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Credit EDA Case Study : Exploratory Data Analysis on Bank Loan Data

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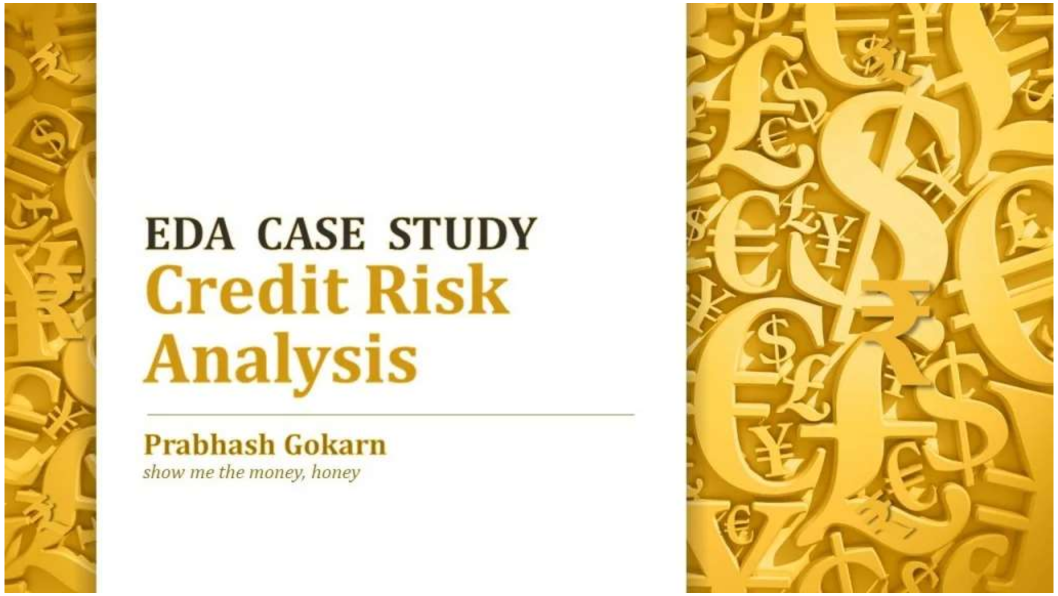


Problem Statement

There are two types of risks associated with any loan request :

- **H0** If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company
- **H1** If the applicant is not likely to repay the loan , i.e. he/she is likely to default , then approving the loan may lead to a financial loss for the company.

Analysis of the data set has been done in Python on a Jupyter Notebook.

2

Analysis Done

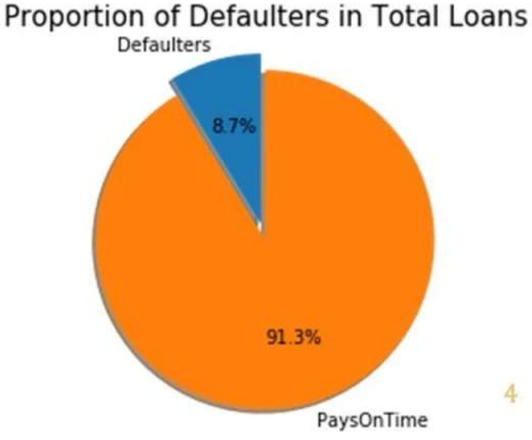
Steps :

- Check Missing Values a. which to handle, how to handle
- Check Outliers; check data imbalance; ratio of imbalance
- Top 10 correlation for the Client with payment difficulties other variables within Application DF & Previous App DF
- Which correlation is most relevant

3

Proportion of Defaulters in the Data Set

- Defaulters are 8.7% of total



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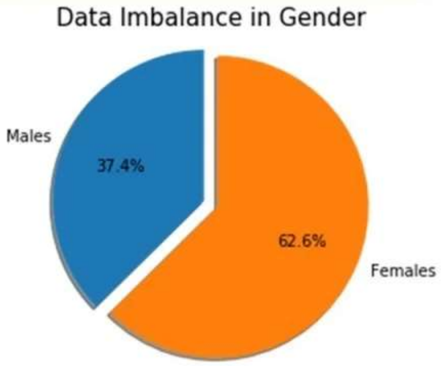
Gender Imbalance

