

# EDA CASE STUDY

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# Problem Statement

Two types of risks are associated with the bank's decision:

- If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company.
- 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.

**The company wants to understand the driving factors (or driver variables) behind loan default, i.e. the variables which are strong indicators of default**

# Initial Steps taken before Analysis:

- Imported the “Application\_data data set
- Checked the structure of the data
- Checked the percentage of missing values.
- Deleted all the columns which are having missing %age more than 45%
- Imputed other columns with missing values less than 45% with either median or mode
- Converted “Days\_Birth” Column into age
- Checked the outliers of the numerical columns (data driven columns)
- Checked the imbalance %age of the Target column
- Divided the Data set into two data set (1 & 0) for EDA Analysis

# Univariate Analysis on Application Data:

- Categorical Univariate Analysis:

**Columns under consideration are:**

- NAME\_INCOME\_TYPE
- OCCUPATION\_TYPE
- ORGANIZATION\_TYPE
- CODE\_GENDER
- NAME\_EDUCATION\_TYPE

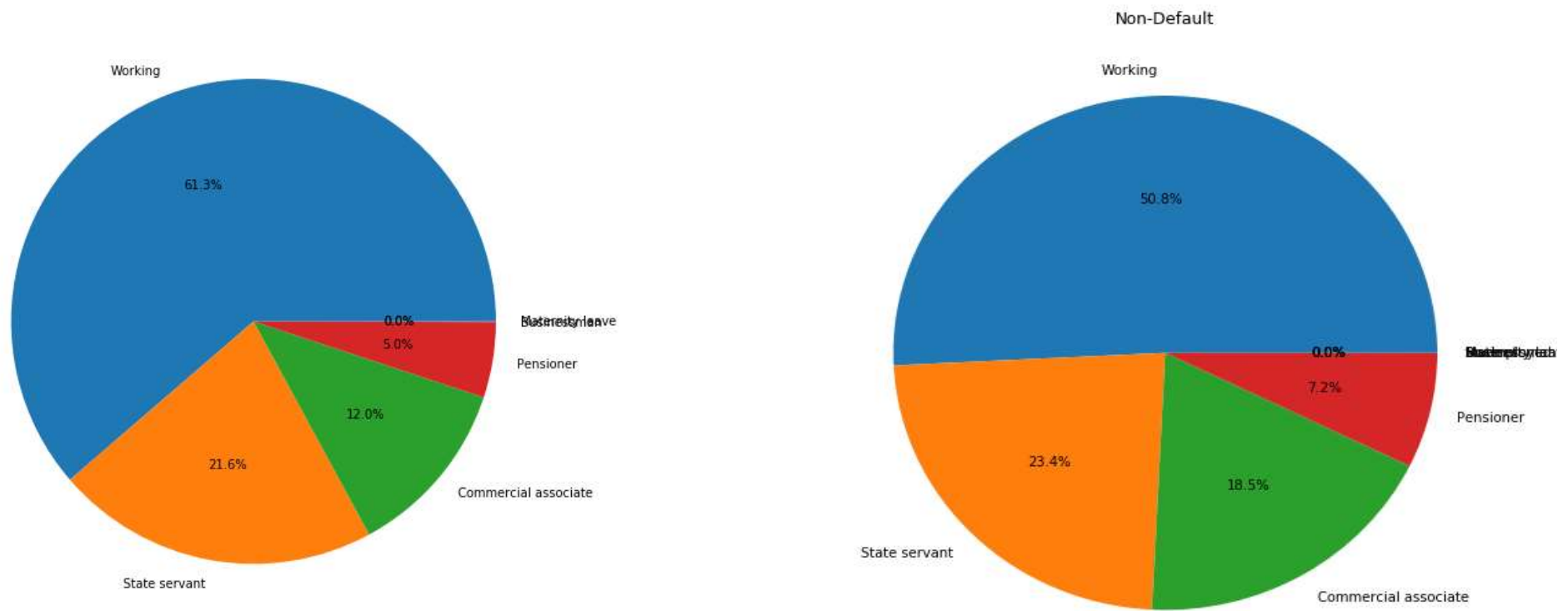
- Continuous Univariate Analysis:

