## Case Study

Case study on Lending Club

## Uploading Data to Analyze

- import numpy as np
- import pandas as pd
- import seaborn as sns
- import matplotlib.pylab as plt
- df = pd.read\_csv("C:\Lending\_Class\ loan\loan1.csv")
- df

Out[78]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	 num_tl_90g_dpd_24m	num_tl_c
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	В	B2	 NaN	
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	С	C4	 NaN	
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	С	C5	 NaN	
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	С	C1	 NaN	
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	В	B5	 NaN	
39712	92187	92174	2500	2500	1075.0	36 months	8.07%	78.42	Α	A4	 NaN	
39713	90665	90607	8500	8500	875.0	36 months	10.28%	275.38	С	C1	 NaN	
39714	90395	90390	5000	5000	1325.0	36 months	8.07%	156.84	Α	A4	 NaN	
39715	90376	89243	5000	5000	650.0	36 months	7.43%	155.38	Α	A2	 NaN	
39716	87023	86999	7500	7500	800.0	36 months	13.75%	255.43	Е	E2	 NaN	

...

### Data cleaning

- # delete the rows where the column contains the NAN values
- # By cleaning this table about 45 columns would be removed
- # it make the analysis little bit handy
- # lets use df\_1 dataframe for our analysis
- cols\_to\_ignore = ['emp\_length']
- #df\_1=df.dropna(axis=1)
- df\_1=df.dropna(axis=1,how='all')
- df\_1

Out[85]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	 next_pymnt_d	last_credit_pull_d
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	В	B2	 NaN	May-16
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	С	C4	 NaN	Sep-13
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	С	C5	 NaN	May-16
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	С	C1	 NaN	Apr-16
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	В	B5	 Jun-16	May-16
39712	92187	92174	2500	2500	1075.0	36 months	8.07%	78.42	Α	A4	 NaN	Jun-10
39713	90665	90607	8500	8500	875.0	36 months	10.28%	275.38	С	C1	 NaN	Jul-10
39714	90395	90390	5000	5000	1325.0	36 months	8.07%	156.84	Α	A4	 NaN	Jun-07
39715	90376	89243	5000	5000	650.0	36 months	7.43%	155.38	Α	A2	 NaN	Jun-07
39716	87023	86999	7500	7500	800.0	36 months	13.75%	255.43	Е	E2	 NaN	Jun-10

39717 rows × 57 columns

#### Columns Details

- ## Data Sourcing 2
- # lets try to understand the columns usage
- # data types of the column

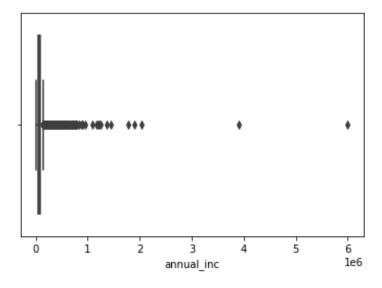
In [86]: 1 df 1.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 39717 entries, 0 to 39716
Data columns (total 57 columns):

Column Non-Null Count Dtype ----id 39717 non-null int64 member id 39717 non-null int64 loan amnt 39717 non-null int64 funded amnt 39717 non-null int64 funded amnt inv 39717 non-null float64 39717 non-null object int rate 39717 non-null object installment 39717 non-null float64 grade 39717 non-null object sub grade 39717 non-null object 10 emp title 37258 non-null object 11 emp length 38642 non-null object 39717 non-null object 12 home ownership 13 annual inc 39717 non-null float64 14 verification\_status 39717 non-null object 15 issue\_d 39717 non-null object 16 loan\_status 39717 non-null object 17 pymnt\_plan 39717 non-null object

#### Finding Outliers

- #### EDA : Explanatory Data Analysis
- # from the above annual data, very very few employees earns 60 Lacs
- # this will lay outlayres
- # now lets us find the out layers



## Removing Outliers

- ## from the above out layers chart,
- # Max number of employees are earning less than 10 Lacs
- # calculating loan eligibility based on annual income will not give oppertunity to the employess having less annual income
- # compared to the max earner.
- ### Considering the employees who are earing more than 12 lacs as outliers
- # Now our dataframe is df\_2

```
In [90]: 1 df_2=df_1.drop(df_1[df_1['annual_inc']>=1200000].index)
2 df_2
```

Out[90]:

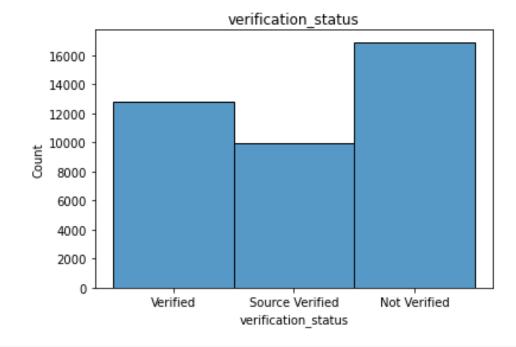
	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	 next_pymnt_d	last_credit_pull_d c
(	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87	В	B2	 NaN	May-16
•	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83	С	C4	 NaN	Sep-13
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33	С	C5	 NaN	May-16
;	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31	С	C1	 NaN	Apr-16
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79	В	B5	 Jun-16	May-16
39712	92187	92174	2500	2500	1075.0	36 months	8.07%	78.42	Α	A4	 NaN	Jun-10
39713	90665	90607	8500	8500	875.0	36 months	10.28%	275.38	С	C1	 NaN	Jul-10
39714	90395	90390	5000	5000	1325.0	36 months	8.07%	156.84	Α	A4	 NaN	Jun-07
3971	90376	89243	5000	5000	650.0	36 months	7.43%	155.38	Α	A2	 NaN	Jun-07
39710	87023	86999	7500	7500	800.0	36 months	13.75%	255.43	Е	E2	 NaN	Jun-10

39705 rows × 57 columns

## Univariate Analysis with Verification Status

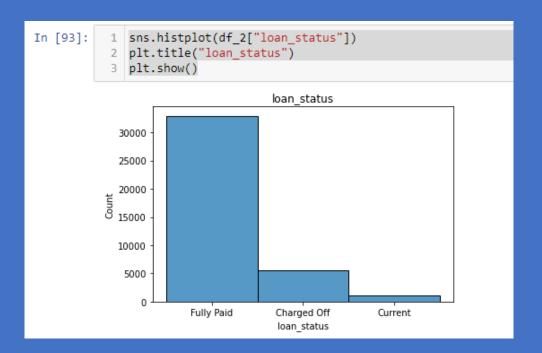
- ### Univariate Analysis
- # Get the chart for Verified users
- # Get the char for loan\_status# Get the chart for Verified users
- # Get the char for loan\_status

```
In [92]: 1 sns.histplot(df_2["verification_status"])
2 plt.title("verification_status")
3 plt.show()
```



# Univariate Analysis on Loan\_Status

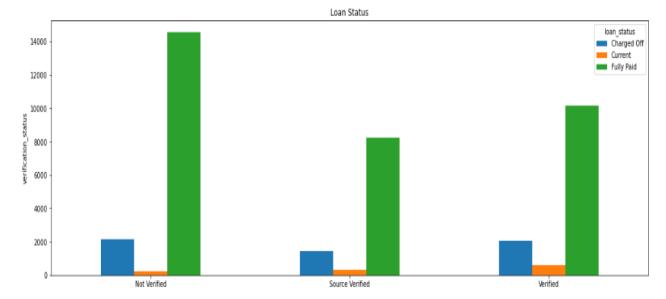
To get the percentage of loan status



### Bivariate Analysis

- ## Analysis made between the loan\_status with respect to verification\_status
- # this is to understand how many verified user are not defaulters
- # We can see max number of applicants are paid their depts promptly irrespective of verification status

```
In [70]: 1  pd.crosstab(df_2.verification_status,df_2.loan_status).plot(kind="bar",figsize=(20,6))
  plt.title('Loan_status')
  plt.xlabel('loan_status')
  plt.ylabel('verification_status')
  plt.xticks(rotation =0)
  plt.savefig('Loan_status.png')
  7  plt.show()
```

