# IMDB_Demo_Project

June 17, 2021

## 1 Import

[621]:
```
import os
from google.colab import drive
from argparse import Namespace
import numpy as np
import pandas as pd
import httpimport
import torch
import torch.optim as optim
from tqdm import tqdm_notebook, tqdm
import math
import statsmodels.formula.api as smf
import statsmodels.api as sm
from numpy import genfromtxt
import csv
import urllib.request
import seaborn as sns
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
from sklearn.preprocessing import StandardScaler
import matplotlib
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso

import torch
import torch.nn as nn
import torch.optim as optim
import torch.nn.functional as F
from torch.utils.data import Dataset, DataLoader
from torch.autograd import Variable
import numpy as np
import pandas as pd
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from torch.utils.data import TensorDataset, DataLoader
```

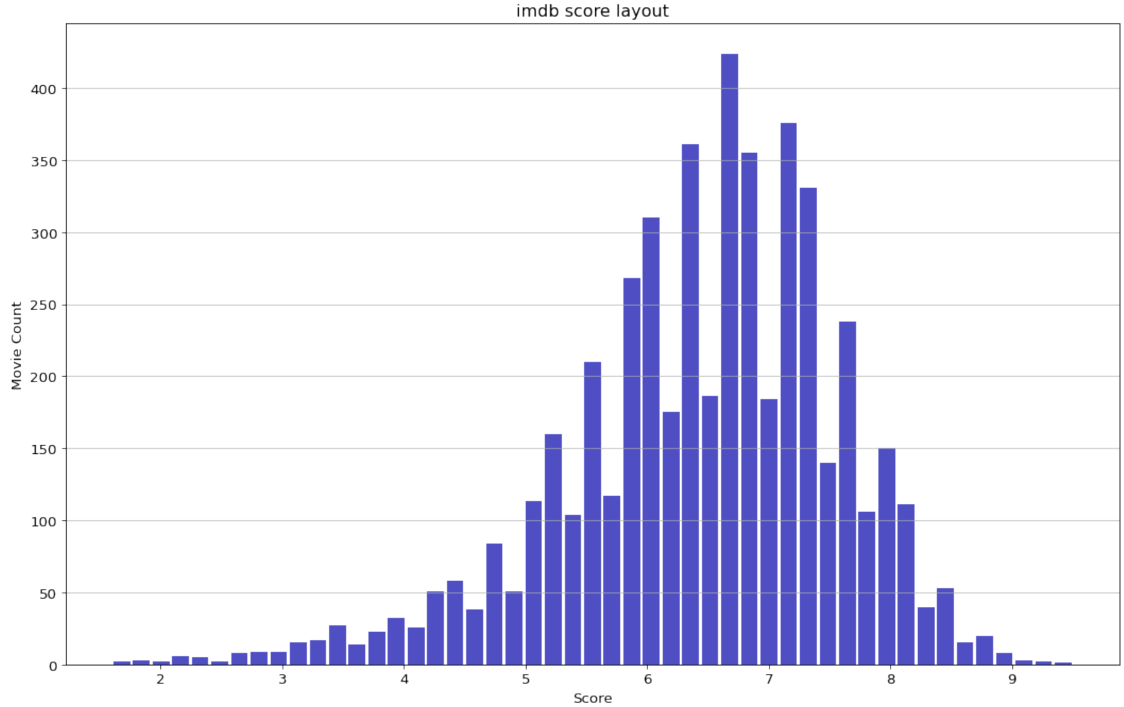
```
from tqdm import tqdm
from datetime import datetime
import torch.nn.functional as F
import random
import statsmodels.api as sm
from sklearn.metrics import mean_squared_error, r2_score
```

#Data Preprocessing and EDA

[622]:
```
url = "https://github.com/sundeepblue/movie_rating_prediction/raw/master/
↪movie_metadata.csv"
data = pd.read_csv(url)
data.head()
```

[622]:
```
   color      director_name  …  aspect_ratio  movie_facebook_likes
0  Color      James Cameron  …          1.78                 33000
1  Color     Gore Verbinski  …          2.35                     0
2  Color         Sam Mendes  …          2.35                 85000
3  Color  Christopher Nolan  …          2.35                164000
4    NaN        Doug Walker  …           NaN                     0

[5 rows x 28 columns]
```

[623]:
```
figure(figsize=(16, 10), dpi=80)
n, bins, patches = plt.hist(x=data['imdb_score'], bins='auto',␣
↪color='#0504aa',alpha=0.7, rwidth=0.85)
plt.grid(axis='y', alpha=0.75)
plt.xlabel('Score')
plt.ylabel('Movie Count')
plt.title('imdb score layout')
maxfreq = n.max()
```




We want to make a prediction for imdb scores. And as we know, the quality of movies is highly related to the person who direct them. Let's make a breif view of our producers.

[624]:
```
director = data.groupby('director_name').size().sort_values(ascending=False).
↪head(20)
director
```

[624]:
```
director_name
Steven Spielberg      26
Woody Allen           22
Martin Scorsese       20
Clint Eastwood        20
Ridley Scott          17
Tim Burton            16
Spike Lee             16
Steven Soderbergh     16
Renny Harlin          15
Oliver Stone          14
Sam Raimi             13
Michael Bay           13
Barry Levinson        13
Robert Zemeckis       13
John Carpenter        13
Joel Schumacher       13
```

```
Ron Howard           13
Robert Rodriguez     13
Richard Donner       12
Shawn Levy           12
dtype: int64
```

Steven Spielberg is a reputated director, so as Woody Allen. I really appreciate their masterpieces during my childhood. I believe lots of audiences facinate their work as well. How about the average scores of their works?