**Columns under consideration are:**

- AMT\_INCOME\_TOTAL
- AGE
- AMT\_CREDIT
- DAYS\_EMPLOYED
- AMT\_ANNUITY

# Insights from Univariate Analysis:

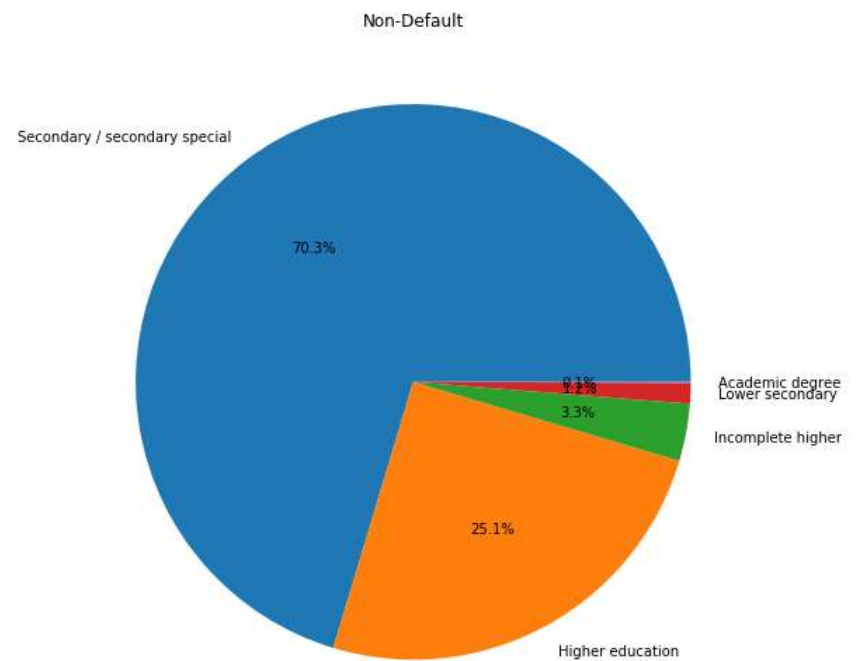
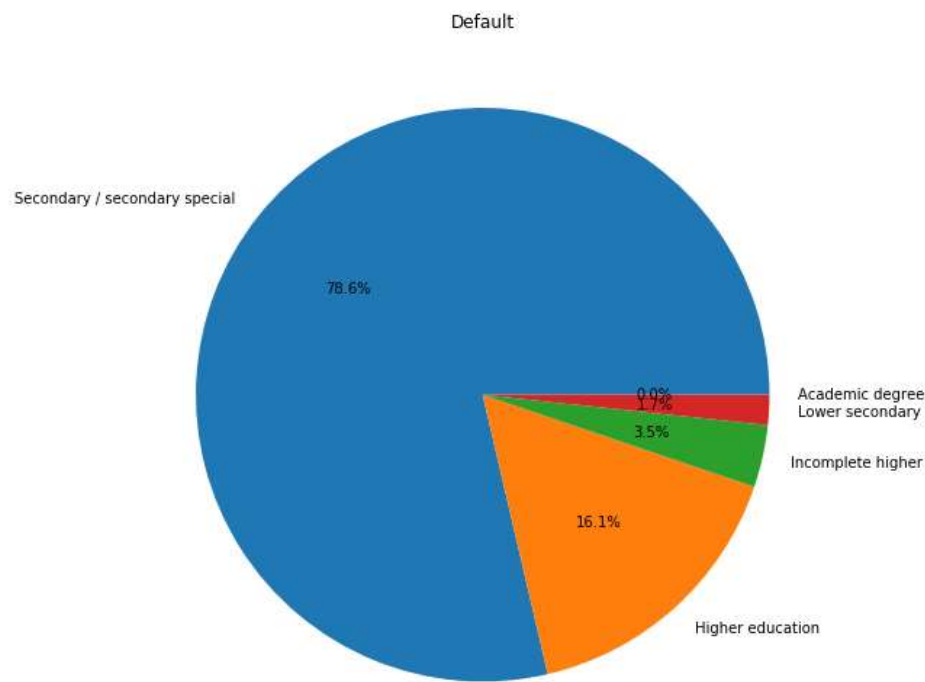
Column : NAME\_INCOME\_TYPE



