In [2]:

```python
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.neighbors import KNeighborsRegressor
import xgboost as xgb
from sklearn.metrics import mean_squared_error, accuracy_score, r2_score, mean_absolute_error
from sklearn import metrics
```

In [3]:

```python
df=pd.read_csv('movie_metadata.csv')
# Reading the dataset
```

In [4]:

```python
pd.set_option('display.max_columns', None)
```

In [5]:

```python
df
# loading the dataset
```

Out[5]:

	color	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_name	actor_1_facebook_li
0	Color	James Cameron	723.0	178.0	0.0	855.0	Joel David Moore	100
1	Color	Gore Verbinski	302.0	169.0	563.0	1000.0	Orlando Bloom	4000
2	Color	Sam Mendes	602.0	148.0	0.0	161.0	Rory Kinnear	1100
3	Color	Christopher Nolan	813.0	164.0	22000.0	23000.0	Christian Bale	2700
4	NaN	Doug Walker	NaN	NaN	131.0	NaN	Rob Walker	13
...	...	...	...	...	...	...	...	
5038	Color	Scott Smith	1.0	87.0	2.0	318.0	Daphne Zuniga	63
5039	Color	NaN	43.0	43.0	NaN	319.0	Valorie Curry	84
5040	Color	Benjamin Roberds	13.0	76.0	0.0	0.0	Maxwell Moody	
5041	Color	Daniel Hsia	14.0	100.0	0.0	489.0	Daniel Henney	94
5042	Color	Jon Gunn	43.0	90.0	16.0	16.0	Brian Herzlinger	8

5043 rows × 28 columns

In [6]:

```python
df.shape
# the dataset has around 5043 rows and 28 columns
```

Out[6]:

```
(5043, 28)
```

In [7]:

```python
df.info()
# Checking the information on the dataset
```

```
<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
```

In [8]:

```
df.isnull().sum()
# There are null values present in this dataset which have to be imputed.
```

Out[8]:

```
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
```

In [9]:

```
df.columns
# Displaying all the column names present in the dataframe.
```

Out[9]:

```
Index(['color', 'director_name', 'num_critic_for_reviews', 'duration',
       'director_facebook_likes', 'actor_3_facebook_likes', 'actor_2_name',
       'actor_1_facebook_likes', 'gross', 'genres', 'actor_1_name',
       'movie_title', 'num_voted_users', 'cast_total_facebook_likes',
       'actor_3_name', 'facenumber_in_poster', 'plot_keywords',
       'movie_imdb_link', 'num_user_for_reviews', 'language', 'country',
       'content_rating', 'budget', 'title_year', 'actor_2_facebook_likes',
       'imdb_score', 'aspect_ratio', 'movie_facebook_likes'],
      dtype='object')
```

In [10]:

```
df['color'].value_counts()
```

```
# We have 4815 colour movies and 209 Black and white movies.
```

Out[10]:
```
Color               4815
 Black and White     209
Name: color, dtype: int64
```

In [11]:
```
df.describe()
# Using the describe function to check the min, max values as well as mean and standard deviation.
```

Out[11]:

	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_1_facebook_likes	gross	num_voted_u
count	4993.000000	5028.000000	4939.000000	5020.000000	5036.000000	4.159000e+03	5.043000e
mean	140.194272	107.201074	686.509212	645.009761	6560.047061	4.846841e+07	8.366816e
std	121.601675	25.197441	2813.328607	1665.041728	15020.759120	6.845299e+07	1.384853e
min	1.000000	7.000000	0.000000	0.000000	0.000000	1.620000e+02	5.000000e
25%	50.000000	93.000000	7.000000	133.000000	614.000000	5.340988e+06	8.593500e
50%	110.000000	103.000000	49.000000	371.500000	988.000000	2.551750e+07	3.435900e
75%	195.000000	118.000000	194.500000	636.000000	11000.000000	6.230944e+07	9.630900e
max	813.000000	511.000000	23000.000000	23000.000000	640000.000000	7.605058e+08	1.689764e

In [12]:
```
df.nunique()
# Displays the total number of variables present in the data frames columns
```

Out[12]:
```
color                          2
director_name               2398
num_critic_for_reviews       528
duration                     191
director_facebook_likes      435
actor_3_facebook_likes       906
actor_2_name                3032
actor_1_facebook_likes       878
gross                       4035
genres                       914
actor_1_name                2097
movie_title                 4917
num_voted_users             4826
cast_total_facebook_likes   3978
actor_3_name                3521
facenumber_in_poster          19
plot_keywords               4760
movie_imdb_link             4919
num_user_for_reviews         954
language                      47
country                       65
content_rating                18
budget                       439
title_year                    91
actor_2_facebook_likes       917
imdb_score                    78
aspect_ratio                  22
movie_facebook_likes         876
dtype: int64
```

In [13]:
```
df['language'].value_counts()
# A lot of movies in this dataset are in English.
```

Out[13]:
```
English       4704
French          73
Spanish         40
Hindi           28
Mandarin        26
German          19
Japanese        18
Cantonese       11
Russian         11
Italian         11
Portuguese       8
Korean           8
Arabic           5
Danish           5
Hebrew           5
Swedish          5
Polish           4
Norwegian        4
```

```
Persian          4
Dutch            4
Thai             3
Chinese          3
Icelandic        2
None             2
Indonesian       2
Aboriginal       2
Romanian         2
Dari             2
Zulu             2
Panjabi          1
Urdu             1
Vietnamese       1
Slovenian        1
Greek            1
Dzongkha         1
Tamil            1
Telugu           1
Kannada          1
Czech            1
Hungarian        1
Bosnian          1
Filipino         1
Mongolian        1
Maya             1
Aramaic          1
Kazakh           1
Swahili          1
Name: language, dtype: int64
```

In [14]:
```
df['movie_title']
# Displaying all the movie names.
```

Out[14]:
```
0                                                  Avatar
1                Pirates of the Caribbean: At World's End
2                                                 Spectre
3                                   The Dark Knight Rises
4        Star Wars: Episode VII - The Force Awakens    ...
                              ...
5038                              Signed Sealed Delivered
5039                            The Following
5040                                 A Plague So Pleasant
5041                                     Shanghai Calling
5042                                    My Date with Drew
Name: movie_title, Length: 5043, dtype: object
```

In [15]:
```
df.movie_title[df.language == 'Hindi']
# printing the name of Hindi movies present in the dataset.
```

Out[15]:
```
1056                                  Earth
3075                  Kabhi Alvida Naa Kehna
3085                              Housefull
3208                                 Krrish
3276                        Jab Tak Hai Jaan
3344                        My Name Is Khan
3348                        Namastey London
3350                 Yeh Jawaani Hai Deewani
3455                            Ta Ra Rum Pum
3510                              Veer-Zaara
3665                            Khiladi 786
3685                        Rang De Basanti
3695                          Dum Maaro Dum
3789                      Gandhi, My Father
3866                                  Fugly
3870                                Airlift
3877                                    Paa
4088                                  Water
4160                    Lage Raho Munna Bhai
4299                  Hum To Mohabbat Karega
4305                          Roadside Romeo
4351               ABCD (Any Body Can Dance)
4385                           The Lunchbox
4490                         Monsoon Wedding
4528    Rocket Singh: Salesman of the Year
4572                                   Fiza
4593             Chocolate: Deep Dark Secrets
4724                       Faith Connections
Name: movie_title, dtype: object
```

In [16]:

```
bw=df[df.language == 'Hindi']
# Saving the Hindi movies into a separate dataframe for futher analysis
```

In [17]:

```
bw
# Dataframe of all hindi movies with high imdb scores
```

Out[17]:

	color	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_name	actor_1_facebook_li
1056	Color	Deepa Mehta	34.0	110.0	375.0	59.0	Gulshan Grover	1
3075	Color	Karan Johar	20.0	193.0	160.0	860.0	John Abraham	80
3085	Color	Sajid Khan	10.0	144.0	0.0	119.0	Boman Irani	5
3208	Color	Rakesh Roshan	20.0	168.0	53.0	45.0	Rekha	3
3276	Color	Yash Chopra	50.0	176.0	147.0	1000.0	Katrina Kaif	80
3344	Color	Karan Johar	210.0	128.0	160.0	81.0	Jimmy Shergill	80
3348	Color	Vipul Amrutlal Shah	15.0	128.0	11.0	119.0	Clive Standen	30
3350	Color	Ayan Mukerji	25.0	160.0	0.0	417.0	Madhuri Dixit	9
3455	Color	Siddharth Anand	16.0	153.0	5.0	60.0	Mary Goggin	5
3510	Color	Yash Chopra	29.0	192.0	147.0	397.0	Preity Zinta	80
3665	Color	Ashish R. Mohan	23.0	141.0	2.0	61.0	Mithun Chakraborty	6
3685	Color	Rakeysh Omprakash Mehra	33.0	157.0	85.0	199.0	Steven Mackintosh	3
3695	Color	Rohan Sippy	24.0	128.0	4.0	47.0	Bipasha Basu	3
3789	Color	Feroz Abbas Khan	16.0	136.0	0.0	14.0	Bhoomika Chawla	
3866	Color	Kabir Sadanand	9.0	134.0	0.0	62.0	Sana Saeed	3
3870	Color	Raja Menon	39.0	130.0	6.0	12.0	Sameer Ali Khan	
3877	Color	R. Balki	12.0	133.0	12.0	106.0	Abhishek Bachchan	4
4088	Color	Deepa Mehta	91.0	117.0	375.0	31.0	Lisa Ray	10
4160	Color	Rajkumar Hirani	15.0	144.0	124.0	327.0	Sanjay Dutt	4
4299	Color	Kundan Shah	1.0	NaN	4.0	72.0	Bobby Deol	3
4305	Color	Jugal Hansraj	6.0	93.0	32.0	24.0	Sanjay Mishra	5
4351	Color	Remo	15.0	160.0	168.0	71.0	Remo	7
4385	Color	Ritesh Batra	195.0	104.0	25.0	73.0	Nimrat Kaur	6
4490	Color	Mira Nair	137.0	114.0	300.0	73.0	Randeep Hooda	3
4528	Color	Shimit Amin	14.0	150.0	6.0	20.0	Shazahn Padamsee	9
4572	Black and White	Khalid Mohamed	1.0	167.0	10.0	97.0	Manoj Bajpayee	3
4593	Color	Vivek Agnihotri	4.0	160.0	5.0	219.0	Anil Kapoor	7
4724	Color	Pan Nalin	19.0	115.0	95.0	0.0	Pant Shirt Baba	

In [18]:
```
scores=bw.imdb_score[bw.imdb_score>=7]
# storing movies with imdb score equal to 8 or above 8
```

In [19]:
```
name=bw.movie_title[bw.imdb_score>=7]
# storing movie_titles with imdb scores above 8 or equal to 8
```

In [20]:
```
genre=bw.genres[bw.imdb_score>=7]
# storing movie genre with imdb score above or equal to 8
```

In [21]:
```
bollywoodmovieratings=pd.concat([name,genre,scores],axis=1)
# creating a dataframe with all values concatenated into one dataframe
```

In [22]:
```
bollywoodmovieratings
# final concatenated dataframe of Indian movies and their genres and imdb_scores
```

Out[22]:

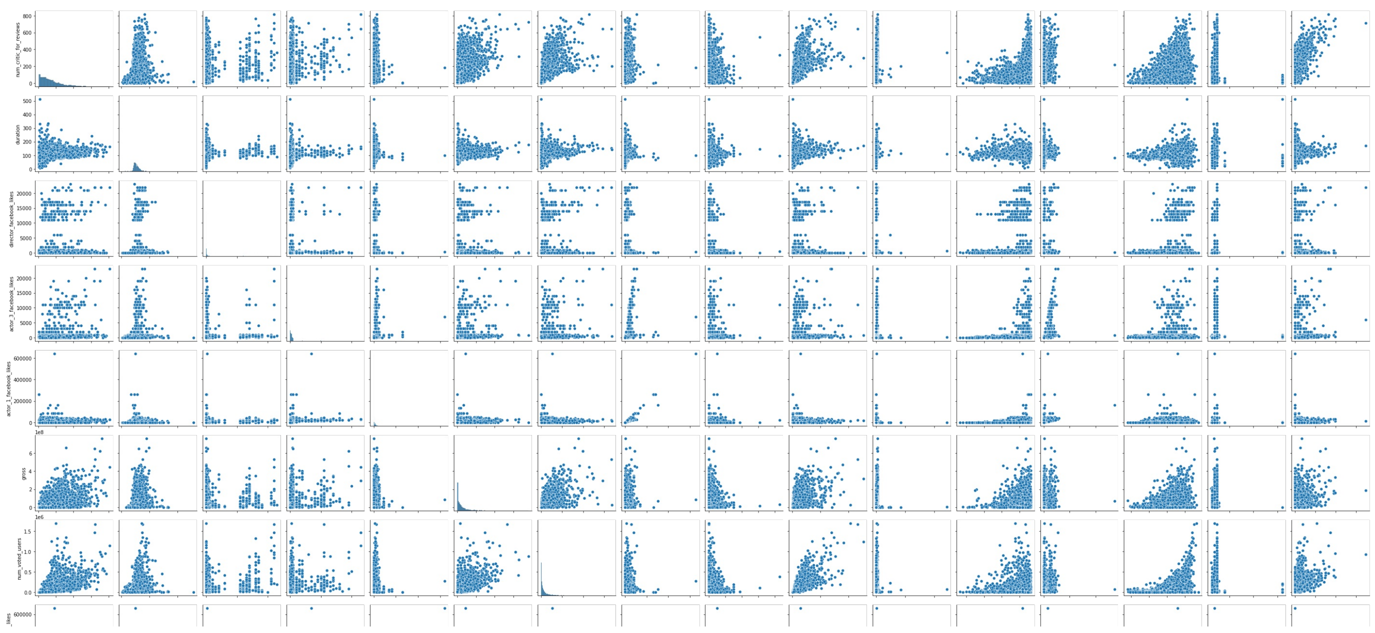
	movie_title	genres	imdb_score
1056	Earth	Drama|Romance|War	7.8
3344	My Name Is Khan	Adventure|Drama|Thriller	8.0
3348	Namastey London	Comedy|Drama|Romance	7.3
3510	Veer-Zaara	Drama|Musical|Romance	7.9
3685	Rang De Basanti	Comedy|Drama|History|Romance	8.4
3789	Gandhi, My Father	Biography|Drama|History	7.4
3870	Airlift	Action|Drama|History|Thriller|War	8.5
3877	Paa	Comedy|Drama	7.2
4088	Water	Drama|Romance	7.8
4160	Lage Raho Munna Bhai	Comedy|Drama|Romance	8.2
4385	The Lunchbox	Drama|Romance	7.8
4490	Monsoon Wedding	Comedy|Drama|Romance	7.4
4528	Rocket Singh: Salesman of the Year	Comedy|Drama	7.5
4724	Faith Connections	Biography|Documentary|Drama	7.0

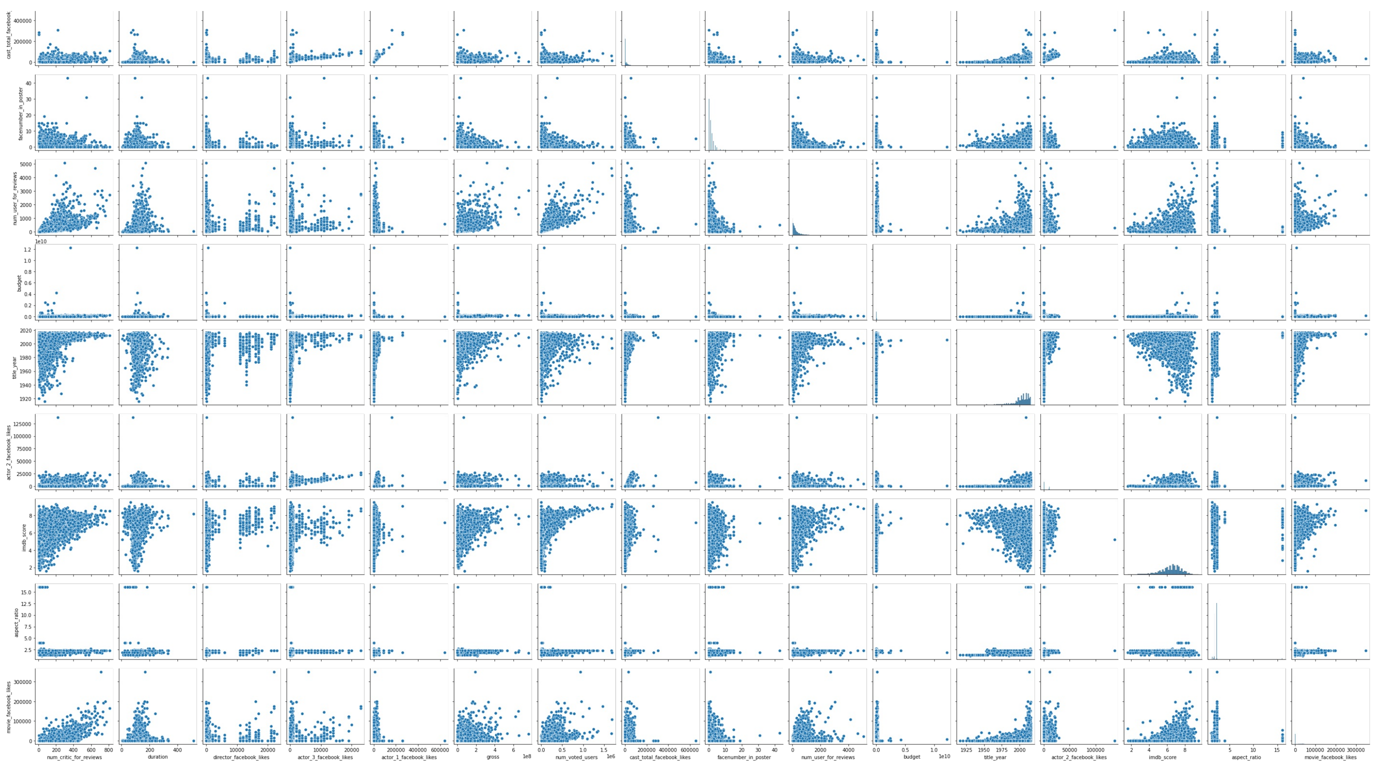
As seen above Indian movies have a higher imdb score if it has a genre with Action|Drama|History|Thriller|War included in it.