- 63% Females



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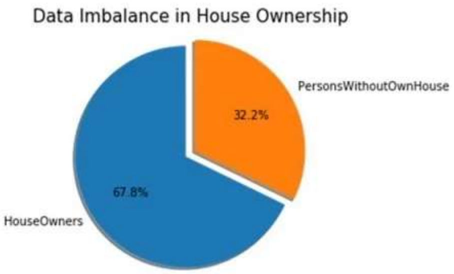
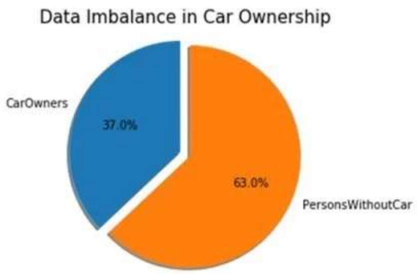
House and Car Ownership (i.e. Gaadi & Baadi)





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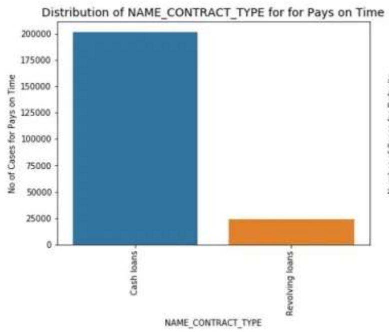
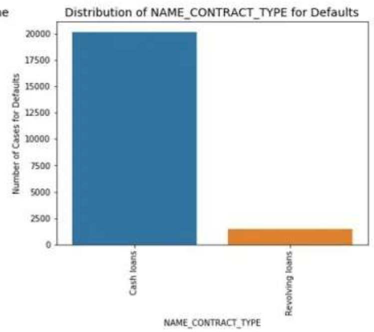
Proportion of Defaulters in the Data Set





- Less defaulters for Revolving Loans

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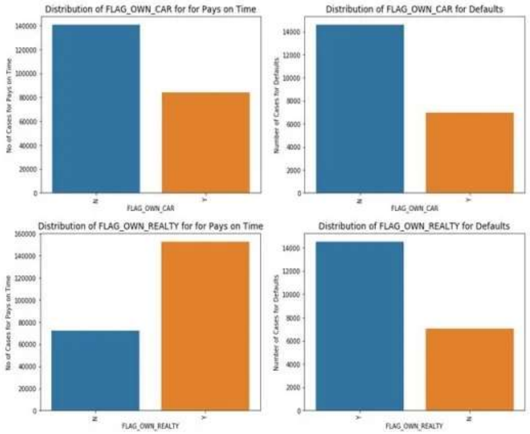
Proportion of Defaulters By Gender

- Females in defaults is higher

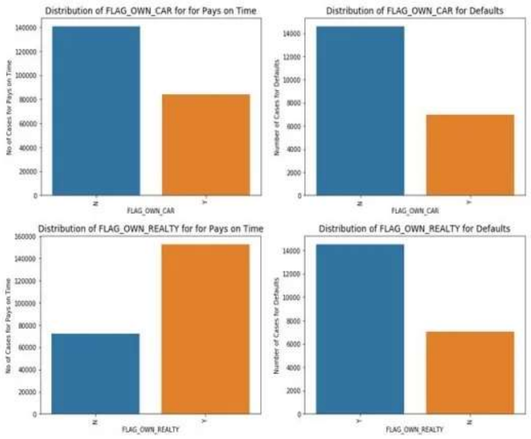
Proportion of Defaulters By Gender

- Own Houses default similar to people without houses, but own car defaults less



Proportion of Defaulters By Gaadi / Baadi

- Own Houses default similar to people without houses, but own car defaults less



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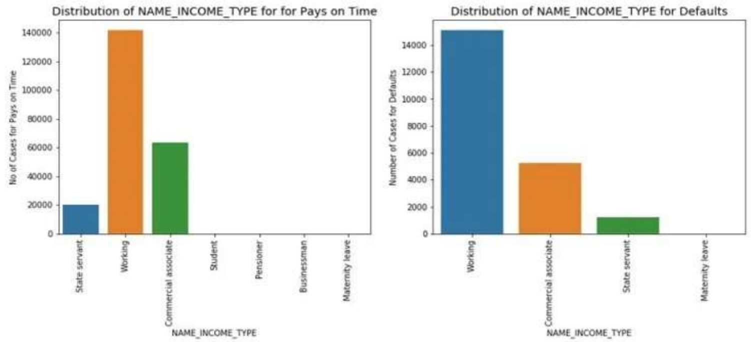
Proportion of Defaulters By Profession



- Proportion of Working Population in defaults is higher and State Servants is lower in Defaults