[625]:
```
name_list = director.index.tolist()
average = {}
for i in name_list:
  sum = data['imdb_score'][data['director_name'] == i].sum()
  average[i] = sum/director[i]
sorted(average.items(), key=lambda x: -x[1])
```

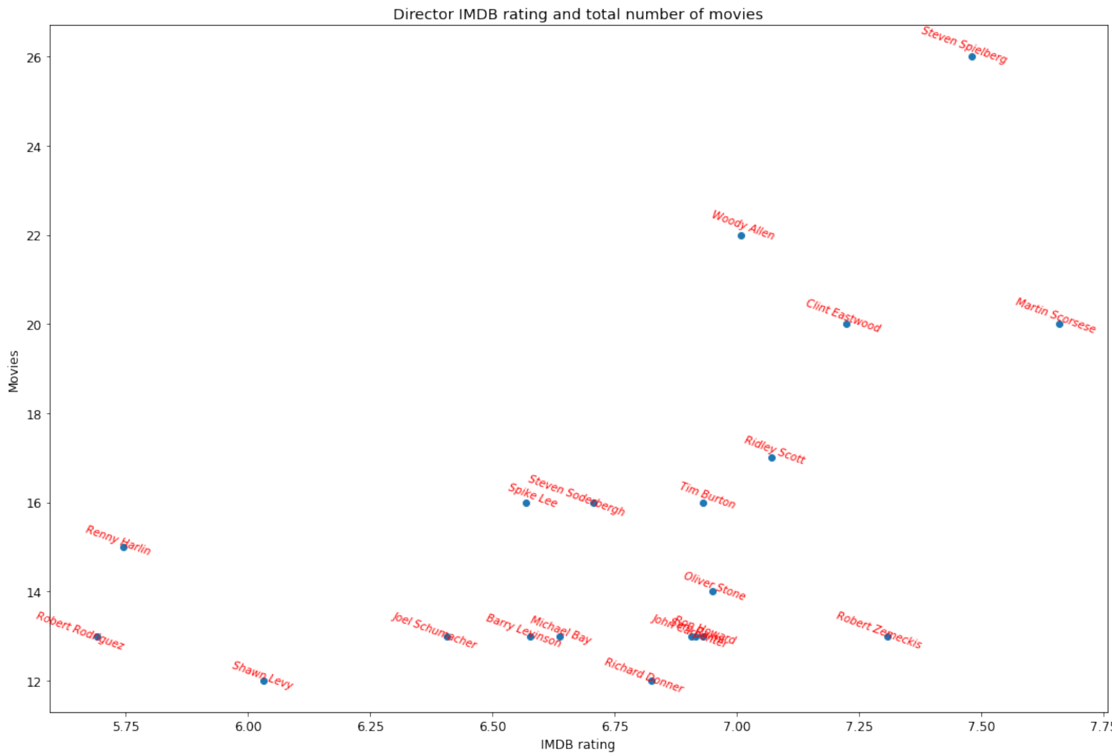
[625]:
```
[('Martin Scorsese', 7.659999999999999),
 ('Steven Spielberg', 7.480769230769232),
 ('Robert Zemeckis', 7.307692307692308),
 ('Clint Eastwood', 7.225),
 ('Ridley Scott', 7.070588235294117),
 ('Woody Allen', 7.00909090909091),
 ('Oliver Stone', 6.95),
 ('Tim Burton', 6.93125),
 ('Ron Howard', 6.930769230769231),
 ('John Carpenter', 6.915384615384615),
 ('Sam Raimi', 6.907692307692307),
 ('Richard Donner', 6.824999999999999),
 ('Steven Soderbergh', 6.70625),
 ('Michael Bay', 6.638461538461538),
 ('Barry Levinson', 6.576923076923076),
 ('Spike Lee', 6.56875),
 ('Joel Schumacher', 6.407692307692307),
 ('Shawn Levy', 6.033333333333334),
 ('Renny Harlin', 5.746666666666666),
 ('Robert Rodriguez', 5.6923076923076925)]
```

Christopher Nolan, my favorite sci-film director has the best overall imdb score. His moive is not just so good, or brilliant. It's beyond that. I have seen Inception for multiple times. Maybe I should do one more time. Ok, so we should agree that talented directors and casts will make a moive more entertaining and quality, which always result in a better rating. And we should consider that in our model.

[626]:
```
director_score = pd.DataFrame(average.items(),columns=['Director','Score'])
director_score['Movies'] = director.to_list()
director_score
```

[626]:
```
              Director     Score  Movies
0     Steven Spielberg  7.480769      26
1          Woody Allen  7.009091      22
2      Martin Scorsese  7.660000      20
3       Clint Eastwood  7.225000      20
4         Ridley Scott  7.070588      17
5           Tim Burton  6.931250      16
6            Spike Lee  6.568750      16
7    Steven Soderbergh  6.706250      16
8         Renny Harlin  5.746667      15
9         Oliver Stone  6.950000      14
10           Sam Raimi  6.907692      13
11         Michael Bay  6.638462      13
12      Barry Levinson  6.576923      13
13     Robert Zemeckis  7.307692      13
14      John Carpenter  6.915385      13
15     Joel Schumacher  6.407692      13
16          Ron Howard  6.930769      13
17    Robert Rodriguez  5.692308      13
18      Richard Donner  6.825000      12
19          Shawn Levy  6.033333      12
```

[627]:
```python
plt.rcParams['axes.unicode_minus']=False
director=director_score['Director']
score=director_score['Score']
movies=director_score['Movies']

fig=plt.figure(figsize=(18,12))
ax=plt.subplot(1,1,1)
ax.scatter(score,movies)
ax.set_title("Director IMDB rating and total number of movies")
ax.set_xlabel("IMDB rating")
ax.set_ylabel("Movies")
for i in range(len(movies)):
    ax.text(score[i]*1.01, movies[i]*1.01, director[i],
            fontsize=10, color = "r", style = "italic", weight = "light",
            verticalalignment='center',␣
 ↪horizontalalignment='right',rotation=-20)
plt.show()
```




As we can see, directors with good reputation also have produced lots of movies. Maybe audiences love those famous figures and lead to celebrity effect.

