LendingClub

EDA Case Study

Objectives

- Build risk profile to enable lending business
  - Develop recommendations on ability to repay loan, which will lead to loan approval, which in turn improve business to company.
- Identify key risks leading to loan default
  - Identify strong drivers (variables) for loan default.

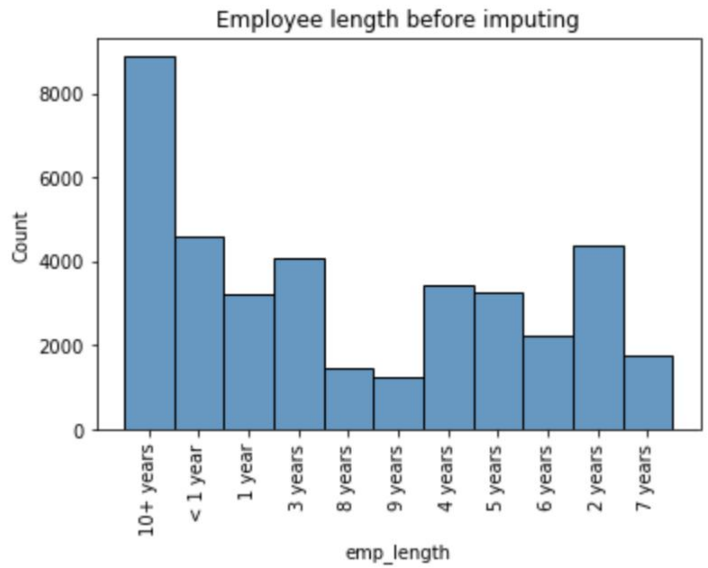
Available Dataset

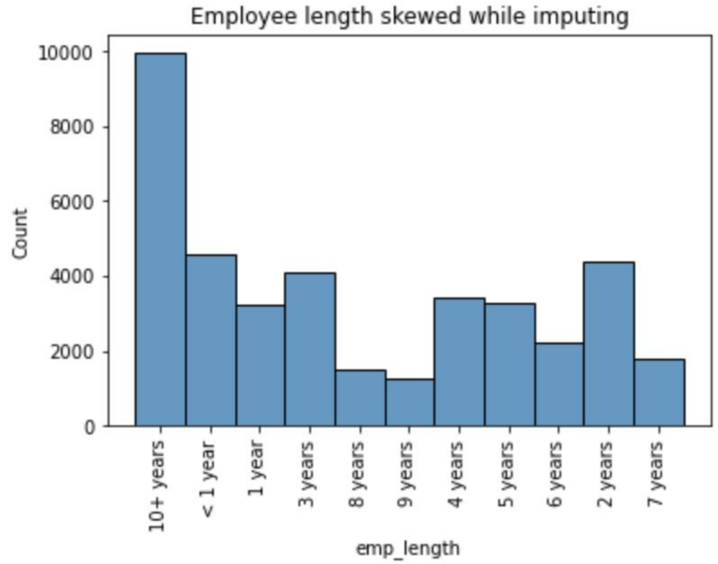
- Dataset contains information about past loan applicants.
- Columns with demographic and customer specific details have been removed from analysis as they do not help in predicting the business.
- Columns with more than 90% missing values
  - There are about 56 columns with more than 90% values missing.
- Rows that has more than 25% data missing has been removed.
- Fields with mixed data type has been converted to usable format (ex. Term field is a string, moved to integer).
- Columns that do not drive any impact has been removed.
- 16 columns have been identified and taken for analysis