**Commercial associates are less likely to default & working class are more likely to Default**

# Insights from Univariate Analysis:

Column : NAME\_EDUCATION\_TYPE

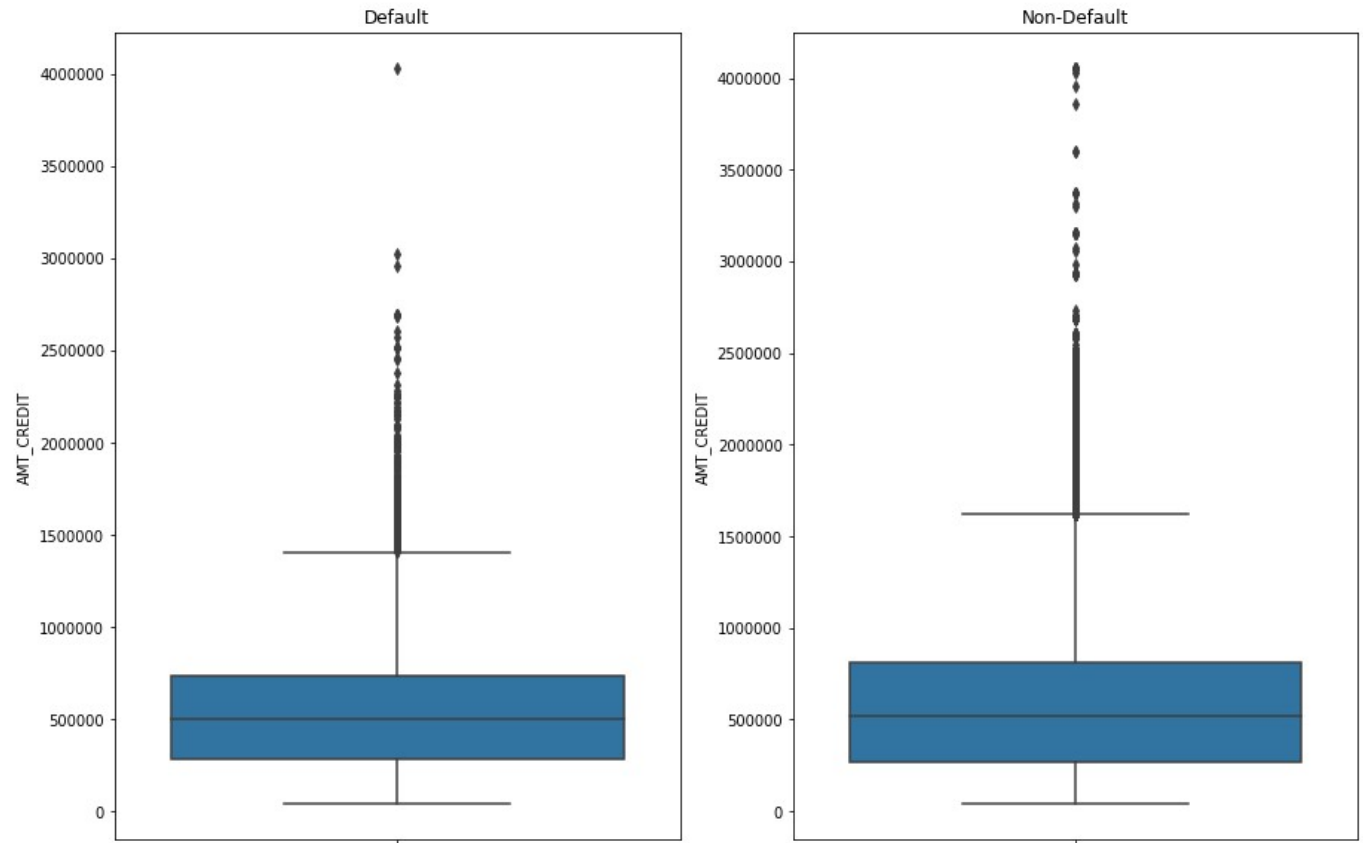


**Applicants with Higher Education are 1.5 times more likely to be Non-defaulters**

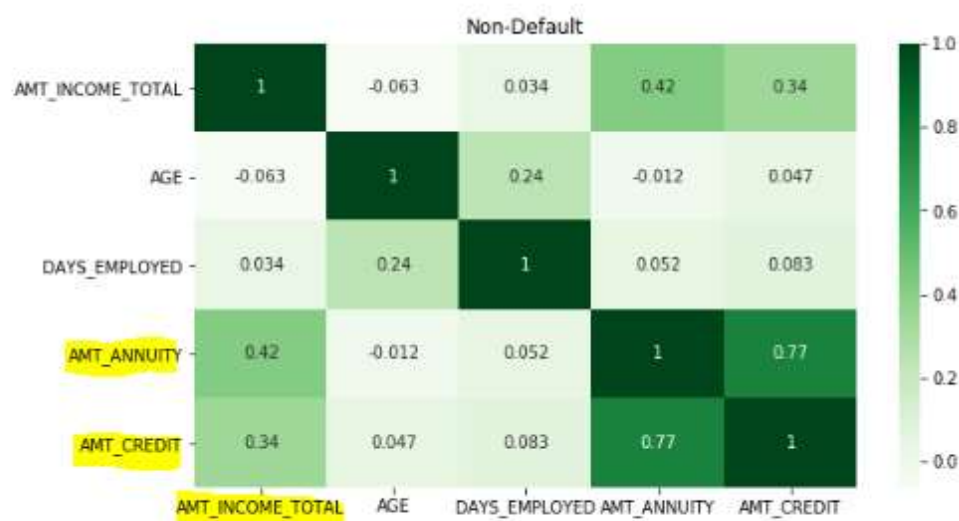
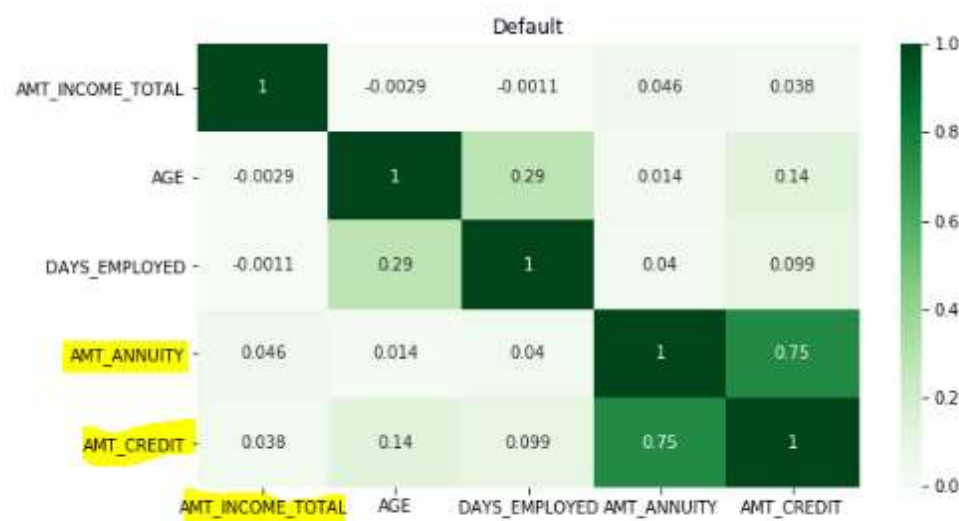
# Insights from Univariate Analysis:

Column : AMT\_CREDIT

**Credit value above 15 Lakhs are less likely to Default**



# Correlation Matrix between numerical columns:



## Inferences :

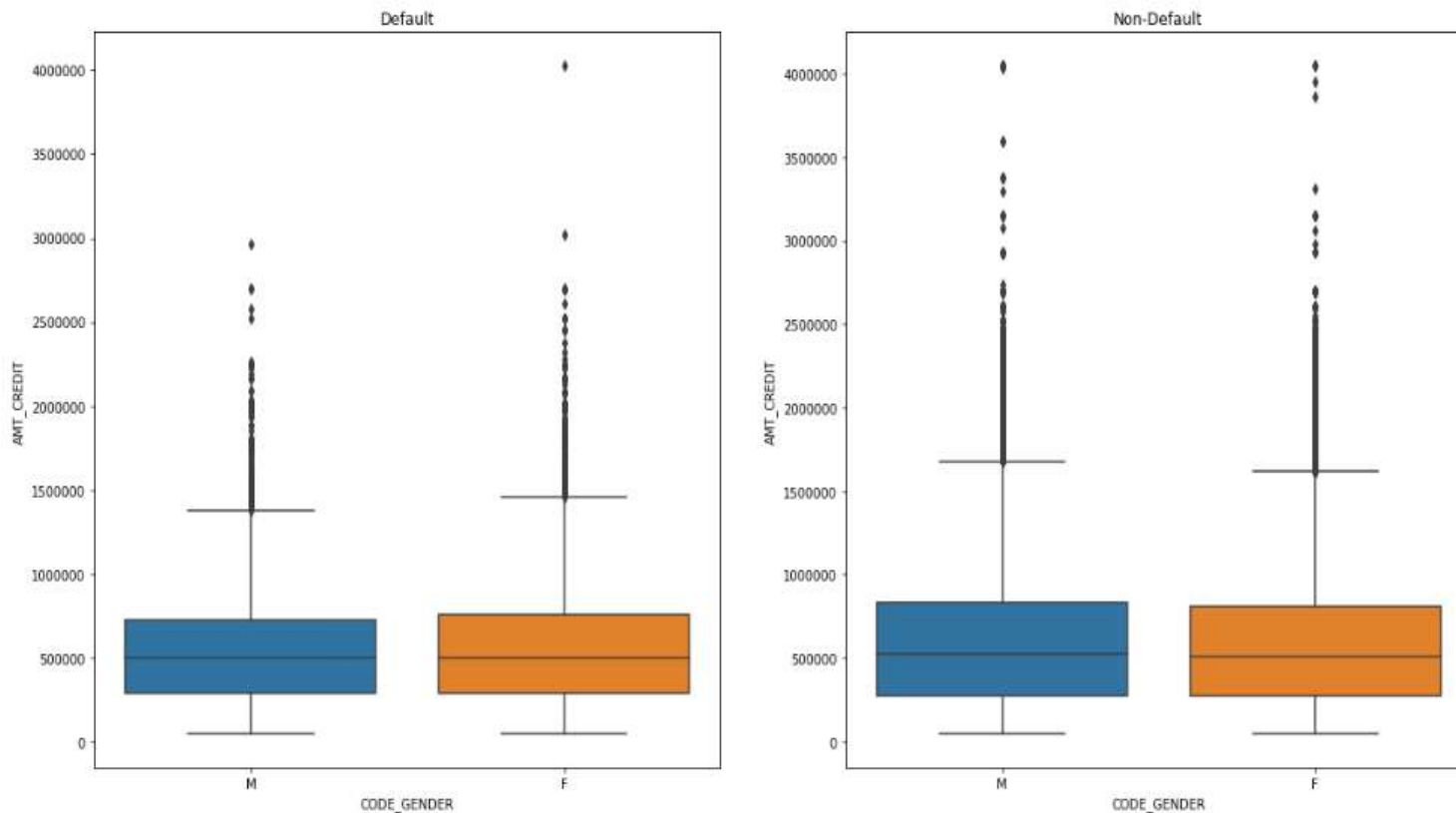
- AMT\_ANNUITY and AMT\_CREDIT are highly co-related columns for both Target values (1&0).
- Non-default has higher co-relation between AMT\_INCOME\_TOTAL VS AMT\_ANNUITY & AMT\_INCOME\_TOTAL VS AMT\_CREDIT vis-a-vis Defaulters.



