SC1015 Mini Project

IMDB Top 2000 Movies Dataset

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Introduction

IMDB Rating

Practical Motivation

Objective:

Determine the influence of various factors (such as Metascore, Votes, Duration, Gross value) on the IMDb ratings of the top 2000 movies.

Primary Data Points in our dataset:
Duration, IMDb ratings, Gross Value, Metascore, Votes

Other Data Points in our dataset:
Name of movie, Release Year, Genre, Director, Cast

02

Exploratory Data Analysis

Initial Data Insights

```
[2]: # Import datasets
data = pd.read_csv('imdb_top_2000_movies.csv')
data.head()
```

[2]:

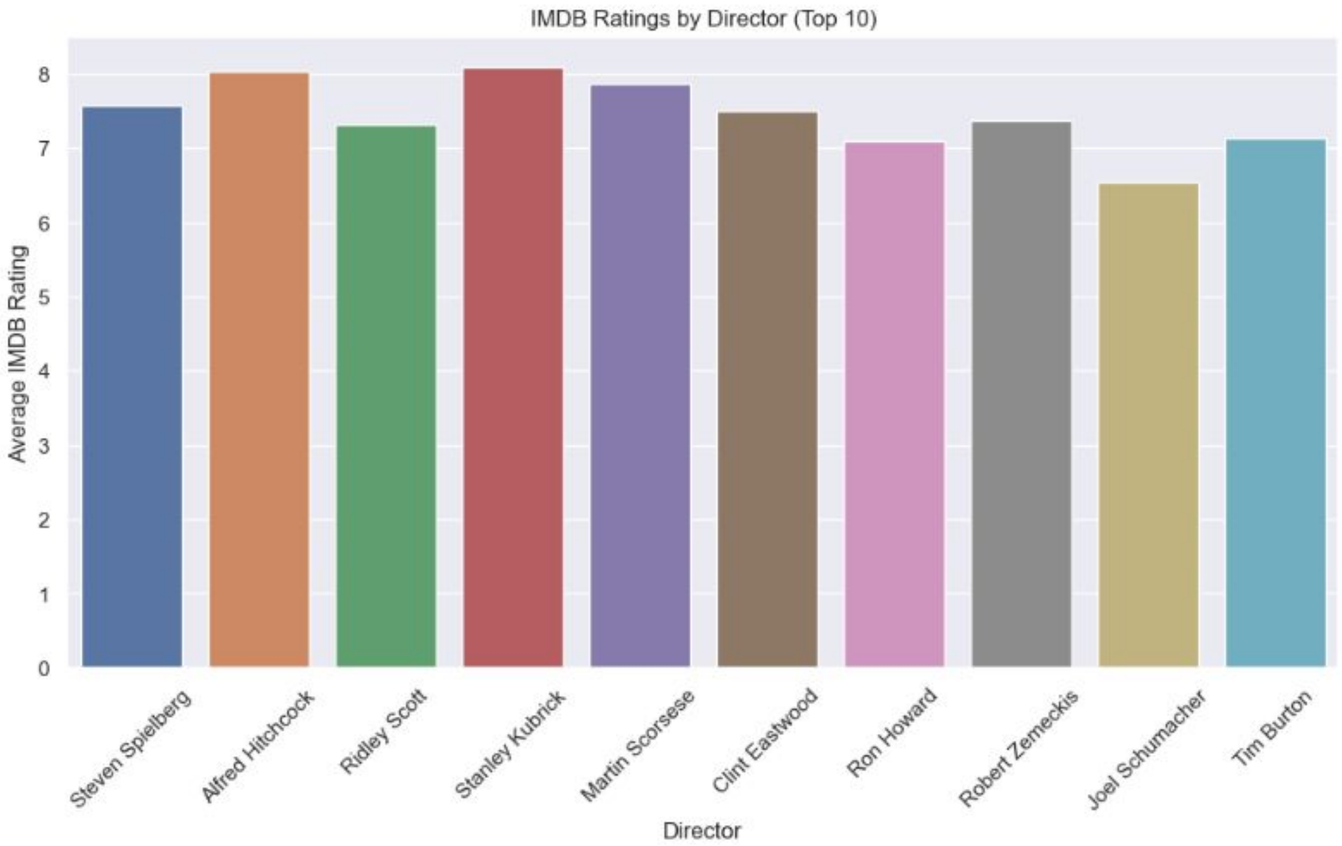
	Movie Name	Release Year	Duration	IMDB Rating	Metascore	Votes	Genre	Director	Cast	Gross
0	The Godfather	1972	175	9.2	100.0	2,002,655	Crime, Drama	Francis Ford Coppola	Marlon Brando	$134.97M
1	The Godfather Part II	1974	202	9.0	90.0	1,358,608	Crime, Drama	Francis Ford Coppola	Al Pacino	$57.30M
2	Ordinary People	1980	124	7.7	86.0	56,476	Drama	Robert Redford	Donald Sutherland	$54.80M
3	Lawrence of Arabia	1962	218	8.3	100.0	313,044	Adventure, Biography, Drama	David Lean	Peter O'Toole	$44.82M
4	Straw Dogs	1971	113	7.4	73.0	64,331	Crime, Drama, Thriller	Sam Peckinpah	Dustin Hoffman	NaN

loaded the top 2000 IMDb movies dataset from a CSV file into a DataFrame and displayed the first five records.

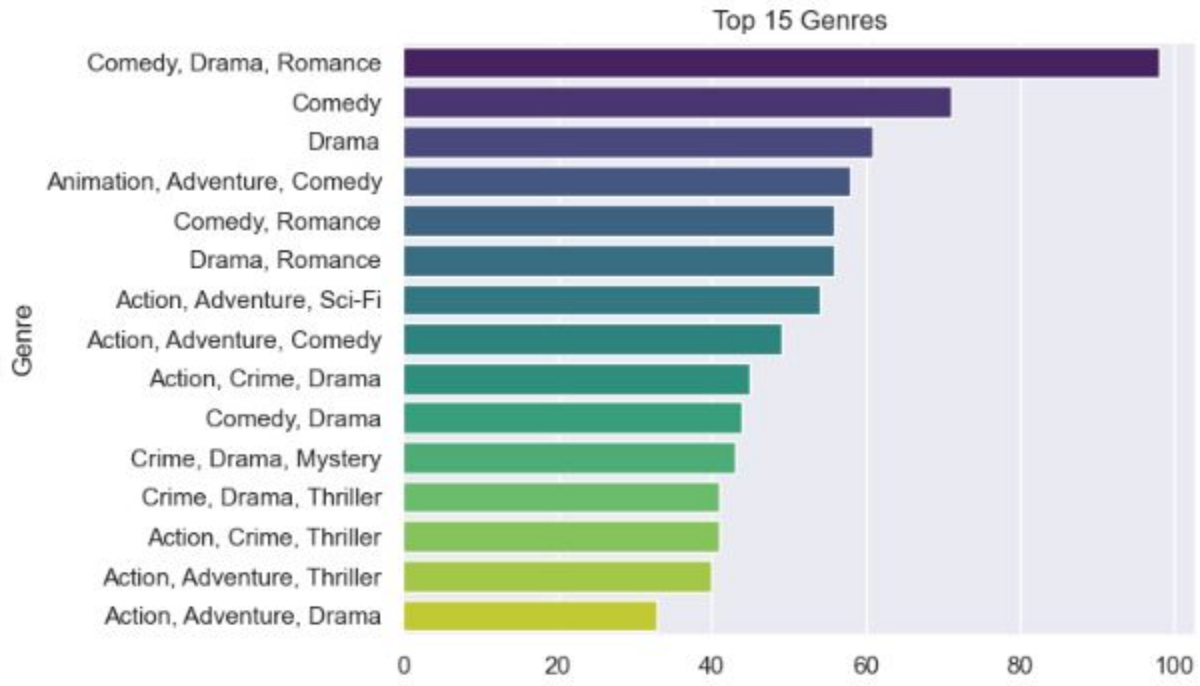
Preliminary exploration

```
[3]: df = pd.DataFrame(data)
     df.info()
```