[628]:
```python
director_score = sorted(average.items(), key=lambda x: -x[1])
type(director_score)
```

[628]:
```
list
```

[629]:
```python
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5043 entries, 0 to 5042
Data columns (total 28 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   color                      5024 non-null   object
 1   director_name              4939 non-null   object
 2   num_critic_for_reviews     4993 non-null   float64
 3   duration                   5028 non-null   float64
 4   director_facebook_likes    4939 non-null   float64
 5   actor_3_facebook_likes     5020 non-null   float64
 6   actor_2_name               5030 non-null   object
 7   actor_1_facebook_likes     5036 non-null   float64
 8   gross                      4159 non-null   float64
```

```
 9   genres                     5043 non-null   object
 10  actor_1_name               5036 non-null   object
 11  movie_title                5043 non-null   object
 12  num_voted_users            5043 non-null   int64
 13  cast_total_facebook_likes  5043 non-null   int64
 14  actor_3_name               5020 non-null   object
 15  facenumber_in_poster       5030 non-null   float64
 16  plot_keywords              4890 non-null   object
 17  movie_imdb_link            5043 non-null   object
 18  num_user_for_reviews       5022 non-null   float64
 19  language                   5031 non-null   object
 20  country                    5038 non-null   object
 21  content_rating             4740 non-null   object
 22  budget                     4551 non-null   float64
 23  title_year                 4935 non-null   float64
 24  actor_2_facebook_likes     5030 non-null   float64
 25  imdb_score                 5043 non-null   float64
 26  aspect_ratio               4714 non-null   float64
 27  movie_facebook_likes       5043 non-null   int64
dtypes: float64(13), int64(3), object(12)
memory usage: 1.1+ MB
```

This dataset contains lots of information, including 9 characteristic variables, 15 numeric variables and 2 categorical variables. Before we processing feature engineering, I want to check data integrity so that missing values and outliers won't affect our prediction result. The first step is to find out how many missing values we have here.

[630]:
```
data.isna().sum()
```

[630]:
```
color                         19
director_name                104
num_critic_for_reviews        50
duration                      15
director_facebook_likes      104
actor_3_facebook_likes        23
actor_2_name                  13
actor_1_facebook_likes         7
gross                        884
genres                         0
actor_1_name                   7
movie_title                    0
num_voted_users                0
cast_total_facebook_likes      0
actor_3_name                  23
facenumber_in_poster          13
plot_keywords                153
movie_imdb_link                0
num_user_for_reviews          21
```

```
language                    12
country                      5
content_rating             303
budget                     492
title_year                 108
actor_2_facebook_likes      13
imdb_score                   0
aspect_ratio               329
movie_facebook_likes         0
dtype: int64
```

That's a lot missing here. It is unpropriate if we processing the raw data without cleaning them out. I would assume that those directors and actors who do not have "facebook likes" is because they do not have a official facebook account or is not avaliable currently. I would fill them as 0 to make it works.

[631]:
```
data['director_facebook_likes'] = data['director_facebook_likes'].fillna(0)
data['actor_1_facebook_likes'] = data['actor_1_facebook_likes'].fillna(0)
data['actor_2_facebook_likes'] = data['actor_2_facebook_likes'].fillna(0)
data['actor_3_facebook_likes'] = data['actor_3_facebook_likes'].fillna(0)
```

Face number in movies' poster should not affect review scores, as well as their imdb links, the number of reviews and aspect ratio. We have to admit that movie title might have positive or negative influence here. For instance, rating of movies in franchise series are affected by their precessors. Audiences always expect more on great movies' successors. On another hand, moives which named after a famous charactor, like spider-man or Donald Duck, will give their audiences a special impression. Still, I will delete these columns because their influence in this dataset is minimal and this will save us some time.

[634]:
```
data_wo_useless_attributes = data.
↪drop(columns=['color','movie_imdb_link','num_user_for_reviews','aspect_ratio','movie_title'
```

[635]:
```
data_wo_useless_attributes = data_wo_useless_attributes.
↪drop(columns=['facenumber_in_poster'])
```

Drop the na rows for numeric varibles. It is not approriate if we just fill them with means or median here. As we have enough samples here and na rows of numeric varibles are no more than 400 rows, I would say it is safer to focus on rows without missing values.

[636]:
```
data_numeric_cleaned = data_wo_useless_attributes.
↪dropna(subset=['num_critic_for_reviews','duration','director_name','title_year','gross','bu
```

[637]:
```
data_categoric_cleaned = data_numeric_cleaned.
↪dropna(subset=['director_name','actor_1_name','actor_2_name','actor_3_name','content_rating
```

[638]:
```
data_categoric_cleaned.isna().sum()
```

[638]:
```
director_name               0
num_critic_for_reviews      0
duration                    0
director_facebook_likes     0
actor_3_facebook_likes      0
actor_2_name                0
actor_1_facebook_likes      0
gross                       0
genres                      0
actor_1_name                0
num_voted_users             0
cast_total_facebook_likes   0
actor_3_name                0
content_rating              0
budget                      0
title_year                  0
actor_2_facebook_likes      0
imdb_score                  0
movie_facebook_likes        0
dtype: int64
```

Index needs to be resets here to make sure following step will work well.

[639]:
```
data_categoric_cleaned = data_categoric_cleaned.reset_index(drop=True)
```

[640]:
```
data_categoric_cleaned.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3833 entries, 0 to 3832
Data columns (total 19 columns):
 #   Column                     Non-Null Count  Dtype
---  ------                     --------------  -----
 0   director_name              3833 non-null   object
 1   num_critic_for_reviews     3833 non-null   float64
 2   duration                   3833 non-null   float64
 3   director_facebook_likes    3833 non-null   float64
 4   actor_3_facebook_likes     3833 non-null   float64
 5   actor_2_name               3833 non-null   object
 6   actor_1_facebook_likes     3833 non-null   float64
 7   gross                      3833 non-null   float64
 8   genres                     3833 non-null   object
 9   actor_1_name               3833 non-null   object
 10  num_voted_users            3833 non-null   int64
 11  cast_total_facebook_likes  3833 non-null   int64
 12  actor_3_name               3833 non-null   object
 13  content_rating             3833 non-null   object
 14  budget                     3833 non-null   float64
 15  title_year                 3833 non-null   float64
```

```
 16   actor_2_facebook_likes     3833 non-null   float64
 17   imdb_score                 3833 non-null   float64
 18   movie_facebook_likes       3833 non-null   int64
dtypes: float64(10), int64(3), object(6)
memory usage: 569.1+ KB
```

## 2 Characteristic Variables and categorical variables

Genres is a little difficult to deal with. It has been put into one column and separate by "|". I will divide them into several columns using one hot coding. This is the only variable I want to use one hot coding since the labels is not so many.

[641]:
```
data_categoric_cleaned['genres'].describe()
```

[641]:
```
count                      3833
unique                      751
top       Comedy|Drama|Romance
freq                        150
Name: genres, dtype: object
```

[642]:
```
genres = []
for i in range(len(data_categoric_cleaned)):
  temp = data_categoric_cleaned['genres'][i].split('|')
  for n in range(len(temp)):
    if temp[n] not in genres:
      genres.append(temp[n])
```

I create a list to store all genres values.

[643]:
```
genres
```

[643]:
```
['Action',
 'Adventure',
 'Fantasy',
 'Sci-Fi',
 'Thriller',
 'Romance',
 'Animation',
 'Comedy',
 'Family',
 'Musical',
 'Mystery',
 'Western',
 'Drama',
 'History',
 'Sport',
 'Crime',
 'Horror',
```

```
 'War',
 'Biography',
 'Music',
 'Documentary',
 'Film-Noir']
```

Create new empty columns for genres.

[644]:
```
for i in genres:
  temp = [0]*len(data_categoric_cleaned)
  col_name = i
  data_categoric_cleaned[col_name] = temp
```

One-hot coding and we have genres attributes separated.

[645]:
```
for i in range(len(data_categoric_cleaned)):
  temp = data_categoric_cleaned['genres'][i].split('|')
  for n in range(len(temp)):
    data_categoric_cleaned[temp[n]][i] = 1
```

[646]:
```
data_categoric_cleaned[genres]
```

[646]:

| | Action | Adventure | Fantasy | … | Music | Documentary | Film-Noir |
|---|---|---|---|---|---|---|---|
| 0 | 1 | 1 | 1 | … | 0 | 0 | 0 |
| 1 | 1 | 1 | 1 | … | 0 | 0 | 0 |
| 2 | 1 | 1 | 0 | … | 0 | 0 | 0 |
| 3 | 1 | 0 | 0 | … | 0 | 0 | 0 |
| 4 | 1 | 1 | 0 | … | 0 | 0 | 0 |
| … | … | … | … | … | … | … | … |
| 3828 | 0 | 0 | 0 | … | 0 | 0 | 0 |
| 3829 | 0 | 0 | 0 | … | 0 | 0 | 0 |
| 3830 | 1 | 0 | 0 | … | 0 | 0 | 0 |
| 3831 | 0 | 0 | 0 | … | 0 | 0 | 0 |
| 3832 | 0 | 0 | 0 | … | 0 | 1 | 0 |

[3833 rows x 22 columns]

Drop the original genres column

[647]:
```
data_categoric_cleaned = data_categoric_cleaned.drop(columns=['genres'])
data_ready = data_categoric_cleaned
```

#One hot encoding for content rating

[648]:
```
content_rating = pd.get_dummies(data_ready.content_rating,␣
 ↪prefix='content_rating')
content_rating
```

[648]:

```
      content_rating_Approved  …  content_rating_X
0                           0  …                 0
1                           0  …                 0
2                           0  …                 0
3                           0  …                 0
4                           0  …                 0
…                         …  …               …
3828                        0  …                 0
3829                        0  …                 0
3830                        0  …                 0
3831                        0  …                 0
3832                        0  …                 0

[3833 rows x 12 columns]
```

[649]:

```python
data_ready= data_ready.drop('content_rating',axis = 1)
data_ready = data_ready.join(content_rating)
data_ready
```

[649]:

```
          director_name  …  content_rating_X
0         James Cameron  …                 0
1        Gore Verbinski  …                 0
2            Sam Mendes  …                 0
3     Christopher Nolan  …                 0
4        Andrew Stanton  …                 0
…                   …  …               …
3828      Shane Carruth  …                 0
3829    Neill Dela Llana  …                 0
3830   Robert Rodriguez  …                 0
3831       Edward Burns  …                 0
3832           Jon Gunn  …                 0

[3833 rows x 51 columns]
```

#Directors and Actors

As I mentioned before, directors and actors have hugh influence on movies' quality. We surely don't want to drop these variables. But we have thounds of labels and one-hot coding won't going to make it. As a result, I will replace their name by average imdb score of their works. And this number would represent their influence on movies' quality. However, it happens when an actor only starred in one movie and it has a pretty high rating, while he is not acutally famous and make contribute to that fancy score. Thus, I will only consider the popular ones, that is, Top 50 for directors and Top 150 for actors. Other people would only get a overall average imdb score.

[650]:

```python
director = data_ready.groupby('director_name').size().
 ↪sort_values(ascending=False).head(50)
name_list = director.index.tolist()
average = {}
```

```
for i in name_list:
  sum = data_ready['imdb_score'][data_ready['director_name'] == i].sum()
  average[i] = sum/director[i]
imdb_average = data_ready['imdb_score'].mean()
score_column = [imdb_average]*len(data_ready)
data_ready['director_score'] = score_column
for i in range(len(data_ready)):
  if data_ready['director_name'][i] in name_list:
    data_ready['director_score'][i] = average[data_ready['director_name'][i]]
```

[651]:
```
df1 = data_ready[['actor_1_name','imdb_score']]
df2 = data_ready[['actor_2_name','imdb_score']]
df3 = data_ready[['actor_3_name','imdb_score']]
df1.columns = ['name','imdb_score']
df2.columns = ['name','imdb_score']
df3.columns = ['name','imdb_score']

actor_concat = pd.concat([df1,df2,df3],axis = 0)
actor = actor_concat.groupby('name').size().sort_values(ascending=False).
↪head(150)
actor
```

