Lending Club Interest Rate Prediction

- Description
    - This data set represents thousands of loans made through the Lending Club platform, which is a platform that allows individuals to lend to other individuals. Of course, not all loans are created equal. Someone who is a essentially a sure bet to pay back a loan will have an easier time getting a loan with a low interest rate than someone who appears to be riskier. And for people who are very risky? They may not even get a loan offer, or they may not have accepted the loan offer due to a high interest rate. It is important to keep that last part in mind, since this data set only represents loans actually made, i.e. do not mistake this data for loan applications!
- Source
    - This data comes from Lending Club (https://www.lendingclub.com/info/statistics.action), which provides a very large, open set of data on the people who received loans through their platform.

Walk-through of the Project

- 1. Cleansing, Preprocessing and EDA
    - Look at missing values
    - Distribution of interes rate
    - Categorical Variables -Explore categorical variables and interest rate
    - Numerical Variables -Explore numerical variables and interest rate
- 1. Feature engineering
    - Adding more variables
    - Scaling & Getting dummy
    - Feature selection(Lasso CV)
- 1. Model
    - Random Forest
    - XGBoost

Import data

In [155…

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.experimental import enable_iterative_imputer
from sklearn.impute import IterativeImputer
from string import ascii_letters
from sklearn.model_selection import RepeatedKFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import mean_squared_error,r2_score
from sklearn.preprocessing import MinMaxScaler,StandardScaler
from sklearn.preprocessing import Normalizer
from sklearn.model_selection import train_test_split
%matplotlib inline
```

In [2]:

```
data=pd.read_csv("loans_full_schema.csv")
```

In [3]:

```
data.head()
```

Out[3]:

	emp_title	emp_length	state	homeownership	annual_income	verified_income	debt_to_in
0	global config engineer	3.0	NJ	MORTGAGE	90000.0	Verified	
1	warehouse office clerk	10.0	HI	RENT	40000.0	Not Verified	
2	assembly	3.0	WI	RENT	40000.0	Source Verified	
3	customer service	1.0	PA	RENT	30000.0	Not Verified	
4	security supervisor	10.0	CA	RENT	35000.0	Verified	

5 rows × 55 columns

Cleansing, Preprocessing and EDA

In [4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 55 columns):
 #   Column                            Non-Null Count  Dtype
---  ------                            --------------  -----
```

```
 0   emp_title                         9167 non-null   object
 1   emp_length                        9183 non-null   float64
 2   state                             10000 non-null  object
 3   homeownership                     10000 non-null  object
 4   annual_income                     10000 non-null  float64
 5   verified_income                   10000 non-null  object
 6   debt_to_income                    9976 non-null   float64
 7   annual_income_joint               1495 non-null   float64
 8   verification_income_joint         1455 non-null   object
 9   debt_to_income_joint              1495 non-null   float64
 10  delinq_2y                         10000 non-null  int64
 11  months_since_last_delinq          4342 non-null   float64
 12  earliest_credit_line              10000 non-null  int64
 13  inquiries_last_12m                10000 non-null  int64
 14  total_credit_lines                10000 non-null  int64
 15  open_credit_lines                 10000 non-null  int64
 16  total_credit_limit                10000 non-null  int64
 17  total_credit_utilized             10000 non-null  int64
 18  num_collections_last_12m          10000 non-null  int64
 19  num_historical_failed_to_pay      10000 non-null  int64
 20  months_since_90d_late             2285 non-null   float64
 21  current_accounts_delinq           10000 non-null  int64
 22  total_collection_amount_ever      10000 non-null  int64
 23  current_installment_accounts      10000 non-null  int64
 24  accounts_opened_24m               10000 non-null  int64
 25  months_since_last_credit_inquiry  8729 non-null   float64
 26  num_satisfactory_accounts         10000 non-null  int64
 27  num_accounts_120d_past_due        9682 non-null   float64
 28  num_accounts_30d_past_due         10000 non-null  int64
 29  num_active_debit_accounts         10000 non-null  int64
 30  total_debit_limit                 10000 non-null  int64
 31  num_total_cc_accounts             10000 non-null  int64
 32  num_open_cc_accounts              10000 non-null  int64
 33  num_cc_carrying_balance           10000 non-null  int64
 34  num_mort_accounts                 10000 non-null  int64
 35  account_never_delinq_percent      10000 non-null  float64
 36  tax_liens                         10000 non-null  int64
 37  public_record_bankrupt            10000 non-null  int64
 38  loan_purpose                      10000 non-null  object
 39  application_type                  10000 non-null  object
 40  loan_amount                       10000 non-null  int64
 41  term                              10000 non-null  int64
 42  interest_rate                     10000 non-null  float64
 43  installment                       10000 non-null  float64
 44  grade                             10000 non-null  object
 45  sub_grade                         10000 non-null  object
 46  issue_month                       10000 non-null  object
 47  loan_status                       10000 non-null  object
 48  initial_listing_status            10000 non-null  object
 49  disbursement_method               10000 non-null  object
 50  balance                           10000 non-null  float64
 51  paid_total                        10000 non-null  float64
 52  paid_principal                    10000 non-null  float64
 53  paid_interest                     10000 non-null  float64
 54  paid_late_fees                    10000 non-null  float64
dtypes: float64(17), int64(25), object(13)
memory usage: 4.2+ MB
```

10000 sample size with 55columns.

In [5]:
```
df_miss=data.isnull().sum()/len(data)*100
df_miss=pd.DataFrame(df_miss,columns=['percentage'])
```

Difficult for to fill in the null values because emp_title are categorical vairables.Too much category.Just delete this colum

In [6]:
```
##delete missing data>50%
df_miss[df_miss['percentage']>50]
```

Out[6]:

	percentage
annual_income_joint	85.05
verification_income_joint	85.45
debt_to_income_joint	85.05
months_since_last_delinq	56.58
months_since_90d_late	77.15

In [7]:
```
##drop vairables missing values percentage>50
data_new=data.drop(df_miss[df_miss['percentage']>50].index,axis=1)
```

In [8]:
```
data_new.columns
```

Out[8]:
```
Index(['emp_title', 'emp_length', 'state', 'homeownership', 'annual_income',
       'verified_income', 'debt_to_income', 'delinq_2y',
       'earliest_credit_line', 'inquiries_last_12m', 'total_credit_lines',
       'open_credit_lines', 'total_credit_limit', 'total_credit_utilized',
       'num_collections_last_12m', 'num_historical_failed_to_pay',
       'current_accounts_delinq', 'total_collection_amount_ever',
       'current_installment_accounts', 'accounts_opened_24m',
       'months_since_last_credit_inquiry', 'num_satisfactory_accounts',
       'num_accounts_120d_past_due', 'num_accounts_30d_past_due',
       'num_active_debit_accounts', 'total_debit_limit',
       'num_total_cc_accounts', 'num_open_cc_accounts',
       'num_cc_carrying_balance', 'num_mort_accounts',
       'account_never_delinq_percent', 'tax_liens', 'public_record_bankrupt',
       'loan_purpose', 'application_type', 'loan_amount', 'term',
       'interest_rate', 'installment', 'grade', 'sub_grade', 'issue_month',
       'loan_status', 'initial_listing_status', 'disbursement_method',
       'balance', 'paid_total', 'paid_principal', 'paid_interest',
       'paid_late_fees'],
      dtype='object')
```

Dealing with categorical variables

In [9]:
```
cat_cols = data_new.select_dtypes(include=("object"))
```

In [10]:
```
cat_cols.columns
```

Out[10]:
```
Index(['emp_title', 'state', 'homeownership', 'verified_income',
       'loan_purpose', 'application_type', 'grade', 'sub_grade', 'issue_month'
,
       'loan_status', 'initial_listing_status', 'disbursement_method'],
      dtype='object')
```

In [11]:
```
cat_cols['emp_title'].nunique()
```

Out[11]:
```
4741
```

In [12]:
```
cat_cols['state'].nunique()
```

Out[12]:
```
50
```

In [13]:
```
cat_cols['emp_title'].value_counts()
```

Out[13]:
```
manager                                  218
owner                                    204
teacher                                  201
driver                                   123
sales                                     97
                                        ...
cooler service technician                  1
its5                                       1
nursing supervisor                         1
partner physician                          1
brand ambassador/promotional model         1
Name: emp_title, Length: 4741, dtype: int64
```

In [14]:
```
## Too many unique values for employment title, which is low
cat_cols=cat_cols.drop(['emp_title'],axis=1)
```

