Peer Group Lending-Interest Rate Prediction (1)

October 30, 2019

Aim : To predict interest rate of credit based on borrower and loan attributes.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

from patsy import dmatrices
import scipy.stats as stats
import statsmodels.formula.api as smf
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn import metrics
from sklearn.model_selection import train_test_split
from sklearn.feature_selection import f_regression, RFE, SelectKBest, f_oneway
from sklearn.linear_model import LinearRegression
```

[2]:
```
loan_data=pd.read_csv('../input/LoansData.csv')
```

[3]:
```
loan_data.tail(2)
```

[3]:
```
      LoanID  Amount.Requested  Amount.Funded.By.Investors Interest.Rate  \
2498    2499            6000.0                     6000.00        12.42%
2499    2500            9000.0                     5242.75        13.79%

     Loan.Length        Loan.Purpose Debt.To.Income.Ratio State  \
2498   36 months      major_purchase               16.66%    NJ
2499   36 months  debt_consolidation                6.76%    NY

     Home.Ownership  Monthly.Income FICO.Range  Open.CREDIT.Lines  \
2498           RENT          3500.0    675-679                8.0
2499           RENT          3875.0    670-674                7.0

      Revolving.CREDIT.Balance  Inquiries.in.the.Last.6.Months  \
2498                    7753.0                             0.0
2499                    7589.0                             0.0

     Employment.Length
2498           5 years
```

```
2499        10+ years
```

0.1 Data Wrangling

[4]:
```python
loan_data.columns
```

[4]:
```
Index(['LoanID', 'Amount.Requested', 'Amount.Funded.By.Investors',
       'Interest.Rate', 'Loan.Length', 'Loan.Purpose', 'Debt.To.Income.Ratio',
       'State', 'Home.Ownership', 'Monthly.Income', 'FICO.Range',
       'Open.CREDIT.Lines', 'Revolving.CREDIT.Balance',
       'Inquiries.in.the.Last.6.Months', 'Employment.Length'],
      dtype='object')
```

[5]:
```python
#replacing '.' with '_' in column names
loan_data.columns=loan_data.columns.str.replace('.','_')
```

[6]:
```python
loan_data.columns
```

[6]:
```
Index(['LoanID', 'Amount_Requested', 'Amount_Funded_By_Investors',
       'Interest_Rate', 'Loan_Length', 'Loan_Purpose', 'Debt_To_Income_Ratio',
       'State', 'Home_Ownership', 'Monthly_Income', 'FICO_Range',
       'Open_CREDIT_Lines', 'Revolving_CREDIT_Balance',
       'Inquiries_in_the_Last_6_Months', 'Employment_Length'],
      dtype='object')
```

[7]:
```python
loan_data.head(2)
```

[7]:
```
   LoanID  Amount_Requested  Amount_Funded_By_Investors Interest_Rate  \
0       1           20000.0                     20000.0         8.90%
1       2           19200.0                     19200.0        12.12%

  Loan_Length        Loan_Purpose Debt_To_Income_Ratio State Home_Ownership  \
0   36 months  debt_consolidation               14.90%    SC       MORTGAGE
1   36 months  debt_consolidation               28.36%    TX       MORTGAGE

   Monthly_Income FICO_Range  Open_CREDIT_Lines  Revolving_CREDIT_Balance  \
0         6541.67    735-739               14.0                   14272.0
1         4583.33    715-719               12.0                   11140.0

   Inquiries_in_the_Last_6_Months Employment_Length
0                             2.0          < 1 year
1                             1.0           2 years
```

[8]:
```python
loan_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2500 entries, 0 to 2499
Data columns (total 15 columns):
LoanID                            2500 non-null int64
Amount_Requested                  2499 non-null float64
```

```
Amount_Funded_By_Investors        2499 non-null float64
Interest_Rate                     2498 non-null object
Loan_Length                       2500 non-null object
Loan_Purpose                      2500 non-null object
Debt_To_Income_Ratio              2499 non-null object
State                             2500 non-null object
Home_Ownership                    2499 non-null object
Monthly_Income                    2499 non-null float64
FICO_Range                        2498 non-null object
Open_CREDIT_Lines                 2497 non-null float64
Revolving_CREDIT_Balance          2497 non-null float64
Inquiries_in_the_Last_6_Months    2497 non-null float64
Employment_Length                 2423 non-null object
dtypes: float64(6), int64(1), object(8)
memory usage: 293.1+ KB
```

[9]:
```
# removing "%" symbol from interest rate column and converting it to float type
loan_data['Interest_Rate'] = loan_data['Interest_Rate'].apply(lambda a : str(a).
 ↪strip('%')).astype('float64')
```

[10]:
```
# stripping " months" from loan length column and converting it to int type
loan_data['Loan_Length'] = loan_data['Loan_Length'].apply(lambda b : str(b).
 ↪strip(' months')).astype('int64')
```

[11]:
```
# Stripping "%" symbol from Debt to Income Ratio column and converting it to␣
 ↪float type
loan_data["Debt_To_Income_Ratio"] = loan_data["Debt_To_Income_Ratio"].
 ↪apply(lambda c :str(c).strip('%')).astype('float64')
```

[12]:
```
# FICO range column gives us range, converting it to single value by taking avg␣
 ↪of range
a=loan_data['FICO_Range'].str.split('-',expand=True).astype('float64')
```

[13]:
```
a['AVG']=(a[0]+a[1])/2
a.head()
```

[13]:
```
       0      1    AVG
0  735.0  739.0  737.0
1  715.0  719.0  717.0
2  690.0  694.0  692.0
3  695.0  699.0  697.0
4  695.0  699.0  697.0
```

[14]:
```
#adding FICO avergae to original dataframe and dropping FICO Range
loan_data['Fico_Avg']=a['AVG']
loan_data.drop(columns=['FICO_Range'],inplace=True)
```

[15]:
```
# correcting emplyment length column
loan_data['Employment_Length']=loan_data['Employment_Length'].str.
 ↪replace('<','')
```

