CSE 4/587 **Spring 2023**
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Due 3/6/23

Phase 1

Problem Statement

Exploring the relationship between User Ratings and Netflix.

As one of the largest streaming platforms in the world, Netflix and IMDB collect a vast amount of data about user preferences. This is a significant problem for Netflix when it comes to investment decisions for making TV Shows, Movies, and even getting rights to stream certain shows and movies. The potential of our project that can contribute to Netflix's problem can be great since it can prevent huge losses in revenue for Netflix. By analyzing user ratings, Netflix can learn and gain insights of the factors that can satisfy or attract consumers.

Our group gathered initially gathered information from (https://www.kaggle.com/datasets/luiscorter/netflix-original-films-imdb-scores) "Netflix Original Films & IMDB Scores" which contains most of Netflix's movies and shows with their respective IMDB and TMDB scores, but the data was not clean. Some data like age-certification, IMDB and TMDB ratings were missing. We ultimately decided to use "Netflix Movies and TV Shows" dataset (https://www.kaggle.com/datasets/shivamb/netflix-shows) which included casts and directors for the movies and shows so we can further see if casts or directors play a role in good ratings. Unfortunately, this dataset doesn't contain most missing data that we can use to fill in for the dirty data of our first dataset. Once we gathered our data be then began the cleaning process.

Data Cleaning

We approached data cleaning in multiple ways:

- Filtering Data
- Sorting Data
- Normalizing the Data
- Merging Data
- Imputation on Data
- Handling Duplicate Data
- Removing Data

Firstly our group **merged** two datasets, one that contained Netflix's shows and movies, and the other that contained the missing ratings. This step involves combining two or more datasets into a single dataset. In this case, the missing ratings were filled in by merging the two datasets. This was done using the merge() function in pandas, with the on argument set to the column to be merged.

Secondly we started with **filtering** the data. In this step, our group filtered the data to preserve only the relevant movies that were past the year 1999. This is a common step in data

cleaning, as it helps to remove irrelevant or outdated data that can affect the analysis. This was done using a filter method that selects only the rows that met the specific criteria of being after the year 1999.

Thirdly we **sorted** our dataset. Sorting was done by movie type, then by IMDB rating. When data is sorted, it is easier to determine the data's distribution and understand the data better. The sorting process also helps identify outliers and inconsistencies in the data. In pandas, the sort_values() function was used with the by argument set to the columns to sort.

Fourth, we began **normalizing** the data. This step involved normalizing the IMDB scores by rounding them to a whole number. This is done to reduce the complexity of the data and to make it easier to analyze. Normalizing the data also helps to reduce any errors or discrepancies that may arise due to decimal places. The round() function in pandas was used to round off the IMDB scores to a whole number.

Then we began the **imputation** which is the process of filling in missing data with values that are likely to be correct. In this case, our group filled in null data in the "seasons" column by placing an integer of 0 for all movies. This was done because not all movies have seasons. Imputation was done using the fillna() function in pandas, with the value set to 0 for all missing values.

After we begin to handle **duplicate** data because it can cause errors in the analysis, and it is important to remove it. My group removed all duplicated data resulting from merging the two datasets. This was done using the drop_duplicates() function in pandas, which removes all rows that are duplicates based on a specific column or set of columns.

Finally, our group **removed** all rows that didn't have age-certification. This is important because some movies may not be suitable for all audiences, and it is necessary to remove them from the analysis. This was done using the dropna() function in pandas, with the subset argument set to the column containing the age-certification. Our group was content with the clean data we had and then we began the next process which is exploratory data analysis.

