Lending Club Case Study

Understanding of Risk Analytics in Banking and Financial Services

Introduction

When a consumer finance company receives a loan application, the company has to make decision for approval based on applicant profile. In this project, we used EDA to understand how consumer attributes and loan attributes influence the tendency of DEFAULT.

Important Terms

* Fully Paid : Applicant has fully paid the loan.

* Current : Applicant in process of paying the loan.

* Charged-off : Applicant has not paid the instalment in due time for a long period of time.

* Univariate Analysis : In this each variables in dataset is analysed separately.

* Bivariate Analysis : In this two variables are observed in an analysis.

# Python Libraries

* Numpy

* Pandas

* Seaborn

* MatplotLib

Steps

* Data Cleaning : Removing null, missing values and drop unnecessary columns.

* Standardisation : removing unnecessary symbols and making each data in columns ready to read in specified format.

* Outlier Treatment : Removing data which are far away from data average, that may negatively affects the results.

* Data Visualisation : Representation of data by the use of graphs, plots etc.
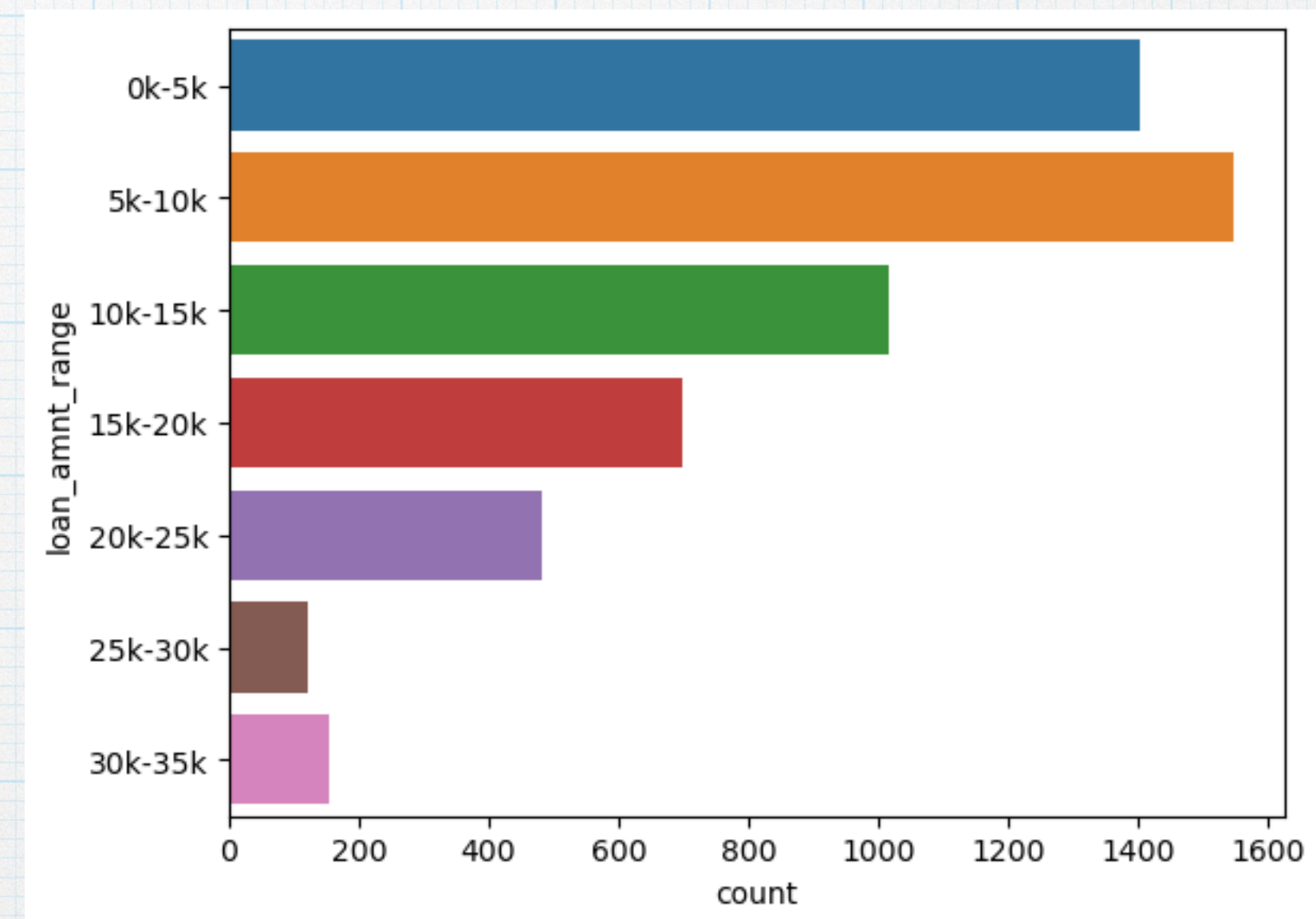
Observations

Based on Annual Income

* People within income range 30k-40k is more likely to default.
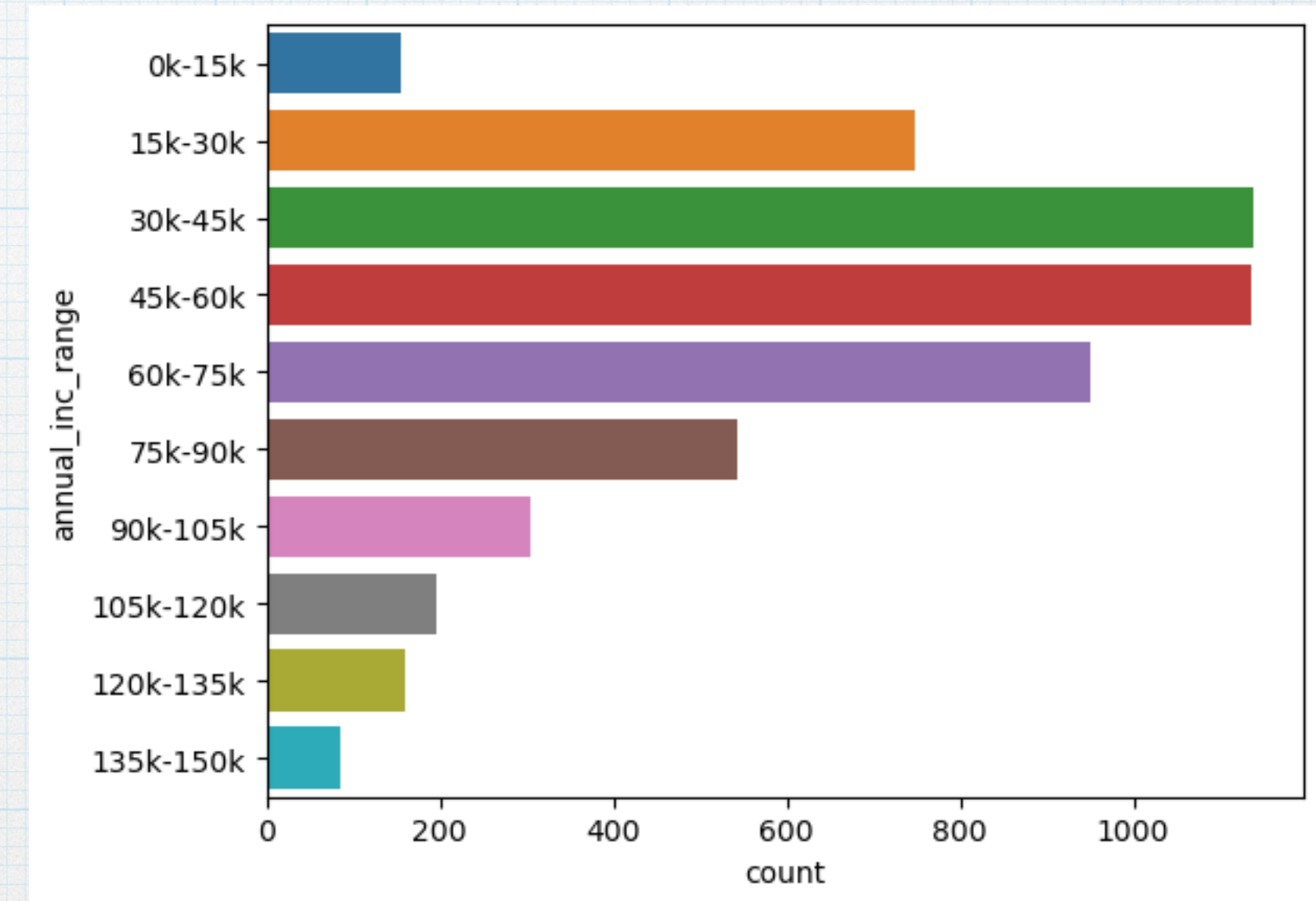
Based on Loan Amount

* People with sanctioned loan of 5k-10k are more likely to default.

