Case Study 1

In [37]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import colors
import plotly.express as px # for USA map
from mpl_toolkits import mplot3d # for 3D graph
%config InlineBackend.figure_format = 'retina'

import seaborn as sns # for heatmap
from sklearn.model_selection import train_test_split # to split the dataset
import statsmodels.api as sm # Linear Regression Approach 1
from sklearn.linear_model import LinearRegression # Linear Regression Approach 2
from sklearn.metrics import r2_score # to evaluate predictions
```

1. Dataset Pre-processing

In [38]:
```
df = pd.read_csv('loans_full_schema.csv')
df.head(10)
```

Out[38]:

	emp_title	emp_length	state	homeownership	annual_income	verified_income	debt_to_income	annual_income_joint	verification_income_joint	c
0	global config engineer	3.0	NJ	MORTGAGE	90000.0	Verified	18.01	NaN	NaN	
1	warehouse office clerk	10.0	HI	RENT	40000.0	Not Verified	5.04	NaN	NaN	
2	assembly	3.0	WI	RENT	40000.0	Source Verified	21.15	NaN	NaN	
3	customer service	1.0	PA	RENT	30000.0	Not Verified	10.16	NaN	NaN	
4	security supervisor	10.0	CA	RENT	35000.0	Verified	57.96	57000.0	Verified	
5	NaN	NaN	KY	OWN	34000.0	Not Verified	6.46	NaN	NaN	
6	hr	10.0	MI	MORTGAGE	35000.0	Source Verified	23.66	155000.0	Not Verified	
7	police	10.0	AZ	MORTGAGE	110000.0	Source Verified	16.19	NaN	NaN	
8	parts	10.0	NV	MORTGAGE	65000.0	Source Verified	36.48	NaN	NaN	
9	4th person	3.0	IL	RENT	30000.0	Not Verified	18.91	NaN	NaN	

10 rows × 55 columns

In [39]:
```
df.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
```

1.1 Remove NULL values

Let's see how many NULL values we have in our dataset.

In [40]:
```
df.isnull().sum()
```

Out[40]:
```
emp_title                           833
emp_length                          817
state                                 0
homeownership                         0
annual_income                         0
verified_income                       0
debt_to_income                       24
annual_income_joint                8505
verification_income_joint          8545
debt_to_income_joint               8505
delinq_2y                             0
months_since_last_delinq           5658
earliest_credit_line                  0
inquiries_last_12m                    0
total_credit_lines                    0
open_credit_lines                     0
total_credit_limit                    0
total_credit_utilized                 0
num_collections_last_12m              0
num_historical_failed_to_pay          0
months_since_90d_late              7715
current_accounts_delinq               0
total_collection_amount_ever          0
current_installment_accounts          0
accounts_opened_24m                   0
months_since_last_credit_inquiry   1271
num_satisfactory_accounts             0
num_accounts_120d_past_due          318
num_accounts_30d_past_due             0
num_active_debit_accounts             0
total_debit_limit                     0
num_total_cc_accounts                 0
num_open_cc_accounts                  0
num_cc_carrying_balance               0
num_mort_accounts                     0
account_never_delinq_percent          0
tax_liens                             0
public_record_bankrupt                0
loan_purpose                          0
application_type                      0
loan_amount                           0
term                                  0
interest_rate                         0
installment                           0
grade                                 0
sub_grade                             0
issue_month                           0
loan_status                           0
initial_listing_status                0
disbursement_method                   0
balance                               0
paid_total                            0
paid_principal                        0
paid_interest                         0
paid_late_fees                        0
dtype: int64
```

Unfortunately there are columns where most of values are NULLs. They are completely useless, so just remove those columns where more than 1% of the rows for that column contain a null value.

In [41]:
```
df_cleaned = df[[label for label in df if df[label].isnull().sum() <= 0.01 * df.shape[0]]]
```

Let's see how it looks like now.

In [42]:
```
df_cleaned.isnull().sum()
```

Out[42]:
```
state                          0
homeownership                  0
annual_income                  0
verified_income                0
debt_to_income                24
delinq_2y                      0
earliest_credit_line           0
inquiries_last_12m             0
total_credit_lines             0
open_credit_lines              0
total_credit_limit             0
total_credit_utilized          0
num_collections_last_12m       0
num_historical_failed_to_pay   0
current_accounts_delinq        0
total_collection_amount_ever   0
current_installment_accounts   0
accounts_opened_24m            0
num_satisfactory_accounts      0
num_accounts_30d_past_due      0
num_active_debit_accounts      0
total_debit_limit              0
num_total_cc_accounts          0
num_open_cc_accounts           0
num_cc_carrying_balance        0
num_mort_accounts              0
account_never_delinq_percent   0
tax_liens                      0
public_record_bankrupt         0
loan_purpose                   0
application_type               0
loan_amount                    0
term                           0
interest_rate                  0
installment                    0
grade                          0
sub_grade                      0
issue_month                    0
loan_status                    0
initial_listing_status         0
disbursement_method            0
balance                        0
paid_total                     0
paid_principal                 0
paid_interest                  0
paid_late_fees                 0
dtype: int64
```

Ok, much better. Now we have to do something with those NULL values. We can:

- remove rows cointain NULL values,
- fill them with median or mode value,
- or use some imputation and try to predict their missing values.

Let's try the first option and see what will happen.

In [43]:
```
df_cleaned = df_cleaned.dropna()
df_cleaned.shape[0] / df.shape[0]
```

Out[43]:
```
0.9976
```

It looks good, we removed less than 0.3% of rows. I think it's good enough and there's no point to do something more with that.

1.2 Remove useless columns

Let's take a look on our cleaned dataset.

In [44]:
```python
df_cleaned.head(10)
```

Out[44]:

	state	homeownership	annual_income	verified_income	debt_to_income	delinq_2y	earliest_credit_line	inquiries_last_12m	total_credit_lines	ope
0	NJ	MORTGAGE	90000.0	Verified	18.01	0	2001	6	28	
1	HI	RENT	40000.0	Not Verified	5.04	0	1996	1	30	
2	WI	RENT	40000.0	Source Verified	21.15	0	2006	4	31	
3	PA	RENT	30000.0	Not Verified	10.16	0	2007	0	4	
4	CA	RENT	35000.0	Verified	57.96	0	2008	7	22	
5	KY	OWN	34000.0	Not Verified	6.46	1	1990	6	32	
6	MI	MORTGAGE	35000.0	Source Verified	23.66	0	2004	1	12	
7	AZ	MORTGAGE	110000.0	Source Verified	16.19	1	2005	1	30	
8	NV	MORTGAGE	65000.0	Source Verified	36.48	1	1998	3	35	
9	IL	RENT	30000.0	Not Verified	18.91	0	2001	0	9	

10 rows × 46 columns

As we can see, "issue_month" only includes three values: "Jan-2018", "Feb-2018", and "Mar-2018". The time does not vary much and its impact to the applicant's credit profile is negligible. Thus column "issue_month" can be dropped.

The same goes for "disbursement_method" which only includes two values: "Cash" and "DirectPay". The impact of these methods to the applicant's credit profile can also be neglected. Thus column "disbursement_method" can also be dropped.

Since "sub_grade" (a grade assigned to the loan applicant based on his credit profile which determines the interest rate) has fully included the information of "grade", column "grade" can be dropped as well. A detailed explanation of subgrade can be found here: https://www.lendingclub.com/public/rates-and-fees.action (https://www.lendingclub.com/public/rates-and-fees.action)

Since the three major US credit bureaus no longer include tax liens on your credit reports, a tax lien is no longer able to affect your credit. Thus, column "tax_liens" can be dropped. Details can be found here: https://www.bankrate.com/finance/credit-cards/how-tax-liens-affect-your-credit-score/ (https://www.bankrate.com/finance/credit-cards/how-tax-liens-affect-your-credit-score/),

In [45]:
```python
df_cleaned = df_cleaned.drop(["grade", "issue_month", "disbursement_method", "tax_liens"], axis=1)
df_cleaned.head(10)
```

Out[45]:

	state	homeownership	annual_income	verified_income	debt_to_income	delinq_2y	earliest_credit_line	inquiries_last_12m	total_credit_lines	ope
0	NJ	MORTGAGE	90000.0	Verified	18.01	0	2001	6	28	
1	HI	RENT	40000.0	Not Verified	5.04	0	1996	1	30	
2	WI	RENT	40000.0	Source Verified	21.15	0	2006	4	31	
3	PA	RENT	30000.0	Not Verified	10.16	0	2007	0	4	
4	CA	RENT	35000.0	Verified	57.96	0	2008	7	22	
5	KY	OWN	34000.0	Not Verified	6.46	1	1990	6	32	
6	MI	MORTGAGE	35000.0	Source Verified	23.66	0	2004	1	12	
7	AZ	MORTGAGE	110000.0	Source Verified	16.19	1	2005	1	30	
8	NV	MORTGAGE	65000.0	Source Verified	36.48	1	1998	3	35	
9	IL	RENT	30000.0	Not Verified	18.91	0	2001	0	9	

10 rows × 42 columns

1.3 Remove columns including values with insignificant frequencies and outlier rows