```
loan_data['Employment_Length']=loan_data['Employment_Length'].str.
↪replace('+','')
loan_data['Employment_Length']=loan_data['Employment_Length'].str.replace('␣
↪years','')
loan_data['Employment_Length']=loan_data['Employment_Length'].str.replace('␣
↪year','')
loan_data['Employment_Length']=loan_data['Employment_Length'].str.lstrip()
loan_data['Employment_Length']=loan_data['Employment_Length'].str.rstrip()
```

[16]:
```
loan_data['Employment_Length'].tail()
```

[16]:
```
2495     8
2496    10
2497    10
2498     5
2499    10
Name: Employment_Length, dtype: object
```

[17]:
```
# for stats of continuous variables
def con_stats(x):
    return pd.Series({'Count':x.count(),'NaNs':x.isnull().sum(),'%NaNs':(x.
↪isnull().sum())/(x.count()),'Sum':x.sum(),'Mean':x.mean(),
                      'Coef. Var':x.std()/x.mean(),'Min':x.min(),'P1':x.
↪quantile(.01),'P10':x.quantile(.1),'P25':x.quantile(.25),'P50':x.quantile(.
↪5),
                      'P75':x.quantile(.75),'P90':x.quantile(.9),'P99':x.
↪quantile(.99),'Max':x.max()})
```

[18]:
```
# for stats of categorical var
def cat_stats(y):
    return pd.Series({'Count':y.count(),'Uniques':y.value_counts().
↪count(),'NaNs':y.isnull().sum(),'%NaNs':(y.isnull().sum())/y.count(),'Mode':
↪y.mode()[0],'Freq. Mode':y.value_counts()[0]})
```

[19]:
```
# missing value imputation
def misses(x):
    if (x.dtype=='int64')|(x.dtype=='float64'):
        x.fillna(value=x.median(),inplace=True)
    else :
        x.fillna(x.mode()[0],inplace=True)
    return x
```

[20]:
```
# outlier treatment
def out(y):
    y.clip(lower=y.quantile(0.01),upper=y.quantile(0.99),inplace=True)
    return y
```

[21]:
```
loan_data.apply(misses)
```

[21]:
```
      LoanID  Amount_Requested  Amount_Funded_By_Investors  Interest_Rate  \
0          1           20000.0                    20000.00           8.90
1          2           19200.0                    19200.00          12.12
2          3           35000.0                    35000.00          21.98
3          4           10000.0                     9975.00           9.99
4          5           12000.0                    12000.00          11.71
...      ...               ...                         ...            ...
2495    2496           30000.0                    29950.00          16.77
2496    2497           16000.0                    16000.00          14.09
2497    2498           10000.0                    10000.00          13.99
2498    2499            6000.0                     6000.00          12.42
2499    2500            9000.0                     5242.75          13.79

      Loan_Length        Loan_Purpose  Debt_To_Income_Ratio State  \
0              36  debt_consolidation                 14.90    SC
1              36  debt_consolidation                 28.36    TX
2              60  debt_consolidation                 23.81    CA
3              36  debt_consolidation                 14.30    KS
4              36         credit_card                 18.78    NJ
...           ...                 ...                   ...   ...
2495           60  debt_consolidation                 19.23    NY
2496           60    home_improvement                 21.54    MD
2497           36  debt_consolidation                  4.89    PA
2498           36      major_purchase                 16.66    NJ
2499           36  debt_consolidation                  6.76    NY

     Home_Ownership  Monthly_Income  Open_CREDIT_Lines  \
0          MORTGAGE         6541.67               14.0
1          MORTGAGE         4583.33               12.0
2          MORTGAGE        11500.00               14.0
3          MORTGAGE         3833.33               10.0
4              RENT         3195.00               11.0
...             ...             ...                ...
2495       MORTGAGE         9250.00               15.0
2496            OWN         8903.25               18.0
2497       MORTGAGE         2166.67                4.0
2498           RENT         3500.00                8.0
2499           RENT         3875.00                7.0

      Revolving_CREDIT_Balance  Inquiries_in_the_Last_6_Months  \
0                      14272.0                             2.0
1                      11140.0                             1.0
2                      21977.0                             1.0
3                       9346.0                             0.0
4                      14469.0                             0.0
...                        ...                             ...
2495                   45880.0                             1.0
```

```
2496               18898.0                             1.0
2497                4544.0                             0.0
2498                7753.0                             0.0
2499                7589.0                             0.0

     Employment_Length  Fico_Avg
0                    1     737.0
1                    2     717.0
2                    2     692.0
3                    5     697.0
4                    9     697.0
...                ...       ...
2495                 8     707.0
2496                10     742.0
2497                10     682.0
2498                 5     677.0
2499                10     672.0

[2500 rows x 15 columns]
```

[22]:
```
#changing employment type and dropping unwanted columns
loan_data['Employment_Length']=loan_data['Employment_Length'].astype('int64')
loan_data.drop(columns=['LoanID','Amount_Funded_By_Investors'],inplace=True)
```

[23]:
```
# Separating Numerical and Categorical features
num=[]
cat=[]
for i in dict(loan_data.dtypes).items():
        if (i[1]=='int64')|(i[1]=='float64'):
            num.append(i[0])
        else:
            cat.append(i[0])
```

[24]:
```
loan_cat=loan_data[cat]
loan_num=loan_data[num]
```

[25]:
```
loan_cat.head(2)
```

[25]:
```
         Loan_Purpose State Home_Ownership
0  debt_consolidation    SC       MORTGAGE
1  debt_consolidation    TX       MORTGAGE
```

[26]:
```
loan_num.head(2)
```

[26]:
```
   Amount_Requested  Interest_Rate  Loan_Length  Debt_To_Income_Ratio  \
0           20000.0           8.90           36                 14.90
1           19200.0          12.12           36                 28.36

   Monthly_Income  Open_CREDIT_Lines  Revolving_CREDIT_Balance  \
0         6541.67               14.0                   14272.0
```

```
1         4583.33                 12.0                    11140.0

   Inquiries_in_the_Last_6_Months  Employment_Length  Fico_Avg
0                             2.0                  1     737.0
1                             1.0                  2     717.0
```

[27]:
```
loan_num.apply(con_stats).T
```

[27]:
```
                                 Count  NaNs  %NaNs          Sum  \
Amount_Requested                2500.0   0.0    0.0  31011250.00
Interest_Rate                   2500.0   0.0    0.0     32663.56
Loan_Length                     2500.0   0.0    0.0    103152.00
Debt_To_Income_Ratio            2500.0   0.0    0.0     38450.99
Monthly_Income                  2500.0   0.0    0.0  14221639.37
Open_CREDIT_Lines               2500.0   0.0    0.0     25179.00
Revolving_CREDIT_Balance        2500.0   0.0    0.0  38045136.00
Inquiries_in_the_Last_6_Months  2500.0   0.0    0.0      2264.00
Employment_Length               2500.0   0.0    0.0     14077.00
Fico_Avg                        2500.0   0.0    0.0   1769750.00

