Data Analysis Project

Your boss has just acquired data about how much audiences and critics like movies as well as numerous other variables about the movies. This dataset is provided below, and it includes information from Rotten Tomatoes and IMDB for a random sample of movies.

She is interested in learning what attributes make a movie popular. She is also interested in learning something new about movies. She wants you team to figure it all out.

As part of this project you will complete exploratory data analysis (EDA), modeling, and prediction.

The data set is comprised of 651 randomly sampled movies produced and released before 2016.

Some of these variables are only there for informational purposes and do not make any sense to include in a statistical analysis. It is up to you to decide which variables are meaningful and which should be omitted. For example information in the the `actor1` through `actor5` variables was used to determine whether the movie casts an actor or actress who won a best actor or actress Oscar.

You might also choose to omit certain observations or restructure some of the variables to make them suitable for answering your research questions.

When you are fitting a model you should also be careful about collinearity, as some of these variables may be dependent on each other.

Create new variable based on `title_type` : New variable should be called `feature_film` with levels yes (movies that are feature films) and no

Create new variable based on `genre` : New variable should be called `drama` with levels yes (movies that are dramas) and no

Create new variable based on `mpaa_rating` : New variable should be called `mpaa_rating_R` with levels yes (movies that are R rated) and no

Create two new variables based on `thtr_rel_month`

New variable called `oscar_season` with levels yes (if movie is released in November, October, or December) and no

New variable called `summer_season` with levels yes (if movie is released in May, June, July, or August) and no

Import Libraries

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

import xgboost as xgb
from xgboost import XGBClassifier, XGBRegressor
from xgboost import to_graphviz, plot_importance

%matplotlib inline
sns.set_style('dark')
sns.set(font_scale=1.2)

from sklearn.model_selection import cross_val_score, train_test_split, GridSearchC
V, RandomizedSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler, MinMaxScaler, OneHo
tEncoder
from sklearn.metrics import confusion_matrix, classification_report, mean_absolute_
error, mean_squared_error,r2_score
from sklearn.metrics import plot_confusion_matrix, plot_precision_recall_curve, plo
t_roc_curve, accuracy_score
from sklearn.metrics import auc, f1_score, precision_score, recall_score, roc_auc_s
core


#import feature_engine.missing_data_imputers as mdi
#from feature_engine.outlier_removers import Winsorizer

import warnings
warnings.filterwarnings('ignore')

import pickle
from pickle import dump, load

np.random.seed(0)

#from pycaret.classification import *
#from pycaret.clustering import *
from pycaret.regression import *

pd.set_option('display.max_columns',100)
#pd.set_option('display.max_rows',100)
pd.set_option('display.width', 1000)
```

Data Exploration and Analysis

In [2]:
```
df = pd.read_csv("movies.csv")
```

In [3]:
```
df
```

Out[3]:

	title	title_type	genre	runtime	mpaa_rating	studio	thtr_rel_year	thtr_rel_month	thtr_r
0	Filly Brown	Feature Film	Drama	80.0	R	Indomina Media Inc.	2013	4	
1	The Dish	Feature Film	Drama	101.0	PG-13	Warner Bros. Pictures	2001	3	
2	Waiting for Guffman	Feature Film	Comedy	84.0	R	Sony Pictures Classics	1996	8	
3	The Age of Innocence	Feature Film	Drama	139.0	PG	Columbia Pictures	1993	10	
4	Malevolence	Feature Film	Horror	90.0	R	Anchor Bay Entertainment	2004	9	
...	...	...	...	...	...	...	...	...	
646	Death Defying Acts	Feature Film	Drama	97.0	PG	Genius Productions	2008	7	
647	Half Baked	Feature Film	Comedy	82.0	R	Universal Pictures	1998	1	
648	Dance of the Dead	Feature Film	Action & Adventure	87.0	R	Grindhouse Entertainment	2008	3	
649	Around the World in 80 Days	Feature Film	Action & Adventure	120.0	PG	Buena Vista Pictures	2004	6	
650	LOL	Feature Film	Comedy	97.0	PG-13	Lionsgate Films	2012	5	

651 rows × 32 columns

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 651 entries, 0 to 650
Data columns (total 32 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   title             651 non-null    object 
 1   title_type        651 non-null    object 
 2   genre             651 non-null    object 
 3   runtime           650 non-null    float64
 4   mpaa_rating       651 non-null    object 
 5   studio            643 non-null    object 
 6   thtr_rel_year     651 non-null    int64  
 7   thtr_rel_month    651 non-null    int64  
 8   thtr_rel_day      651 non-null    int64  
 9   dvd_rel_year      643 non-null    float64
 10  dvd_rel_month     643 non-null    float64
 11  dvd_rel_day       643 non-null    float64
 12  imdb_rating       651 non-null    float64
 13  imdb_num_votes    651 non-null    int64  
 14  critics_rating    651 non-null    object 
 15  critics_score     651 non-null    int64  
 16  audience_rating   651 non-null    object 
 17  audience_score    651 non-null    int64  
 18  best_pic_nom      651 non-null    object 
 19  best_pic_win      651 non-null    object 
 20  best_actor_win    651 non-null    object 
 21  best_actress_win  651 non-null    object 
 22  best_dir_win      651 non-null    object 
 23  top200_box        651 non-null    object 
 24  director          649 non-null    object 
 25  actor1            649 non-null    object 
 26  actor2            644 non-null    object 
 27  actor3            642 non-null    object 
 28  actor4            638 non-null    object 
 29  actor5            636 non-null    object 
 30  imdb_url          651 non-null    object 
 31  rt_url            651 non-null    object 
dtypes: float64(5), int64(6), object(21)
memory usage: 162.9+ KB
```

In [5]:
```
df.describe(include='all')
```

Out[5]:

	title	title_type	genre	runtime	mpaa_rating	studio	thtr_rel_year	thtr_rel_month	thtr_rel_da
count	651	651	651	650.000000	651	643	651.000000	651.000000	651.0000(
unique	647	3	11	NaN	6	211	NaN	NaN	Na
top	Where the Heart Is	Feature Film	Drama	NaN	R	Paramount Pictures	NaN	NaN	Na
freq	2	591	305	NaN	329	37	NaN	NaN	Na
mean	NaN	NaN	NaN	105.821538	NaN	NaN	1997.941628	6.740399	14.41628
std	NaN	NaN	NaN	19.445047	NaN	NaN	10.974501	3.554223	8.86116
min	NaN	NaN	NaN	39.000000	NaN	NaN	1970.000000	1.000000	1.0000(
25%	NaN	NaN	NaN	92.000000	NaN	NaN	1990.000000	4.000000	7.0000(
50%	NaN	NaN	NaN	103.000000	NaN	NaN	2000.000000	7.000000	15.0000(
75%	NaN	NaN	NaN	115.750000	NaN	NaN	2007.000000	10.000000	21.0000(
max	NaN	NaN	NaN	267.000000	NaN	NaN	2014.000000	12.000000	31.0000(

In [6]:
```
df.shape
```

Out[6]:
```
(651, 32)
```

In [7]:
```
df.columns
```

Out[7]:
```
Index(['title', 'title_type', 'genre', 'runtime', 'mpaa_rating', 'studio', 'thtr
_rel_year', 'thtr_rel_month', 'thtr_rel_day', 'dvd_rel_year', 'dvd_rel_month', '
dvd_rel_day', 'imdb_rating', 'imdb_num_votes', 'critics_rating', 'critics_score
', 'audience_rating', 'audience_score', 'best_pic_nom', 'best_pic_win', 'best_ac
tor_win', 'best_actress_win', 'best_dir_win', 'top200_box', 'director', 'actor1
', 'actor2', 'actor3', 'actor4', 'actor5', 'imdb_url', 'rt_url'], dtype='object
')
```

create new features

In [8]:
```
df["title_type"].value_counts()
```

Out[8]:
```
Feature Film    591
Documentary      55
TV Movie          5
Name: title_type, dtype: int64
```