```
In [46]: for label in list(df_cleaned):
             if len(df_cleaned[label].unique()) < 20:
                 print(df_cleaned[label].value_counts())
                 print("\n")
```

```
MORTGAGE    4778
RENT        3848
OWN         1350
Name: homeownership, dtype: int64


Source Verified    4115
Not Verified       3573
Verified           2288
Name: verified_income, dtype: int64


0     8556
1     1008
2      257
3       88
4       34
5       10
8        7
```

We can see that features "current_accounts_delinq" and "num_accounts_30d_past_due" have only two possible values: 0 and 1, but with only 1 occurrences of 1 (less than 1%), so definitely they are insignificant.

The same goes for "num_collections_last_12m" feature (non-zero values have only 1.3% frequency).

Therefore we can drop these three columns.

Since >1 values in "num_historical_failed_to_pay", >1 values in "public_record_bankrupt", >2 values in "delinq_2y", >6 values in "num_mort_accounts" and values other than "Current" and "Fully Paid" in "loan_status" have very low frequency (less than 2%), we can remove these outliers. The same goes with "moving", "vacation" and "renewable energy" values in "loan_purpose".

```
In [47]: df_cleaned = df_cleaned.drop(["current_accounts_delinq", "num_accounts_30d_past_due", "num_collections_last_12m"], axis=
         df_cleaned = df_cleaned[df_cleaned['num_historical_failed_to_pay'] <= 2]
         df_cleaned = df_cleaned[df_cleaned['public_record_bankrupt'] <= 1]
         df_cleaned = df_cleaned[df_cleaned['delinq_2y'] <= 3]
         df_cleaned = df_cleaned[df_cleaned['num_mort_accounts'] <= 7]
         df_cleaned = df_cleaned[(df_cleaned['loan_status'] == "Current") | (df_cleaned['loan_status'] == "Fully Paid")]
         df_cleaned = df_cleaned[(df_cleaned['loan_purpose'] == "debt_consolidation") | (df_cleaned['loan_purpose'] == "credit_ca
                                 | (df_cleaned['loan_purpose'] == "other") | (df_cleaned['loan_purpose'] == "home_improvement")
                                 | (df_cleaned['loan_purpose'] == "major_purchase") | (df_cleaned['loan_purpose'] == "medical")
                                 | (df_cleaned['loan_purpose'] == "house") | (df_cleaned['loan_purpose'] == "car")
                                 | (df_cleaned['loan_purpose'] == "small_business") | (df_cleaned['loan_purpose'] == "moving")]
         df_cleaned.head(10)
```

Out[47]:

	state	homeownership	annual_income	verified_income	debt_to_income	delinq_2y	earliest_credit_line	inquiries_last_12m	total_credit_lines	ope
0	NJ	MORTGAGE	90000.0	Verified	18.01	0	2001	6	28	
1	HI	RENT	40000.0	Not Verified	5.04	0	1996	1	30	
2	WI	RENT	40000.0	Source Verified	21.15	0	2006	4	31	
3	PA	RENT	30000.0	Not Verified	10.16	0	2007	0	4	
4	CA	RENT	35000.0	Verified	57.96	0	2008	7	22	
5	KY	OWN	34000.0	Not Verified	6.46	1	1990	6	32	
6	MI	MORTGAGE	35000.0	Source Verified	23.66	0	2004	1	12	
7	AZ	MORTGAGE	110000.0	Source Verified	16.19	1	2005	1	30	
8	NV	MORTGAGE	65000.0	Source Verified	36.48	1	1998	3	35	
9	IL	RENT	30000.0	Not Verified	18.91	0	2001	0	9	

10 rows × 39 columns

