Lending Club Data Set Prediction

Company Information:

Lending Club is a peer to peer lending company based in the United States, in which investors provide funds for potential borrowers and investors earn a profit depending on the risk they take (the borrowers credit score). Lending Club provides the "bridge" between investors and borrowers.

Questions to be Answered:

We will use data science and exploratory data analysis to take a peek Lending Club's loan data from 2007 to 2011, focusing on the following questions regarding this period:

Loan Absolute Variables Distribution: How does loan value, amount funded by lender and total committed by investors distribution looks like? Applicants income range: Range of Applicants income for both good and bad loans

Defaults Volume: How many loans were defaulted?

Average Interest Rates: What was the range of interest rate for the loans?

Loan Purpose: What were the most frequent Loan Purposes?

Loan Grades: Variation of interest rates for the different grades of loans

Delinquency Breakdown: How many loans were Charged Off(Bad loans)?

How does the loan data distribution look like? Using Data Science, we will paint a picture detailing the most important aspects related to the loans and perform EDA (Exploratory Data Analysis).

Can we create a better, optimized model to predict credit risk using machine learning?

By analyzing these aspects, we will be able to understand our data better and also get to know a bit of Lending Club's story. The dataset contains 43K loan applications from 2007 through 2011 and it can be downloaded from the url [www.lendingclub.com (http://www.lendingclub.com)](http://www.lendingclub.com).

In [1]:

```
#import warnings
#warnings.filterwarnings("ignore")
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import t
from numpy.random import seed
from scipy.stats import norm
from scipy.stats import ttest_ind_from_stats
df= pd.read_csv('LoanStats3a_securev1_new.csv',low_memory=False)
```

Understanding the various features (columns) of the dataset

In [2]:

```
print(df.info())
df.head()
df.columns
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42542 entries, 0 to 42541
Columns: 150 entries, id to settlement_term
dtypes: float64(120), object(30)
memory usage: 48.7+ MB
None
```

Out[2]:

```
Index(['id', 'member_id', 'loan_amnt', 'funded_amnt', 'funded_amnt_in
v',
       'term', 'int_rate', 'installment', 'grade', 'sub_grade',
       ...
       'orig_projected_additional_accrued_interest',
       'hardship_payoff_balance_amount', 'hardship_last_payment_amoun
t',
       'debt_settlement_flag', 'debt_settlement_flag_date',
       'settlement_status', 'settlement_date', 'settlement_amount',
       'settlement_percentage', 'settlement_term'],
      dtype='object', length=150)
```

In [3]:

```
print(df.shape)
```

```
(42542, 150)
```

In [4]:

```
df.head()
```

Out[4]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment
0	1077501	NaN	5000.0	5000.0	4975.0	36 months	10.65%	162.87
1	1077430	NaN	2500.0	2500.0	2500.0	60 months	15.27%	59.83
2	1077175	NaN	2400.0	2400.0	2400.0	36 months	15.96%	84.33
3	1076863	NaN	10000.0	10000.0	10000.0	36 months	13.49%	339.31
4	1075358	NaN	3000.0	3000.0	3000.0	60 months	12.69%	67.79

5 rows × 150 columns

Data Wrangling

In [5]:

```
#rename the column names

df = df.rename(columns={"loan_amnt": "loan_amount", "funded_amnt": "funded_amount",
                        "int_rate": "interest_rate", "annual_inc": "annual_income"})
```

In [6]:

```
df.head()
print(type(df['interest_rate'][0]))
```

```
<class 'str'>
```

In [7]:

```
#removing percentage sign from the interest_rate and convert it to float from string
df.interest_rate = df.interest_rate.str.replace('%', '').astype('float64')
print(df.interest_rate.head())
```

```
0    10.65
1    15.27
2    15.96
3    13.49
4    12.69
Name: interest_rate, dtype: float64
```

In [8]:

```
#remove months from term colums
df.term = df.term.str.replace('months', '')
df.term.head()
```

Out[8]:

```
0    36
1    60
2    36
3    36
4    60
Name: term, dtype: object
```

In [9]:

```
#setting up the index
df.set_index('id')

#member_id column shows Nan value and is of less significance hence we drop it
df.drop(['member_id'],axis=1,inplace=True)
```

In [10]:

```
missing_fractions = df.isnull().mean().sort_values(ascending=False)
missing_fractions.head(20)
```

Out[10]:

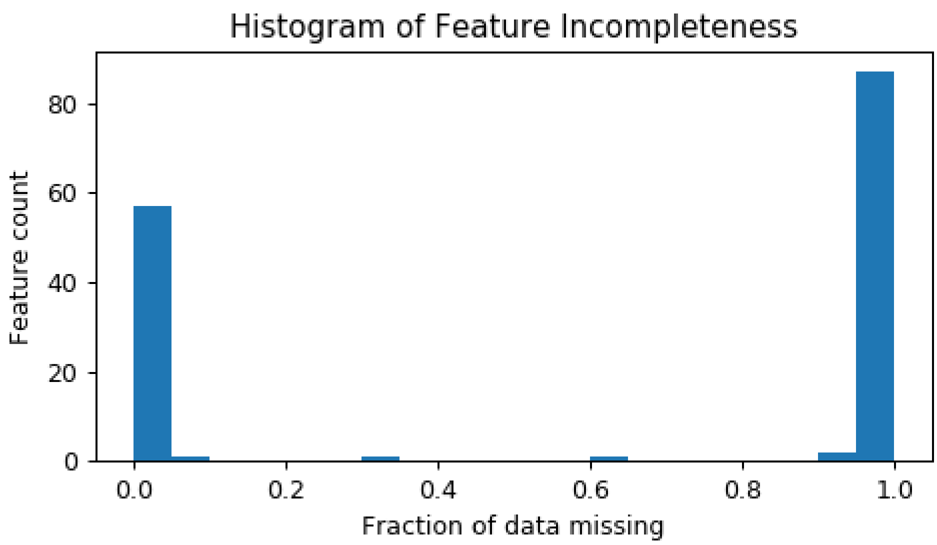
```
inq_fi                            1.0
percent_bc_gt_75                  1.0
mths_since_recent_bc_dlq          1.0
mths_since_recent_inq             1.0
mths_since_recent_revol_delinq    1.0
num_accts_ever_120_pd             1.0
num_actv_bc_tl                    1.0
num_actv_rev_tl                   1.0
num_bc_sats                       1.0
num_bc_tl                         1.0
num_il_tl                         1.0
num_op_rev_tl                     1.0
num_rev_accts                     1.0
num_rev_tl_bal_gt_0               1.0
num_sats                          1.0
num_tl_120dpd_2m                  1.0
num_tl_30dpd                      1.0
num_tl_90g_dpd_24m                1.0
num_tl_op_past_12m                1.0
mths_since_recent_bc              1.0
dtype: float64
```

In [11]:

```
plt.figure(figsize=(6,3), dpi=90)
missing_fractions.plot.hist(bins=20)
plt.title('Histogram of Feature Incompleteness')
plt.xlabel('Fraction of data missing')
plt.ylabel('Feature count')
```

Out[11]:

```
Text(0, 0.5, 'Feature count')
```



From the above histogram, we see there's a large gap between features missing "some" data (<20%) and those missing "lots" of data (>40%). Because it's generally very difficult to accurately impute data with more than 30% missing values, we drop such columns. First store all variables missing more than 30% data in an alphabetical list:

In [12]:

```
drop_list = sorted(list(missing_fractions[missing_fractions > 0.3].index))
print(len(drop_list))
df.drop(labels=drop_list, axis=1, inplace=True)
df.shape
```

```
91
```

Out[12]:

```
(42542, 58)
```

So now we dropped the columns with more than 30% missing values and hare left with 58 columns.

In [13]:

```
print(df.columns)
df.info()
```

```
Index(['id', 'loan_amount', 'funded_amount', 'investor_funds', 'term',
       'interest_rate', 'installment', 'grade', 'sub_grade', 'emp_titl
e',
       'emp_length', 'home_ownership', 'annual_income', 'verification_
status',
       'issue_d', 'loan_status', 'pymnt_plan', 'url', 'purpose', 'titl
e',
       'zip_code', 'addr_state', 'dti', 'delinq_2yrs', 'earliest_cr_li
ne',
       'fico_range_low', 'fico_range_high', 'inq_last_6mths', 'open_ac
c',
       'pub_rec', 'revol_bal', 'revol_util', 'total_acc',
       'initial_list_status', 'out_prncp', 'out_prncp_inv', 'total_pym
nt',
       'total_pymnt_inv', 'total_rec_prncp', 'total_rec_int',
       'total_rec_late_fee', 'recoveries', 'collection_recovery_fee',
       'last_pymnt_d', 'last_pymnt_amnt', 'last_credit_pull_d',
       'last_fico_range_high', 'last_fico_range_low',
       'collections_12_mths_ex_med', 'policy_code', 'application_typ
e',
       'acc_now_delinq', 'chargeoff_within_12_mths', 'delinq_amnt',
       'pub_rec_bankruptcies', 'tax_liens', 'hardship_flag',
       'debt_settlement_flag'],
      dtype='object')
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 42542 entries, 0 to 42541
Data columns (total 58 columns):
id                            42538 non-null object
loan_amount                   42535 non-null float64
funded_amount                 42535 non-null float64
investor_funds                42535 non-null float64
term                          42535 non-null object
interest_rate                 42535 non-null float64
installment                   42535 non-null float64
grade                         42535 non-null object
sub_grade                     42535 non-null object
emp_title                     39909 non-null object
emp_length                    41423 non-null object
home_ownership                42535 non-null object
annual_income                 42531 non-null float64
verification_status           42535 non-null object
issue_d                       42535 non-null object
loan_status                   42535 non-null object
pymnt_plan                    42535 non-null object
url                           42535 non-null object
purpose                       42535 non-null object
title                         42522 non-null object
zip_code                      42535 non-null object
addr_state                    42535 non-null object
dti                           42535 non-null float64
delinq_2yrs                   42506 non-null float64
earliest_cr_line              42506 non-null object
fico_range_low                42535 non-null float64
fico_range_high               42535 non-null float64
inq_last_6mths                42506 non-null float64
open_acc                      42506 non-null float64
```

```
pub_rec                       42506 non-null float64
revol_bal                     42535 non-null float64
revol_util                    42445 non-null object
total_acc                     42506 non-null float64
initial_list_status           42535 non-null object
out_prncp                     42535 non-null float64
out_prncp_inv                 42535 non-null float64
total_pymnt                   42535 non-null float64
total_pymnt_inv               42535 non-null float64
total_rec_prncp               42535 non-null float64
total_rec_int                 42535 non-null float64
total_rec_late_fee            42535 non-null float64
recoveries                    42535 non-null float64
collection_recovery_fee       42535 non-null float64
last_pymnt_d                  42452 non-null object
last_pymnt_amnt               42535 non-null float64
last_credit_pull_d            42531 non-null object
last_fico_range_high          42535 non-null float64
last_fico_range_low           42535 non-null float64
collections_12_mths_ex_med    42390 non-null float64
policy_code                   42535 non-null float64
application_type              42535 non-null object
acc_now_delinq                42506 non-null float64
chargeoff_within_12_mths      42390 non-null float64
delinq_amnt                   42506 non-null float64
pub_rec_bankruptcies          41170 non-null float64
tax_liens                     42430 non-null float64
hardship_flag                 42535 non-null object
debt_settlement_flag          42535 non-null object
dtypes: float64(34), object(24)
memory usage: 18.8+ MB
```

In [14]:

```
df['emp_title'].describe()
```

Out[14]:

```
count       39909
unique      30656
top       US Army
freq          139
Name: emp_title, dtype: object
```

There are too many different job titles for this feature to be useful, so we drop it.