In [9]:
```
df["feature_film"]= np.where(df["title_type"] == "Feature Film",1,0)
```

In [10]:
```
df["feature_film"].value_counts()
```

Out[10]:
```
1    591
0     60
Name: feature_film, dtype: int64
```

In [11]:
```
df["genre"].value_counts()
```

Out[11]:
```
Drama                        305
Comedy                        87
Action & Adventure            65
Mystery & Suspense            59
Documentary                   52
Horror                        23
Other                         16
Art House & International     14
Musical & Performing Arts     12
Animation                      9
Science Fiction & Fantasy      9
Name: genre, dtype: int64
```

In [12]:
```
df["drama"] = np.where(df["genre"] == "Drama",1,0)
```

In [13]:
```
df["drama"].value_counts()
```

Out[13]:
```
0    346
1    305
Name: drama, dtype: int64
```

In [14]:
```
df["mpaa_rating"].value_counts()
```

Out[14]:
```
R          329
PG-13      133
PG         118
Unrated     50
G           19
NC-17        2
Name: mpaa_rating, dtype: int64
```

In [15]:
```
df["mpaa_rating_R"] = np.where(df["mpaa_rating"] == "R",1,0)
```

In [16]:
```
df["mpaa_rating_R"].value_counts()
```

Out[16]:
```
1    329
0    322
Name: mpaa_rating_R, dtype: int64
```

In [17]:
```
df["thtr_rel_month"].value_counts()
```

Out[17]:
```
6     72
12    70
10    70
1     69
9     53
11    51
3     51
7     48
4     45
8     44
5     44
2     34
Name: thtr_rel_month, dtype: int64
```

In [18]:
```
conditions = [df["thtr_rel_month"] == 10, df["thtr_rel_month"] == 11, df["thtr_rel_
month"] == 12]
```

In [19]:
```
values = [1,1,1]
```

In [20]:
```
df["oscar_season"] = np.select(conditions,values)
```

In [21]:
```
df["oscar_season"].value_counts()
```

Out[21]:
```
0    460
1    191
Name: oscar_season, dtype: int64
```

In [22]:
```
conditions1 = [df["thtr_rel_month"] == 5, df["thtr_rel_month"] == 6, df["thtr_rel_m
onth"] == 7, df["thtr_rel_month"] == 8]
```

In [23]:
```
values1 = [1,1,1,1]
```

In [24]:
```
df["summer_season"] = np.select(conditions1,values1)
```

In [25]:
```
df["summer_season"].value_counts()
```

Out[25]:
```
0    443
1    208
Name: summer_season, dtype: int64
```

In [26]:
```
df
```

Out[26]:

	title	title_type	genre	runtime	mpaa_rating	studio	thtr_rel_year	thtr_rel_month	thtr_r
0	Filly Brown	Feature Film	Drama	80.0	R	Indomina Media Inc.	2013	4	
1	The Dish	Feature Film	Drama	101.0	PG-13	Warner Bros. Pictures	2001	3	
2	Waiting for Guffman	Feature Film	Comedy	84.0	R	Sony Pictures Classics	1996	8	
3	The Age of Innocence	Feature Film	Drama	139.0	PG	Columbia Pictures	1993	10	
4	Malevolence	Feature Film	Horror	90.0	R	Anchor Bay Entertainment	2004	9	
...	...	...	...	...	...	...	...	...	
646	Death Defying Acts	Feature Film	Drama	97.0	PG	Genius Productions	2008	7	
647	Half Baked	Feature Film	Comedy	82.0	R	Universal Pictures	1998	1	
648	Dance of the Dead	Feature Film	Action & Adventure	87.0	R	Grindhouse Entertainment	2008	3	
649	Around the World in 80 Days	Feature Film	Action & Adventure	120.0	PG	Buena Vista Pictures	2004	6	
650	LOL	Feature Film	Comedy	97.0	PG-13	Lionsgate Films	2012	5	