[651]:
```
name
Robert De Niro         47
Morgan Freeman         44
Johnny Depp            39
Bruce Willis           39
Matt Damon             35
                       ..
David Oyelowo          11
Kristin Scott Thomas   11
Tom Hardy              11
Nathan Lane            11
Romany Malco           10
Length: 150, dtype: int64
```

[652]:
```
name_list = actor.index.tolist()
average = {}
for i in name_list:
  sum = actor_concat['imdb_score'][actor_concat['name'] == i].sum()
  average[i] = sum/actor[i]
imdb_average = data_ready['imdb_score'].mean()
score_column = [imdb_average]*len(data_ready)
data_ready['actor_1_score'] = score_column
data_ready['actor_2_score'] = score_column
data_ready['actor_3_score'] = score_column
for i in range(len(data_ready)):
```

```
  if data_ready['actor_1_name'][i] in name_list:
    data_ready['actor_1_score'][i] = average[data_ready['actor_1_name'][i]]
for i in range(len(data_ready)):
  if data_ready['actor_2_name'][i] in name_list:
    data_ready['actor_2_score'][i] = average[data_ready['actor_2_name'][i]]
for i in range(len(data_ready)):
  if data_ready['actor_3_name'][i] in name_list:
    data_ready['actor_3_score'][i] = average[data_ready['actor_3_name'][i]]
data_finished = data_ready.
 ↪drop(columns=['director_name','actor_1_name','actor_2_name','actor_3_name'])
```

[653]:
```
data_finished
```

[653]:
```
      num_critic_for_reviews  duration  …  actor_2_score  actor_3_score
0                      723.0     178.0  …       6.459144       6.459144
1                      302.0     169.0  …       6.459144       6.459144
2                      602.0     148.0  …       6.459144       6.459144
3                      813.0     164.0  …       7.266667       7.055556
4                      462.0     132.0  …       6.459144       6.459144
…                        …       …   …           …              …
3828                   143.0      77.0  …       6.459144       6.459144
3829                    35.0      80.0  …       6.459144       6.459144
3830                    56.0      81.0  …       6.459144       6.459144
3831                    14.0      95.0  …       6.459144       6.459144
3832                    43.0      90.0  …       6.459144       6.459144

[3833 rows x 51 columns]
```

# 3 Dataset Split

[654]:
```
df = data_finished.sample(n = len(data_finished), random_state = 1)
df_data = df.reset_index(drop = True)
df_test=df_data.sample(frac=0.30,random_state=42)
print('Split size: %.3f'%(len(df_valid_test)/len(df_data)))
```

```
Split size: 0.300
```

[664]:
```
df_train = df_data.drop(df_test.index)
```

[666]:
```
col_to_use = [c for c in list(df_train.columns) if c != 'imdb_score']
print('Number of attributes:', len(col_to_use))
```

```
Number of attributes: 50
```

[669]:
```
X_train = df_train[col_to_use].values
X_test = df_test[col_to_use].values
```

```
y_train = df_train['imdb_score'].values
y_test = df_test['imdb_score'].values
print('Training shapes:',X_train.shape, y_train.shape)
print('Testing shapes:',X_test.shape, y_test.shape)
```

```
Training shapes: (2683, 50) (2683,)
Testing shapes: (1150, 50) (1150,)
```

#Simple Multiple Linear Regression

In this section, I build a very simple linear regression model as baseline.

[671]:
```
y_train_a = y_train[:, np.newaxis]
model = LinearRegression()
model.fit(X_train, y_train_a)
predicts = model.predict(X_train)
R2 = model.score(X_train, y_train_a)
print('R2 = %.3f' % R2)
coef = model.coef_
intercept = model.intercept_
```

```
R2 = 0.510
```

Print out the coefficients

[672]:
```
print(model.coef_, model.intercept_)
```

```
[[ 2.70883066e-03  3.55507208e-03 -5.59449149e-06  2.06409374e-05
   3.38771744e-05 -7.55508897e-10  2.40908781e-06 -3.25872946e-05
   2.80442009e-11 -2.74853818e-02  2.70217136e-05 -5.56086774e-07
  -2.15239587e-01 -3.61999366e-02 -1.04619311e-01 -1.26337145e-01
  -1.47651091e-01 -4.67495234e-02  8.27405488e-01 -1.25923585e-01
  -1.28848276e-01  4.21869143e-02  2.11041090e-02 -1.15995904e-01
   4.46069174e-01  8.36354779e-02  1.29653834e-01  6.68189254e-02
  -4.09519883e-01  1.00665257e-01  1.51313349e-01  1.20464296e-02
   9.68588259e-01 -7.48238020e-01  9.31309005e-04 -1.47046577e-01
  -5.97934228e-02  3.50160474e-02 -1.88684141e-01  5.03294612e-01
  -3.46058594e-02 -1.44973975e-01 -7.33025727e-01  4.76272706e-02
   3.25879720e-01  3.95380744e-01  1.43622546e-01  1.79400114e-01
   2.87293649e-01  1.06431000e-01]] [55.82515277]
```

[673]:
```
LR_result = model.predict(X_test)
```

#Ridge and LASSO Regression

In order to prevent over-fitting of the model, we often need to add regularization items when building a linear model, generally there are L1 regularization and L2 regularization. Ridge regression(L2) and Lasso(L1) can prevet overfitting. Ridge regression reduces the regression coefficients without abandoning any feature, making the model relatively stable, but compared with Lasso regression, this will leave a lot of model features and poor model interpretation. The regularization term of ridge regression has a constant coefficient alpha to adjust the weight of the mean square error term and the regularization term of the loss function. Larger alpha means more penalty. I set two initial alpha to find their difference.