In [15]:
```
for i in cat_cols.columns.tolist():
    print(data_new[i].value_counts())
```

```
CA    1330
TX     806
NY     793
FL     732
```

```
IL     382
NJ     338
OH     338
GA     334
NC     299
PA     298
VA     261
AZ     255
MD     247
MI     245
MA     237
WA     235
CO     235
CT     181
IN     178
TN     167
MO     159
MN     159
NV     158
SC     145
OR     130
WI     128
AL     122
KY      97
LA      96
KS      89
OK      81
MS      72
AR      70
WV      68
UT      61
NE      56
RI      53
NH      47
NM      43
ID      38
HI      35
AK      33
ME      26
MT      24
DE      24
VT      23
SD      20
WY      19
DC      19
ND      14
Name: state, dtype: int64
MORTGAGE    4789
RENT        3858
OWN         1353
Name: homeownership, dtype: int64
Source Verified    4116
Not Verified       3594
Verified           2290
Name: verified_income, dtype: int64
debt_consolidation    5144
credit_card           2249
```

```
other                    914
home_improvement         680
major_purchase           303
medical                  162
house                    151
car                      131
small_business           125
moving                    69
vacation                  62
renewable_energy          10
Name: loan_purpose, dtype: int64
individual    8505
joint         1495
Name: application_type, dtype: int64
B    3037
C    2653
A    2459
D    1446
E     335
F      58
G      12
Name: grade, dtype: int64
B1    647
B2    638
B5    631
C1    597
B4    581
C2    572
A4    568
B3    540
A3    504
C4    503
C3    501
A5    485
A2    480
C5    480
A1    422
D2    323
D1    319
D3    311
D5    262
D4    231
E5     91
E3     73
E4     73
E2     57
E1     41
F1     31
G1     11
F2      9
F3      9
F4      5
F5      4
G4      1
Name: sub_grade, dtype: int64
Mar-2018    3617
Jan-2018    3395
```

```
Feb-2018    2988
Name: issue_month, dtype: int64
Current                 9375
Fully Paid               447
In Grace Period           67
Late (31-120 days)        66
Late (16-30 days)         38
Charged Off                7
Name: loan_status, dtype: int64
whole          8206
fractional     1794
Name: initial_listing_status, dtype: int64
Cash         9284
DirectPay     716
Name: disbursement_method, dtype: int64
```

In [16]:

```
from scipy.stats import spearmanr
```

In [17]:

```
## Not much correlaiton between state and interest rate
data_new['state'].corr(data_new['interest_rate'],method='spearman')
```

Out[17]:

```
0.0011210910173769094
```

In [18]:

```
cat_cols=cat_cols.drop(['state'],axis=1)
```

the correlation is not strong and delete the state columns

In [19]:

```
for i in cat_cols.columns.tolist():
    cor=data_new[i].corr(data_new['interest_rate'],method='spearman')
    print(i,cor)
```

```
homeownership 0.08748952903152749
verified_income 0.24571897146283708
loan_purpose 0.0476652973560531
application_type 0.053857860348730205
grade 0.9666157034979389
sub_grade 0.9981746241279144
issue_month -0.03445875962956296
loan_status 0.08271675152667414
initial_listing_status -0.10904837269519452
disbursement_method -0.18045601139148257
```

In [222…

```
for i in cat_cols.columns.tolist():
    cor=data_new[i].corr(data_new['grade'],method='spearman')
    print(i,cor)
```

```
homeownership 0.07812752527000763
verified_income 0.23479181403496524
loan_purpose 0.05090817031653836
application_type 0.05495150790610031
grade 0.9999999999999999
sub_grade 0.968431774166524
issue_month -0.012100618280686318
loan_status 0.07546741175826262
initial_listing_status -0.11377718580877846
disbursement_method -0.17106527952418277
```

In [21]:

```
data_new['interest_rate'].round().value_counts()
```

Out[21]:

```
10.0    1178
14.0    1073
7.0     1072
9.0      647
12.0     631
13.0     597
11.0     581
15.0     503
8.0      485
6.0      482
16.0     480
5.0      422
18.0     322
17.0     319
19.0     311
20.0     230
21.0     172
26.0     126
22.0      90
25.0      73
24.0      57
23.0      41
27.0      38
29.0      31
31.0      21
30.0      18
Name: interest_rate, dtype: int64
```

In [224…

```
data_new.describe()
```

Out[224...

	emp_length	annual_income	debt_to_income	delinq_2y	earliest_credit_line	inquirie
count	9183.000000	1.000000e+04	9976.000000	10000.00000	10000.00000	1
mean	5.930306	7.922215e+04	19.308192	0.21600	2001.29000	
std	3.703734	6.473429e+04	15.004851	0.68366	7.79551	
min	0.000000	0.000000e+00	0.000000	0.00000	1963.00000	
25%	2.000000	4.500000e+04	11.057500	0.00000	1997.00000	
50%	6.000000	6.500000e+04	17.570000	0.00000	2003.00000	
75%	10.000000	9.500000e+04	25.002500	0.00000	2006.00000	
max	10.000000	2.300000e+06	469.090000	13.00000	2015.00000	

8 rows × 42 columns

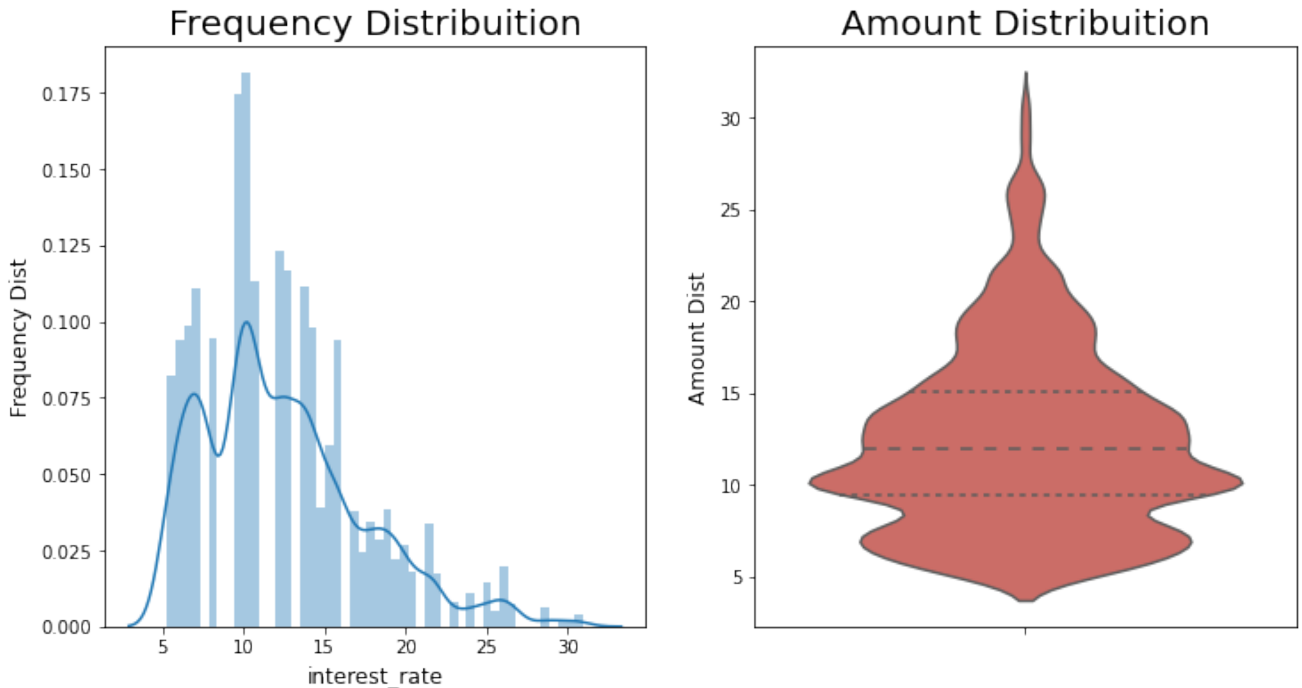
Many variables containing outliers and missing values

Distribution of interest rate

In [22]:

```
plt.figure(figsize=(12,6))
plt.subplot(121)
g = sns.distplot(data_new["interest_rate"])
g.set_xlabel("interest_rate", fontsize=12)
g.set_ylabel("Frequency Dist", fontsize=12)
g.set_title("Frequency Distribuition", fontsize=20)
plt.subplot(122)
g1 = sns.violinplot(y="interest_rate", data=data_new,
               inner="quartile", palette="hls")
g1.set_xlabel("", fontsize=12)
g1.set_ylabel("Amount Dist", fontsize=12)
g1.set_title("Amount Distribuition", fontsize=20)

plt.show()
```