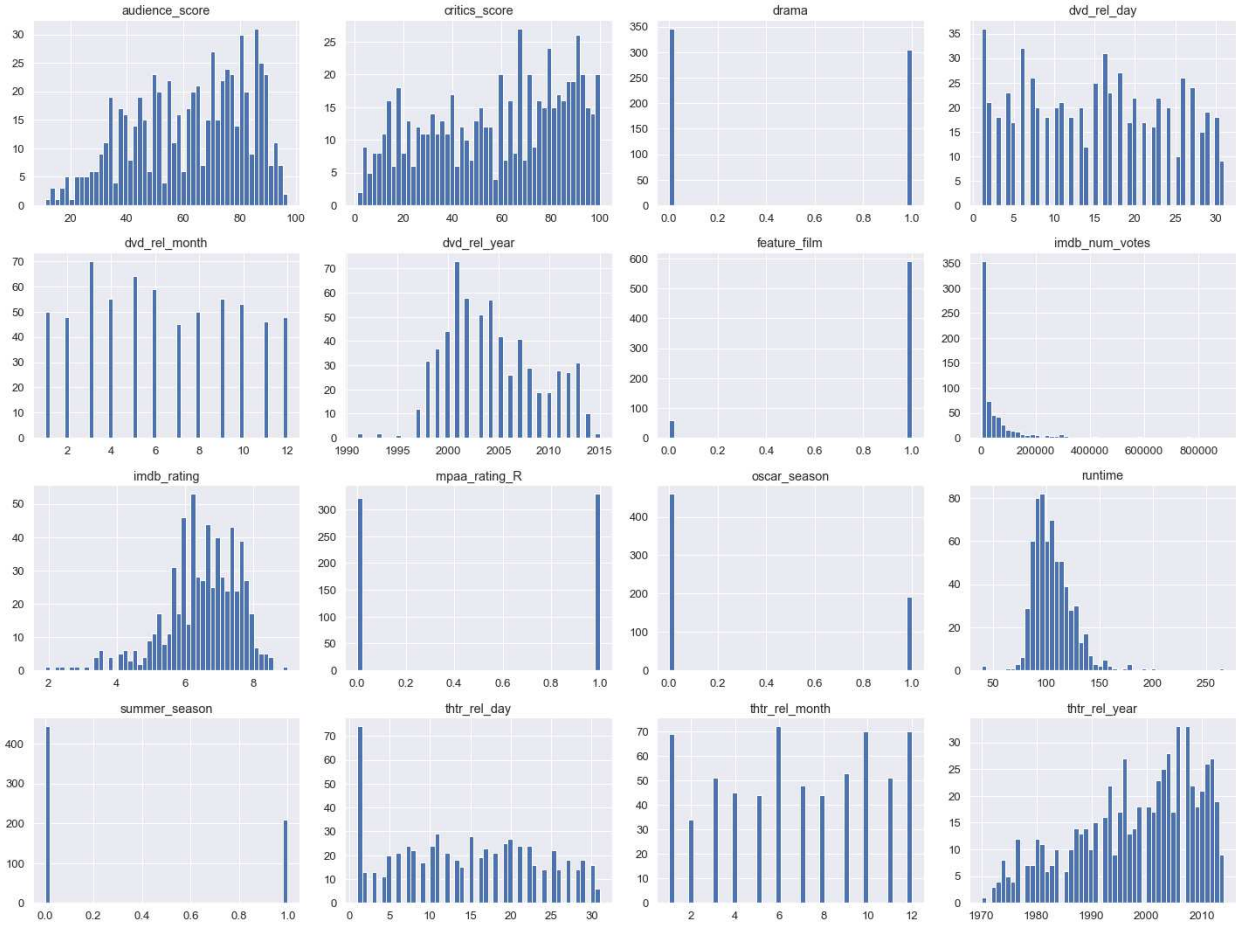
651 rows × 37 columns

In [ ]:
```

```

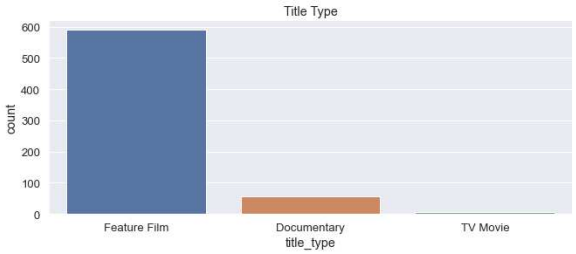
Data Visualization

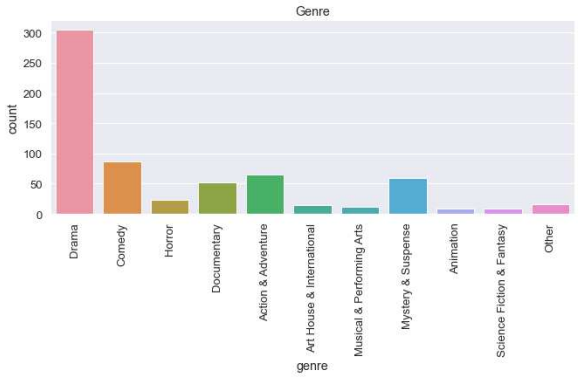
Univariate Data Exploration

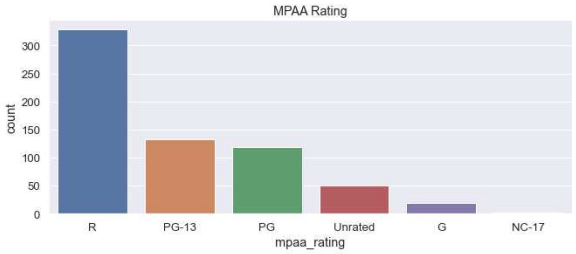
In [27]:
```
df.hist(bins=50, figsize=(20,15))
plt.tight_layout()
plt.show()
```

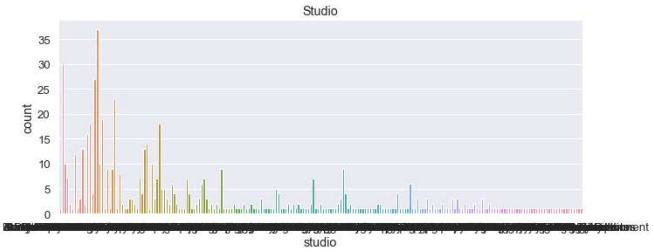


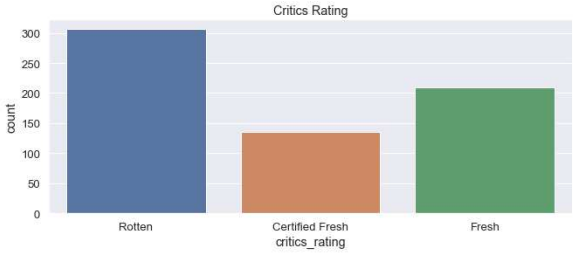
In [28]:
```
fig = plt.figure(figsize=(20,40))

plt.subplot(7,2,1)
plt.title("Title Type")
sns.countplot(df.title_type)

plt.subplot(7,2,2)
plt.title("Genre")
plt.xticks(rotation=90)
sns.countplot(df.genre)

plt.subplot(7,2,3)
plt.title("MPAA Rating")
sns.countplot(df.mpaa_rating)

plt.subplot(7,2,4)
plt.title("Studio")
sns.countplot(df.studio)

plt.subplot(7,2,5)
plt.title("Critics Rating")
sns.countplot(df.critics_rating)

plt.subplot(7,2,6)
plt.title("Audience Rating")
sns.countplot(df.audience_rating)

plt.subplot(7,2,7)
plt.title("Best Pic Nominee")
sns.countplot(df.best_pic_nom)

plt.subplot(7,2,8)
plt.title("Best Picture Winner")
sns.countplot(df.best_pic_win)

plt.subplot(7,2,9)
plt.title("Best Actor Winner")
sns.countplot(df.best_actor_win)

plt.subplot(7,2,10)
plt.title("Best Actress Winner")
sns.countplot(df.best_actress_win)

plt.subplot(7,2,11)
plt.title("Best Director Winner")
sns.countplot(df.best_dir_win)

plt.subplot(7,2,12)
plt.title("Box Office Top 200")
sns.countplot(df.top200_box)

plt.tight_layout()
plt.show()
```

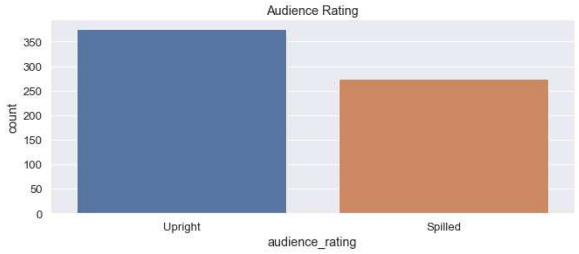

Title Type
count
Feature Film
Documentary
TV Movie
title_type

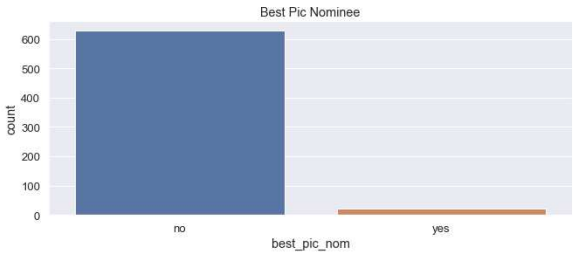

Genre
count
Drama
Comedy
Horror
Documentary
Action & Adventure
Art House & International
Musical & Performing Arts
Mystery & Suspense
Animation
Science Fiction & Fantasy
Other
genre