                                        Mean  Coef. Var      Min         P1  \
Amount_Requested                12404.500000   0.628927  1000.00  1500.0000
Interest_Rate                      13.065424   0.319586     5.42     5.9880
Loan_Length                        41.260800   0.240686    36.00    36.0000
Debt_To_Income_Ratio               15.380396   0.487865     0.00     0.7190
Monthly_Income                   5688.655748   0.696535   588.50  1416.5366
Open_CREDIT_Lines                  10.071600   0.447284     2.00     3.0000
Revolving_CREDIT_Balance        15218.054400   1.200590     0.00     0.0000
Inquiries_in_the_Last_6_Months      0.905600   1.359111     0.00     0.0000
Employment_Length                   5.630800   0.617481     1.00     1.0000
Fico_Avg                          707.900000   0.049482   642.00   662.0000

                                     P10      P25       P50         P75  \
Amount_Requested                4000.000  6000.00  10000.00  17000.0000
Interest_Rate                      7.620    10.16     13.11     15.8000
Loan_Length                       36.000    36.00     36.00     36.0000
Debt_To_Income_Ratio               5.309     9.75     15.32     20.6725
Monthly_Income                  2600.000  3500.00   5000.00   6800.0000
Open_CREDIT_Lines                  5.000     7.00      9.00     13.0000
Revolving_CREDIT_Balance        2299.700  5589.25  10948.00  18843.7500
Inquiries_in_the_Last_6_Months     0.000     0.00      0.00      1.0000
Employment_Length                  1.000     2.00      5.00     10.0000
Fico_Avg                         667.000   682.00    702.00    727.0000

                                      P90         P99       Max
Amount_Requested                24000.000  35000.0000  35000.00
Interest_Rate                      18.640     22.9533     24.89
Loan_Length                        60.000     60.0000     60.00
```

```
Debt_To_Income_Ratio              25.012     33.2300      34.91
Monthly_Income                  9292.830  18750.0000  102750.00
Open_CREDIT_Lines                 16.000     23.0000      38.00
Revolving_CREDIT_Balance       29976.500  92407.6600  270800.00
Inquiries_in_the_Last_6_Months     3.000      5.0000       9.00
Employment_Length                 10.000     10.0000      10.00
Fico_Avg                         757.000    807.0000     832.00
```

[28]:
```
loan_cat.apply(cat_stats).T
```

[28]:
```
               Count Uniques NaNs %NaNs                Mode Freq. Mode
Loan_Purpose    2500      14    0     0  debt_consolidation       1307
State           2500      46    0     0                  CA        433
Home_Ownership  2500       5    0     0            MORTGAGE       1148
```

[29]:
```
loan_num.apply(out)
```

[29]:
```
      Amount_Requested  Interest_Rate  Loan_Length  Debt_To_Income_Ratio  \
0              20000.0           8.90           36                 14.90
1              19200.0          12.12           36                 28.36
2              35000.0          21.98           60                 23.81
3              10000.0           9.99           36                 14.30
4              12000.0          11.71           36                 18.78
...                ...            ...          ...                   ...
2495           30000.0          16.77           60                 19.23
2496           16000.0          14.09           60                 21.54
2497           10000.0          13.99           36                  4.89
2498            6000.0          12.42           36                 16.66
2499            9000.0          13.79           36                  6.76

      Monthly_Income  Open_CREDIT_Lines  Revolving_CREDIT_Balance  \
0            6541.67               14.0                   14272.0
1            4583.33               12.0                   11140.0
2           11500.00               14.0                   21977.0
3            3833.33               10.0                    9346.0
4            3195.00               11.0                   14469.0
...              ...                ...                       ...
2495         9250.00               15.0                   45880.0
2496         8903.25               18.0                   18898.0
2497         2166.67                4.0                    4544.0
2498         3500.00                8.0                    7753.0
2499         3875.00                7.0                    7589.0

      Inquiries_in_the_Last_6_Months  Employment_Length  Fico_Avg
0                                2.0                  1     737.0
1                                1.0                  2     717.0
2                                1.0                  2     692.0
3                                0.0                  5     697.0
4                                0.0                  9     697.0
```

```
...                                  ...                 ...      ...
2495                                 1.0                   8    707.0
2496                                 1.0                  10    742.0
2497                                 0.0                  10    682.0
2498                                 0.0                   5    677.0
2499                                 0.0                  10    672.0

[2500 rows x 10 columns]
```

[30]:
```
loan_num.apply(con_stats).T
```

[30]:
```
                                 Count  NaNs  %NaNs           Sum  \
Amount_Requested                2500.0   0.0    0.0  3.102028e+07
Interest_Rate                   2500.0   0.0    0.0  3.265089e+04
Loan_Length                     2500.0   0.0    0.0  1.031520e+05
Debt_To_Income_Ratio            2500.0   0.0    0.0  3.844629e+04
Monthly_Income                  2500.0   0.0    0.0  1.402077e+07
Open_CREDIT_Lines               2500.0   0.0    0.0  2.513200e+04
Revolving_CREDIT_Balance        2500.0   0.0    0.0  3.691085e+07
Inquiries_in_the_Last_6_Months  2500.0   0.0    0.0  2.216000e+03
Employment_Length               2500.0   0.0    0.0  1.407700e+04
Fico_Avg                        2500.0   0.0    0.0  1.769785e+06

                                        Mean  Coef. Var        Min  \
Amount_Requested                12408.110000   0.628328  1500.0000
Interest_Rate                      13.060357   0.317552     5.9880
Loan_Length                        41.260800   0.240686    36.0000
Debt_To_Income_Ratio               15.378514   0.486326     0.7190
Monthly_Income                   5608.306794   0.549858  1416.5366
Open_CREDIT_Lines                  10.052800   0.435441     3.0000
Revolving_CREDIT_Balance        14764.339000   0.999536     0.0000
Inquiries_in_the_Last_6_Months      0.886400   1.288087     0.0000
Employment_Length                   5.630800   0.617481     1.0000
Fico_Avg                          707.914000   0.049090   662.0000

                                         P1       P10      P25       P50  \
Amount_Requested                1500.000000  4000.000  6000.00  10000.00
Interest_Rate                      5.989980     7.620    10.16     13.11
Loan_Length                       36.000000    36.000    36.00     36.00
Debt_To_Income_Ratio               0.719990     5.309     9.75     15.32
Monthly_Income                  1416.668666  2600.000  3500.00   5000.00
Open_CREDIT_Lines                  3.000000     5.000     7.00      9.00
Revolving_CREDIT_Balance           0.000000  2299.700  5589.25  10948.00
Inquiries_in_the_Last_6_Months     0.000000     0.000     0.00      0.00
Employment_Length                  1.000000     1.000     2.00      5.00
Fico_Avg                         662.000000   667.000   682.00    702.00

                                       P75       P90            P99  \
```

```
Amount_Requested                 17000.0000  24000.000  35000.000000
Interest_Rate                       15.8000     18.640     22.950033
Loan_Length                         36.0000     60.000     60.000000
Debt_To_Income_Ratio                20.6725     25.012     33.230000
Monthly_Income                    6800.0000   9292.830  18750.000000
Open_CREDIT_Lines                   13.0000     16.000     23.000000
Revolving_CREDIT_Balance         18843.7500  29976.500  92399.086600
Inquiries_in_the_Last_6_Months       1.0000      3.000      5.000000
Employment_Length                   10.0000     10.000     10.000000
Fico_Avg                           727.0000    757.000    807.000000

                                        Max
Amount_Requested                 35000.0000
Interest_Rate                       22.9533
Loan_Length                         60.0000
Debt_To_Income_Ratio                33.2300
Monthly_Income                   18750.0000
Open_CREDIT_Lines                   23.0000
Revolving_CREDIT_Balance         92407.6600
Inquiries_in_the_Last_6_Months       5.0000
Employment_Length                   10.0000
Fico_Avg                           807.0000
```

[31]:
```
loan_cat.apply(cat_stats).T
```

[31]:
```
               Count Uniques NaNs %NaNs                Mode Freq. Mode
Loan_Purpose    2500      14    0     0  debt_consolidation       1307
State           2500      46    0     0                  CA        433
Home_Ownership  2500       5    0     0            MORTGAGE       1148
```

[32]:
```
loan_cat=pd.get_dummies(loan_cat,prefix='Dum',drop_first=True)
```

[33]:
```
data_new=pd.concat([loan_num,loan_cat],axis=1)
```

[34]:
```
data_new.head(2)
```

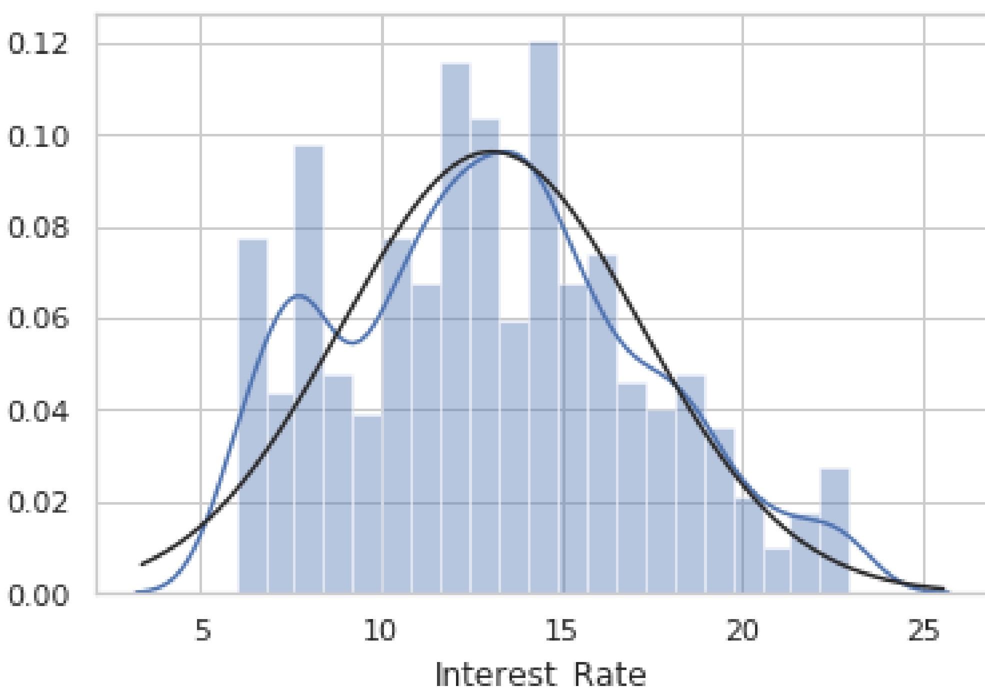
[34]:
```
   Amount_Requested  Interest_Rate  Loan_Length  Debt_To_Income_Ratio  \
0           20000.0           8.90           36                 14.90
1           19200.0          12.12           36                 28.36

   Monthly_Income  Open_CREDIT_Lines  Revolving_CREDIT_Balance  \
0         6541.67               14.0                   14272.0
1         4583.33               12.0                   11140.0

   Inquiries_in_the_Last_6_Months  Employment_Length  Fico_Avg  ...  Dum_VA  \
0                             2.0                  1     737.0  ...       0
1                             1.0                  2     717.0  ...       0

   Dum_VT  Dum_WA  Dum_WI  Dum_WV  Dum_WY  Dum_NONE  Dum_OTHER  Dum_OWN  \
0       0       0       0       0       0         0          0        0
```

```
1        0        0        0        0        0          0            0          0

   Dum_RENT
0          0
1          0

[2 rows x 72 columns]
```

0.2 Essential Assumptions Check

[35]:
```
# checking normality of target
sns.set(style='whitegrid')
sns.distplot(data_new["Interest_Rate"],fit=stats.norm)
print(stats.skew(data_new["Interest_Rate"]))
```

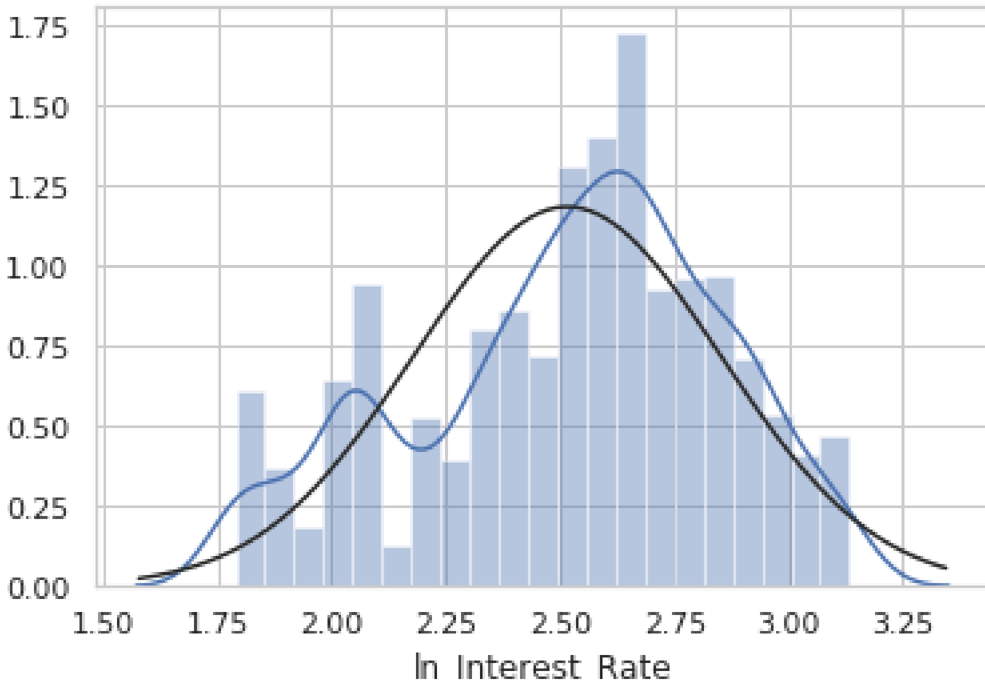
```
0.2570280292745423
```



[36]:
```
# applying log transform on target variable
data_new['ln_Interest_Rate']=np.log(data_new['Interest_Rate'])
```

[37]:
```
sns.distplot(data_new.ln_Interest_Rate,fit=stats.norm)
```

[37]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fa4a94e2208>`

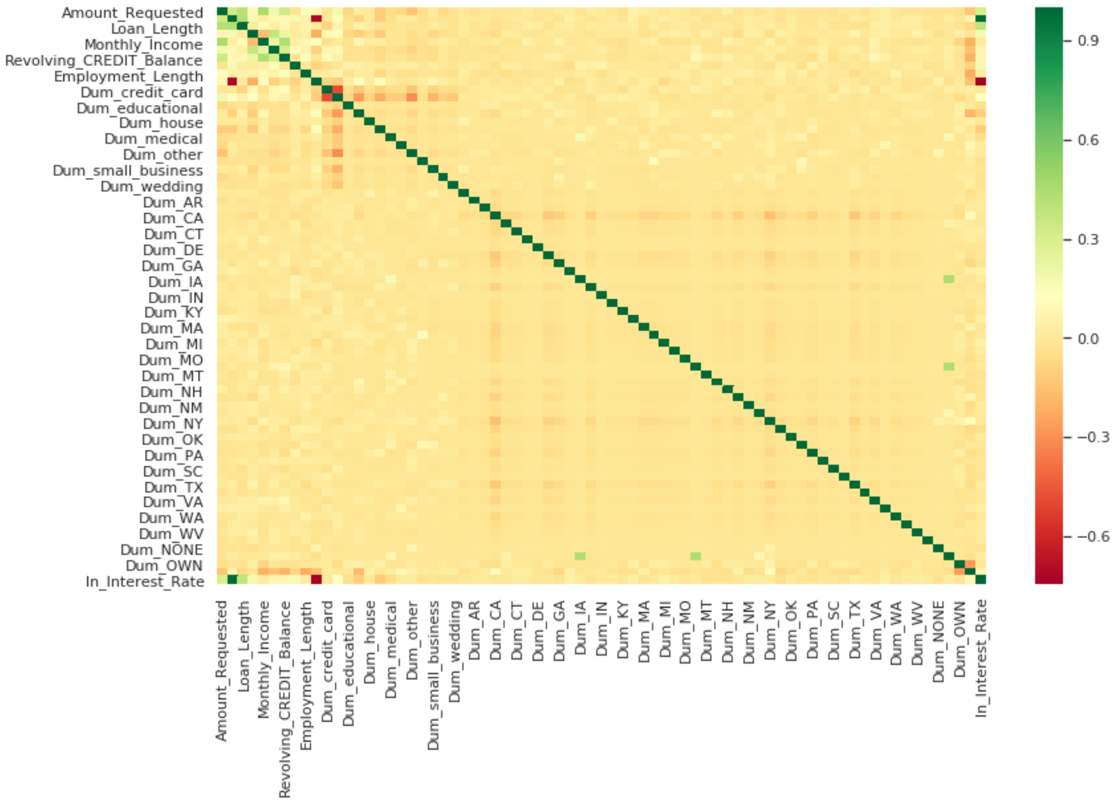


[38]:
```
# chekcing collinearity
plt.figure(figsize=(10,7))
sns.heatmap(loan_num.corr(),annot=True,cmap='RdYlGn')
```

[38]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fa4a93a1320>`

[39]:
```
# checking multicollinearity
plt.figure(figsize=(13,8))
cormat=data_new.corr()
sns.heatmap(cormat,cmap='RdYlGn')
```

[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7fa4a908d7b8>



- Since most of the heatmap is yellow/near yellow color, it indicates that Multi-collinearity is less.

0.3 Feature Engineering

[40]:
```
feature_cols=data_new.columns.difference(['Interest_Rate','ln_Interest_Rate'])
```

[41]:
```
feature_cols
```

[41]:
```
Index(['Amount_Requested', 'Debt_To_Income_Ratio', 'Dum_AL', 'Dum_AR',
       'Dum_AZ', 'Dum_CA', 'Dum_CO', 'Dum_CT', 'Dum_DC', 'Dum_DE', 'Dum_FL',
       'Dum_GA', 'Dum_HI', 'Dum_IA', 'Dum_IL', 'Dum_IN', 'Dum_KS', 'Dum_KY',
       'Dum_LA', 'Dum_MA', 'Dum_MD', 'Dum_MI', 'Dum_MN', 'Dum_MO', 'Dum_MS',
       'Dum_MT', 'Dum_NC', 'Dum_NH', 'Dum_NJ', 'Dum_NM', 'Dum_NONE', 'Dum_NV',
       'Dum_NY', 'Dum_OH', 'Dum_OK', 'Dum_OR', 'Dum_OTHER', 'Dum_OWN',
       'Dum_PA', 'Dum_RENT', 'Dum_RI', 'Dum_SC', 'Dum_SD', 'Dum_TX', 'Dum_UT',
       'Dum_VA', 'Dum_VT', 'Dum_WA', 'Dum_WI', 'Dum_WV', 'Dum_WY',
       'Dum_credit_card', 'Dum_debt_consolidation', 'Dum_educational',
       'Dum_home_improvement', 'Dum_house', 'Dum_major_purchase',
       'Dum_medical', 'Dum_moving', 'Dum_other', 'Dum_renewable_energy',
       'Dum_small_business', 'Dum_vacation', 'Dum_wedding',
       'Employment_Length', 'Fico_Avg', 'Inquiries_in_the_Last_6_Months',
```

```
       'Loan_Length', 'Monthly_Income', 'Open_CREDIT_Lines',
       'Revolving_CREDIT_Balance'],
      dtype='object')
```

[42]:
```
X=data_new[feature_cols]
y=data_new['ln_Interest_Rate']
```

[43]:
```
# feature reduction using f_regression
F,p=f_regression(X,y)
```

[44]:
```
f_reg_result=pd.DataFrame({'Feature':X.columns,'F-Score':F,'p-value':p.
 ↪round(2)})
```

[45]:
```
f_reg_result[f_reg_result['p-value']<0.05]
```

[45]:

	Feature	F-Score	p-value
0	Amount_Requested	250.655568	0.00
1	Debt_To_Income_Ratio	82.470669	0.00
12	Dum_HI	4.923247	0.03
21	Dum_MI	6.405998	0.01
39	Dum_RENT	18.614306	0.00
46	Dum_VT	4.364751	0.04
52	Dum_debt_consolidation	45.367333	0.00
54	Dum_home_improvement	24.090299	0.00
56	Dum_major_purchase	31.625414	0.00
57	Dum_medical	5.121854	0.02
65	Fico_Avg	3100.706573	0.00
66	Inquiries_in_the_Last_6_Months	81.193336	0.00
67	Loan_Length	438.264400	0.00
69	Open_CREDIT_Lines	11.717766	0.00
70	Revolving_CREDIT_Balance	16.008023	0.00

[46]:
```
# taking all those features where p-values are significant and making into a␣
 ↪list for further use
freg_list=f_reg_result[f_reg_result['p-value']<0.05]['Feature'].to_list()
```

[47]:
```
a=X.columns.to_list()
```

[48]:
```
# Variance Inflation Factor
vif=pd.DataFrame()
y,X=dmatrices(formula_like=('ln_Interest_Rate~'+'+'.
 ↪join(a)),data=data_new,return_type='dataframe')
vif['Features']=X.columns
vif['VI_Factor']=[variance_inflation_factor(X.values,i) for i in range(X.
 ↪shape[1])]
```

[49]:
```
# filtering those features which have VIF less than equal to 4
vif[vif['VI_Factor']<=4]
```

[49]:

	Features	VI_Factor
1	Amount_Requested	1.818637
2	Debt_To_Income_Ratio	1.470721

4	Dum_AR	2.182424
9	Dum_DC	2.002709
10	Dum_DE	1.728900
13	Dum_HI	2.095982
14	Dum_IA	1.472315
16	Dum_IN	1.280990
17	Dum_KS	2.897962
18	Dum_KY	3.086953
19	Dum_LA	2.987798
24	Dum_MO	3.967140
25	Dum_MS	1.447565
26	Dum_MT	1.650255
28	Dum_NH	2.373304
30	Dum_NM	2.182915
31	Dum_NONE	1.014630
32	Dum_NV	3.890309
35	Dum_OK	2.899566
36	Dum_OR	3.714044
37	Dum_OTHER	1.700518
38	Dum_OWN	1.165418
40	Dum_RENT	1.457914
41	Dum_RI	2.361520
42	Dum_SC	3.533856
43	Dum_SD	1.369142
45	Dum_UT	2.451401
47	Dum_VT	1.464987
49	Dum_WI	3.343840
50	Dum_WV	2.364758
51	Dum_WY	1.370035
54	Dum_educational	1.317734
55	Dum_home_improvement	3.941051
56	Dum_house	1.416191
57	Dum_major_purchase	2.942105
58	Dum_medical	1.654397
59	Dum_moving	1.606262
61	Dum_renewable_energy	1.106934
62	Dum_small_business	2.715147
63	Dum_vacation	1.425516
64	Dum_wedding	1.788753
65	Employment_Length	1.124680
66	Fico_Avg	1.181571
67	Inquiries_in_the_Last_6_Months	1.083839
68	Loan_Length	1.284651
69	Monthly_Income	1.810004
70	Open_CREDIT_Lines	1.378919
71	Revolving_CREDIT_Balance	1.549811

[50]:
```
vif_list=vif[vif['VI_Factor']<=4]['Features'].to_list()
```

[51]:
```
# selecting common features resultant from the various feature reduction␣
↪methods, these features shall be used for model building
set(vif_list).intersection(freg_list)
```

[51]:
```
{'Amount_Requested',
 'Debt_To_Income_Ratio',
 'Dum_HI',
 'Dum_RENT',
 'Dum_VT',
 'Dum_home_improvement',
 'Dum_major_purchase',
 'Dum_medical',
 'Fico_Avg',
 'Inquiries_in_the_Last_6_Months',
 'Loan_Length',
 'Open_CREDIT_Lines',
 'Revolving_CREDIT_Balance'}
```

0.4 Model Building

[52]:
```
X_new=['Amount_Requested',
 'Debt_To_Income_Ratio',
 'Dum_HI',
 'Dum_RENT',
 'Dum_VT',
 'Dum_home_improvement',
 'Dum_major_purchase',
 'Dum_medical',
 'Fico_Avg',
 'Inquiries_in_the_Last_6_Months',
 'Loan_Length',
 'Open_CREDIT_Lines',
 'Revolving_CREDIT_Balance']
```

[53]:
```
# final data containing selected features and transformed target
data_final=pd.concat([data_new[X_new],y],axis=1)
```

[54]:
```
# train-test splitting
train,test=train_test_split(data_final,test_size=0.3, random_state=3994)
```

[55]:
```
fm=('ln_Interest_Rate~'+'+'.join(train.columns.
↪difference(['ln_Interest_Rate','Dum_VT','Dum_major_purchase','Dum_HI',␣
↪'Dum_RENT','Dum_medical','Revolving_CREDIT_Balance','Debt_To_Income_Ratio'])))
model=smf.ols(fm,data=train).fit()
```

[56]:
```
print(model.summary())
```

```
                              OLS Regression Results
==============================================================================
Dep. Variable:       ln_Interest_Rate   R-squared:                       0.778
Model:                            OLS   Adj. R-squared:                  0.777
Method:                 Least Squares   F-statistic:                     1017.
Date:                Tue, 29 Oct 2019   Prob (F-statistic):               0.00
Time:                        18:44:06   Log-Likelihood:                 727.95
No. Observations:                1750   AIC:                            -1442.
Df Residuals:                    1743   BIC:                            -1404.
Df Model:                           6
Covariance Type:            nonrobust
================================================================================
==================
                                     coef    std err          t      P>|t|
[0.025      0.975]
--------------------------------------------------------------------------------
------------------
Intercept                          7.2133      0.081     88.628      0.000
7.054       7.373
Amount_Requested                1.126e-05   5.59e-07     20.151      0.000
1.02e-05    1.24e-05
Dum_home_improvement              -0.0358      0.016     -2.231      0.026
-0.067      -0.004
Fico_Avg                          -0.0074      0.000    -66.260      0.000
-0.008      -0.007
Inquiries_in_the_Last_6_Months     0.0379      0.003     10.962      0.000
0.031       0.045
Loan_Length                        0.0099      0.000     23.276      0.000
0.009       0.011
Open_CREDIT_Lines                 -0.0066      0.001     -7.196      0.000
-0.008      -0.005
==============================================================================
Omnibus:                       62.108   Durbin-Watson:                   2.021
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              171.721
Skew:                           0.027   Prob(JB):                     5.14e-38
Kurtosis:                       4.534   Cond. No.                     3.13e+05
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 3.13e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
```

- All features have significant p-values.
- R2 and adjR2- both are high and close to each other.

[57]:
```python
# VIF Check
y2,X2=dmatrices(fm,data=train,return_type='dataframe')
vif2=pd.DataFrame()
vif2['Features']=X2.columns
vif2['VI_Factor']=[variance_inflation_factor(X2.values,j) for j in range(X2.
↪shape[1])]
vif2.sort_values(by='VI_Factor',ascending=False)
```

[57]:

	Features	VI_Factor
0	Intercept	453.113246
1	Amount_Requested	1.298702
5	Loan_Length	1.251839
6	Open_CREDIT_Lines	1.056014
3	Fico_Avg	1.047440
4	Inquiries_in_the_Last_6_Months	1.031065
2	Dum_home_improvement	1.027989

- No Multi-collinearity among features in the model we made.

[58]:
```python
# reverse transformation of our target using exponential
train_y=np.exp(train['ln_Interest_Rate'])
test_y=np.exp(test['ln_Interest_Rate'])
```

[59]:
```python
# predicting for train and test data
train_pred=np.exp(model.predict(train))
test_pred=np.exp(model.predict(test))
```

[60]:
```python
# evaluation metrics calculation

r2_train=metrics.r2_score(y_true=train_y,y_pred=train_pred)
r2_test=metrics.r2_score(y_true=test_y,y_pred=test_pred)
mae_train=metrics.mean_absolute_error(y_true=train_y,y_pred=train_pred)
mae_test=metrics.mean_absolute_error(y_true=test_y,y_pred=test_pred)
mse_test=metrics.mean_squared_error(y_true=test_y,y_pred=test_pred)
mse_train=metrics.mean_squared_error(y_true=train_y,y_pred=train_pred)
train_cor=np.corrcoef(train_y,train_pred)[0][1]
test_cor=np.corrcoef(test_y,test_pred)[0][1]
```

[61]:
```python
model_eva=pd.DataFrame(index=['MAE','MSE','R2_Score','Corr.Coeff.
↪'],columns=['Train',"Test"],data={'Train':
↪[mae_train,mse_train,r2_train,train_cor],
                                                                        ␣
↪     'Test':[mae_test,mse_test,r2_test,test_cor]})
```

[62]:
```python
model_eva
```

[62]:

	Train	Test
MAE	1.462760	1.473775
MSE	3.790132	3.887454
R2_Score	0.780478	0.771540

```
Corr.Coeff.  0.884218  0.879476
```

- The metrics for both train and test are similar, also correlation of predicted values with actual values is high.

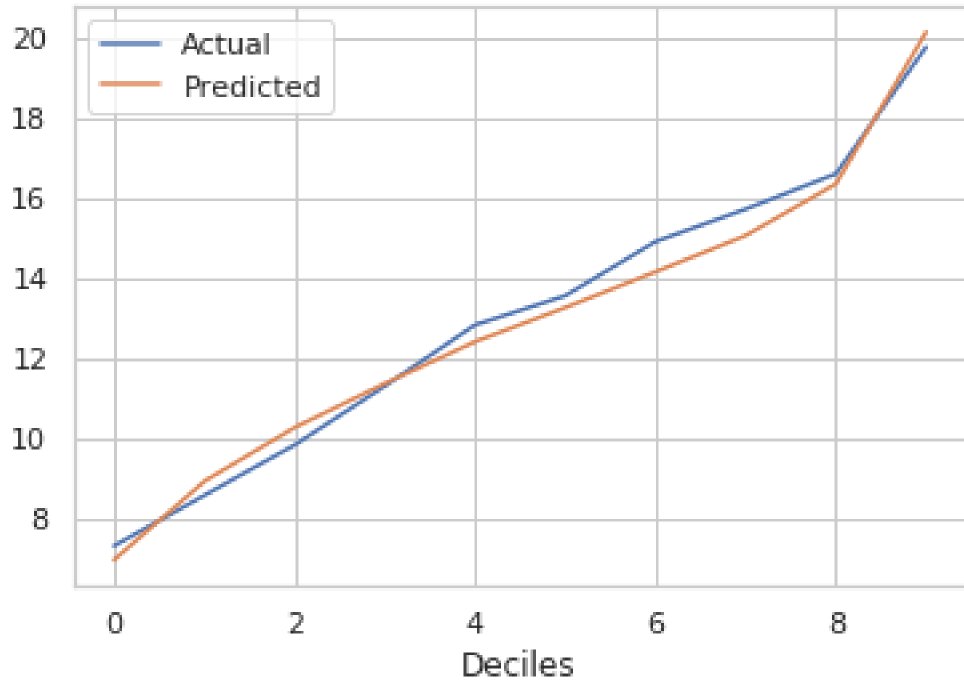
[63]:
```
# Decile Analysis for train data
train_new=pd.concat([train_y,train_pred],axis=1)
train_new.columns=['Actual','Predicted']
train_new['Deciles']=pd.qcut(train_new.Predicted,10,labels=False)
df1=train_new.groupby('Deciles').mean()
df1
```

[63]:

Deciles	Actual	Predicted
0	7.299657	6.949984
1	8.561977	8.911147
2	9.814629	10.251335
3	11.286400	11.351755
4	12.810629	12.393421
5	13.540343	13.245215
6	14.892686	14.137388
7	15.705029	15.043598
8	16.581829	16.329988
9	19.748682	20.117431

[64]:
```
sns.lineplot(x=df1.index,y='Actual',data=df1,label='Actual')
ax=sns.lineplot(x=df1.index,y='Predicted',data=df1,label='Predicted')
ax.set(ylabel='')
```

[64]:
```
[Text(0, 0.5, '')]
```



- From above dataframe and plot :
  - We see that for our training data both Actual and the predicted values increase with increasing deciles, i.e rank order is mainteined.

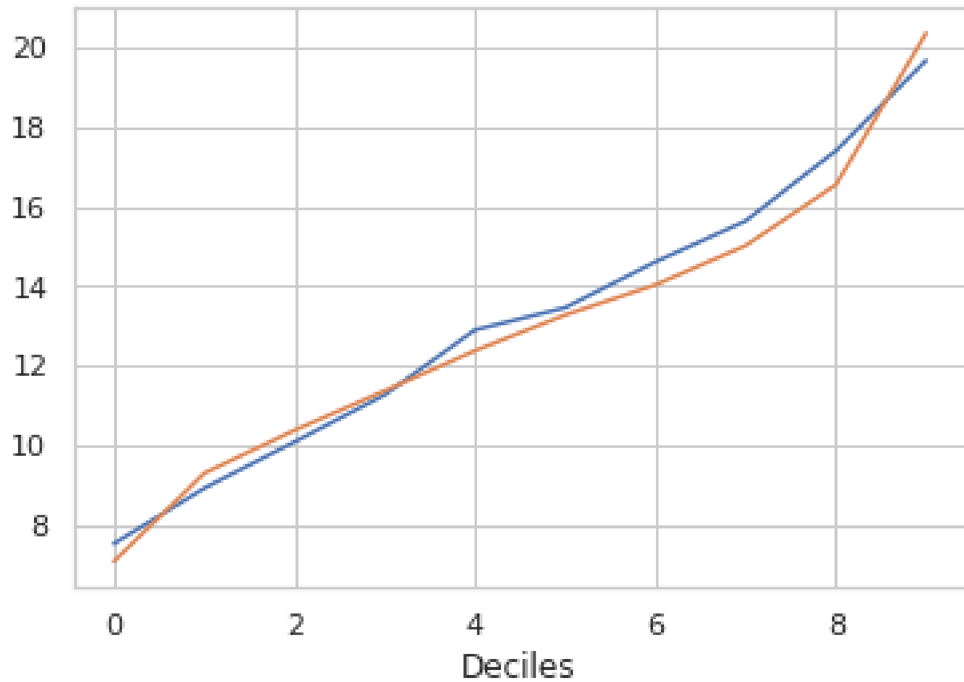
[65]:
```
test_new=pd.concat([test_y,test_pred],axis=1)
test_new.columns=['Actual','Predicted']
test_new['Deciles']=pd.qcut(test_new.Predicted,10,labels=False)
df2=test_new.groupby('Deciles').mean()
df2
```

[65]:

Deciles	Actual	Predicted
0	7.519547	7.072150
1	8.913440	9.290742
2	10.077333	10.370272
3	11.262800	11.364735
4	12.893600	12.373910
5	13.455467	13.270763
6	14.608667	14.029818
7	15.637200	15.017392
8	17.400933	16.545269
9	19.678575	20.361034

[66]:
```
sns.lineplot(x=df2.index,y='Actual',data=df2)
ax=sns.lineplot(x=df2.index,y='Predicted',data=df2)
ax.set(ylabel='')
```

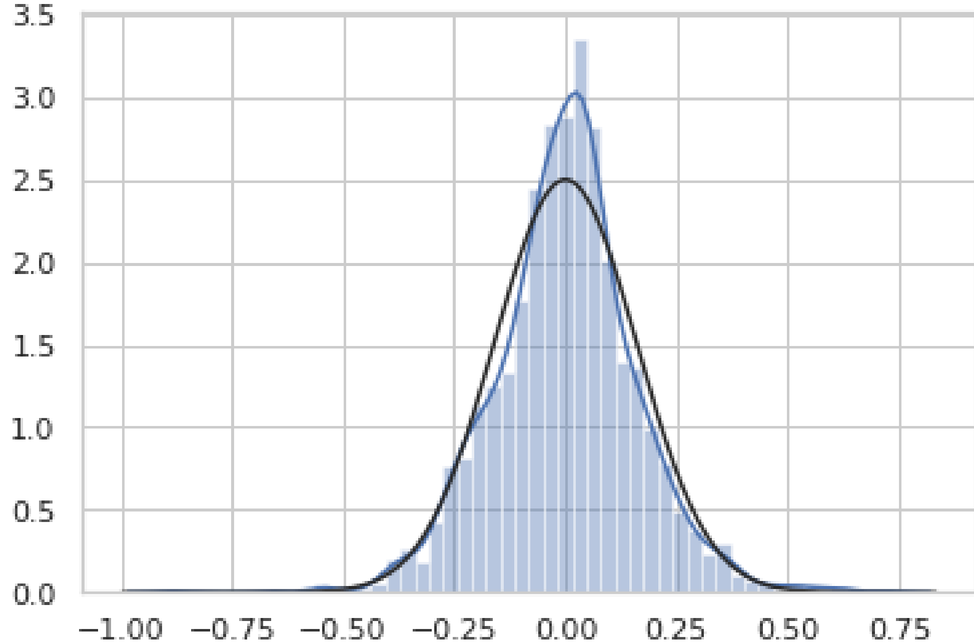
[66]: `[Text(0, 0.5, '')]`



- From above dataframe and plot :
  - We see that for our testing data both Actual and the predicted values increase with increasing deciles, i.e rank order is mainteined here also.

[67]:
```
# distribution of residuals
sns.distplot(model.resid,fit=stats.norm)
```

[67]: `<matplotlib.axes._subplots.AxesSubplot at 0x7fa4a856e978>`



-C.Varun END ~