```
In [48]: df_cleaned.shape[0] / df.shape[0]
Out[48]: 0.9541
```

So the removed records are no more than 5%, which means the cleaned dataset can still represent the original dataset well.

1.4 Categorical features

To use any machine learning model we have to have only numerical data. So, let's do something with our non-numerical features.

In [49]:
```
df_cleaned.select_dtypes(include=["object"]).head()
```

Out[49]:

	state	homeownership	verified_income	loan_purpose	application_type	sub_grade	loan_status	initial_listing_status
0	NJ	MORTGAGE	Verified	moving	individual	C3	Current	whole
1	HI	RENT	Not Verified	debt_consolidation	individual	C1	Current	whole
2	WI	RENT	Source Verified	other	individual	D1	Current	fractional
3	PA	RENT	Not Verified	debt_consolidation	individual	A3	Current	whole
4	CA	RENT	Verified	credit_card	joint	C3	Current	whole

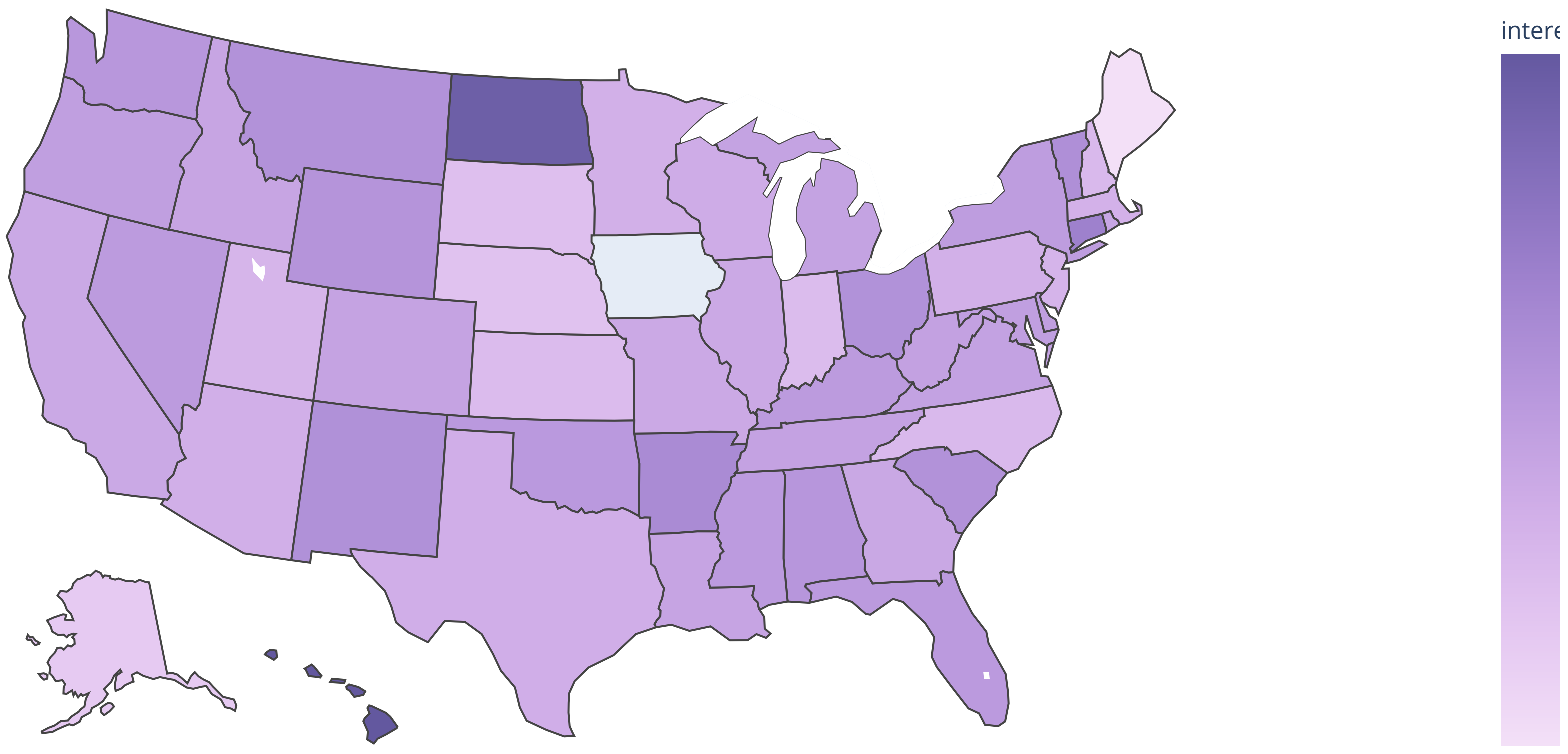
Since each grade (A, B, C, D, E, F) and the associated subgrade have its own sequence, we can map them into integers.

In [50]:
```
def subgrade_mapping(lst: list) -> dict:
    mapping = {}
    for subgrade in lst:

        subgrade = subgrade.strip()
        letter = subgrade[0]
        num = int(subgrade[1])
        if letter == 'A':
            m = 0
        elif letter == 'B':
            m = 1
        elif letter == 'C':
            m = 2
        elif letter == 'D':
            m = 3
        elif letter == 'E':
            m = 4
        elif letter == 'F':
            m = 5
        elif letter == 'G':
            m = 6
        else:
            m = np.nan

        mapping[subgrade] = m*5+num
    return mapping

df_cleaned["sub_grade"] = df_cleaned["sub_grade"].map(subgrade_mapping(df_cleaned["sub_grade"].unique()))
```

To show the impact of states, let's plot the average interest rate by states on the US map:

In [51]:
```
df_avg_by_state = df_cleaned.groupby('state').mean()
df_avg_by_state = df_avg_by_state.reset_index()