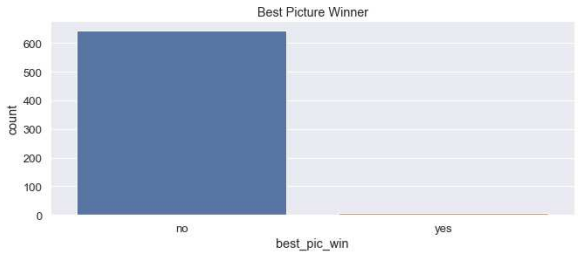

MPAA Rating
count
R
PG-13
PG
Unrated
G
NC-17
mpaa_rating

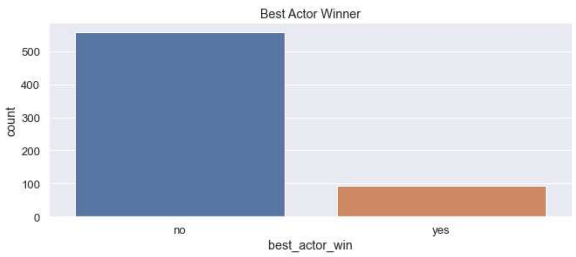

Studio
count
studio

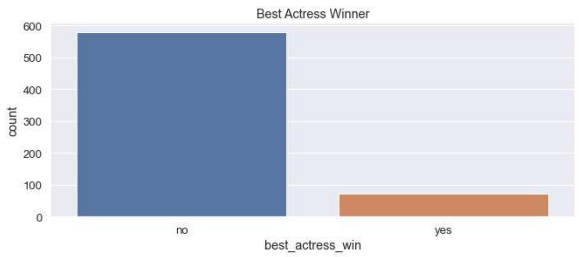

Critics Rating
count
Rotten
Certified Fresh
Fresh
critics_rating


Audience Rating
count
Upright
Spilled
audience_rating

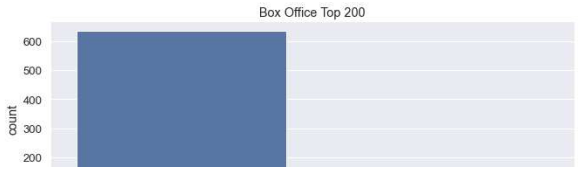

Best Pic Nominee
count
no
yes
best_pic_nom


Best Picture Winner
count
no
yes
best_pic_win


Best Actor Winner
count
no
yes
best_actor_win


Best Actress Winner
count
no
yes
best_actress_win


Best Director Winner
count

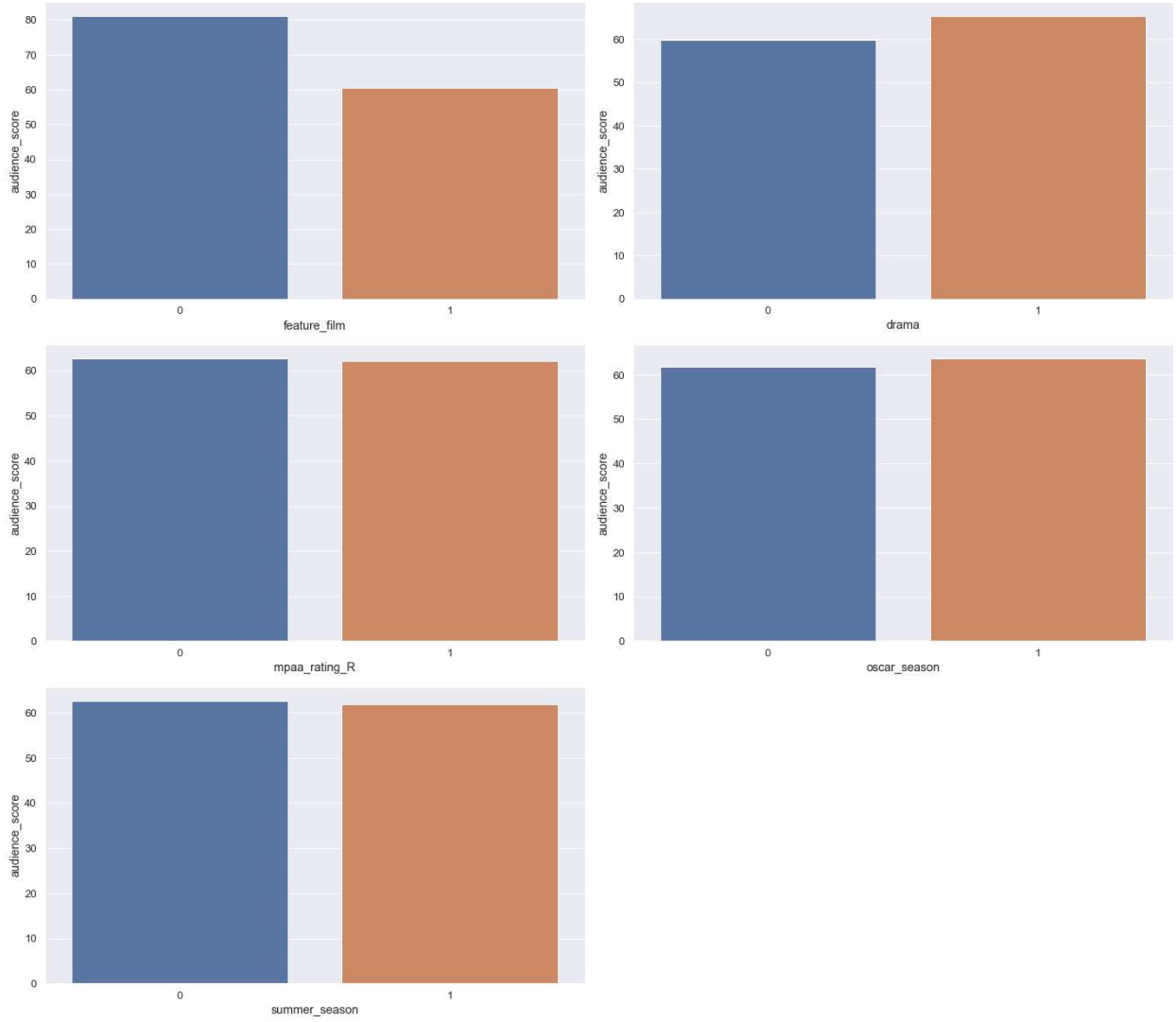

Box Office Top 200
count

Perform exploratory data analysis (EDA) of the relationship between audience_score and the new variables constructed in the previous part. Your EDA should contain numerical summaries and visualizations. This might mean you initially create a lot more visualizations and summary statistics than what you finally choose to include in your paper. Each R output and plot should be accompanied by a brief interpretation.

In [29]:
```
df.columns
```

Out[29]:
```
Index(['title', 'title_type', 'genre', 'runtime', 'mpaa_rating', 'studio', 'thtr
_rel_year', 'thtr_rel_month', 'thtr_rel_day', 'dvd_rel_year', 'dvd_rel_month', '
dvd_rel_day', 'imdb_rating', 'imdb_num_votes', 'critics_rating', 'critics_score
', 'audience_rating', 'audience_score', 'best_pic_nom', 'best_pic_win', 'best_ac
tor_win', 'best_actress_win', 'best_dir_win', 'top200_box', 'director', 'actor1
', 'actor2', 'actor3', 'actor4', 'actor5', 'imdb_url', 'rt_url', 'feature_film',
'drama', 'mpaa_rating_R', 'oscar_season', 'summer_season'], dtype='object')
```

In [30]:
```
fig = plt.figure(figsize=(20,40))

plt.subplot(7,2,1)
plt.title("")
sns.barplot(x="feature_film", y='audience_score', data=df, ci=None)

plt.subplot(7,2,2)
plt.title("")
sns.barplot(x="drama", y='audience_score', data=df, ci=None)

plt.subplot(7,2,3)
plt.title("")
sns.barplot(x="mpaa_rating_R", y='audience_score', data=df, ci=None)

plt.subplot(7,2,4)
plt.title("")
sns.barplot(x="oscar_season", y='audience_score', data=df, ci=None)

plt.subplot(7,2,5)
plt.title("")
sns.barplot(x="summer_season", y='audience_score', data=df, ci=None)

plt.tight_layout()
plt.show()
```



Drop unwanted features

In [31]:
```
df.columns
```

Out[31]:
```
Index(['title', 'title_type', 'genre', 'runtime', 'mpaa_rating', 'studio', 'thtr
_rel_year', 'thtr_rel_month', 'thtr_rel_day', 'dvd_rel_year', 'dvd_rel_month', '
dvd_rel_day', 'imdb_rating', 'imdb_num_votes', 'critics_rating', 'critics_score
', 'audience_rating', 'audience_score', 'best_pic_nom', 'best_pic_win', 'best_ac
tor_win', 'best_actress_win', 'best_dir_win', 'top200_box', 'director', 'actor1
', 'actor2', 'actor3', 'actor4', 'actor5', 'imdb_url', 'rt_url', 'feature_film',
'drama', 'mpaa_rating_R', 'oscar_season', 'summer_season'], dtype='object')
```