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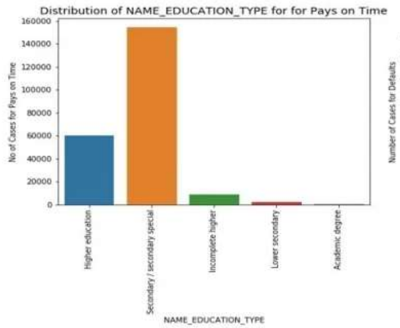
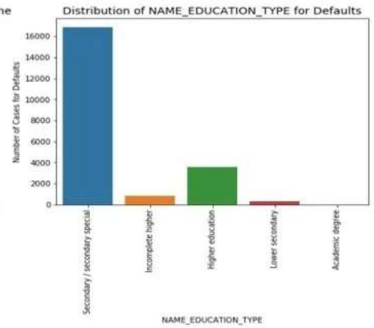
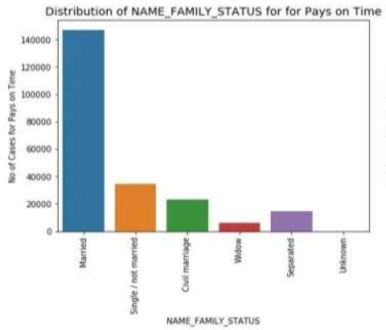
Proportion of Defaulters By Education

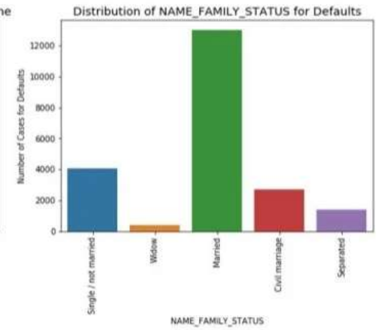




- Higher Education default less

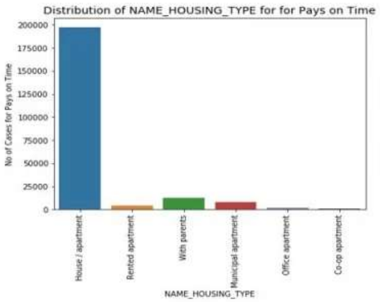
Proportion of Defaulters By Family Status

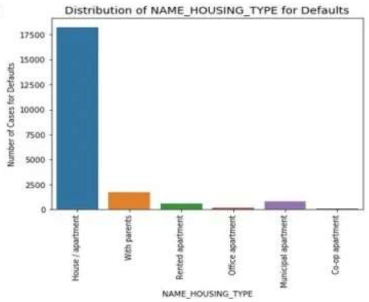




- Married people default less

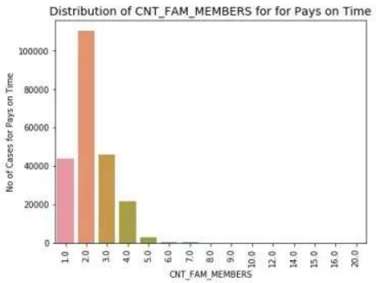
Proportion of Defaulters By House Status

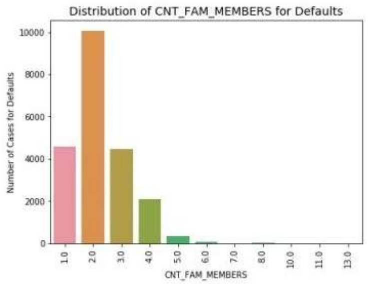




- People staying in own house default less

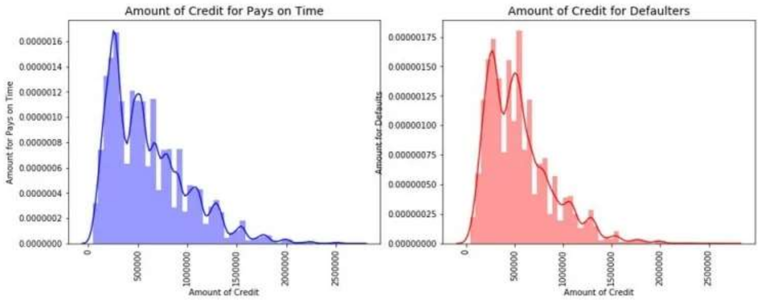
Proportion of Defaulters By No of Kids





- No difference in Count of Family Members

Proportion of Defaulters By Credit Amount



- Better return of loans as loan size increases

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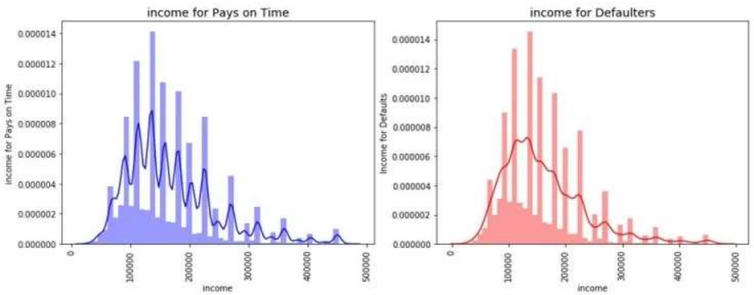
Proportion of Defaulters By Income Level