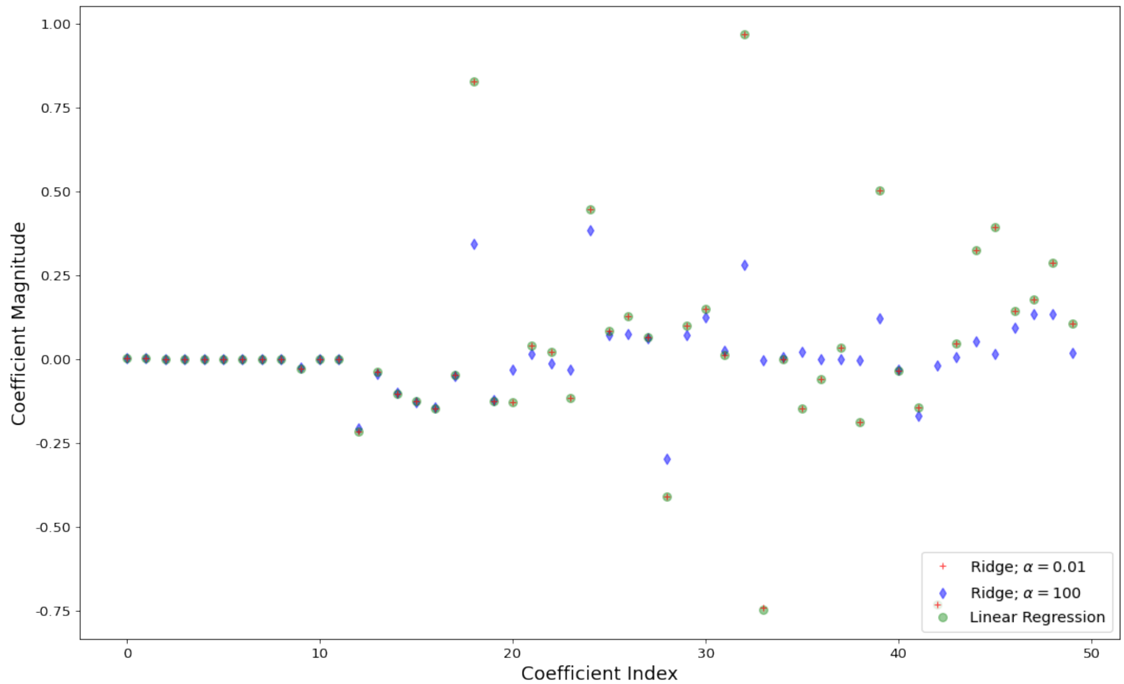
[674]:
```
lr = LinearRegression()
lr.fit(X_train, y_train)

rr = Ridge(alpha=0.01)
rr.fit(X_train, y_train)

rr100 = Ridge(alpha=100)
rr100.fit(X_train, y_train)

train_score=lr.score(X_train, y_train)
test_score=lr.score(X_valid, y_valid)

Ridge_train_score = rr.score(X_train,y_train)
Ridge_test_score = rr.score(X_valid, y_valid)

Ridge_train_score100 = rr100.score(X_train,y_train)
Ridge_test_score100 = rr100.score(X_valid, y_valid)

print ("linear regression train score:", train_score)
print ("linear regression test score:", test_score)
print ("ridge regression train score low alpha:", Ridge_train_score)
print ("ridge regression test score low alpha:", Ridge_test_score)
print ("ridge regression train score high alpha:", Ridge_train_score100)
print ("ridge regression test score high alpha:", Ridge_test_score100)
```

```
linear regression train score: 0.5098707388489385
linear regression test score: 0.4793769609946402
ridge regression train score low alpha: 0.5098707081208159
ridge regression test score low alpha: 0.479384777543556
ridge regression train score high alpha: 0.49196034919115267
ridge regression test score high alpha: 0.4653872606092868
```

[675]:
```
figure(figsize=(16, 10), dpi=80)
plt.plot(rr.coef_,alpha=0.
 ↪7,linestyle='none',marker='+',markersize=5,color='red',label=r'Ridge;␣
 ↪$\alpha = 0.01$',zorder=7)
plt.plot(rr100.coef_,alpha=0.
 ↪5,linestyle='none',marker='d',markersize=6,color='blue',label=r'Ridge;␣
 ↪$\alpha = 100$')
plt.plot(lr.coef_,alpha=0.
 ↪4,linestyle='none',marker='o',markersize=7,color='green',label='Linear␣
 ↪Regression')
```

```
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.legend(fontsize=13,loc=4)
plt.show()
```

```
findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans.
findfont: Font family ['sans-serif'] not found. Falling back to DejaVu Sans.
```




As we can see, when alpha = 0.01, the coefficient is pretty close to linear regression. Lots of coefficient remain the same. We are still going to have much overfitting. To save some time, I evade creating a loop to find the best alpha, but rather using sklearn to calculate it at once.

[676]:
```
from sklearn.linear_model import RidgeCV
ridgecv = RidgeCV(alphas=[0.01, 0.1, 0.5, 1, 5, 7, 10, 30,100, 200])
ridgecv.fit(X_train, y_train)
print("Best alpha should be:" + str(ridgecv.alpha_))
```

```
Best alpha should be:5.0
```

Ok, alpha = 5. Fit the model again and we will make comparision later.