In [32]:
```
df.drop(['title', 'title_type', 'genre','mpaa_rating', 'studio', 'thtr_rel_year', '
thtr_rel_month', 'thtr_rel_day', 'dvd_rel_year',
       'dvd_rel_month', 'dvd_rel_day','critics_rating','audience_rating','best_pic
_nom', 'best_pic_win', 'best_actor_win', 'best_actress_win',
       'best_dir_win', 'top200_box', 'director', 'actor1', 'actor2', 'actor3', 'ac
tor4', 'actor5', 'imdb_url', 'rt_url'],axis=1,inplace=True)
```

In [33]:
```
df
```

Out[33]:

	runtime	imdb_rating	imdb_num_votes	critics_score	audience_score	feature_film	drama	mpaa_rating_R
0	80.0	5.5	899	45	73	1	1	1
1	101.0	7.3	12285	96	81	1	1	0
2	84.0	7.6	22381	91	91	1	0	1
3	139.0	7.2	35096	80	76	1	1	0
4	90.0	5.1	2386	33	27	1	0	1
...	...	...	...	...	...	...	...	...
646	97.0	5.9	8345	44	26	1	1	0
647	82.0	6.7	46794	29	81	1	0	1
648	87.0	5.9	10087	80	52	1	0	1
649	120.0	5.8	66054	31	34	1	0	0
650	97.0	4.2	43574	17	51	1	0	0

651 rows × 10 columns

In [34]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 651 entries, 0 to 650
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   runtime         650 non-null    float64
 1   imdb_rating     651 non-null    float64
 2   imdb_num_votes  651 non-null    int64  
 3   critics_score   651 non-null    int64  
 4   audience_score  651 non-null    int64  
 5   feature_film    651 non-null    int32  
 6   drama           651 non-null    int32  
 7   mpaa_rating_R   651 non-null    int32  
 8   oscar_season    651 non-null    int32  
 9   summer_season   651 non-null    int32  
dtypes: float64(2), int32(5), int64(3)
memory usage: 38.3 KB
```

Bivariate Data Exploration

In [35]:
```
# sns.jointplot(x='runtime', y='audience_score',data=df, kind='scatter')

# sns.jointplot(x='imdb_rating', y='audience_score',data=df, kind='scatter')

# sns.jointplot(x='imdb_num_votes', y='audience_score',data=df, kind='scatter')

# sns.jointplot(x='critics_score', y='audience_score',data=df, kind='scatter')

# plt.show()
```

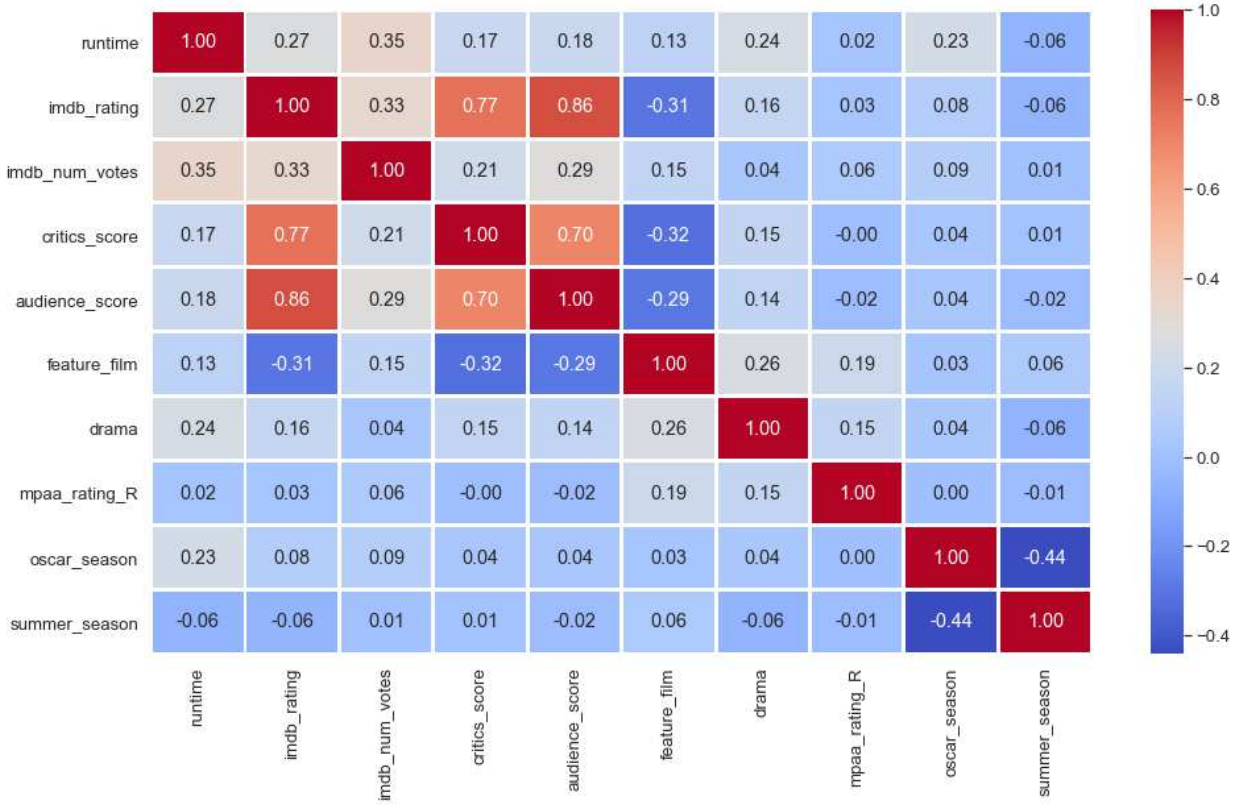
Correlation

In [36]:
```
df.corr()
```

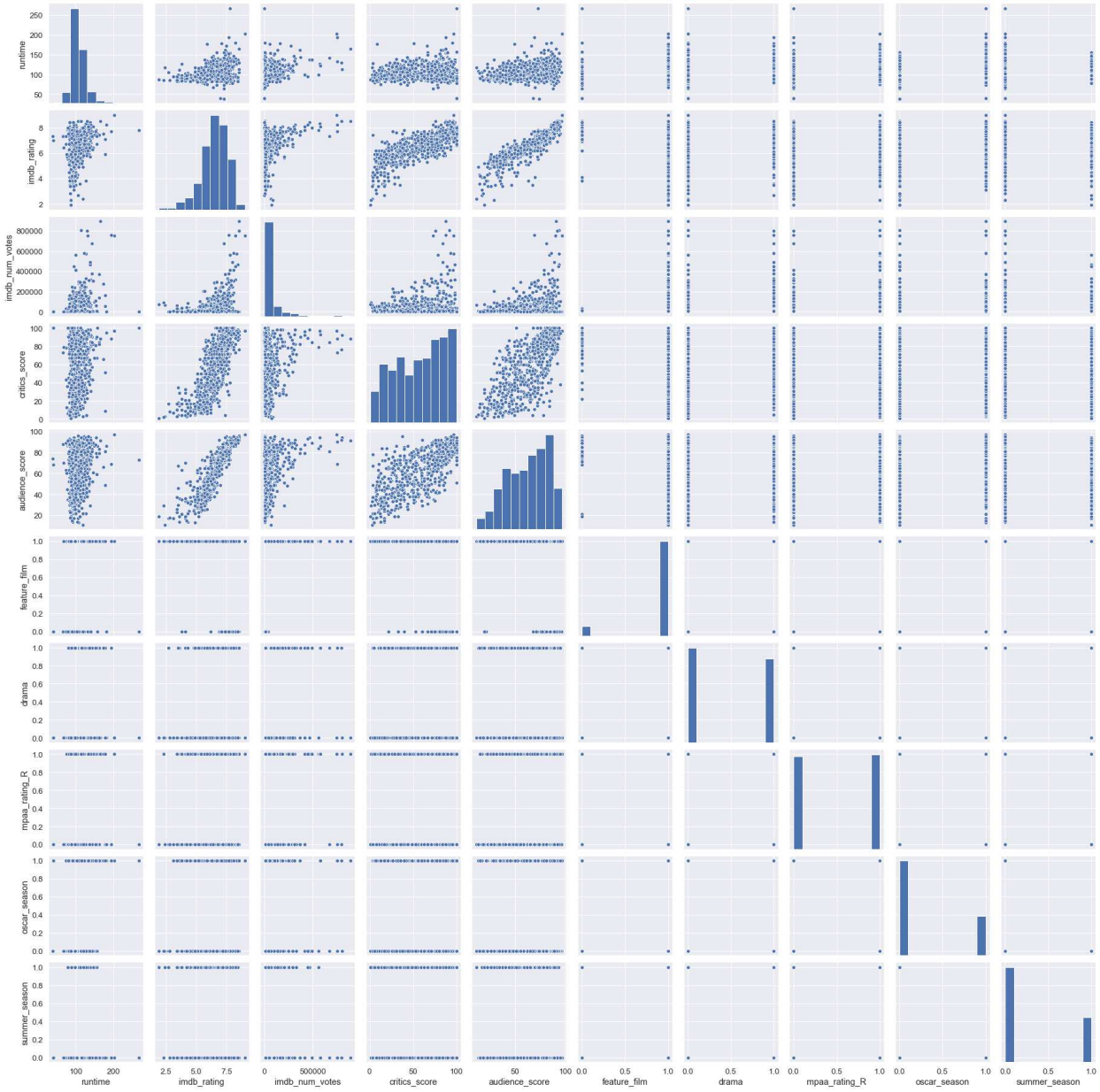
Out[36]:

	runtime	imdb_rating	imdb_num_votes	critics_score	audience_score	feature_film	dram
runtime	1.000000	0.268240	0.347215	0.172499	0.180963	0.125811	0.2410
imdb_rating	0.268240	1.000000	0.331152	0.765036	0.864865	-0.305790	0.1562
imdb_num_votes	0.347215	0.331152	1.000000	0.209251	0.289813	0.149259	0.0415
critics_score	0.172499	0.765036	0.209251	1.000000	0.704276	-0.321403	0.1499
audience_score	0.180963	0.864865	0.289813	0.704276	1.000000	-0.294665	0.1386
feature_film	0.125811	-0.305790	0.149259	-0.321403	-0.294665	1.000000	0.2565
drama	0.241072	0.156223	0.041516	0.149908	0.138693	0.256585	1.0000
mpaa_rating_R	0.024185	0.027138	0.062865	-0.003184	-0.016006	0.194613	0.1530
oscar_season	0.227343	0.084412	0.088860	0.039532	0.042199	0.030367	0.0440
summer_season	-0.061425	-0.057936	0.007786	0.011011	-0.018814	0.058886	-0.0623

In [37]:
```
plt.figure(figsize=(16,9))
sns.heatmap(df.corr(),cmap="coolwarm",annot=True,fmt='.2f',linewidths=2)
plt.show()
```



In [38]:
```
sns.pairplot(df)
plt.show()
```



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

Out[39]:
```
Index(['runtime', 'imdb_rating', 'imdb_num_votes', 'critics_score', 'audience_sc
ore', 'feature_film', 'drama', 'mpaa_rating_R', 'oscar_season', 'summer_season
'], dtype='object')
```

In [40]:
```
#Rearrange the features