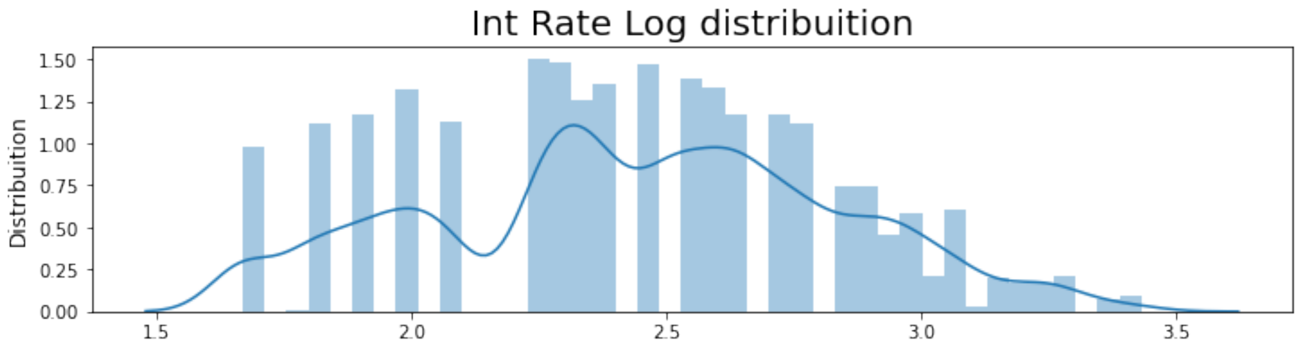
```
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributi
ons.py:2557: FutureWarning: `distplot` is a deprecated function and will be re
moved in a future version. Please adapt your code to use either `displot` (a f
igure-level function with similar flexibility) or `histplot` (an axes-level fu
nction for histograms).
  warnings.warn(msg, FutureWarning)
```



In [24]:

```
## The distribution of interest rate is right-skewed, we should log transfrom
#Exploring the Int_rate
data_new['log_int_rate']=np.log(data_new["interest_rate"])
plt.figure(figsize=(12,6))
plt.subplot(211)
g = sns.distplot(data_new['log_int_rate'])
g.set_xlabel("", fontsize=12)
g.set_ylabel("Distribuition", fontsize=12)
g.set_title("Int Rate Log distribuition", fontsize=20)
plt.show()
```

```
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributi
ons.py:2557: FutureWarning: `distplot` is a deprecated function and will be re
moved in a future version. Please adapt your code to use either `displot` (a f
igure-level function with similar flexibility) or `histplot` (an axes-level fu
nction for histograms).
  warnings.warn(msg, FutureWarning)
```



If we are transform the distribution of interest rate, we can apply linear regression

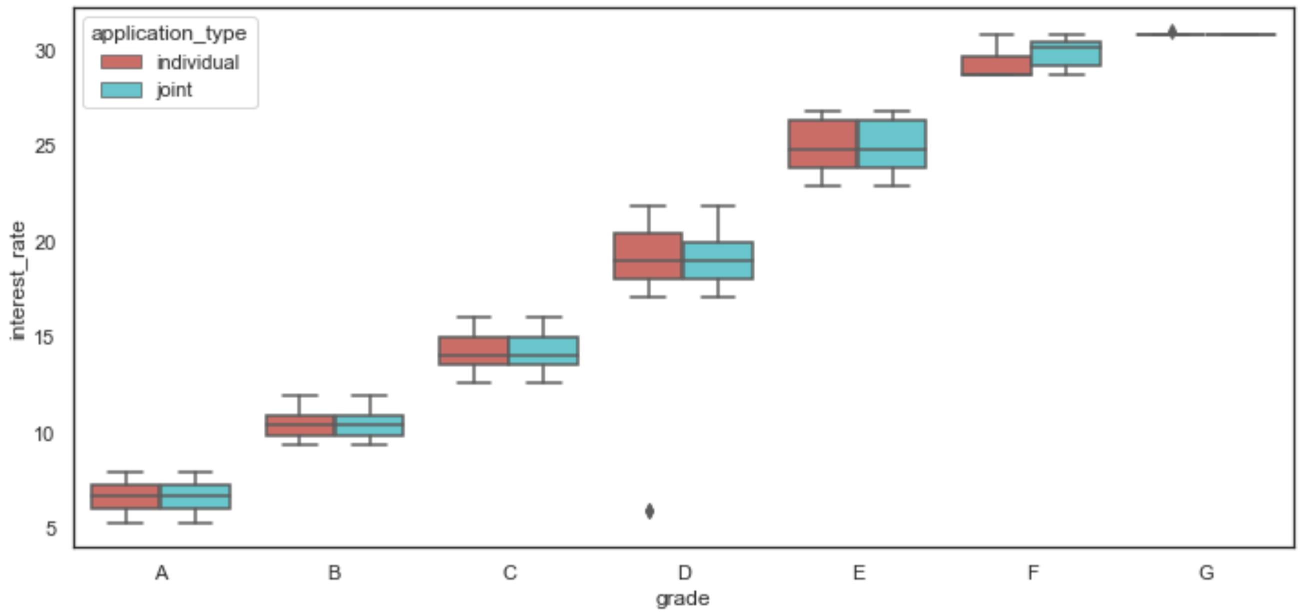
Explore categorical variables and interest rate

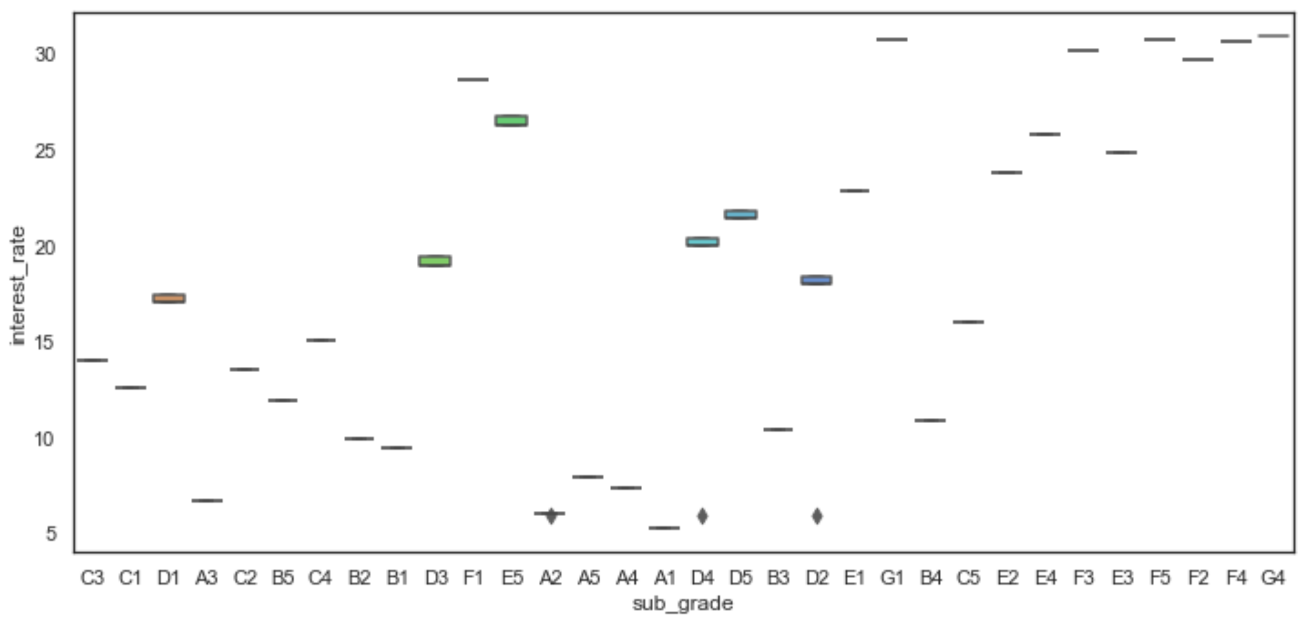
Grades and Subgrades

In [96]:

```
##Grade& interest rate
plt.figure(figsize=(12,12))
plt.subplot(211)
sns.boxplot(x="grade", y="interest_rate", data=data_new,palette="hls", hue="a
plt.subplot(212)
sns.boxenplot(x="sub_grade", y="interest_rate", data=data_new,palette="hls")
```