Data visualization

In [23]:
```
sns.pairplot(data=df)
```

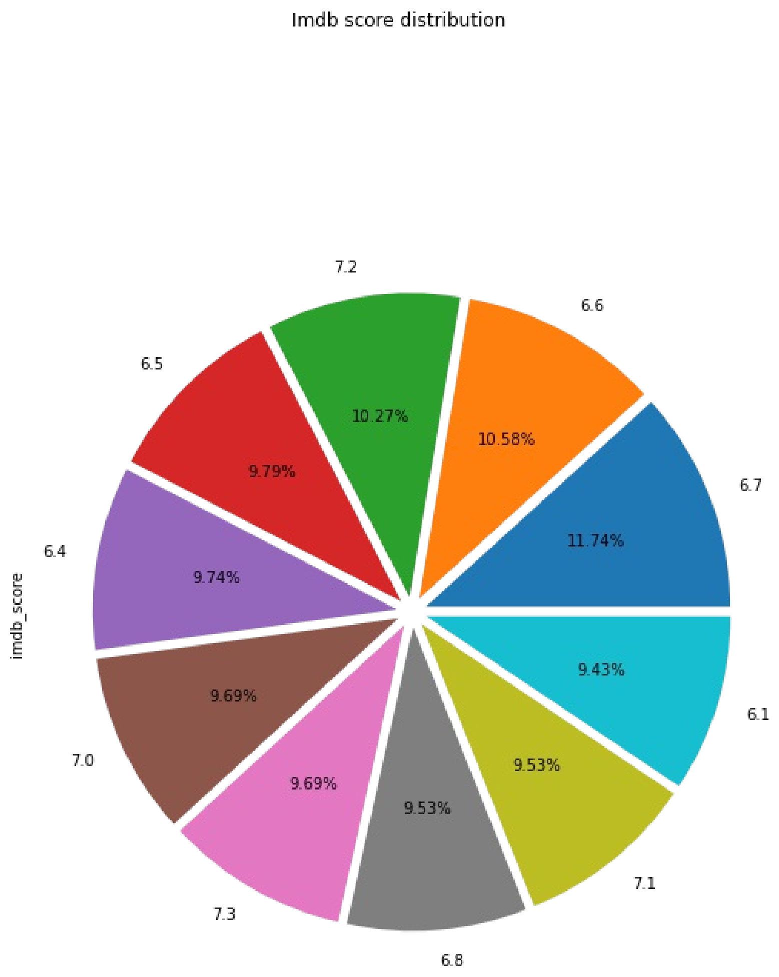
Out[23]:
```
<seaborn.axisgrid.PairGrid at 0x21d14f72610>
```





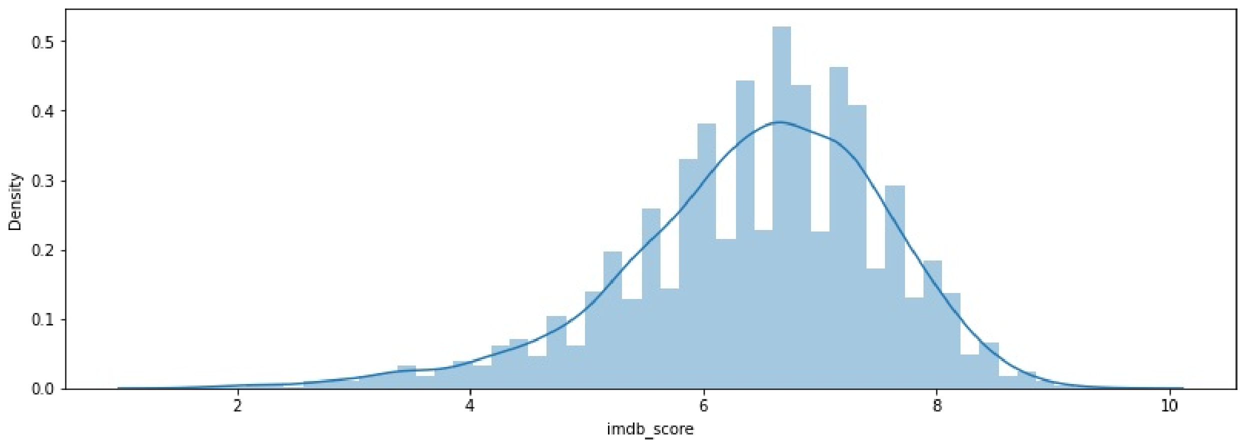
```
In [25]:
f,ax=plt.subplots(figsize=(10,20))
ax1=plt.subplot(211)
f.suptitle("Imdb score distribution")
explode=(0.05,0.05,0.05,0.05,0.05,0.05,0.05,0.05,0.05,0.05)
df['imdb_score'].value_counts(ascending=False).head(10).plot(kind='pie',autopct="%0.2f%%",explode=explode,ax=ax1)
# Pie plot for top 10 Imdb_scores.
# Around 11.74 percent of the data has a imdb_score which is 6.7
```

```
Out[25]: <AxesSubplot:ylabel='imdb_score'>
```

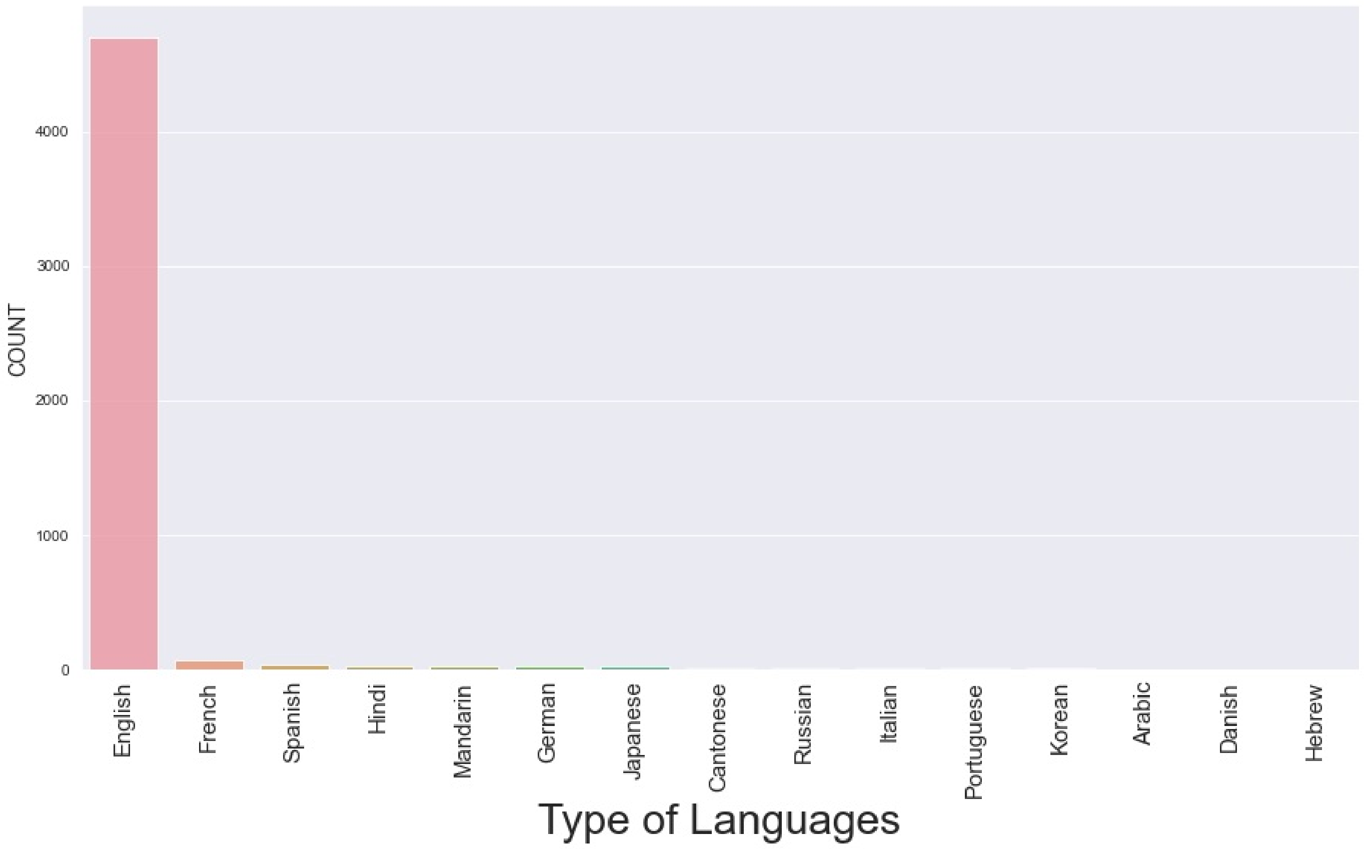


In [26]:
```
# Distribution plot for all prices.
f,ax=plt.subplots(figsize=(30,10))
ax3=plt.subplot(224)
sns.distplot(df['imdb_score'],ax=ax3)
# Using the distribution plot we can see that the imdb score is the highest at a imdb score which is between 6 ar
```

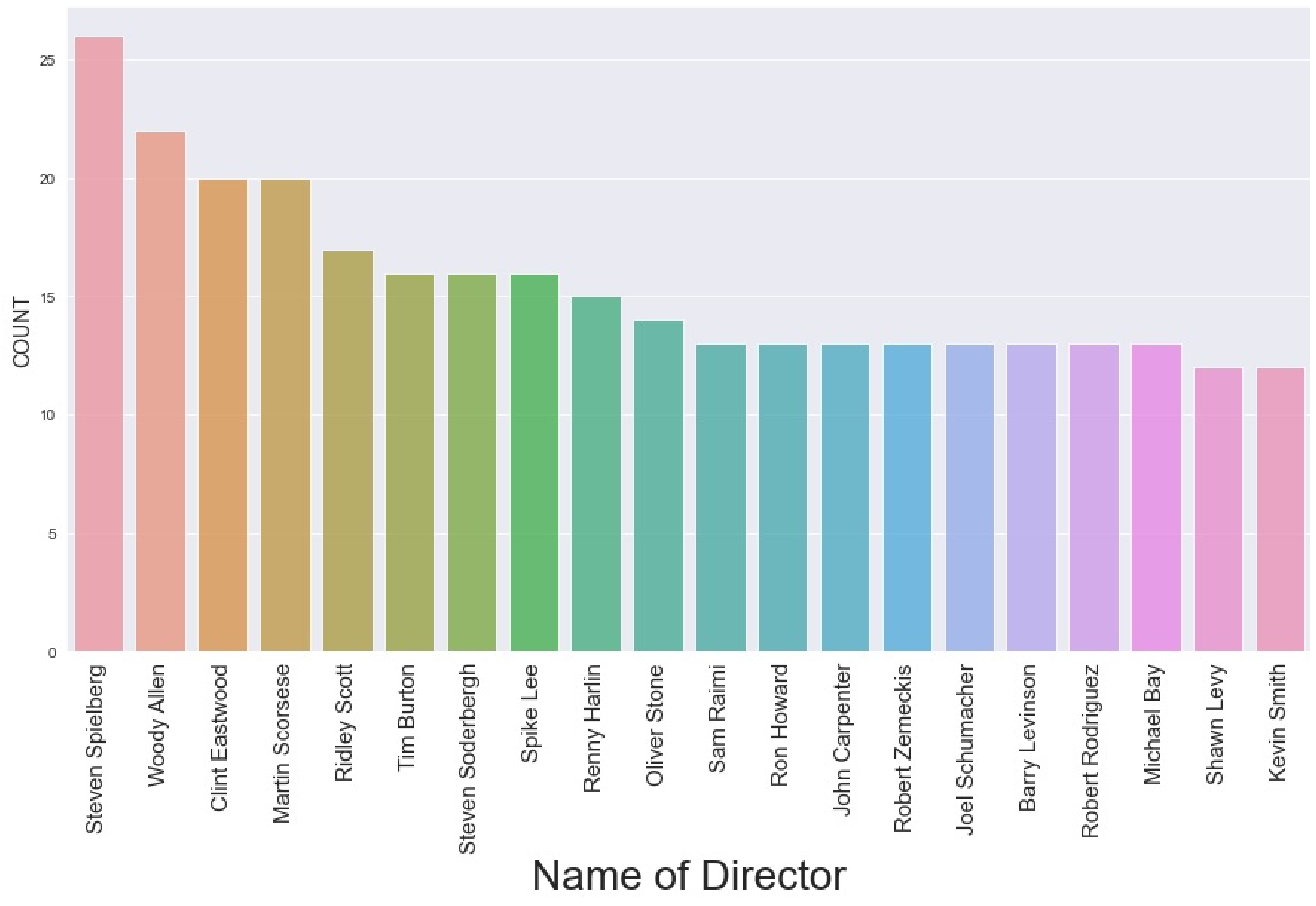
Out[26]:
```
<AxesSubplot:xlabel='imdb_score', ylabel='Density'>
```



In [27]:
```
sns.set_style("darkgrid")
ls=df['language'].value_counts().head(15).sort_values(ascending=False)
plt.figure(figsize=(15,8))
temp =sns.barplot(ls.index, ls.values, alpha=0.8)
plt.ylabel('COUNT', fontsize=14)
plt.xlabel('Type of Languages', fontsize=28)
temp.set_xticklabels(rotation=90,labels=ls.index,fontsize=15)
plt.show()
# Visualizing the count of languages in the dataset.
```

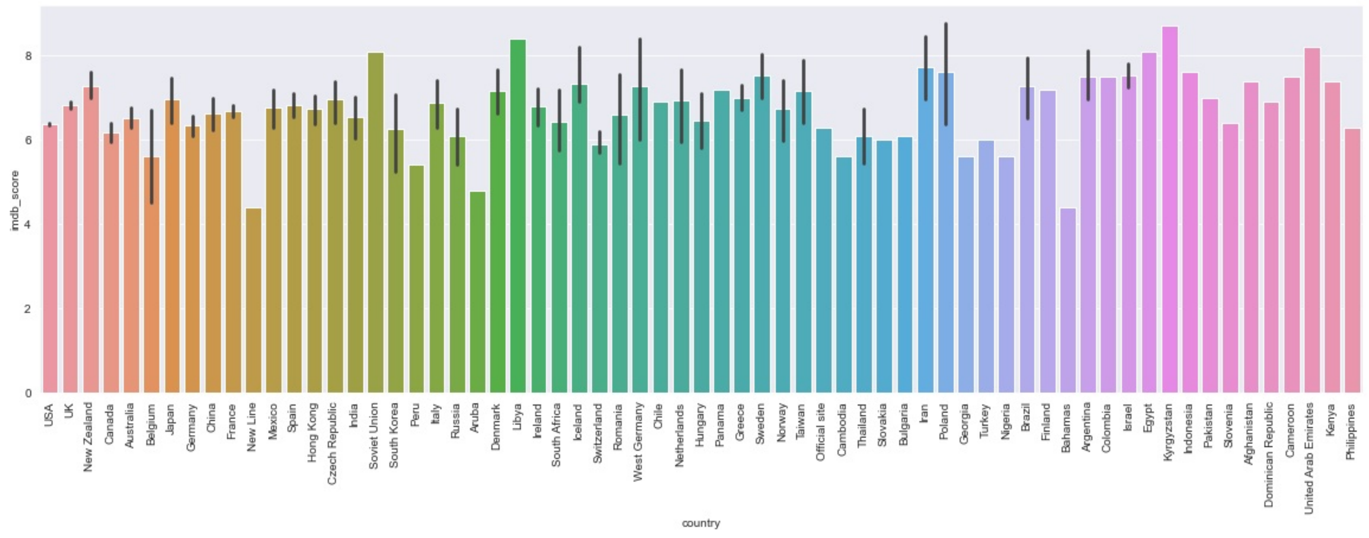


In [28]:
```
sns.set_style("darkgrid")
ls=df['director_name'].value_counts().head(20).sort_values(ascending=False)
plt.figure(figsize=(15,8))
temp =sns.barplot(ls.index, ls.values, alpha=0.8)
plt.ylabel('COUNT', fontsize=14)
plt.xlabel('Name of Director', fontsize=28)
temp.set_xticklabels(rotation=90,labels=ls.index,fontsize=15)
plt.show()
# Visualizing the Directors names present in the dataset.
```



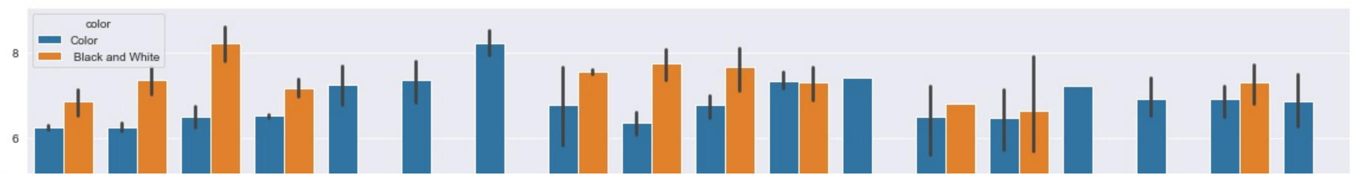
In [29]:
```
plt.figure(figsize=(20, 6))
sns.barplot(x='country',y='imdb_score',data=df);
plt.xticks(rotation=90)
# Visualizing the barplot of countries and the imdb scores.
```

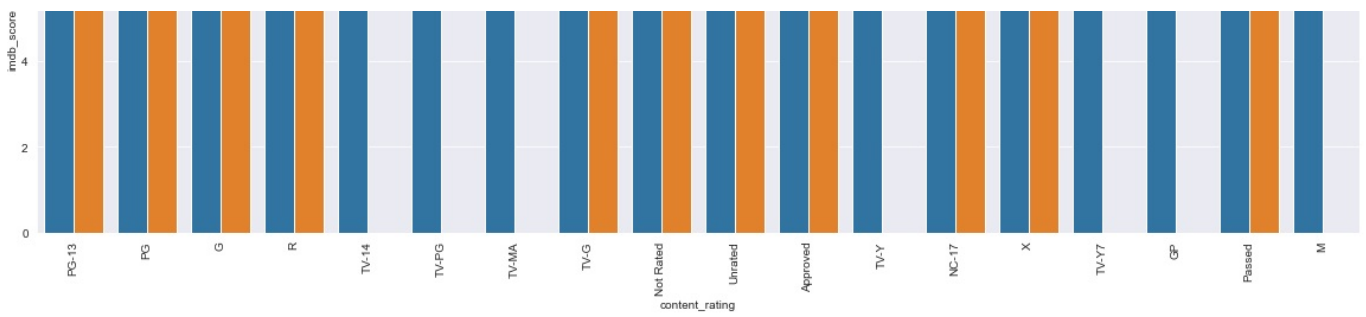
Out[29]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33,
        34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50,
        51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64]),
 [Text(0, 0, 'USA'),
  Text(1, 0, 'UK'),
  Text(2, 0, 'New Zealand'),
  Text(3, 0, 'Canada'),
  Text(4, 0, 'Australia'),
  Text(5, 0, 'Belgium'),
  Text(6, 0, 'Japan'),
  Text(7, 0, 'Germany'),
  Text(8, 0, 'China'),
  Text(9, 0, 'France'),
  Text(10, 0, 'New Line'),
  Text(11, 0, 'Mexico'),
  Text(12, 0, 'Spain'),
  Text(13, 0, 'Hong Kong'),
  Text(14, 0, 'Czech Republic'),
  Text(15, 0, 'India'),
  Text(16, 0, 'Soviet Union'),
  Text(17, 0, 'South Korea'),
  Text(18, 0, 'Peru'),
  Text(19, 0, 'Italy'),
  Text(20, 0, 'Russia'),
  Text(21, 0, 'Aruba'),
  Text(22, 0, 'Denmark'),
  Text(23, 0, 'Libya'),
  Text(24, 0, 'Ireland'),
  Text(25, 0, 'South Africa'),
  Text(26, 0, 'Iceland'),
  Text(27, 0, 'Switzerland'),
  Text(28, 0, 'Romania'),
  Text(29, 0, 'West Germany'),
  Text(30, 0, 'Chile'),
  Text(31, 0, 'Netherlands'),
  Text(32, 0, 'Hungary'),
  Text(33, 0, 'Panama'),
  Text(34, 0, 'Greece'),
  Text(35, 0, 'Sweden'),
  Text(36, 0, 'Norway'),
 Text(37, 0, 'Taiwan'),
 Text(38, 0, 'Official site'),
 Text(39, 0, 'Cambodia'),
 Text(40, 0, 'Thailand'),
 Text(41, 0, 'Slovakia'),
 Text(42, 0, 'Bulgaria'),
 Text(43, 0, 'Iran'),
 Text(44, 0, 'Poland'),
 Text(45, 0, 'Georgia'),
 Text(46, 0, 'Turkey'),
 Text(47, 0, 'Nigeria'),
 Text(48, 0, 'Brazil'),
 Text(49, 0, 'Finland'),
 Text(50, 0, 'Bahamas'),
 Text(51, 0, 'Argentina'),
 Text(52, 0, 'Colombia'),
 Text(53, 0, 'Israel'),
 Text(54, 0, 'Egypt'),
 Text(55, 0, 'Kyrgyzstan'),
 Text(56, 0, 'Indonesia'),
 Text(57, 0, 'Pakistan'),
 Text(58, 0, 'Slovenia'),
 Text(59, 0, 'Afghanistan'),
 Text(60, 0, 'Dominican Republic'),
 Text(61, 0, 'Cameroon'),
 Text(62, 0, 'United Arab Emirates'),
 Text(63, 0, 'Kenya'),
 Text(64, 0, 'Philippines')])
```



In [30]:
```python
plt.figure(figsize=(20, 6))
sns.barplot(x='content_rating',y='imdb_score',hue='color',data=df);
plt.xticks(rotation=90)
# This visualization shows the type of content having higher imdbscore and shows us the type of movie color prese
```

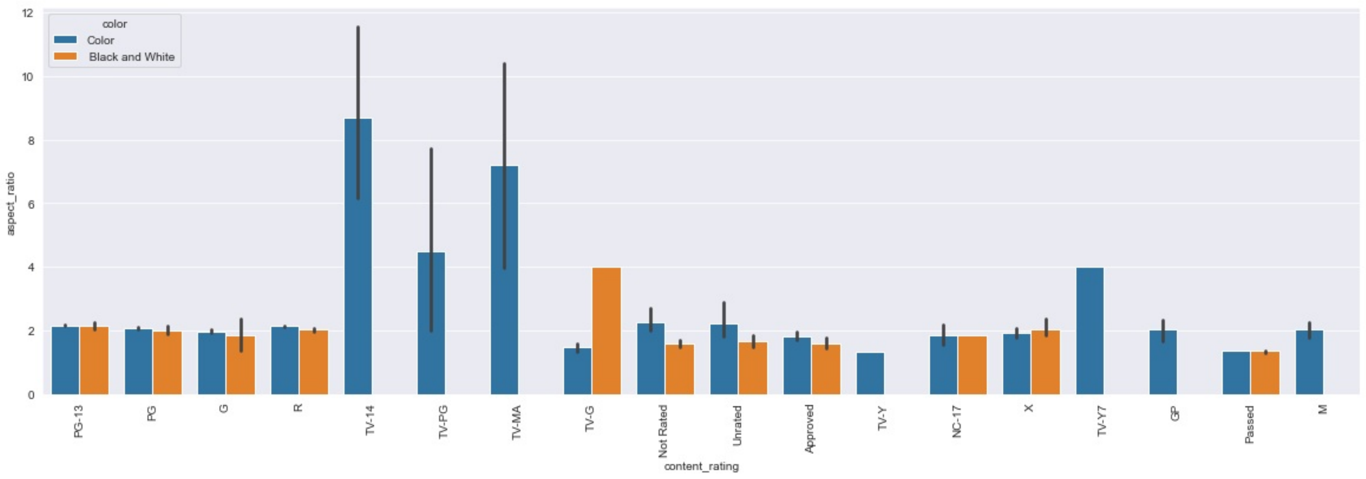
Out[30]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17]),
 [Text(0, 0, 'PG-13'),
  Text(1, 0, 'PG'),
  Text(2, 0, 'G'),
  Text(3, 0, 'R'),
  Text(4, 0, 'TV-14'),
  Text(5, 0, 'TV-PG'),
  Text(6, 0, 'TV-MA'),
  Text(7, 0, 'TV-G'),
  Text(8, 0, 'Not Rated'),
  Text(9, 0, 'Unrated'),
  Text(10, 0, 'Approved'),
  Text(11, 0, 'TV-Y'),
  Text(12, 0, 'NC-17'),
  Text(13, 0, 'X'),
  Text(14, 0, 'TV-Y7'),
  Text(15, 0, 'GP'),
  Text(16, 0, 'Passed'),
  Text(17, 0, 'M')])
```





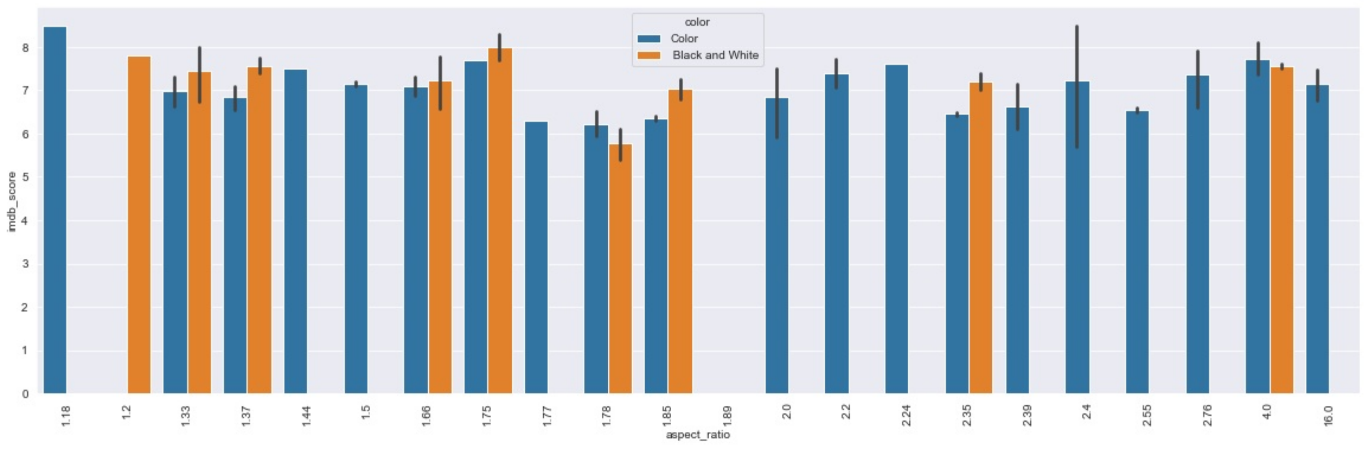
In [31]:
```
plt.figure(figsize=(20, 6))
sns.barplot(x='content_rating',y='aspect_ratio',hue='color',data=df);
plt.xticks(rotation=90)
# This visualization shows the type of content rating on X-axis having aspect ratio on Y-axis and hue with type c
```

Out[31]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17]),
 [Text(0, 0, 'PG-13'),
  Text(1, 0, 'PG'),
  Text(2, 0, 'G'),
  Text(3, 0, 'R'),
  Text(4, 0, 'TV-14'),
  Text(5, 0, 'TV-PG'),
  Text(6, 0, 'TV-MA'),
  Text(7, 0, 'TV-G'),
  Text(8, 0, 'Not Rated'),
  Text(9, 0, 'Unrated'),
  Text(10, 0, 'Approved'),
  Text(11, 0, 'TV-Y'),
  Text(12, 0, 'NC-17'),
  Text(13, 0, 'X'),
  Text(14, 0, 'TV-Y7'),
  Text(15, 0, 'GP'),
  Text(16, 0, 'Passed'),
  Text(17, 0, 'M')])
```



In [32]:
```
plt.figure(figsize=(20, 6))
sns.barplot(x='aspect_ratio',y='imdb_score',hue='color',data=df);
plt.xticks(rotation=90)
# This visualization shows the aspect ratio and its imdb score with hue as the color column.
```

Out[32]:
```
(array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
        17, 18, 19, 20, 21]),
 [Text(0, 0, '1.18'),
  Text(1, 0, '1.2'),
  Text(2, 0, '1.33'),
  Text(3, 0, '1.37'),
  Text(4, 0, '1.44'),
  Text(5, 0, '1.5'),
  Text(6, 0, '1.66'),
  Text(7, 0, '1.75'),
  Text(8, 0, '1.77'),
  Text(9, 0, '1.78'),
  Text(10, 0, '1.85'),
  Text(11, 0, '1.89'),
  Text(12, 0, '2.0'),
  Text(13, 0, '2.2'),
  Text(14, 0, '2.24'),
  Text(15, 0, '2.35'),
 Text(16, 0, '2.39'),
 Text(17, 0, '2.4'),
 Text(18, 0, '2.55'),
 Text(19, 0, '2.76'),
 Text(20, 0, '4.0'),
 Text(21, 0, '16.0')])
```



In [33]:
```
df=df.dropna()
# Removing null values
```

In [34]:
```
df.isnull().sum()
# As you can see there is no null values present in the dataset now.
```

Out[34]:
```
color                        0
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
movie_title                  0
num_voted_users              0
cast_total_facebook_likes    0
actor_3_name                 0
facenumber_in_poster         0
plot_keywords                0
movie_imdb_link              0
num_user_for_reviews         0
language                     0
country                      0
content_rating               0
budget                       0
title_year                   0
actor_2_facebook_likes       0
imdb_score                   0
aspect_ratio                 0
movie_facebook_likes         0
dtype: int64
```

In [35]:
```
df.columns
```

Out[35]:
```
Index(['color', 'director_name', 'num_critic_for_reviews', 'duration',
       'director_facebook_likes', 'actor_3_facebook_likes', 'actor_2_name',
       'actor_1_facebook_likes', 'gross', 'genres', 'actor_1_name',
       'movie_title', 'num_voted_users', 'cast_total_facebook_likes',
       'actor_3_name', 'facenumber_in_poster', 'plot_keywords',
       'movie_imdb_link', 'num_user_for_reviews', 'language', 'country',
       'content_rating', 'budget', 'title_year', 'actor_2_facebook_likes',
       'imdb_score', 'aspect_ratio', 'movie_facebook_likes'],
      dtype='object')
```

In [36]:
```
df=df.drop(columns=['movie_imdb_link','color','movie_title','facenumber_in_poster', 'plot_keywords',
                    'actor_3_name','movie_imdb_link','aspect_ratio','language'])
```

In [37]:
```
df
```

Out[37]:

	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_name	actor_1_facebook_likes	
0	James Cameron	723.0	178.0	0.0	855.0	Joel David Moore	1000.0	76
1	Gore Verbinski	302.0	169.0	563.0	1000.0	Orlando Bloom	40000.0	30
2	Sam Mendes	602.0	148.0	0.0	161.0	Rory Kinnear	11000.0	20
3	Christopher Nolan	813.0	164.0	22000.0	23000.0	Christian Bale	27000.0	44
5	Andrew Stanton	462.0	132.0	475.0	530.0	Samantha Morton	640.0	7
...	...	...	...	...	...	...	...	
5026	Olivier Assayas	81.0	110.0	107.0	45.0	Béatrice Dalle	576.0	
5027	Jafar Panahi	64.0	90.0	397.0	0.0	Nargess Mamizadeh	5.0	
5033	Shane Carruth	143.0	77.0	291.0	8.0	David Sullivan	291.0	
5035	Robert Rodriguez	56.0	81.0	0.0	6.0	Peter Marquardt	121.0	
5042	Jon Gunn	43.0	90.0	16.0	16.0	Brian Herzlinger	86.0	

3756 rows × 20 columns

In [38]:
```
df.shape
# The number of columns have now been reduced to 20
```

Out[38]:
```
(3756, 20)
```

Label Encoding Categorical data

In [39]:
```
cat_cols=['content_rating','director_name','genres','actor_1_name','actor_2_name','country']
le=LabelEncoder()
for i in cat_cols:
    df[i]=le.fit_transform(df[i])
df.dtypes
## We have label encoded the categorical columns in the dataset and transformed them to numeric values.
```

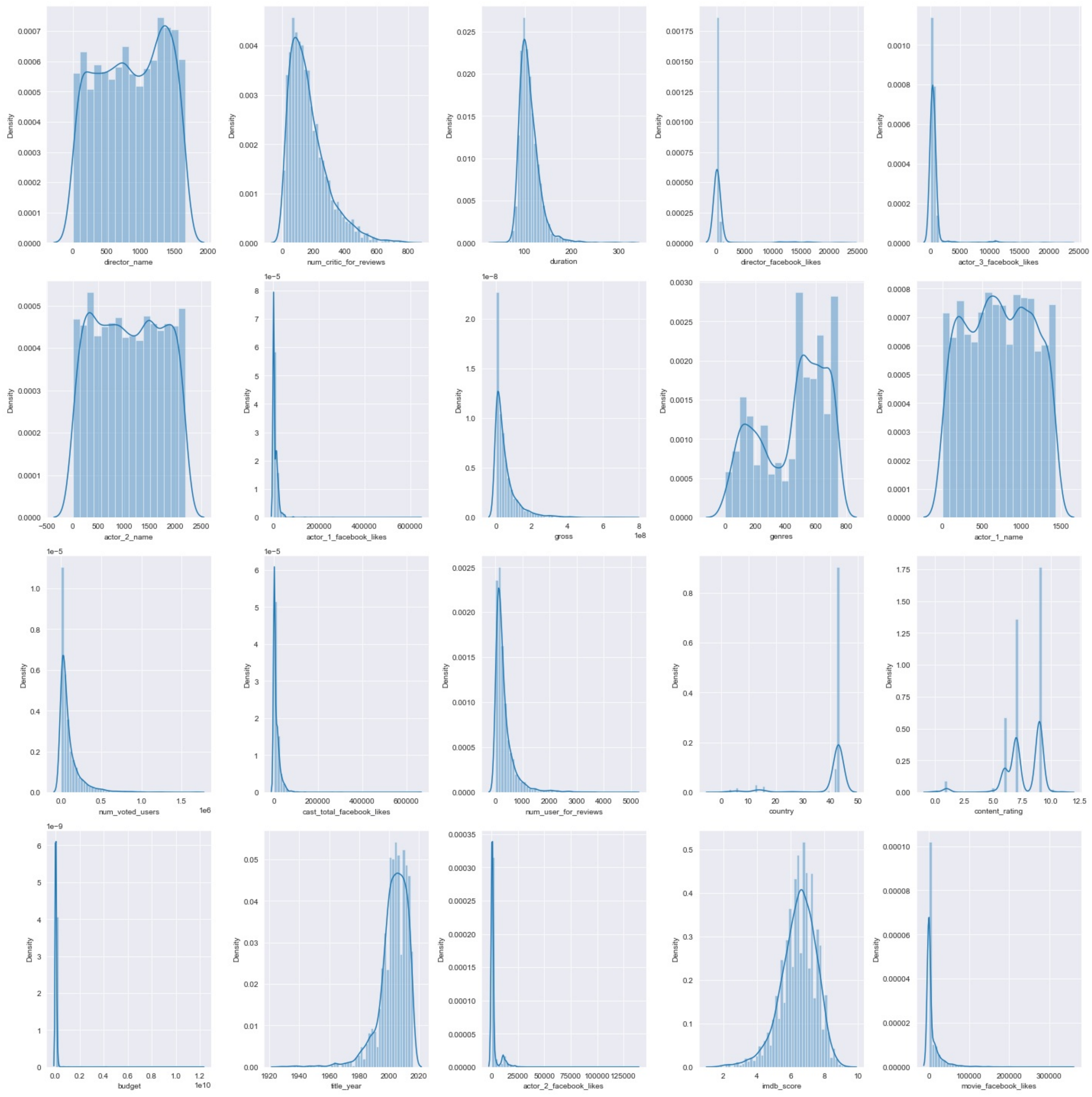
Out[39]:
```
director_name                  int32
num_critic_for_reviews       float64
duration                     float64
director_facebook_likes      float64
actor_3_facebook_likes       float64
actor_2_name                   int32
actor_1_facebook_likes       float64
gross                        float64
genres                         int32
actor_1_name                   int32
num_voted_users                int64
cast_total_facebook_likes      int64
num_user_for_reviews         float64
country                        int32
content_rating                 int32
budget                       float64
title_year                   float64
actor_2_facebook_likes       float64
imdb_score                   float64
movie_facebook_likes           int64
dtype: object
```

Distribution Plot

In [40]:
```
rows=4
cols=5
fig, ax=plt.subplots(nrows=rows,ncols=cols,figsize=(20,20))
col=df.columns
```