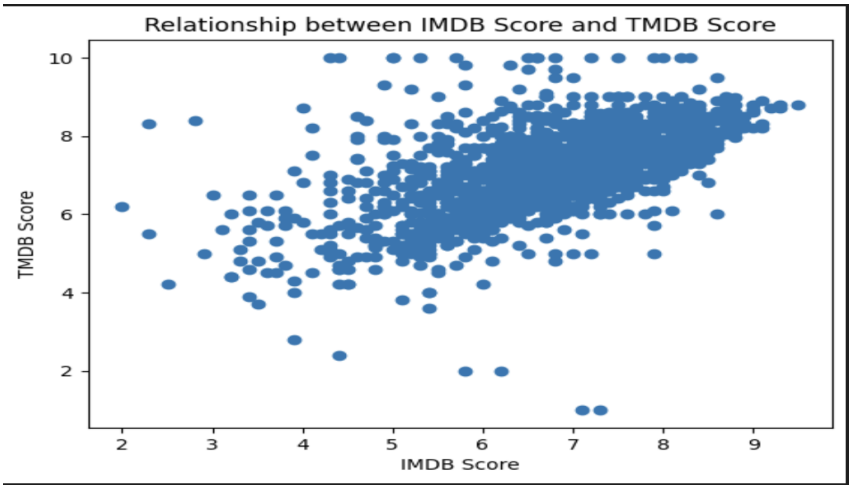
Exploratory Data Analysis

As the entertainment sector expands and changes, Netflix has emerged as one of the top streaming services, with these series' rankings being determined by well-known databases like IMDB and TMDB. Due to the fact that these businesses have millions of customers worldwide, they gather a lot of information regarding user preferences and behavior. This poses a huge difficulty when Netflix decides to make investments in things like buying streaming rights and generating original content. We are investigating what motivates contentment and attraction in order to address this difficulty. Our objective is to give Netflix useful information so that it can make informed decisions and avoid losing money. By promoting more effective and lucrative content generation, we can have a big impact on the entertainment sector.

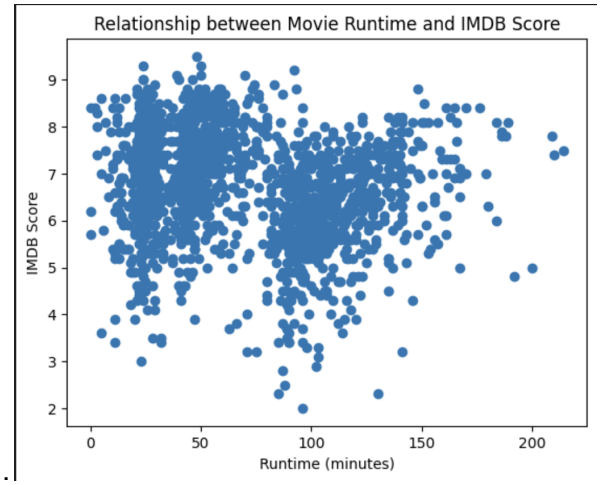
To arrive at our results, we conducted exploratory data analysis on the ratings of movies and shows on Netflix. We began by plotting the distribution of IMDB scores and TMDB scores, which allowed us to see the scores' range and the data's central tendency. We created these plots using Python's data visualization libraries, such as Matplotlib. We sparked our initial thinking by looking at the top 25 IMDB rated movies and shows Netflix has to offer. By looking at the data below we wanted to further explore and analyze what factors led these shows and movies to be rated highly.

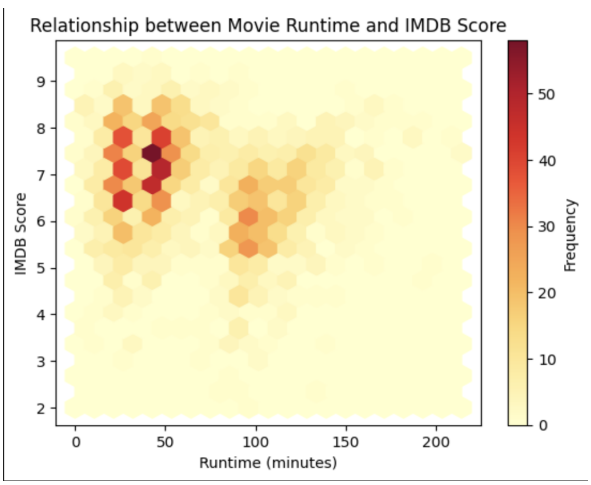
	title	type	imdb_score
3963	Breaking Bad	SHOW	9.5
2664	Our Planet	SHOW	9.3
1743	Avatar: The Last Airbender	SHOW	9.3
2088	Reply 1988	SHOW	9.2
4	Kota Factory	SHOW	9.1
440	The Last Dance	SHOW	9.1
1684	My Mister	SHOW	9.1
3832	DEATH NOTE	SHOW	9.0
282	Okupas	SHOW	9.0
1180	Leah Remini: Scientology and the Aftermath	SHOW	9.0
513	Attack on Titan	SHOW	9.0
2568	When They See Us	SHOW	8.9
979	Still Game	SHOW	8.9
1279	David Attenborough: A Life on Our Planet	MOVIE	8.9
3594	Narcos	SHOW	8.8
2557	Black Mirror	SHOW	8.8
1994	Better Call Saul	SHOW	8.8
864	Chappelle's Show	SHOW	8.8
2268	Vientos de agua	SHOW	8.8
444	Hospital Playlist	SHOW	8.8
2290	The Untamed	SHOW	8.8
2336	Peaky Blinders	SHOW	8.8
2279	BoJack Horseman	SHOW	8.8
222	Inception	MOVIE	8.8
...			
3037	The Haunting of Hill House	SHOW	8.6
21	Love on the Spectrum	SHOW	8.6
1817	Middleditch & Schwartz	SHOW	8.6
351	Shtisel	SHOW	8.6

Next, we compared the IMDB and TMDB scores by plotting them on a graph, which helped us determine the ratings' accuracy and consistency. We also plotted the average IMDB scores by release year and directors by IMDB score to understand the trends in ratings over time and identify the top and bottom-rated directors. Again, we used Python's data visualization libraries to create these plots.

