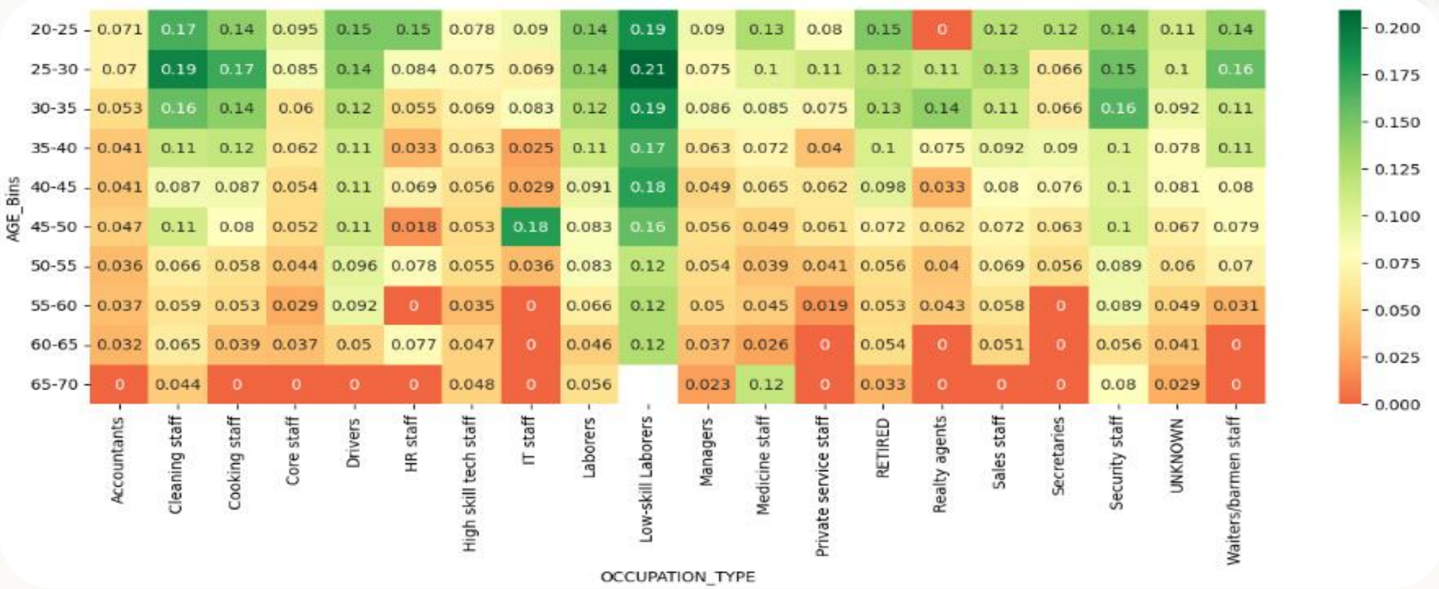
INCOME_Bins
vs
NAME_CONTRACT_STATUS
VS
OCCUPATION_TYPE



✓Low-skill laborers and waiters/barmen staff face maximum payment difficulty.

✓Income range of 250k-300k seems incorrect for Low-skill-Laborers observation.



✓ Customers over 40 mostly make payments on time across all occupations.

✓Customers under 40 struggle with timely payments in specific occupations: cleaning staff, cooking staff, drivers, Laborers, low-skill laborers, security staff, waiters, sales staff

AGE_Bins
VS
NAME_CONTRACT_STATUS
VS
OCCUPATION_TYPE

Conclusion

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Customers to be targeted for Providing Loan:

- ✓ Customers in occupations such as Accountant, retired, and students tend to make payments on time.
- ✓Customers with higher education or academic degrees are favorable targets for lenders.
- ✓Customers who have been employed for more than 10 years should be considered.
- ✓Customers aged over 40 are considered reliable borrowers.

Customers to be avoided from Providing Loan:

- ✓ Customers in occupations such as drivers and low-skill laborers often face difficulties in making payments on time.
- ✓Customers with lower secondary education tend not to make payments on time.
- ✓It is advisable to avoid working-class and unemployed customers.
- ✓Customers who have been employed for less than 10 years should not be considered for loans.
- ✓Customers under the age of 30 frequently encounter difficulties in making payments