```python
index=0
for i in range(rows):
    for j in range(cols):
        sns.distplot(df[col[index]],ax=ax[i][j])
        index=index+1

plt.tight_layout()
# The distribution plot shows us the overall distribution of the data.
```



Log Transformation

In [41]:
```python
df.columns
# Displaying all column names,copypaste this in the next cell.
```

Out[41]:
```
Index(['director_name', 'num_critic_for_reviews', 'duration',
       'director_facebook_likes', 'actor_3_facebook_likes', 'actor_2_name',
       'actor_1_facebook_likes', 'gross', 'genres', 'actor_1_name',
       'num_voted_users', 'cast_total_facebook_likes', 'num_user_for_reviews',
       'country', 'content_rating', 'budget', 'title_year',
       'actor_2_facebook_likes', 'imdb_score', 'movie_facebook_likes'],
      dtype='object')
```

In [42]:
```python
skewed_features=['director_name', 'num_critic_for_reviews', 'duration',
       'director_facebook_likes', 'actor_3_facebook_likes', 'actor_2_name',
       'actor_1_facebook_likes', 'gross', 'genres', 'actor_1_name',
       'num_voted_users', 'cast_total_facebook_likes', 'num_user_for_reviews',
       'country', 'content_rating', 'budget', 'title_year',
       'actor_2_facebook_likes', 'imdb_score', 'movie_facebook_likes']
# Selecting all features which are skewed and storing them i n the skewed_features
```

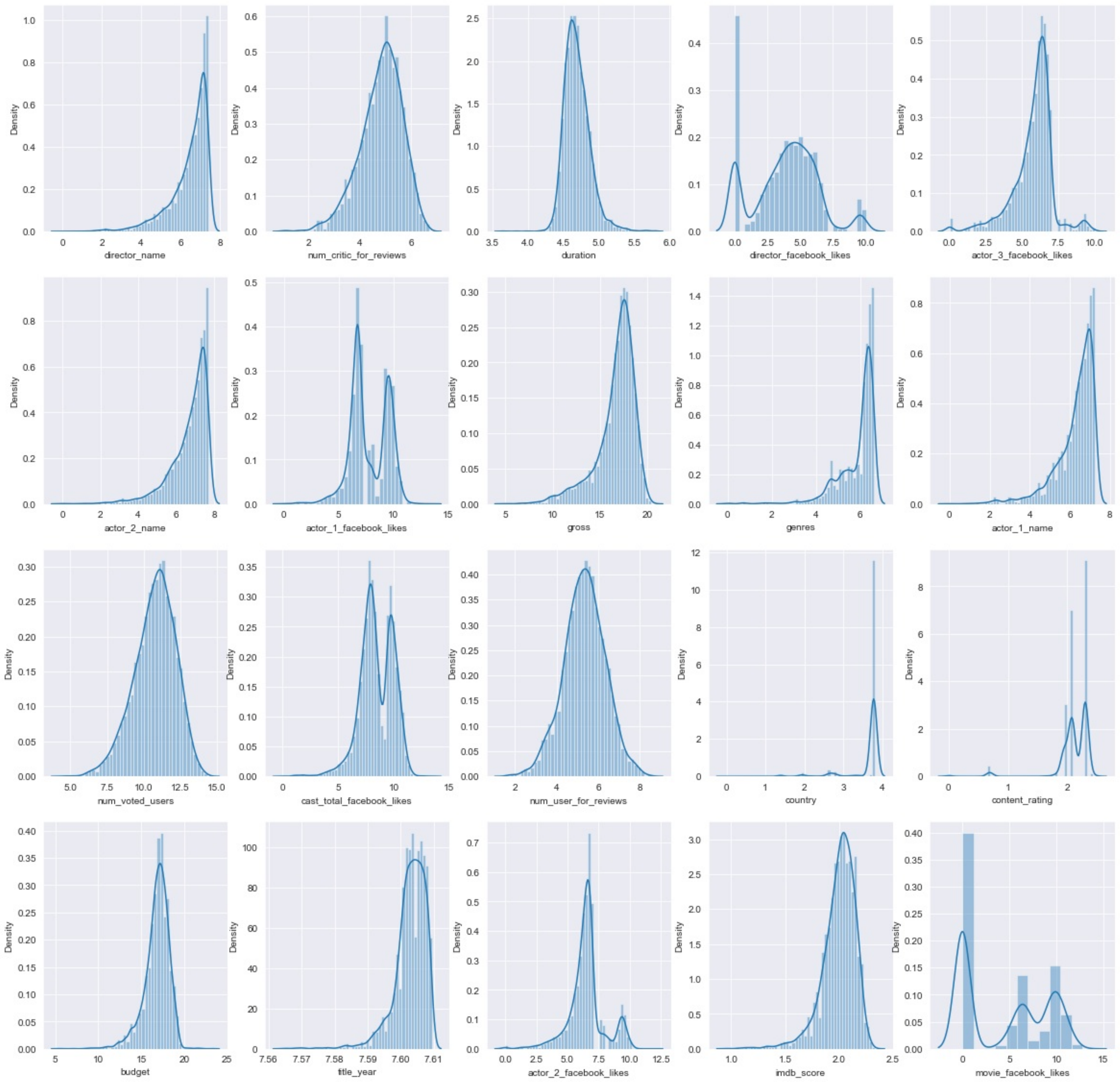
In [43]:

```
for i in skewed_features:
    df[i]=np.log(df[i]+1)
# Applying log transformation on the skewed features
```

In [44]:

```
rows=4
cols=5
fig, ax=plt.subplots(nrows=rows,ncols=cols,figsize=(20,20))
col=df.columns
index=0
for i in range(rows):
    for j in range(cols):
        sns.distplot(df[col[index]],ax=ax[i][j])
        index=index+1

plt.show()
# Checking the changes in the distribution of data after applying log transformation.
```



Splitting dataset

In [45]:

```
X=df.drop(labels=['imdb_score'],axis=1)
```

```
Y=df['imdb_score']
X.head()
# splitting data into dependent and independent variables
```

Out[45]:

	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_name	actor_1_facebook_likes	g
0	6.431331	6.584791	5.187386	0.000000	6.752270	6.910751	6.908755	20.44
1	6.289716	5.713733	5.135798	6.335054	6.908755	7.373374	10.596660	19.55
2	7.241366	6.401917	5.003946	0.000000	5.087596	7.493317	9.305741	19.11
3	5.529429	6.701960	5.105945	9.998843	10.043293	5.945421	10.203629	19.92
5	4.143135	6.137727	4.890349	6.165418	6.274762	7.516433	6.463029	18.10

In [46]:

```
Y.head()
# target column
```

Out[46]:

```
0    2.186051
1    2.091864
2    2.054124
3    2.251292
5    2.028148
Name: imdb_score, dtype: float64
```

In [47]:

```
# Train_test_split
X_train,X_test,Y_train,Y_test=train_test_split(X,Y,test_size=0.2,random_state=40)
print(X_train.shape,X_test.shape,Y_train.shape,Y_test.shape)
# Splitting data set into training and testing.
```

```
(3004, 19) (752, 19) (3004,) (752,)
```

Machine Learning

Linear Regression

In [48]:

```
lm=LinearRegression()
lm = lm.fit(X_train,Y_train)

#Traindata Predictions
train_pred = lm.predict(X_train)

#testdata predictions
test_pred = lm.predict(X_test)


RMSE_test = np.sqrt(mean_squared_error(Y_test, test_pred))
RMSE_train= np.sqrt(mean_squared_error(Y_train,train_pred))
print("RMSE TrainingData = ",str(RMSE_train))
print("RMSE TestData = ",str(RMSE_test))
print('-'*50)
print('RSquared value on train:',lm.score(X_train, Y_train))
print('RSquared value on test:',lm.score(X_test, Y_test))
```

```
RMSE TrainingData =  0.12041595568987466
RMSE TestData =  0.11861105307571092
--------------------------------------------------
RSquared value on train: 0.4080095055085231
RSquared value on test: 0.4021001552231914
```

In [49]:

```
errors = abs(test_pred - Y_test)
# Calculating errors for using error values in mean absolute percentage error
```

In [50]:

```
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / Y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Accuracy: 95.5 %.
```

Decision Tree Regressor

In [51]:
```
DT=DecisionTreeRegressor(max_depth=9)
DT.fit(X_train,Y_train)

#predicting train
train_preds=DT.predict(X_train)
#predicting on test
test_preds=DT.predict(X_test)

RMSE_train=(np.sqrt(metrics.mean_squared_error(Y_train,train_preds)))
RMSE_test=(np.sqrt(metrics.mean_squared_error(Y_test,test_preds)))
print("RMSE TrainingData = ",str(RMSE_train))
print("RMSE TestData = ",str(RMSE_test))
print('-'*50)
print('RSquared value on train:',DT.score(X_train, Y_train))
print('RSquared value on test:',DT.score(X_test, Y_test))
```

```
RMSE TrainingData =  0.08302711763715252
RMSE TestData =  0.1236935818341301
--------------------------------------------------
RSquared value on train: 0.7185595074222233
RSquared value on test: 0.34976184664184484
```

In [52]:
```
errors = abs(test_preds - Y_test)
# Calculating errors for using error values in mean absolute percentage error
```

In [53]:
```
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / Y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Accuracy: 95.45 %.
```

Random Forest Regressor

In [54]:
```
RF=RandomForestRegressor().fit(X_train,Y_train)

#predicting train
train_preds1=RF.predict(X_train)
#predicting on test
test_preds1=RF.predict(X_test)

RMSE_train=(np.sqrt(metrics.mean_squared_error(Y_train,train_preds1)))
RMSE_test=(np.sqrt(metrics.mean_squared_error(Y_test,test_preds1)))
print("RMSE TrainingData = ",str(RMSE_train))
print("RMSE TestData = ",str(RMSE_test))
print('-'*50)
print('RSquared value on train:',RF.score(X_train, Y_train))
print('RSquared value on test:',RF.score(X_test, Y_test))
```

```
RMSE TrainingData =  0.041777050727261886
RMSE TestData =  0.10071294969265117
--------------------------------------------------
RSquared value on train: 0.928743872783211
RSquared value on test: 0.568929057755184
```

In [55]:
```
errors = abs(test_preds1 - Y_test)
# Calculating errors for using error values in mean absolute percentage error
```

In [56]:
```
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / Y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Accuracy: 96.28 %.
```

K-Nearest Neighbours

In [57]:

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

#predicting train
train_preds2=knn.predict(X_train)
#predicting on test
test_preds2=knn.predict(X_test)

RMSE_train=(np.sqrt(metrics.mean_squared_error(Y_train,train_preds2)))
RMSE_test=(np.sqrt(metrics.mean_squared_error(Y_test,test_preds2)))
print("RMSE TrainingData = ",str(RMSE_train))
print("RMSE TestData = ",str(RMSE_test))
print('-'*50)
print('RSquared value on train:',knn.score(X_train, Y_train))
print('RSquared value on test:',knn.score(X_test, Y_test))
```

```
RMSE TrainingData =  0.10856954037953365
RMSE TestData =  0.13173731630991498
--------------------------------------------------
RSquared value on train: 0.518758958219276
RSquared value on test: 0.2624427420400328
```

In [58]:

```
# More machine learning algorithms.
```

In [59]:

```
from sklearn.linear_model import LassoCV
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import ElasticNetCV
from sklearn.ensemble import GradientBoostingRegressor
```

Lasso Regression

In [60]:

```
lasso = LassoCV(cv=10).fit(X_train, Y_train)


#predicting train
train_preds3=lasso.predict(X_train)
#predicting on test
test_preds3=lasso.predict(X_test)

RMSE_train=(np.sqrt(metrics.mean_squared_error(Y_train,train_preds3)))
RMSE_test=(np.sqrt(metrics.mean_squared_error(Y_test,test_preds3)))
print("RMSE TrainingData = ",str(RMSE_train))
print("RMSE TestData = ",str(RMSE_test))
print('-'*50)
print('RSquared value on train:',lasso.score(X_train, Y_train))
print('RSquared value on test:',lasso.score(X_test, Y_test))
```

```
RMSE TrainingData =  0.12196766732315874
RMSE TestData =  0.1180980393494159
--------------------------------------------------
RSquared value on train: 0.39265411206730183
RSquared value on test: 0.40726101480444266
```

Ridge Regression

In [61]:

```
ridge = RidgeCV(cv=10).fit(X_train, Y_train)
#predicting train
train_preds4=ridge.predict(X_train)
#predicting on test
test_preds4=ridge.predict(X_test)

RMSE_train=(np.sqrt(metrics.mean_squared_error(Y_train,train_preds4)))
RMSE_test=(np.sqrt(metrics.mean_squared_error(Y_test,test_preds4)))
print("RMSE TrainingData = ",str(RMSE_train))
print("RMSE TestData = ",str(RMSE_test))
print('-'*50)
print('RSquared value on train:',ridge.score(X_train, Y_train))
print('RSquared value on test:',ridge.score(X_test, Y_test))
```

```
RMSE TrainingData =  0.12123661279697667
RMSE TestData =  0.11784386021079903
```

```
--------------------------------------------------
RSquared value on train: 0.39991295908767055
RSquared value on test: 0.40980974047017416
```

Elastic Net

In [62]:
```
elastic_net = ElasticNetCV(cv = 10).fit(X_train, Y_train)
#predicting train
train_preds5=elastic_net.predict(X_train)
#predicting on test
test_preds5=elastic_net.predict(X_test)

RMSE_train=(np.sqrt(metrics.mean_squared_error(Y_train,train_preds5)))
RMSE_test=(np.sqrt(metrics.mean_squared_error(Y_test,test_preds5)))
print("RMSE TrainingData = ",str(RMSE_train))
print("RMSE TestData = ",str(RMSE_test))
print('-'*50)
print('RSquared value on train:',elastic_net.score(X_train, Y_train))
print('RSquared value on test:',elastic_net.score(X_test, Y_test))
```

```
RMSE TrainingData =  0.1219689940230489
RMSE TestData =  0.11810830677152079
--------------------------------------------------
RSquared value on train: 0.3926408992196212
RSquared value on test: 0.4071579450846382
```

XG-Boost Regressor

In [63]:
```
xgbr =xgb.XGBRegressor().fit(X_train, Y_train)
#predicting train
train_preds6=xgbr.predict(X_train)
#predicting on test
test_preds6=xgbr.predict(X_test)

RMSE_train=(np.sqrt(metrics.mean_squared_error(Y_train,train_preds6)))
RMSE_test=(np.sqrt(metrics.mean_squared_error(Y_test,test_preds6)))
print("RMSE TrainingData = ",str(RMSE_train))
print("RMSE TestData = ",str(RMSE_test))
print('-'*50)
print('RSquared value on train:',xgbr.score(X_train, Y_train))
print('RSquared value on test:',xgbr.score(X_test, Y_test))
```

```
RMSE TrainingData =  0.016453210384851504
RMSE TestData =  0.09549969503973747
--------------------------------------------------
RSquared value on train: 0.9889478196861716
RSquared value on test: 0.612401500913349
```

In [64]:
```
errors = abs(test_preds6 - Y_test)
# Calculating errors for using error values in mean absolute percentage error
```

In [65]:
```
# Calculate mean absolute percentage error (MAPE)
mape = 100 * (errors / Y_test)
# Calculate and display accuracy
accuracy = 100 - np.mean(mape)
print('Accuracy:', round(accuracy, 2), '%.')
```

```
Accuracy: 96.49 %.
```

In [66]:
```
# Before log transformation the xg boost Accuracy was 91.87 % and now accuracy has improved to 96.49 percent.
```

In [ ]:
```

```

Loading [MathJax]/extensions/Safe.js