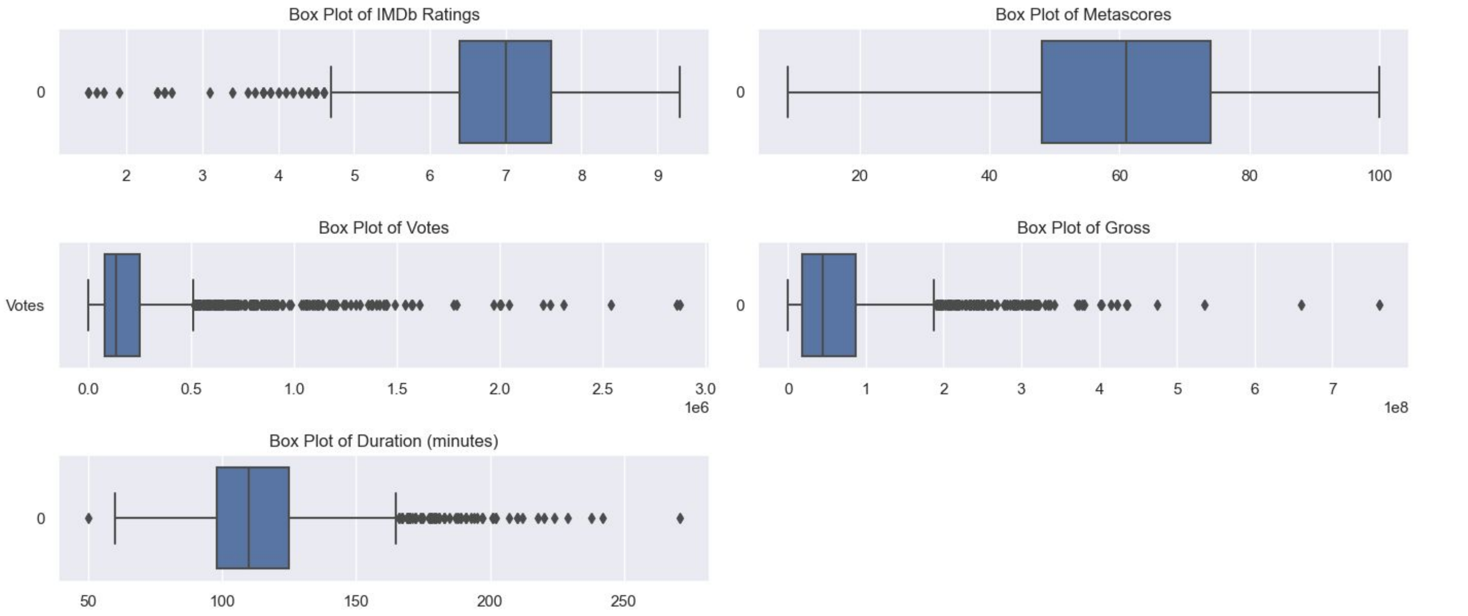
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 10 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Movie Name     2000 non-null   object
 1   Release Year   2000 non-null   object
 2   Duration       2000 non-null   int64
 3   IMDB Rating    2000 non-null   float64
 4   Metascore      1919 non-null   float64
 5   Votes          2000 non-null   object
 6   Genre          2000 non-null   object
 7   Director       2000 non-null   object
 8   Cast           2000 non-null   object
 9   Gross          1903 non-null   object
dtypes: float64(2), int64(1), object(7)
memory usage: 156.4+ KB
```


IMDB Ratings by Director (Top 10)
Average IMDB Rating
0
1
2
3
4
5
6
7
8
Steven Spielberg
Alfred Hitchcock
Ridley Scott
Stanley Kubrick
Martin Scorsese
Clint Eastwood
Ron Howard
Robert Zemeckis
Joel Schumacher
Tim Burton
Director

```
Text(0.5, 1.0, 'Top 15 Genres')
```



bar chart illustrating the top 15 movie genres or genre combinations from a dataset, ranked by their frequency of occurrence, with the genre comedy, drama and romance being most common.



boxplots to rep the distribution of IMDb ratings, Metascores, number of votes, gross revenue, and duration for a set of movies, indicating variability and outliers within these data points.

03
Data preparation & cleaning

Data Preparation

[3]:
```python
# Remove all commas convert object to float for Votes
data['Votes'] = data['Votes'].str.replace(',', '')
data['Votes'] = data['Votes'].astype(float)

# Remove $ sign and M symbol and convert to float for Gross
data['Gross'] = data['Gross'].str.replace('$', '')
data['Gross'] = data['Gross'].str.replace('M', '')
data['Gross'] = data['Gross'].astype(float)
data['Gross'] = data['Gross'] * (10 ** 6)
# Convert Release Year from object to float
data['Release Year'] = pd.to_numeric(data['Release Year'], errors='coerce')
df = pd.DataFrame(data)
```

[4]:
```python
df
```

[4]:

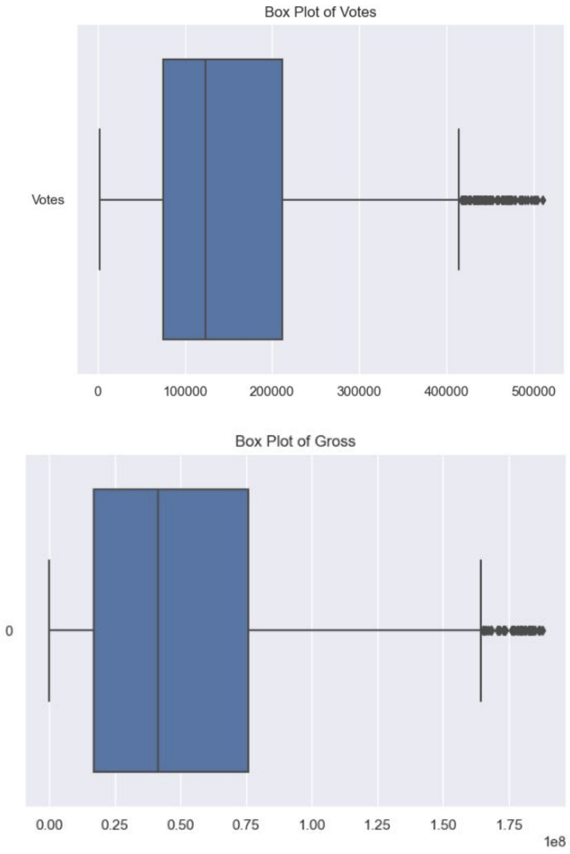
	Movie Name	Release Year	Duration	IMDB Rating	Metascore	Votes	Genre	Director	Cast	Gross
0	The Godfather	1972.0	175	9.2	100.0	2002655.0	Crime, Drama	Francis Ford Coppola	Marlon Brando	134970000.0
1	The Godfather Part II	1974.0	202	9.0	90.0	1358608.0	Crime, Drama	Francis Ford Coppola	Al Pacino	57300000.0
2	Ordinary People	1980.0	124	7.7	86.0	56476.0	Drama	Robert Redford	Donald Sutherland	54800000.0
3	Lawrence of Arabia	1962.0	218	8.3	100.0	313044.0	Adventure, Biography, Drama	David Lean	Peter O'Toole	44820000.0
4	Straw Dogs	1971.0	113	7.4	73.0	64331.0	Crime, Drama, Thriller	Sam Peckinpah	Dustin Hoffman	NaN
...	...	...	...	...	...	...	...	...	...	...
1995	The Young Victoria	2009.0	105	7.2	64.0	66235.0	Biography, Drama, History	Jean-Marc Vallée	Emily Blunt	11000000.0
1996	Tooth Fairy	NaN	101	5.0	36.0	49527.0	Comedy, Family, Fantasy	Michael Lembeck	Dwayne Johnson	60020000.0
1997	The Informant!	2009.0	108	6.5	66.0	67318.0	Biography, Comedy, Crime	Steven Soderbergh	Matt Damon	33310000.0
1998	Youth in Revolt	2009.0	90	6.4	63.0	75956.0	Comedy, Drama, Romance	Miguel Arteta	Michael Cera	15280000.0
1999	Quarantine	2008.0	89	6.0	53.0	77075.0	Horror, Sci-Fi, Thriller	John Erick Dowdle	Jennifer Carpenter	31690000.0

2000 rows × 10 columns

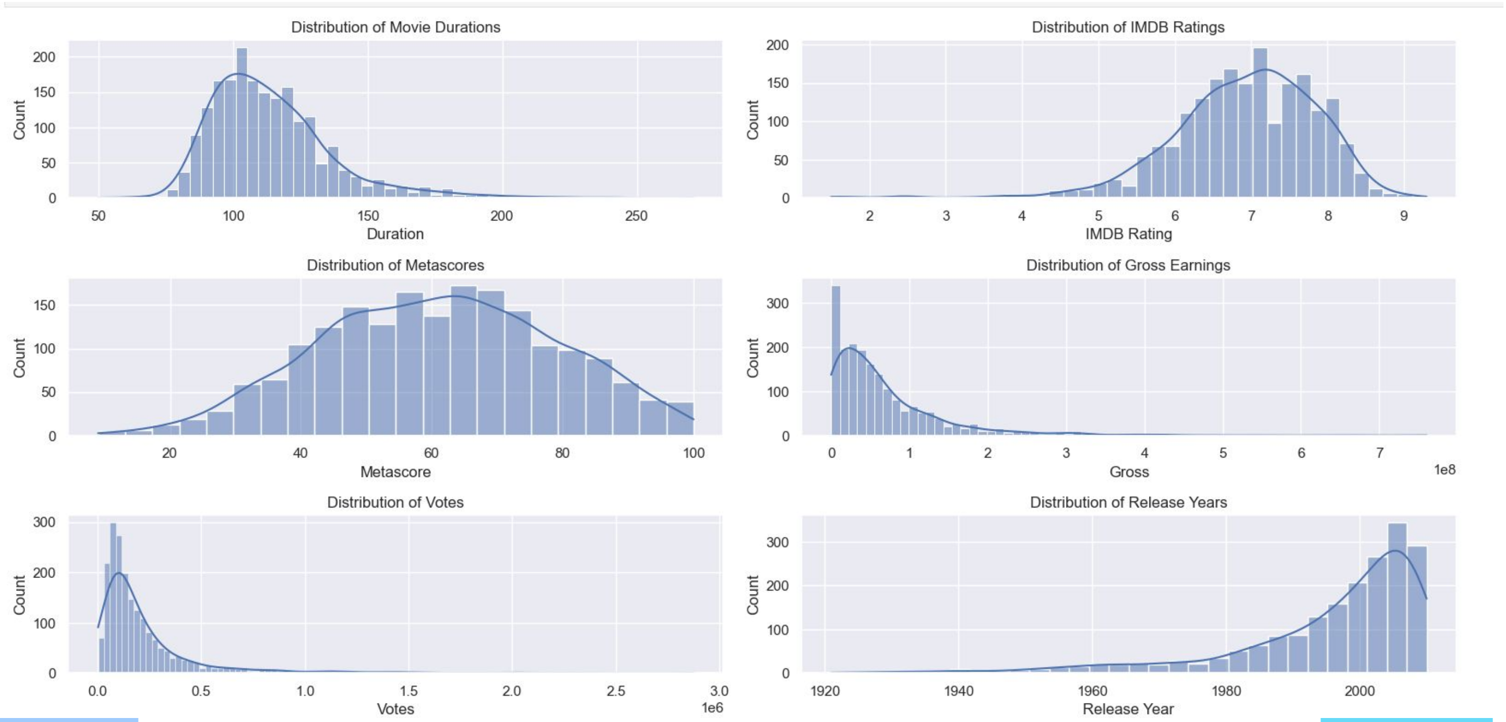
Keep	Remove
1. Duration, 2. IMDb ratings 3. Gross Value 4. Metascore 5. Votes 6. Release Year	1. Name of movie 2. Genre 3. Director 4. Cast

Cleaning data