- Better return of loans as Income increases
- Very Unlike in India where Middle Class Returns Loans and Rich like Mallya flee

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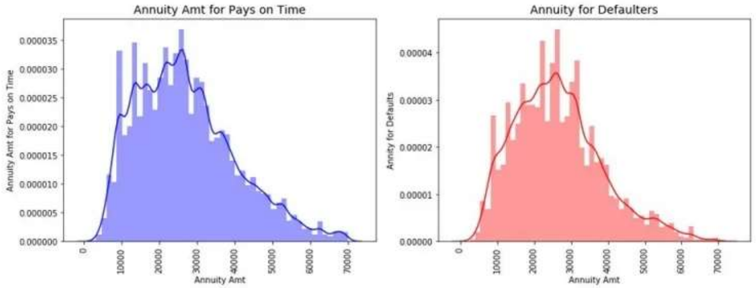
Proportion of Defaulters By Annuity Amt



- Better return of loans as Amt of Annuity Increases.

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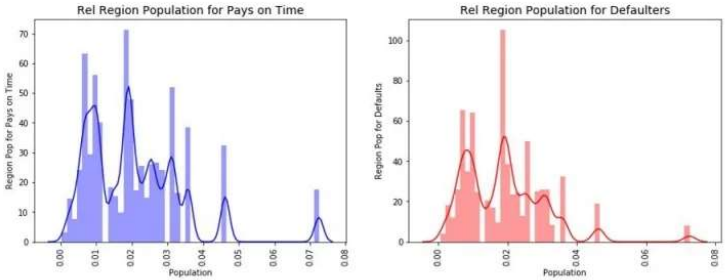
Proportion of Defaulters By Rel Region



- Better return of loans for higher Relative Region Population

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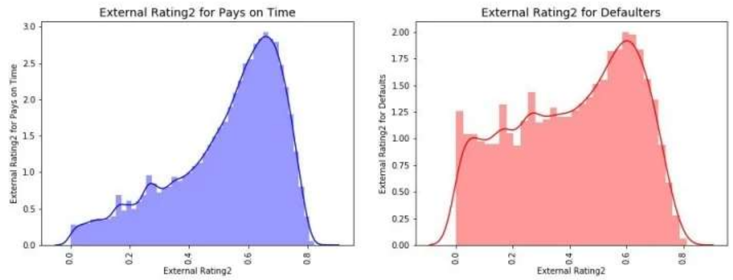
Proportion of Defaulters By External Rating



- Better Rating – Better Return

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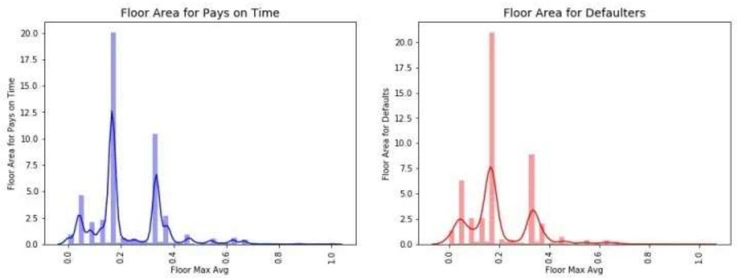
Proportion of Defaulters By No of Kids



- Lower Floor area – More default

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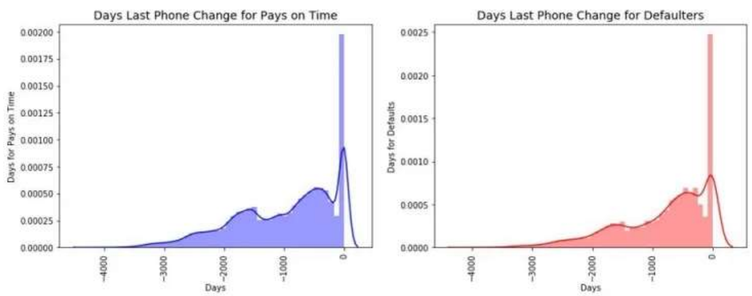
Proportion of Defaulters By No of Kids



