# “TO LEND OR NOT TO LEND?”

Exploratory data analysis on Kaggle’s lending club loan data  by Gregory Ausu

# KAGGLE LENDING CLUB LOAN PROPOSAL

**Problem:**

**Borrowers defaulting on their loans is a growing problem in the U.S. According to CNBC by 2023, nearly 40 percent of borrowers are expected to default on their student loans. Also, according to the S&P Dow Jones Indices and Experian, December of 2018 marked the first time since January of 2017 that all loan types and all metropolitan statistical areas saw an increase in sequential default rates. These issues are further compounded by auto loan defaults being at record highs. Using exploratory data analysis to accurately predict and/or prevent loan defaults or charge off's is of great importance. This will be of great help to traditional financial institutions as well as growing fintech and mobile banking companies.**

**Intent:**

**To extract and perform exploratory data analysis to assess markers that indicate the risk of a loan being charged off.**

**Hypothesis:**

**Features in this dataset such as employment title, loan amount, interest rate, and location will be used to analyze the risk of a loan being charge off.**

# DATA SOURCES

- https://www.kaggle.com/wendykan/lending-club-loan-data
- https://www.bls.gov/ooh/education-training-and-library/career-and-technical-education-teachers.htm
- https://www.cnbc.com/2018/08/13/twenty-two-percent-of-student-loan-borrowers-fall-into-default.html
- https://www.citylab.com/transportation/2019/02/subprime-car-loans-buy-automobile-lending-debt-trap/582652/
- https://github.com/gausu/EDA-Projects

# DATA IMPORTS

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from matplotlib import rcParams

loan = pd.read_csv('loan.csv')



%matplotlib inline

rcParams['figure.figsize'] = 16,6
```

```
.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 887379 entries, 0 to 887378
Data columns (total 74 columns):
id                              887379 non-null int64
member_id                       887379 non-null int64
loan_amnt                       887379 non-null float64
funded_amnt                     887379 non-null float64
funded_amnt_inv                 887379 non-null float64
term                            887379 non-null object
int_rate                        887379 non-null float64
installment                     887379 non-null float64
grade                           887379 non-null object
sub_grade                       887379 non-null object
emp_title                       835917 non-null object
emp_length                      842554 non-null object
home_ownership                  887379 non-null object
annual_inc                      887375 non-null float64
verification_status             887379 non-null object
issue_d                         887379 non-null object
loan_status                     887379 non-null object
pymnt_plan                      887379 non-null object
url                             887379 non-null object
desc                            126028 non-null object
purpose                         887379 non-null object
title                           887227 non-null object
zip_code                        887379 non-null object
addr_state                      887379 non-null object
dti                             887379 non-null float64
delinq_2yrs                     887350 non-null float64
earliest_cr_line                887350 non-null object
inq_last_6mths                  887350 non-null float64
mths_since_last_delinq          433067 non-null float64
mths_since_last_record          137053 non-null float64
open_acc                        887350 non-null float64
pub_rec                         887350 non-null float64
revol_bal                       887379 non-null float64
revol_util                      886877 non-null float64
```

```
loan.shape
```

```
(887379, 74)
```

```
loan.head()
```

| | id | member_id | loan_amnt | funded_amnt | funded_amnt_inv | term | int_rate | installment | grade | sub_grade | ... | total_bal_il | il_util | open_rv_12m |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 1077501 | 1296599 | 5000.0 | 5000.0 | 4975.0 | 36 months | 10.65 | 162.87 | B | B2 | ... | NaN | NaN | NaN |
| 1 | 1077430 | 1314167 | 2500.0 | 2500.0 | 2500.0 | 60 months | 15.27 | 59.83 | C | C4 | ... | NaN | NaN | NaN |
| 2 | 1077175 | 1313524 | 2400.0 | 2400.0 | 2400.0 | 36 months | 15.96 | 84.33 | C | C5 | ... | NaN | NaN | NaN |
| 3 | 1076863 | 1277178 | 10000.0 | 10000.0 | 10000.0 | 36 months | 13.49 | 339.31 | C | C1 | ... | NaN | NaN | NaN |
| 4 | 1075358 | 1311748 | 3000.0 | 3000.0 | 3000.0 | 60 months | 12.69 | 67.79 | B | B5 | ... | NaN | NaN | NaN |

5 rows × 74 columns

# EXPLORATORY DATA ANALYSIS

- loan.head() reveals that this dataset has 5 rows and 74 columns.
- loan.info() reveals that there are 887,379 entries over the 74 columns. The datatypes consist of 49 floats, 2 integers, and 23 objects also revealing that there a large number of null values.
- loan.shape combines and confirms the above information

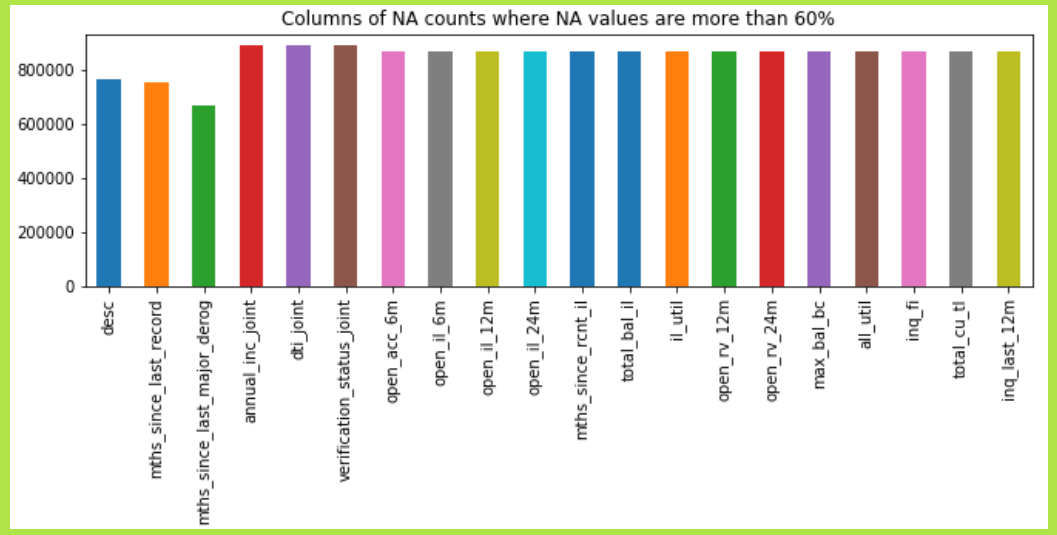
# EXPLORATORY DATA ANALYSIS(NULL VALUES)