In [15]:

```
df.drop(labels='emp_title', axis=1, inplace=True)
```

In [16]:

```
df['emp_length'].value_counts(dropna=False).sort_index()
```

Out[16]:

```
1 year        3595
10+ years     9369
2 years       4743
3 years       4364
4 years       3649
5 years       3458
6 years       2375
7 years       1875
8 years       1592
9 years       1341
< 1 year      5062
NaN           1119
Name: emp_length, dtype: int64
```

In the above column we need to change the details of 10+ years and <1 year into a readable format which is done below:

In [17]:

```
df['emp_length'].replace(to_replace='10+ years', value='10 years', inplace=True)
df['emp_length'].replace('< 1 year', '0 years', inplace=True)
```

Now we convert hte employee length into an int value :

In [18]:

```
def emp_length_to_int(s):
    if pd.isnull(s):
        return s
    else:
        return np.int8(s.split()[0])
df['emp_length'] = df['emp_length'].apply(emp_length_to_int)
df['emp_length'].value_counts(dropna=False).sort_index()
```

Out[18]:

```
0.0     5062
1.0     3595
2.0     4743
3.0     4364
4.0     3649
5.0     3458
6.0     2375
7.0     1875
8.0     1592
9.0     1341
10.0    9369
NaN     1119
Name: emp_length, dtype: int64
```

Because of the large range of incomes, we should take a log transform of the annual income variable.

In [19]:

```
df['log_annual_inc'] = df['annual_income'].apply(lambda x: np.log10(x+1))
df['log_annual_inc'].describe()
```

Out[19]:

```
count    42531.000000
mean         4.764398
std          0.246615
min          3.278067
25%          4.602071
50%          4.770859
75%          4.916459
max          6.778151
Name: log_annual_inc, dtype: float64
```

In [20]:

```
df["loan_status"].value_counts()
```

Out[20]:

```
Fully Paid                                             34116
Charged Off                                             5670
Does not meet the credit policy. Status:Fully Paid      1988
Does not meet the credit policy. Status:Charged Off      761
Name: loan_status, dtype: int64
```

In [21]:

```
# Determining the loans that are bad from loan_status column

bad_loan = ["Charged Off", "Default", "Does not meet the credit policy. Status:Charg
            "Late (16-30 days)", "Late (31-120 days)"]


df['loan_condition'] = np.nan

def loan_condition(status):
    if status in bad_loan:
        return 'Bad Loan'
    else:
        return 'Good Loan'


df['loan_condition'] = df['loan_status'].apply(loan_condition)
```

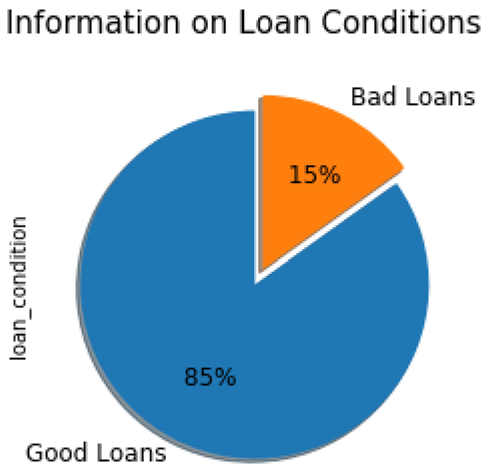
Pie Chart for Loan Conditions

In [22]:

```
#f, ax = plt.subplots(1,2, figsize=(16,8))

labels ="Good Loans", "Bad Loans"

plt.suptitle('Information on Loan Conditions', fontsize=15)

df["loan_condition"].value_counts().plot.pie(explode=[0,0.10],autopct='%3.0f%%', sha
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a2236a550>
```



The above pie chart shows that the data is imbalanced and it has 85% of good loans and 15% of bad loans . We might have to do oversampling of the bad loans for better results at the end . That will be decided after building the model for this data at later stage.

In [23]:

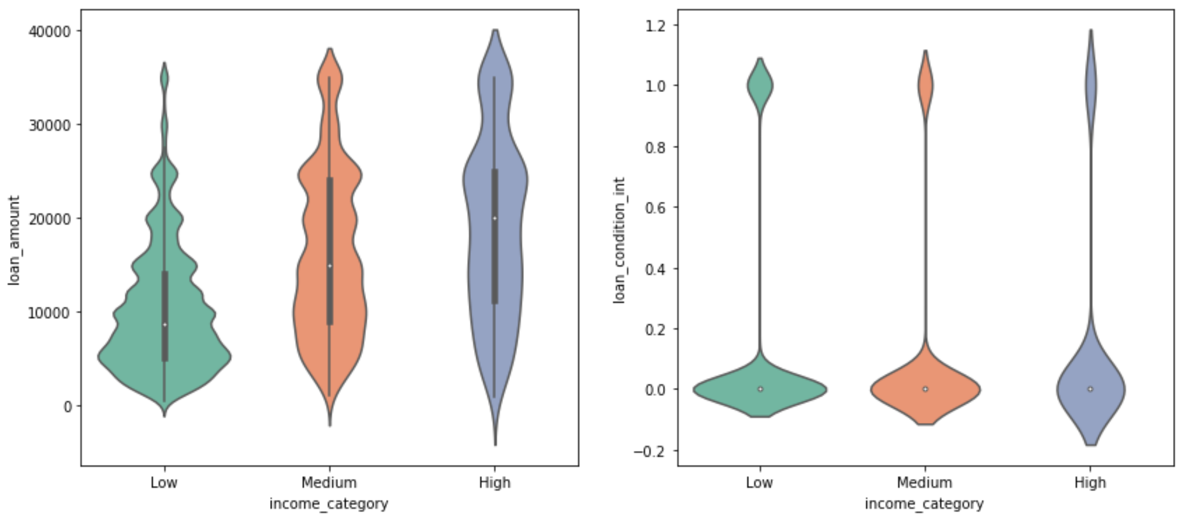
```
df['income_category'] = np.nan
lst = [df]

for col in lst:
    col.loc[col['annual_income'] <= 100000, 'income_category'] = 'Low'
    col.loc[(col['annual_income'] > 100000) & (col['annual_income'] <= 200000), 'inc
    col.loc[col['annual_income'] > 200000, 'income_category'] = 'High'
```

In [24]:

```
# Let's transform the column loan_condition into integrers.

lst = [df]
df['loan_condition_int'] = np.nan

for col in lst:
    col.loc[df['loan_condition'] == 'Good Loan', 'loan_condition_int'] = 0 # Negati
    col.loc[df['loan_condition'] == 'Bad Loan', 'loan_condition_int'] = 1 # Positive

# Convert from float to int the column (This is our label)
df['loan_condition_int'] = df['loan_condition_int'].astype(int)
fig, (ax1, ax2)= plt.subplots(nrows=1, ncols=2, figsize=(14,6))

sns.violinplot(x="income_category", y="loan_amount", data=df, palette="Set2", ax=ax1
sns.violinplot(x="income_category", y="loan_condition_int", data=df, palette="Set2",
```

Out[24]:

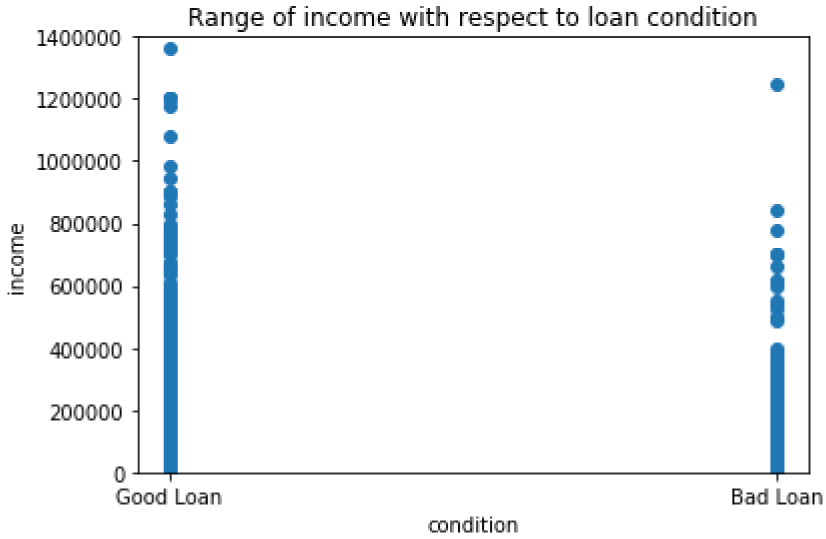
```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1bd2eba8>
```



Loan Condition V/s Income

In [25]:

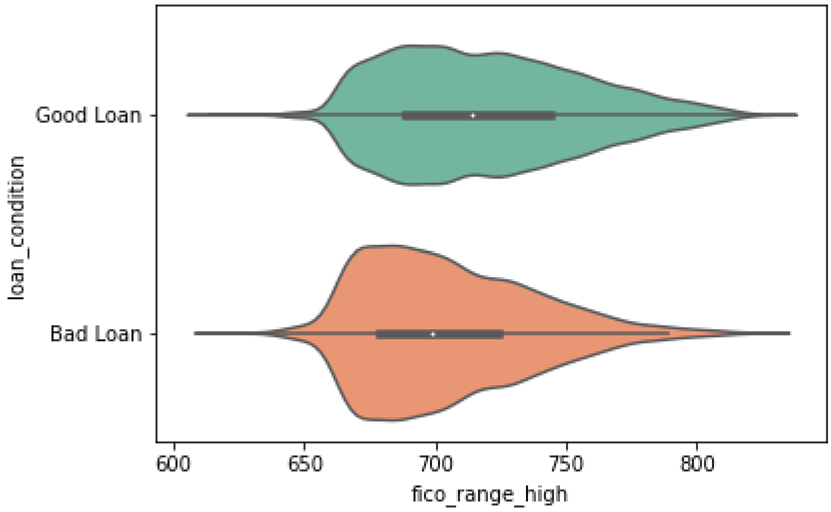
```
plt.scatter(df.loan_condition,df.annual_income)
plt.xlabel("condition")
plt.ylabel("income")
plt.ylim(0,1400000)
plt.title("Range of income with respect to loan condition")
plt.show()
```



Loan Condition V/s Fico Scores

In [26]:

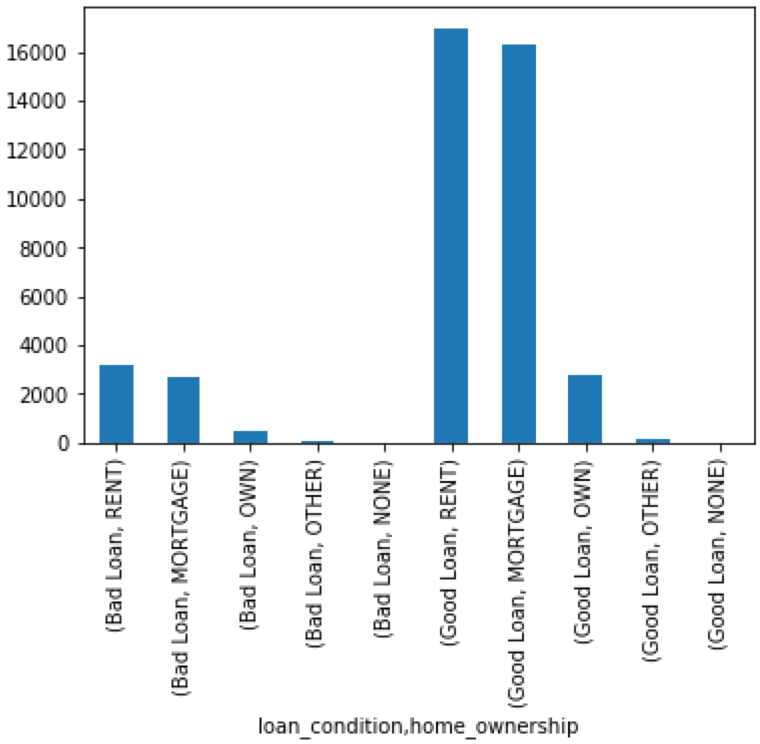
```
sns.violinplot(x="fico_range_high", y="loan_condition", data=df, palette="Set2" )
plt.show()
```



The mean of the good loans is more than 700 and most of the values of fico_score lies near 700 score hence the fico score for good loans should be closer to 700.

In [27]:

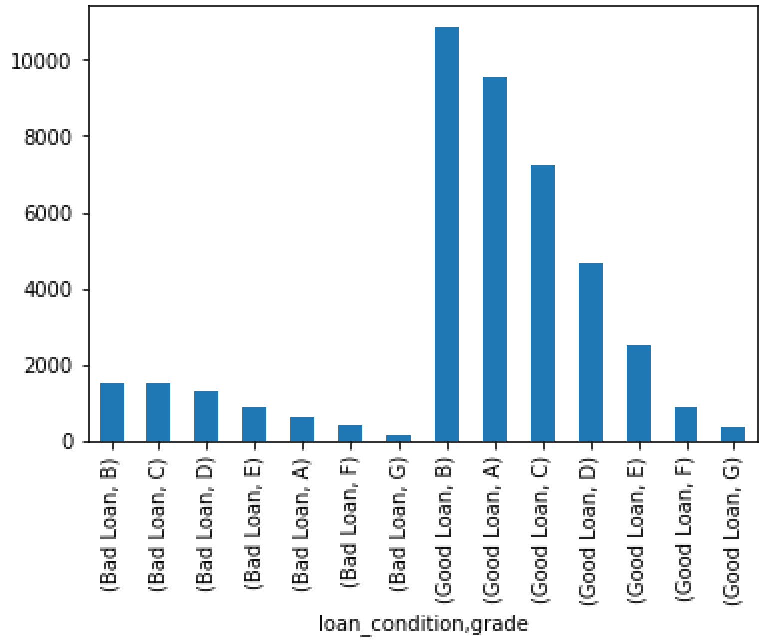
```
df.home_ownership.groupby(df.loan_condition).value_counts().plot.bar()
plt.show()
```



Loan Grades and Subgrades are assigned by Lending Club based on the borrower's credit worthiness and also on some variables specific to that Loan.

In [28]:

```
df.grade.groupby(df.loan_condition).value_counts().plot.bar()
plt.show()
```



The majority of loans is either graded as B or C — together these correspond to more than 50% of the loan population. While there is a considerable amount of A graded or “prime” loans (~17%), there is a small amount of E graded, or “uncollectible” loans (~0,06%). Which is a good sign for Lending Club. But, are these the right grades?

Data visualization to see how the loan value, amount funded by lender and total committed by investors distribution looks like?

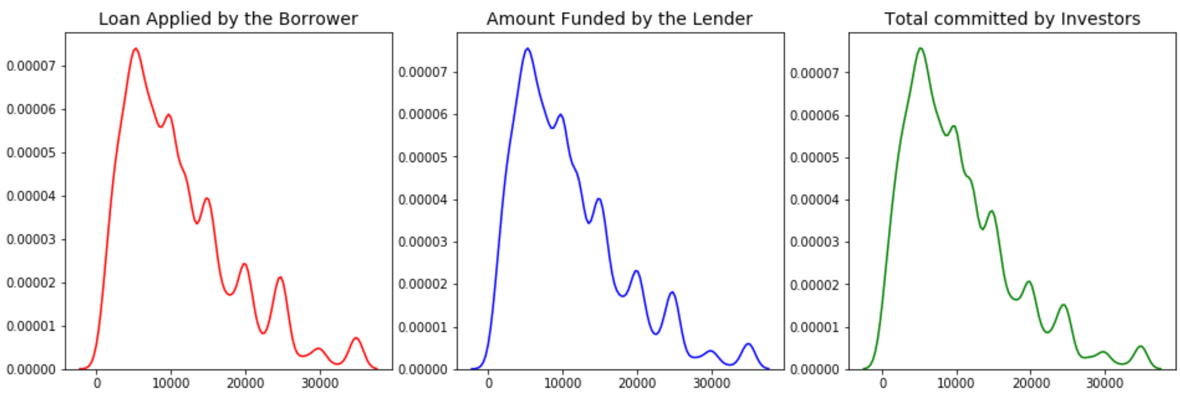
In [29]:

```
fig, ax = plt.subplots(1, 3, figsize=(16,5))

loan_amount = df["loan_amount"].values
funded_amount = df["funded_amount"].values
investor_funds = df["investor_funds"].values
sns.distplot(loan_amount, ax=ax[0], color="red",bins=(100,100))
ax[0].set_title("Loan Applied by the Borrower", fontsize=14)
sns.distplot(funded_amount, ax=ax[1], color="blue",bins=(100,100))
ax[1].set_title("Amount Funded by the Lender", fontsize=14)
sns.distplot(investor_funds, ax=ax[2], color="green",bins=(100,100))
ax[2].set_title("Total committed by Investors", fontsize=14)
```

```
/Users/ankit/anaconda3/lib/python3.7/site-packages/numpy/lib/histogram
s.py:893: RuntimeWarning: invalid value encountered in true_divide
  return n/db/n.sum(), bin_edges
/Users/ankit/anaconda3/lib/python3.7/site-packages/statsmodels/nonpara
metric/kde.py:448: RuntimeWarning: invalid value encountered in greate
r
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two
columns.
/Users/ankit/anaconda3/lib/python3.7/site-packages/statsmodels/nonpara
metric/kde.py:448: RuntimeWarning: invalid value encountered in less
  X = X[np.logical_and(X > clip[0], X < clip[1])] # won't work for two
columns.
/Users/ankit/anaconda3/lib/python3.7/site-packages/numpy/lib/histogram
s.py:893: RuntimeWarning: divide by zero encountered in true_divide
  return n/db/n.sum(), bin_edges
```

Out[29]:

```
Text(0.5, 1.0, 'Total committed by Investors')
```

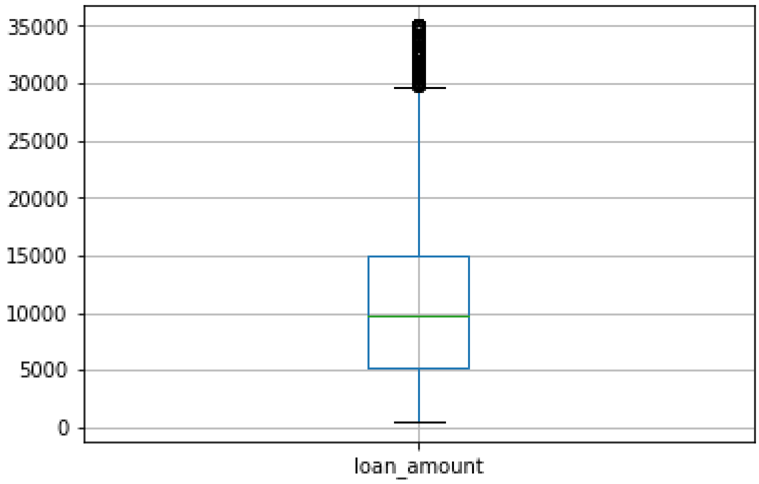


In [30]:

```
df.boxplot(column='loan_amount')
```

Out[30]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1bce6a58>
```



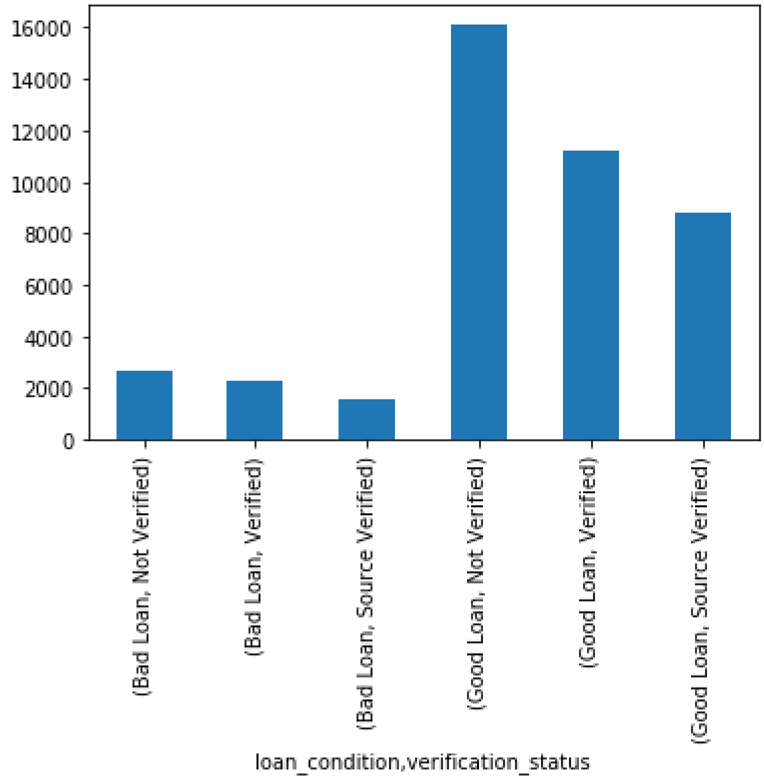
In [31]:

```
mean =np.mean(df.funded_amount)
std =np.std(df.funded_amount)
print(mean)
print(std)
```