fig = px.choropleth(df_avg_by_state,  # Input Pandas DataFrame
                    locations="state",  # DataFrame column with locations
                    color="interest_rate",  # DataFrame column with color values
                    hover_name="state", # DataFrame column hover info
                    locationmode = 'USA-states',# Set to plot as US States
                    color_continuous_scale="purp") #set color scale
fig.update_layout(
    title_text = 'Interest Rate by States', # Create a Title
    geo_scope='usa',  # Plot only the USA instead of globe
)
fig.show()
```

Interest Rate by States



As we can see from the plot above, the average interest rate has no significant difference among different states, and there is also no significant trend on the map. Thus, we decide to drop this feature otherwise too many dummy indicators will be created.

In [52]:
```
df_cleaned = df_cleaned.drop(["state"], axis=1)
```

The rest of the categorical features can be either mapped to integers, or to dummy indicators.

In [53]:
```
#df_cleaned["initial_list_status"] = df_cleaned["initial_list_status"].map({"fractional": 1, "whole": 0})
df_cleaned["application_type"] = df_cleaned["application_type"].map({"individual": 1, "joint": 0})
df_cleaned["loan_status"] = df_cleaned["loan_status"].map({"Current": 1, "Fully Paid": 0})
df_cleaned["verified_income"] = df_cleaned["verified_income"].map({"Not Verified": 2, "Source Verified": 1, "Verified": (
df_cleaned["homeownership"] = df_cleaned["homeownership"].map({"RENT": 2, "MORTGAGE": 1, "OWN": 0})
df_cleaned = pd.get_dummies(df_cleaned, columns=list(df_cleaned.select_dtypes(include=["object"])))
```

We can calculate the correlation matrix for the cleaned dataset, and then plot the values int the heatmap:

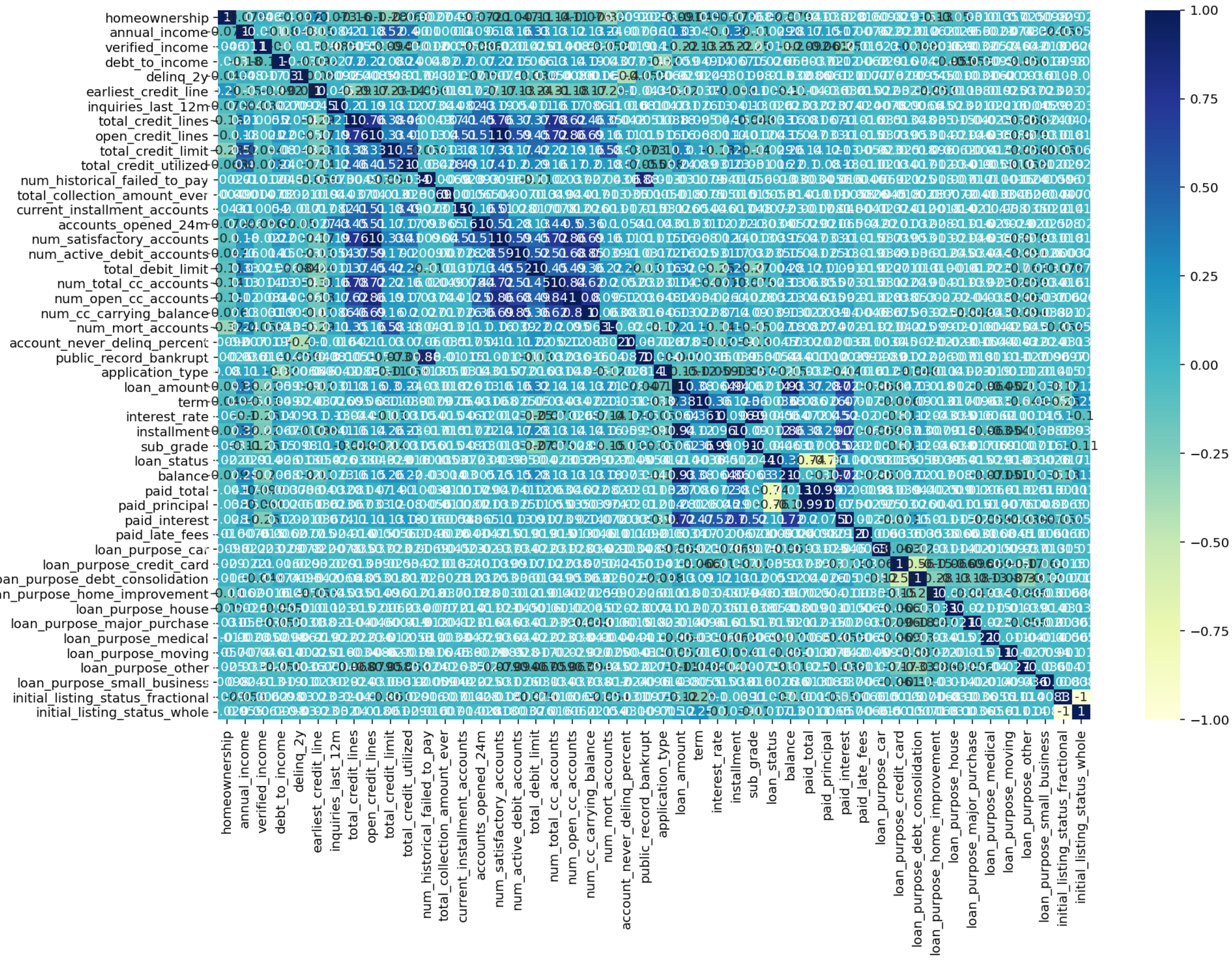
```
In [54]: C = df_cleaned.corr()
         C
```

Out[54]:

	homeownership	annual_income	verified_income	debt_to_income	delinq_2y	earliest_credit_line	inquiries_last_12m
homeownership	1.000000	-0.079151	0.046019	-0.042820	-0.046980	0.211652	-0.072834
annual_income	-0.079151	1.000000	-0.010704	-0.178030	0.048327	-0.149604	0.083841
verified_income	0.046019	-0.010704	1.000000	-0.104378	-0.016718	-0.028915	-0.085276
debt_to_income	-0.042820	-0.178030	-0.104378	1.000000	-0.030423	-0.091753	0.026617
delinq_2y	-0.046980	0.048327	-0.016718	-0.030423	1.000000	-0.079991	0.009196
earliest_credit_line	0.211652	-0.149604	-0.028915	-0.091753	-0.079991	1.000000	0.045049
inquiries_last_12m	-0.072834	0.083841	-0.085276	0.026617	0.009196	0.045049	1.000000
total_credit_lines	-0.157440	0.213732	-0.005464	0.200139	0.053625	-0.292755	0.211719
open_credit_lines	-0.104927	0.183229	-0.020913	0.216616	0.008526	-0.171671	0.190512
total_credit_limit	-0.283807	0.516991	-0.094120	0.079804	0.047853	-0.227273	0.132627
total_credit_utilized	-0.068260	0.404094	-0.070793	0.238920	-0.017248	-0.138721	0.122710
num_historical_failed_to_pay	-0.002658	0.010090	-0.011963	0.004759	-0.043315	-0.055915	0.073274
total_collection_amount_ever	-0.004945	-0.000138	-0.000731	0.019678	0.020699	-0.018980	0.043737
current_installment_accounts	0.043023	0.099841	-0.005425	0.199417	-0.017115	0.016830	0.082437
accounts_opened_24m	-0.071533	0.095786	-0.085576	0.070386	-0.049808	0.027144	0.430137
num_satisfactory_accounts	-0.104639	0.183401	-0.020235	0.216519	0.007397	-0.169864	0.190106
num_active_debit_accounts	-0.047257	0.162406	-0.014165	0.146236	-0.022765	-0.126503	0.053699
total_debit_limit	-0.114023	0.332041	0.025117	0.065923	-0.084205	-0.236824	0.010620
num_total_cc_accounts	-0.138289	0.128651	0.014430	0.128460	0.054412	-0.310141	0.158445
num_open_cc_accounts	-0.107153	0.118596	-0.008414	0.135926	0.008561	-0.182461	0.165867
num_cc_carrying_balance	-0.076228	0.132248	-0.031361	0.188512	0.000160	-0.165881	0.085907
num_mort_accounts	-0.321788	0.239187	-0.057784	0.043056	0.065874	-0.286874	0.110957
account_never_delinq_percent	0.009235	-0.006972	-0.001943	0.077484	-0.403156	0.099801	-0.015678
public_record_bankrupt	-0.002558	-0.035825	-0.013765	0.013845	-0.059265	-0.042526	0.080805
application_type	0.080238	0.106248	0.111252	-0.318629	-0.006613	0.045813	0.004163
loan_amount	-0.090876	0.327749	-0.220700	0.058515	-0.029017	-0.118449	0.031044
term	-0.049457	0.045115	-0.130138	0.049488	-0.024053	-0.037255	0.026177
interest_rate	0.065004	-0.104302	-0.247306	0.142798	0.092866	0.103934	0.127561