df = df[['runtime', 'imdb_rating', 'imdb_num_votes', 'critics_score','feature_film
', 'drama', 'mpaa_rating_R', 'oscar_season',
         'summer_season', 'audience_score']]
```

In [41]:
```
df
```

Out[41]:

	runtime	imdb_rating	imdb_num_votes	critics_score	feature_film	drama	mpaa_rating_R	oscar_season
0	80.0	5.5	899	45	1	1	1	0
1	101.0	7.3	12285	96	1	1	0	0
2	84.0	7.6	22381	91	1	0	1	0
3	139.0	7.2	35096	80	1	1	0	1
4	90.0	5.1	2386	33	1	0	1	0
...	...	...	...	...	...	...	...	...
646	97.0	5.9	8345	44	1	1	0	0
647	82.0	6.7	46794	29	1	0	1	0
648	87.0	5.9	10087	80	1	0	1	0
649	120.0	5.8	66054	31	1	0	0	0
650	97.0	4.2	43574	17	1	0	0	0

651 rows × 10 columns

Data Preprocessing

Treat Missing Values

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

Out[42]:
```
runtime           1
imdb_rating       0
imdb_num_votes    0
critics_score     0
feature_film      0
drama             0
mpaa_rating_R     0
oscar_season      0
summer_season     0
audience_score    0
dtype: int64
```

In [43]:
```
df.dropna(inplace=True)
```

In [44]:
```
df.isnull().sum()
```

Out[44]:
```
runtime           0
imdb_rating       0
imdb_num_votes    0
critics_score     0
feature_film      0
drama             0
mpaa_rating_R     0
oscar_season      0
summer_season     0
audience_score    0
dtype: int64
```

Treat Duplicate Values

In [45]:
```
df.duplicated(keep='first').sum()
```

Out[45]: 1

Create and save processed dataset

In [46]:
```
#df.to_csv("moviestrain2.csv",index=False)
```

In [47]:
```
df.shape
```

Out[47]: (650, 10)

Predict Audience Score

Train Test Split

In [48]:
```
X = df.iloc[:,0:9]
y = df.iloc[:,9]
```

In [49]:
```
X.values, y.values
```

Out[49]:
```
(array([[8.0000e+01, 5.5000e+00, 8.9900e+02, ..., 1.0000e+00, 0.0000e+00,
         0.0000e+00],
        [1.0100e+02, 7.3000e+00, 1.2285e+04, ..., 0.0000e+00, 0.0000e+00,
         0.0000e+00],
        [8.4000e+01, 7.6000e+00, 2.2381e+04, ..., 1.0000e+00, 0.0000e+00,
         1.0000e+00],
        ...,
        [8.7000e+01, 5.9000e+00, 1.0087e+04, ..., 1.0000e+00, 0.0000e+00,
         0.0000e+00],
        [1.2000e+02, 5.8000e+00, 6.6054e+04, ..., 0.0000e+00, 0.0000e+00,
         1.0000e+00],
        [9.7000e+01, 4.2000e+00, 4.3574e+04, ..., 0.0000e+00, 0.0000e+00,
         1.0000e+00]]),
 array([73, 81, 91, 76, 27, 86, 76, 47, 89, 66, 75, 46, 89, 53, 36, 64, 80,
        92, 24, 19, 73, 86, 42, 71, 77, 41, 81, 43, 61, 91, 71, 77, 85, 70,
        57, 55, 70, 51, 94, 81, 64, 88, 64, 40, 94, 62, 64, 49, 17, 40, 88,
        75, 56, 52, 83, 72, 59, 38, 35, 43, 54, 44, 96, 89, 58, 52, 90, 55,
        52, 85, 43, 30, 38, 75, 55, 39, 59, 47, 24, 87, 83, 81, 35, 34, 92,
        55, 54, 14, 76, 40, 82, 87, 41, 75, 43, 52, 25, 74, 93, 90, 80, 34,
        37, 86, 33, 45, 81, 48, 24, 35, 91, 69, 75, 43, 35, 78, 78, 64, 40,
        88, 43, 65, 46, 55, 75, 67, 54, 41, 75, 76, 74, 87, 37, 86, 79, 42,
        63, 38, 51, 84, 44, 33, 74, 78, 59, 74, 55, 52, 89, 82, 22, 85, 66,
        61, 33, 43, 50, 49, 84, 62, 63, 83, 65, 74, 61, 70, 62, 69, 63, 39,
        32, 79, 87, 70, 71, 86, 33, 70, 87, 68, 83, 85, 39, 44, 17, 58, 11,
        41, 85, 49, 79, 54, 41, 77, 79, 85, 80, 89, 31, 46, 92, 62, 36, 80,
        57, 55, 55, 90, 75, 40, 71, 86, 73, 61, 45, 70, 56, 56, 91, 81, 46,
        65, 21, 49, 48, 90, 31, 84, 77, 48, 45, 58, 73, 27, 85, 86, 83, 25,
        61, 78, 40, 51, 40, 87, 66, 52, 75, 40, 38, 49, 63, 83, 81, 61, 80,
        46, 64, 19, 78, 80, 33, 51, 81, 65, 90, 85, 71, 90, 50, 51, 87, 69,
        87, 84, 86, 71, 82, 72, 59, 76, 45, 63, 29, 72, 40, 76, 84, 71, 42,
        88, 85, 75, 76, 66, 55, 76, 42, 74, 79, 64, 48, 23, 61, 66, 45, 54,
        49, 59, 60, 48, 58, 28, 31, 87, 68, 47, 37, 83, 84, 74, 79, 44, 84,
        27, 51, 64, 41, 35, 78, 72, 66, 37, 82, 63, 89, 56, 62, 46, 38, 92,
        89, 82, 41, 72, 83, 87, 29, 45, 34, 79, 97, 84, 63, 44, 68, 61, 86,
        50, 65, 49, 83, 57, 40, 69, 63, 85, 79, 57, 53, 65, 66, 35, 95, 33,
        19, 17, 89, 86, 55, 72, 84, 82, 94, 55, 88, 68, 89, 76, 43, 62, 36,
        60, 89, 74, 78, 71, 82, 89, 91, 44, 56, 45, 70, 89, 35, 13, 30, 68,
        49, 63, 81, 47, 51, 50, 78, 93, 35, 29, 31, 85, 31, 85, 49, 69, 80,
        79, 43, 37, 86, 55, 52, 75, 49, 74, 58, 65, 67, 60, 83, 57, 37, 29,
        78, 67, 76, 49, 51, 92, 78, 87, 60, 32, 67, 47, 39, 24, 93, 24, 57,
        47, 77, 72, 72, 49, 78, 29, 70, 94, 14, 70, 30, 35, 73, 28, 37, 92,
        76, 81, 58, 72, 66, 23, 70, 81, 60, 52, 49, 46, 79, 86, 63, 88, 86,
        34, 59, 87, 50, 62, 25, 82, 85, 26, 38, 45, 70, 86, 28, 81, 32, 77,
        72, 72, 53, 60, 49, 36, 59, 49, 73, 59, 49, 65, 64, 68, 64, 19, 93,
        76, 77, 31, 72, 78, 44, 52, 44, 73, 85, 46, 77, 80, 71, 91, 42, 61,
        37, 67, 65, 54, 76, 15, 79, 49, 86, 77, 67, 87, 44, 65, 78, 87, 22,
        35, 80, 79, 32, 44, 73, 69, 71, 39, 82, 46, 68, 87, 85, 89, 71, 62,
        68, 80, 34, 81, 80, 89, 72, 86, 29, 59, 81, 71, 94, 54, 79, 82, 87,
        87, 71, 88, 50, 70, 92, 70, 38, 44, 80, 66, 55, 79, 69, 91, 38, 67,
        58, 89, 88, 52, 89, 55, 53, 65, 33, 74, 78, 73, 89, 35, 70, 48, 18,
        41, 22, 81, 35, 73, 95, 37, 40, 72, 55, 65, 81, 81, 73, 74, 35, 26,
        81, 52, 34, 51], dtype=int64))
```

In [50]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_sta
te=0)
```