Out[96]: <AxesSubplot:xlabel='sub_grade', ylabel='interest_rate'>



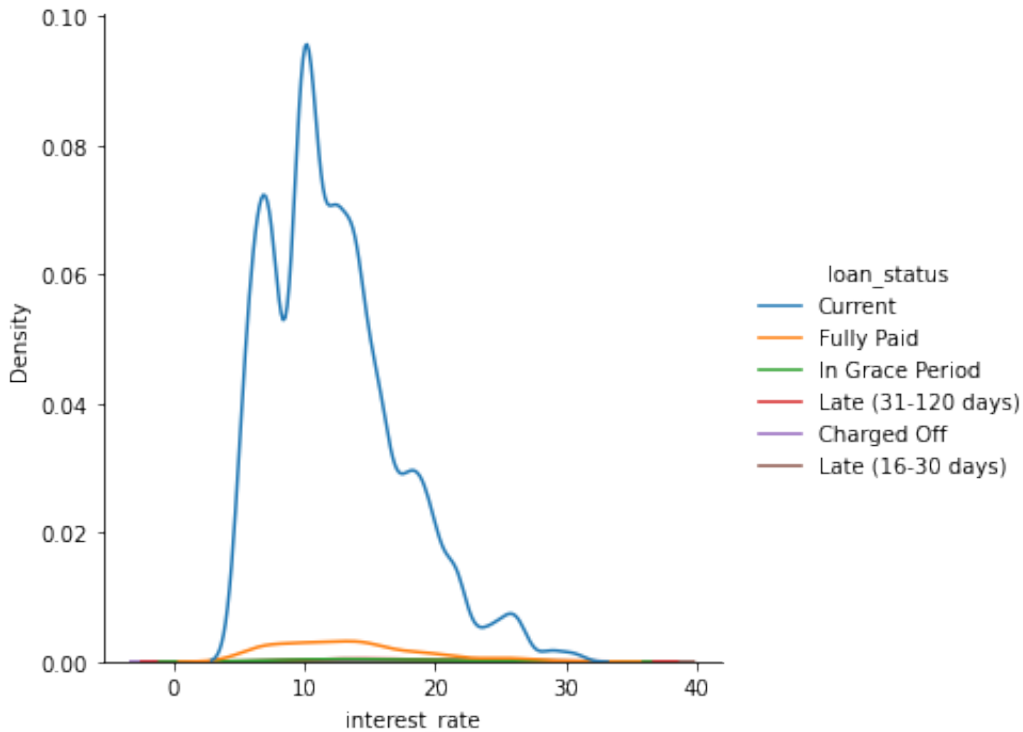


It is obvious that grade had high correlation with interest rate Higher grade, higher interest rate

In [25]:

```
##Loan_status& interest rate
sns.displot(data=data_new,x="interest_rate",hue='loan_status',kind='kde')
```

Out[25]: <seaborn.axisgrid.FacetGrid at 0x7ffc8ae32eb0>



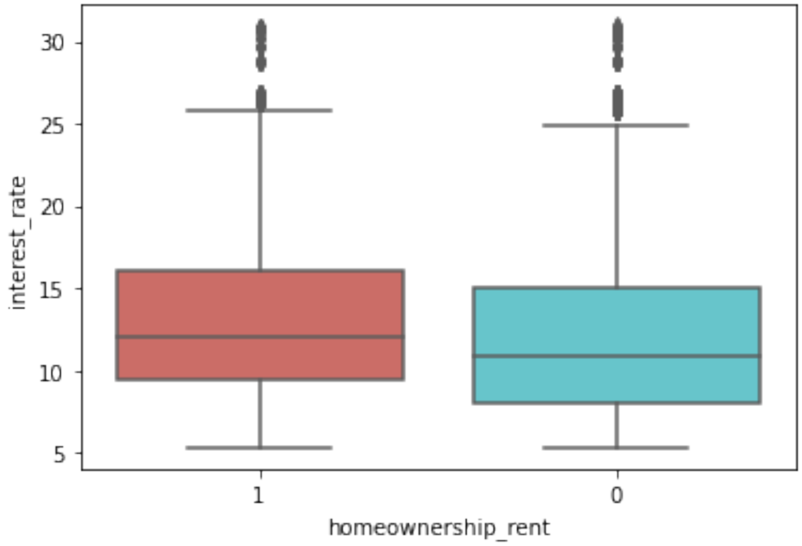
In [28]:
```
##Homeownership& interest rate
data_new['homeownership'].value_counts()
```

Out[28]:
```
MORTGAGE    4789
RENT        3858
OWN         1353
Name: homeownership, dtype: int64
```

In [30]:
```
data_new['homeownership_rent']=np.where(data_new['homeownership']=='RENT',1,0
```

In [33]:
```
fig= plt.figsize=(24,10)
sns.boxplot(x="homeownership_rent", y="interest_rate", data=data_new,palette=
```

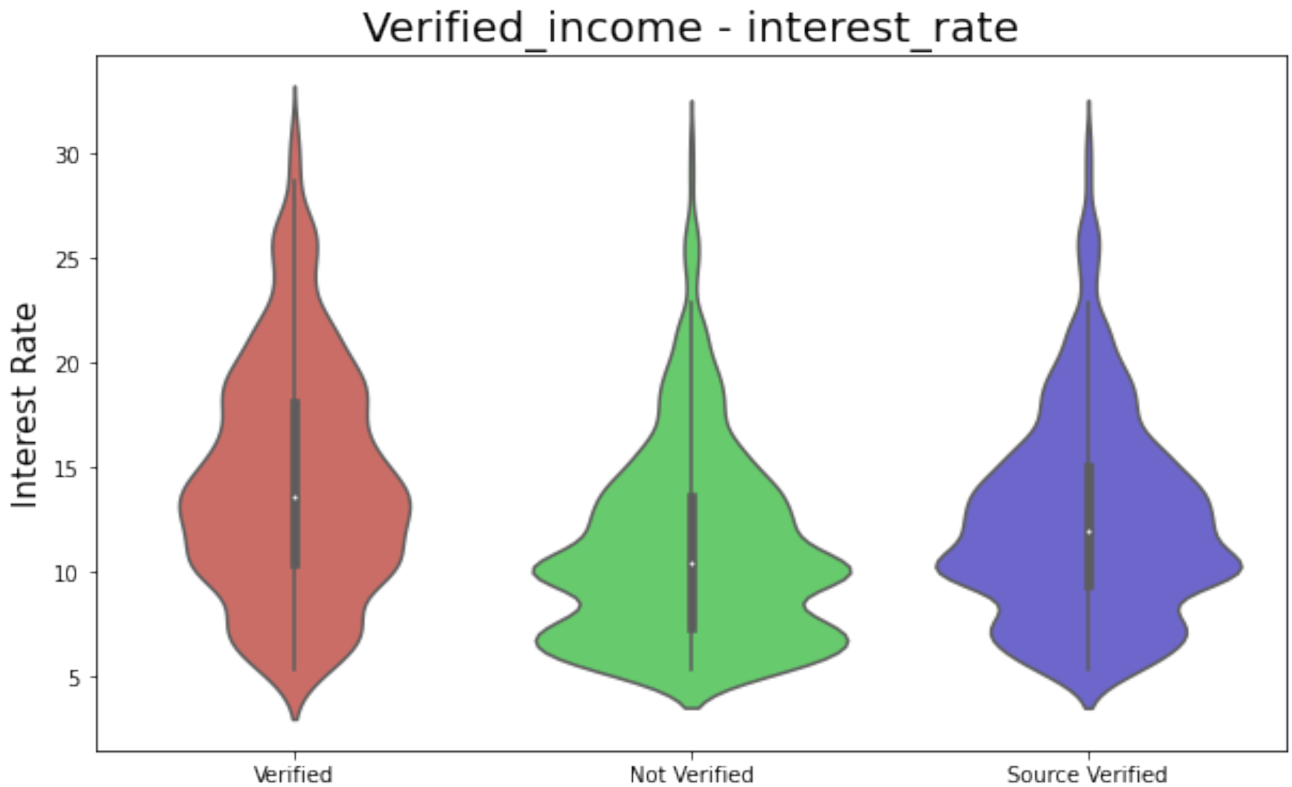
Out[33]: <AxesSubplot:xlabel='homeownership_rent', ylabel='interest_rate'>



In [34]:
```
##Homeownership& interest rate
data_new['verified_income'].value_counts()
```

Out[34]:
```
Source Verified    4116
Not Verified       3594
Verified           2290
Name: verified_income, dtype: int64
```