installment	-0.073472	0.318780	-0.221725	0.067457	-0.009993	-0.098462	0.040505
sub_grade	0.067836	-0.109953	-0.250659	0.146867	0.098128	0.110941	0.132838
loan_status	0.021573	-0.028886	0.014012	0.026220	-0.012819	0.005429	-0.025729
balance	-0.078949	0.281012	-0.204414	0.068380	-0.032429	-0.108358	0.023203
paid_total	-0.041171	0.166830	-0.091650	-0.003740	0.008633	-0.040014	0.031759
paid_principal	-0.038193	0.147156	-0.060669	-0.019796	0.006073	-0.035979	0.022577
paid_interest	-0.028390	0.172583	-0.247743	0.121262	0.020649	-0.036245	0.074013
paid_late_fees	0.015689	-0.007632	-0.015268	-0.006199	-0.007722	0.015065	0.023854
loan_purpose_car	0.009826	-0.022375	0.023286	-0.029387	0.007828	0.021914	-0.007839
loan_purpose_credit_card	0.028877	-0.021906	0.103593	0.015702	-0.028821	0.032448	-0.029106
loan_purpose_debt_consolidation	0.015785	-0.011737	-0.047814	0.074237	0.009500	-0.041879	-0.006617
loan_purpose_home_improvement	-0.127068	0.062172	0.000157	-0.014206	0.045316	-0.053206	0.045085
loan_purpose_house	-0.050094	0.002867	-0.029334	-0.054975	-0.010271	-0.011045	0.022800
loan_purpose_major_purchase	0.030829	0.055108	-0.003245	-0.055496	-0.003097	0.037923	0.020930
loan_purpose_medical	-0.012787	-0.002275	-0.005214	-0.009831	-0.006186	-0.019169	-0.021809
loan_purpose_moving	0.057043	-0.007368	-0.046367	-0.013856	-0.002045	0.024761	0.016098
loan_purpose_other	0.024794	-0.032712	-0.042363	-0.055895	-0.003603	0.037019	-0.000452
loan_purpose_small_business	0.009756	0.023846	-0.013484	-0.018991	-0.010292	0.022811	0.002927
initial_listing_status_fractional	0.029464	-0.055484	-0.006187	0.009768	0.030267	0.023377	0.031578
initial_listing_status_whole	-0.029464	0.055484	0.006187	-0.009768	-0.030267	-0.023377	-0.031578

48 rows × 48 columns

In [55]:
```python
# Visualizing the data using heatmap
fig, ax = plt.subplots(figsize = (15,10))
sns.heatmap(df_cleaned.corr(), cmap="YlGnBu", annot = True)
plt.show()
```

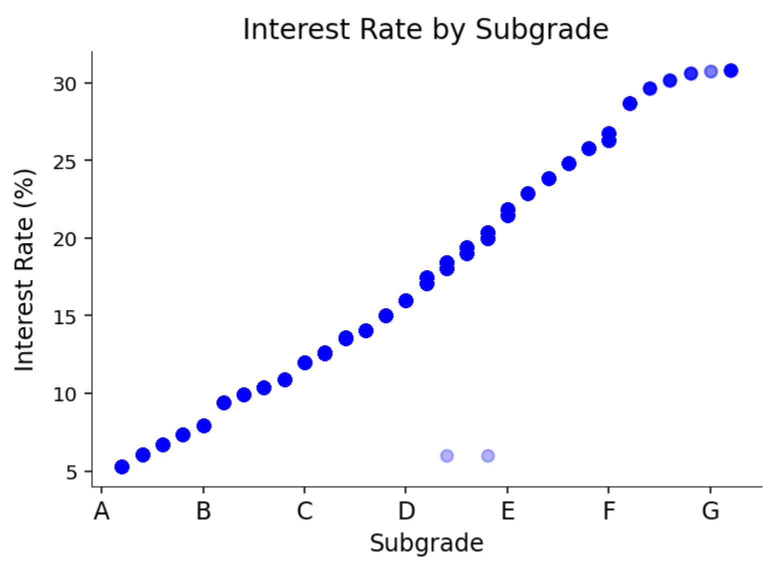


In [56]:
```
C['interest_rate']
```

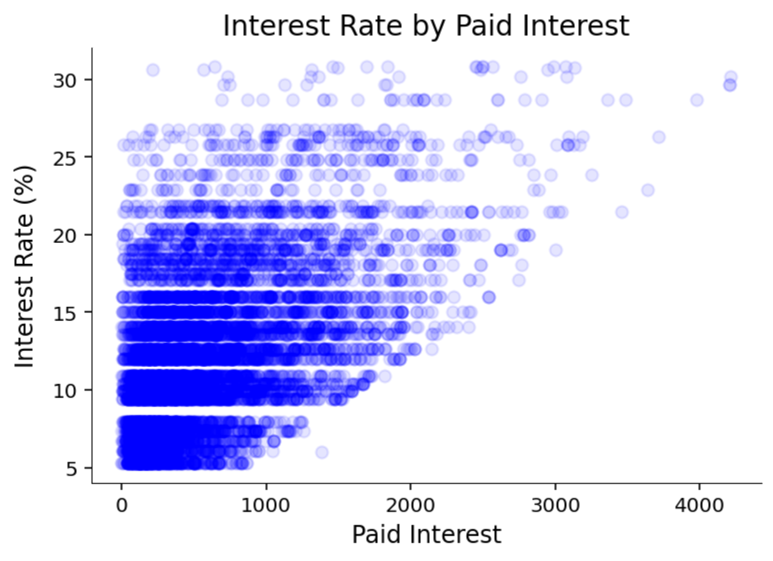
Out[56]:
```
homeownership                      0.065004
annual_income                     -0.104302
verified_income                   -0.247306
debt_to_income                     0.142798
delinq_2y                          0.092866
earliest_credit_line               0.103934
inquiries_last_12m                 0.127561
total_credit_lines                -0.044336
open_credit_lines                 -0.010868
total_credit_limit                -0.131637
total_credit_utilized              0.030728
num_historical_failed_to_pay       0.053766
total_collection_amount_ever       0.014539
current_installment_accounts       0.046329
accounts_opened_24m                0.121979
num_satisfactory_accounts         -0.011504
num_active_debit_accounts          0.031269
total_debit_limit                 -0.254728
num_total_cc_accounts             -0.070805
num_open_cc_accounts              -0.026397
num_cc_carrying_balance            0.086763
num_mort_accounts                 -0.140148
account_never_delinq_percent      -0.121952
public_record_bankrupt             0.050280
application_type                  -0.058784
loan_amount                        0.063872
term                               0.360431
interest_rate                      1.000000
installment                        0.095762
sub_grade                          0.992881
loan_status                       -0.045264
balance                            0.064318
paid_total                         0.072036
paid_principal                     0.004505
paid_interest                      0.522166
paid_late_fees                     0.019839
loan_purpose_car                  -0.007848
loan_purpose_credit_card          -0.106871
loan_purpose_debt_consolidation    0.124058
loan_purpose_home_improvement     -0.042889
loan_purpose_house                -0.035385
loan_purpose_major_purchase       -0.015513
loan_purpose_medical              -0.006185
loan_purpose_moving                0.010780
loan_purpose_other                -0.001368
loan_purpose_small_business        0.015426
initial_listing_status_fractional    0.104154
initial_listing_status_whole      -0.104154
Name: interest_rate, dtype: float64
```

As we can see from the graph and table above, the most relevant variable is sub_grade (0.993) and paid_interest(0.522) We can plot them as scatter plots to see the data distribution!