```
10821.585752909368
7146.830662349949
```

In [32]:

```
df.verification_status.groupby(df.loan_condition).value_counts().plot.bar()
plt.show()
```



In [33]:

```
pd.crosstab(df ['verification_status'], df ['loan_condition'], margins=True)
```

Out[33]:

loan_condition	Bad Loan	Good Loan	All
verification_status			
Not Verified	2655	16103	18758
Source Verified	1534	8772	10306
Verified	2242	11229	13471
All	6431	36104	42535

This shows that 41.3% of the bad loans were not verified.

In [34]:

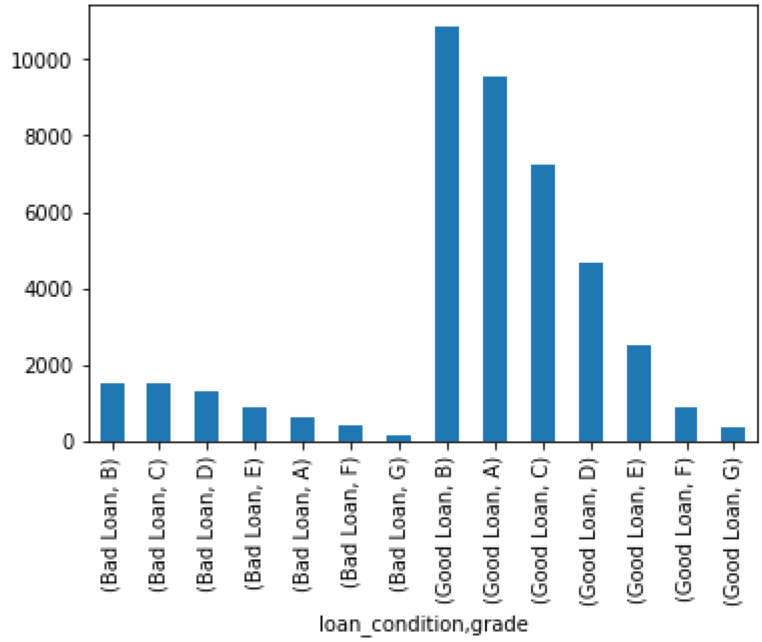
```
df[['fico_range_low', 'fico_range_high']].describe()
```

Out[34]:

	fico_range_low	fico_range_high
count	42535.000000	42535.000000
mean	713.052545	717.052545
std	36.188439	36.188439
min	610.000000	614.000000
25%	685.000000	689.000000
50%	710.000000	714.000000
75%	740.000000	744.000000
max	825.000000	829.000000

In [35]:

```
df.grade.groupby(df.loan_condition).value_counts().plot.bar()
plt.show()
```



Number of bad loans were less in the category A jobs and it had more number of good loans as compared to the other category.

Statistical Inferences

We want to check whether the interest rates offered for A grade loans were lesser than the other grades hence we are going to use single tail Welch's t-test as the variance is not equal.

H_0 : The interest rates offered for other grade loans is greater than the A grade loan.

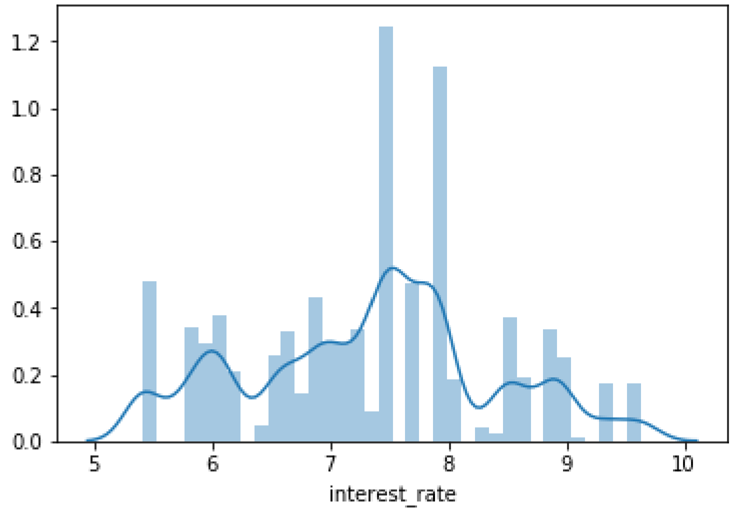
H_1 : The interest rates offered for other grade loans is not greater than the A grade loan.

In [36]:

```
x=df.interest_rate[df.grade=='A']
sns.distplot(x)
```

Out[36]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a1c190cf8>

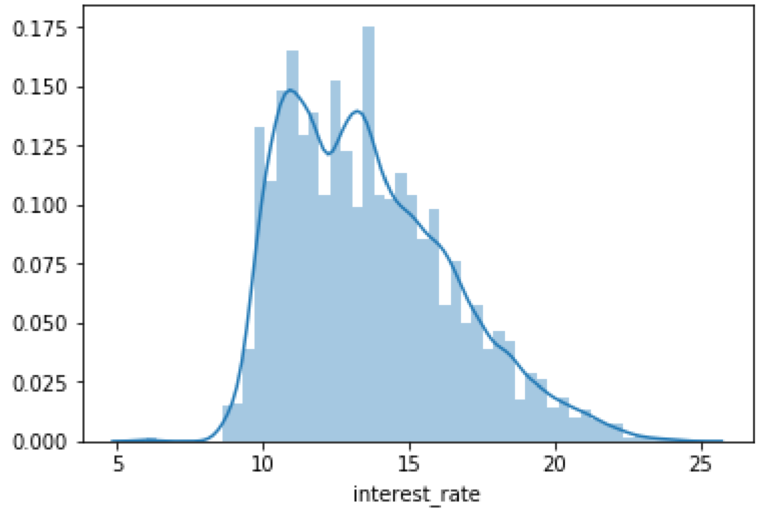


In [37]:

```
x=df.interest_rate[df.grade!='A']
x = x[np.logical_not(np.isnan(x))]
sns.distplot(x)
```

Out[37]:

<matplotlib.axes._subplots.AxesSubplot at 0x1a1cbbf198>



In [38]:

```
def loan_sampler_A(n):
    return np.random.choice(df.interest_rate[df.grade=='A'].astype('float64'), n)
def loan_sampler_other(n):
    return np.random.choice(df.interest_rate[df.grade!='A'].astype('float64'),n)
```

In [39]:

```
seed(47)
size=50
sample1 = loan_sampler_A(size)
sample2 = loan_sampler_other(size)
type(sample1[0])
```

Out[39]:

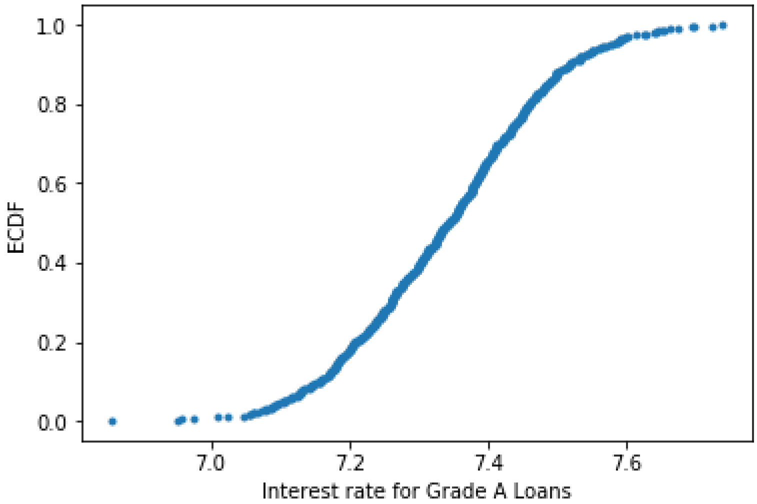
```
numpy.float64
```

In [40]:

```
mean_A = np.mean(sample1)
mean_other = np.mean(sample2)
std_A=np.std(sample1)
std_other=np.std(sample2)
seed(47)
N=500
# take your samples here
total_mean_A=np.empty(N)
total_mean_other=np.empty(N)
for i in range (N):
    total_mean_A[i]=np.mean(loan_sampler_A(size))
    total_mean_other[i]=np.mean(loan_sampler_other(size))
```

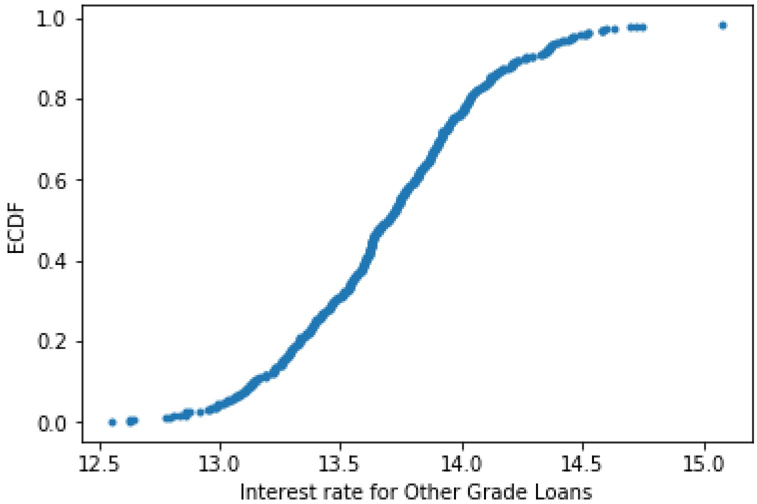
In [41]:

```
n=len(total_mean_A)
x=np.sort(total_mean_A)
y=np.arange(1,n+1)/n
plt.plot(x,y,marker='.',linestyle='none')
# Label the axes
plt.xlabel('Interest rate for Grade A Loans')
plt.ylabel('ECDF')
plt.show()
```



In [42]:

```
n=len(total_mean_other)
x=np.sort(total_mean_other)
y=np.arange(1,n+1)/n
plt.plot(x,y,marker='.',linestyle='none')
# Label the axes
plt.xlabel('Interest rate for Other Grade Loans')
plt.ylabel('ECDF')
plt.show()
```



It is very much clear from the above ECDF graph that the interest rates for the other grades lies in the range of (12.5,15)

In [43]:

```
total_mean_other = total_mean_other[np.logical_not(np.isnan(total_mean_other))]
```

In [44]:

```
 import stats
py.stats
s.ttest_ind(total_mean_other,total_mean_A,equal_var=False))

onfidence_interval(data, confidence=0.95):
0 * np.array(data)
n(a)
= np.mean(a), scipy.stats.sem(a)
 * scipy.stats.t.ppf((1 + confidence) / 2., n-1)
 m, m-h, m+h
 confidence interval for A grade loans is: "+str(mean_confidence_interval(total_mean_
 confidence interval for all other loan other than A grade loans is:"+ str(mean_conf
```