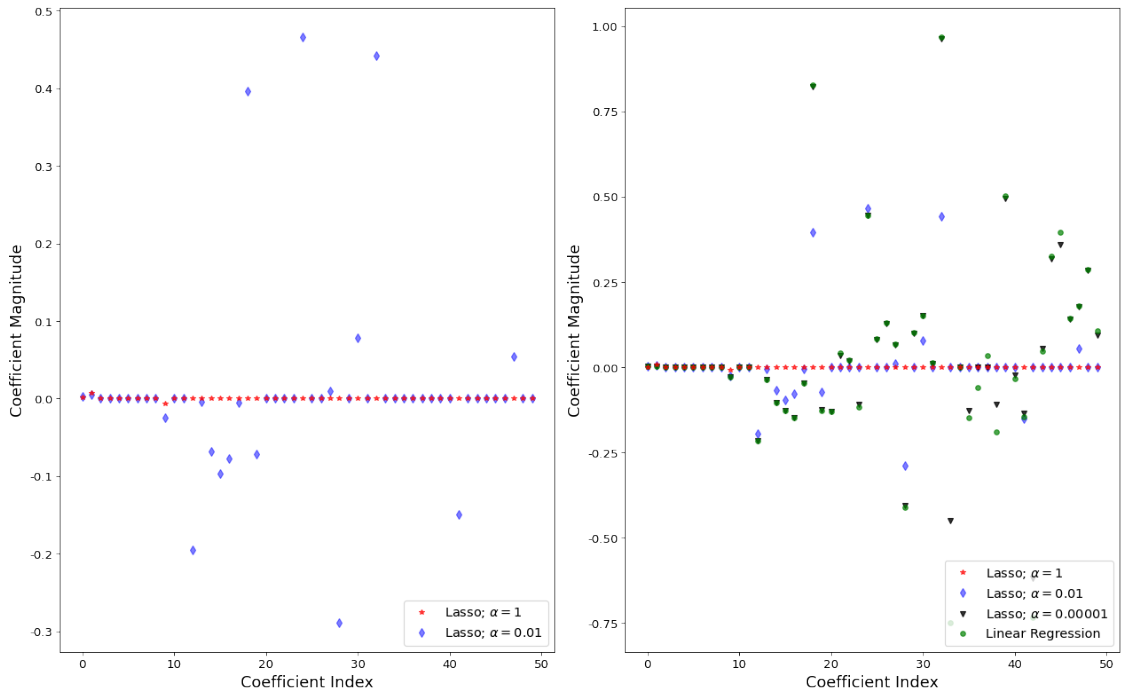
[677]:
```
rr5 = Ridge(alpha=5)
rr5.fit(X_train, y_train)
rr_result = rr5.predict(X_test)
```

Without abandoning any feature, ridge regression reduces the regression coefficients, making the model relatively stable. But compared with Lasso regression, this will leave a lot of model features and poor model interpretation.

[678]:
```
lasso = Lasso() #  alpha =1
lasso.fit(X_train,y_train)

train_score=lasso.score(X_train,y_train)
test_score=lasso.score(X_valid,y_valid)

coeff_used = np.sum(lasso.coef_!=0)
print("training score:", train_score )
print ("test score: ", test_score)
print ("number of features used: ", coeff_used)

lasso001 = Lasso(alpha=0.01, max_iter=10e5)
lasso001.fit(X_train,y_train)

train_score001=lasso001.score(X_train,y_train)
test_score001=lasso001.score(X_valid,y_valid)

coeff_used001 = np.sum(lasso001.coef_!=0)
print ("training score for alpha=0.01:", train_score001 )
print ("test score for alpha =0.01: ", test_score001)
print ("number of features used: for alpha =0.01:", coeff_used001)

lasso00001 = Lasso(alpha=0.0001, max_iter=10e5)
lasso00001.fit(X_train,y_train)

train_score00001=lasso00001.score(X_train,y_train)
test_score00001=lasso00001.score(X_valid,y_valid)

coeff_used00001 = np.sum(lasso00001.coef_!=0)
print ("training score for alpha=0.0001:", train_score00001 )
print( "test score for alpha =0.0001: ", test_score00001)
print ("number of features used: for alpha =0.0001:", coeff_used00001)

lr = LinearRegression()
lr.fit(X_train,y_train)
lr_train_score=lr.score(X_train,y_train)
lr_test_score=lr.score(X_valid,y_valid)
print ("LR training score:", lr_train_score )
print ("LR test score: ", lr_test_score)
figure(figsize=(16, 10), dpi=80)

plt.subplot(1,2,1)
```

```
plt.plot(lasso.coef_,alpha=0.
 ↪7,linestyle='none',marker='*',markersize=5,color='red',label=r'Lasso;␣
 ↪$\alpha = 1$',zorder=7) # alpha here is for transparency
plt.plot(lasso001.coef_,alpha=0.
 ↪5,linestyle='none',marker='d',markersize=6,color='blue',label=r'Lasso;␣
 ↪$\alpha = 0.01$') # alpha here is for transparency

plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.legend(fontsize=13,loc=4)
plt.subplot(1,2,2)
plt.plot(lasso.coef_,alpha=0.
 ↪7,linestyle='none',marker='*',markersize=5,color='red',label=r'Lasso;␣
 ↪$\alpha = 1$',zorder=7) # alpha here is for transparency
plt.plot(lasso001.coef_,alpha=0.
 ↪5,linestyle='none',marker='d',markersize=6,color='blue',label=r'Lasso;␣
 ↪$\alpha = 0.01$') # alpha here is for transparency
plt.plot(lasso00001.coef_,alpha=0.
 ↪8,linestyle='none',marker='v',markersize=6,color='black',label=r'Lasso;␣
 ↪$\alpha = 0.00001$') # alpha here is for transparency
plt.plot(lr.coef_,alpha=0.
 ↪7,linestyle='none',marker='o',markersize=5,color='green',label='Linear␣
 ↪Regression',zorder=2)
plt.xlabel('Coefficient Index',fontsize=16)
plt.ylabel('Coefficient Magnitude',fontsize=16)
plt.legend(fontsize=13,loc=4)
plt.tight_layout()
plt.show()
```

```
training score: 0.3354963706780224
test score:  0.2790770637234491
number of features used:  12
training score for alpha=0.01: 0.4852405649033092
test score for alpha =0.01:  0.4572169458961612
number of features used: for alpha =0.01: 27
training score for alpha=0.0001: 0.5098119359755454
test score for alpha =0.0001:  0.4797847516161179
number of features used: for alpha =0.0001: 47
LR training score: 0.5098707388489385
LR test score:  0.4793769609946402
```




When we look at the picture on the left, we can see that for alpha = 1,most of the coefficients are zero or close to zero. Lasso kills too many features. And with alpha = 0.01, this model has more features. When we set alpha = 0.0001, 47 non-zero feature attributes remain in the model and the training and test scores are the same as the basic linear regression. Based on this result, alpha = 0.01 could be a little better.