* People who sanctioned with 17500k-20000k and having income of 105k-135k are more likely to default.

Based on Term

* People with loan term of 36 month are more likely to default.

* People with loan amount 14k-16k with term period of 60 months are more likely to default.
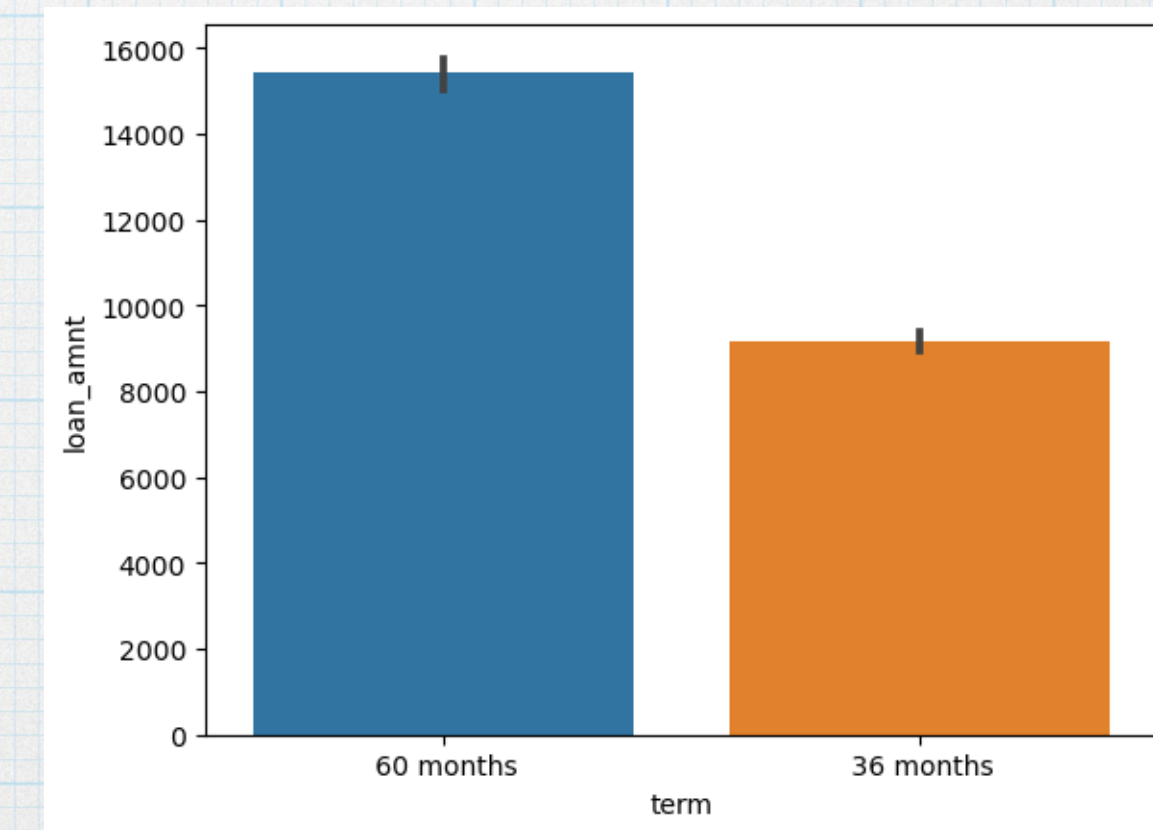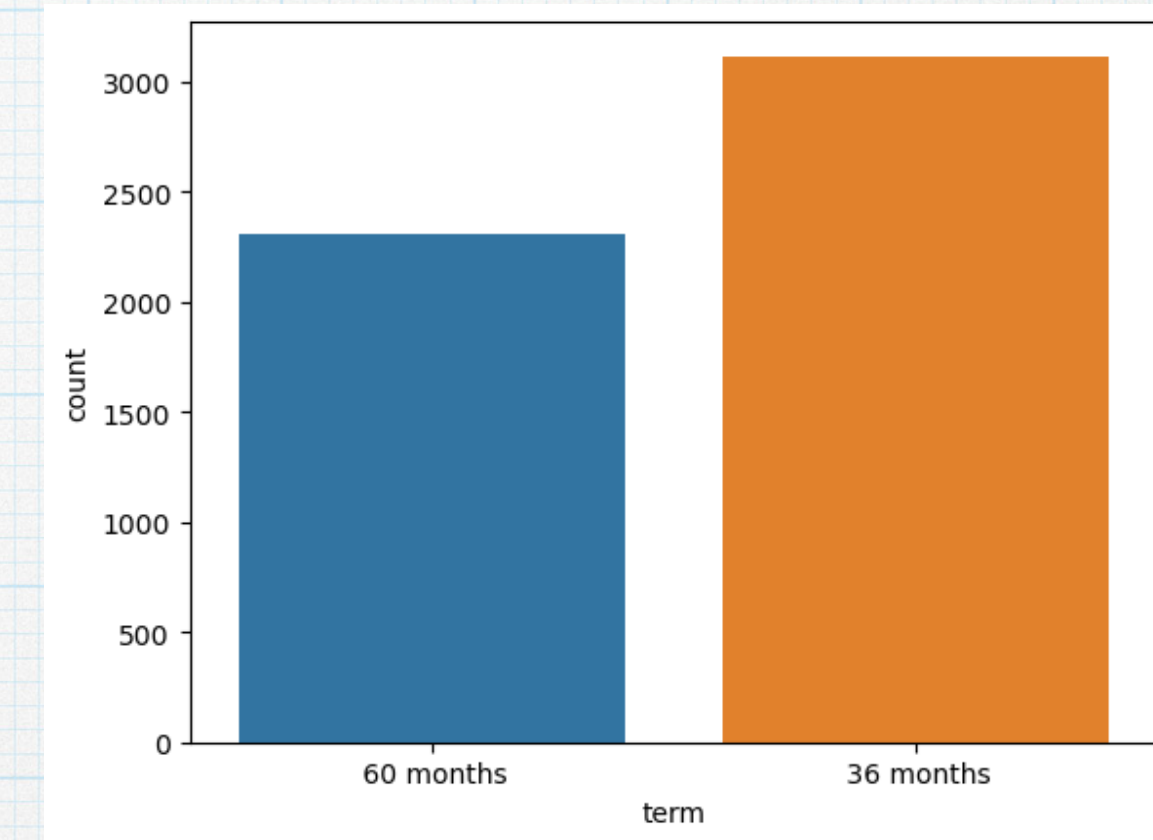
Based on Verification status

* People NOT VERIFIED are more likely to default.