```
[6]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Movie Name    2000 non-null   object
 1   Release Year  1921 non-null   float64
 2   Duration      2000 non-null   int64
 3   IMDB Rating   2000 non-null   float64
 4   Metascore     1919 non-null   float64
 5   Votes         2000 non-null   float64
 6   Genre         2000 non-null   object
 7   Director      2000 non-null   object
 8   Cast          2000 non-null   object
 9   Gross         1903 non-null   float64
dtypes: float64(5), int64(1), object(4)
memory usage: 156.4+ KB
```



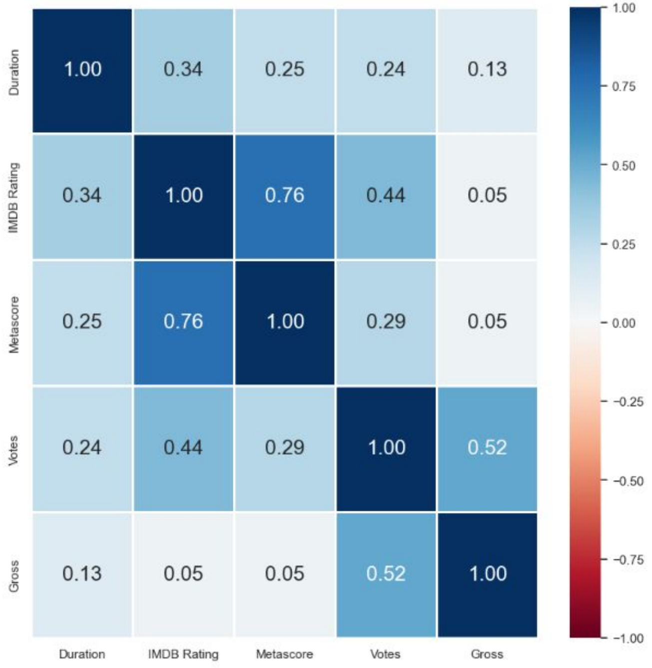
Analysis of data



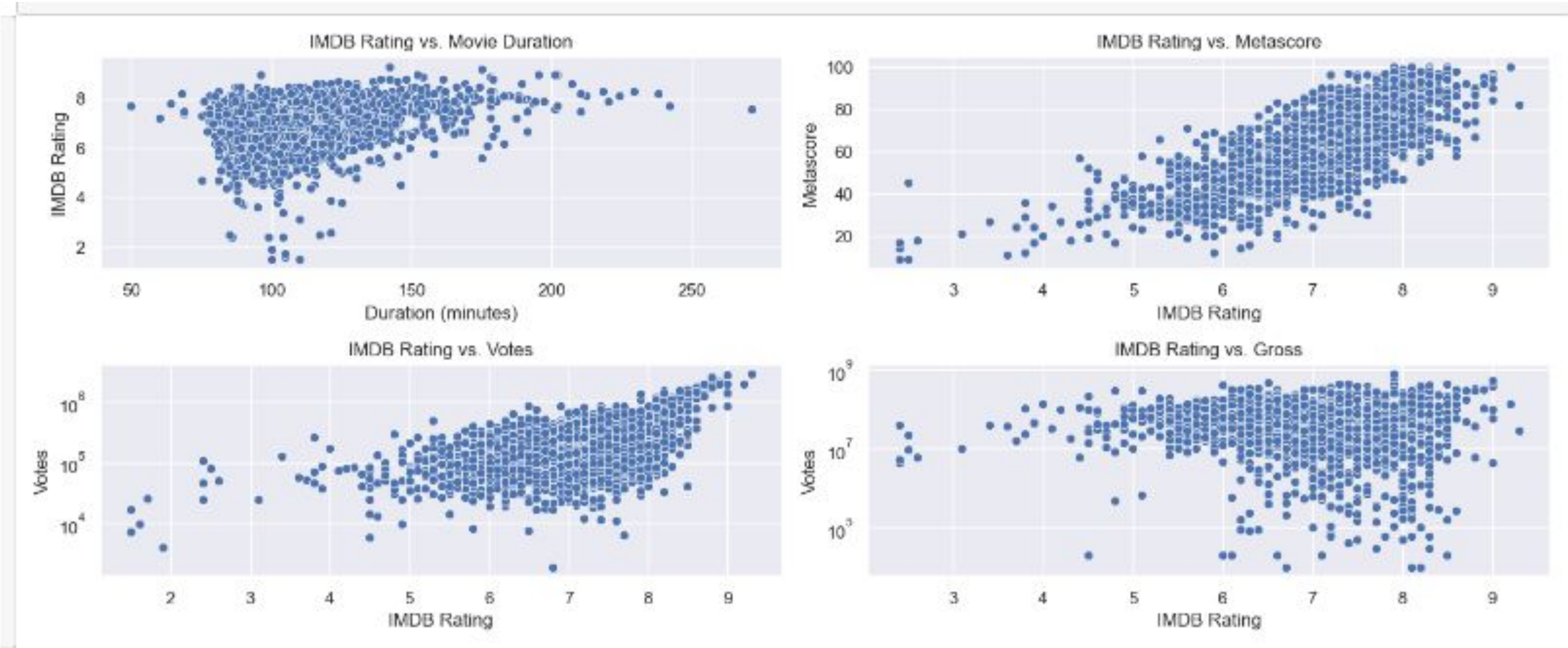
Analysis of data

Heatmap