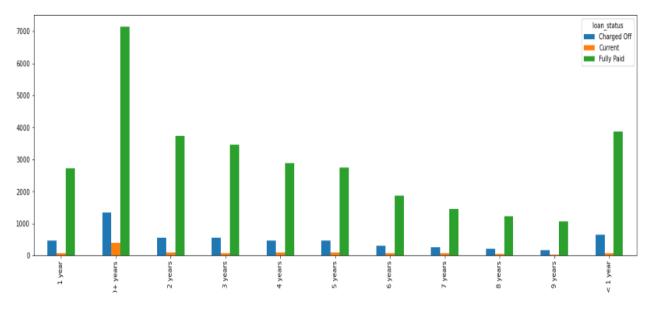


### Bivariate Analysis between loanstatus wrt Exp

- # In the below Bar plots with respect to Annual\_Income and Loan\_status along with candiates work experience
- # We can see higer number of applicants paid fully, at the same time we can notice quitly some high defaulters in all exp levels.
- # in such case we can have trade-off for charged\_off canditates

In [113]: | 1 | pd.crosstab(df\_2.emp\_length,df\_2.loan\_status).plot(kind="bar",figsize=(20,6))

Out[113]: <AxesSubplot:xlabel='emp\_length'>

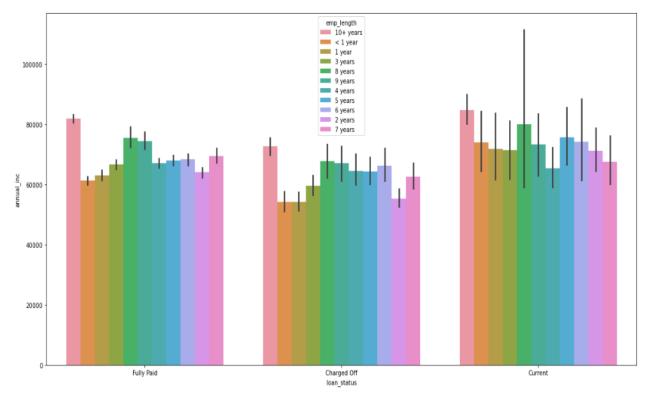


## Trade-Off decision

- # The trade-off for applicants having charged\_off value can be set,
- # the loan sanction can be considered for the applicants who are haveing >60K as annual income with trade-off condition
- ### Condtions
- # 1. defaulters : missed payment not more than 3 monthts
- # 2. Current loan : 40% of (applicants monthly\_income current\_emi)
- # 3. Fully Paid : requested amount can be granted

```
In [112]: 1 plt.figure(figsize=(20,10))
2 sns.barplot(x=df_2["loan_status"],y=df_2["annual_inc"], hue=df_2["emp_length"])
3 #sns.barplot(x=df_2["emp_length"],y=df_2["annual_inc"])
```

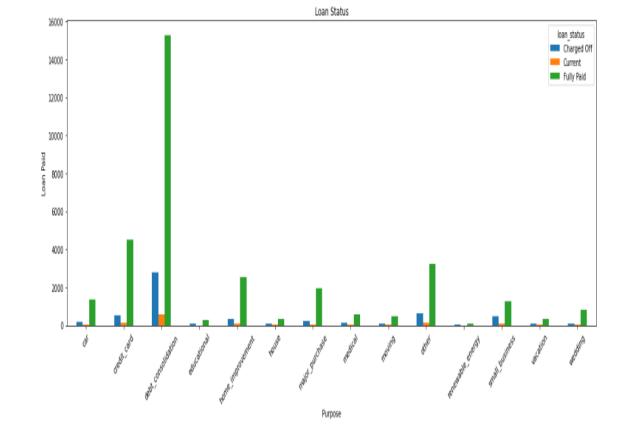
Out[112]: <AxesSubplot:xlabel='loan\_status', ylabel='annual\_inc'>



# Understanding on Loan Recovery

## From the below gragh we can notice loan recovery is high for Balance Transfer applicants

```
In [116]: 1 pd.crosstab(df_2.purpose,df_2.loan_status).plot(kind="bar",figsize=(20,6))
2 plt.title('Loan Status')
3 plt.xlabel('Purpose')
4 plt.ylabel('Loan Paid')
5 plt.xticks(rotation =45)
6 plt.show()
```



### Thank You