- More defaults if phone changed more recently

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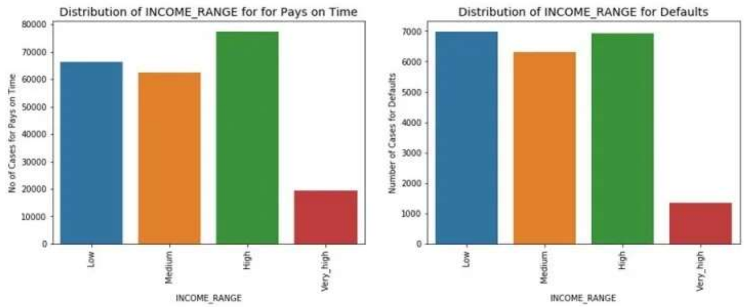
Proportion of Defaulters By Income



- Fewer Defaults when Income Range is higher

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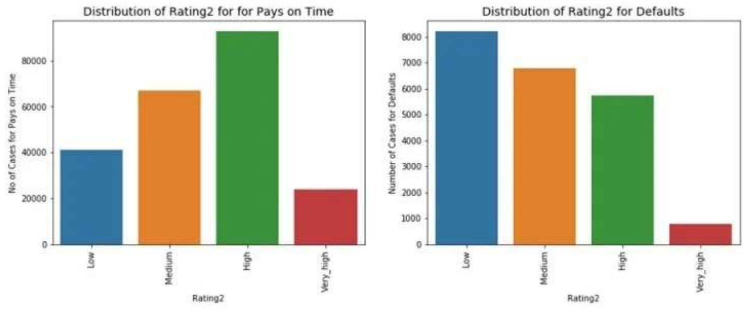
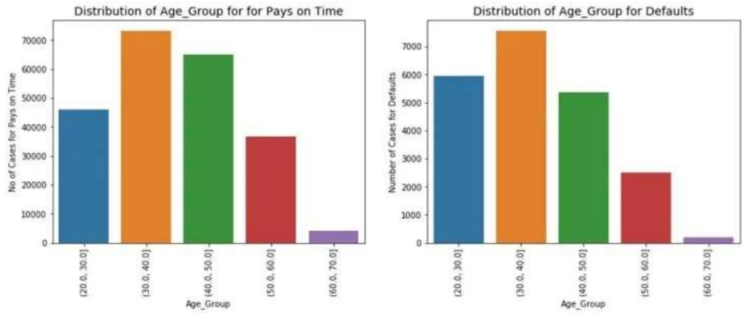
Proportion of Defaulters By Rating



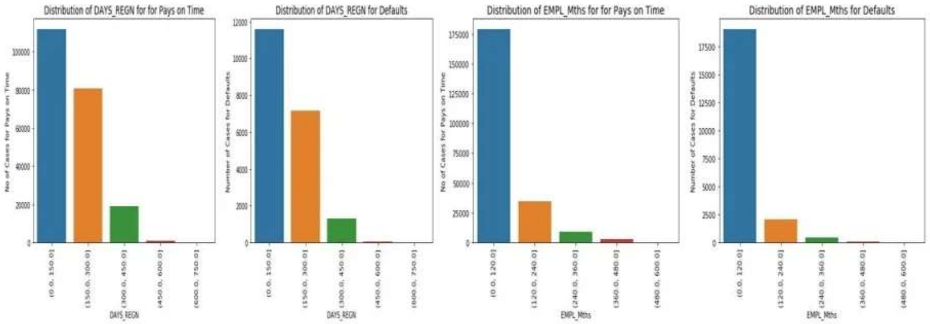
- Better Rating Better Return

Proportion of Defaulters By Age



- Older People – more likely to return

Proportion of Defaulters By Days Regn, Emp



- Recent Employment or Recent Change in Regn – Defaults more

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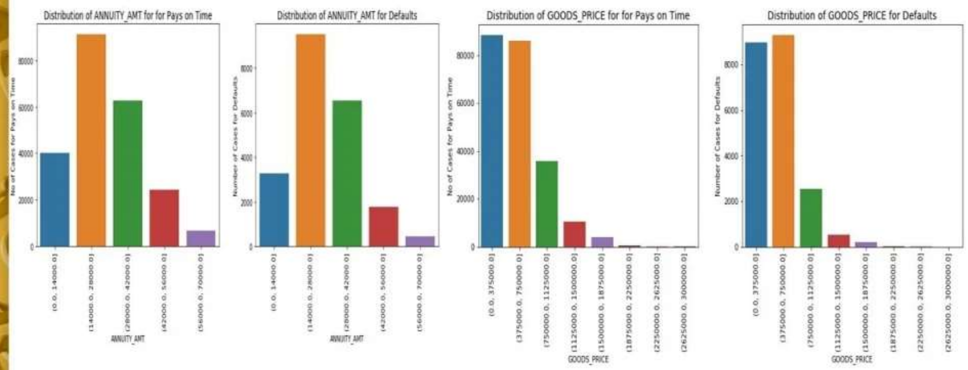
Proportion of Defaulters By Annuity Amt, Goods Price



