Lending club case study

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General info

- Goal
  - Analyse loan data provided
  - Understand relationships between variables
  - Find factors which influence loan defaults
- Methodology
  - Data will first be cleaned
  - EDA will be used to analyse the data
  - No machine learning methods are used

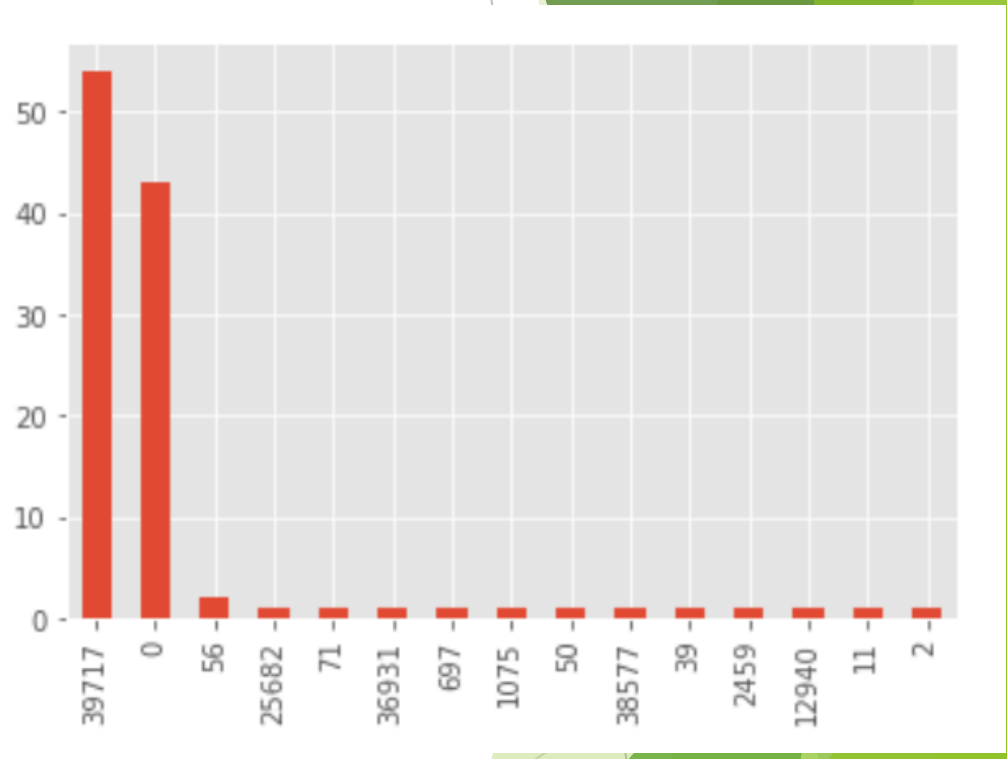
Data info

Item	Description
filename	Loans.csv
File describing data	Data_Dictionary.xlsx
Number of rows	39717
Number of columns	111

- Data was imported into a Jupyter notebook
- All analysis was done with python

Cleaning

- The following columns were dropped:
  - 54 columns with 39717 'nans'
  - 9 columns with all values same
  - Columns with more than 50% missing values
  - Columns not useful for prediction of default were dropped



Missing values

- **'desc', 'emp_title', 'title'**
  - had too many unique text values. Entire columns were dropped.
- **`'revol_util', 'last_pymnt_d', 'last_credit_pull_d'`**
  - `combined missing values were less than 0.3%`
  - `hence rows with missing values were dropped`
- **'pub_rec_bankruptcies'**: Imputed with mode 0
- **'emp_length':** imputed with value "unknown"

Size of data after cleaning: (39598 rows, 37 columns)

Cleaning

- All date columns converted from object to datetime64
- Columns ending with % were converted to float64
- Leading and trailing spaces were removed
- Annual_inc made more readable by dividing by 1000

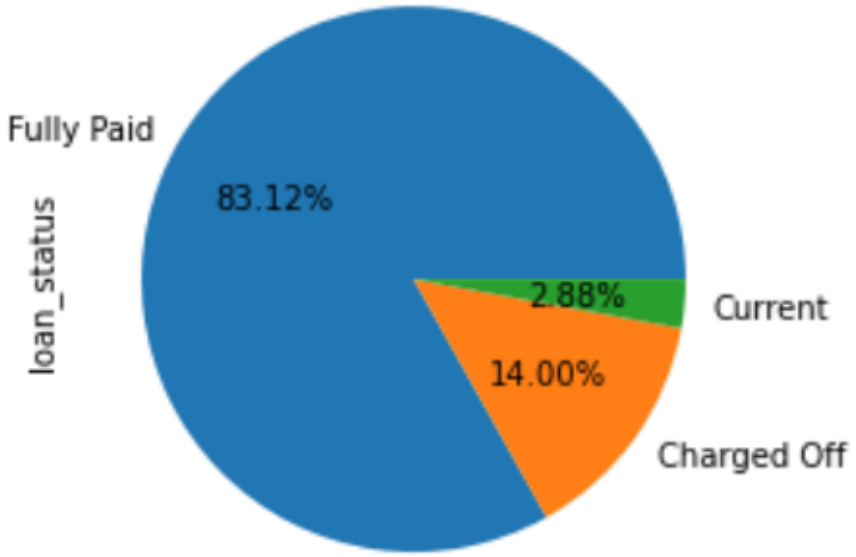
```
# Make annual_inc more readable
df1.annual_inc = df1.annual_inc / 1000
df1.annual_inc.describe()
```

```
count    39598.000000
mean        69.035085
std         63.828578
min          4.000000
25%         40.632500
50%         59.000000
75%         82.500000
max       6000.000000
Name: annual_inc, dtype: float64
```

Univariate Analysis

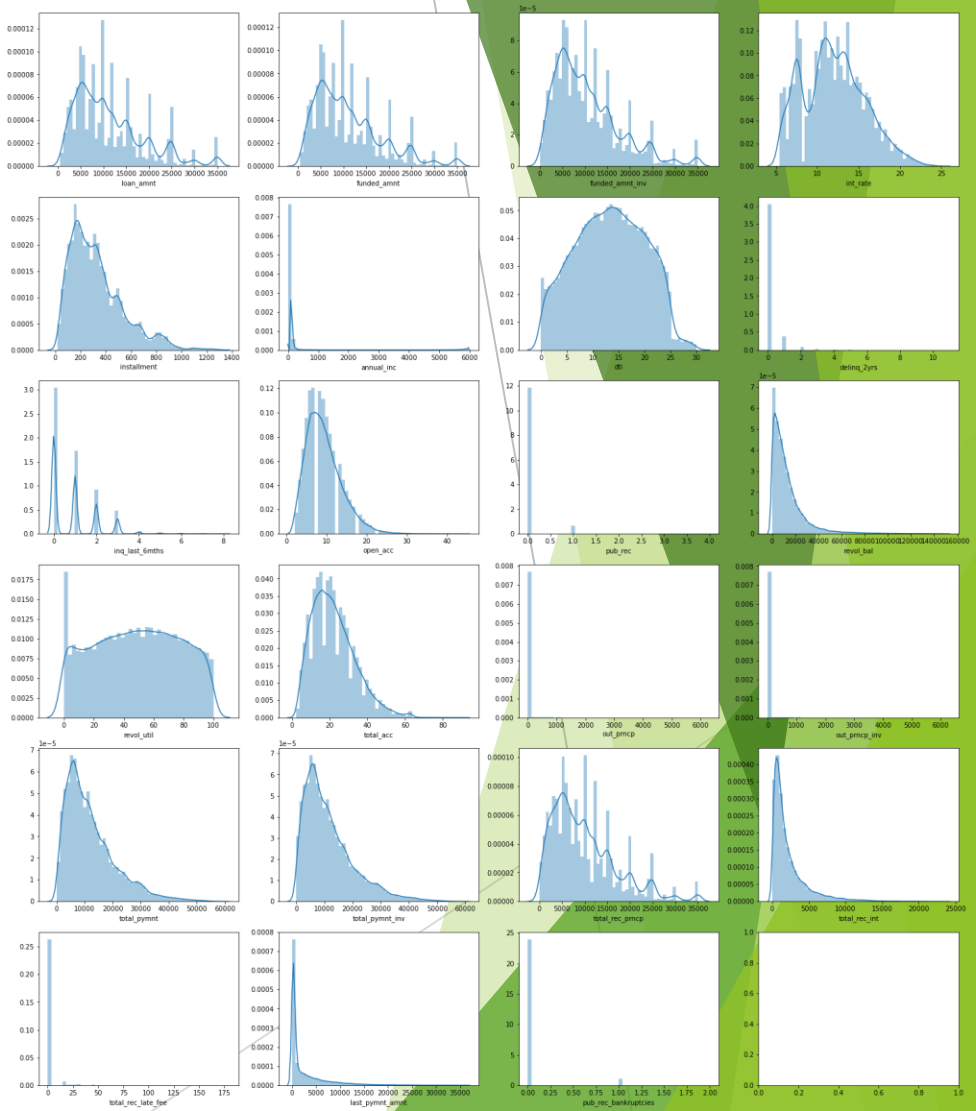
- loan_status is our target variable

```
Fully Paid     32915
Charged Off     5543
Current         1140
Name: loan_status, dtype: int64
```



Univariate Analysis

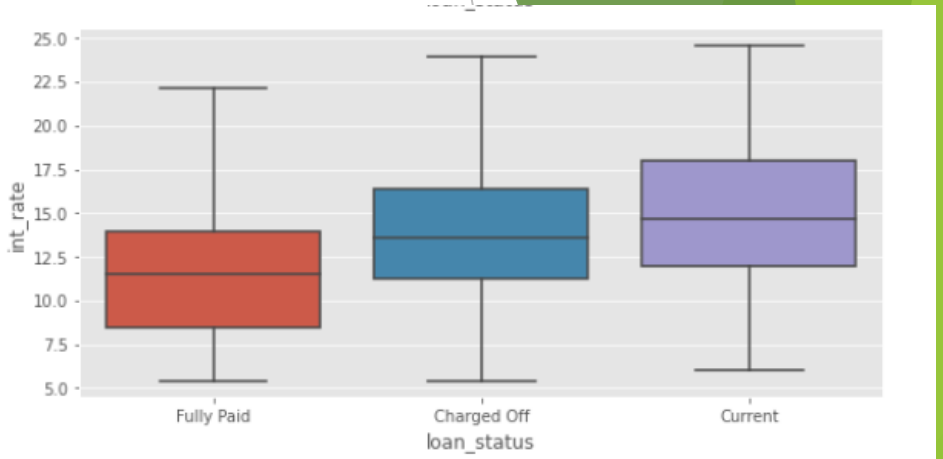
- Initial plot of continuous variables was made
  - Columns with similar distribution were dropped - *'funded_amnt', 'funded_amnt_inv'*
  - Columns with more than 95% same values and more than 15 unique values were dropped - *'total_rec_late_fee', 'out_prncp_inv', 'out_prncp'*
  - Total payment and total recovery cannot help in predicting default. Drop these features - *'total_pymnt','total_pymnt_inv','total_rec_int', 'total_rec_prncp'*



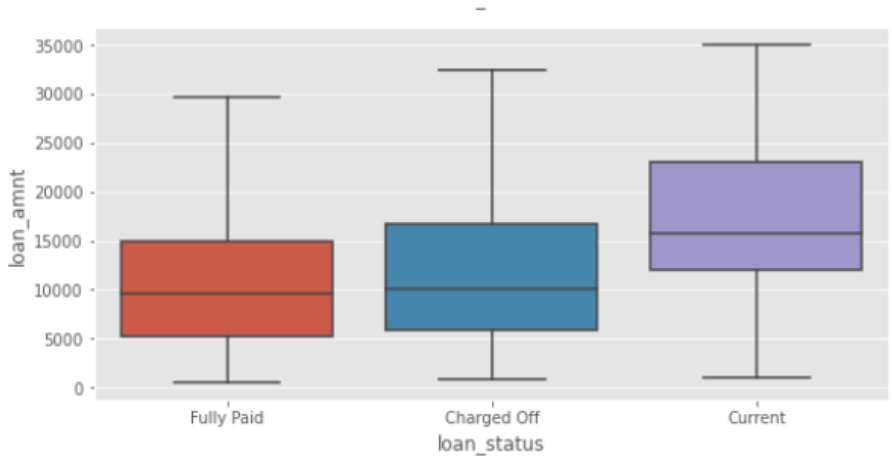
Continuous columns – impact on default

- `['open_acc', 'last_pymnt_amnt', 'revol_bal', 'installment', 'int_rate', 'dti', 'total_acc', 'revol_util', 'loan_amnt']`
- **Observations**
  - int_rate and revol_util seem to be only two variables really impacting default.
  - loan_amnt seems to have a slight impact. higher loans mean higher default.

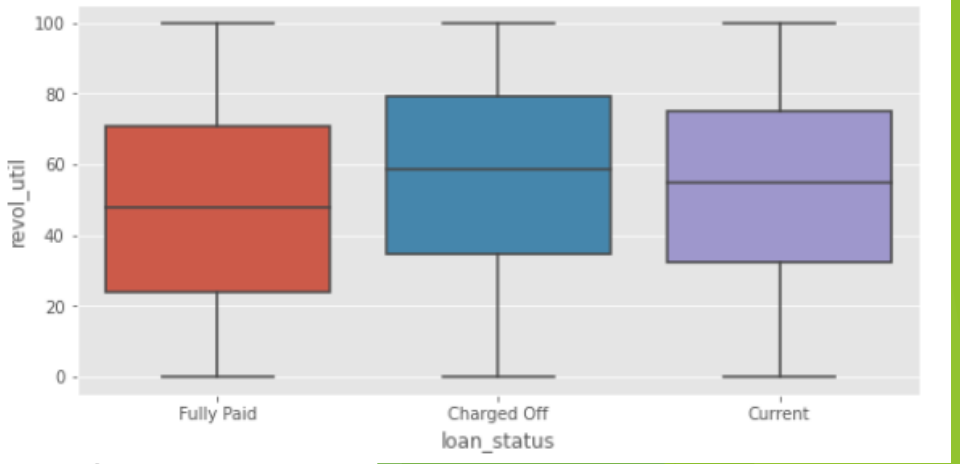
int_rate



loan_amnt



revol_bal



Categorical columns impact

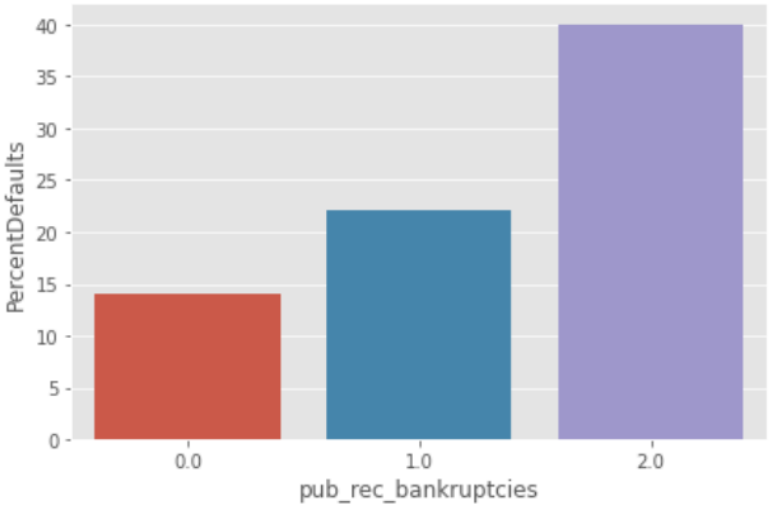
- Columns with few distinct values were treated as categorical
- `['delinq_2yrs', 'inq_last_6mths', 'pub_rec',`
- `'pub_rec_bankruptcies', 'annual_inc']`

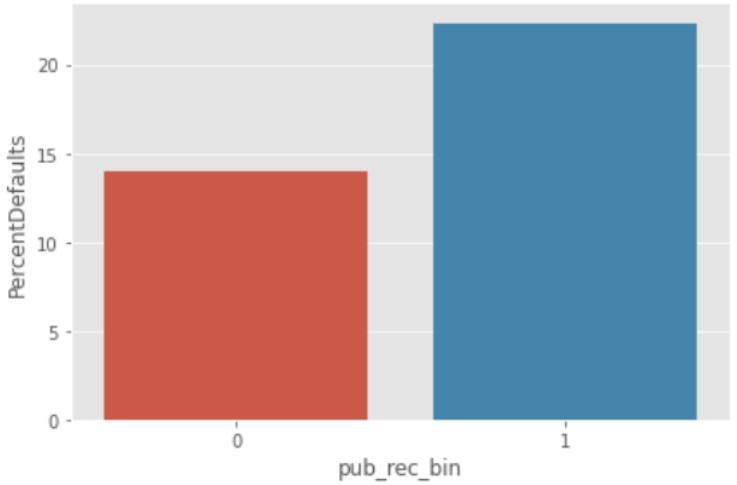
- **Observations**
- **All variables treated as categorical seem to have direct impact on defaults.**
- 'pub_rec_bankruptcies' have only 3 distinct values
- 'pub_rec_bin', 'delinq_2yrs', 'inq_last_6mths' were converted to fewer categories to make analysis easier

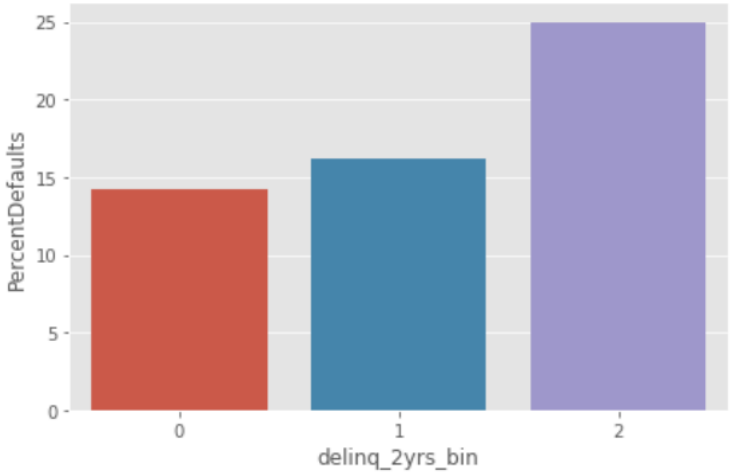
Percent defaults is used as the metric to analyze effect of categorical variables

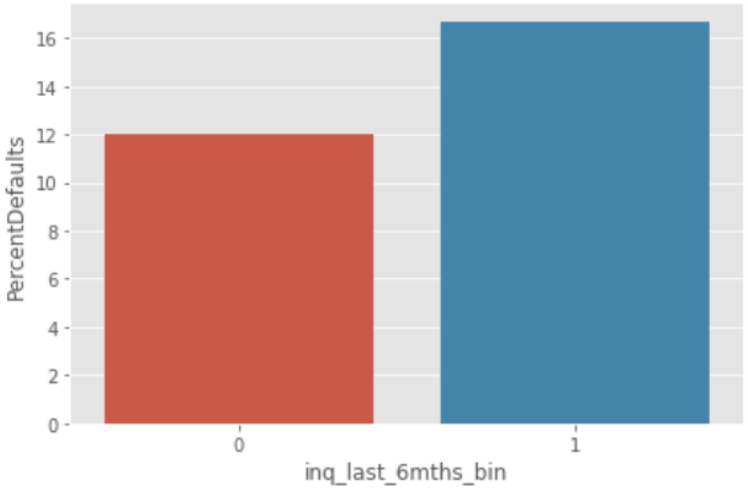
PercentDefaults = ['Charged Off' / ('Charged Off' + 'Fully Paid')] * 100