# Bivariate Analysis on Application Data:

- In Categorical-Categorical, columns considered are:
  - NAME\_CONTRACT\_TYPE with CODE\_GENDER
  - FLAG\_OWN\_REALTY with CODE\_GENDER
  - NAME\_EDUCATION\_TYPE with FLAG\_OWN\_REALTY
  - NAME\_HOUSING\_TYPE with FLAG\_OWN\_REALTY
  - NAME\_CONTRACT\_TYPE with NAME\_FAMILY\_STATUS
- In Categorical-Continuous, columns considered are:
  - CODE\_GENDER with AMT\_CREDIT
  - AMT\_INCOME\_TOTAL with CODE\_GENDER
  - FLAG\_OWN\_REALTY with AMT\_INCOME\_TOTAL
  - FLAG\_OWN\_REALTY with AGE
  - NAME\_CONTRACT\_TYPE with AGE
- In Continuous-Continuous, columns considered are:
  - AMT\_INCOME\_TOTAL with AGE
  - AMT\_INCOME\_TOTAL with AMT\_ANNUITY
  - DAYS\_EMPLOYED with AMT\_CREDIT
  - AGE with DAYS\_EMPLOYED
  - AMT\_GOODS\_PRICE with AGE

# Insights from Bivariate Analysis:



Columns:  
AMT\_CREDIT vs  
CODE\_GENDER

Outcome:

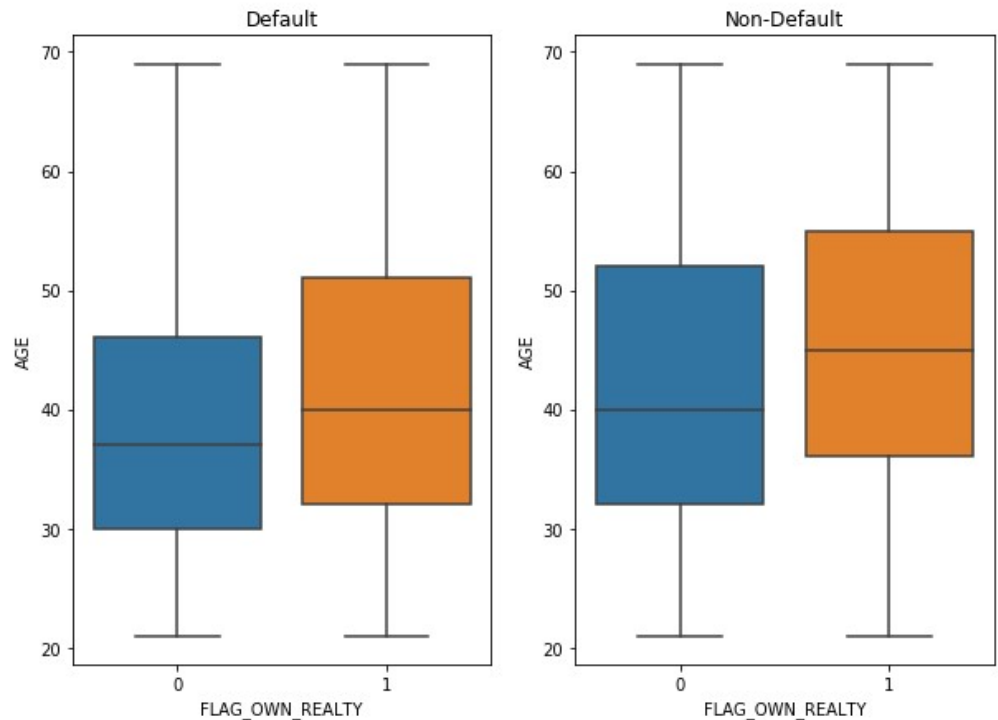
**In case of Defaulters, 75% percentile is greater for Females whereas in case of non-defaulters it is greater for Males.**