- Annuity Amount, Goods Price lower more at risk for default

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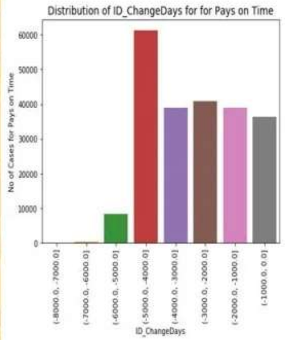
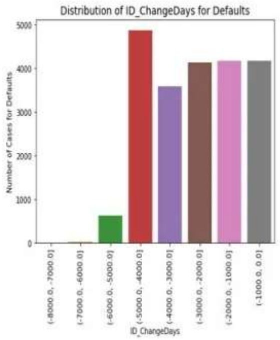
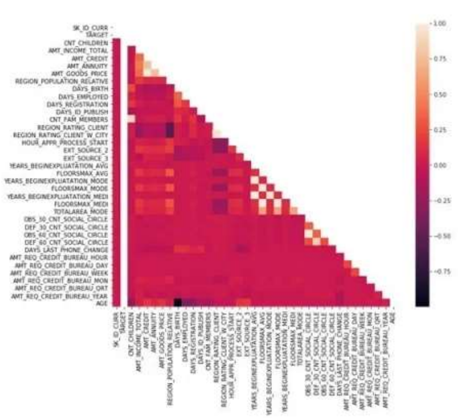
Proportion of Defaulters ID Change, Region

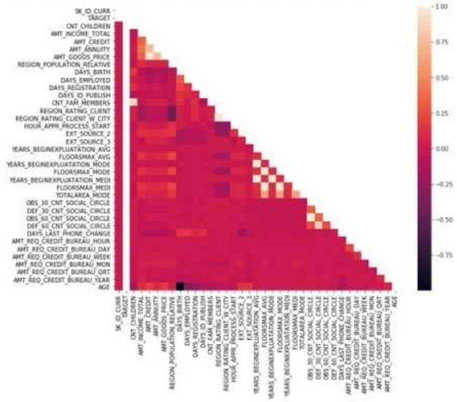




- Recent ID Change, Region Rating of City 2 to 2.5 hogher default

Correlations - Defaults and Pays on Time





Both Correlations look similar

Top Co Relations For Non Defaulters & Defaulters

```
AMT_REQ_CREDIT_BUREAU_YEAR   AMT_REQ_CREDIT_BUREAU_YEAR    1.000000
OBS_30_CNT_SOCIAL_CIRCLE     OBS_60_CNT_SOCIAL_CIRCLE      0.998495
FLOORSMAX_MEDI               FLOORSMAX_AVG                 0.997089
YEARS_BEGINEXPLUATATION_MEDI YEARS_BEGINEXPLUATATION_AVG   0.993061
FLOORSMAX_MEDI               FLOORSMAX_MODE                0.988055
                                                             ...
AGE                          DAYS_EMPLOYED                -0.352339
REGION_RATING_CLIENT_W_CITY  REGION_POPULATION_RELATIVE   -0.529862
REGION_POPULATION_RELATIVE   REGION_RATING_CLIENT         -0.532110
DAYS_BIRTH                   AGE                          -0.999593
SK_ID_CURR                   TARGET                             NaN
Length: 597, dtype: float64
```

```
]: AMT_REQ_CREDIT_BUREAU_YEAR   AMT_REQ_CREDIT_BUREAU_YEAR     1.000000
   OBS_30_CNT_SOCIAL_CIRCLE     OBS_60_CNT_SOCIAL_CIRCLE       0.998279
   FLOORSMAX_AVG                FLOORSMAX_MEDI                 0.997492
   YEARS_BEGINEXPLUATATION_AVG  YEARS_BEGINEXPLUATATION_MEDI   0.995884
   FLOORSMAX_MEDI               FLOORSMAX_MODE                 0.989253
                                                                 ...
   DAYS_EMPLOYED                AGE                           -0.306965
   REGION_POPULATION_RELATIVE   REGION_RATING_CLIENT          -0.437613
   REGION_RATING_CLIENT_W_CITY  REGION_POPULATION_RELATIVE    -0.441615
   AGE                          DAYS_BIRTH                    -0.999566
   SK_ID_CURR                   TARGET                              NaN
   Length: 597, dtype: float64
```

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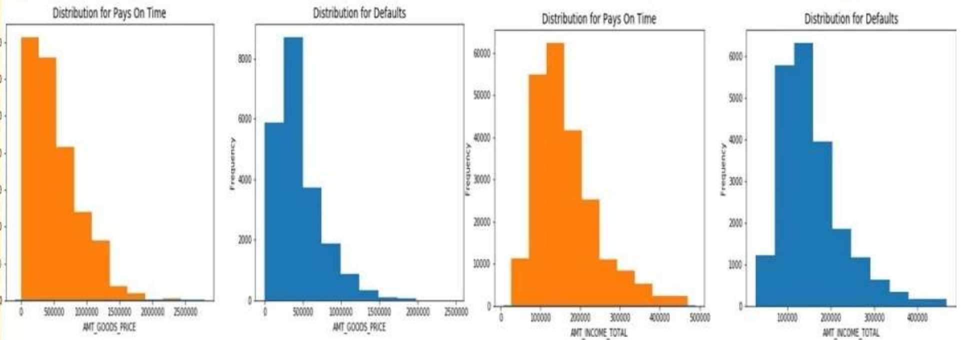
Top ten CoRelations in Both Population who Pays and Population who Defaults Same

Proportion of Defaulters



- Defaults higher for loans < 500,000
- Defaults are higher when Income lower

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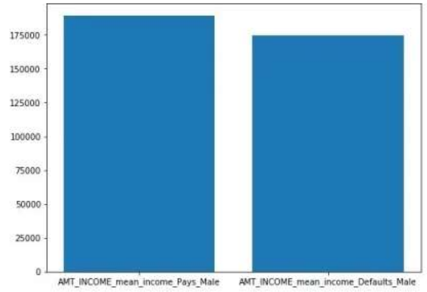
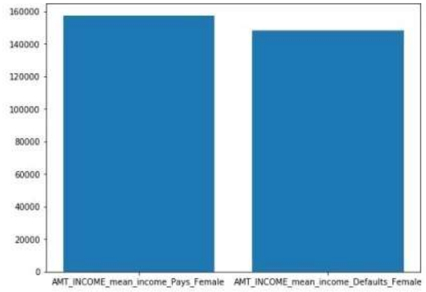
Proportion of Defaulters





- Mean Income generally lower for defaulters Male Defaulters have lowest mean income

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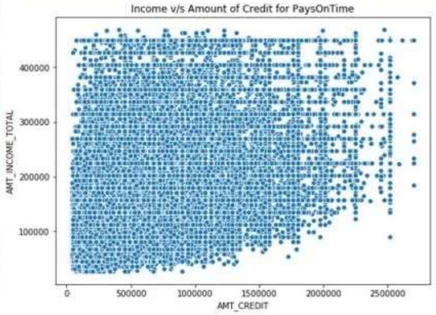
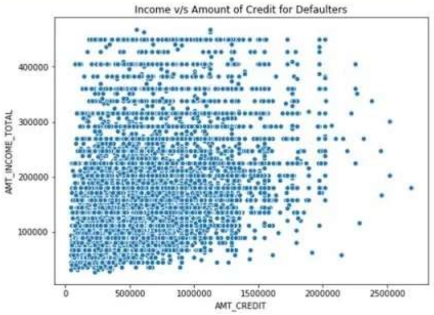
Defaulters Density





- Default Density is lower where Amount of Credit > 150,000 or Income > 300,000

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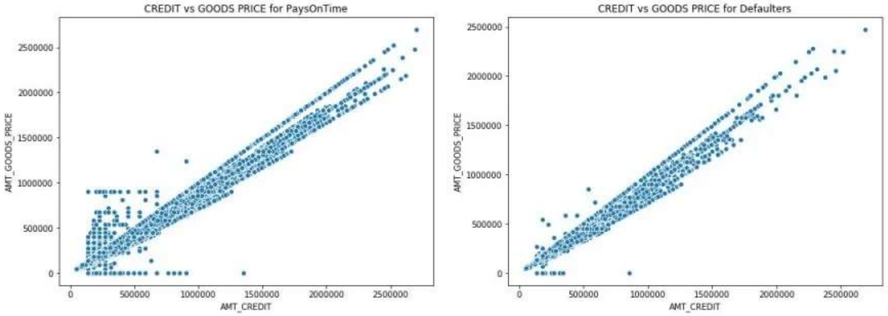
Defaulters Correlations



- Strong Correlation between Credit Amount and Price of Goods. Defaults are lower where Amount of Credit and the Price of Goods is > 150,000