```
[9]: corrDF=pd.DataFrame(df[['Duration', 'IMDB Rating', 'Metascore', 'Votes', 'Gross']])
     f = plt.figure(figsize=(10, 10))
     sb.heatmap(corrDF.corr(), vmin = -1, vmax = 1, linewidths = 1,
                annot = True, fmt = ".2f", annot_kws = {"size": 18}, cmap = "RdBu")

[9]: <Axes: >
```



strong positive correlation between imdb ratings and metascore of 0.76, a moderate positive correlation between votes and IMDb ratings, and a weaker positive correlation between gross revenue and IMDb ratings.

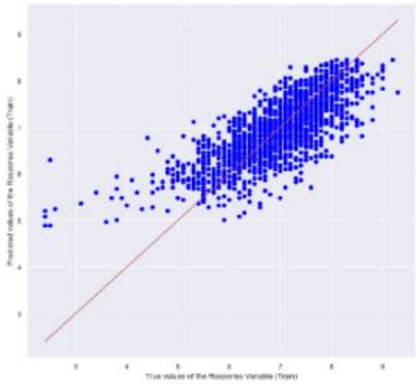

IMDB Rating vs. Movie Duration
IMDB Rating
Duration (minutes)
IMDB Rating vs. Metascore
Metascore
IMDB Rating
IMDB Rating vs. Votes
Votes
IMDB Rating
IMDB Rating vs. Gross
Votes
IMDB Rating

04

Machine Learning

Regression, Decision Tree, Random Forest

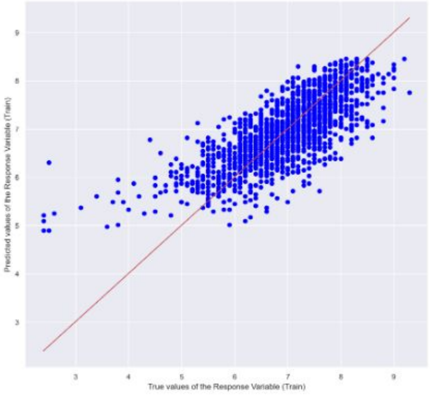
Regression

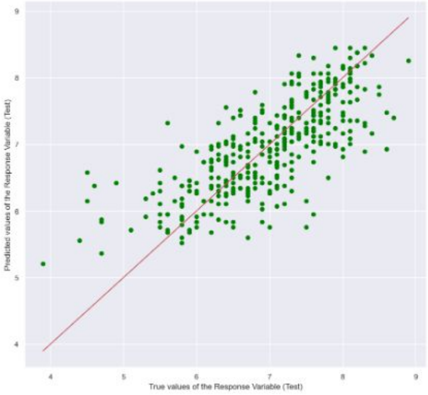


Predicted values of the Response Variable (Train)
True values of the Response Variable (Train)

IMDB Rating vs Metascore

```
Intercept of Regression          : b =  [4.5455173]
Coefficients of Regression       : a =  [[0.03909264]]

Goodness of Fit of Model         Train Dataset
Explained Variance (R^2)         : 0.5733895815463212
Mean Squared Error (MSE)         : 0.36699191732906405

Goodness of Fit of Model         Test Dataset
Explained Variance (R^2)         : 0.563041155223023
Mean Squared Error (MSE)         : 0.31406405115077946
```

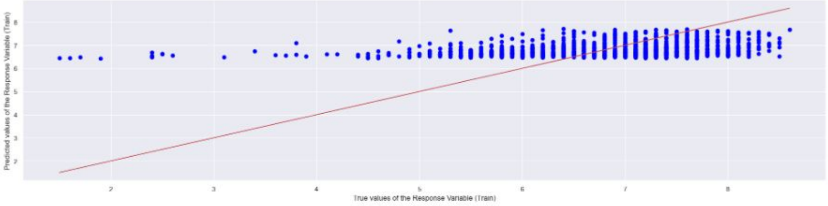


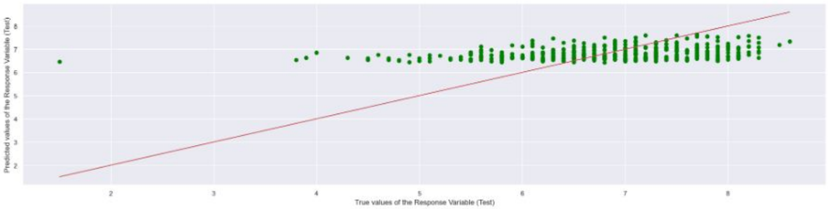


strongest positive correlation between imdb ratings and metascore

IMDB Rating vs Votes

```
Intercept of Regression          : b =  [6.42455104]
Coefficients of Regression       : a =  [[2.50708159e-06]]

Goodness of Fit of Model         Train Dataset
Explained Variance (R^2)         : 0.08738906508938515
Mean Squared Error (MSE)         : 0.7869578513104797

Goodness of Fit of Model         Test Dataset
Explained Variance (R^2)         : 0.11139791960741419
Mean Squared Error (MSE)         : 0.7025562930518372
```

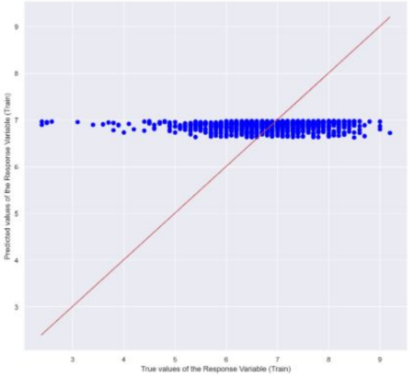


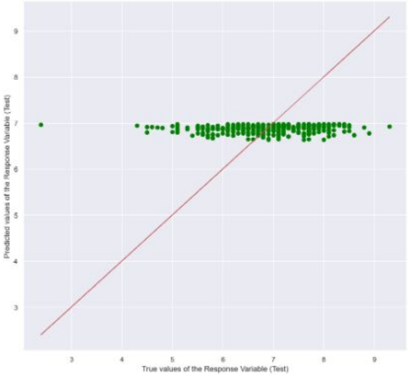


Much weaker and nearly linear correlation with other factors such as votes and duration

IMDB Rating vs Gross

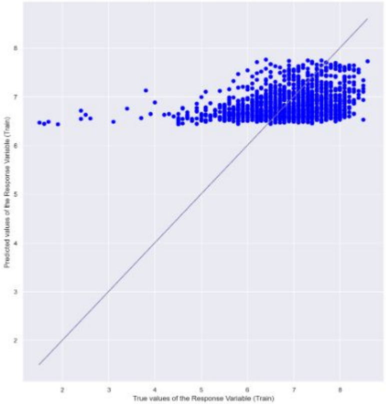
```
Intercept of Regression        : b =  [6.97735058]
Coefficients of Regression     : a =  [[-1.8426805e-09]]

Goodness of Fit of Model        Train Dataset
Explained Variance (R^2)        : 0.008315503020466797
Mean Squared Error (MSE)        : 0.814371021646203

Goodness of Fit of Model        Test Dataset
Explained Variance (R^2)        : 0.004015663672795378
Mean Squared Error (MSE)        : 0.8098473878865355
```

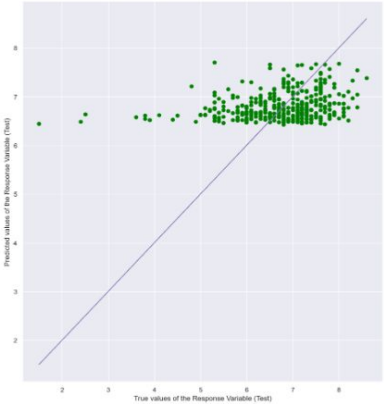




IMDB Rating vs Duration

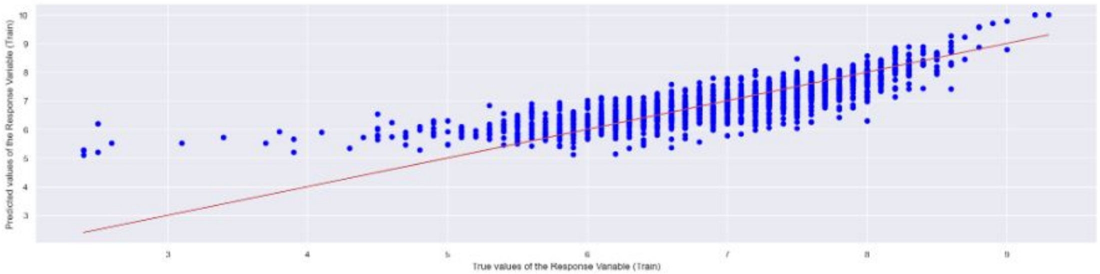
```
Intercept of Regression         : b =  [6.4246543]
Coefficients of Regression      : a =  [[2.631455e-06]]

Goodness of Fit of Model        Train Dataset
Explained Variance (R^2)        : 0.09849251217694732
Mean Squared Error (MSE)        : 0.7450839952763629
Root Mean Squared Error (RMSE)  : 0.8631824808673789

Goodness of Fit of Model        Test Dataset
Explained Variance (R^2)        : 0.06118727426560344
Mean Squared Error (MSE)        : 0.8499283539214618
Root Mean Squared Error (RMSE)  : 0.9219155893689301
```

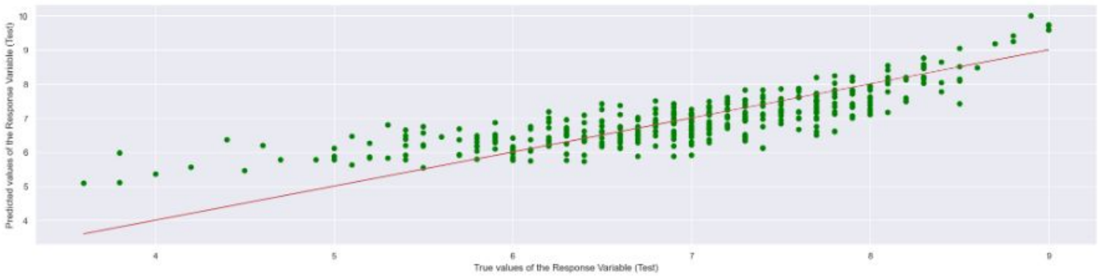




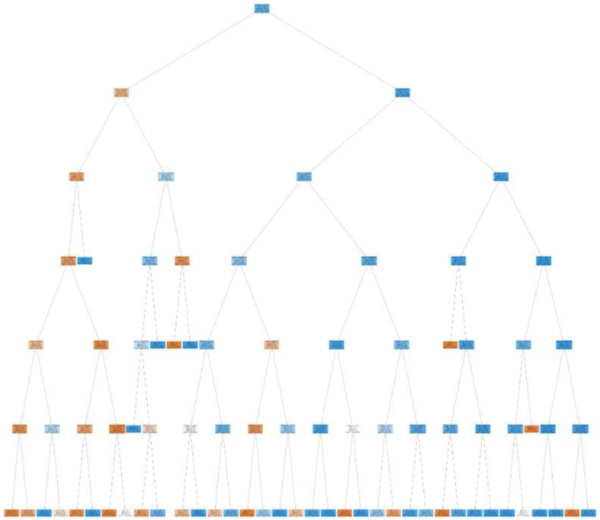
IMDB Rating vs Duration+Gross+Votes+MetaScore

```
Intercept of Regression         : b =  [4.21918997]
Coefficients of Regression      : a =  [[ 1.07726340e-06 -1.95981609e-09  5.63590533e-03  3.20035084e-02]]

Goodness of Fit of Model        Train Dataset
Explained Variance (R^2)        : 0.6653574052063997
Mean Squared Error (MSE)        : 0.27248534538253527

Goodness of Fit of Model        Test Dataset
Explained Variance (R^2)        : 0.6646272068009653
Mean Squared Error (MSE)        : 0.2893297167187535
```





Decision Tree

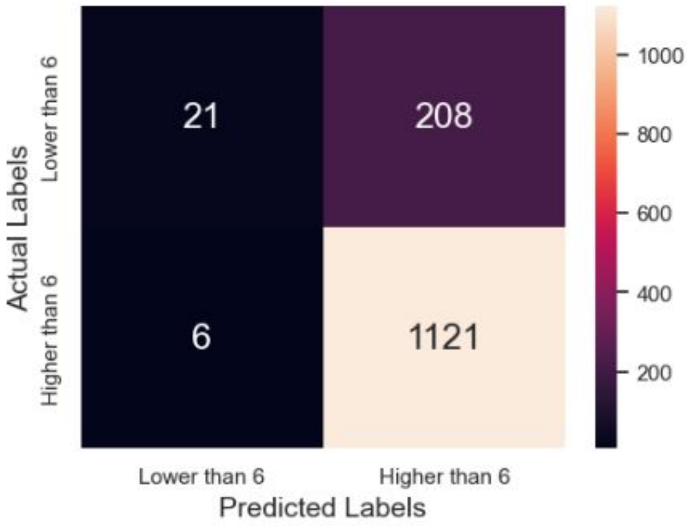


Limitations

- Even though it maintained a consistently low true positive rate, it also had a rather high false positive rate.
  - Likely due to the nature of our dataset we chose
  - Resulting in class imbalance
    - a majority of the movies are all “hits” rather than “flops”
    - less popular movies are underrepresented in our dataset
- Hence, the decision tree is likely to be biased towards predicting the majority class, which is already made up of all the hit movies of all time with mostly high ratings, resulting in much more false positives.
- Hence our data becomes rather skewed, making it difficult to mitigate despite data cleaning.

IMDB Rating vs Votes

```
Goodness of Fit of Model        Train Dataset
Classification Accuracy         : 0.8421828908554573
TPR for train    : 0.9946761313220941
FPR for train    : 0.9082969432314411

Goodness of Fit of Model        Test Dataset
Classification Accuracy         : 0.8259587020648967
TPR for train    : 0.9755244755244755
FPR for train    : 0.9811320754716981


Text(624.5227272727271, 0.5, 'Actual Labels')
```

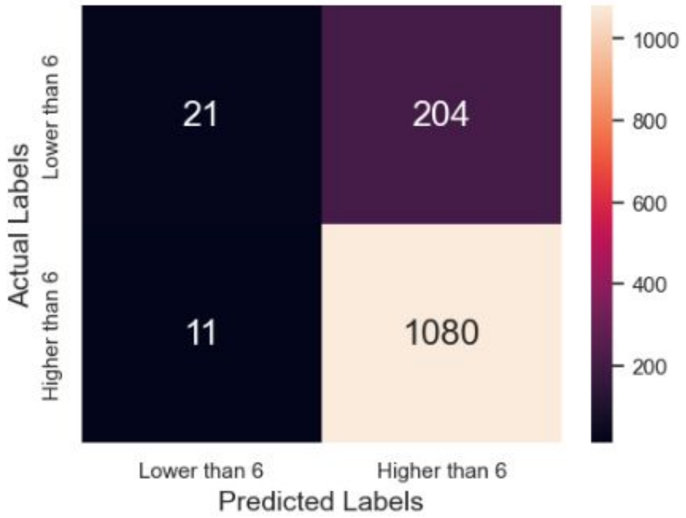


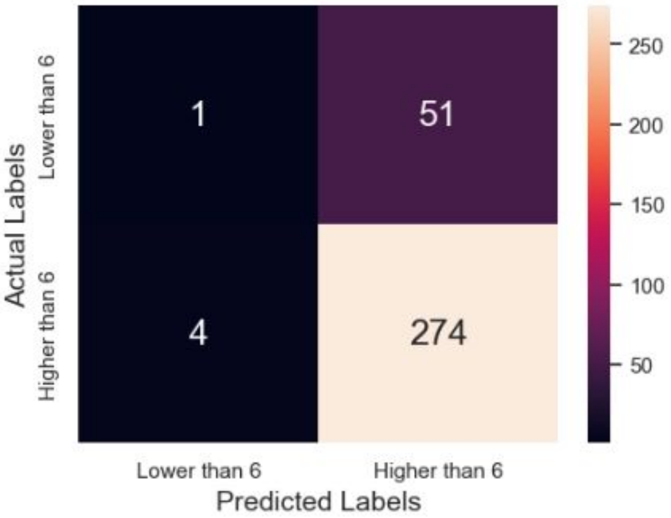
IMDB Rating vs Metascore

```
Goodness of Fit of Model        Train Dataset
Classification Accuracy         : 0.883480825958702
TPR for train    : 0.9654561558901683
FPR for train    : 0.5242290748898678

Goodness of Fit of Model        Test Dataset
Classification Accuracy         : 0.887905604719764
TPR for train    : 0.9471830985915493
FPR for train    : 0.41818181818181815