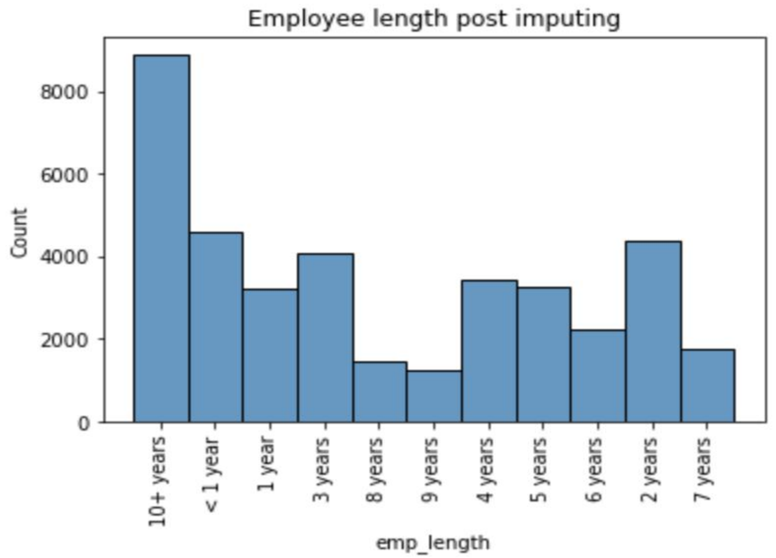
```
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 16 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   loan_amnt            39717 non-null  int64
 1   funded_amnt          39717 non-null  int64
 2   funded_amnt_inv      39717 non-null  float64
 3   term                 39717 non-null  object
 4   int_rate             39717 non-null  object
 5   installment          39717 non-null  float64
 6   grade                39717 non-null  object
 7   sub_grade            39717 non-null  object
 8   emp_length           38642 non-null  object
 9   home_ownership       39717 non-null  object
 10  annual_inc           39717 non-null  float64
 11  verification_status  39717 non-null  object
 12  loan_status          39717 non-null  object
 13  purpose              39717 non-null  object
 14  addr_state           39717 non-null  object
 15  dti                  39717 non-null  float64
dtypes: float64(4), int64(2), object(10)
memory usage: 4.8+ MB
```

Variables

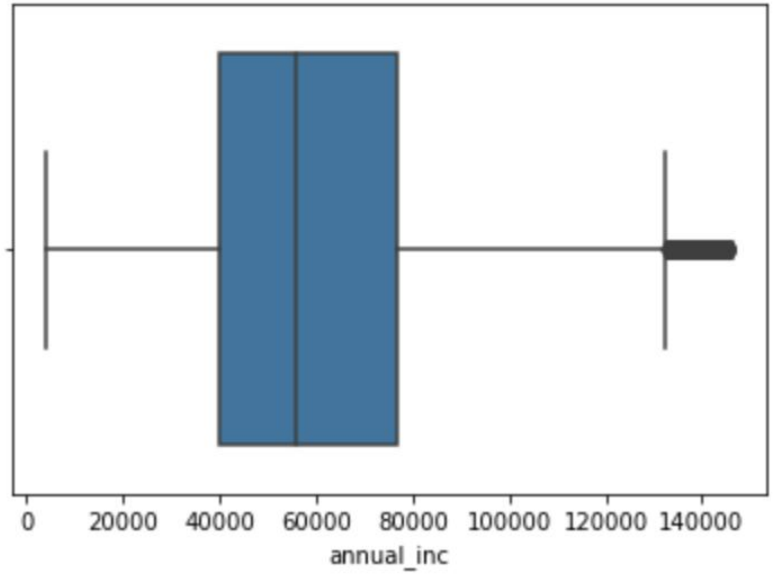
- Null values imputation
  - emp_length variable need to be imputed as it had 1000+ null data.
  - Using mode function, data was left skewed.
  - Hence removed the null values.

