EDA Assignment Submission

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Batch: DSC 68

upGrad

upGrad & IIITB | Data Science Program - May 2024

Approach Note

Missing Values

- Exported null columns information , ordered by percentage of null descending.
- Checked the Distribution of Significant columns using value_counts(normalize=True)
- Handled the null values basis the type of null columns, for example Occupation Type fill na is done as 'NOT DECLARED' as per my observation it is MNAR.

Outlier Handling

- To Check and Remove outliers, implemented IQR calculation, created a new Outlier flag column with 1 if value is less the IQRmin or greater than IQR max and removed the records with Outlier flag column.
- Implemented this approach for AMT_INCOME_TOTAL, DAYS_BIRTH, CNT_CHILDREN, CNT_FAM_MEMBERS

Data Transformations

- Created new columns like YRS_BIRTH, by converting absolute(Days) into Years, and implemented the same logic for similar type of columns.
- Flag columns like FLAG OWN CAR, FLAG OWN REALTY are translated to 1 for Y and 0 for N, so that it can be used for Correlations.

Group Column Creation

- Wherever applicable, group columns are created for having proper dimension of data analysis, like AGE, INCOME and EXPERIENCE GROUPS are created.

File Segregation

- Segregated application data basis the Loan Type (NAME_CONTRACT_TYPE) and TARGET values (0,1) and merged with previous data file for necessary columns

Correlation Study

Correlation Study - Insights

- Considered below attributes for further analysis
- GENDER | Education Type | Occupation Type | Income Group | Family Status | Housing Type | Owns Realty | Owns Car |
 #Children | #Family Members | Previous Application approval Status |
- **REASON FOR COLUMN SELECTION:** These columns are selected basis the events that will influence the income and expenditure of a house hould that could cause delay of the loan payment.
 - For Instance if OWN_REALTY is 1, the client may be already paying an EMI
 - INCOME GROUP may is lesser range.
 - #Children and Family members may cause payment difficulties.
 - Prior Loan if approved and if payment term for that is due and conflicting with current one.
 - Housing Type is considered to understand the investments already made.
 - Occupation Type, Education Type, Family Status are all considered to understand which combination is having more difficulty so that, such categories can be avoided to award loan sanctions

Payment Difficulty observations

Revolving Loans

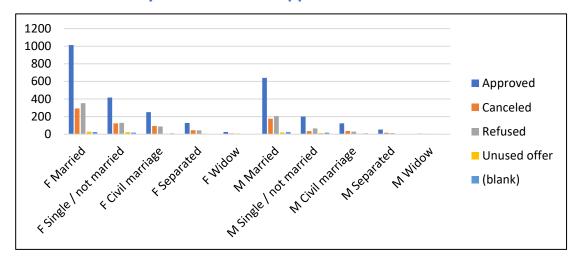
- MALE has more payment difficulties than Female
- MALE Married and prior application approved has more payment difficulties
- Person who owns realty has more difficulties, regardless of GENDER
- Owning car and realty does not have effect in payment difficulties
- Owning car and realty has relatively less effect compared to Cash loans
- Owning REALTY seems to have more effect than #Children regardless of GENDER
- Occupation Type of Labourers with Exp bucket of 0-5 tends to have more difficulties but far less when compared to Cash loans of same Criteria

Cash Loans

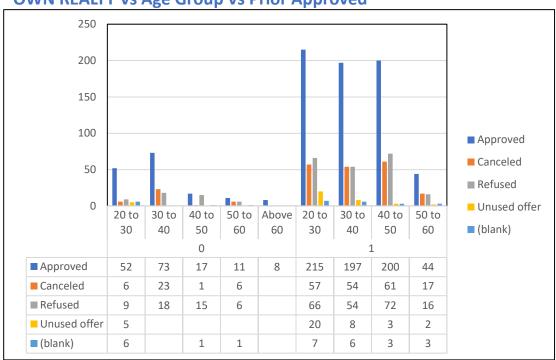
- Female has more payment difficulties than Male.
- MALE Married and prior application approved has more payment difficulties
- Person who owns realty has more difficulties, regardless of GENDER
- Person who Owns car and realty has more further more difficulties in payment
- Owning car and realty has relatively high effect compared to Revolving loans
- Owning REALTY seems to have more effect than #Children regardless of GENDER
- Occupation Type of Labourers with Exp bucket of 0-5 tends to have more difficulties but far high when compared to Cash loans of same Criteria.
- 0-5 Exp Group with 1.25 1.5 Lakh Income group tends to have more difficulties where REALTY is 1

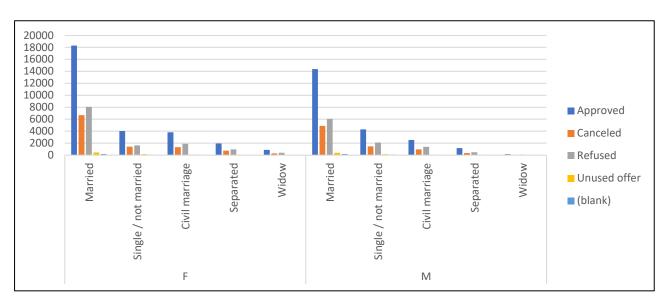
Revolving Loans (Left) vs Cash Loans (Right)