Text(624.5227272727271, 0.5, 'Actual Labels')
```

IMDB Rating vs Gross

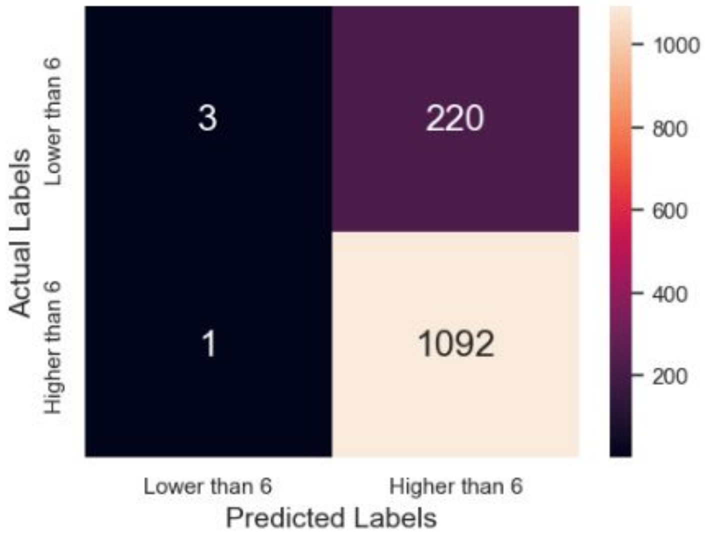
```
Goodness of Fit of Model        Train Dataset
Classification Accuracy         : 0.8366261398176292
TPR for train    : 0.9899175068744271
FPR for train    : 0.9066666666666666

Goodness of Fit of Model        Test Dataset
Classification Accuracy         : 0.8333333333333334
TPR for train    : 0.9856115107913669
FPR for train    : 0.9807692307692307


Text(624.5227272727271, 0.5, 'Actual Labels')
```

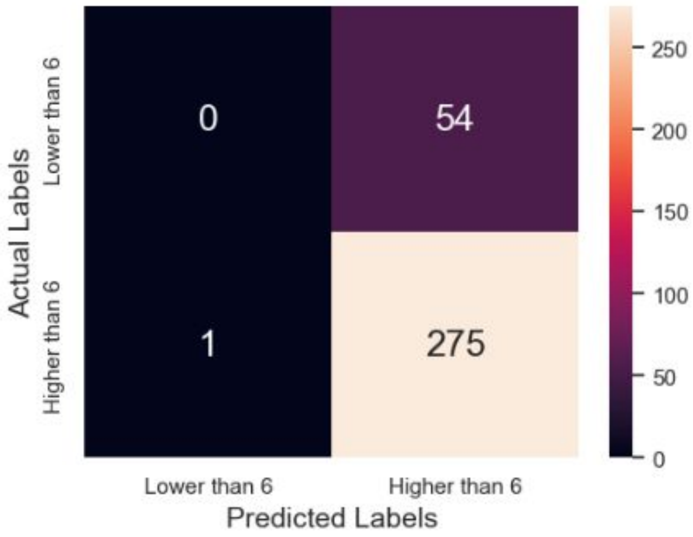




IMDB Rating vs Duration

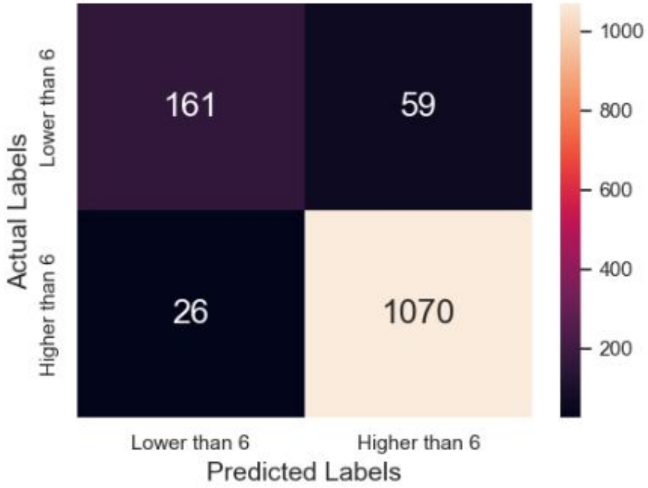
```
Goodness of Fit of Model        Train Dataset
Classification Accuracy         : 0.8320668693009119
TPR for train    : 0.9990850869167429
FPR for train    : 0.9865470852017937

Goodness of Fit of Model        Test Dataset
Classification Accuracy         : 0.8333333333333334
TPR for train    : 0.9963768115942029
FPR for train    : 1.0


Text(624.5227272727271, 0.5, 'Actual Labels')
```

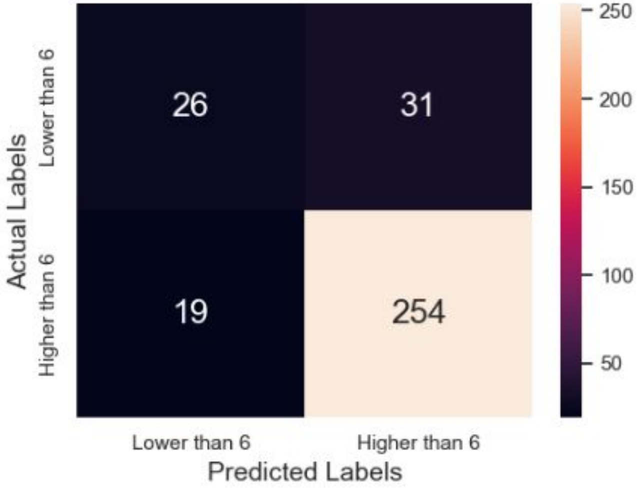




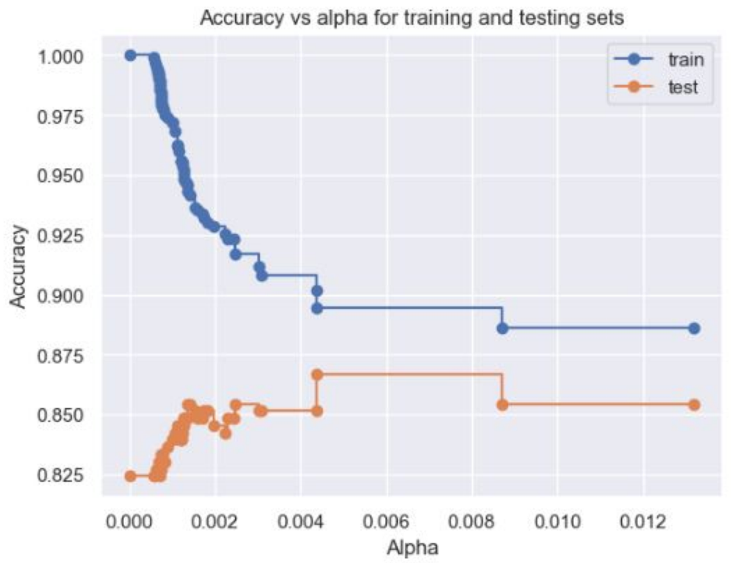
IMDB Rating vs Duration+Gross+Votes+MetaScore

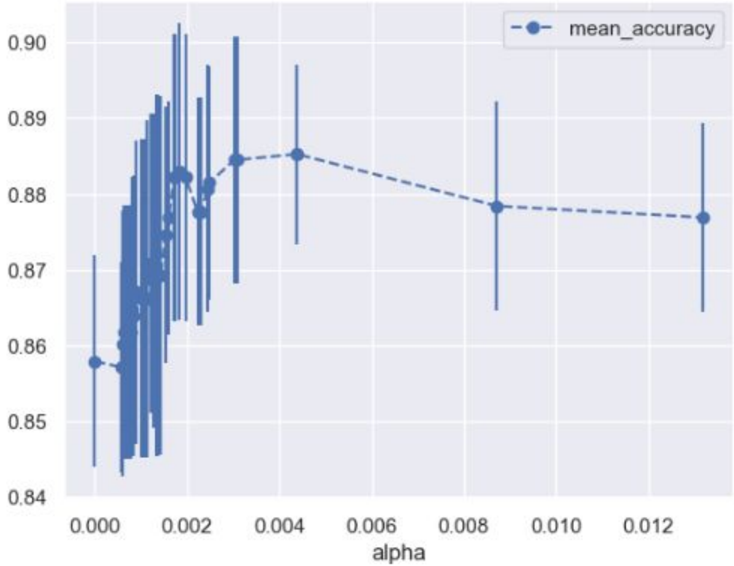
```
Goodness of Fit of Model        Train Dataset
Classification Accuracy         : 0.9354103343465046
TPR for train    : 0.9762773722627737
FPR for train    : 0.2681818181818182

Goodness of Fit of Model        Test Dataset
Classification Accuracy         : 0.8484848484848485
TPR for train    : 0.9304029304029304
FPR for train    : 0.543859649122807