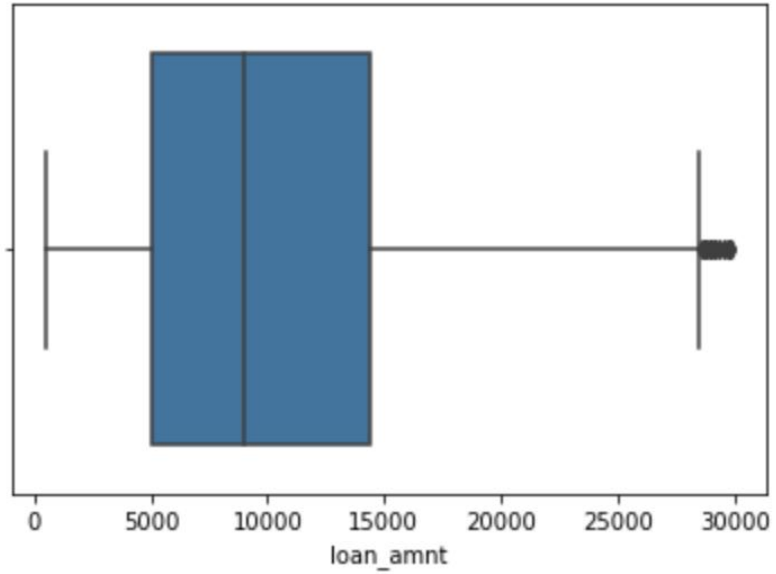






- Target Variables
  - loan_default_status variable has been identified to classify target as fully paid or defaulted
  - Current employees are not added for analysis as we do not have information regarding they have defaulted any payment.
- Outlier Treatment
  - annual inc & loan_amnt variabled are treated for outliers using IRQ. Hence data used for analysis represents the entire customer database.





- Driver Variables
    - grade
    - purpose
    - emp_length
    - home_ownership
    - addr_state
    - annual_inc
    - funded_amnt

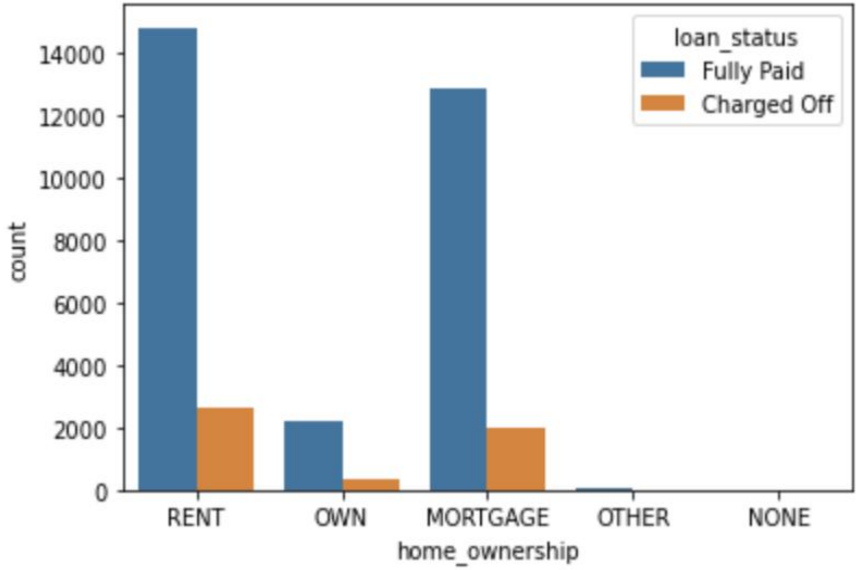
  are identified to have business impact on determining if a borrower tends to pay fully or default.

Conclusions

Risk profile recommendations based on loan data set research

Risk Profile based on Home Ownership

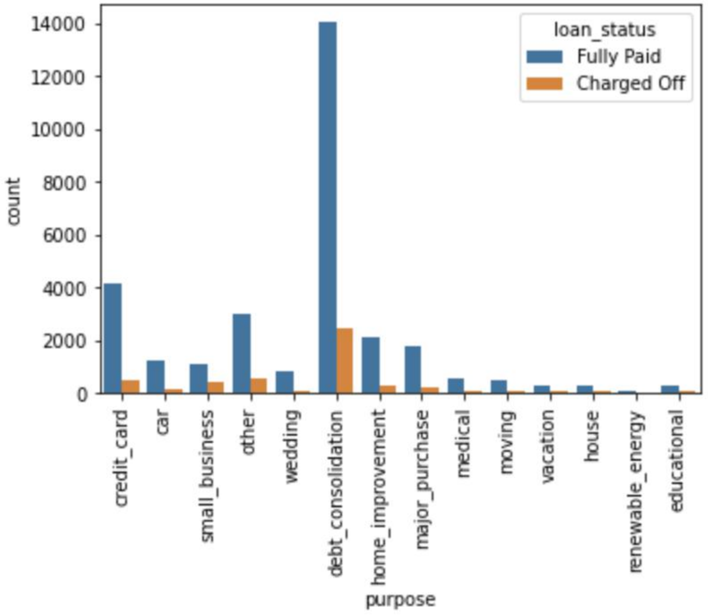
```
home_ownership  loan_status
MORTGAGE        Charged Off     1993
                Fully Paid     12860
NONE            Fully Paid         3
OTHER           Charged Off       17
                Fully Paid        76
OWN             Charged Off      379
                Fully Paid      2235
RENT            Charged Off     2609
                Fully Paid     14833
Name: loan_status, dtype: int64
```



An applicant is more likely to default loan re-payment, when type of residence is Rented or Mortgaged when compared to Owned.

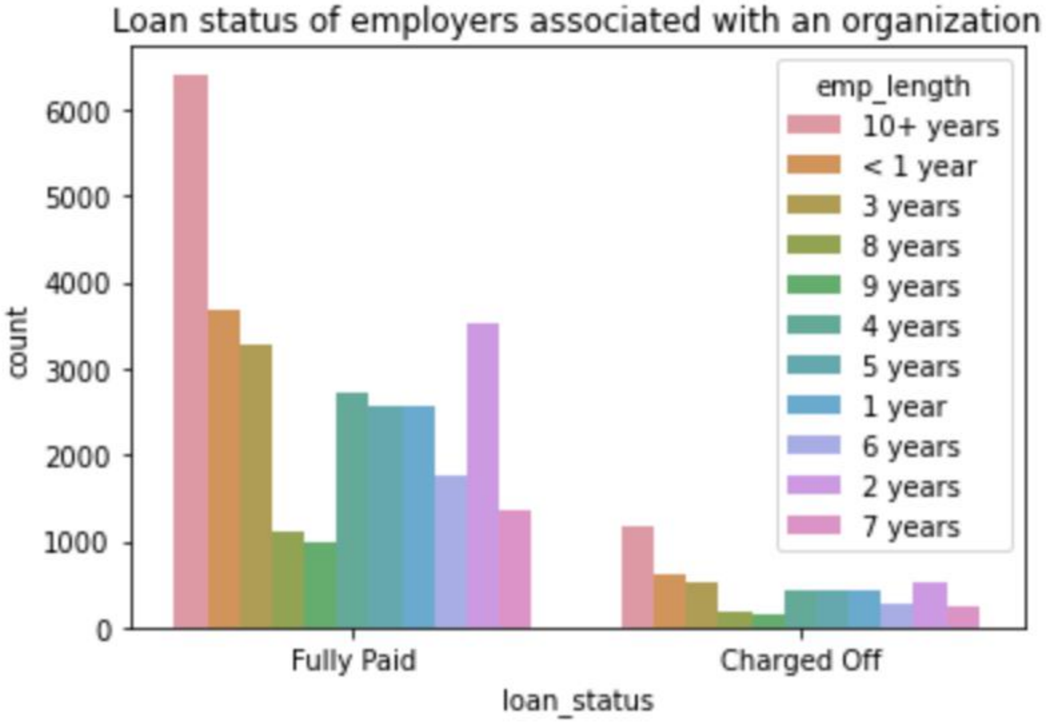
Risk Profile based on Loan purpose

```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13]),
 [Text(0, 0, 'credit_card'),
  Text(1, 0, 'car'),
  Text(2, 0, 'small_business'),
  Text(3, 0, 'other'),
  Text(4, 0, 'wedding'),
  Text(5, 0, 'debt_consolidation'),
  Text(6, 0, 'home_improvement'),
  Text(7, 0, 'major_purchase'),
  Text(8, 0, 'medical'),
  Text(9, 0, 'moving'),
  Text(10, 0, 'vacation'),
  Text(11, 0, 'house'),
  Text(12, 0, 'renewable_energy'),
  Text(13, 0, 'educational')])
```



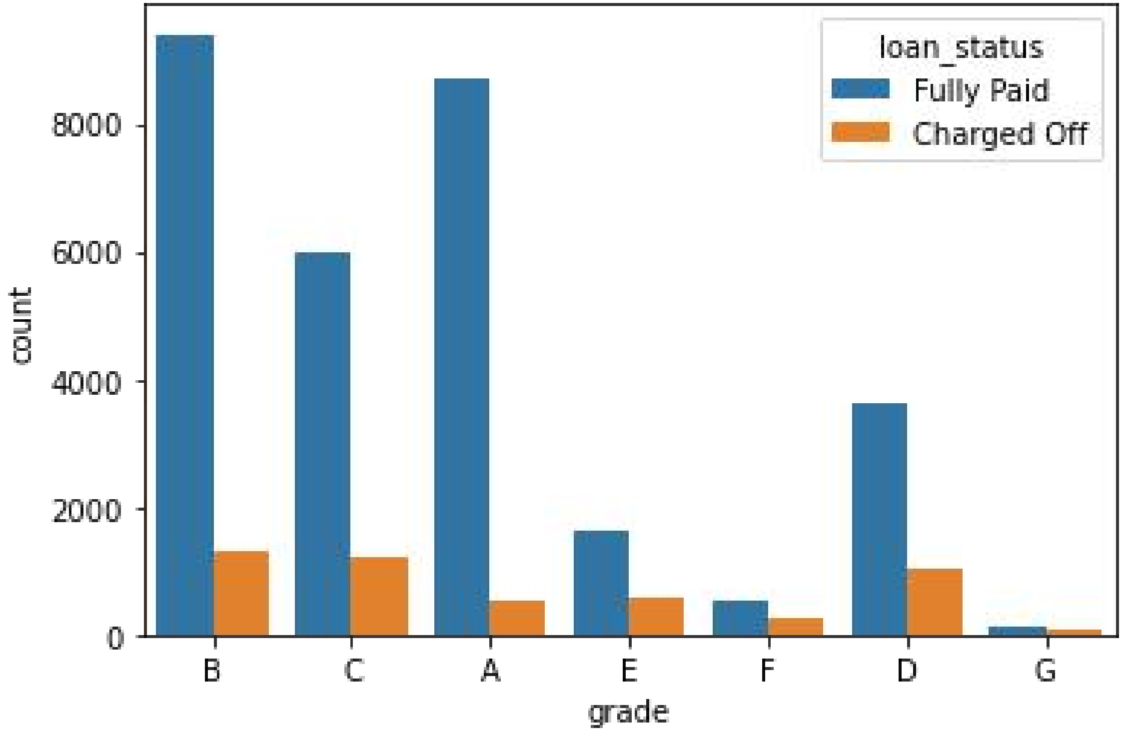
An applicant is more likely to default loan re-payment, when purpose of loan is for debt consolidation as opposed to any other purpose.