```
In [57]: fig, ax = plt.subplots(figsize = (6,4))
         ax.scatter(df_cleaned['sub_grade'], df_cleaned['interest_rate'], color='blue', alpha=0.3)

         ax.set_xlabel('Subgrade', fontsize=12)
         ax.set_ylabel('Interest Rate (%)', fontsize=12)
         ax.set_title("Interest Rate by Subgrade", size=14)
         # Set numerical y axis
         ax.yaxis.set_label_coords(-0.08, 0.5)
         # Set categorical ticks for x axis
         ax.set_xticks(np.arange(7)*5)
         ax.set_xticklabels(['A','B','C','D', 'E', 'F', 'G'], size=12)
         #ax.tick_params(axis='x', length=0)    #Hide ticks in x axis
         ax.spines['top'].set_visible(False)
         ax.spines['right'].set_visible(False)
         ax.spines['left'].set_linewidth(.5)
         ax.spines['bottom'].set_linewidth(.5)

         plt.show()
```

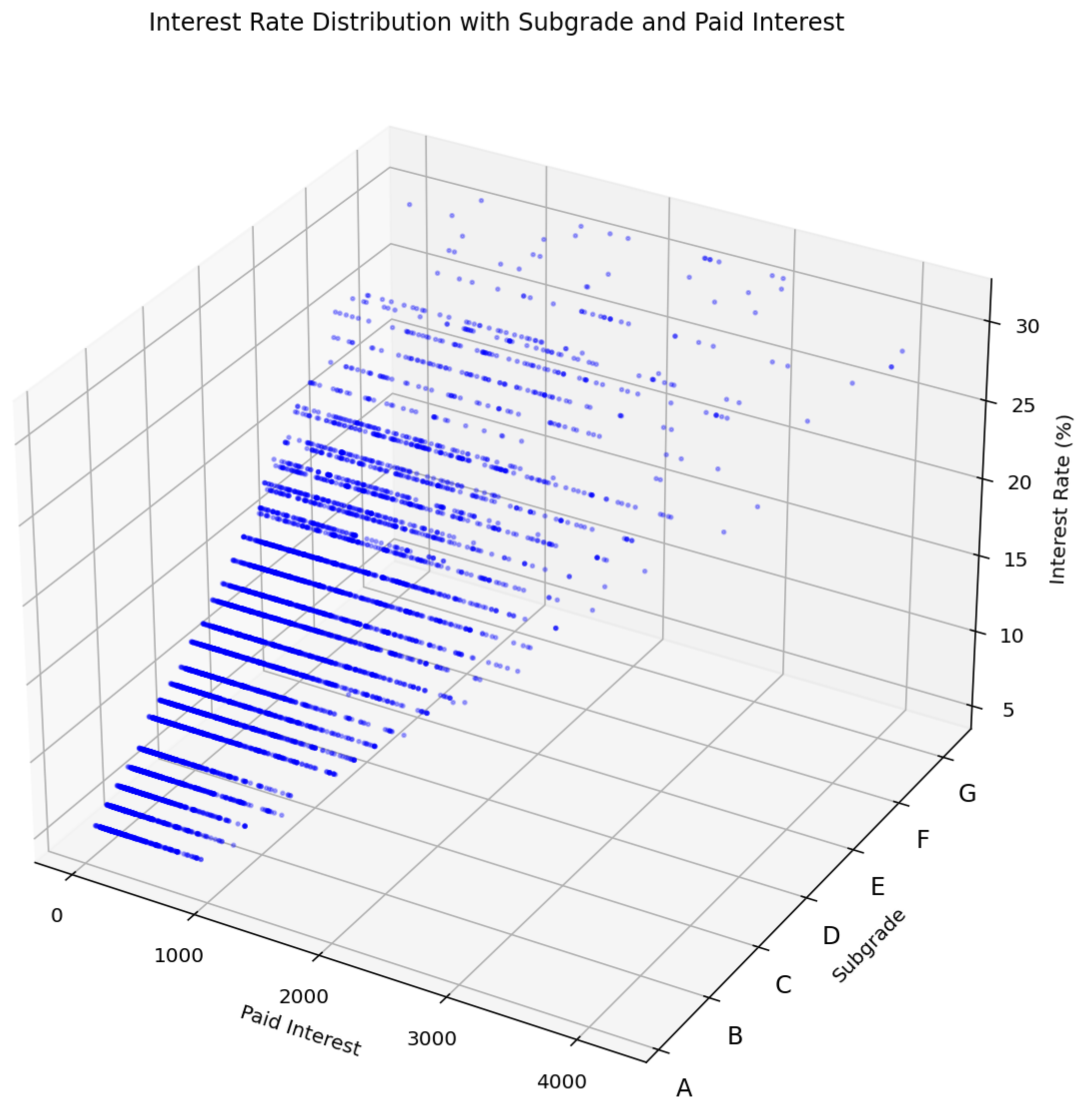


```
In [58]: fig, ax = plt.subplots(figsize = (6,4))
         ax.scatter(df_cleaned['paid_interest'], df_cleaned['interest_rate'], color='blue', alpha=0.1)

         ax.set_xlabel('Paid Interest', fontsize=12)
         ax.set_ylabel('Interest Rate (%)', fontsize=12)
         ax.set_title("Interest Rate by Paid Interest", size=14)
         # Set numerical y axis
         ax.yaxis.set_label_coords(-0.08, 0.5)
         ax.spines['top'].set_visible(False)
         ax.spines['right'].set_visible(False)
         ax.spines['left'].set_linewidth(.5)
         ax.spines['bottom'].set_linewidth(.5)


         plt.show()
```



We can even plot them into 3D graph:

In [59]:
```
# Creating figure
fig = plt.figure(figsize = (30, 10))
ax = plt.axes(projection ="3d")

# Creating plot
ax.scatter3D(df_cleaned['paid_interest'], df_cleaned['sub_grade'], df_cleaned['interest_rate'],
             color = 'blue', s=3,alpha=0.3)

# Set categorical ticks for y axis
ax.set_yticks(np.arange(7)*5)
ax.set_yticklabels(['A','B','C','D', 'E', 'F', 'G'], size=12)

ax.set_xlabel('Paid Interest')
ax.set_ylabel('Subgrade')
ax.set_zlabel('Interest Rate (%)')
plt.title("Interest Rate Distribution with Subgrade and Paid Interest")

# show plot
plt.show()
```



As we can see from the graphs above, subgrade has a strong linear correlation to interest rate; paid interest mainly determine the lower limit of the interest rate, but has no restraint to the upper limit.

2. Modeling Approach 1: Linear Regression Using `statsmodel`

2.1 Perform Linear Regression

In [60]:
```
X = df_cleaned['sub_grade']
y = df_cleaned['interest_rate']
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7,
                                                    test_size = 0.3, random_state = 100)
```

In [61]:
```
'''
By default, the statsmodel library fits a line that passes through the origin.
But if we observe the simple linear regression equation y = c + mX,
it has an intercept value as c.
So, to have an intercept, we need to add the add_constant attribute manually.
'''
X_train_sm = sm.add_constant(X_train)
# Fitting the resgression line using Ordinary Least Square method
lr = sm.OLS(y_train, X_train_sm).fit()