```
Ttest_indResult(statistic=324.96013788823643, pvalue=0.0)
The confidence interval for A grade loans is: (7.339761200000001, 7.32
7202348671294, 7.352320051328707)
The confidence interval for all other loan other than A grade loans i
s:(13.687281466395113, 13.651015426092169, 13.723547506698058)
```

Here, the p value is less than 0.05 hence the result is of high significance .Hence, we reject the null hypothesis.

Correlation among the features

Few important columns are selected from the full dataset based on the significance and the data present prior to the approval of the loan. The columns are saved in 'imp_columns' list.

Now we will see the correlation between the numerical data

In [45]:

```
imp_columns=['loan_amount','term','interest_rate','grade','emp_length','home_ownersh
df2=df[imp_columns]
df2.corr()
```

Out[45]:

	loan_amount	interest_rate	emp_length	annual_income	fico_range_low	fico_rar
loan_amount	1.000000	0.292346	0.158339	0.276122	0.133232	(
interest_rate	0.292346	1.000000	0.000062	0.054365	-0.702587	-(
emp_length	0.158339	0.000062	1.000000	0.115990	0.089997	(
annual_income	0.276122	0.054365	0.115990	1.000000	0.052027	(
fico_range_low	0.133232	-0.702587	0.089997	0.052027	1.000000	·
fico_range_high	0.133232	-0.702587	0.089997	0.052027	1.000000	·

employee length,annual income and fico scores have strong positive correlation with the loan amount .

In [46]:

```
df[imp_columns].head()
```

Out[46]:

	loan_amount	term	interest_rate	grade	emp_length	home_ownership	annual_income	verific
0	5000.0	36	10.65	B	10.0	RENT	24000.0	
1	2500.0	60	15.27	C	0.0	RENT	30000.0	S
2	2400.0	36	15.96	C	10.0	RENT	12252.0	
3	10000.0	36	13.49	C	10.0	RENT	49200.0	S
4	3000.0	60	12.69	B	1.0	RENT	80000.0	S

Correlation between all the important columns:

In [47]:

```
df2.apply(lambda x: x.factorize()[0]).corr()
corr_imp=df2.apply(lambda x: x.factorize()[0]).corr()
print(corr_imp)
```

```
                     loan_amount      term  interest_rate     grade  \
loan_amount             1.000000  0.049321       0.004888  0.038821
term                    0.049321  1.000000      -0.229188  0.174308
interest_rate           0.004888 -0.229188       1.000000  0.080418
grade                   0.038821  0.174308       0.080418  1.000000
emp_length             -0.015373 -0.021818      -0.002423  0.001704
home_ownership          0.015785  0.101269      -0.046499 -0.007129
annual_income           0.022134 -0.036130       0.180196  0.011177
verification_status    -0.019865 -0.260850       0.216612 -0.076179
loan_status             0.049661  0.008709       0.273700  0.193024
loan_condition          0.032362  0.133752       0.023507  0.112504
purpose                -0.027695  0.001936       0.018901  0.010115
title                   0.003469 -0.200983       0.570702  0.033934
addr_state              0.005964  0.012570       0.027204  0.004016
fico_range_low          0.009369 -0.039866       0.060645  0.001520
fico_range_high         0.009369 -0.039866       0.060645  0.001520
income_category        -0.015621  0.036324      -0.003993  0.040700

                     emp_length  home_ownership  annual_income  \
loan_amount           -0.015373        0.015785       0.022134
term                  -0.021818        0.101269      -0.036130
interest_rate         -0.002423       -0.046499       0.180196
grade                  0.001704       -0.007129       0.011177
emp_length             1.000000       -0.070542      -0.017164
home_ownership        -0.070542        1.000000       0.009486
annual_income         -0.017164        0.009486       1.000000
verification_status    0.039064       -0.074966       0.009812
loan_status           -0.012969       -0.000060       0.051434
loan_condition        -0.020226       -0.020695       0.000376
purpose               -0.003795       -0.001644       0.020303
title                 -0.000502       -0.016955       0.131895
addr_state            -0.018810        0.065866       0.020443
fico_range_low        -0.035675        0.068482       0.003770
fico_range_high       -0.035675        0.068482       0.003770
income_category       -0.040154        0.201819       0.089805

                     verification_status  loan_status  loan_condition
\
loan_amount                    -0.019865     0.049661        0.032362
term                           -0.260850     0.008709        0.133752
interest_rate                   0.216612     0.273700        0.023507
grade                          -0.076179     0.193024        0.112504
emp_length                      0.039064    -0.012969       -0.020226
home_ownership                 -0.074966    -0.000060       -0.020695
annual_income                   0.009812     0.051434        0.000376
verification_status             1.000000     0.058409       -0.029244
loan_status                     0.058409     1.000000        0.635935
loan_condition                 -0.029244     0.635935        1.000000
purpose                        -0.004351     0.022216        0.013826
title                           0.183712     0.233310        0.010506
addr_state                      0.019698     0.021418       -0.008037
fico_range_low                  0.046653     0.051280       -0.039701
fico_range_high                 0.046653     0.051280       -0.039701
income_category                -0.151210    -0.005405       -0.036119
```

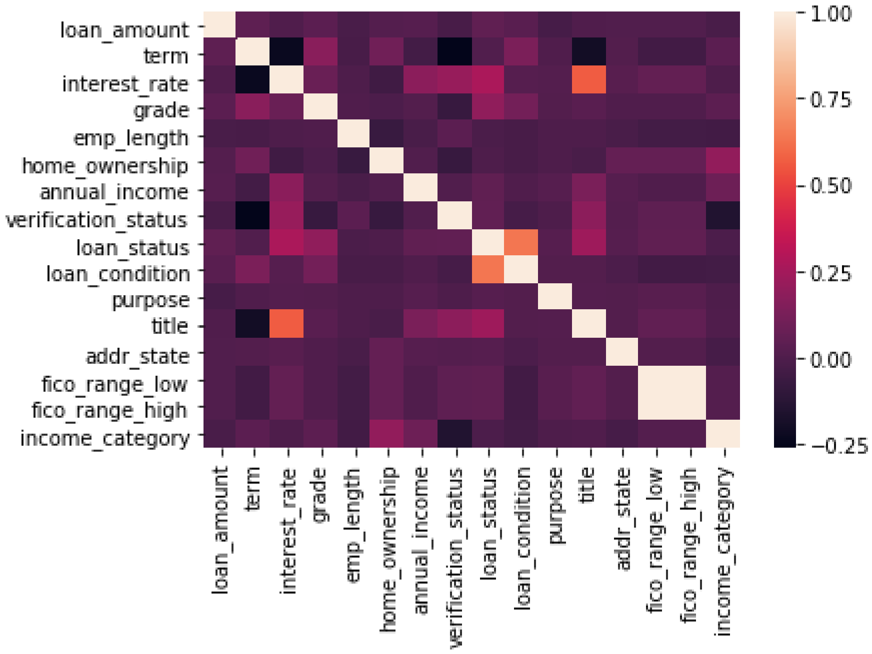
```
                      purpose     title  addr_state  fico_range_low  \
loan_amount         -0.027695  0.003469    0.005964        0.009369
term                 0.001936 -0.200983    0.012570       -0.039866
interest_rate        0.018901  0.570702    0.027204        0.060645
grade                0.010115  0.033934    0.004016        0.001520
emp_length          -0.003795 -0.000502   -0.018810       -0.035675
home_ownership      -0.001644 -0.016955    0.065866        0.068482
annual_income        0.020303  0.131895    0.020443        0.003770
verification_status -0.004351  0.183712    0.019698        0.046653
loan_status          0.022216  0.233310    0.021418        0.051280
loan_condition       0.013826  0.010506   -0.008037       -0.039701
purpose              1.000000  0.019102    0.014780        0.026234
title                0.019102  1.000000    0.014666        0.057461
addr_state           0.014780  0.014666    1.000000        0.014521
fico_range_low       0.026234  0.057461    0.014521        1.000000
fico_range_high      0.026234  0.057461    0.014521        1.000000
income_category     -0.001880  0.000589   -0.026015        0.017565

                     fico_range_high  income_category
loan_amount                 0.009369        -0.015621
term                       -0.039866         0.036324
interest_rate               0.060645        -0.003993
grade                       0.001520         0.040700
emp_length                 -0.035675        -0.040154
home_ownership              0.068482         0.201819
annual_income               0.003770         0.089805
verification_status         0.046653        -0.151210
loan_status                 0.051280        -0.005405
loan_condition             -0.039701        -0.036119
purpose                     0.026234        -0.001880
title                       0.057461         0.000589
addr_state                  0.014521        -0.026015
fico_range_low              1.000000         0.017565
fico_range_high             1.000000         0.017565
income_category             0.017565         1.000000
```

In [48]:

```
import seaborn as sns

sns.heatmap(corr_imp,
        xticklabels=corr_imp.columns,
        yticklabels=corr_imp.columns)
```

Out[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1a1e766a58>
```



In [ ]:

```

```

Model Building

In [49]:

```
# Convert all non-numeric values to number
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
for var in df.columns:
    le = LabelEncoder()
    df[var]=df[var].astype('str')
    df[var]=le.fit_transform(df[var])
```

In [50]:

```
from sklearn import preprocessing
target_name='loan_condition'
y= df.loan_condition
X= df.drop(target_name,axis=1)
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, y, stratify=y, random_state=1
from sklearn import neighbors
knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

In [51]:

```
knn.fit(X_train, Y_train)
```

Out[51]:

```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowsk
i',
                     metric_params=None, n_jobs=None, n_neighbors=5, p
=2,
                     weights='uniform')
```

In [52]:

```
Y_predict=knn.predict(X_test)
#y_predict=y_predict.reshape(-1,1)
```

In [53]:

```
from sklearn import metrics
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(Y_test, Y_predict))
```

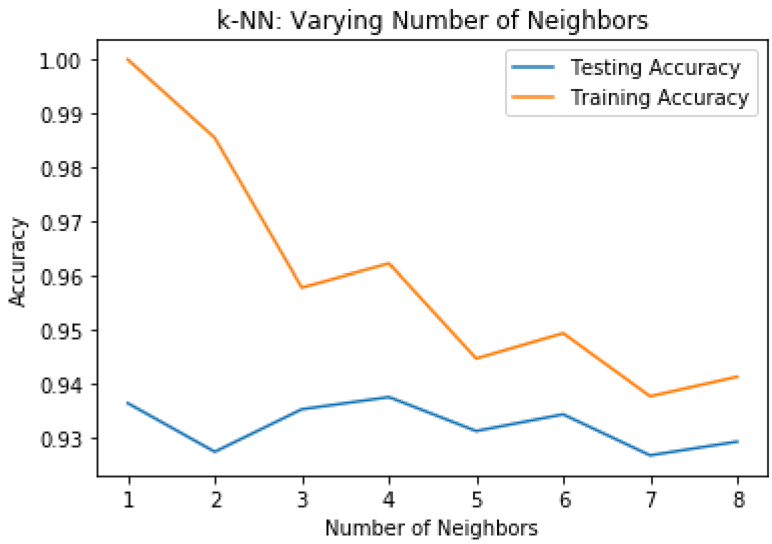
```
Accuracy: 0.9310831139526138
```

We got an accuracy of 0.93 . As our model has good loans dominating the sample we may need to over sample our data with bad sample.

We would now check the effect on the accuracy by changing n in the model and the graph is plotted below:

In [54]:

```
neighbors = np.arange(1, 9)
train_accuracy = np.empty(len(neighbors))
test_accuracy = np.empty(len(neighbors))
from sklearn.neighbors import KNeighborsClassifier
# Loop over different values of k
for i, k in enumerate(neighbors):
    # Setup a k-NN Classifier with k neighbors: knn
    knn = KNeighborsClassifier(n_neighbors=k)

    # Fit the classifier to the training data
    knn.fit(X_train,Y_train)

    #Compute accuracy on the training set
    train_accuracy[i] = knn.score(X_train, Y_train)

    #Compute accuracy on the testing set
    test_accuracy[i] = knn.score(X_test, Y_test)

# Generate plot
plt.title('k-NN: Varying Number of Neighbors')
plt.plot(neighbors, test_accuracy, label = 'Testing Accuracy')
plt.plot(neighbors, train_accuracy, label = 'Training Accuracy')
plt.legend()
plt.xlabel('Number of Neighbors')
plt.ylabel('Accuracy')
plt.show()
```



From the above graph we can see that we get best result at n= 4 which gives us training accuracy as 0.96 and testing accuracy as 0.94

Confusion Matrix

In [55]:

```
#Random Forest
from sklearn.metrics import confusion_matrix
from sklearn.ensemble import RandomForestClassifier
rf = RandomForestClassifier(n_estimators = 10000, random_state = 42)
rf.fit(X_train, Y_train);
predictions = rf.predict(X_test)
cm = confusion_matrix(Y_test,predictions)
print(cm)

#Decision Tree

from sklearn import tree
clf = tree.DecisionTreeClassifier()
clf = clf.fit(X_train, Y_train)
predictions = clf.predict(X_test)
cm2 = confusion_matrix(Y_test,predictions)
print(cm2)
```

```
[[1608    0]
 [   0 9028]]
[[1608    0]
 [   0 9028]]
```

In [56]:

```
from sklearn.metrics import recall_score
print (clf.score(X_test, Y_test))
print (recall_score(Y_test, clf.predict(X_test)))
```

```
1.0
1.0
```

Imbalanced datasets can be seen everywhere. Usually banks want to predict fraudulent credit card charges but only a small fraction of observations are actually positives. I'd guess that only 1 in 10,000 credit card charges are fraudulent, at most. Recently, oversampling the minority class observations has become a common approach to improve the quality of predictive modeling. By oversampling, models are sometimes better able to learn patterns that differentiate classes.

Using imblearn for oversampling

In [57]:

```
!pip install imblearn
```

```
Requirement already satisfied: imblearn in /Users/ankit/anaconda3/lib/
python3.7/site-packages (0.0)
Requirement already satisfied: imbalanced-learn in /Users/ankit/anacon
da3/lib/python3.7/site-packages (from imblearn) (0.5.0)
Requirement already satisfied: joblib>=0.11 in /Users/ankit/anaconda3/
lib/python3.7/site-packages (from imbalanced-learn->imblearn) (0.12.5)
Requirement already satisfied: scikit-learn>=0.21 in /Users/ankit/anac
onda3/lib/python3.7/site-packages (from imbalanced-learn->imblearn)
(0.21.3)
Requirement already satisfied: numpy>=1.11 in /Users/ankit/anaconda3/l
ib/python3.7/site-packages (from imbalanced-learn->imblearn) (1.16.2)
Requirement already satisfied: scipy>=0.17 in /Users/ankit/anaconda3/l
ib/python3.7/site-packages (from imbalanced-learn->imblearn) (1.2.1)
```

In [56]:

```
from imblearn.over_sampling import SMOTE
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import recall_score

x_train, x_val, y_train, y_val = train_test_split(X_train, Y_train,
                                                  test_size = .3,
                                                  random_state=123)
sm = SMOTE(random_state=123)
x_train_res, y_train_res = sm.fit_sample(x_train, y_train)
clf_rf = RandomForestClassifier(n_estimators=1000, random_state=123)
clf_rf.fit(x_train_res, y_train_res)
print(y_train_res)
print ('Validation Results')
print( clf_rf.score(x_val, y_val))
print (recall_score(y_val, clf_rf.predict(x_val)))
print (clf_rf.score(X_test, Y_test))
print (recall_score(Y_test, clf_rf.predict(X_test)))
```

```
[0 1 1 ... 0 0 0]
Validation Results
1.0
1.0
1.0
1.0
```

We see that the recall score and precision score comes out to be 1, which does not seen to be right. it can also be because of the dominating class of good loans or some other dominating features.

We can use check the important features in the model:

In [ ]:

```
!pip install tabulate
```

In [57]:

```
from tabulate import tabulate
model = clf_rf.fit(X_train, Y_train)
headers = ["name", "score"]
values = sorted(zip(X_train.columns, model.feature_importances_), key=lambda x: x[1]
print(tabulate(values, headers, tablefmt="plain"))
```

```
name                           score
loan_status                 0.281725
loan_condition_int          0.273198
recoveries                  0.225039
collection_recovery_fee     0.120456
last_credit_pull_d          0.0258278
last_fico_range_low         0.0220151
last_fico_range_high        0.0217922
total_rec_late_fee          0.00312538
funded_amount               0.00264734
total_rec_prncp             0.00251706
sub_grade                   0.00244401
debt_settlement_flag        0.00231675
grade                       0.00168734
loan_amount                 0.00159987
interest_rate               0.00154694
term                        0.00137368
investor_funds              0.00127642
total_rec_int               0.00107401
installment                 0.000915142
total_pymnt                 0.000866923
last_pymnt_d                0.000742396
total_pymnt_inv             0.000717986
fico_range_low              0.000619525
last_pymnt_amnt             0.000614174
fico_range_high             0.000577185
inq_last_6mths              0.000335434
log_annual_inc              0.000286089
id                          0.000265829
url                         0.000241269
revol_util                  0.000175763
zip_code                    0.000175039
title                       0.000167329
revol_bal                   0.000150034
dti                         0.000145773
annual_income               0.00014392
earliest_cr_line            0.00013537
pub_rec_bankruptcies        0.000111475
addr_state                  0.00010987
issue_d                     0.000108215
purpose                     0.000100904
total_acc                   9.55752e-05
emp_length                  9.02301e-05
open_acc                    8.75193e-05
verification_status         6.49991e-05
pub_rec                     4.74653e-05
income_category             4.68721e-05
home_ownership              4.01721e-05
delinq_2yrs                 3.21821e-05
policy_code                 1.56433e-05
initial_list_status         1.55937e-05
application_type            1.55427e-05

out_prncp_inv               1.43194e-05
```

```
out_prncp_inv                 1.43194e-05
pymnt_plan                    1.21278e-05
out_prncp                     1.1293e-05
tax_liens                     1.11435e-05
collections_12_mths_ex_med    9.41221e-06
hardship_flag                 8.11167e-06
delinq_amnt                   6.06368e-06
acc_now_delinq                5.19062e-06
chargeoff_within_12_mths      3.07781e-06
```

We can see that few features such as: loan_status,loan_condition_int,recoveries,collection_recovery_fee,last_credit_pull_d,total_rec_late_fee,total_rec_i are to be dropped due to there insignificance/unavailability before the approval or similar terms to the loan_condition(target variable).

Hence we drop the above columns from the new data set and train our model again.

In [58]:

```
type(df)
```

Out[58]:

```
pandas.core.frame.DataFrame
```

In [59]:

```
delete=['loan_status','recoveries','collection_recovery_fee','last_credit_pull_d','t
df.drop(delete,axis=1,inplace=True)
```

In [60]:

```
for var in df.columns:
    le = LabelEncoder()
    df[var]=df[var].astype('str')
    df[var]=le.fit_transform(df[var])
df.drop('loan_condition_int',axis=1,inplace=True)
target_name='loan_condition'
y= df.loan_condition
X= df.drop(target_name,axis=1)
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, y, stratify=y, random_state=1
x_train, x_val, y_train, y_val = train_test_split(X_train, Y_train,
                                                  test_size = .3,
                                                  random_state=123)
sm = SMOTE(random_state=12, ratio = 1.0)
x_train_res, y_train_res = sm.fit_sample(x_train, y_train)
clf_rf = RandomForestClassifier(n_estimators=1000, random_state=123)
clf_rf.fit(x_train_res, y_train_res)
print ('Validation Results')
print( clf_rf.score(x_val, y_val))
print (recall_score(y_val, clf_rf.predict(x_val)))
print ('Test Results')
print (clf_rf.score(X_test, Y_test))
print (recall_score(Y_test, clf_rf.predict(X_test)))
```

```
Validation Results
0.8879022147931467
0.9444308145240432
Test Results
0.8820985332831892
0.9388568896765618
```

Now we can see some realistic results when we have removed the after approval columns from the data set.

Hence, few features were dominating our model which have been removed from the feature list. This gives us a validation score of 0.86

We can see the model seems pretty good as their has been very less variation in the score of the test set and the validation set. We will also deal with the same dataset by oversampling manually.

Creating a Balanced Dataset Manually

In [61]:

```
print(df.loan_condition.values)
```

```
[1 0 1 ... 1 1 1]
```

In [62]:

```
bad_loans=df[df.loan_condition.values==0]
print(bad_loans.shape)
good_loans=df[df.loan_condition.values==1][:int(bad_loans.shape[0]*0.66)]
print(good_loans.shape)
```

```
(6431, 50)
(4244, 50)
```

It shows that out of 43000 datasets 6431 data represents the bad loans . So to make our dataset balanced we will create a new dataset "balanced" coprising both the type in 3:2 ratio

In [63]:

```
balanced_df=pd.concat([bad_loans,good_loans])
balanced_df.shape
```

Out[63]:

```
(10675, 50)
```

In [64]:

```
# Convert all non-numeric values to number
from sklearn import preprocessing
from sklearn.preprocessing import LabelEncoder
for var in balanced_df.columns:
    le = LabelEncoder()
    balanced_df[var]=balanced_df[var].astype('str')
    balanced_df[var]=le.fit_transform(balanced_df[var])
```

Now we will use the above balanced data set to run and improve our model

Wewill be using two models separately to plot the ROC curve using the manually over sampled data.The two models to be used are:

1) KNN Classifier 2)Logistic Regression

In [65]:

```
#knn Classifier
from sklearn import preprocessing
target_name='loan_condition'
y_balanced= balanced_df['loan_condition']
X_balanced= balanced_df.drop(target_name,axis=1)
```

In [66]:

```
port train_test_split
ed, Y_train_balanced, Y_test_balanced = train_test_split(X_balanced, y_balanced, str

ifier(n_neighbors=5)
in_balanced)
X_test_balanced)

the classifier correct?
acy_score(Y_test_balanced, Y_predict_balanced))
```

```
Accuracy: 0.6489321843387036
```

In [67]:

```
recall_score(Y_test_balanced,Y_predict_balanced)
```

Out[67]:

```
0.5240339302544769
```

In [68]:

```
from sklearn.metrics import classification_report
print(classification_report(Y_test_balanced, knn.predict(X_test_balanced), digits=4)
```

```
              precision    recall  f1-score   support

           0     0.6996    0.7313    0.7151      1608
           1     0.5628    0.5240    0.5427      1061

    accuracy                         0.6489      2669
   macro avg     0.6312    0.6277    0.6289      2669
weighted avg     0.6452    0.6489    0.6466      2669
```

In [69]:

```
fpr, tpr, thresholds = metrics.roc_curve(Y_test_balanced, Y_predict_balanced)
```

In [70]:

```
print("False Positive Rate"+str(fpr))
print("True Positive Rate"+str(tpr))
print("Treshold"+str(thresholds))
```

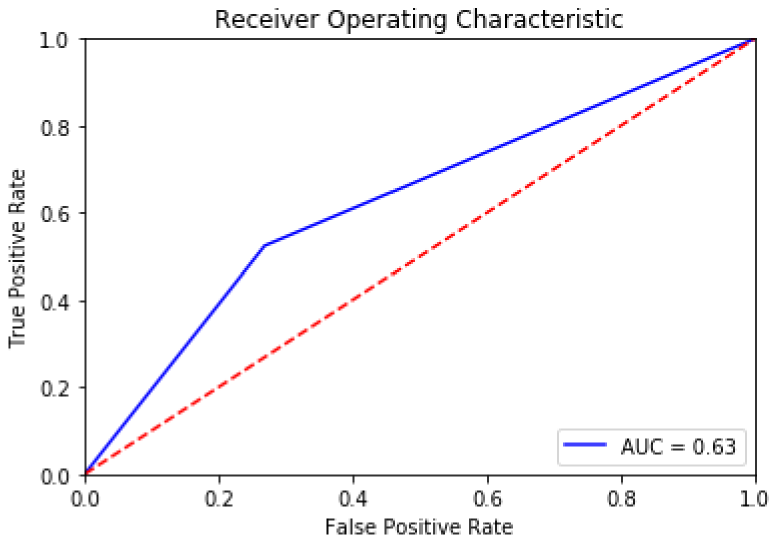
```
False Positive Rate[0.         0.26865672 1.        ]
True Positive Rate[0.         0.52403393 1.        ]
Treshold[2 1 0]
```

In [71]:

```
roc_auc=metrics.auc(fpr, tpr)
```

In [72]:

```
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



Using Logistic Regression for the above balanced dataset

In [73]:

```
from sklearn.linear_model import LogisticRegression
lr= LogisticRegression()
X_lr_train,X_lr_test,y_lr_train,y_lr_test=train_test_split(X_balanced, y_balanced, r
```

In [99]:

```
lr.fit(X_lr_train, y_lr_train)
```

Out[99]:

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept
=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='warn', n_jobs=None, penalty='l2',
                   random_state=None, solver='warn', tol=0.0001, verbo
se=0,
                   warm_start=False)
```

In [75]:

```
print(lr.coef_)
print(lr.intercept_)
```

```
[[ 1.05069031e-01  1.49945157e-04 -7.25457286e-05 -1.27129403e-04
  -3.76923827e-01 -6.34920728e-04 -4.84585748e-01 -1.92713323e-02
   1.12096218e-02 -6.44587457e-03 -7.75467719e-06  2.13250233e-01
   6.58307616e-02  0.00000000e+00 -1.05006988e-01 -3.47476731e-02
  -9.90186147e-05 -3.49859121e-04 -4.30537653e-03 -1.12202737e-04
  -4.57324888e-02 -1.46064695e-04  3.79923786e-03  3.79923786e-03
  -1.01768128e-02 -6.84276577e-03 -1.54298585e-01 -4.23143936e-05
   2.09164153e-04 -7.96188612e-04  0.00000000e+00  0.00000000e+00
   0.00000000e+00 -6.34169300e-05 -1.45056225e-05  1.67153643e-02
   9.31524391e-03 -1.47967487e-02  0.00000000e+00  0.00000000e+00
  -1.83464674e-03 -1.47967487e-02 -1.83464674e-03 -8.50066863e-01
  -3.28132888e-03  0.00000000e+00 -5.78765791e-01 -1.23786561e-04
   6.58666819e-02]]
[-0.79670961]
```

In [76]:

```
y_lr_pred = lr.predict(X_lr_test)
```

In [79]:

```
confusion_matrix(y_lr_test, y_lr_pred)
```

Out[79]:

```
array([[1299,  321],
       [ 373,  676]])
```

In [80]:

```
recall_score(y_lr_test, y_lr_pred, average='macro')
```

Out[80]:

```
0.7231375560498534
```

In [81]:

```
from sklearn.metrics import precision_score

precision_score(y_lr_test, y_lr_pred, average='macro')
```

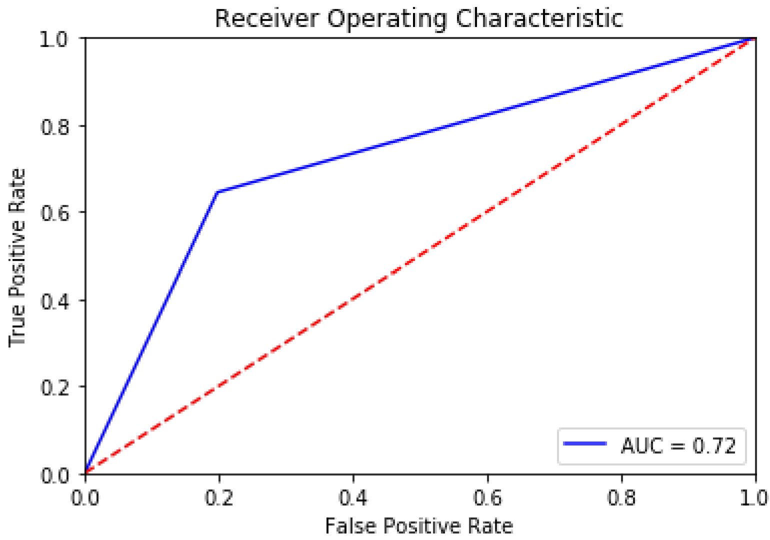
Out[81]:

```
0.7274739889525035
```

Our precision score has improved to 0.73 using logistic regression.

In [82]:

```
fpr, tpr, thresholds = metrics.roc_curve(y_lr_test, y_lr_pred)
roc_auc=metrics.auc(fpr, tpr)
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
print("False Positive Rate"+str(fpr))
print("True Positive Rate"+str(tpr))
print("Treshold"+str(thresholds))
```




```
False Positive Rate[0.         0.19814815 1.        ]
True Positive Rate[0.         0.64442326 1.        ]
Treshold[2 1 0]
```

In [83]:

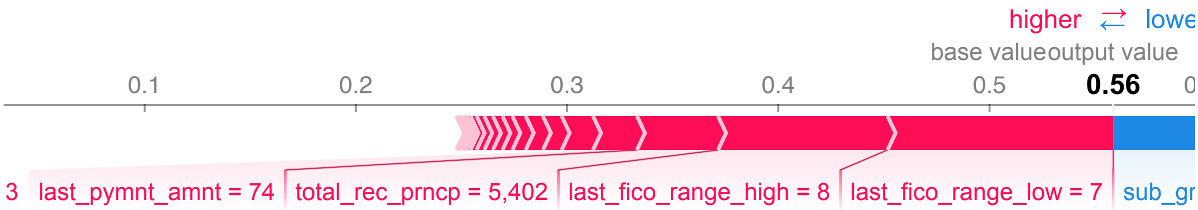
```
!pip install shap
```

```
Requirement already satisfied: shap in /Users/ankit/anaconda3/lib/pyth
on3.7/site-packages (0.31.0)
Requirement already satisfied: tqdm>4.25.0 in /Users/ankit/anaconda3/l
ib/python3.7/site-packages (from shap) (4.31.1)
Requirement already satisfied: scikit-learn in /Users/ankit/anaconda3/
lib/python3.7/site-packages (from shap) (0.21.3)
Requirement already satisfied: numpy in /Users/ankit/anaconda3/lib/pyt
hon3.7/site-packages (from shap) (1.16.2)
Requirement already satisfied: pandas in /Users/ankit/anaconda3/lib/py
thon3.7/site-packages (from shap) (0.24.2)
Requirement already satisfied: scipy in /Users/ankit/anaconda3/lib/pyt
hon3.7/site-packages (from shap) (1.2.1)
Requirement already satisfied: joblib>=0.11 in /Users/ankit/anaconda3/
lib/python3.7/site-packages (from scikit-learn->shap) (0.12.5)
Requirement already satisfied: python-dateutil>=2.5.0 in /Users/ankit/
anaconda3/lib/python3.7/site-packages (from pandas->shap) (2.8.0)
Requirement already satisfied: pytz>=2011k in /Users/ankit/anaconda3/l
ib/python3.7/site-packages (from pandas->shap) (2018.9)
Requirement already satisfied: six>=1.5 in /Users/ankit/anaconda3/lib/
python3.7/site-packages (from python-dateutil>=2.5.0->pandas->shap)
(1.12.0)
```

In [84]:

```
import shap
shap.initjs()
explainer = shap.TreeExplainer(clf_rf)
shap_values = explainer.shap_values(X_test_balanced.iloc[0,:])
X_test_balanced.iloc[0,:]
shap.force_plot(explainer.expected_value[0],shap_values[0],X_test_balanced.iloc[0,:]
```

Out[84]:



On the training set, we compute the Pearson correlation, F-statistic, and p value of each predictor with the response variable charged_off.

In [85]:

```
linear_dep = pd.DataFrame()
for col in X_lr_train.columns:
    linear_dep.loc[col, 'pearson_corr'] = X_lr_train[col].corr(y_lr_train)
linear_dep['abs_pearson_corr'] = abs(linear_dep['pearson_corr'])
```

In [98]:

```
n sklearn.feature_selection import f_classif
col in X_lr_train.columns:
mask = X_lr_train[col].notnull()
(linear_dep.loc[col, 'F'], linear_dep.loc[col, 'p_value']) = f_classif(pd.DataFrame(
```

Sort the results by the absolute value of the Pearson correlation:

In [87]:

```
linear_dep.sort_values('abs_pearson_corr', ascending=False, inplace=True)
linear_dep.drop('abs_pearson_corr', axis=1, inplace=True)
```

Reset the index:

In [88]:

```
linear_dep.reset_index(inplace=True)
linear_dep.rename(columns={'index':'variable'}, inplace=True)
```

View the results for the top 20 predictors most correlated with charged_off:

In [89]:

```
linear_dep.head(20)
```

Out[89]:

	variable	pearson_corr	F	p_value
0	issue_d	0.348538	1106.765682	2.013476e-227
1	grade	-0.303534	812.270913	2.966116e-170
2	last_fico_range_high	0.261521	587.607228	2.518588e-125
3	last_fico_range_low	0.240806	492.701703	5.529379e-106
4	pub_rec_bankruptcies	-0.168312	233.354705	5.951227e-52
5	term	-0.129487	136.491143	2.793326e-31
6	pub_rec	-0.110699	99.299270	2.964555e-23
7	debt_settlement_flag	-0.100951	82.409046	1.372916e-19
8	verification_status	0.077342	48.166643	4.220454e-12
9	interest_rate	0.074254	44.376214	2.888735e-11
10	inq_last_6mths	-0.072144	41.877128	1.029112e-10
11	fico_range_low	-0.067423	36.551566	1.553460e-09
12	fico_range_high	-0.067423	36.551566	1.553460e-09
13	delinq_2yrs	-0.059986	28.904947	7.816236e-08
14	purpose	-0.056531	25.660973	4.160692e-07
15	income_category	0.054551	23.889128	1.040306e-06
16	title	-0.053206	22.722351	1.904806e-06
17	emp_length	0.048351	18.755458	1.504092e-05
18	chargeoff_within_12_mths	-0.044686	16.014382	6.343011e-05
19	collections_12_mths_ex_med	-0.044686	16.014382	6.343011e-05

We will be proceeding for an Ensembled Learning Model to give much better result and hence we will now observe the performance of Six models together using a FOR loop.

The six models used below are:

1)LogisticRegression

2)DecisionTreeClassifier

3)LinearDiscriminantAnalysis

4)SVC

5)KNeighborsClassifier

6)MultinomialNB

Six models on the balanced data:

In [91]:

```
import warnings
warnings.filterwarnings("ignore")
from sklearn.model_selection import train_test_split
train_X,val_X,train_y,val_y=train_test_split(X_train_balanced,Y_train_balanced,rando
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB

models=[]
models.append(("logreg",LogisticRegression()))
models.append(("tree",DecisionTreeClassifier()))
models.append(("lda",LinearDiscriminantAnalysis()))
models.append(("svc",SVC()))
models.append(("knn",KNeighborsClassifier()))
models.append(("nb",MultinomialNB()))
seed=123
scoring='accuracy'
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
result=[]
names=[]
for name,model in models:
    #print(model)
    kfold=KFold(n_splits=10,random_state=seed)
    model.fit(train_X,train_y)
    y1_predict=model.predict(val_X)
    cv_result=cross_val_score(model,train_X,train_y,cv=kfold,scoring=scoring)
    result.append(cv_result)
    names.append(name)
    print("Results on the Test Data: %s %f %f %f %f" % (name,cv_result.mean(),cv_res
    print("Results on the Validation data: %f %f" % (recall_score(val_y, model.pred
```

```
Results on the Test Data: logreg 0.729180 0.022243 0.737546 0.742152
Results on the Validation data: 0.721736 0.726542
Results on the Test Data: tree 0.882908 0.016949 0.886533 0.889800
Results on the Validation data: 0.887871 0.887723
Results on the Test Data: lda 0.738006 0.024670 0.738838 0.741548
Results on the Validation data: 0.725525 0.728460
Results on the Test Data: svc 0.605763 0.022685 0.500000 0.301236
Results on the Validation data: 0.500000 0.296204
Results on the Test Data: knn 0.641071 0.018189 0.622495 0.626699
Results on the Validation data: 0.640372 0.644752
Results on the Test Data: nb 0.534643 0.025895 0.537188 0.535632
Results on the Validation data: 0.548731 0.547077
```

It seems like logistic regressio, Decision Tree and LDA models agree to each other.Hence we will finally use this models into our Ensemble Techniques as our main aim is to increase the Precision and accuracy(decrease the False Positives which are more dangerous in our case).

Ensemble Model

This method combines the decisions from multiple models to improve the overall performance. This can be achieved in various ways,the first method which we would use is Max Voting.

Max voting Ensemble Method

In [92]:

```
from sklearn.ensemble import VotingClassifier
model1 = LogisticRegression()
model2 = LinearDiscriminantAnalysis()
model3 = DecisionTreeClassifier()
model_final = VotingClassifier(estimators=[('lr', model1), ('ld', model2),('tree',mo
model_final.fit(train_X,train_y)
print("The accuracy score of the test model using the Max Voting Ensemble Method is:
print (model_final.score(X_test_balanced,Y_test_balanced))
```

```
The accuracy score of the test model using the Max Voting Ensemble Met
hod is:
0.7680779318096665
```

In [93]:

```
print(classification_report(Y_test_balanced, model_final.predict(X_test_balanced), d
```

```
              precision    recall  f1-score   support

           0     0.8006    0.8190    0.8097      1608
           1     0.7158    0.6909    0.7031      1061

    accuracy                         0.7681      2669
   macro avg     0.7582    0.7549    0.7564      2669
weighted avg     0.7669    0.7681    0.7673      2669
```

We can see that the Ensemble Method has improved our model to a great extend. Our precision for both 0 and 1 has increaed.

The last model which we can train our model is the

Advanced Ensemble Method of Bagging meta-estimator

Bagging meta-estimator is an ensembling algorithm that can be used for both classification (BaggingClassifier) and regression (BaggingRegressor) problems. It follows the typical bagging technique to make predictions. Following are the steps for the bagging meta-estimator algorithm:

Random subsets are created from the original dataset (Bootstrapping). The subset of the dataset includes all features. A user-specified base estimator is fitted on each of these smaller sets. Predictions from each model are combined to get the final result.:

In [94]:

```
from sklearn.ensemble import BaggingClassifier
from sklearn import tree
model1 = BaggingClassifier(DecisionTreeClassifier())
model1.fit(train_X, train_y)
print("The score using the Decision Tree bagging Classifier is:")
print(model1.score(X_test_balanced,Y_test_balanced))
```

```
The score using the Decision Tree bagging Classifier is:
0.9119520419632822
```

We can see that there has been a good increase in the score using bagging classifier and the score has now become 0.91.

In [95]:

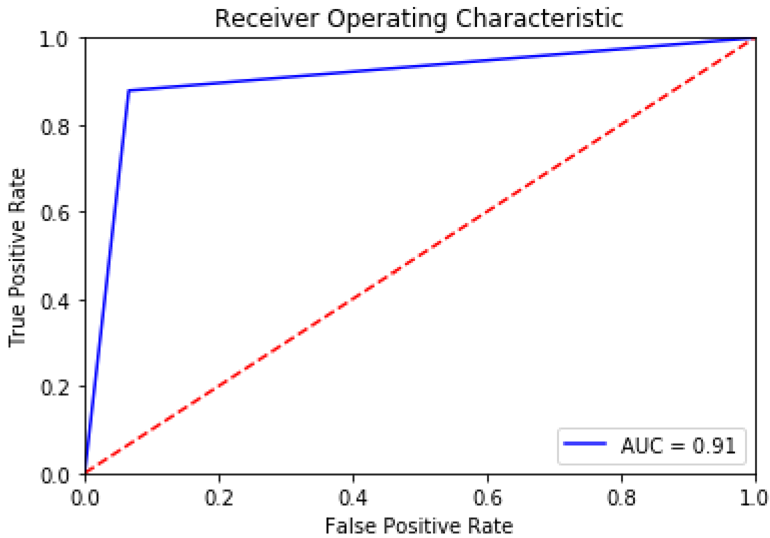
```
from sklearn.metrics import roc_auc_score
y_score = model1.predict_proba(X_test_balanced)[:,1]
roc_auc_score(Y_test_balanced, y_score)
```

Out[95]:

```
0.9752216767247646
```

In [96]:

```
fpr, tpr, thresholds = metrics.roc_curve(Y_test_balanced, model1.predict(X_test_bala
roc_auc=metrics.auc(fpr, tpr)
import matplotlib.pyplot as plt
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
print("False Positive Rate"+str(fpr))
print("True Positive Rate"+str(tpr))
print("Treshold"+str(thresholds))
```




```
False Positive Rate[0.         0.0659204 1.        ]
True Positive Rate[0.         0.87841659 1.        ]
Treshold[2 1 0]
```

In [97]:

```
print(classification_report(Y_test_balanced, model1.predict(X_test_balanced), digits
```

```
              precision    recall  f1-score   support

           0     0.9209    0.9341    0.9274      1608
           1     0.8979    0.8784    0.8880      1061

    accuracy                         0.9120      2669
   macro avg     0.9094    0.9062    0.9077      2669
weighted avg     0.9118    0.9120    0.9118      2669
```

Here we generate a classification report to check the performance of our Bagging Classifier model. You can see the random forest works on “0” prediction very well, which means it can confidently tell you who is the bad customer which was the main importance for our model. Also, it has a pretty good recall when predicting the loan default behaviours. In laymen’s terms, recall means how many cases are predicted correctly among all the true conditions.

Conclusion

We applied machine learning methods to predict the probability that a requested loan on LendingClub will charge off/turn into a bad loan. After training and evaluating with different models (logistic regression, random forest, and Decision tree)and finally using ensemble method we found that in all the cases Decision tree performed the best.We selected RandomForestClassifier (using SMOTE)with the results: Validation Results 0.8879022147931467 0.9444308145240432 Test Results 0.8820985332831892 0.9388568896765618

and Decision tree Bagging Classifier as our final model with AUC SCORE 0.9 on a test set.

Using this model can provide a somewhat informed prediction of the likelihood that a loan will charge off, using only data available to potential investors before the loan is fully funded.The major importance by far was found as the FICO score and the annual income. Hence, deviating from the basic prnciples of banking(FICO) would be risky for an investor.

We also found that, according to the Pearson correlations between the predictors and the response, the most important variables for predicting charge-off are the loan interest rate and term, and the borrower's FICO score and debt-to-income ratio.

Scope for Future work:

We can also try Boosting and Stacking method to give much better results. As our major concern was to increase precision these other models can help us to to the same.

Some more datasets of different quarter can be downloaded directly from the [www.lendingclub.com (http://www.lendingclub.com)](http://www.lendingclub.com) website and the model can be tested for much better accuracy.

All of the important features can be examined for further correlations/patterns. A model predicting ROI and diversification of funds allocation based on the risk factor can be generated.

Risk assessment for specific customer types could be carried out using these same techniques.

Safest category of investement can be predicted and given to the clients so as to ensure good return on investment.

The project could be wrapped in a web application and tested on real world data, asking loan applicants to input their info and report back their results, which could be compared to the model's prediction. When new quarterly data are published, the model's predictive capabilities can be tested in earnest.

This projects also acts as a proof-of-concept for application analysis. It could easily be applied to other types of applications for which large data sets exist. For example, Credit card defaults.

Client Recommendations

To minimize the risk of a costly rejection, lending club should screen the applicants and choose the best qualified, with the lowest chances of rejection. Screened applicants should then have their applications prepared either in house or in the office itself

If all available candidates are risky, the company should look at the application features that are most significantly increasing risk and alter the application to reduce risk.

All the cases should be verified as we saw 41% of unverified loans turned Bad. Hence verification is highly recomended.