[679]:
```
lasso_result = lasso001.predict(X_test)
```

#Model Comparation

[680]:
```
result_table = pd.DataFrame(y_test)
result_table.columns = ['IMDB_score']
result_table['Linear'] = LR_result
result_table['Ridge'] = rr_result
result_table['Lasso'] = lasso_result
result_table.sort_values(by=['IMDB_score'])
new_table = result_table.reset_index(drop=True)
new_table
```

[680]:

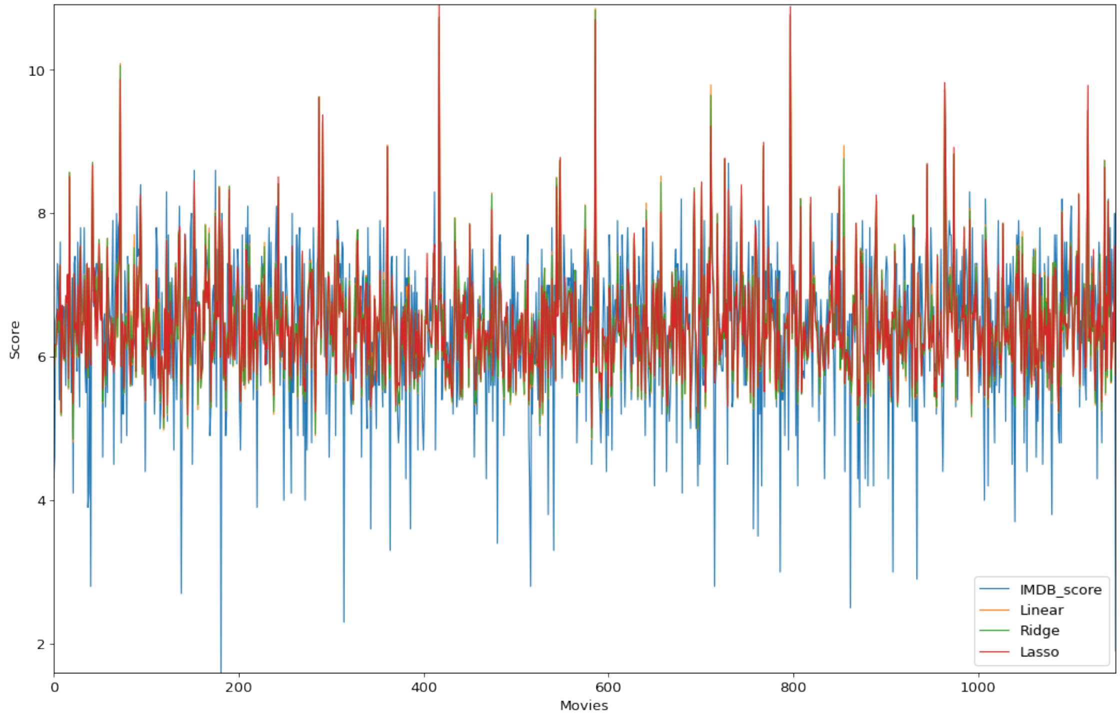
| | IMDB_score | Linear | Ridge | Lasso |
|---|---|---|---|---|
| 0 | 4.3 | 5.688365 | 5.695836 | 5.806589 |
| 1 | 4.6 | 6.126685 | 6.118443 | 6.167607 |
| 2 | 6.5 | 5.987510 | 5.995089 | 6.169073 |
| 3 | 6.6 | 6.307683 | 6.302308 | 6.168252 |
| 4 | 7.3 | 6.662066 | 6.663338 | 6.661530 |

```
…          …      …         …         …
1145         7.5  5.984478  6.002163  6.017775
1146         6.8  6.471635  6.487194  6.620229
1147         6.7  6.435611  6.386730  6.210141
1148         8.0  7.287553  7.291819  7.550669
1149         1.9  5.736781  5.746833  5.763123

[1150 rows x 4 columns]
```

[681]:
```
IMDB_score = new_table['IMDB_score']
linear = new_table['Linear']
ridge = new_table['Ridge']
lasso = new_table['Lasso']
index = range(len(new_table))
```

[688]:
```
figure(figsize=(16, 10), dpi=80)
plt.plot(index,  IMDB_score,label='IMDB_score',linewidth=1)
plt.plot(index, linear, label='Linear',linewidth=1)
plt.plot(index, ridge, label='Ridge',linewidth=1)
plt.plot(index, lasso, label='Lasso',linewidth=1)
plt.legend()

plt.margins(0)
plt.subplots_adjust(bottom=0.10)
plt.xlabel('Movies')
plt.ylabel("Score")
```

[688]:
```
Text(0, 0.5, 'Score')
```




We can hardly see anything here, it is a mess. But we can tell that for some movies with pretty low score, three models cannot tell precisely. And their predictions are sometimes staying higher than the real score.

[683]:
```
print(f"Linear Regression MSE {mean_squared_error(LR_result, y_test)}")
print(f"Linear Regression RMSE {np.sqrt(mean_squared_error(LR_result,␣
↪y_test))}")
print(f"Linear Regression R^2 {r2_score(y_test, LR_result)}")
```

```
Linear Regression MSE 0.584968462720589
Linear Regression RMSE 0.7648323101965483
Linear Regression R^2 0.46195133755505724
```

[684]:
```
print(f"Ridge Regression MSE {mean_squared_error(rr_result, y_test)}")
print(f"Ridge Regression RMSE {np.sqrt(mean_squared_error(rr_result, y_test))}")
print(f"Ridge Regression R^2 {r2_score(y_test, rr_result)}")
```

```
Ridge Regression MSE 0.5835446818982589
Ridge Regression RMSE 0.7639009634096942
Ridge Regression R^2 0.4632609181835694
```

[685]:
```
print(f"Lasso Regression MSE {mean_squared_error(lasso_result, y_test)}")
print(f"Lasso Regression RMSE {np.sqrt(mean_squared_error(lasso_result,␣
↪y_test))}")
print(f"Lasso Regression R^2 {r2_score(y_test, lasso_result)}")
```

```
Lasso Regression MSE 0.6004378791253496
Lasso Regression RMSE 0.7748792674509686
Lasso Regression R^2 0.4477227092856373
```

Compared to the baseline model, lasso and ridge both did good job while ridge regression is a little better. I would say this model cannot make a perfect prediction of IMDB score yet, but it do tell some story about it and can be tuned further.