Text(624.5227272727271, 0.5, 'Actual Labels')
```





Visualizing alpha



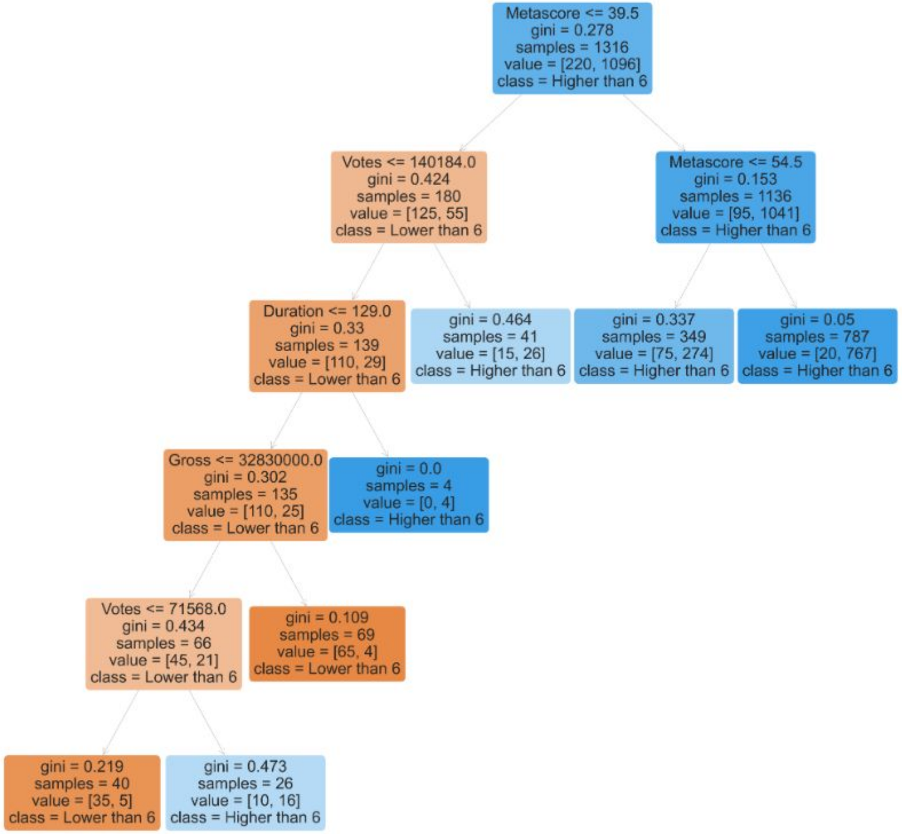


	alpha	mean_accuracy	std
55	0.002228	0.877662	0.015077
56	0.002293	0.877662	0.015077
57	0.002453	0.880709	0.016333
58	0.002486	0.881470	0.015380
59	0.003018	0.884509	0.016335
60	0.003096	0.884509	0.016335
61	0.004362	0.885260	0.011857
62	0.004383	0.885260	0.011857
63	0.008712	0.878416	0.013840

	alpha	mean_accuracy	std
61	0.004362	0.88526	0.011857

It helps control the size of a tree by selectively removing nodes based on a cost complexity parameter called ccp_alpha, which determines the trade off between tree complexity and accuracy.

Cost Complexity Pruning



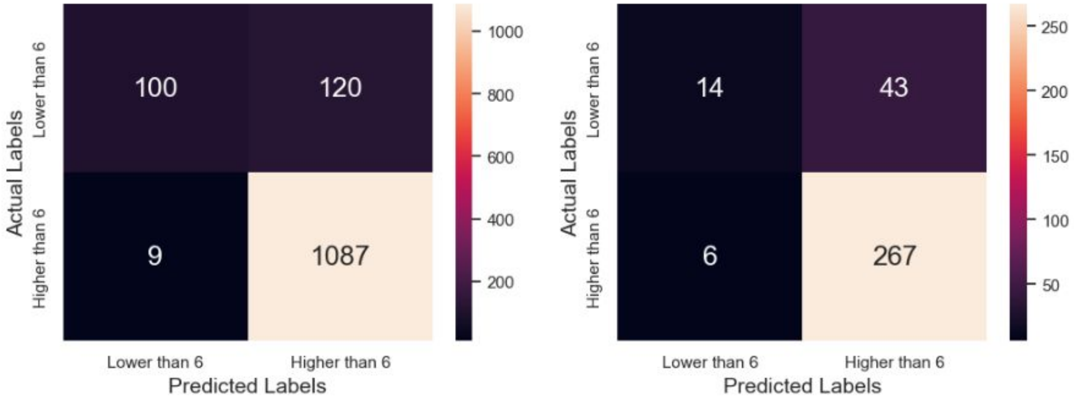
Although pruning is designed to prevent overfitting by excluding noise and outliers, our specific application of alpha pruning slightly reduced accuracy in predicting IMDb ratings.

The pruning may have removed nodes that contained relevant information for our dataset.

A balance must be struck to maintain sufficient model complexity to capture important patterns while avoiding the pitfalls of overfitting.

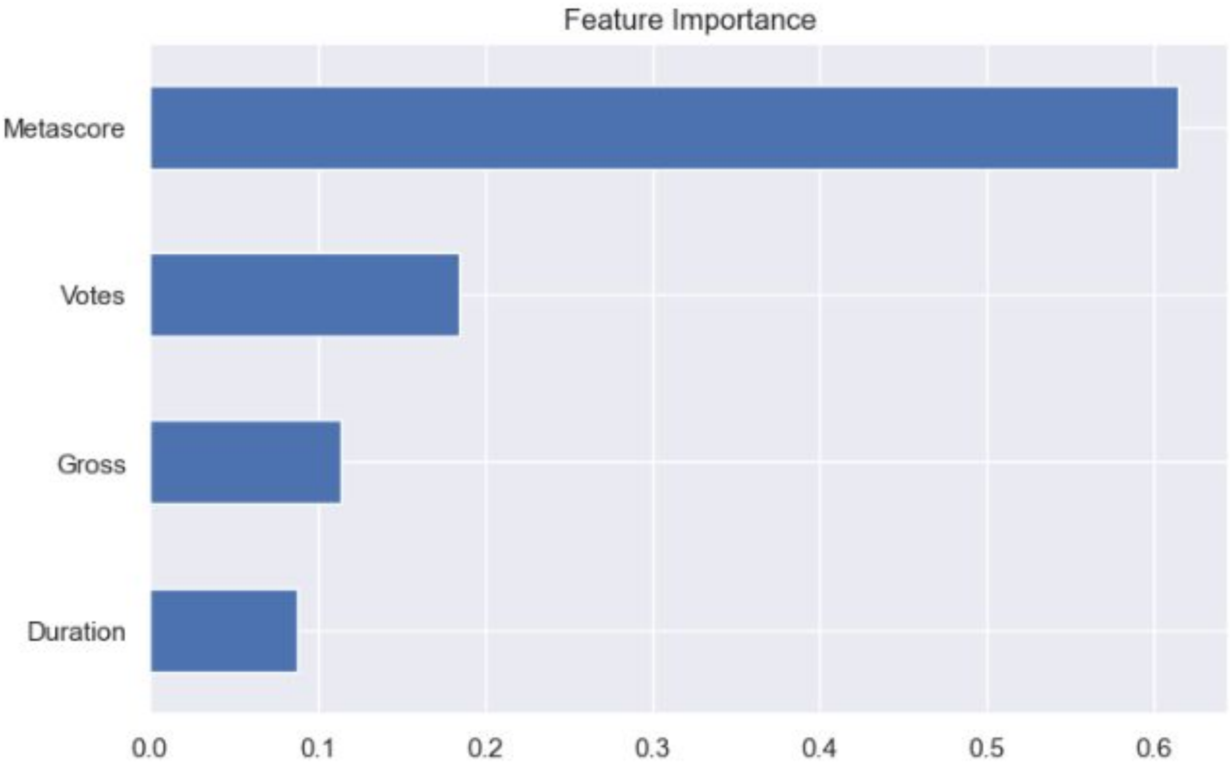
Cost Complexity Pruning

```
Goodness of Fit of Model        Train Dataset
Classification Accuracy         : 0.9019756838905775
TPR for train    : 0.9917883211678832
FPR for train    : 0.5454545454545454

Goodness of Fit of Model        Test Dataset
Classification Accuracy         : 0.8515151515151516
TPR for train    : 0.978021978021978
FPR for train    : 0.7543859649122807


Text(624.5227272727271, 0.5, 'Actual Labels')
```

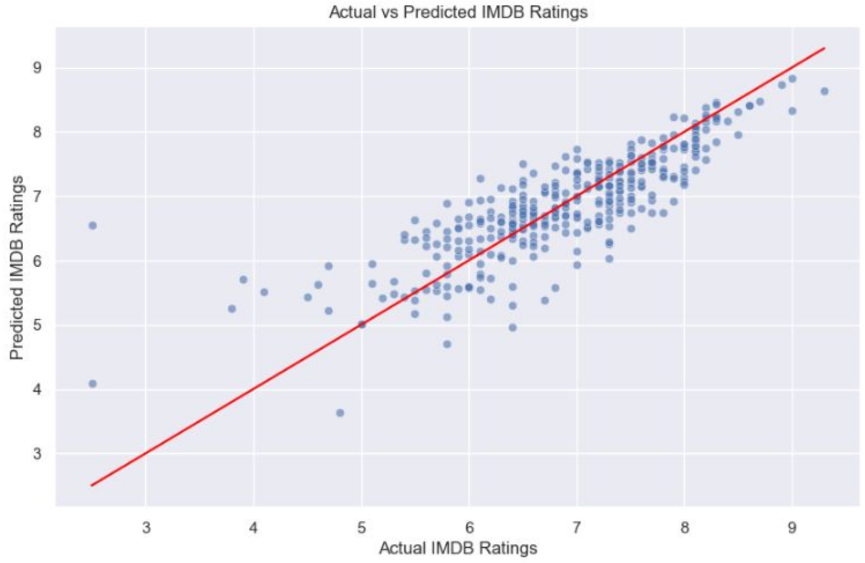


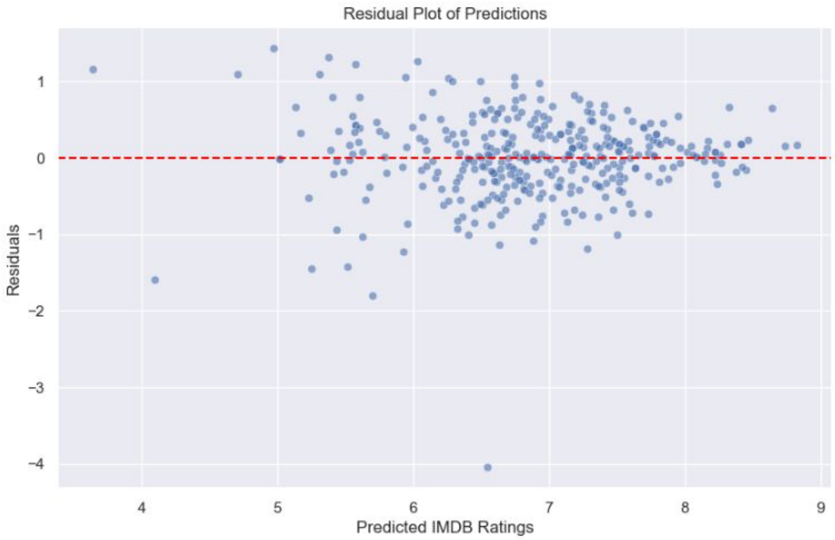
Random Forest

```
Mean Squared Error: 0.2891176221590909
R-squared: 0.6898316378080778
```

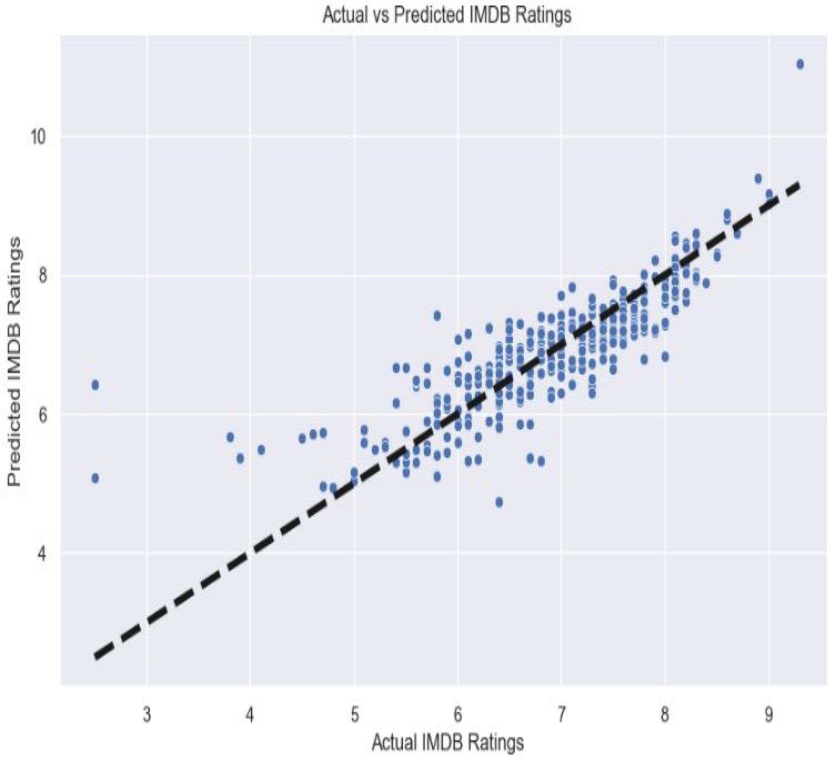


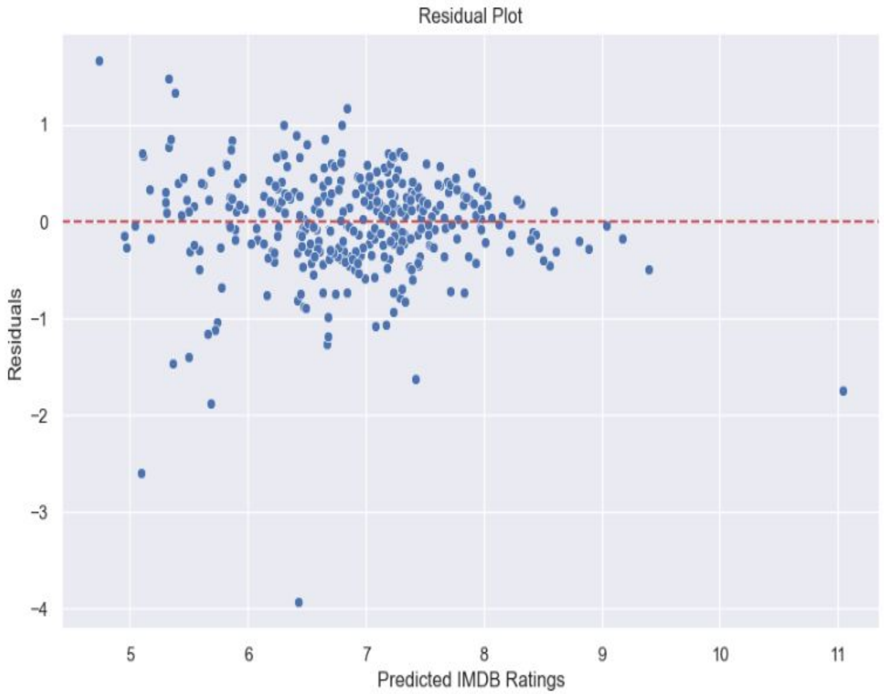
Feature importance bar chart: shows which features our model relies on the most to predict the imdb ratings
metascore played the largest role in determining IMDB ratings





Actual vs predicted plot generally shows a positive linear relationship between the actual and predicted imdb ratings,
The residual plot also shows the residuals randomly scatter around the zero line, suggesting that our model does not have much systematic error over the range of predicted imdb ratings.


Actual vs Predicted IMDB Ratings
Predicted IMDB Ratings
Actual IMDB Ratings
10
8
6
4
3
4
5
6
7
8
9


Residual Plot
Residuals
Predicted IMDB Ratings
1
0
−1
−2
−3
−4
5
6
7
8
9
10
11

Data Insights/Conclusion

1. All in all, we found that Metascore has the highest correlation with IMDB Ratings
2. Dataset is skewed towards higher IMDB Ratings due to nature of our dataset.
3. Model created using Decision tree has a high False Positive Rate
4. Model for Logistic Regression created using this data can only predict IMDB rating above 6 due to the dataset constraints.
5. Multivariate linear regression produced the most accurate results in predicting the ratings of the movie as compared to using univariate regression, with Metascore being the most important variable.