Risk Profile based on Employment Length



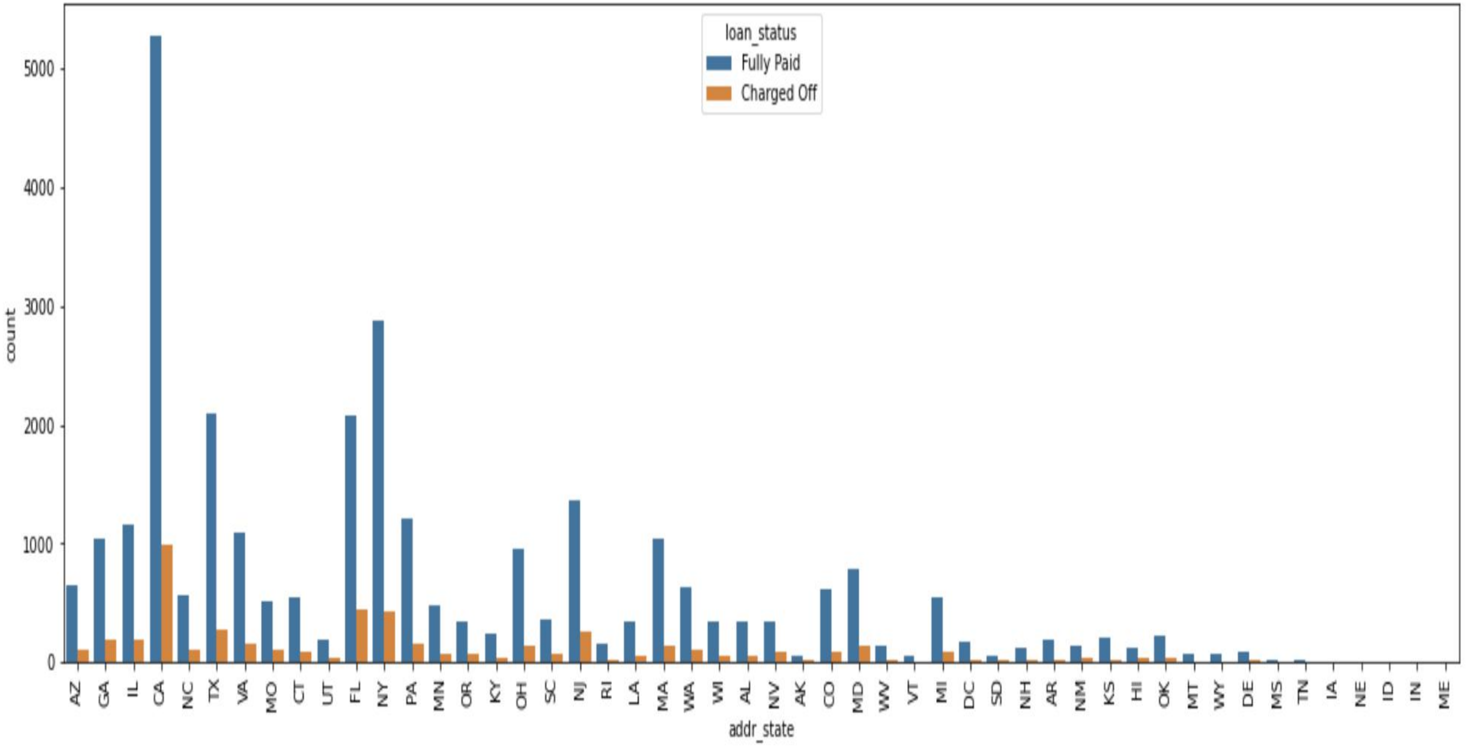
Applicant's that has worked at an employer for longer term, i.e., 10+ years tend to re-pay better.