# Insights from Bivariate Analysis:

Columns:  
AGE vs FLAG\_OWN\_REALTY

Outcome:

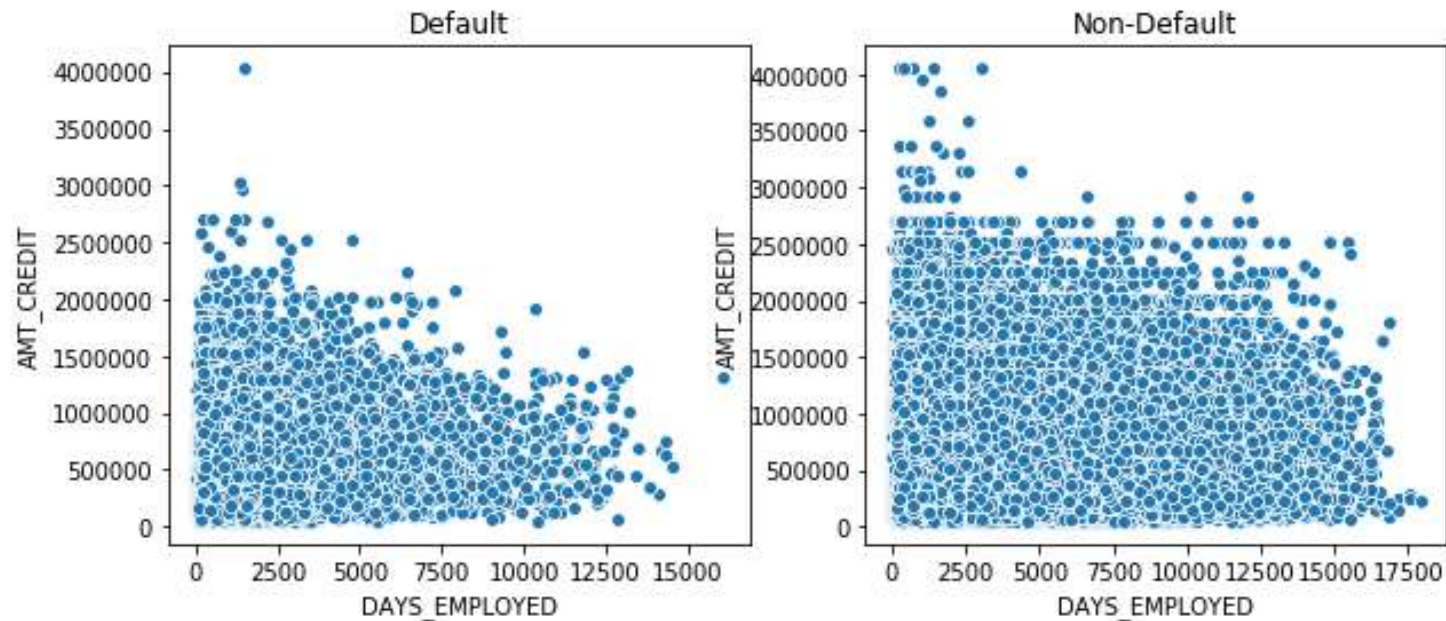
**Applicants who are above 45 years of age and do not own a property are less likely to be Defaulters.**



# Insights from Bivariate Analysis:

Columns: AMT\_CREDIT vs DAYS\_EMPLOYED

Outcome: **Applicants with more Work Experience and less credit amount are less likely to Default**



# Merging with previous application data

- Merged application\_data.csv with previous\_application.csv using LEFT JOIN.
- Dropped columns with missing values more than 45%.
- Performed Univariate and Bivariate analysis on combined dataset.

```
In [67]: df2 = pd.read_csv("previous_application.csv")
```

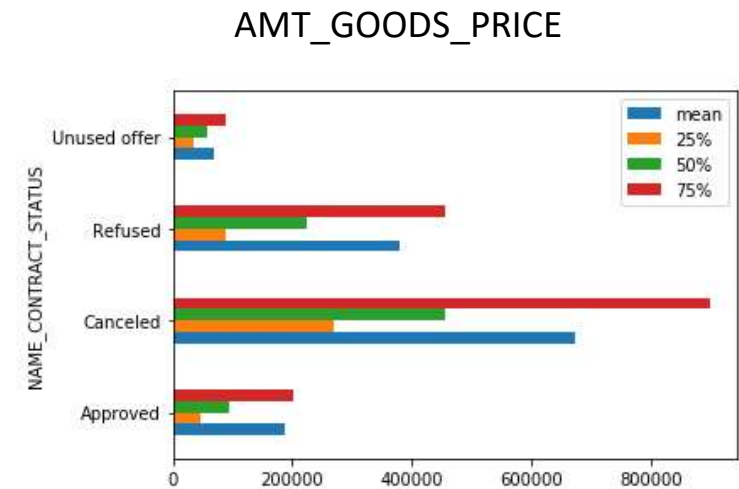
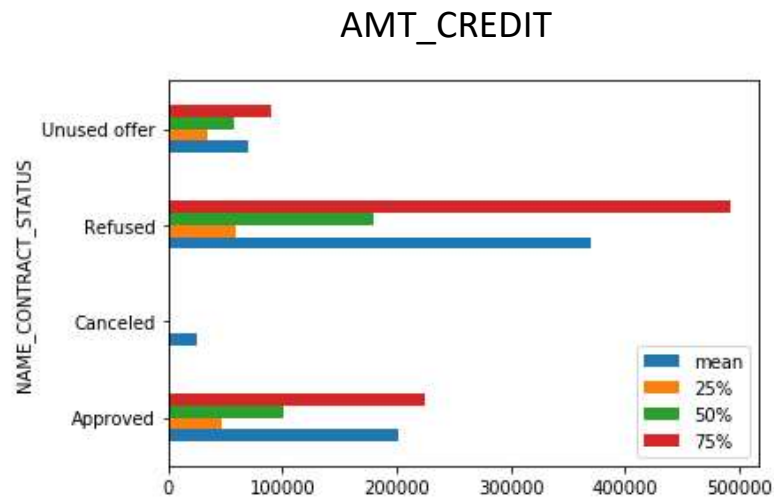
**Merging of both Application data and Previous application data**

```
In [68]: df12 = pd.merge(left=df1, right=df2, how='left', on='SK_ID_CURR')
```

```
In [70]: df12.head()
```

```
: # Shape of the combined data set after dropping columns with more than 45% missing values
df12.shape
: (1430155, 107)
```

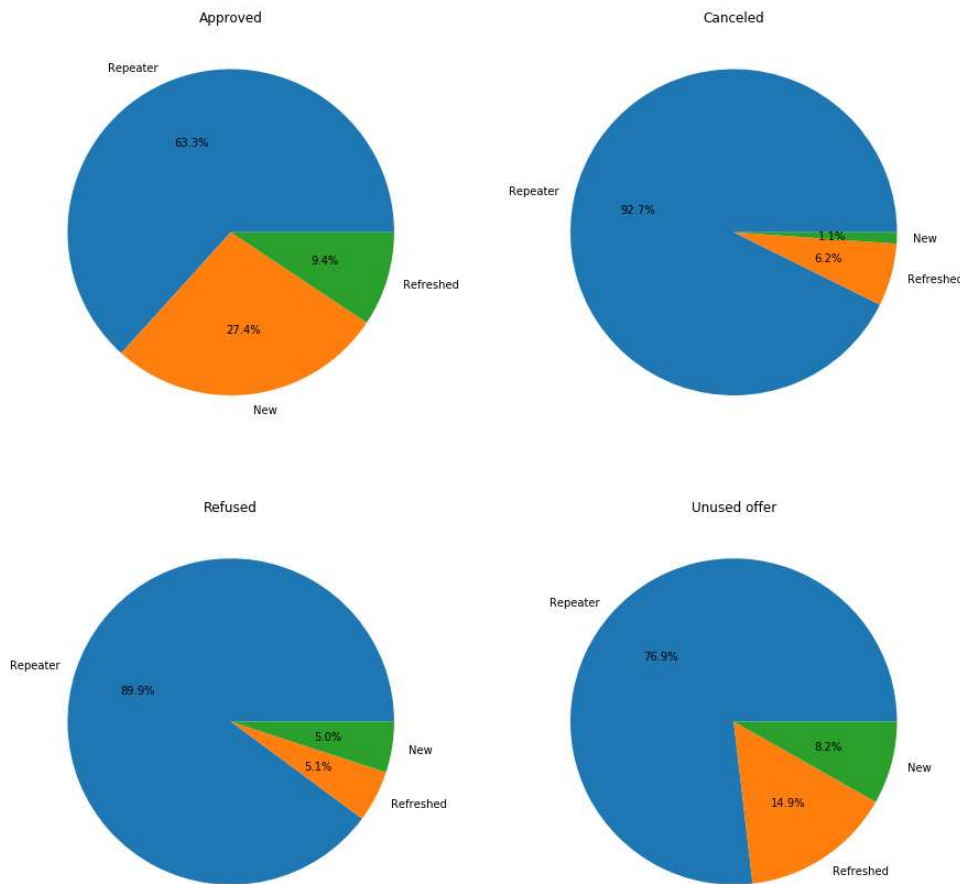
# Insights from Univariate Analysis on Combined Dataset:



Outcomes:

- Chances of Application being Refused is more if the Credit Amount is more than 2 Lakhs
- Chances of Application being Refused or getting cancelled is more if the Amount Goods price is more than 2 Lakhs

# Insights from Univariate Analysis on Combined Dataset:

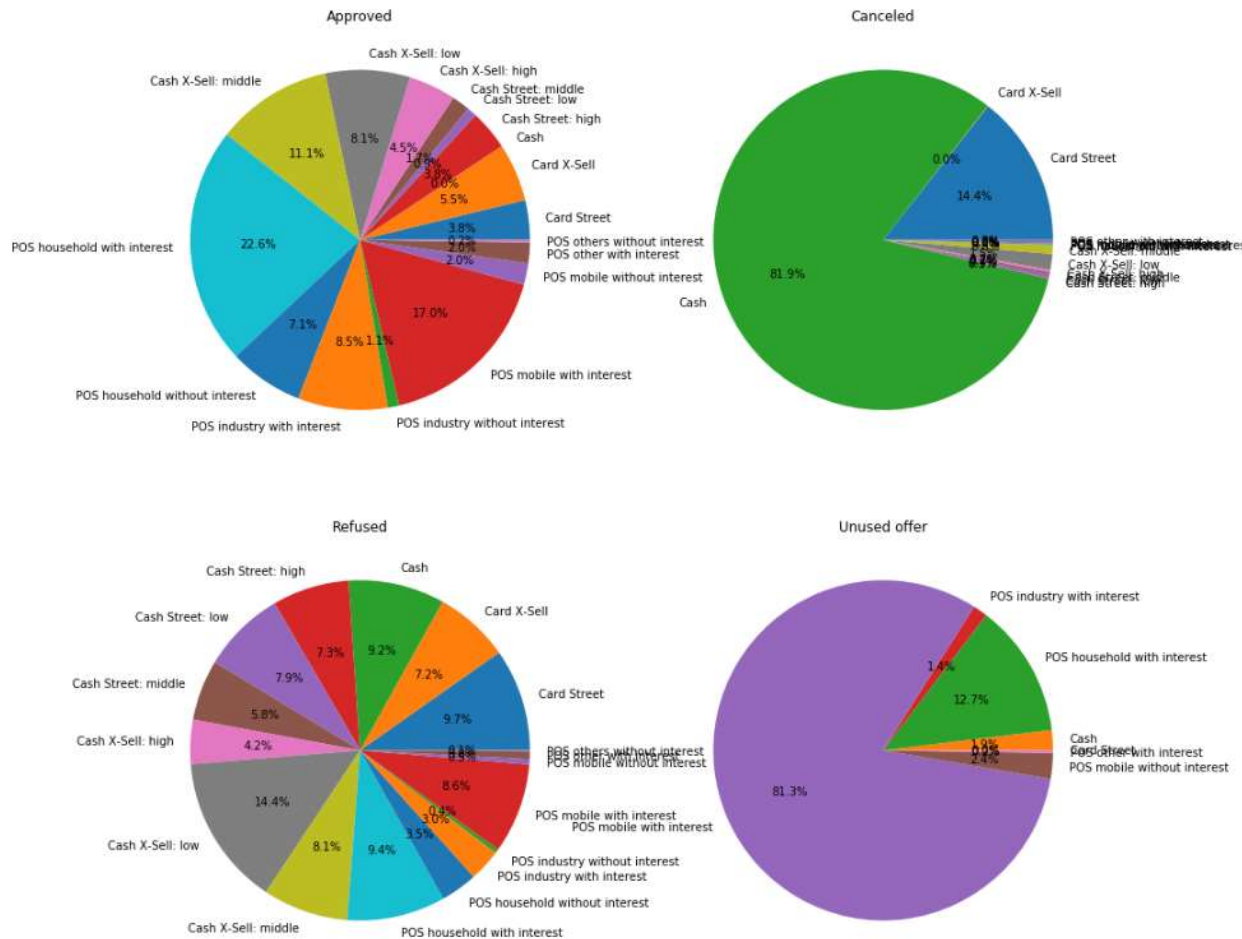


Column : NAME\_CLIENT\_TYPE

Outcomes:

- **Chances of an Application getting Approved is more for a New Applicant**
- **Chances of an applicant Un-use the offer is more for a Refreshed Applicant**
- **Chances of an Application getting Cancelled or Refused is very high for a Repeater**

# Insights from Univariate Analysis on Combined Dataset:



Column: PRODUCT\_COMBINATION

Outcomes:

- Chances of an Application getting approved is more for POS household with Interest and overall POS products (>50%)
- Chances of an Application getting Either Cancelled or Refused is more for all Cash products (>50%)



# Conclusion:

- These are driving factors behind load default:
  - AMT\_CREDIT
  - NAME\_EDUCATION\_TYPE
  - NAME\_INCOME\_TYPE
  - NAME\_CLIENT\_TYPE
  - PRODUCT\_COMBINATION
  - AGE
  - DAYS\_EMPLOYED
  - AMT\_INCOME\_TOTAL
  - CODE\_GENDER

Thank you!