* People VERIFIED and with 60k+ income are more likely to default.
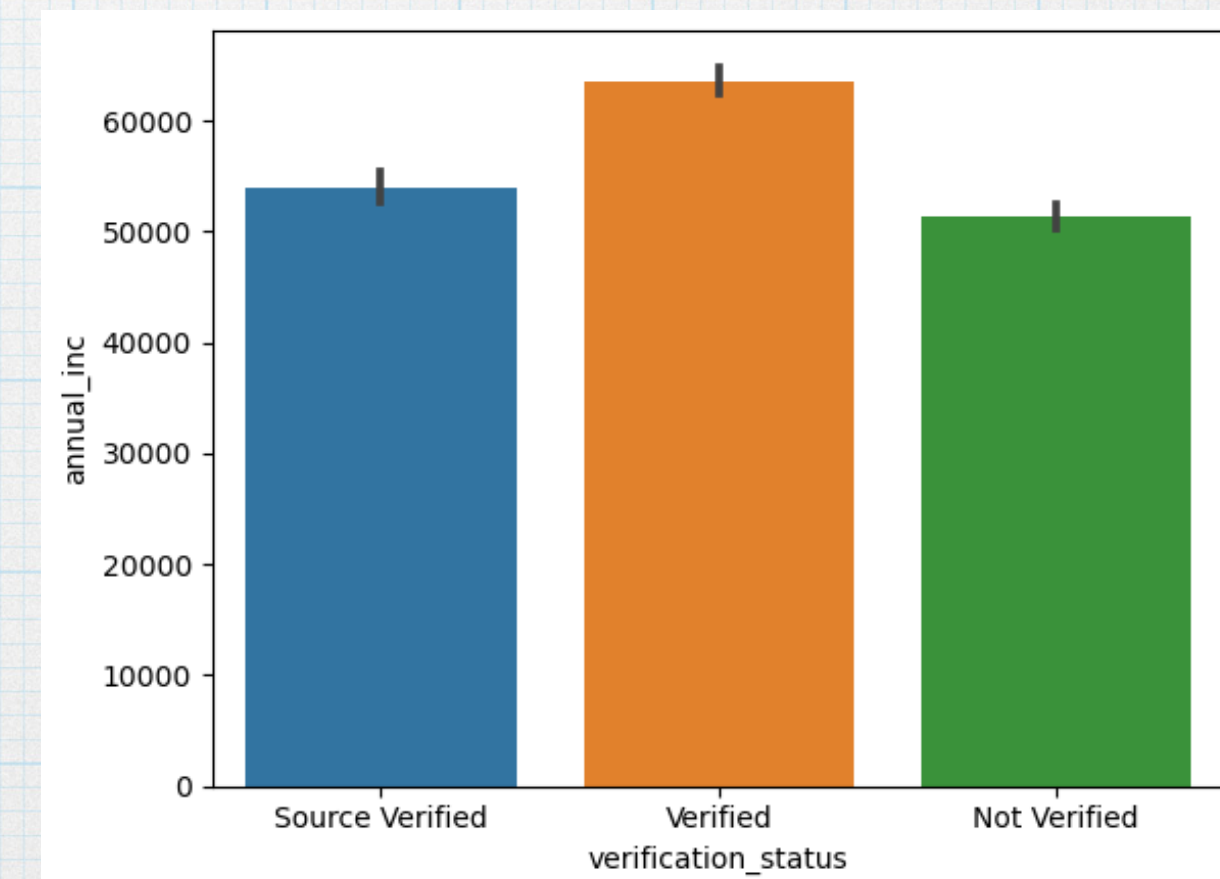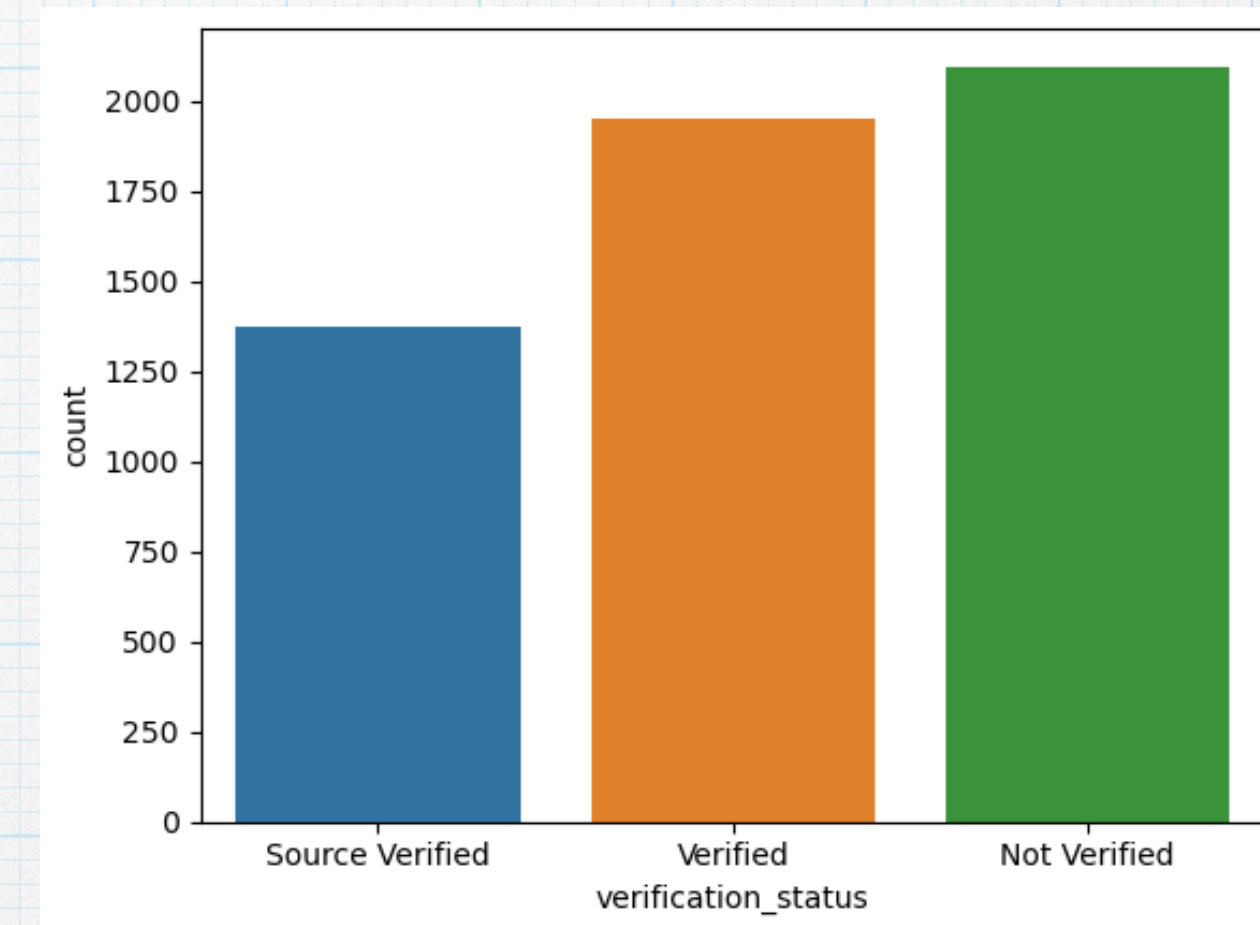
Based on Interest Rate

* People with interest rate of 13-17% are more likely to default.

* People with loan amount 20k-35k with interest rate of 15-17% are more likely to default.
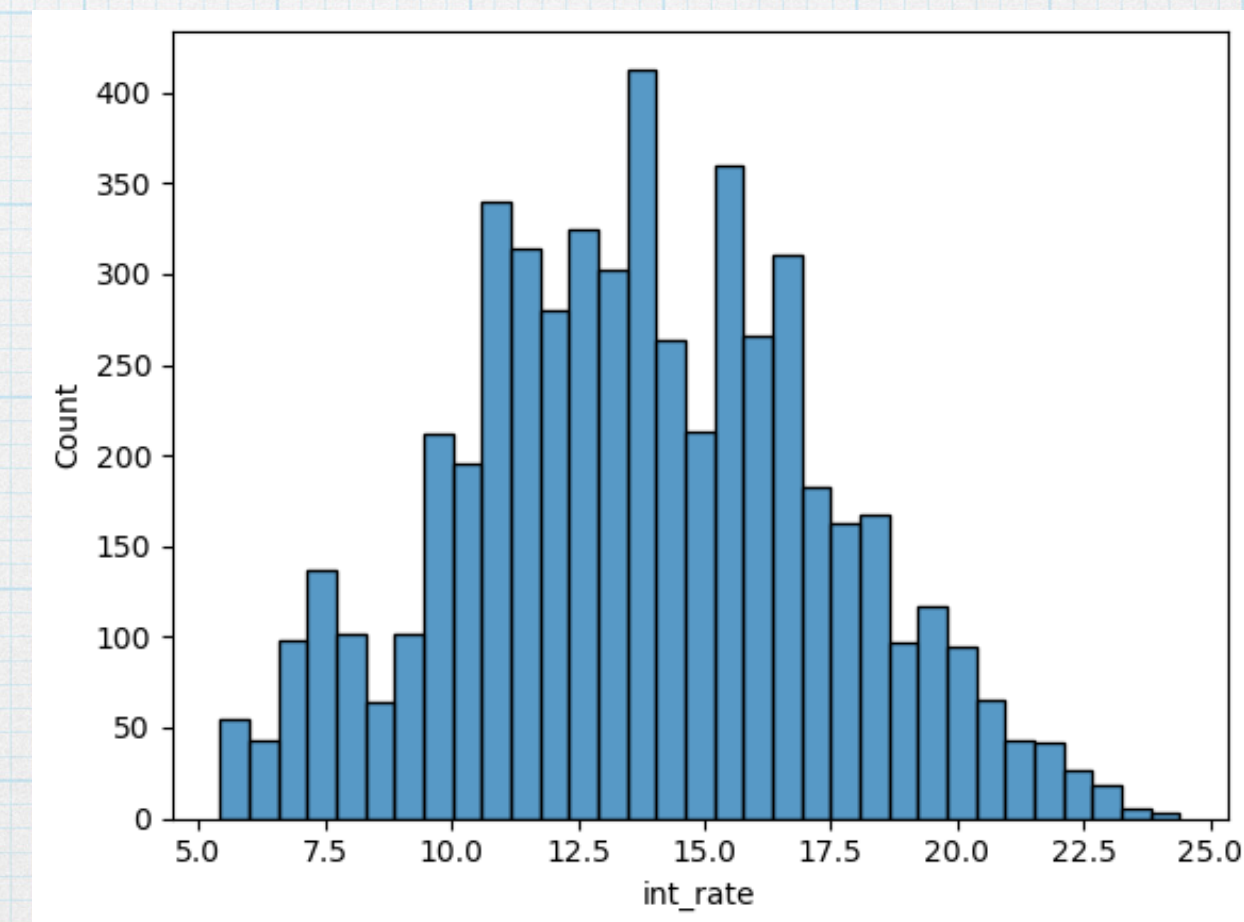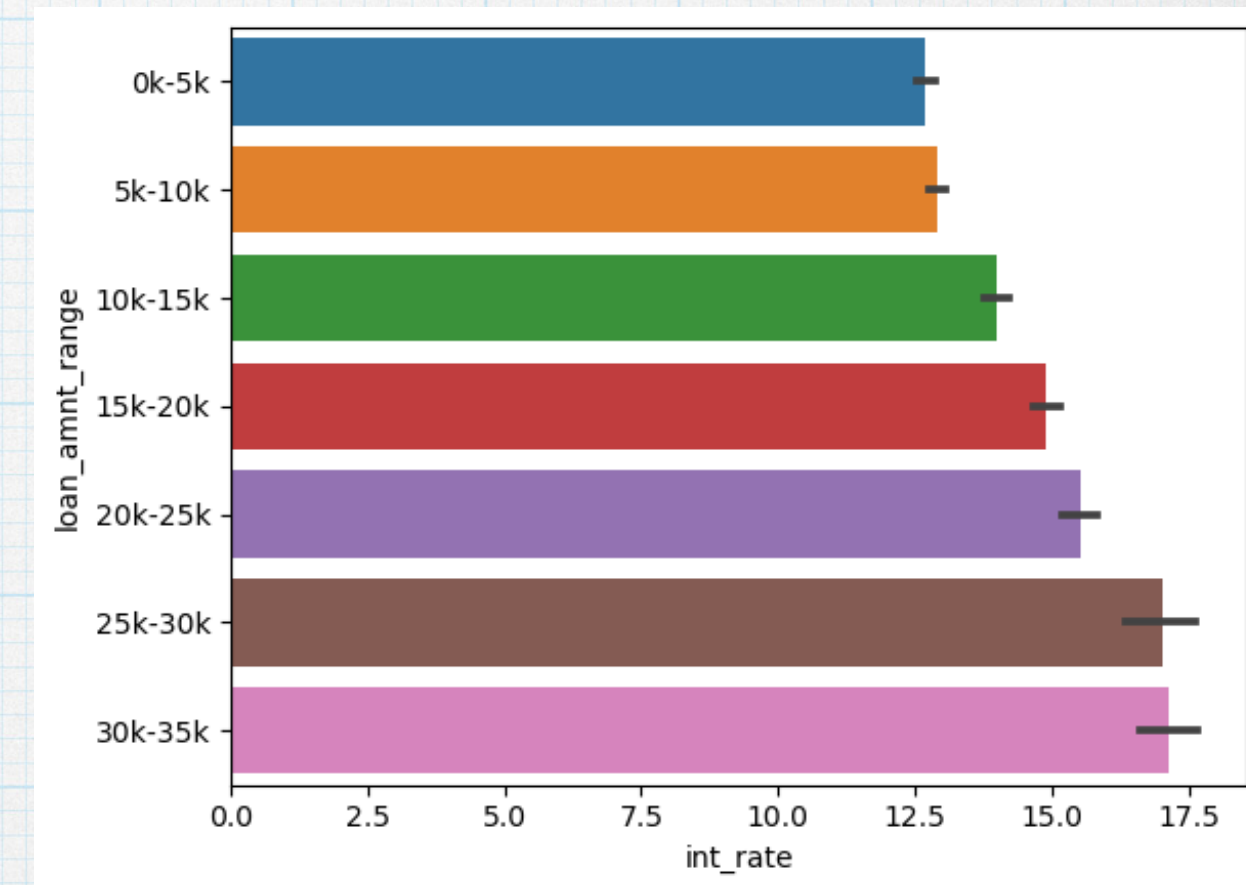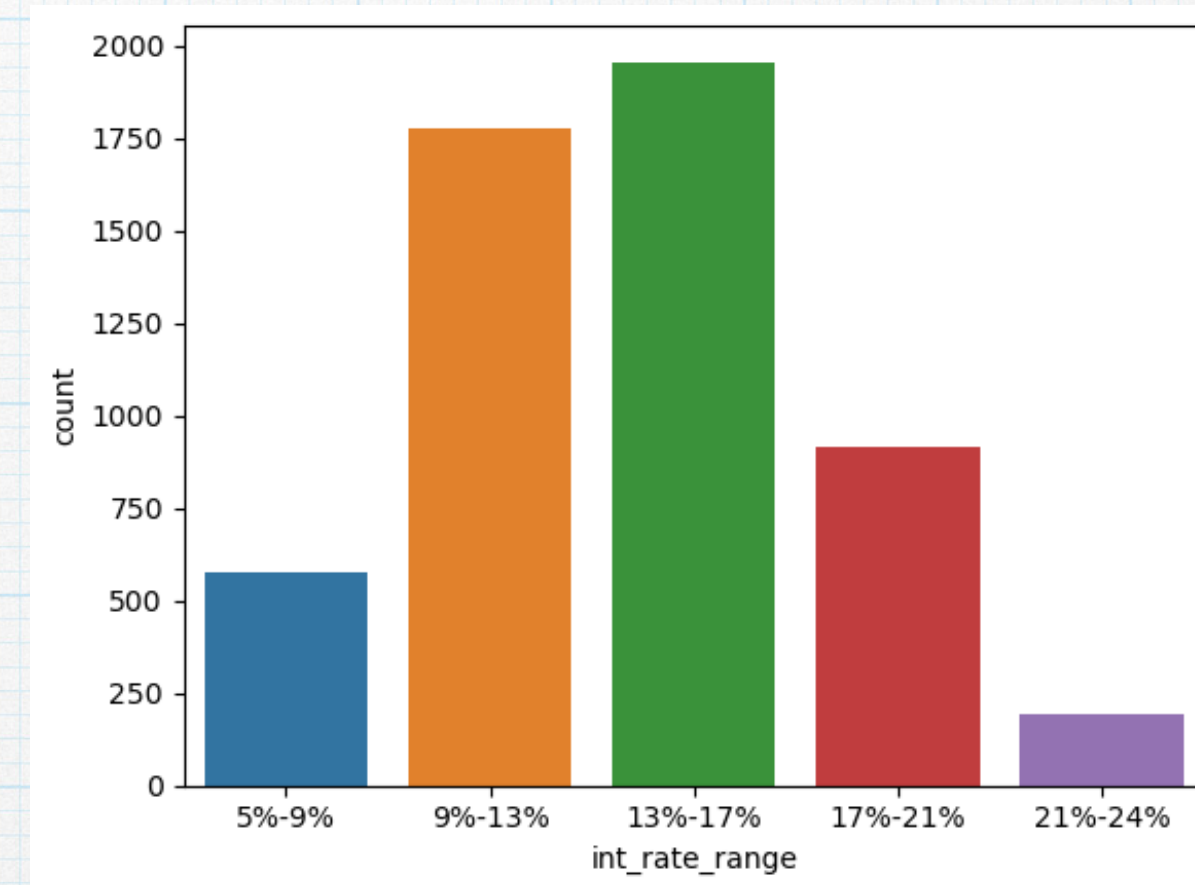
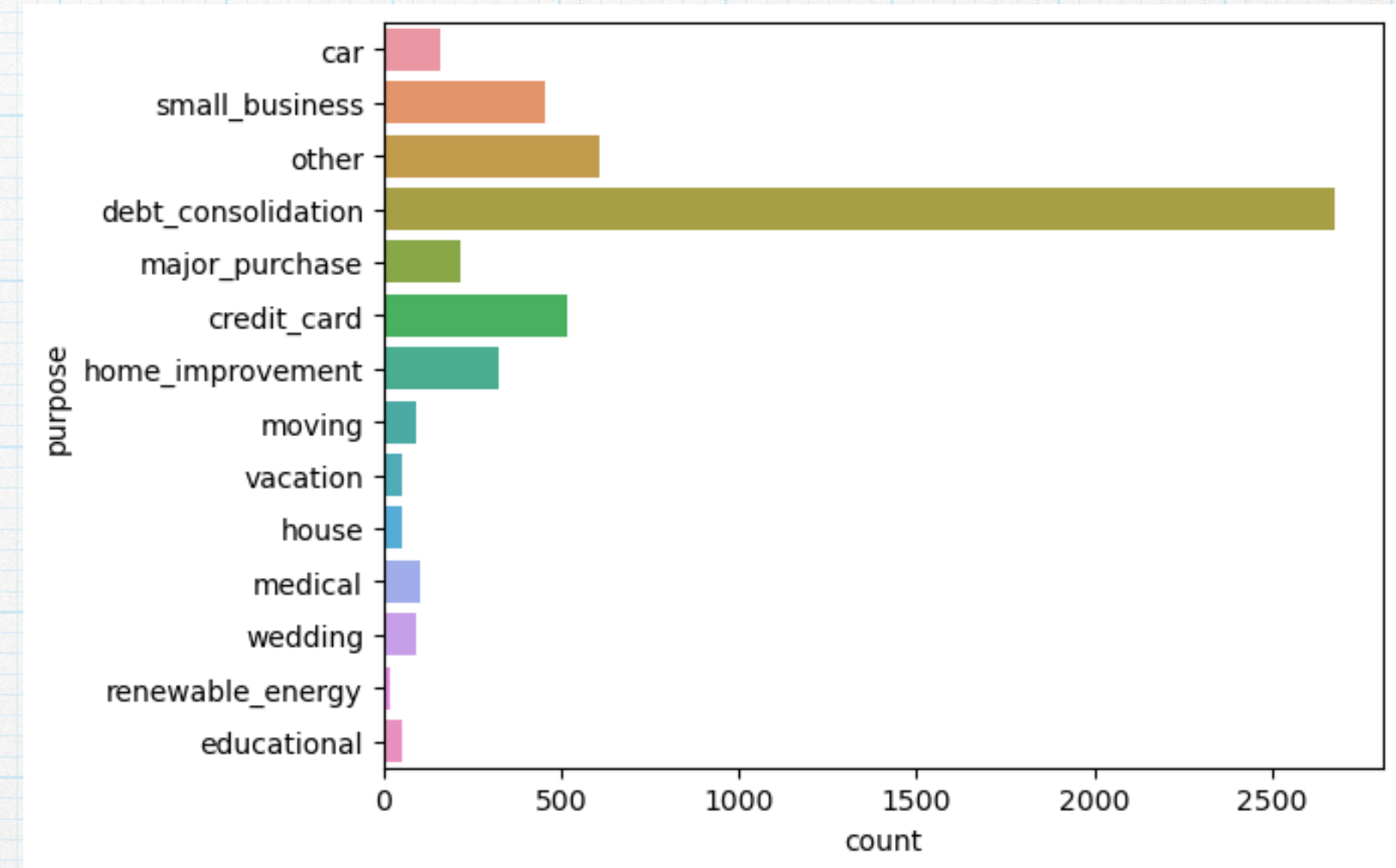# Based on Employment Period

* People with experience of 10 years are more likely to default.

* People with 10 years of experience and 12k-14k loan amount are more likely to default.
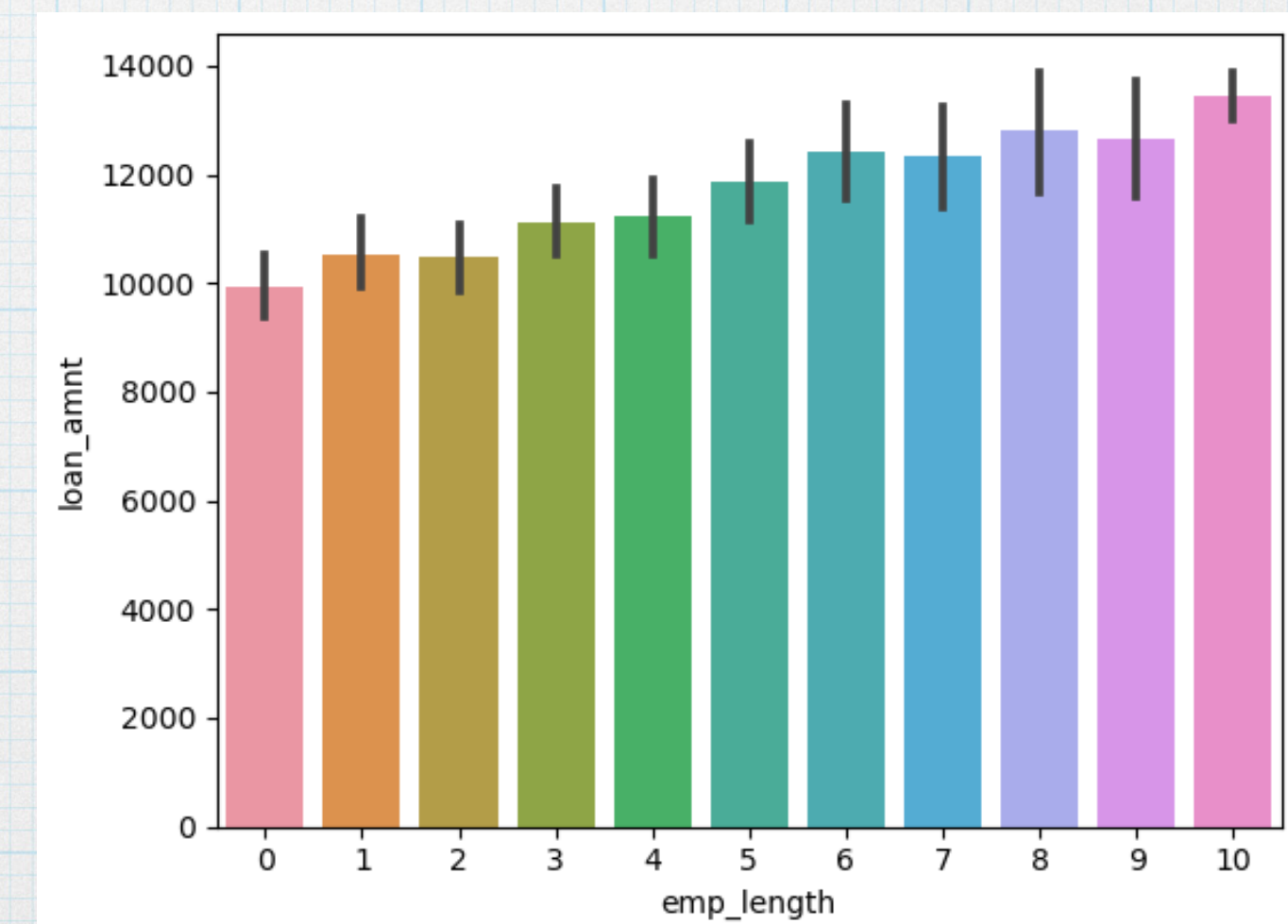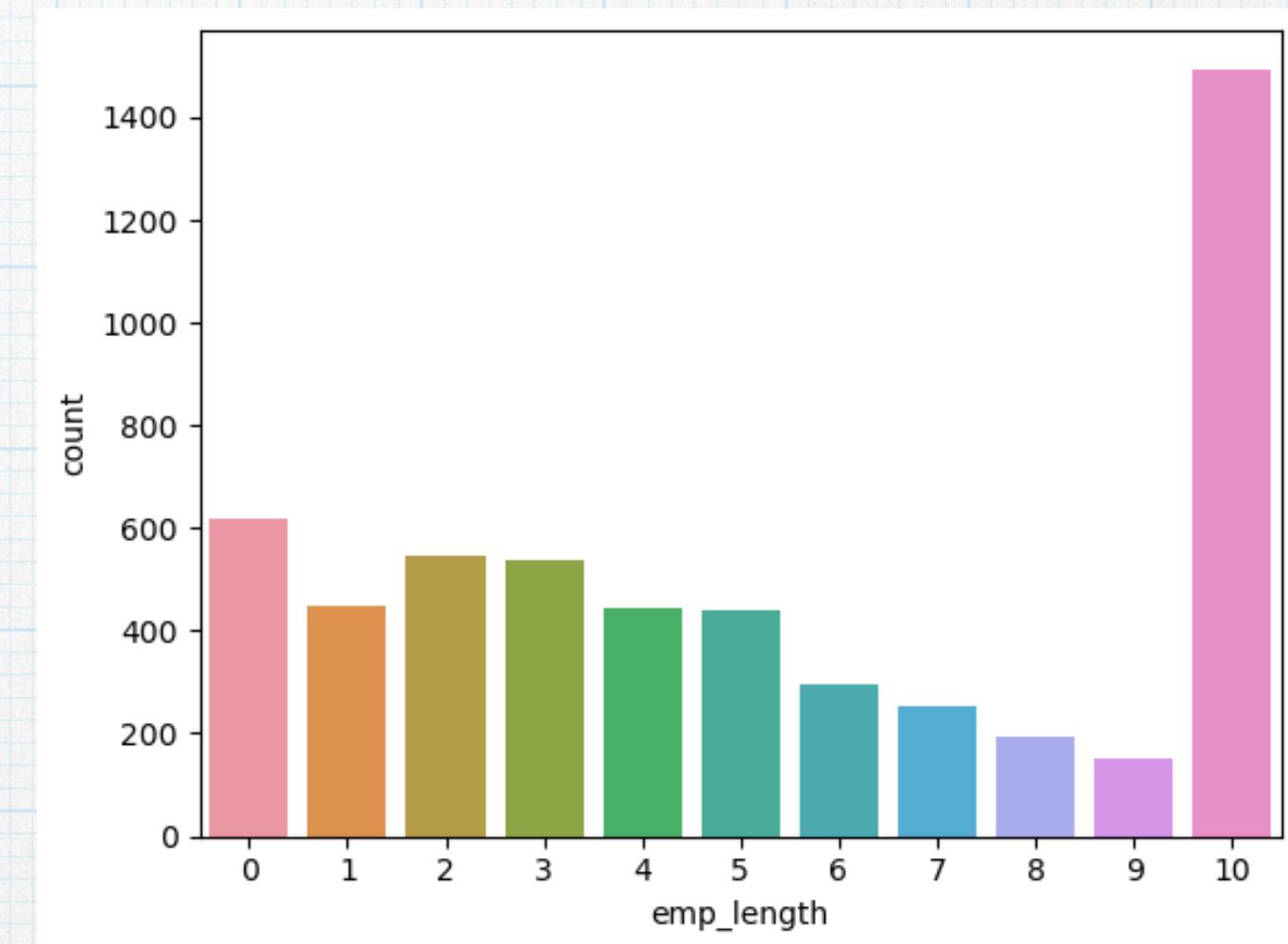
Based on Purpose

* People with purpose of Debt Consolidation are more likely to default.

* People with purpose of HOME IMPROVEMENT and annual income of 60k-70k are more likely to default.
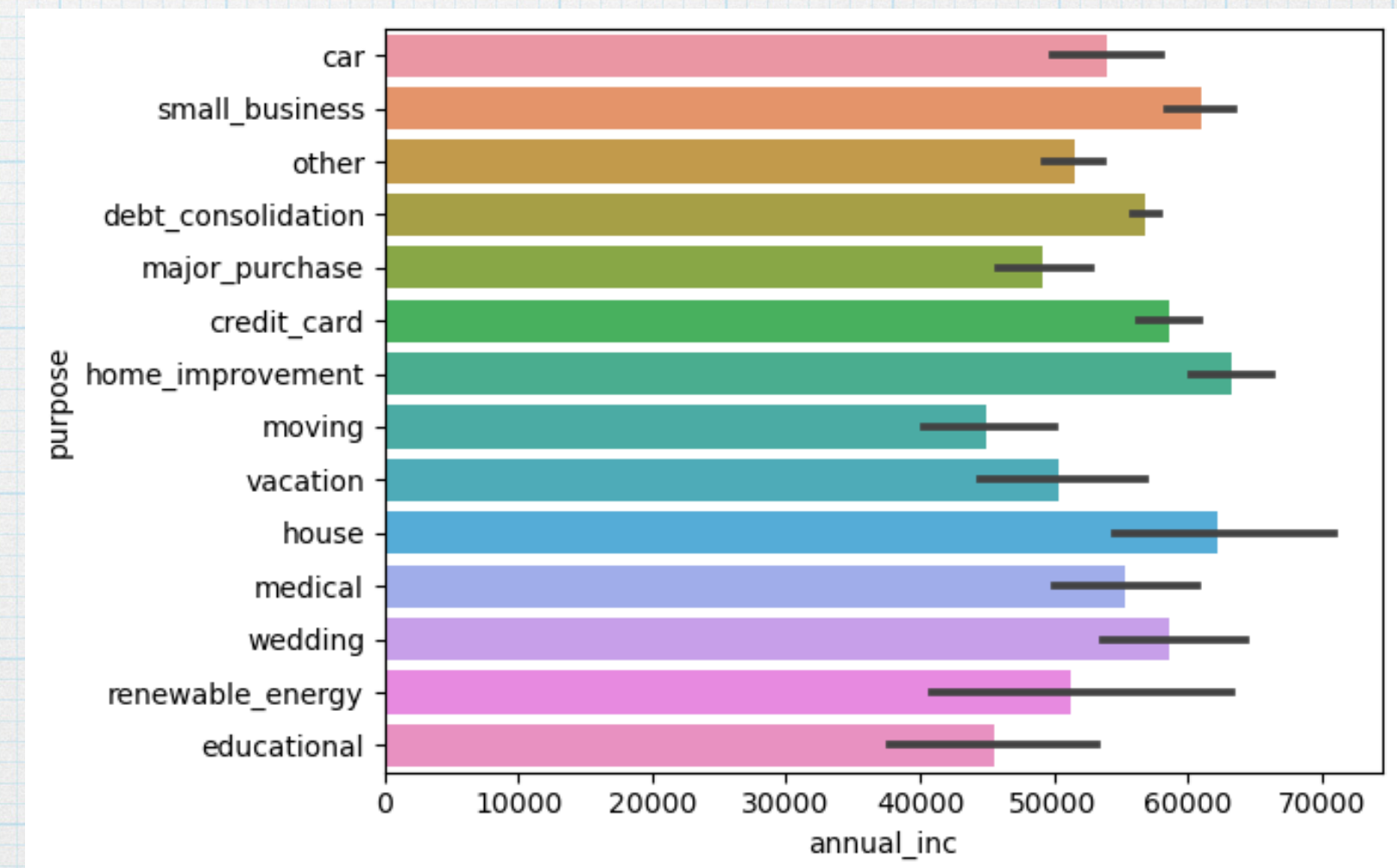
Based on Home Ownership

* People with RENT are more likely to default.

* People with MORTGAGE and loan amount of 12k-14k are more likely to default.
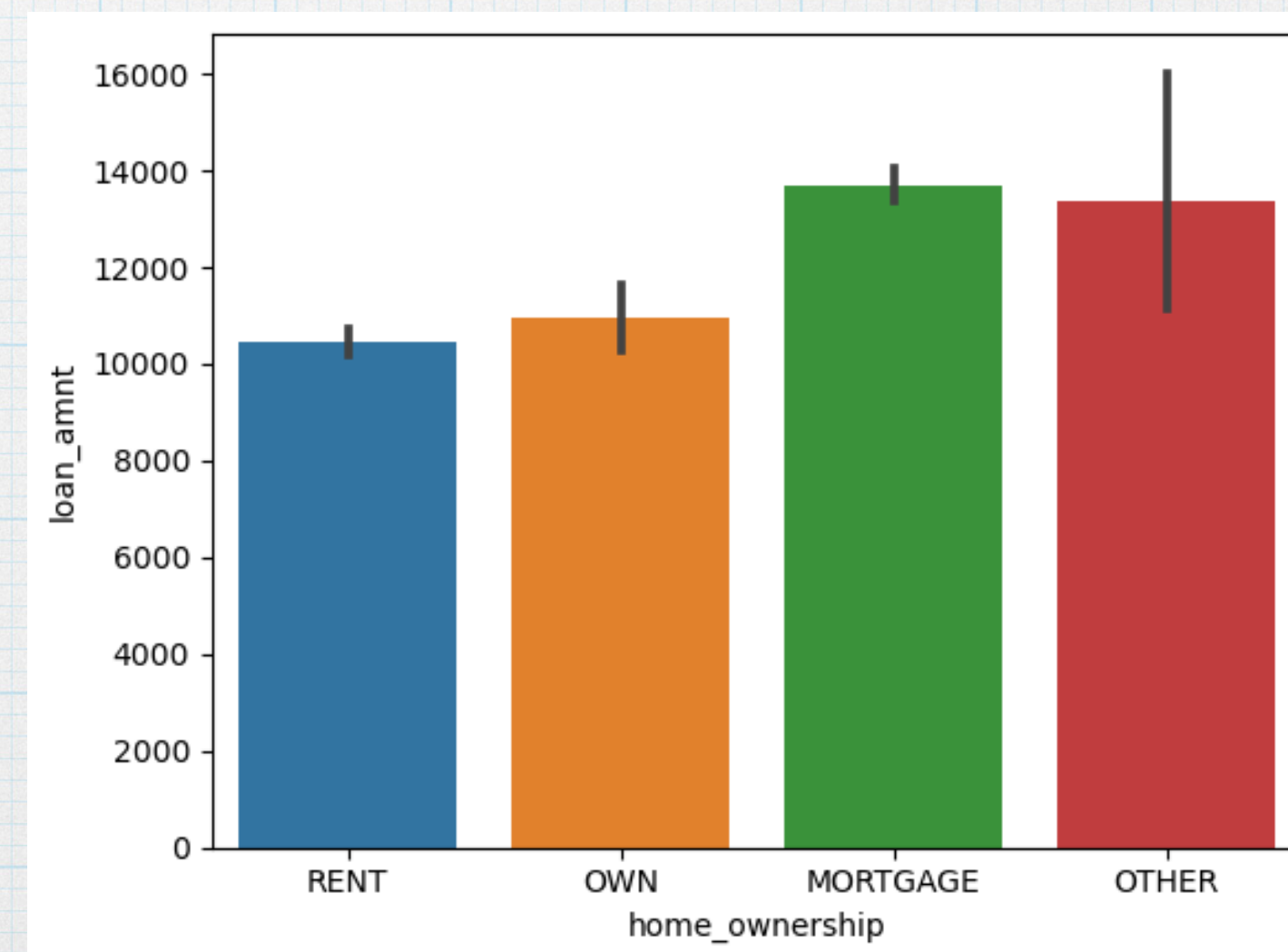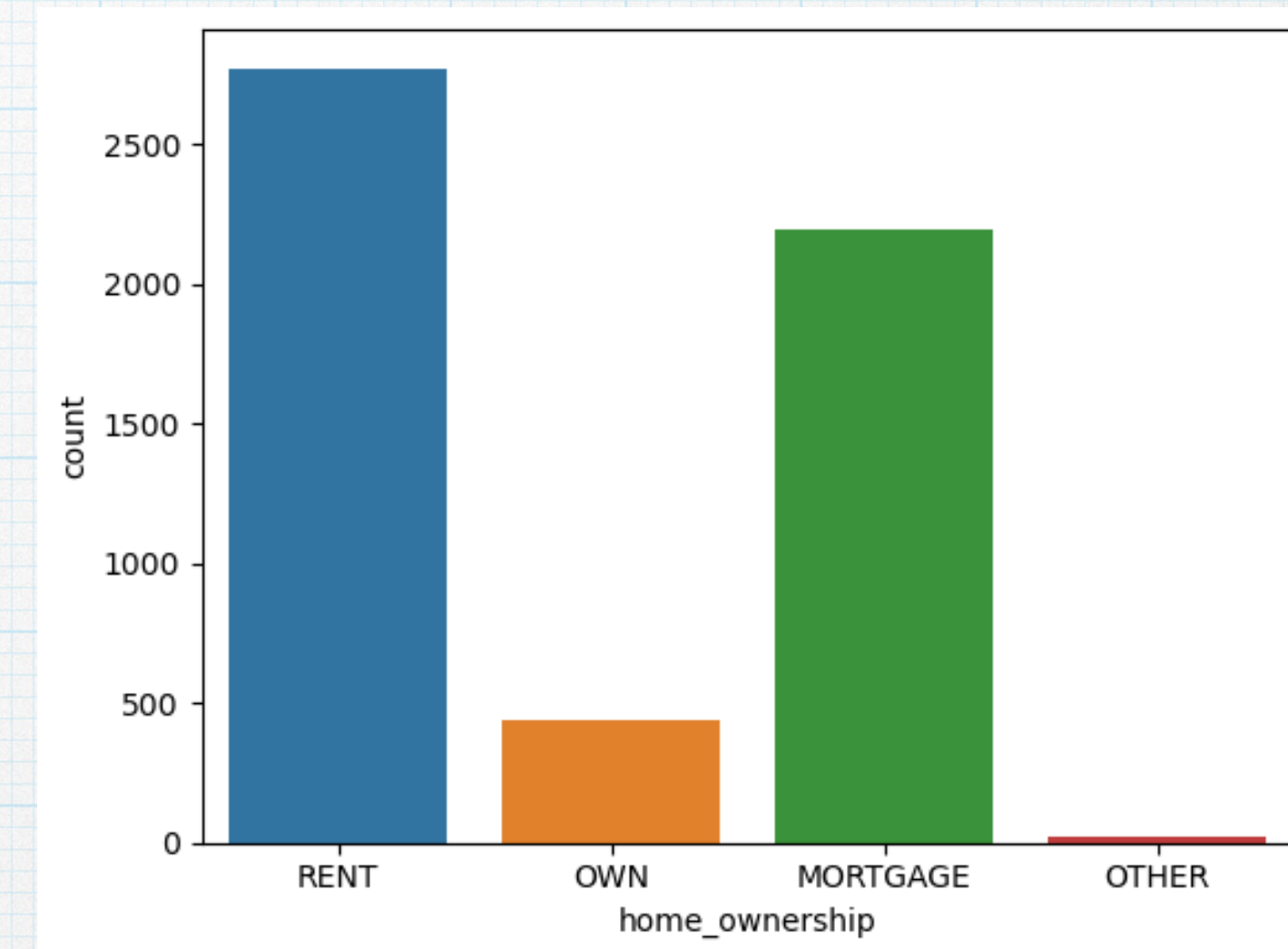
Based on Grade and Sub-Grade