In [51]:
```
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[51]:
```
((520, 9), (130, 9), (520,), (130,))
```

Feature Scaling

In [52]:
```
X_train
```

Out[52]:

	runtime	imdb_rating	imdb_num_votes	critics_score	feature_film	drama	mpaa_rating_R	oscar_season
34	112.0	6.6	4908	40	1	0	1	0
433	105.0	5.9	33040	43	1	0	0	0
400	112.0	5.8	1816	38	1	0	0	0
347	86.0	2.3	87652	2	1	0	1	0
543	128.0	5.8	6418	50	1	1	1	0
...	...	...	...	...	...	...	...	...
9	119.0	6.6	12496	83	1	1	0	0
360	98.0	6.0	109633	60	1	0	0	0
192	112.0	5.9	725	33	1	1	1	0
630	119.0	5.7	8818	26	1	1	1	0
560	106.0	7.5	10250	97	1	1	1	0

520 rows × 9 columns

In [53]:
```
minmax = MinMaxScaler()
```

In [54]:
```
X_train_scaled = minmax.fit_transform(X_train)
```

In [55]:
```
X_test_scaled = minmax.transform(X_test)
```

In [56]:
```
X_train_scaled
```

Out[56]:
```
array([[3.20175439e-01, 6.61971831e-01, 5.29553285e-03, ...,
        1.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [2.89473684e-01, 5.63380282e-01, 3.68044013e-02, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [3.20175439e-01, 5.49295775e-01, 1.83237981e-03, ...,
        0.00000000e+00, 0.00000000e+00, 1.00000000e+00],
       ...,
       [3.20175439e-01, 5.63380282e-01, 6.10419924e-04, ...,
        1.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [3.50877193e-01, 5.35211268e-01, 9.67487579e-03, ...,
        1.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [2.93859649e-01, 7.88732394e-01, 1.12787681e-02, ...,
        1.00000000e+00, 0.00000000e+00, 1.00000000e+00]])
```

In [57]:
```
X_test_scaled
```

Out[57]:
```
array([[0.23684211, 0.53521127, 0.02125941, ..., 0.        , 0.        ,
        0.        ],
       [0.24561404, 0.16901408, 0.00911598, ..., 0.        , 1.        ,
        0.        ],
       [0.24122807, 0.61971831, 0.07060598, ..., 1.        , 1.        ,
        0.        ],
       ...,
       [0.21491228, 0.69014085, 0.01812891, ..., 0.        , 0.        ,
        1.        ],
       [0.22368421, 0.81690141, 0.06354975, ..., 0.        , 0.        ,
        1.        ],
       [0.25438596, 0.5915493 , 0.00295466, ..., 1.        , 0.        ,
        1.        ]])
```

Model Training

Using PyCaret

In [58]:
```
exp_reg = setup(data = df, target = 'audience_score', session_id=0, normalize=True,
train_size=0.8,
                categorical_features=['feature_film', 'drama', 'mpaa_rating_R', 'osc
ar_season', 'summer_season'],
                normalize_method='minmax')
```