```
loan.isnull().sum()
```

| | |
|---|---|
| id | 0 |
| member_id | 0 |
| loan_amnt | 0 |
| funded_amnt | 0 |
| funded_amnt_inv | 0 |
| term | 0 |
| int_rate | 0 |
| installment | 0 |
| grade | 0 |
| sub_grade | 0 |
| emp_title | 51462 |
| emp_length | 44825 |
| home_ownership | 0 |
| annual_inc | 4 |
| verification_status | 0 |
| issue_d | 0 |
| loan_status | 0 |
| pymnt_plan | 0 |
| url | 0 |
| desc | 761351 |
| purpose | 0 |
| title | 152 |
| zip_code | 0 |
| addr_state | 0 |
| dti | 0 |
| delinq_2yrs | 29 |
| earliest_cr_line | 29 |
| inq_last_6mths | 29 |
| mths_since_last_delinq | 454312 |
| mths_since_last_record | 750326 |

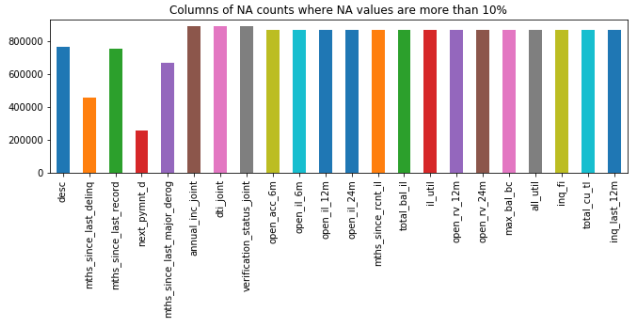
- loan.is.null.sum() REVEALS A LARGE NUMBER OF NULL VALUES.

# EXPLORATORY DATA ANALYSIS(NULL VALUES)




```
nan_col = loan.isnull().sum()
nan_col = nan_col[nan_col.values >(0.6*len(loan))]
plt.figure(figsize=(11,3))
nan_col.plot(kind='bar')
plt.title('Columns of NA counts where NA values are more than 60%')
plt.show()
```

- Null values that are greater than 60% in this dataset.




```
nan_col = loan.isnull().sum()
nan_col = nan_col[nan_col.values >(0.1*len(loan))]
plt.figure(figsize=(11,3))
nan_col.plot(kind='bar')
plt.title('Columns of NA counts where NA values are more than 10%')
plt.show()
```

# EXPLORATORY DATA ANALYSIS(NULL VALUES)

- Null values that are greater than 10%

# EXPLORATORY DATA ANALYSIS(NULL VALUES)

- Of the selected features being used to assess the risk of a loan being “charged off”, employment title is the only feature that has null values.

```
loan.notnull().sum()
```

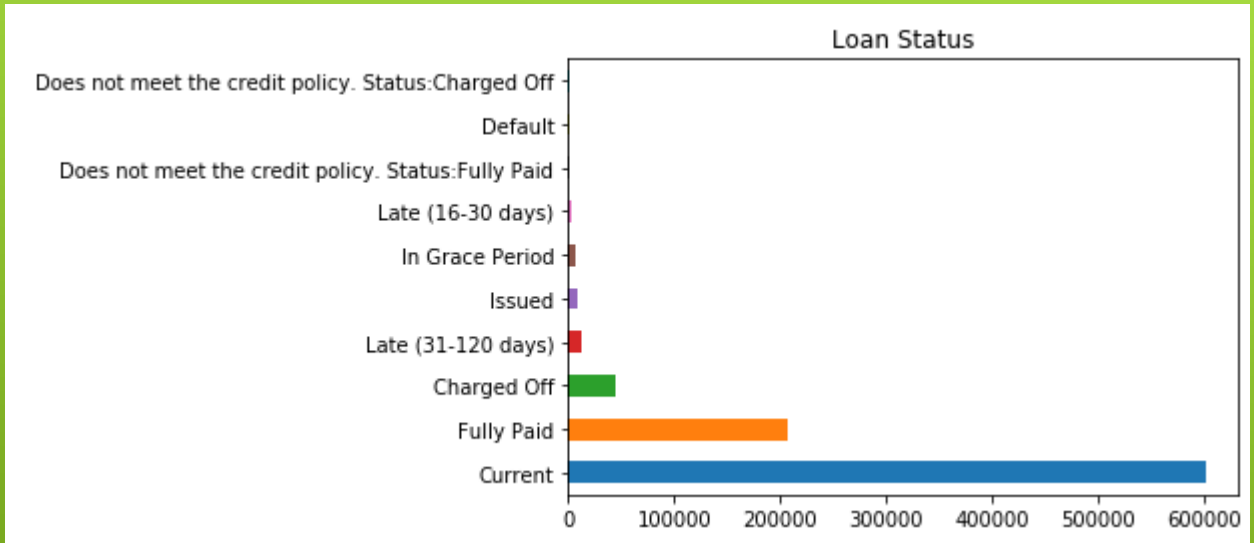
| | |
|---|---|
| id | 887379 |
| member_id | 887379 |
| loan_amnt | 887379 |
| funded_amnt | 887379 |
| funded_amnt_inv | 887379 |
| term | 887379 |
| int_rate | 887379 |
| installment | 887379 |
| grade | 887379 |
| sub_grade | 887379 |
| emp_title | 835917 |
| emp_length | 842554 |
| home_ownership | 887379 |
| annual_inc | 887375 |
| verification_status | 887379 |
| issue_d | 887379 |
| loan_status | 887379 |
| pymnt_plan | 887379 |
| url | 887379 |
| desc | 126028 |
| purpose | 887379 |
| title | 887227 |
| zip_code | 887379 |
| addr_state | 887379 |

# LOAN STATUS

- 69% of loans are current
- 24% of loans are fully paid including 'Does not meet credit policy. Status: Fully Paid'
- 5% of loans have been charged off including 'Does not meet credit policy. Status: Charged off'
- <1% of the borrowers have defaulted
- 2% of the loans are late(16-120 days)

```
loan.loan_status.value_counts()
```

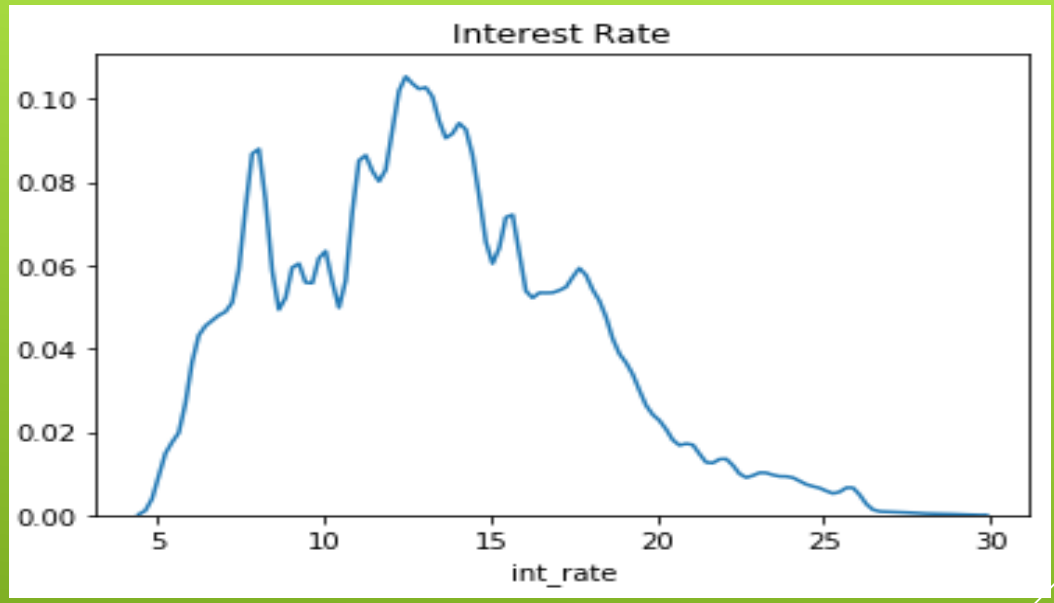
| | |
|---|---|
| Current | 601779 |
| Fully Paid | 207723 |
| Charged Off | 45248 |
| Late (31-120 days) | 11591 |
| Issued | 8460 |
| In Grace Period | 6253 |
| Late (16-30 days) | 2357 |
| Does not meet the credit policy. Status:Fully Paid | 1988 |
| Default | 1219 |
| Does not meet the credit policy. Status:Charged Off | 761 |


Loan Status
Does not meet the credit policy. Status:Charged Off
Default
Does not meet the credit policy. Status:Fully Paid
Late (16-30 days)
In Grace Period
Issued
Late (31-120 days)
Charged Off
Fully Paid
Current
0
100000
200000
300000
400000
500000
600000

# LOAN STATUS

# DESCRIPTIVE STATISTICS(INTEREST RATE)

- In this dataset, the highest interest rate is at 29%, the lowest is 5.32% and the average interest rate is 13.24%

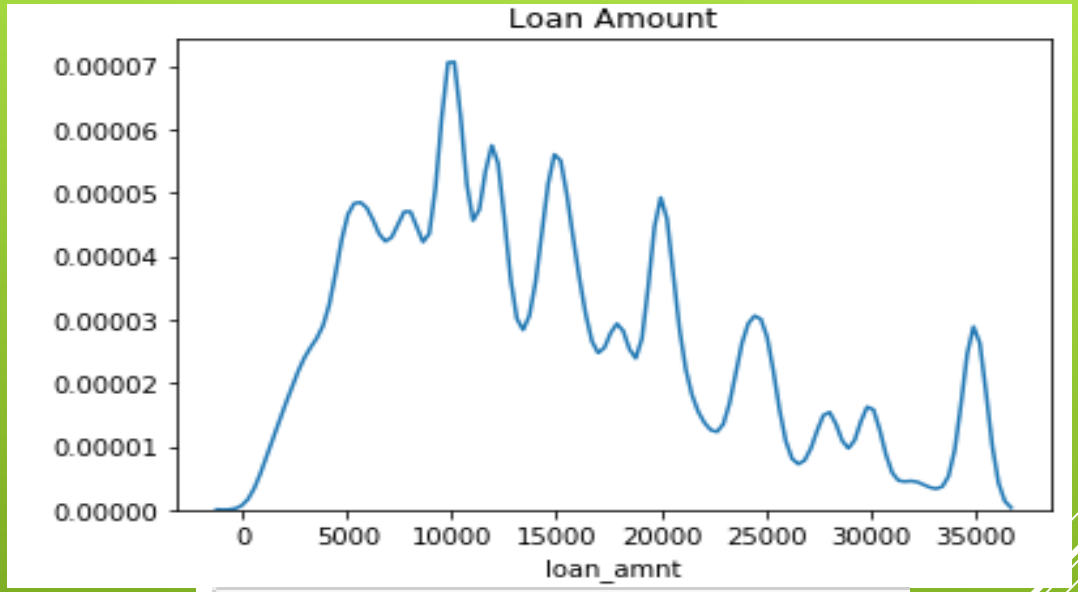



```
loan.int_rate.describe()
```

| | |
|---|---|
| count | 887379.000000 |
| mean | 13.246740 |
| std | 4.381867 |
| min | 5.320000 |
| 25% | 9.990000 |
| 50% | 12.990000 |
| 75% | 16.200000 |
| max | 28.990000 |

# DESCRIPTIVE STATISTICS(LOAN AMOUNT)

- In this dataset, the highest amount of loan borrowed is $35,000, the lowest $500.00 and the average amount borrowed is $14,755.26.

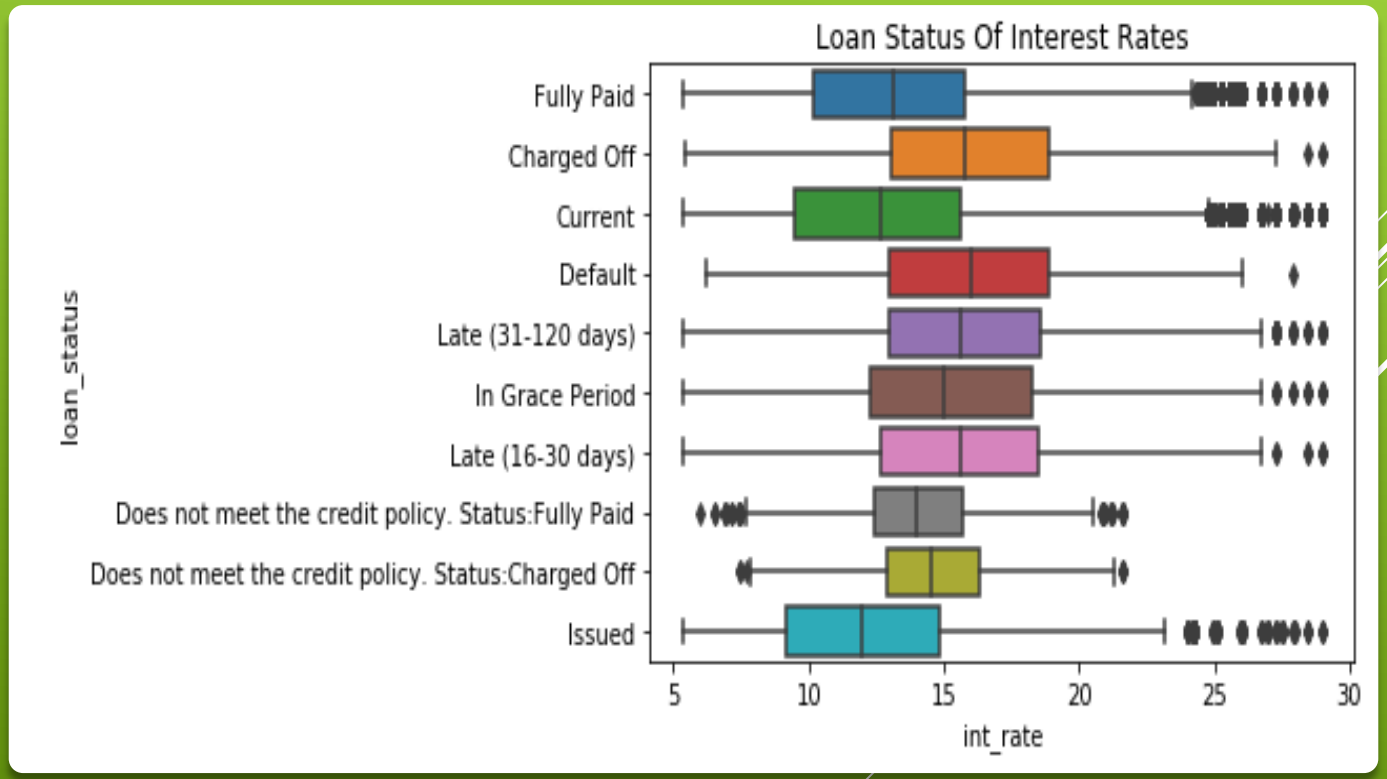