Categorical columns impact



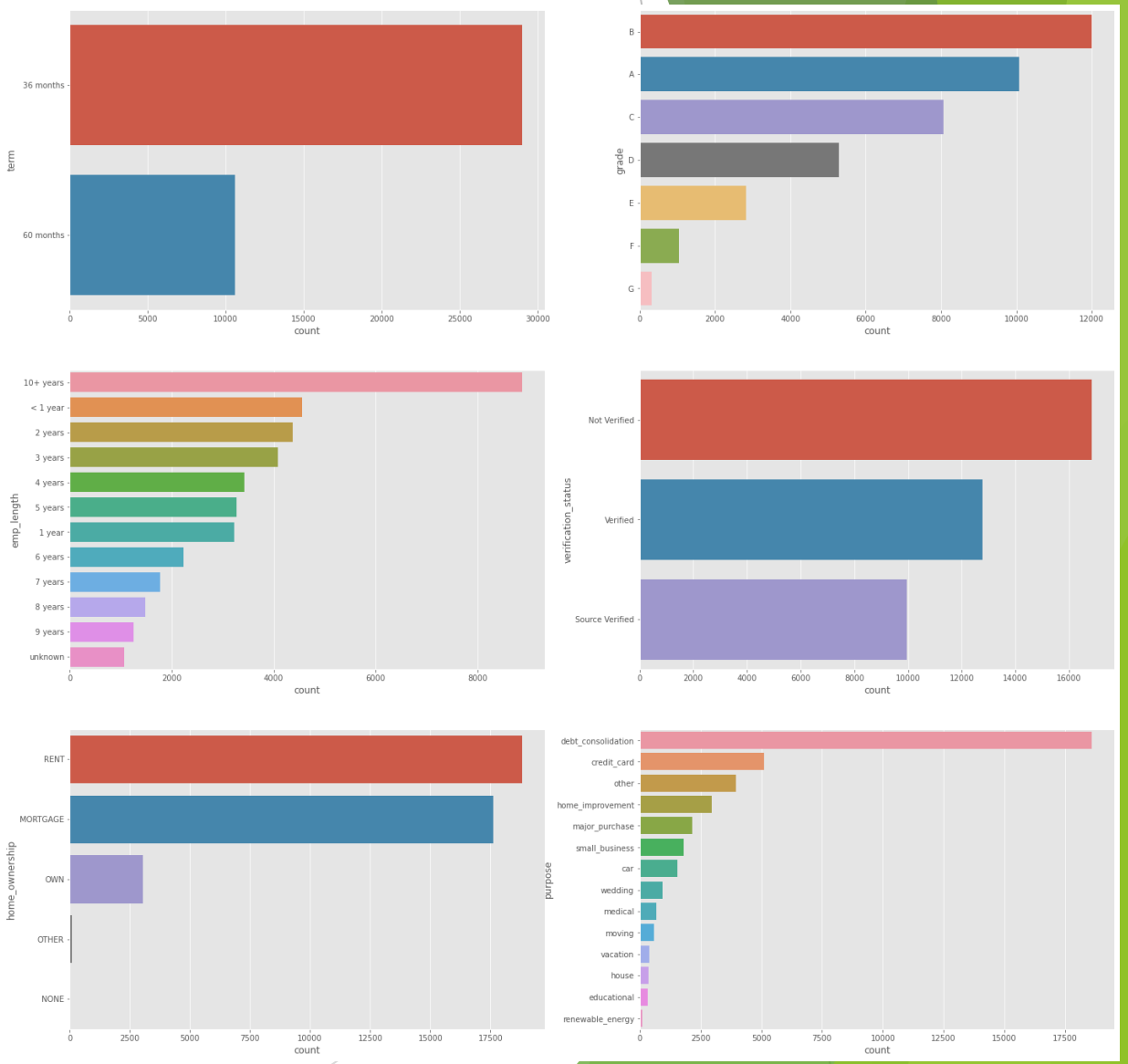






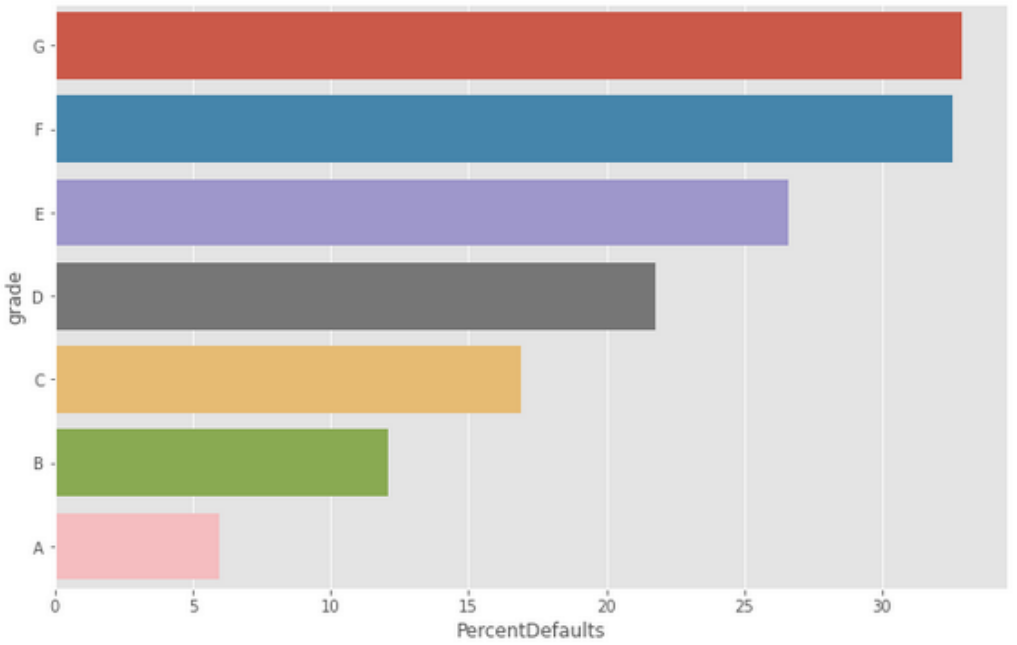
Categorical columns impact

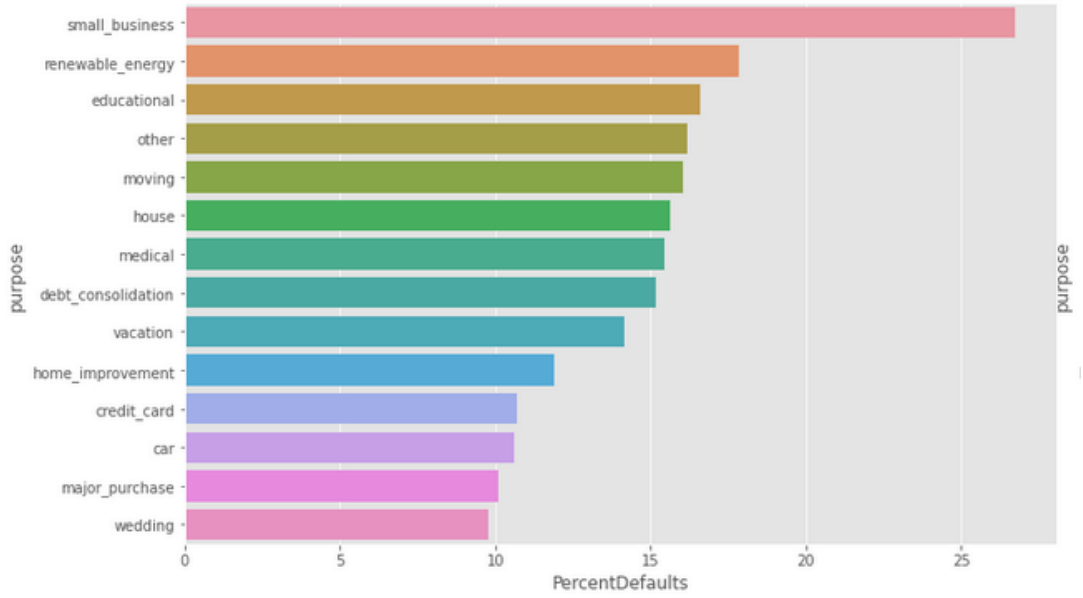
- Other Categorical variables
- ['term',
- 'grade',
- 'emp_length',
- 'verification_status',
- 'home_ownership',
- 'purpose']
- zip_code is part of state so dropped
- sub_grade is part of grade so dropped