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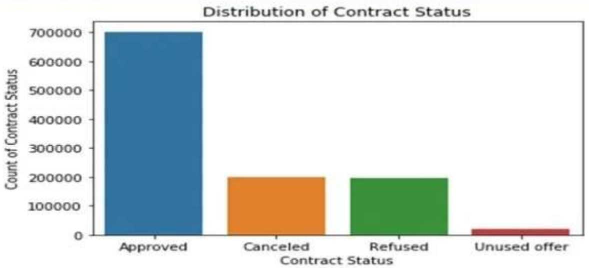
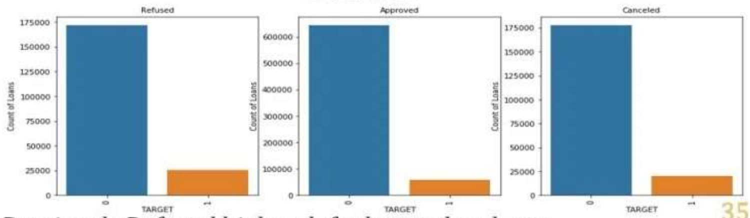
Contract Status





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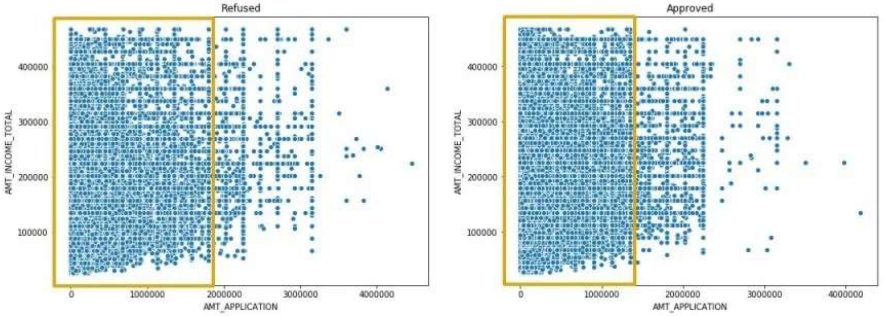
- Loans Previously Refused higher default rate than loans

Loan Rejection Rate



- Loans higher than 200,000 have a higher rejection rate
- Rejection rate is lower if income higher than 500,000

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Conclusions

EDA for the banking data set revealed that :

- The proportion of defaulters is 8.7%
- The bank lends more to females
- More Cash Loans go into default : bank should give more Revolving Loans.
- Proportion of Working defaults more / State Servants less
- People with Higher Education; Older People default less
- Single People Default more : giving loans to married safer
- Higher Amount loans; Higher Income – less defaults
- Longer employment history, longer registration days less default
- Loans Previously Refused or Cancelled - higher default rate

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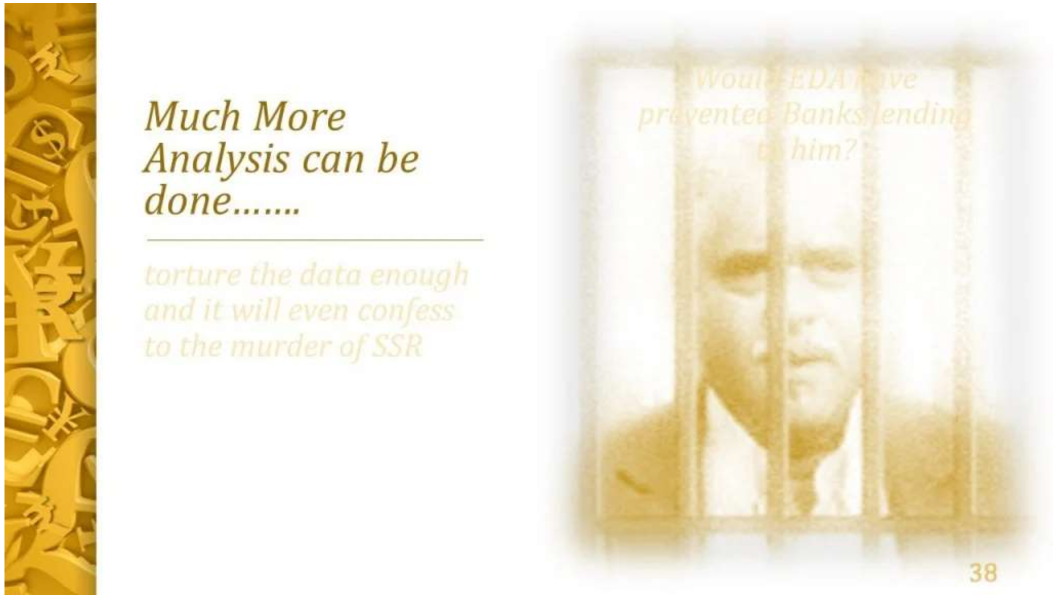

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