```
loan.loan_amnt.describe()
```

```
count    887379.000000
mean      14755.264605
std        8435.455601
min         500.000000
25%        8000.000000
50%       13000.000000
75%       20000.000000
max       35000.000000
```

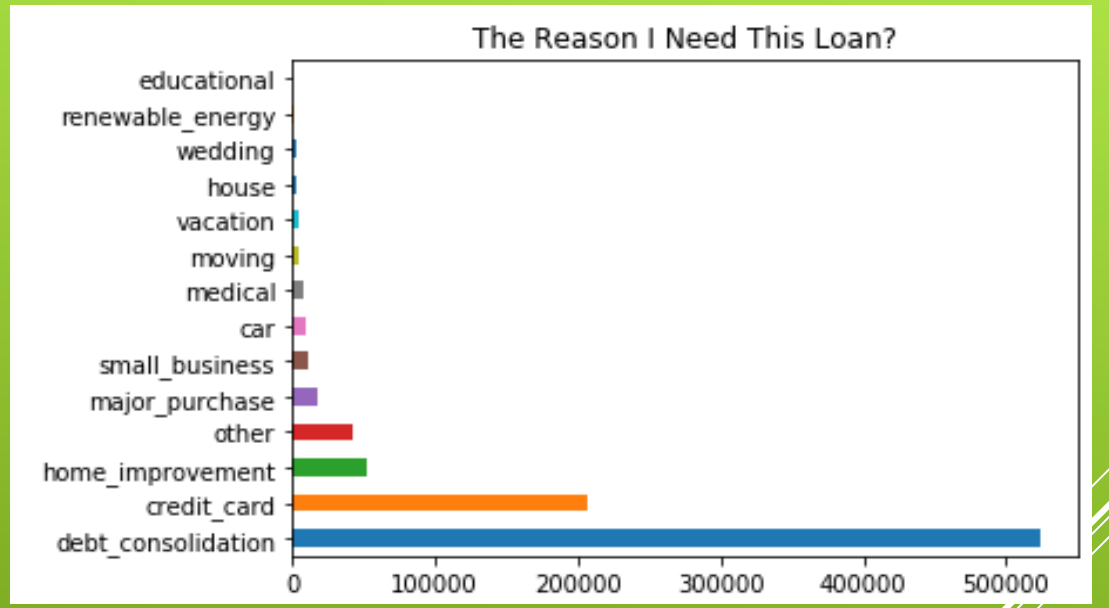
# INTEREST RATE AND LOAN STATUS

- ❖ From this boxplot, we can see that the highest interest rates(25-29%) correlate with the loan status' charged off, late(16-30 days) late(31-120 days), and default. We can surmise that applications that have these interest rates are at high risk. However, this dataset has many outliers and there are individuals who are current and that have fully paid their loans with those same interest rates.
- ❖ We can also see that the average interest rate (13.24%) correlates with the median values of the loan status' fully paid and current. We can surmise that this interest rate is an optimal rate



# PURPOSE OF LOAN

- Debt consolidation and credit cards account for 82% of all the purposes listed on loan applications with debt consolidation being 59% respectively.
- Car loans and student loans only account for 10% of all listed purposes. However, it is reasonable to conclude that they would be apart of debt consolidation and credit card debt considering the high amounts of debt in the U.S for student and auto loans.



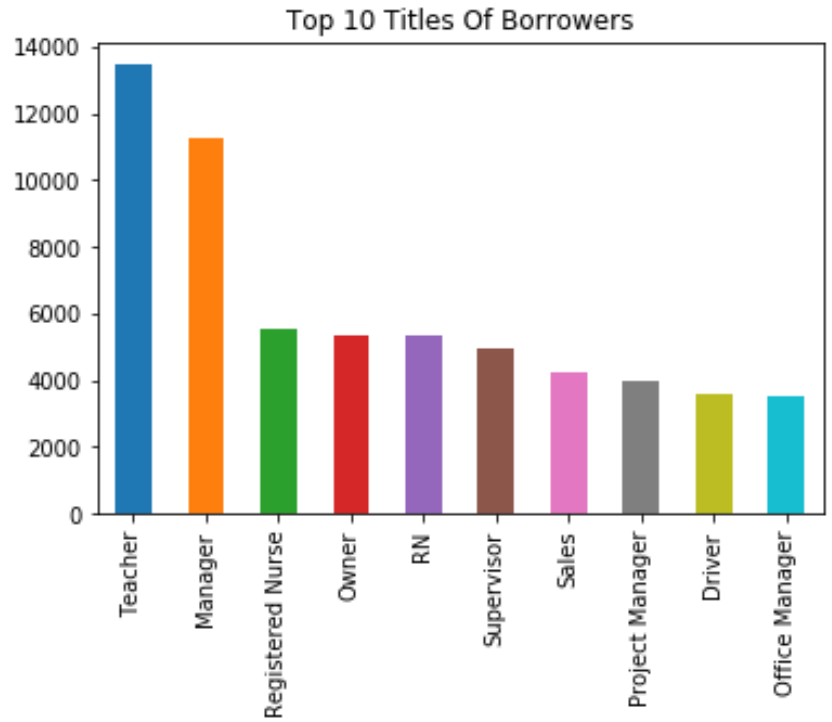

```
loan.purpose.value_counts()
```

| | |
|---|---|
| debt_consolidation | 524215 |
| credit_card | 206182 |
| home_improvement | 51829 |
| other | 42894 |
| major_purchase | 17277 |
| small_business | 10377 |
| car | 8863 |
| medical | 8540 |
| moving | 5414 |
| vacation | 4736 |
| house | 3707 |
| wedding | 2347 |
| renewable_energy | 575 |
| educational | 423 |

# TOP 10 EMPLOYMENT TITLES

```
loan.emp_title.value_counts()[:10].plot(kind = 'bar')
plt.title("Top 10 Titles Of Borrowers")
```

```
Text(0.5,1,'Top 10 Titles Of Borrowers')
```




- The top employment title is a teacher. However, this section of the data could be more helpful if employment metrics were more specific such as field or industry. Titles such as “owner”, “office manager”, and “supervisor” are undetailed and do not give us an accurate indicator of the possibility of a loan being charged off. The employment titles that are specific in the data do not have great numerical representation for analysis for ex., “airport operations supervisor” accounts for only 1 title out of 835,917 entries.
- Employment titles such as teachers and registered nurses are more useful for analysis because we can locate their median incomes and job growth expectancies at the bureau of labor statistics.

# TOP EMPLOYMENT TITLES(CONT.)

- This handicap in the employment titles column of the data is further elucidated in the fact that the graphical and numerical representations of this feature show an overrepresentation of the title teacher which could lead to an assumption or bias towards lending to teachers. However, upon further inspection teachers account for only 2% of the total employment titles and there are 2 different titles for the title teacher in the dataset.

```
loan.emp_title.value_counts()
```

| | |
|---|---|
| Teacher | 13469 |
| Manager | 11240 |
| Registered Nurse | 5525 |
| Owner | 5376 |
| RN | 5355 |
| Supervisor | 4983 |
| Sales | 4212 |
| Project Manager | 3988 |
| Driver | 3569 |
| Office Manager | 3510 |
| General Manager | 3178 |
| Director | 3156 |
| manager | 3138 |
| teacher | 2925 |

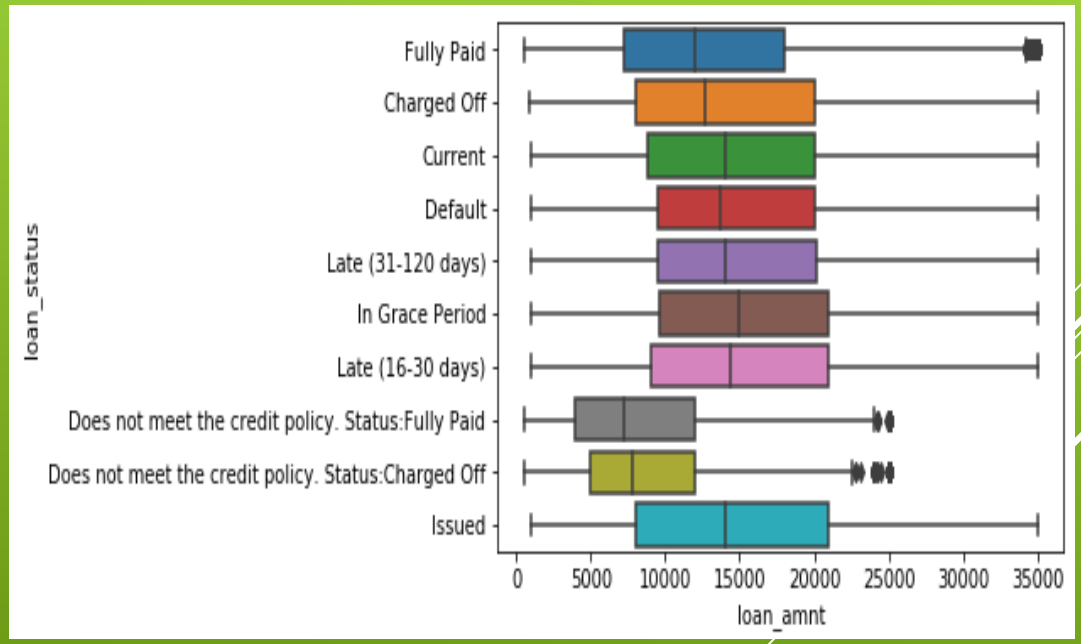
```
loan.emp_title.value_counts("teacher")
```

| | |
|---|---|
| Teacher | 0.016113 |
| Manager | 0.013446 |
| Registered Nurse | 0.006610 |
| Owner | 0.006431 |
| RN | 0.006406 |
| Supervisor | 0.005961 |
| Sales | 0.005039 |
| Project Manager | 0.004771 |
| Driver | 0.004270 |
| Office Manager | 0.004199 |
| General Manager | 0.003802 |
| Director | 0.003775 |
| manager | 0.003754 |
| teacher | 0.003499 |
| owner | 0.003408 |

# LOAN STATUS AND LOAN AMOUNT RELATIONSHIP

- As we saw earlier, there is a relationship between the loan status "charged off" and interest rates. Here we see the relationships with the loan amount.
- The highest loan borrowed is between $33,000 and $35,000 dollars and it appears across all loan status'(Excluding the "Does not meet the credit policy" categories).
- The median value of all the loan status' and loan amounts is between $14,000 and $15,000 dollars which confirms the average loan borrowed is at $14,755.26. This amount is also the median amount for loans that have been "Charged Off" therefore the loan amount is not a reliable indicator of a loan being charged off.

```
ax= sns.boxplot(x="loan_amnt", y="loan_status", data=loan);
plt.figure(figsize=(16,6))
```



# TOP 10 STATES

## LOCATION OF BORROWERS

```
loan.addr_state.value_counts()
```

| | |
|---|---|
| CA | 129517 |
| NY | 74086 |
| TX | 71138 |
| FL | 60935 |
| IL | 35476 |
| NJ | 33256 |
| PA | 31393 |
| OH | 29631 |
| GA | 29085 |
| VA | 26255 |

- California is #1 and accounts for 15% of the total loans granted. New York and Texas are next at 8% and Virginia at the #10 accounts for 3% of all loans granted. It must be noted that Lending Club is headquartered in San Francisco, California so that could explain why as a state it has the most loans.

- This chart indicates that the state of California is #1 in loans that have been charged off at 7,332 loans. New York is second at 4,124 loans and the state of Texas is third at 3,035.
- Interestingly, Maine and North Dakota have zero charged off loans.

```
address_loan = ['addr_state', 'loan_status']
cm = sns.light_palette("green", as_cmap=True)
pd.crosstab(loan[address_loan[0]],
            loan[address_loan[1]]).style.background_gradient(cmap = cm)
```

| addr_state | Charged Off | Current | Default | Does not meet the credit policy. Status:Charged Off | Does not meet the credit policy. Status:Fully Paid | Fully Paid | In Grace Period | Issued | Late (16-30 days) | Late (31-120 days) |
|---|---|---|---|---|---|---|---|---|---|---|
| AK | 96 | 1469 | 2 | 1 | 4 | 567 | 15 | 14 | 6 | 31 |
| AL | 662 | 7576 | 9 | 8 | 24 | 2485 | 111 | 122 | 43 | 160 |
| AR | 337 | 4637 | 8 | 6 | 9 | 1417 | 57 | 70 | 13 | 86 |
| AZ | 1049 | 13577 | 39 | 18 | 33 | 5028 | 143 | 193 | 50 | 282 |
| CA | 7332 | 81851 | 211 | 101 | 223 | 35778 | 906 | 1147 | 327 | 1641 |
| CO | 784 | 12573 | 25 | 13 | 52 | 4829 | 106 | 166 | 57 | 202 |
| CT | 614 | 9353 | 8 | 12 | 50 | 3067 | 126 | 139 | 29 | 133 |
| DC | 87 | 1543 | 2 | 2 | 8 | 750 | 10 | 13 | 0 | 17 |
| DE | 121 | 1730 | 5 | 4 | 18 | 546 | 21 | 28 | 7 | 31 |
| FL | 3524 | 40999 | 95 | 72 | 160 | 14021 | 408 | 607 | 162 | 887 |
| GA | 1360 | 19993 | 36 | 35 | 69 | 6654 | 211 | 308 | 75 | 344 |
| HI | 276 | 2894 | 8 | 2 | 5 | 1202 | 45 | 42 | 13 | 83 |
| IA | 1 | 1 | 0 | 2 | 5 | 5 | 0 | 0 | 0 | 0 |
| ID | 1 | 3 | 0 | 0 | 3 | 5 | 0 | 0 | 0 | 0 |
| IL | 1542 | 25098 | 28 | 36 | 111 | 7711 | 219 | 298 | 56 | 377 |
| IN | 626 | 10529 | 19 | 7 | 3 | 2174 | 95 | 122 | 34 | 180 |
| KS | 356 | 5605 | 5 | 5 | 21 | 1727 | 35 | 82 | 21 | 69 |
| KY | 436 | 6016 | 15 | 10 | 22 | 1832 | 40 | 76 | 16 | 87 |
| LA | 566 | 7216 | 18 | 5 | 20 | 2386 | 81 | 110 | 30 | 155 |
| MA | 1017 | 13667 | 29 | 24 | 70 | 5122 | 140 | 211 | 54 | 259 |
| MD | 1100 | 14179 | 23 | 23 | 47 | 4907 | 175 | 215 | 55 | 307 |
| ME | 0 | 478 | 0 | 0 | 0 | 13 | 1 | 33 | 0 | 0 |
| MI | 1150 | 16147 | 32 | 19 | 55 | 4846 | 152 | 222 | 76 | 286 |
| MN | 803 | 10944 | 20 | 11 | 25 | 3657 | 112 | 148 | 37 | 200 |
| MO | 781 | 9773 | 16 | 26 | 53 | 3173 | 78 | 124 | 33 | 150 |
| MS | 86 | 3228 | 4 | 4 | 3 | 335 | 31 | 52 | 17 | 59 |
| MT | 95 | 1724 | 6 | 6 | 5 | 641 | 14 | 21 | 6 | 40 |
| NC | 1306 | 16835 | 33 | 12 | 29 | 5613 | 198 | 272 | 76 | 346 |
| ND | 0 | 444 | 0 | 0 | 0 | 8 | 1 | 23 | 2 | 1 |
| NE | 4 | 1086 | 0 | 3 | 3 | 34 | 8 | 29 | 2 | 7 |
| NH | 157 | 3005 | 3 | 2 | 14 | 991 | 36 | 39 | 12 | 35 |
| NJ | 1841 | 22411 | 49 | 26 | 107 | 7760 | 251 | 296 | 96 | 419 |
| NM | 269 | 3372 | 8 | 3 | 12 | 1108 | 39 | 45 | 15 | 68 |
| NV | 803 | 8136 | 27 | 16 | 13 | 3006 | 79 | 115 | 22 | 226 |
| NY | 4124 | 49670 | 106 | 57 | 191 | 17214 | 619 | 722 | 233 | 1150 |
| OH | 1472 | 20873 | 40 | 18 | 85 | 6266 | 162 | 272 | 67 | 376 |
| OK | 421 | 5620 | 8 | 3 | 14 | 1710 | 71 | 76 | 25 | 137 |
| OR | 544 | 7201 | 8 | 6 | 11 | 2809 | 80 | 96 | 22 | 116 |
| PA | 1557 | 21812 | 39 | 43 | 89 | 6842 | 243 | 252 | 93 | 423 |
| RI | 191 | 2661 | 5 | 2 | 7 | 896 | 27 | 37 | 8 | 59 |
| SC | 449 | 7469 | 15 | 4 | 13 | 2369 | 64 | 110 | 27 | 119 |
| SD | 90 | 1200 | 1 | 1 | 2 | 454 | 8 | 18 | 3 | 38 |
| TN | 563 | 9944 | 22 | 4 | 11 | 1863 | 114 | 146 | 28 | 192 |
| TX | 3035 | 49254 | 111 | 55 | 126 | 16308 | 455 | 691 | 183 | 920 |
| UT | 349 | 3935 | 8 | 5 | 14 | 1763 | 43 | 45 | 22 | 80 |
| VA | 1438 | 17263 | 29 | 16 | 63 | 6504 | 205 | 258 | 92 | 387 |
| VT | 70 | 1324 | 1 | 1 | 2 | 358 | 7 | 15 | 5 | 14 |
| WA | 986 | 12879 | 22 | 16 | 30 | 4929 | 118 | 188 | 64 | 202 |
| WI | 536 | 8107 | 14 | 14 | 42 | 2542 | 56 | 104 | 23 | 136 |
| WV | 159 | 3104 | 6 | 2 | 8 | 978 | 28 | 32 | 14 | 55 |
| WY | 82 | 1371 | 1 | 0 | 4 | 520 | 9 | 16 | 6 | 19 |

# CONCLUSION

- In conclusion, of the features used(employment title, loan amount, interest rate, and location), interest rate appears to be a major indicator of a loan being charged off.
- The location of the borrower is biased towards the state of California which is the headquarters of the lending company. It therefore has the most loan applications, charge offs, defaults, and borrowers who are current.
- The loan amount is consistent across all of the loan status' and therefore not a reliable indicator of a loan being charged off.
- The data in the employment title column is imprecise and can not be used as an accurate indicator of a loan being charged off.