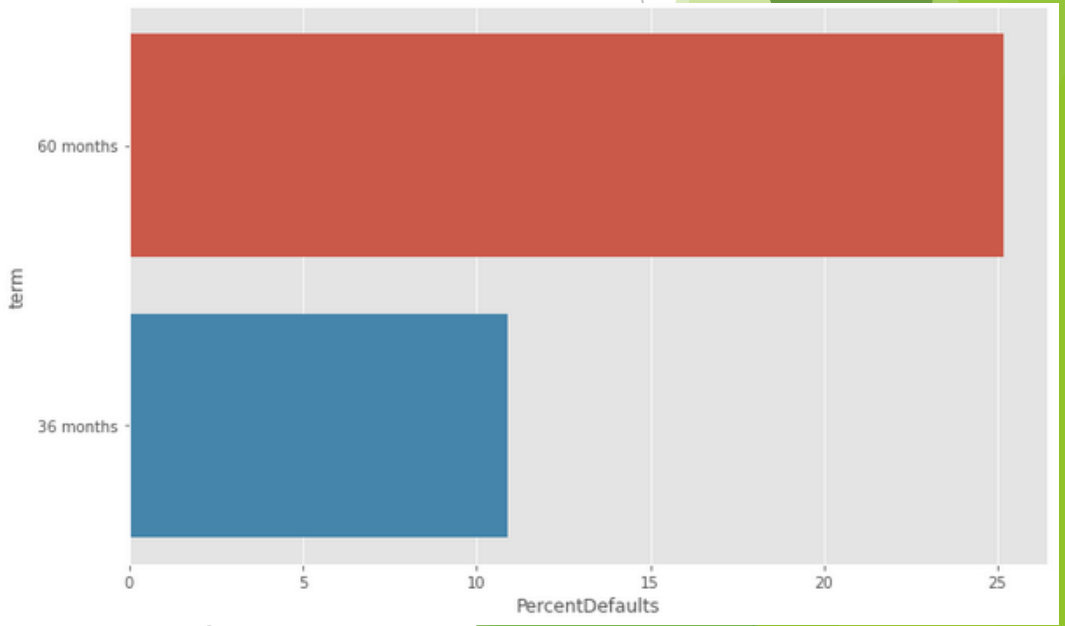


Categorical columns impact

- **Grade:** Better the Loan grade lower is the default percentage.
- **Term:** Shorter loans have much smaller default rates.
- **Purpose:** Small business loans have the highest rate of defaults.

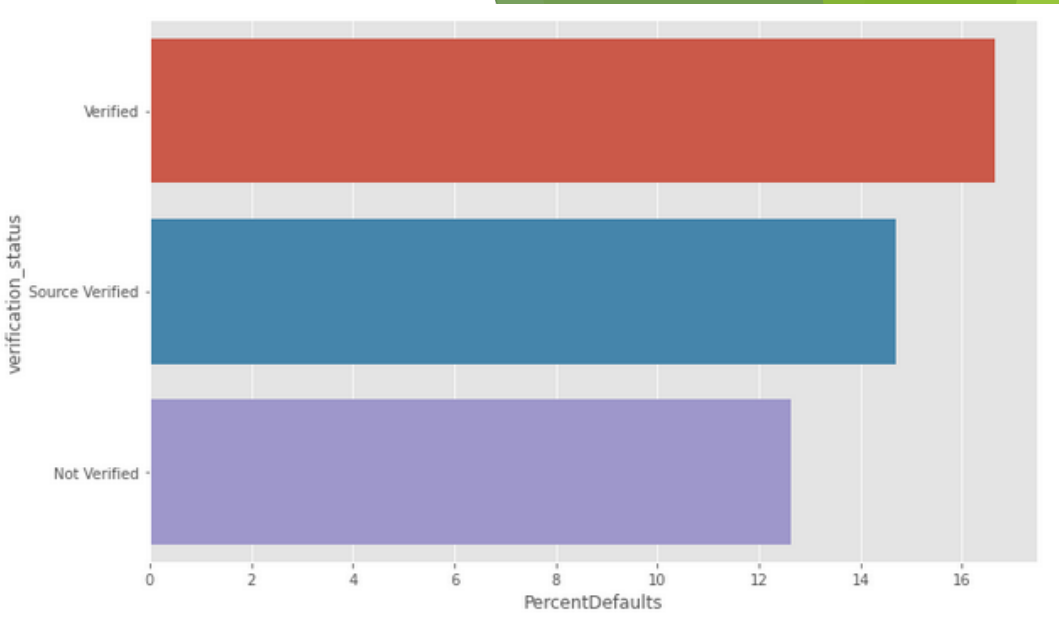


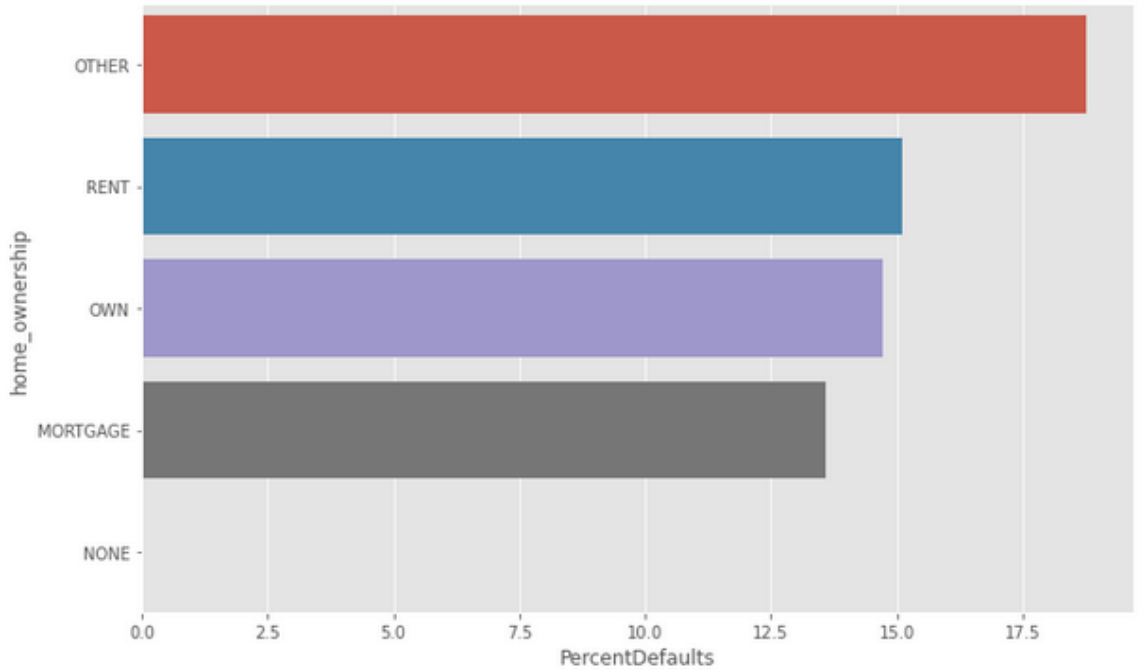


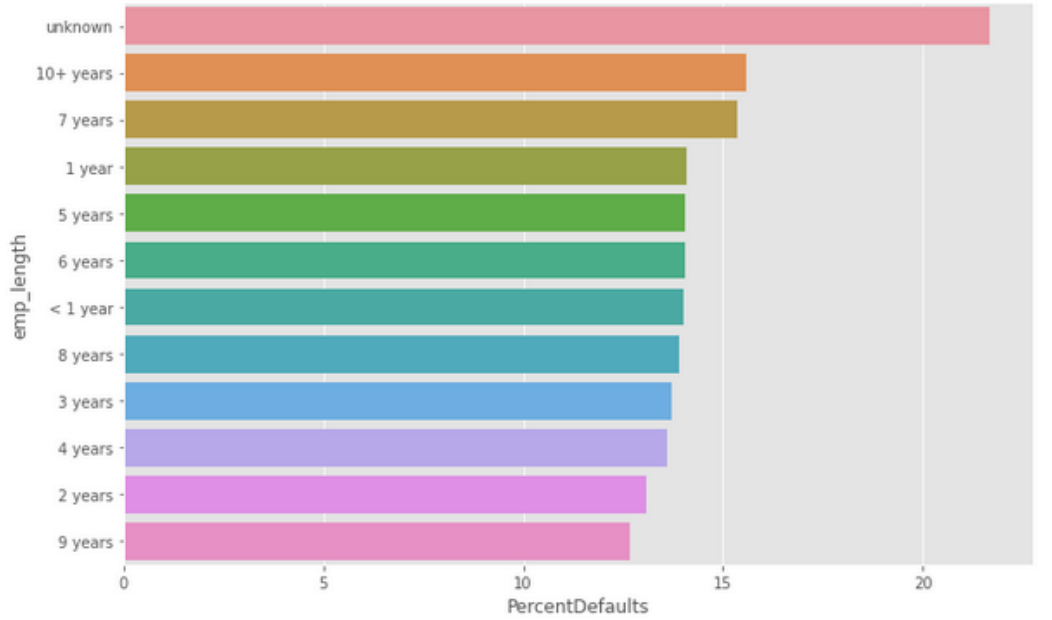


Categorical columns impact

- **Verification:** Strangely, Verified loans have high default rates. This needs further investigation.
- **Emp_length:** If employment length is "unknown" the rate of default is high - needs further investigation.
- **Home ownership:** "Other" has high defaults, but number of loans in this are very low



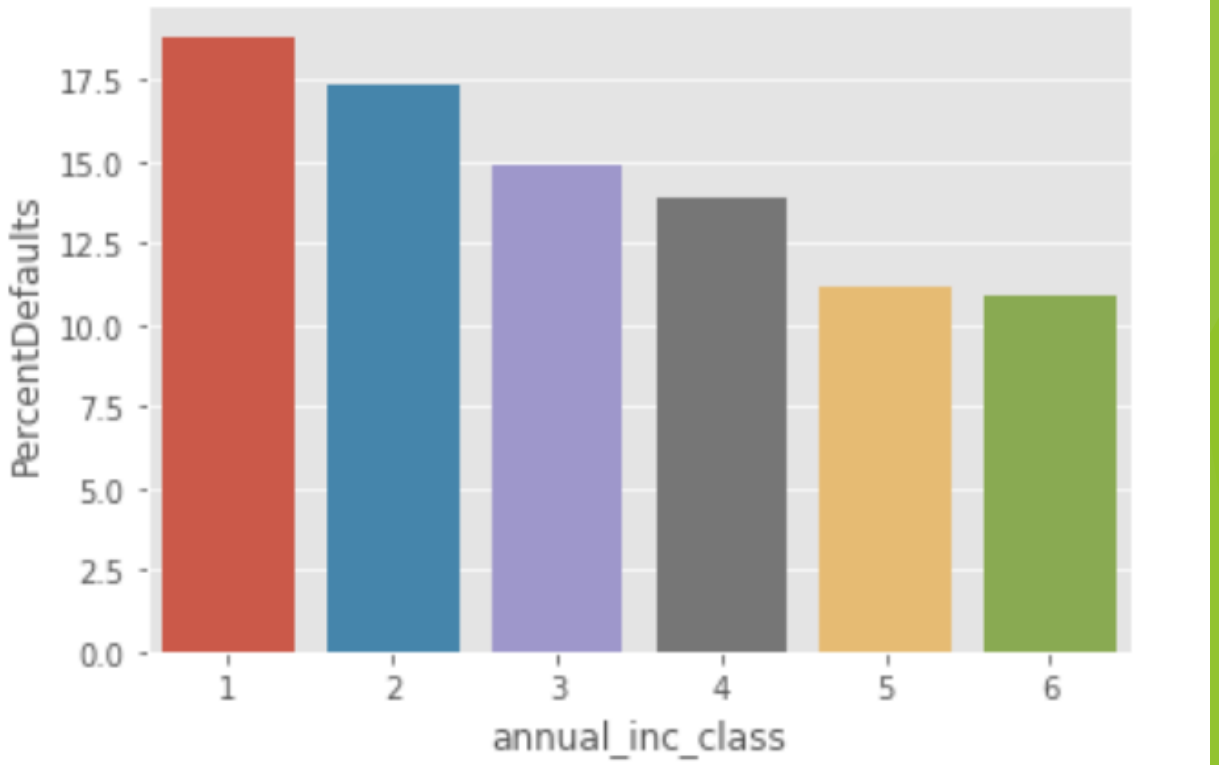




Categorical columns impact

- Convert annual income into a categorical
  - Annual income is very skewed and hence difficult to analyse without dropping outliers.
  - We convert it to a categorical with 6 levels using quantiles [0, .05, .25, .5, .75, 0.95, 1.]