Risk Profile based on Applicant's grade



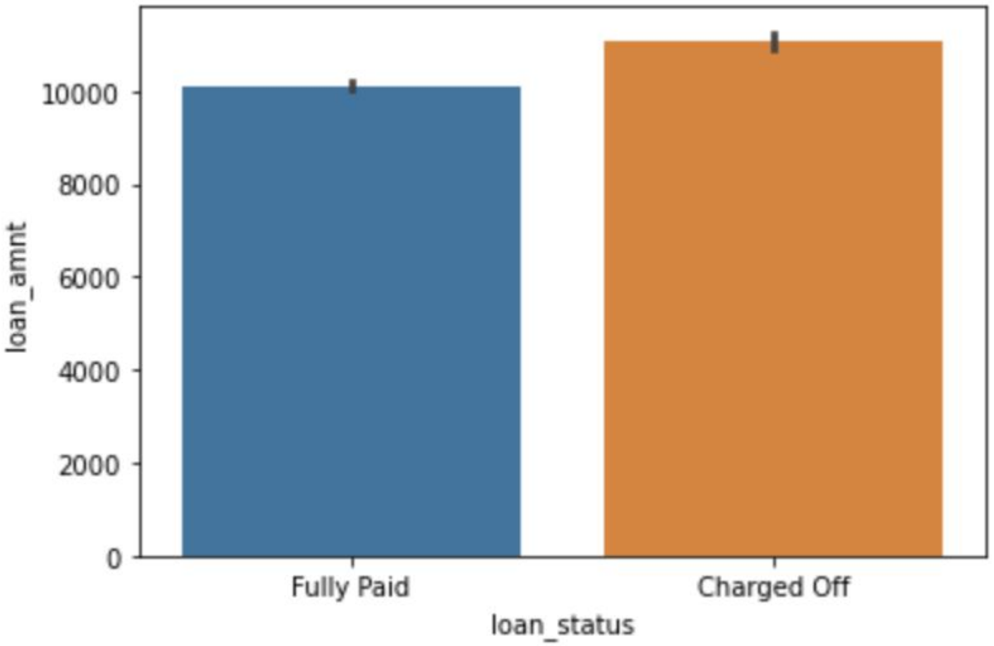
Applicants belonging to E,F,G grades are more likely to default on loan re-payment.

Risk Profile based on Home Ownership



Applicants from state of California has higher changes of a loan default than most other states.