# Printing the parameters
lr.params
```

Out[61]:
```
const        3.837193
sub_grade    0.845659
dtype: float64
```

In [62]:
```
# Performing a summary to list out all the different parameters of the regression line fitted
lr.summary()
```

Out[62]:

OLS Regression Results

Dep. Variable:	interest_rate	**R-squared:**	0.986
Model:	OLS	**Adj. R-squared:**	0.986
Method:	Least Squares	**F-statistic:**	4.809e+05
Date:	Tue, 12 Apr 2022	**Prob (F-statistic):**	0.00
Time:	21:19:51	**Log-Likelihood:**	-5802.8
No. Observations:	6678	**AIC:**	1.161e+04
Df Residuals:	6676	**BIC:**	1.162e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3.8372	0.014	271.123	0.000	3.809	3.865
sub_grade	0.8457	0.001	693.494	0.000	0.843	0.848

Omnibus:	2067.897	**Durbin-Watson:**	2.023
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	286826.053
Skew:	-0.331	**Prob(JB):**	0.00
Kurtosis:	35.100	**Cond. No.**	23.4

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Discussions:

- The coefficient for `sub_grade` is 0.8457, and its corresponding p-value is very low (almost 0). That means the coefficient is statistically significant.
- R-squared value is 0.986, which means that 98.6% of the interest rate variance can be explained by the subgrade column using this line.
- Prob (F-statistic) has a very low p-value, practically zero, which gives us that the model fit is statistically significant.

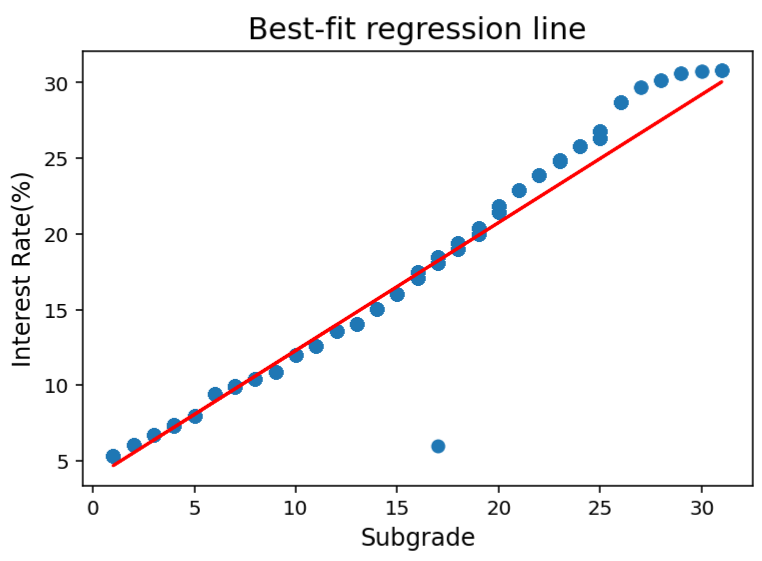
Since the fit is significant, let's go ahead and visualize how well the straight-line fits the scatter plot between `sub_grade` and `interest_rate` columns.

2.2 Visualization of the Regression Line

From the parameters shown above, we have obtained the values of the intercept and the slope of the straight line. The equation of the line is

$$interest\ rate = 3.8372 + 0.8457 * subgrade$$

In [63]:
```python
# Visualizing the regression line
fig, ax = plt.subplots(figsize=(6,4))
ax.scatter(X_train, y_train)
ax.plot(X_train, 3.8372 + 0.8457*X_train, 'r')
ax.set_title('Best-fit regression line', fontsize = 15)
ax.set_xlabel('Subgrade', fontsize = 12)
ax.set_ylabel('Interest Rate(%)', fontsize = 12)
plt.show()
```



2.3 Residual Analysis

One of the major assumptions of the linear regression model is the error terms are normally distributed.

$$Error = y - \hat{y}$$

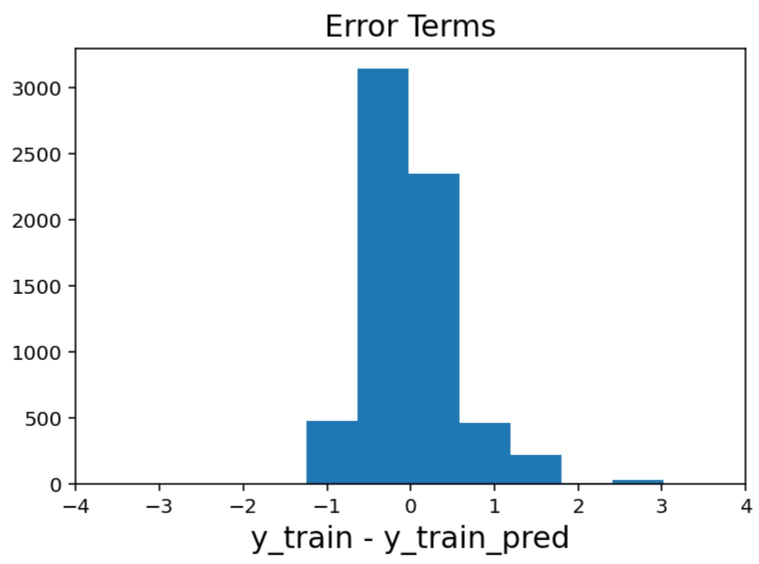
where y is the actual y value, and $\hat{y}$ is the predicted y value.

Now from the dataset, we have to predict the y value from the training dataset of X using the predict attribute. After that, we'll create the error terms(Residuals) from the predicted data.

In [64]:
```python
# Predictingg y_value using traingn data of X
y_train_pred = lr.predict(X_train_sm)