* People grade B is more likely to default.

* People sub grade B5 is more likely to default.
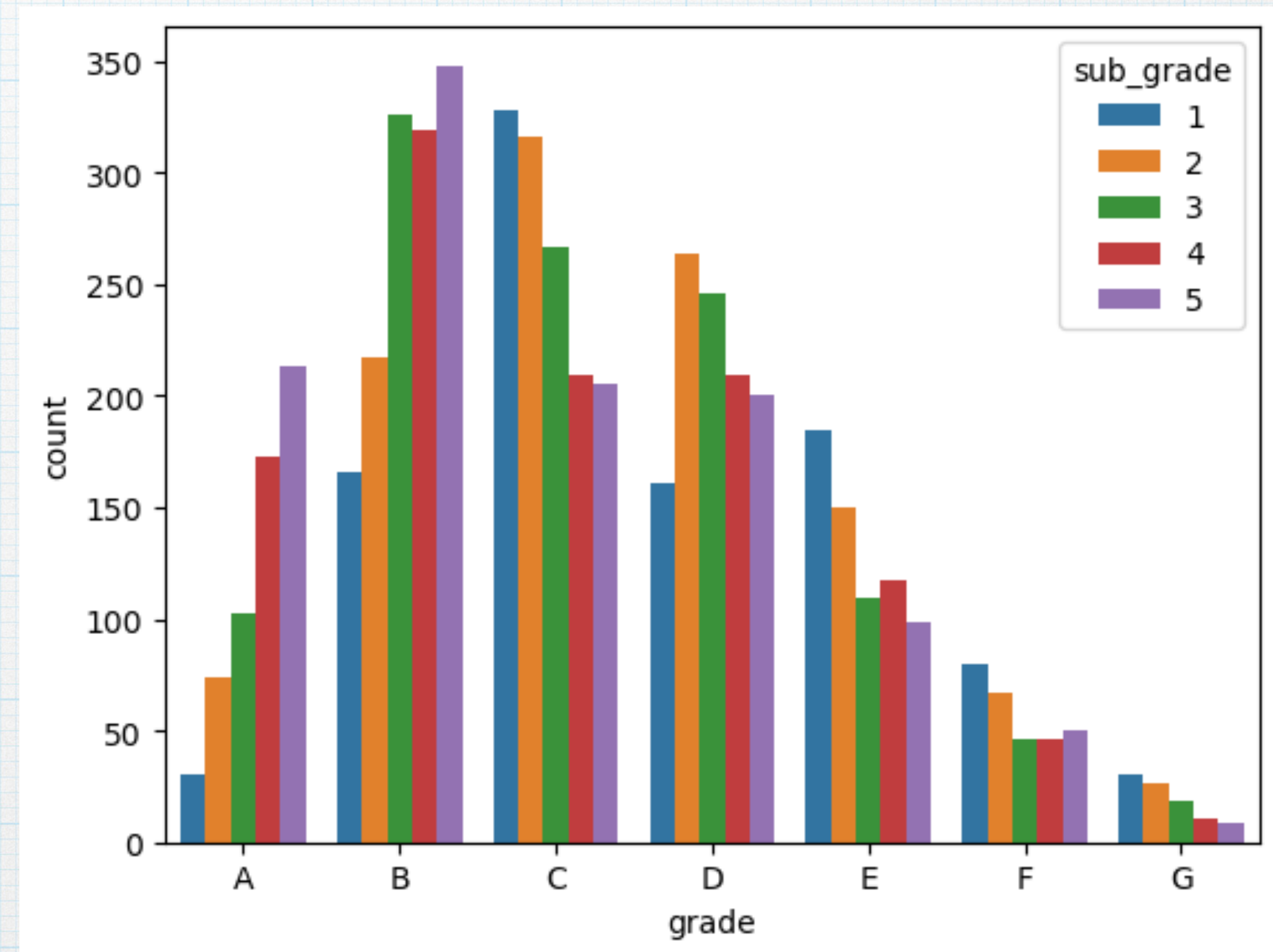
FINAL OBSERVATIONS(UNIVARIATE)

* People with annual income 30k-60k are more likely to default.

* People with sanctioned loan amount of 5k-10k are more likely to default.

* People with term period of 36 months are more likely to default.

* People Not Verified are more likely to default.

* People with interest rate of 13%-17% are more likely to default.

* People with work experience of 10/10+ years are more likely to default.

* People who apply loan for clearing other loan are more likely to default.

* People with RENT are more likely to default.

* People under B5 grade are more likely to default.

FINAL OBSERVATIONS(BIVARIATE)

* People who sanctioned with 17500k - 20000k and having an annual income of 105k-135k are more likely to default.

* People with LOAN AMOUNT 14k-16k with term period of 60 months are more likely to default.

* People with LOAN AMOUNT 20k-35k with Interest Rate of 15%-17% are more likely to default.

* People with 10 years of exp and having 12k-14k LOAN AMOUNT are more likely to default.

* People with purpose home_improvement and annual_inc of 60k-70k are more likely to default.

* People with MORTGAGE and with LOAN AMOUNT of 12k-14k are more likely to default.

* People Verified and with 60k+ ANNUAL INCOME are more likely to default.

"One learns from books and example only that certain things can be done. Actual learning requires that you do those things."

-Frank Herbert

References

* Pandas Library Docs : https://pandas.pydata.org

* Seaborn Library Docs : https://seaborn.pydata.org/

* MatplotLib Docs : https://matplotlib.org/

Group Members

* Abhishek Mishra : mishra.abhi8888@gmail.com

* Sujan Polasa : sujanpolasa48m@gmail.com