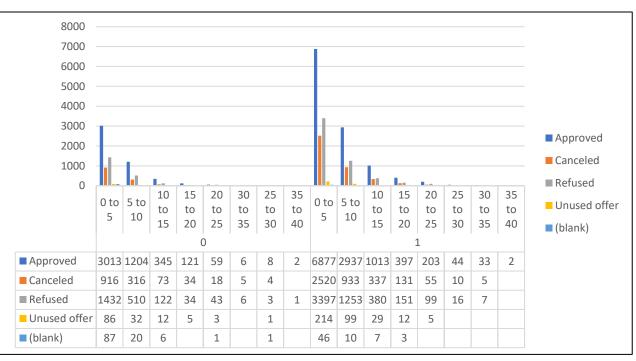
GENDER Vs Family Status Vs Prior Approved



OWN REALTY Vs Age Group Vs Prior Approved

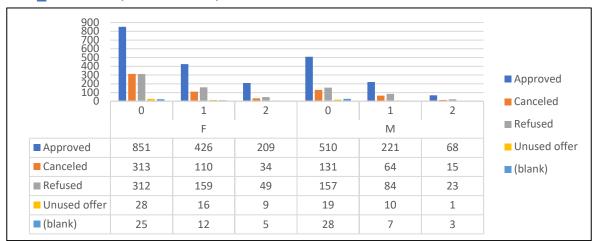






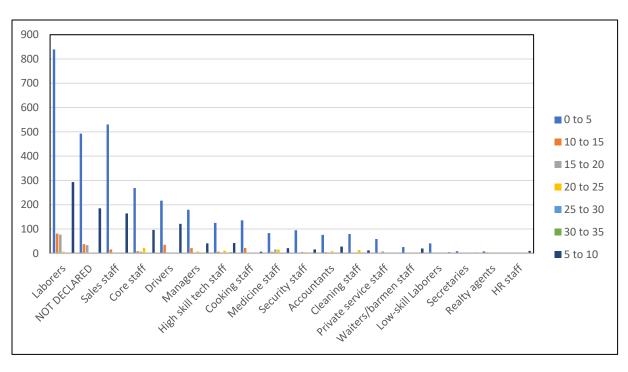
Revolving Loans (Left) vs Cash Loans (Right)

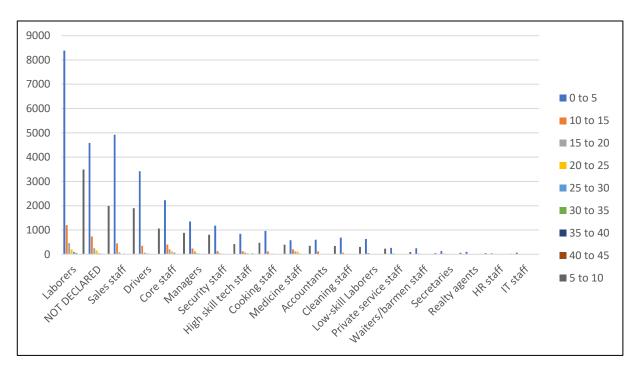
OWN_REALTY=1, vs GENDER, Vs #Children





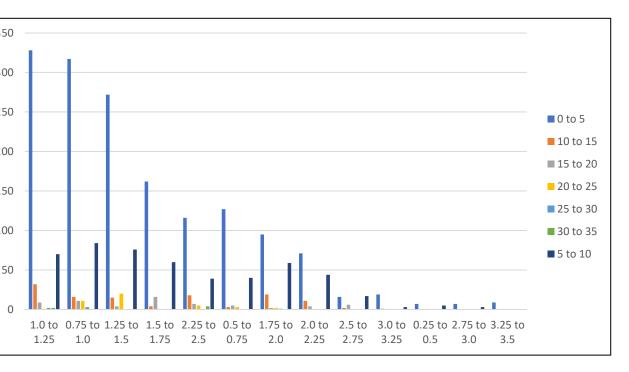
OCCUPATION TYPE vs EXPERIENCE GROUP vs PRIOR APPROVED

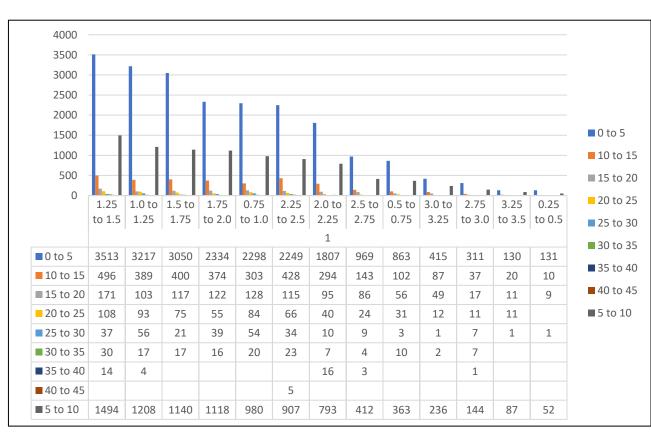




Revolving Loans (Left) vs Cash Loans (Right)

EXPERIENCE GROUP Vs INCOME_GROUP Vs PRIOR APPROVED





THANK YOU