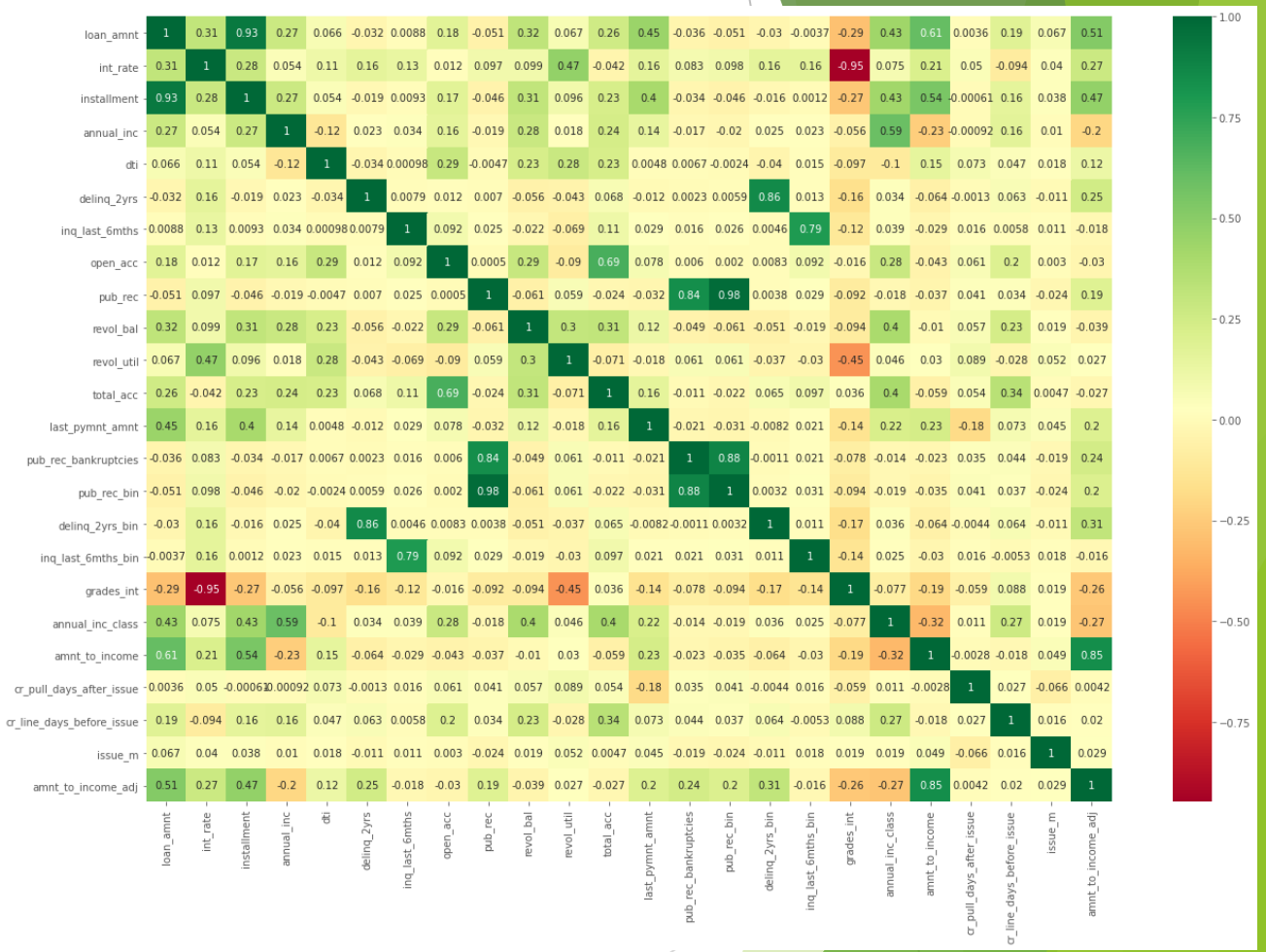
It is clearly seen that people with higher annual incomes have lower default rates.



Bivariate analysis

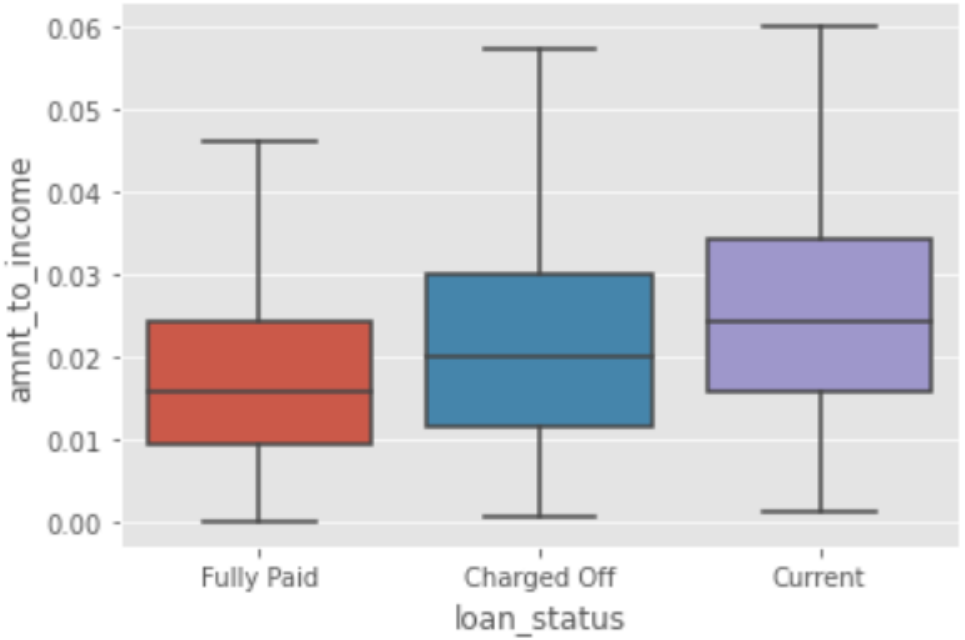
Observations

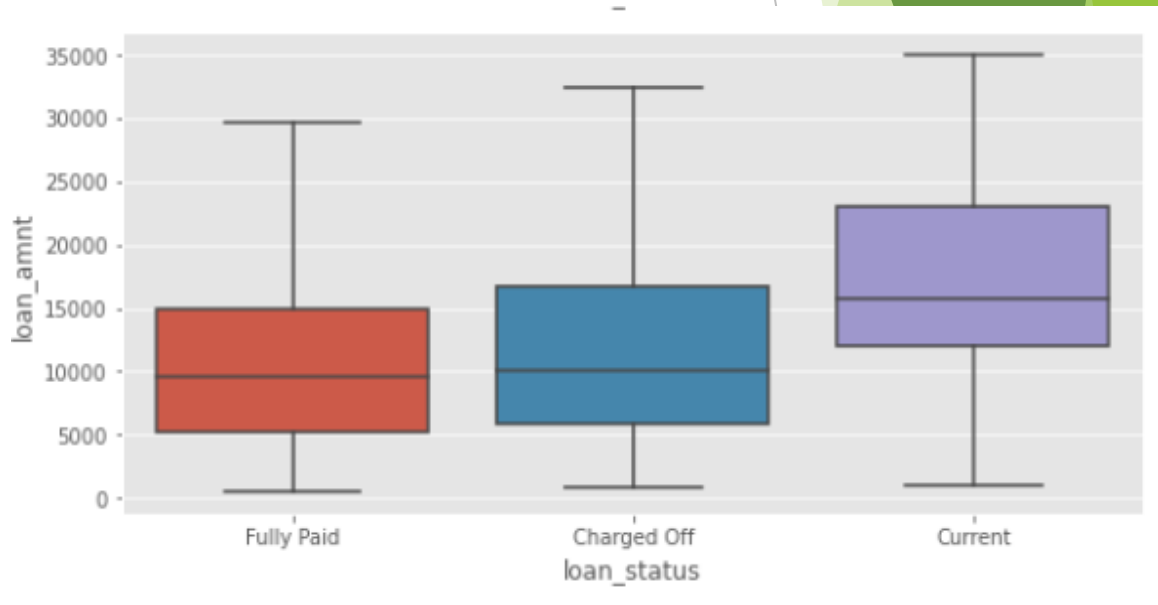
- pub_rec_bin and pub_rec_bankruptcies are highly correlated - can ignore one with lower number of non-zero values
- loan_amnt and installment are highly correlated - can ignore installment
- grades have high negative correlation with int_rate - Can ignore grade or int_rate