# Creating residuals from the y_train data and predicted y_data
res = (y_train - y_train_pred)
```

Now, let's plot the histogram of the residuals and see whether it looks like normal distribution or not.

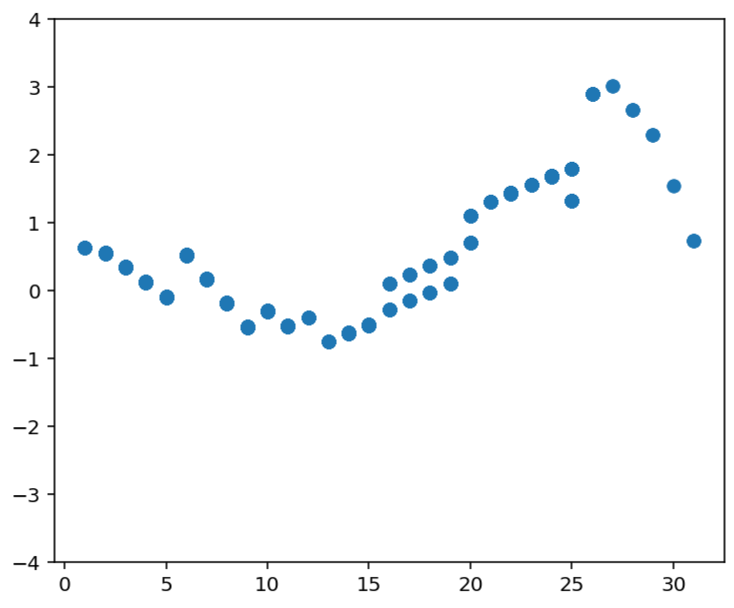
In [65]:
```python
# Plotting the histogram using the residual values
fig, ax = plt.subplots(figsize=(6,4))
n, bins, patches = ax.hist(res, bins=25)
ax.set_title('Error Terms', fontsize = 15)
ax.set_xlabel('y_train - y_train_pred', fontsize = 15)
ax.set_xlim(-4, 4)
plt.show()
```



As we can see, the residuals are following the normal distribution graph with a mean 0.

Now, make sure that the residuals are not following any specific pattern.

In [66]:
```
# Looking for any patterns in the residuals
fig, ax = plt.subplots(figsize=(6,5))
ax.scatter(X_train, res)
ax.set_ylim(-4, 4)
plt.show()
```



Since the Residuals follow a normal distribution and do not follow any specific pattern, we can use the linear regression model we have built to evaluate test data.

2.4. Predictions on the Test Data and Evaluations

Now that we have fitted the regression line on our train dataset, we can make some predictions to the test data. Similar to the training dataset, we have to `add_constant` to the test data and predict the y values using the `predict` attribute present in the `statsmodel` .

In [67]:
```
# Adding a constant to X_test
X_test_sm = sm.add_constant(X_test)

# Predicting the y values corresponding to X_test_sm
y_test_pred = lr.predict(X_test_sm)

# Printing the first 15 predicted values
y_test_pred
```

Out[67]:
```
2044    13.985098
3989    13.985098
4833    15.676416
5141     9.756804
1861     5.528510
          ...
8123    12.293781
1380     9.756804
9262     9.756804
6231    16.522075
1699    13.139439
Length: 2863, dtype: float64
```

Now, let's calculate the `R2` value for the above-predicted y-values. We can do that by merely importing the `r2_score` library from `sklearn.metrics` package.

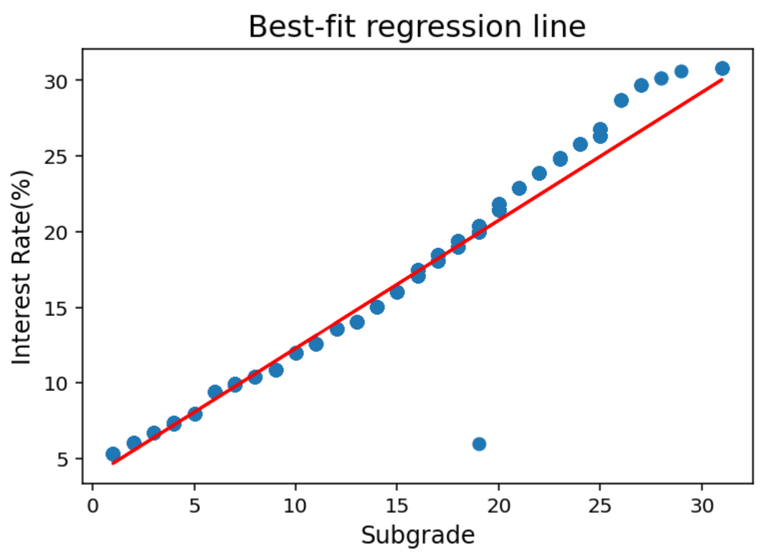
In [68]:
```
# Checking the R-squared value
r_squared = r2_score(y_test, y_test_pred)
r_squared
```

Out[68]:
```
0.9846913347652099
```

Since the R2 value on training data is 0.986, the R2 value on test data is within 5% of the R2 value on training data. In this case we can conclude that the model is pretty stable. This means, what the model has learned on the trainign set can generalize on the unseen test set.

Let's visualize the line on the test data.

In [69]:
```
fig, ax = plt.subplots(figsize=(6,4))
ax.scatter(X_test, y_test)
ax.plot(X_test, y_test_pred, 'r')
ax.set_title('Best-fit regression line', fontsize = 15)
ax.set_xlabel('Subgrade', fontsize = 12)
ax.set_ylabel('Interest Rate(%)', fontsize = 12)
plt.show()
```



3. Modeling Approach 2: Linear Regression Using `sklearn`

3.1 Perform Linear Regression

In [70]:
```
X_train_lm, X_test_lm, y_train_lm, y_test_lm = train_test_split(X, y, train_size = 0.7,
                                                                  test_size = 0.3, random_state = 100)
```

For simple linear regression, we need to add a column to perform the regression fit properly.

In [71]:
```
# Shape of the train set without adding column
print("The shape of X_train before adding a column is ", X_train_lm.shape)

# Adding additional column to the train and test data
X_train_lm = X_train_lm.values.reshape(-1,1)
X_test_lm = X_test_lm.values.reshape(-1,1)

print("The shape of X_train after adding a column is ", X_train_lm.shape)
print("The shape of X_test after adding a column is ", X_test_lm.shape)
```

```
The shape of X_train before adding a column is  (6678,)
The shape of X_train after adding a column is  (6678, 1)
The shape of X_test after adding a column is  (2863, 1)
```

Now we can conduct the linear regression using `sklearn.linear_model`

In [72]:
```
# Creating an object of Linear Regression
lm = LinearRegression()

# Fit the model using .fit() method
lm.fit(X_train_lm, y_train_lm)

# Intercept value
print("Intercept :",lm.intercept_)

# Slope value
print('Slope :',lm.coef_)
```

```
Intercept : 3.8371927815254256
Slope : [0.84565879]
```

The straight-line equation we get for the above values is,

$$interest\ rate = 3.8372 + 0.8467 * subgrade$$

If we observe, the equation we got here is the same as the one we got in the `statsmodel` .

3.2 Predictions on the Test Data and Evaluations¶

In [73]:
```python
# Making Predictions of y_value
y_train_pred = lm.predict(X_train_lm)
y_test_pred = lm.predict(X_test_lm)

# Comparing the r2 value of both train and test data
print(r2_score(y_train,y_train_pred))
print(r2_score(y_test,y_test_pred))
```

```
0.9863087206973497
0.9846913347652099
```

Same as the statesmodel, the R² value on test data is within 5% of the R² value on training data. We can apply the model to the unseen test set in the future.

4. Conclusions

- Data cleaning is performed to the original dataset. Unrelevant columns and outlier rows are removed.
- After calculating the correlation coefficients, it is found that `sub_grade` is able to dominate the target variable `interest_rate` .
- In this case, we can simply use numerized `sub_grade` value to build up linear regression model in `statsmodel` and `sklearn` . Both of the model predictions have shown good agreement with the actual values.
- Model evaluations are made to both modeling approaches and r2 score is used to prove the model has enough robustness and stability.

5. Reference

https://towardsdatascience.com/simple-linear-regression-model-using-python-machine-learning-eab7924d18b4 (https://towardsdatascience.com/simple-linear-regression-model-using-python-machine-learning-eab7924d18b4)

In [ ]: