



## LENDING CLUB CASE STUDY

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### Objective

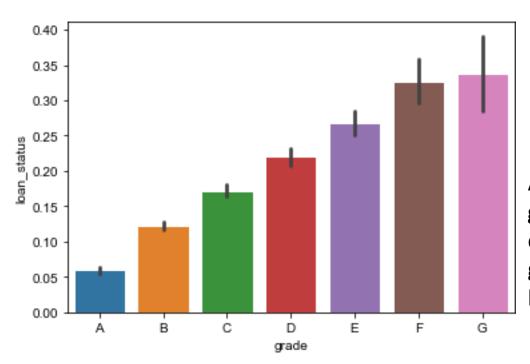
• The data in the loan.csv file contains information about past loan applicants and whether they 'defaulted' or not. The aim is to identify patterns that indicate if a person is likely to default, which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc.





# UNIVARIATE AND BIVARIATE ANALYSIS Analysis (Loan\_status vs Grade)

#### loan\_status vs grade

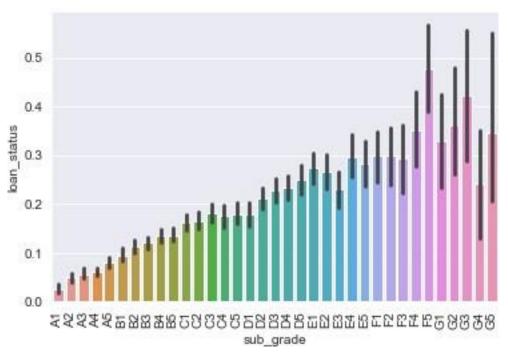


After analysing the dataset with respect to **grades** and **loan\_status** we came to the conclusion that the loans belonging to the grades D, E, F and G are considered to be a high-risk cases in increasing order.



# Analysis (Loan\_status vs Sub\_Grade)

#### loan\_status vs sub\_grade

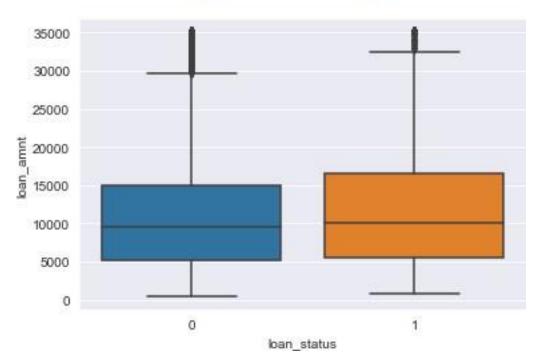


After analysing the dataset with respect to **sub\_grades** and **loan\_status** we came to the conclusion that the loans belonging to the sub\_grades after D are considered to be a high-risk cases in increasing order.



### Analysis (Loan\_status vs Loan\_amnt)

#### loan\_amnt vs loan\_status

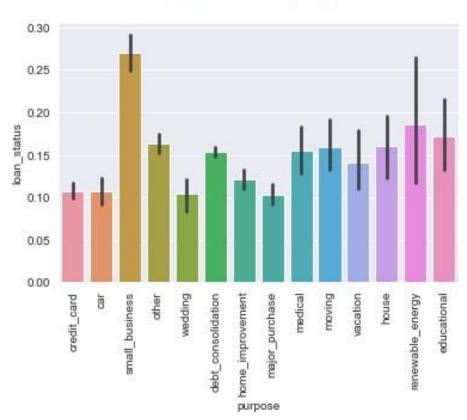


After analysing the dataset with respect to **loan\_amnt** and **loan\_status** we came to the conclusion that these two columns do not have significant correlation and they do not affect each other.



### Analysis (Loan\_status vs Purpose)

#### loan\_status vs purpose

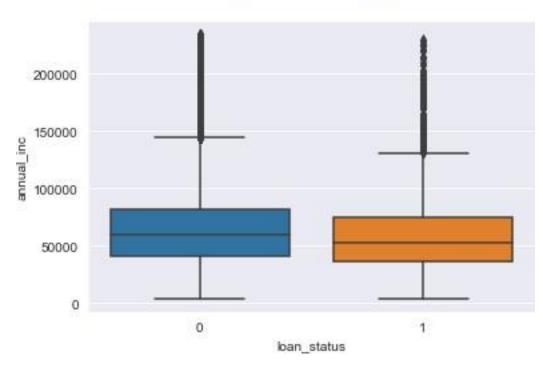


After analysing the dataset with respect to loan\_status and purpose we came to the conclusion that small\_business, renewable\_energy and educational are having more chances to become a defaulter.



### Analysis (Annual\_inc vs Loan\_status)

#### annual\_inc vs loan\_status

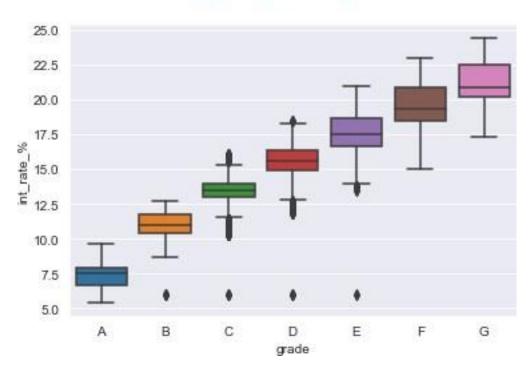


After analysing the dataset with respect to annual\_inc and loan\_status we came to the conclusion that these two columns do not have any significant correlation. The annual income of the borrower doesn't have any impact on their repaying capacity.



### Analysis (int\_rate\_% vs Grade)

#### int\_rate\_% vs grade

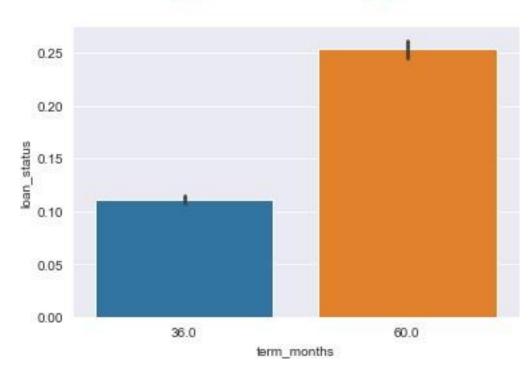


After analysing the dataset with respect to **int\_rate\_%** and **Grade** we came to the conclusion that both the columns are linearly correlated and as the grades increase the interest rate percentage is increasing.



# Analysis (Term\_months vs Loan\_status)

#### term\_months vs loan\_status



After analysing the dataset with respect to **term\_months** and **loan\_status** we came to the conclusion that people opting for 60 months of tenure are more likely to default as compared to 36 months.

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### **Correlation Matrix**

### upGrad #LifeKoKaroLift

#### HeatMap



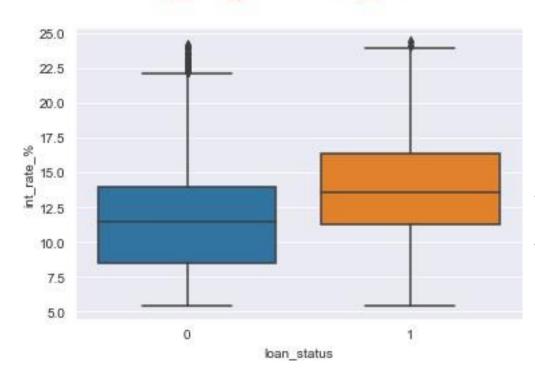
This Heat Map represents all the correlation value for the different columns. It shows which two numeric variables are highly linearly correlated.

In the correlation matrix, the only non-trivial linear correlation that we can find is between installment and loan\_amnt, but they both don't have any correlation with the target variable loan\_status. If we check the row(or column) corresponding to loan\_status, we don't observe any 'strong' positive or negative linear correlation between loan\_status and most other numerical variable.



### Analysis (int\_rate\_% vs Loan\_status)

#### int\_rate\_% vs loan\_status

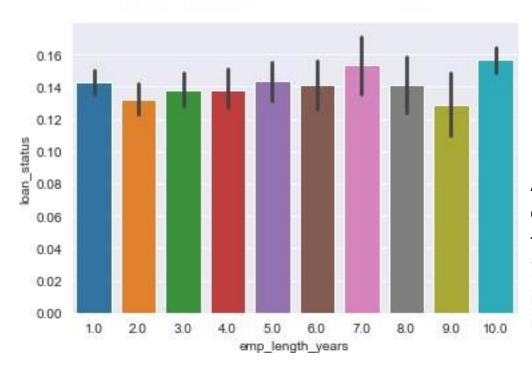


After analysing the dataset with respect to int\_rate\_% and loan\_status we came to the conclusion that as the interest rate is increasing the number of defaulters are increasing.



### Analysis (emp\_length\_years vs Loan\_status)

#### emp\_length\_years vs loan\_status

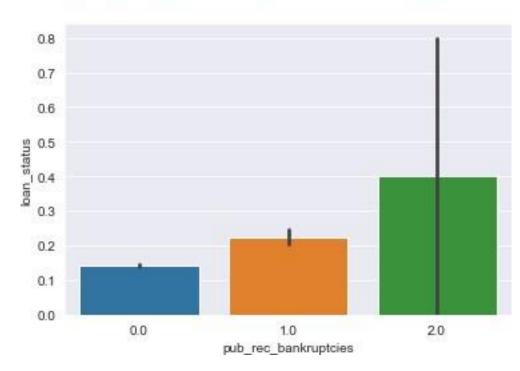


After analysing the dataset with respect to **emp\_length\_years** and **loan\_status** we came to the conclusion that the employment length is not correlated with loan status which means that there is no impact of employment length on the loan status.



### Analysis (pub\_rec\_bankruptcies vs Loan\_status)

#### pub\_rec\_bankruptcies vs loan\_status

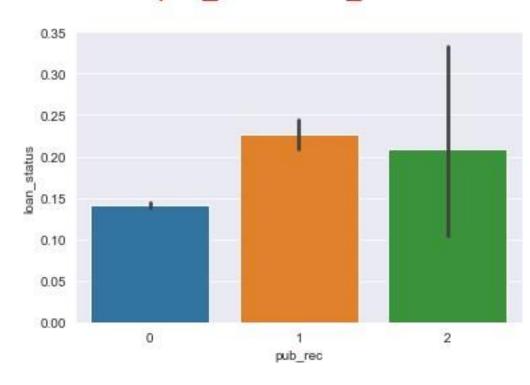


After analysing the dataset with respect to pub\_rec\_bankruptcies
and loan\_status we came to the conclusion that the people having two public record bankruptcies are highly likely to default.



### Analysis (pub\_rec vs Loan\_status)

#### pub\_rec vs loan\_status



After analysing the dataset with respect to **pub\_rec** and **loan\_status** we came to the conclusion that people having any derogatory public record are more likely to default.



### Conclusion

The following are the variables that has considerable impact on the repayment of the loan:

- grade → particularly starting from D has higher default rate
- sub\_grade → particularly starting from D2 has higher default rate
- int rate → higher the interest rate, higher default rate
- term → people opting for 60 months has higher default rate
- purpose → particularly small\_business has higher default rate
- pub\_rec → having derogatory public record significantly increases the chances of defaulting
- pub\_rec\_bankruptcies → having public record bankruptcies significantly increases the chances of defaulting