Derived Metric

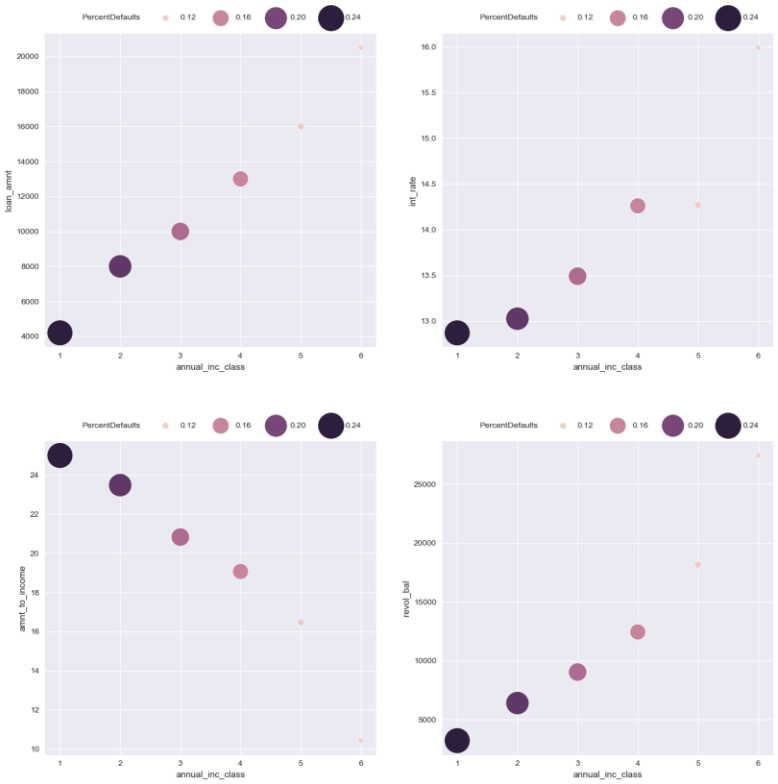
- Loan Amount as percentage of annual income
- This shows slightly better distinction than just loan_amnt
- Customers who default have higher loans as percentage of income

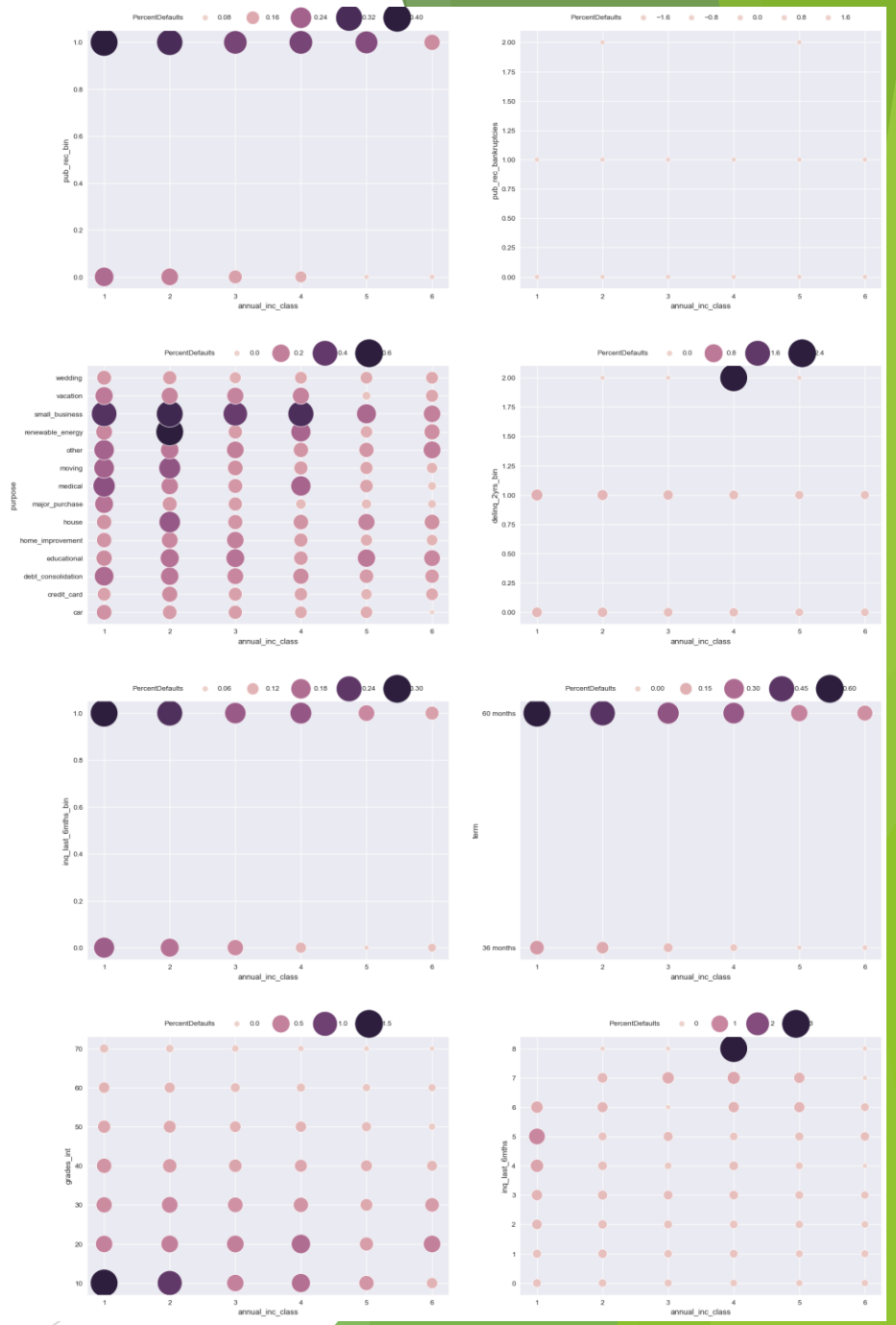




2-factor effect on default rate

- 2 factor effect on defauts was plotted
- Annual income class was treated as x axis





Final list of features affecting defaults

Feature	Description	Dangerous level – Can lead to higher default rate
annual_inc_class	Annual income categorical – derived from annual_inc	Under 25th percentile
amnt_to_income	Loan amount as % of annual income	Above median
loan_amnt	Amount of loan taken	Above Median
int_rate	Interest rate	Above Median
pub_rec_bin	Public derogatory records - 0 or 1 – derived from pub_rec	Above 0
purpose	Why the loan was taken	Small_business, Other
addr_state	State	'NE', 'NV', 'SD', 'AK', 'FL', 'MO', 'OR'
delinq_2yrs_bin	delinquencies in last 2 years – derived from delinq_2yrs	Above 4
inq_last_6mths_bin	inquiries in last 2 years – derived from inq_last_6mths	Above 0
term	Loan term	60 months

High default combinations

Default rate in data is 14.4%

Combination for default rate higher than 14.4%	Default rate
annual_inc_class < 25th percentile int_rate > median small_business loan	41.66%
annual_inc_class < 25th percentile int_rate > median small_business loan term = 60 months	54.43%
annual_inc_class < 25th percentile amnt_to_income > median small_business loan term = 60 months	48.78%
annual_inc_class < 25th percentile revol_bal > median small_business loan	43.75%

Conclusion

- EDA was performed to understand loan defaults
- Univariate, bivariate and multi-level interactions were studied
- Factors affecting defaults were identified
- Factor combinations that lead to higher defaults were identified
- No machine learning methods were used
- further analysis with a method such as gradient boosting may be useful