In [35]:
```
plt.figure(figsize = (10,6))

g = sns.violinplot(x="verified_income",y="interest_rate",data=data_new,
               kind="violin",
               split=True,palette="hls")
g.set_title("Verified_income - interest_rate", fontsize=20)
g.set_xlabel("", fontsize=15)
g.set_ylabel("Interest Rate", fontsize=15)

plt.show()
```



higher correlation with grade, maintain the columns

All categorical variables are bearable number of categories

In [72]:
```
df_cat = pd.get_dummies(cat_cols,columns=cat_cols.columns.tolist(),drop_first
```

df_cat

Numerical columns processing

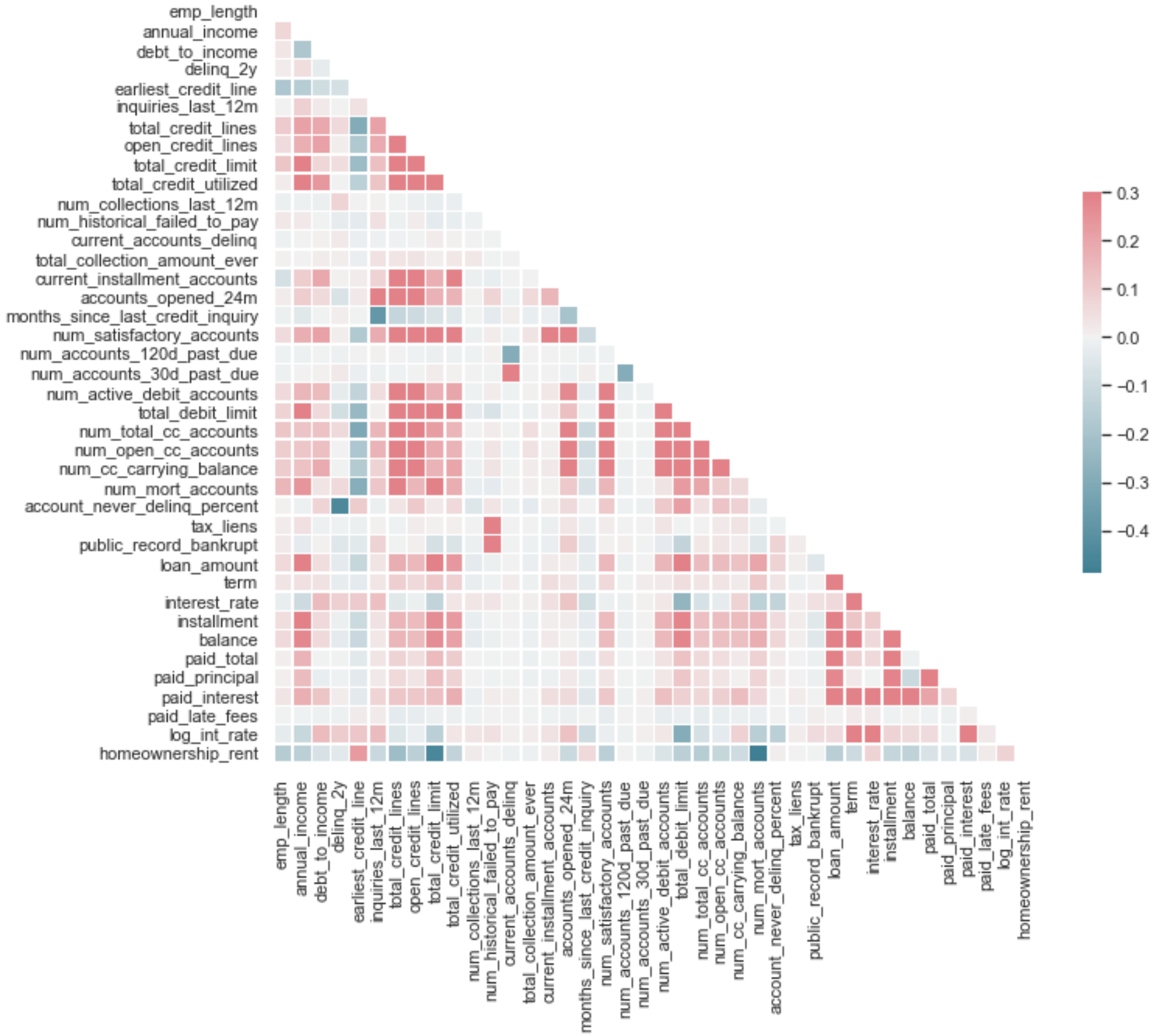
In [39]:
```
# Subset numeric features: numeric_cols
numeric_cols = data_new.select_dtypes(include=[np.number])
# Iteratively impute
imp_iter = IterativeImputer(max_iter=5, sample_posterior=True, random_state=1
loans_imp_iter = imp_iter.fit_transform(numeric_cols)
# Convert returned array to DataFrame
loans_imp_iterDF = pd.DataFrame(loans_imp_iter, columns=numeric_cols.columns)
```

In [40]:
```
numeric_cols.columns
```

Out[40]:
```
Index(['emp_length', 'annual_income', 'debt_to_income', 'delinq_2y',
       'earliest_credit_line', 'inquiries_last_12m', 'total_credit_lines',
       'open_credit_lines', 'total_credit_limit', 'total_credit_utilized',
       'num_collections_last_12m', 'num_historical_failed_to_pay',
       'current_accounts_delinq', 'total_collection_amount_ever',
       'current_installment_accounts', 'accounts_opened_24m',
       'months_since_last_credit_inquiry', 'num_satisfactory_accounts',
       'num_accounts_120d_past_due', 'num_accounts_30d_past_due',
       'num_active_debit_accounts', 'total_debit_limit',
       'num_total_cc_accounts', 'num_open_cc_accounts',
       'num_cc_carrying_balance', 'num_mort_accounts',
       'account_never_delinq_percent', 'tax_liens', 'public_record_bankrupt',
       'loan_amount', 'term', 'interest_rate', 'installment', 'balance',
       'paid_total', 'paid_principal', 'paid_interest', 'paid_late_fees',
       'log_int_rate', 'homeownership_rent'],
      dtype='object')
```

In [41]:
```
##correlations
sns.set(style="white")

corr = loans_imp_iterDF.corr()

mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

f, ax = plt.subplots(figsize=(11, 9))

cmap = sns.diverging_palette(220, 10, as_cmap=True)

sns.heatmap(corr, mask=mask, cmap=cmap, vmax=.3, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})
```

Out[41]: <AxesSubplot:>



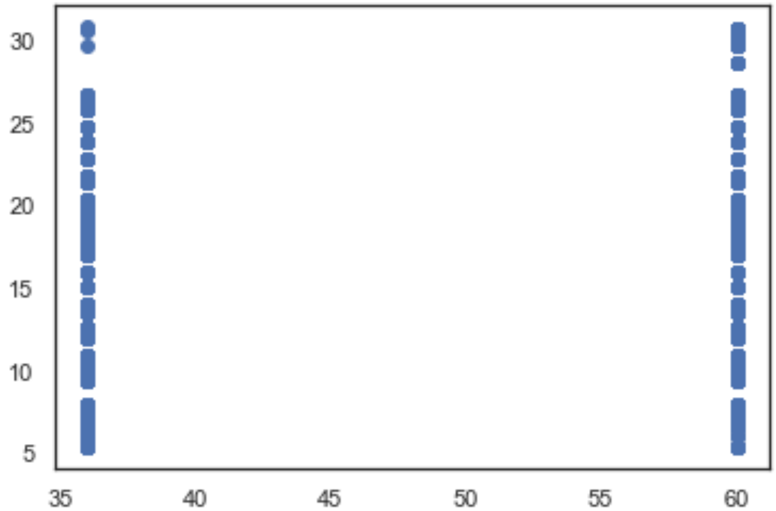
In [81]:

```
X_num=loans_imp_iterDF.drop(['interest_rate'],axis=1)
for i in X_num.columns.tolist():
    cor=loans_imp_iterDF[i].corr(loans_imp_iterDF['interest_rate'])
    print(i,cor)
```

```
emp_length -0.022864260617945827
annual_income -0.09958433559316995
debt_to_income 0.14013187435197783
delinq_2y 0.09045622123463228
earliest_credit_line 0.10363461600403122
inquiries_last_12m 0.13119296831174532
total_credit_lines -0.04443485546943214
open_credit_lines -0.012773330697410155
total_credit_limit -0.1304965801657026
total_credit_utilized 0.03152743152587917
num_collections_last_12m 0.02990136827787591
num_historical_failed_to_pay 0.03756269731790593
current_accounts_delinq 0.007184083055156142
total_collection_amount_ever 0.013532163648097315
current_installment_accounts 0.047131258024430724
accounts_opened_24m 0.120656747256795
months_since_last_credit_inquiry -0.08684992876486065
num_satisfactory_accounts -0.013329575570643909
num_accounts_120d_past_due -0.012513901637688854
num_accounts_30d_past_due 0.007184083055156142
num_active_debit_accounts 0.0268002604908547
total_debit_limit -0.254225259596709
num_total_cc_accounts -0.07123798773636468
num_open_cc_accounts -0.028891174410642345
num_cc_carrying_balance 0.0817406949144792
num_mort_accounts -0.13835135211087057
account_never_delinq_percent -0.12470193063277377
tax_liens 0.016547306573736924
public_record_bankrupt 0.047476574571926194
loan_amount 0.06452688502519918
installment 0.09881137993313831
balance 0.067569664942812
paid_total 0.06533871565081698
paid_principal -0.0019527818264753116
paid_interest 0.514507529964494
paid_late_fees 0.02310998704692934
log_int_rate 0.9720199909247791
homeownership_rent 0.07883478471311552
```