```
Setup Succesfully Completed.
```

	Description	Value
0	session_id	0
1	Transform Target	False
2	Transform Target Method	None
3	Original Data	(650, 10)
4	Missing Values	False
5	Numeric Features	4
6	Categorical Features	5
7	Ordinal Features	False
8	High Cardinality Features	False
9	High Cardinality Method	None
10	Sampled Data	(650, 10)
11	Transformed Train Set	(520, 14)
12	Transformed Test Set	(130, 14)
13	Numeric Imputer	mean
14	Categorical Imputer	constant
15	Normalize	True
16	Normalize Method	minmax
17	Transformation	False
18	Transformation Method	None
19	PCA	False
20	PCA Method	None
21	PCA Components	None
22	Ignore Low Variance	False
23	Combine Rare Levels	False
24	Rare Level Threshold	None
25	Numeric Binning	False
26	Remove Outliers	False
27	Outliers Threshold	None
28	Remove Multicollinearity	False
29	Multicollinearity Threshold	None
30	Clustering	False
31	Clustering Iteration	None
32	Polynomial Features	False
33	Polynomial Degree	None
34	Trignometry Features	False
35	Polynomial Threshold	None

	Description	Value
36	Group Features	False

In [59]:
```
compare_models()
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE	TT (Sec)
0	Random Forest	6.7427	86.7840	9.2398	0.7755	0.2017	0.1429	0.2499
1	CatBoost Regressor	6.7425	88.1822	9.3030	0.7704	0.2009	0.1409	2.0891
2	Extra Trees Regressor	6.9914	91.9652	9.5333	0.7614	0.2056	0.1473	0.1929
3	Gradient Boosting Regressor	6.8254	93.7363	9.5803	0.7562	0.2082	0.1447	0.1094
4	Light Gradient Boosting Machine	6.9725	95.2568	9.6376	0.7506	0.2090	0.1446	0.0973
5	AdaBoost Regressor	7.4243	98.8017	9.8935	0.7464	0.2216	0.1666	0.1441
6	Extreme Gradient Boosting	7.2543	102.6510	10.0494	0.7349	0.2141	0.1500	0.1427
7	Least Angle Regression	7.8093	103.1230	10.0840	0.7343	0.2474	0.1623	0.0076
8	Linear Regression	7.7977	103.4796	10.0958	0.7332	0.2475	0.1615	0.0047
9	Bayesian Ridge	7.8215	103.5642	10.1041	0.7330	0.2484	0.1617	0.0064
10	Orthogonal Matching Pursuit	7.8109	106.0200	10.2173	0.7270	0.2401	0.1643	0.0058
11	TheilSen Regressor	7.6836	106.2045	10.1947	0.7257	0.2484	0.1587	0.8417
12	Ridge Regression	8.1142	106.8981	10.2980	0.7250	0.2317	0.1659	0.0089
13	Huber Regressor	7.5575	106.9409	10.2230	0.7241	0.2501	0.1590	0.0214
14	Random Sample Consensus	7.6111	107.4837	10.2516	0.7224	0.2459	0.1577	0.1209
15	K Neighbors Regressor	9.3996	140.0385	11.7925	0.6417	0.2364	0.1908	0.0078
16	Passive Aggressive Regressor	9.3541	149.7619	12.0095	0.6124	0.2937	0.1819	0.0062
17	Decision Tree	8.9673	149.7404	12.0990	0.6101	0.2478	0.1836	0.0022
18	Lasso Regression	10.4960	154.3314	12.4003	0.6092	0.2509	0.2192	0.0022
19	Support Vector Machine	13.2847	260.7380	16.0849	0.3456	0.3263	0.3020	0.0161
20	Elastic Net	15.6055	331.1392	18.1565	0.1670	0.3536	0.3390	0.0075
21	Lasso Least Angle Regression	17.2340	403.9848	20.0582	-0.0168	0.3827	0.3742	0.0046

Out[59]:
```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=-1, oob_score=False,
                      random_state=0, verbose=0, warm_start=False)
```

In [60]:
```
rf = create_model('rf')
```

	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	5.8202	78.0767	8.8361	0.8302	0.1906	0.1154
1	6.9652	92.3806	9.6115	0.7785	0.2034	0.1482
2	6.5858	72.1866	8.4963	0.7915	0.2250	0.1666
3	7.5908	92.4536	9.6153	0.8081	0.2166	0.1810
4	6.3860	69.5025	8.3368	0.8148	0.1585	0.1222
5	5.5556	56.2920	7.5028	0.8452	0.1331	0.0907
6	7.3292	145.2290	12.0511	0.5230	0.2756	0.1394
7	7.3779	104.7064	10.2326	0.7742	0.2421	0.1797
8	6.5133	74.6975	8.6428	0.8124	0.1713	0.1304
9	7.3037	82.3154	9.0728	0.7767	0.2011	0.1555
Mean	6.7427	86.7840	9.2398	0.7755	0.2017	0.1429
SD	0.6554	23.4177	1.1875	0.0871	0.0394	0.0276

In [61]:
```
print(rf)
```

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=-1, oob_score=False,
                      random_state=0, verbose=0, warm_start=False)
```

In [62]:
```
tuned_rf = tune_model(rf, optimize='RMSE')
```

	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	5.5978	74.5193	8.6325	0.8379	0.1872	0.1116
1	6.4140	83.9263	9.1611	0.7988	0.1963	0.1382
2	6.6092	75.1340	8.6680	0.7830	0.2230	0.1633
3	7.4272	91.9287	9.5879	0.8092	0.2111	0.1741
4	6.4163	73.2815	8.5605	0.8048	0.1622	0.1231
5	5.7255	59.1193	7.6889	0.8374	0.1350	0.0930
6	7.3258	144.4914	12.0205	0.5254	0.2742	0.1379
7	6.8528	88.5898	9.4122	0.8089	0.2145	0.1585
8	6.0770	68.6431	8.2851	0.8276	0.1662	0.1226
9	7.4556	81.4794	9.0266	0.7789	0.1939	0.1534
Mean	6.5901	84.1113	9.1043	0.7812	0.1964	0.1376
SD	0.6416	22.1080	1.1057	0.0874	0.0364	0.0241

In [63]:
```
print(tuned_rf)
```

```
RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mae',
                      max_depth=110, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=2,
                      min_samples_split=7, min_weight_fraction_leaf=0.0,
                      n_estimators=140, n_jobs=-1, oob_score=False,
                      random_state=0, verbose=0, warm_start=False)
```

In [64]:
```
evaluate_model(tuned_rf)
```

In [65]:
```
predict_model(tuned_rf)
```

	Model	MAE	MSE	RMSE	R2	RMSLE	MAPE
0	Random Forest Regressor	6.7141	71.4891	8.4551	0.8346	0.1931	0.1512

Out[65]:

	runtime	imdb_rating	imdb_num_votes	critics_score	feature_film_0	feature_film_1	drama_0	drama_1
0	0.236842	0.535211	0.021259	0.161616	0.0	1.0	0.0	1.0
1	0.245614	0.169014	0.009116	0.060606	0.0	1.0	1.0	0.0
2	0.241228	0.619718	0.070606	0.797980	0.0	1.0	0.0	1.0
3	0.359649	0.676056	0.065776	0.666667	0.0	1.0	1.0	0.0
4	0.359649	0.661972	0.003976	0.484848	0.0	1.0	1.0	0.0
...	...	...	...	...	...	...	...	...
125	0.429825	0.859155	0.548947	0.838384	0.0	1.0	0.0	1.0
126	0.271930	0.676056	0.010205	0.757576	0.0	1.0	0.0	1.0
127	0.214912	0.690141	0.018129	0.767677	0.0	1.0	1.0	0.0
128	0.223684	0.816901	0.063550	0.545455	0.0	1.0	0.0	1.0
129	0.254386	0.591549	0.002955	0.555556	0.0	1.0	1.0	0.0

130 rows × 16 columns

In [ ]:
```

```