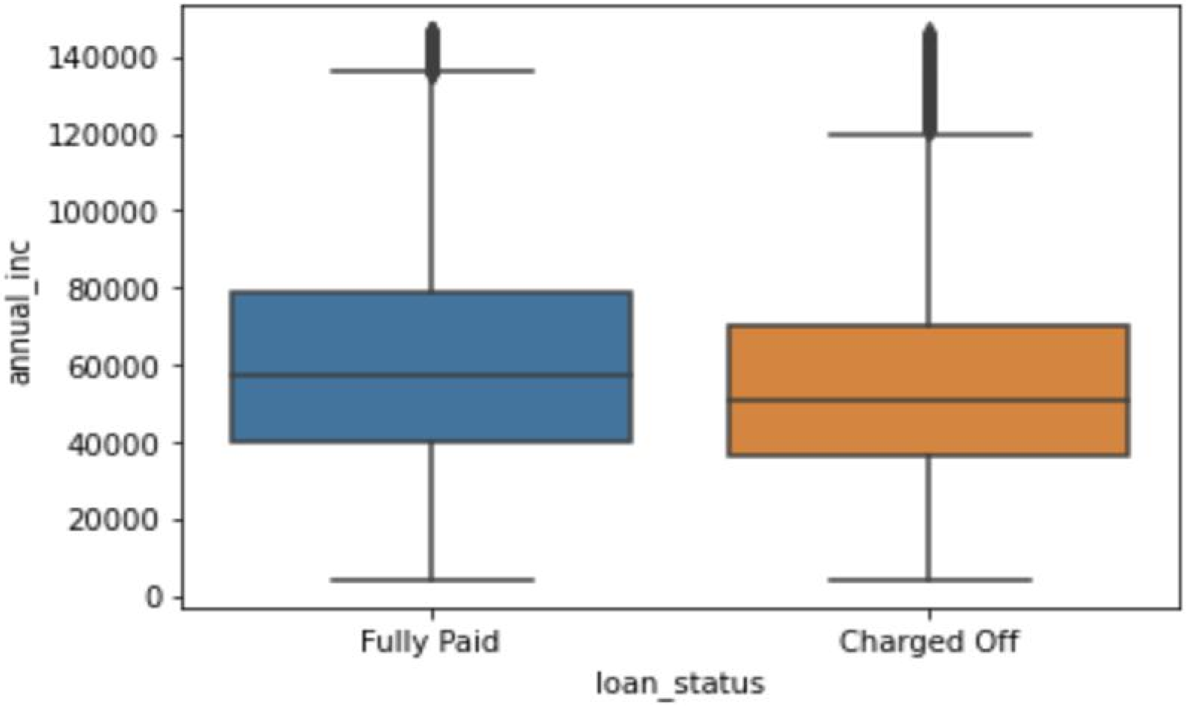
Risk Profile based on loan amount



Applicants requesting for higher loan amount tends to default more.

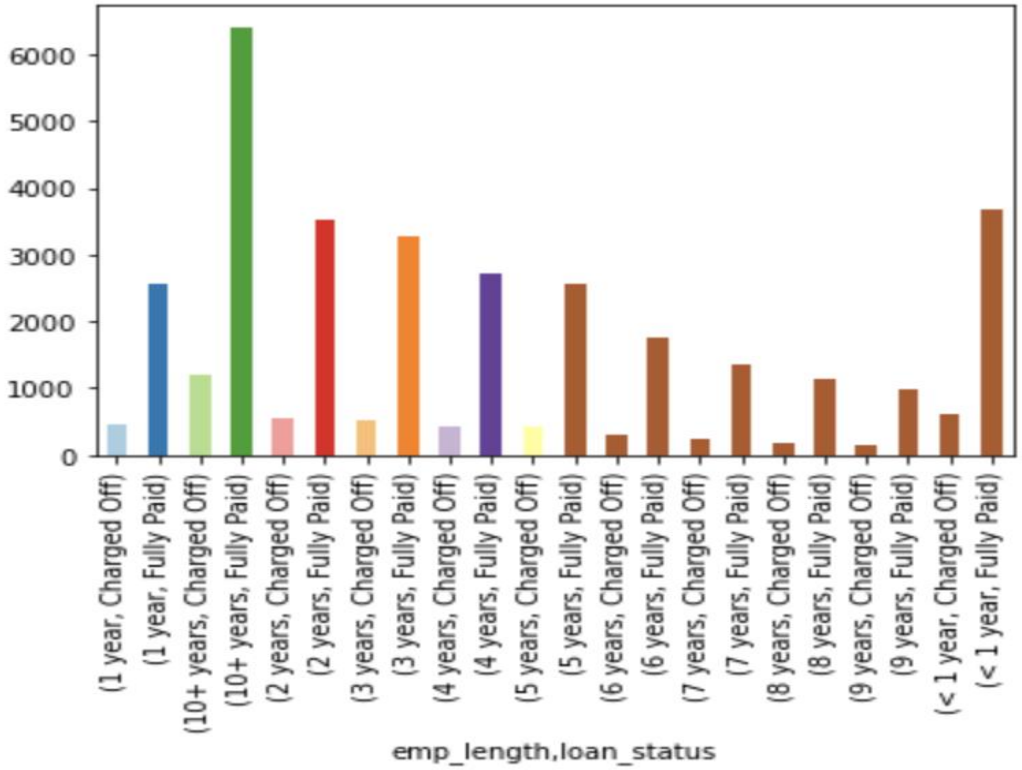
Lesser the loan amount, lesser chances of defaulting

Risk Profile based on annual income



Applicants having lesser annual income more likely to default.

Risk Profile based on funded amount vs emp _length



Applicants having lesser annual income more likely to default.

Thank you!

Univariate and bivariate analysis of variables in the ipynb files