In [43]:

```
plt.plot(data_new['term'],data_new['interest_rate'],'bo')
plt.show()
```

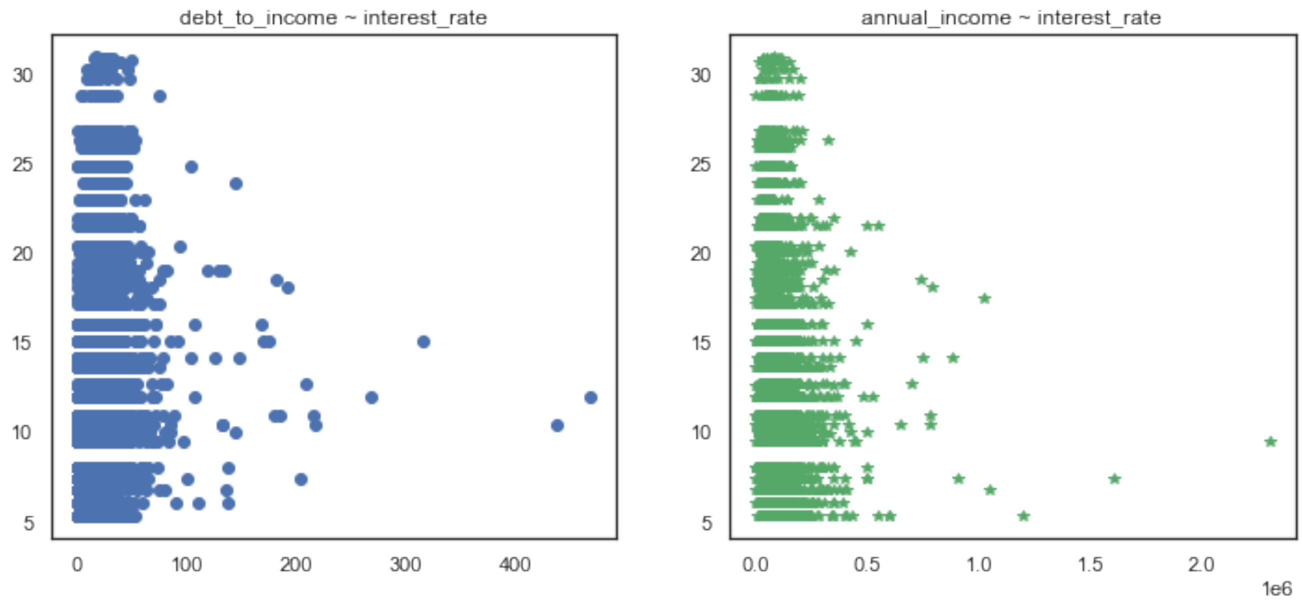


In [45]:
```
data_new['term_36']=data_new['term'][data_new['term']==36]
data_new['term_60']=data_new['term'][data_new['term']==60]
```

In [46]:
```
data_new['term_36']=np.where(data_new['term_36']==36,1,0)
data_new['term_60']=np.where(data_new['term_60']==60,1,0)
```

In [47]:
```
loans_imp_iterDF=loans_imp_iterDF.drop(['term'],axis=1)
```

In [221…
```
plt.figure(figsize=(12,5))
plt.subplot(121)
plt.plot(data_new['debt_to_income'],data_new['interest_rate'],'bo')
plt.title('debt_to_income ~ interest_rate')
plt.subplot(122)
plt.plot(data_new['annual_income'],data_new['interest_rate'],'g*')
plt.title('annual_income ~ interest_rate')
plt.show()
```



In [82]:
```
df_for_RF=pd.concat([df_cat,loans_imp_iterDF],axis=1)
```

In [83]:
```
len(df_for_RF.columns)
```

Out[83]: 101

In [84]:
```
df_total['log_int_rate'].isnull().sum()
```

Out[84]: 0

df_total.to_csv('df_total.csv')

DATA Scaling

In [127…
```
#normalise the data
X_train, y_train = Train.drop(['log_int_rate','interest_rate'], axis=1), Trai
X_test, y_test = Test.drop(['log_int_rate','interest_rate'], axis=1), Test.in
scaler = StandardScaler().fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
df_for_RF=pd.merge(X_train,)
```

Feature selection

Too much variables for 10000 samples

In [ ]:
```
df_for_RF
```

In [90]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [101…
```
df_for_RF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Columns: 101 entries, homeownership_OWN to homeownership_rent
dtypes: float64(39), uint8(62)
memory usage: 3.6 MB
```

In [109…
```
size = df_for_RF.shape[0]

Train, Test_new = train_test_split(df_for_RF, test_size= 0.3, random_state= 1

CV, Test_new = train_test_split(Test_new, test_size=0.5, random_state = 1)

print(Train.shape, CV.shape, Test_new.shape)
```

```
(7000, 101) (1500, 101) (1500, 101)
```

In [115…
```
CV
```

Out[115…

	homeownership_OWN	homeownership_RENT	verified_income_Source Verified	verified_income_V
4940	0	0	1	
7276	0	0	0	
7829	0	0	1	
9466	1	0	1	
8477	0	0	0	
...	...	...	...	
401	0	0	1	
6899	0	0	0	
5938	0	1	1	
3632	0	0	0	
2247	0	0	0	

1500 rows × 101 columns

In [133…

```
X_train, y_train = Train.drop(['log_int_rate','interest_rate'], axis=1), Trai
X_test, y_test = Test_new.drop(['log_int_rate','interest_rate'], axis=1), Tes
CV_x,CV_y= CV.drop(['log_int_rate','interest_rate'], axis=1), CV.interest_rat
x_col=X_train.columns
```

In [134…

```
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)
CV_x=scaler.transform(CV_x)
```

In [135…

```
Test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1500 entries, 5309 to 5509
Columns: 101 entries, homeownership_OWN to homeownership_rent
dtypes: float64(39), uint8(62)
memory usage: 559.6 KB
```

In [136…

```
CV_x
```

Out[136…

```
array([[-0.39384707, -0.79743102,  1.19570561, ..., -0.50967092,
        -0.06058442, -0.79743102],
       [-0.39384707, -0.79743102, -0.83632626, ...,  0.22273732,
        -0.06058442, -0.79743102],
       [-0.39384707, -0.79743102,  1.19570561, ...,  1.4397422 ,
        -0.06058442, -0.79743102],
       ...,
       [-0.39384707,  1.25402696,  1.19570561, ...,  0.26850925,
        -0.06058442,  1.25402696],
       [-0.39384707, -0.79743102, -0.83632626, ..., -0.53002038,
        -0.06058442, -0.79743102],
       [-0.39384707, -0.79743102, -0.83632626, ..., -0.75516619,
        -0.06058442, -0.79743102]])
```

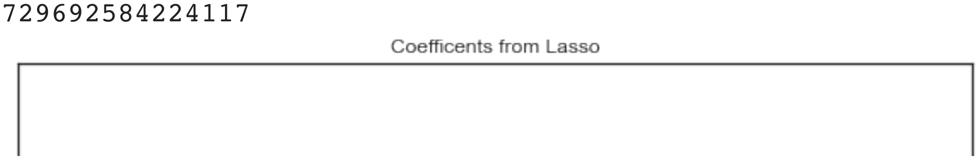
In [137…

```
from sklearn.linear_model import LassoCV
```

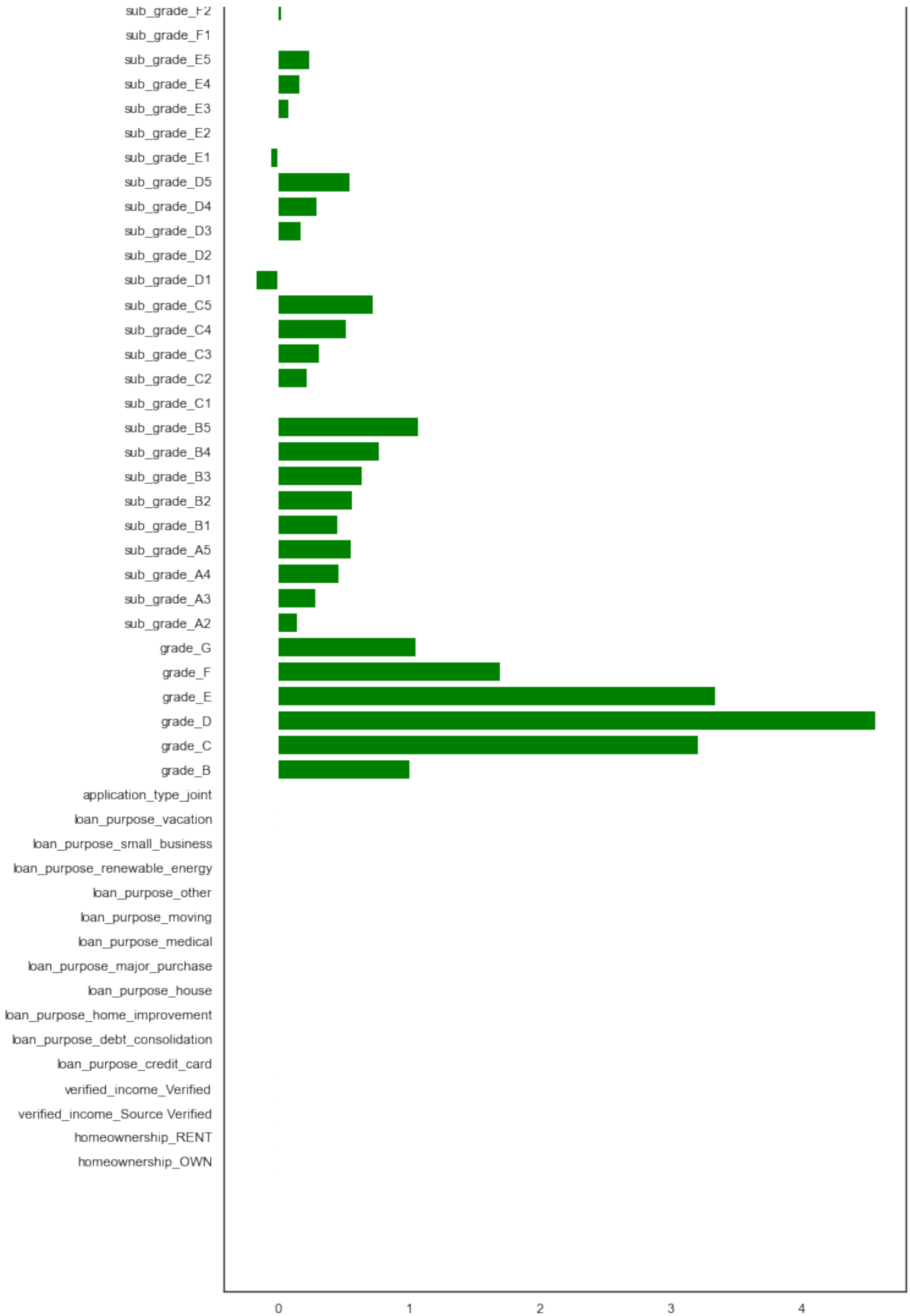
In [140…

```
modellasso = LassoCV(alphas = [1, 0.1, 0.001, 0.0001, 10, 1000]).fit(X_train,
lassopred = modellasso.predict(CV_x)
print("RMSE of Lasso: ", np.sqrt(mean_squared_error(lassopred, CV_y)))

coeff = modellasso.coef_

x = list(x_col)
x_pos = [i for i, _ in enumerate(x)]


plt.figure(figsize = (10,40))
plt.barh(x_pos, coeff, color='green')
plt.ylabel("Features -->")
plt.xlabel("Coefficents -->")
plt.title("Coefficents from Lasso")
plt.yticks(x_pos, x)

plt.show()
```

```
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_mod
el/_coordinate_descent.py:526: ConvergenceWarning: Objective did not converge.
You might want to increase the number of iterations. Duality gap: 47.482425143
210094, tolerance: 13.976402134792863
  model = cd_fast.enet_coordinate_descent_gram(
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_mod
el/_coordinate_descent.py:526: ConvergenceWarning: Objective did not converge.
You might want to increase the number of iterations. Duality gap: 47.748994576
64486, tolerance: 14.105763850998242
  model = cd_fast.enet_coordinate_descent_gram(
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_mod
el/_coordinate_descent.py:526: ConvergenceWarning: Objective did not converge.
You might want to increase the number of iterations. Duality gap: 48.381526926
15847, tolerance: 14.244188974555362
  model = cd_fast.enet_coordinate_descent_gram(
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_mod
el/_coordinate_descent.py:526: ConvergenceWarning: Objective did not converge.
You might want to increase the number of iterations. Duality gap: 40.249599592
524504, tolerance: 13.933095255312502
  model = cd_fast.enet_coordinate_descent_gram(
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_mod
el/_coordinate_descent.py:526: ConvergenceWarning: Objective did not converge.
You might want to increase the number of iterations. Duality gap: 48.324623627
30462, tolerance: 14.07528496898393
  model = cd_fast.enet_coordinate_descent_gram(
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_mod
el/_coordinate_descent.py:530: ConvergenceWarning: Objective did not converge.
You might want to increase the number of iterations. Duality gap: 117.74069625
64507, tolerance: 17.58403962490858
  model = cd_fast.enet_coordinate_descent(
RMSE of Lasso:  0.3729692584224117
```




homeownership_rent
paid_late_fees
paid_interest
paid_principal
paid_total
balance
installment
loan_amount
public_record_bankrupt
tax_liens
account_never_delinq_percent
num_mort_accounts
num_cc_carrying_balance
num_open_cc_accounts
num_total_cc_accounts
total_debit_limit
num_active_debit_accounts
num_accounts_30d_past_due
num_accounts_120d_past_due
num_satisfactory_accounts
months_since_last_credit_inquiry
accounts_opened_24m
current_installment_accounts
total_collection_amount_ever
current_accounts_delinq
num_historical_failed_to_pay
num_collections_last_12m
total_credit_utilized
total_credit_limit
open_credit_lines
total_credit_lines
inquiries_last_12m
earliest_credit_line
delinq_2y
debt_to_income
annual_income
emp_length
disbursement_method_DirectPay
initial_listing_status_whole
loan_status_Late (31-120 days)
loan_status_Late (16-30 days)
loan_status_In Grace Period
loan_status_Fully Paid
loan_status_Current
issue_month_Mar-2018
issue_month_Jan-2018
sub_grade_G4
sub_grade_G1
sub_grade_F5
sub_grade_F4
sub_grade_F3
Features -->


sub_grade_F2
sub_grade_F1
sub_grade_E5
sub_grade_E4
sub_grade_E3
sub_grade_E2
sub_grade_E1
sub_grade_D5
sub_grade_D4
sub_grade_D3
sub_grade_D2
sub_grade_D1
sub_grade_C5
sub_grade_C4
sub_grade_C3
sub_grade_C2
sub_grade_C1
sub_grade_B5
sub_grade_B4
sub_grade_B3
sub_grade_B2
sub_grade_B1
sub_grade_A5
sub_grade_A4
sub_grade_A3
sub_grade_A2
grade_G
grade_F
grade_E
grade_D
grade_C
grade_B
application_type_joint
loan_purpose_vacation
loan_purpose_small_business
loan_purpose_renewable_energy
loan_purpose_other
loan_purpose_moving
loan_purpose_medical
loan_purpose_major_purchase
loan_purpose_house
loan_purpose_home_improvement
loan_purpose_debt_consolidation
loan_purpose_credit_card
verified_income_Verified
verified_income_Source Verified
homeownership_RENT
homeownership_OWN
0
1
2
3
4

Coefficents -->

In [142…

```
data_col=pd.DataFrame(columns=['name','coeff'])
co=list(coeff)
```

In [143…

```
data_col['name']=x_col
data_col['coeff']=co
```

In [144…

```
data_col.sort_values(by='coeff',ascending=False)
```

Out[144…

	name	coeff
18	grade_D	4.557579
19	grade_E	3.333528
17	grade_C	3.205376
20	grade_F	1.692306
30	sub_grade_B5	1.067477
...	...	...
53	issue_month_Jan-2018	-0.004499
68	total_credit_lines	-0.005607
31	sub_grade_C1	-0.005758
41	sub_grade_E1	-0.062488
36	sub_grade_D1	-0.175357

99 rows × 2 columns

In [145…

```
data_col.count()
```

Out[145…

```
name      99
coeff     99
dtype: int64
```

In [183…

```
col=data_col[abs(data_col['coeff'])>0.5]
```

In [184…

```
col.count()
```

Out[184…
```
name     14
coeff    14
dtype: int64
```

In [185…
```
col['name'].tolist()
```

Out[185…
```
['grade_B',
 'grade_C',
 'grade_D',
 'grade_E',
 'grade_F',
 'grade_G',
 'sub_grade_A5',
 'sub_grade_B2',
 'sub_grade_B3',
 'sub_grade_B4',
 'sub_grade_B5',
 'sub_grade_C4',
 'sub_grade_C5',
 'sub_grade_D5']
```

Random Forest

- Advantages of random forest
  - It can perform both regression and classification tasks.
  - A random forest produces good predictions that can be understood easily.
  - It can handle large datasets efficiently.
  - The random forest algorithm provides a higher level of accuracy in predicting outcomes over the decision tree algorithm.
- Disadvantages of random forest
  - When using a random forest, more resources are required for computation.
  - It consumes more time compared to a decision tree algorithm.

In [186…
```
features= df_for_RF[col['name'].tolist()]
labels=df_total['interest_rate']
```

In [187…
```
train_features, test_features, train_labels, test_labels = train_test_split(f
```

In [188…
```
print('Training Features Shape:', train_features.shape)
print('Testing Features Shape:', test_features.shape)
print('Training Labels Shape:', train_labels.shape)
print('Testing Labels Shape:', test_labels.shape)
```

```
Training Features Shape: (7000, 14)
Testing Features Shape: (3000, 14)
Training Labels Shape: (7000,)
Testing Labels Shape: (3000,)
```

In [189…

```
from sklearn.ensemble import RandomForestRegressor
```

In [209…

```
# Instantiate model (Using Default 10 Estimators)
rf = RandomForestRegressor(n_estimators= 10, random_state=42)

# Using Evaluation Function on our First Model

rf.fit(train_features, train_labels)

y_test_pred = rf.predict(test_features)
```

In [210…

```
y_test_pred.shape
```

Out[210… (3000,)

In [211…

```
# Mean squared error
from sklearn import metrics
print("Mean squared error: %.2f" % mean_squared_error(test_labels, y_test_pre
print('Mean Absolute Percentage Error (MAPE):', round(metrics.mean_absolute_p
print('Accuracy:', round(100*(1 - metrics.mean_absolute_percentage_error(test_
```

```
Mean squared error: 0.36
Mean Absolute Percentage Error (MAPE): 3.55
Accuracy: 96.45
```

Randomforest tuning

For model performance improvement, We should use parameter tunning

- n_estimators
    - The n_estimators parameter specifies the number of trees in the forest of the model. The default value for this parameter is 10, which means that 10 different decision trees will be constructed in the random forest.
- max_depth
    - The max_depth parameter specifies the maximum depth of each tree. The default value for max_depth is None, which means that each tree will expand until every leaf is pure. A pure leaf is one where all of the data on the leaf comes from the same class.
- min_samples_split
    - The min_samples_split parameter specifies the minimum number of samples required to split an internal leaf node. The default value for this parameter is 2, which means that an internal node must have at least two samples before it can be split to have a more specific classification.
- min_samples_leaf
    - The min_samples_leaf parameter specifies the minimum number of samples required to be at a leaf node. The default value for this parameter is 1, which means that every leaf must have at least 1 sample that it classifies.

param_test1 = {'n_estimators':range(10,71,10), {'max_depth':range(3,14,2), 'min_samples_split':range(50,201,20), 'min_samples_leaf':range(30,60,10) } gsearch1 = GridSearchCV(estimator = RandomForestClassifier(min_samples_split=100 min_samples_leaf=20,max_depth=8,max_features=' param_grid = param_test1, scoring='roc_auc',cv=5) gsearch1.fit(X,y) gsearch1.bestparams, gsearch1.bestscore

XGBoost

XGBoost is a highly optimized framework for gradient boosting, an algorithm that iteratively combines the predictions of several weak learners such as decision trees to produce a much stronger and more robust model.

In [193…

```
from scipy import stats
from sklearn.metrics import (
    accuracy_score, confusion_matrix, classification_report,
    roc_auc_score, roc_curve, auc,
    plot_confusion_matrix, plot_roc_curve
)
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from xgboost import XGBClassifier
```

param_grid = dict(n_estimators=stats.randint(10, 500), max_depth=stats.randint(1, 10), learning_rate=stats.uniform(0, 1))

xgb_clf = XGBClassifier() xgb_cv = RandomizedSearchCV(xgb_clf, param_grid, cv=3, n_iter=60, scoring='roc_auc', n_jobs=-1, verbose=1) xgb_cv.fit(X_train, y_train)

best_params = xgb_cv.best*params* print(best_params)

In [175…

```
best_params['booster'] = 'gblinear'
print(f"Best Parameters: {best_params}")
```

```
Best Parameters: {'learning_rate': 0.0012592383320760847, 'max_depth': 8, 'n_e
stimators': 204, 'booster': 'gblinear'}
```

In [212…

```
xgb_clf = XGBClassifier({'learning_rate': 0.0012592383320760847, 'max_depth':


xgb_clf.fit(train_features, train_labels)

y_test_pred = xgb_clf.predict(test_features)
```

```
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/xgboost/core.py:41
6: FutureWarning: Pass `objective` as keyword args.  Passing these as position
al arguments will be considered as error in future releases.
  warnings.warn(
/Users/yanzhenlei/opt/anaconda3/lib/python3.8/site-packages/xgboost/sklearn.py
:888: UserWarning: The use of label encoder in XGBClassifier is deprecated and
will be removed in a future release. To remove this warning, do the following:
1) Pass option use_label_encoder=False when constructing XGBClassifier object;
and 2) Encode your labels (y) as integers starting with 0, i.e. 0, 1, 2, ...,
[num_class - 1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
[19:54:39] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691
-43e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Sta
rting in XGBoost 1.3.0, the default evaluation metric used with the objective
'multi:softprob' was changed from 'merror' to 'mlogloss'. Explicitly set eval_
metric if you'd like to restore the old behavior.
```

In [213…

```
print("Mean squared error: %.2f" % mean_squared_error(test_labels, y_test_pre
print('Mean Absolute Percentage Error (MAPE):', round(metrics.mean_absolute_p
print('Accuracy:', round(100*(1 - metrics.mean_absolute_percentage_error(test_
```

```
Mean squared error: 0.62
Mean Absolute Percentage Error (MAPE): 4.64
Accuracy: 95.36
```

In [204…

```
# define model evaluation method
cv = RepeatedKFold(n_splits=5, n_repeats=3, random_state=1)
# evaluate model
scores = cross_val_score(xgb_clf, train_features, train_labels, scoring='neg_
print('Mean MAE: %.3f (%.3f)' % (scores.mean(), scores.std()) )
```

```
Mean MAE: -0.491 (0.042)
```

In [203…

```
# define model evaluation method
cv = RepeatedKFold(n_splits=5, n_repeats=3, random_state=1)
# evaluate model
scores = cross_val_score(rf, train_features, train_labels, scoring='neg_mean_
print('Mean MAE: %.3f (%.3f)' % (scores.mean(), scores.std()) )
```

```
Mean MAE: -0.383 (0.015)
```

Conclusion

- EDA
  - 10000 sample size with 55columns.
  - Many variables containing outliers and missing values
  - many variables are high-imbalanced.
  - Interest rate distribution are right-skewed. If we use linear regression, we should log-transform the interest rate
  - Grades an subgrades are highly correlated to interest rate
- Model Selection
  - Randomforest Model has mean MAE-0.383 and MAPE 3.55
  - XGBoost Model has mean MAE -0.491 and MAPE 4.64
  - Randomforest would be a better choice
- Feature Selection
  - The feature I choose are basily about Grade and Subgrade -grade: Grade associated with the loan. -sub_grade: Detailed grade associated with the loan.
  - However, we don't know what does grade are given. Only when we find out what influence grades, we can deep dive into different variables that affecting interest rate.
- Next step:
  - Add more models(Neural Networks and Linear regression)
  - Explore more about how does grades and sub-grades influences the interest rate. Correlaiton does not mean causual inferences
  - Explore more on the parameters,optimizing the performance of the model

In [ ]:

```

```