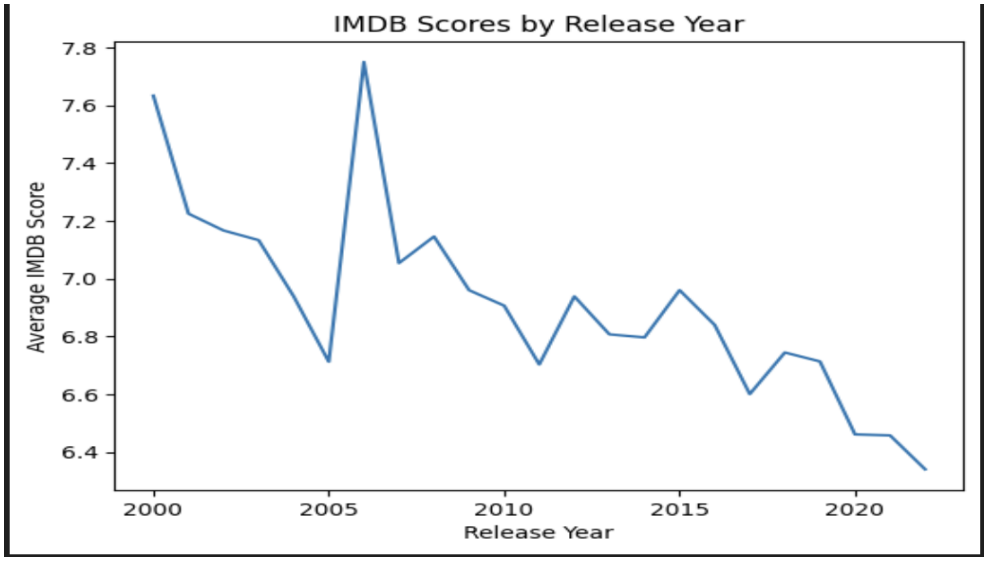


We plotted the data on a scatter plot and heat map to investigate the relationship between runtime and IMDB score. We used the Pandas library to manipulate and analyze the data and Matplotlib to create the visualizations

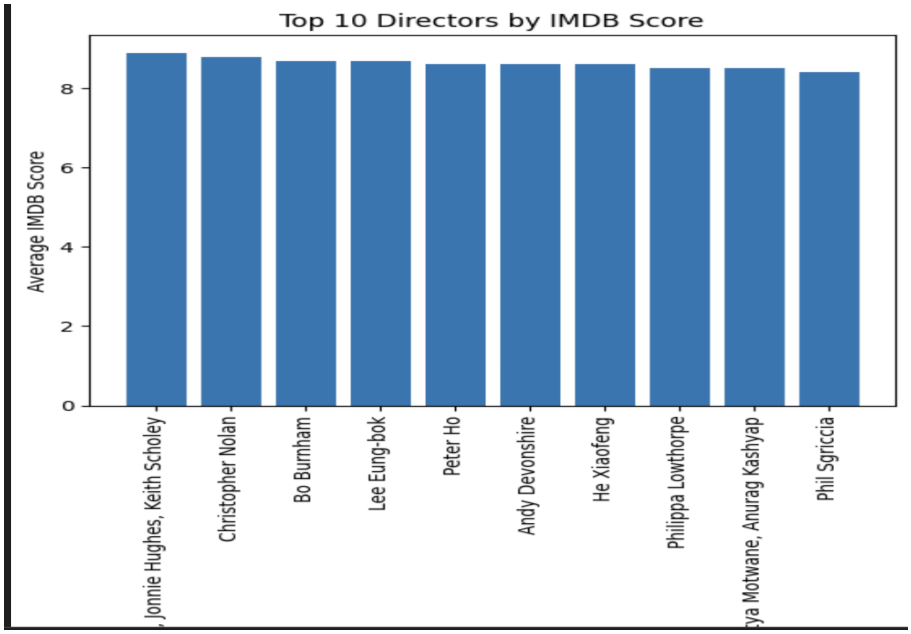




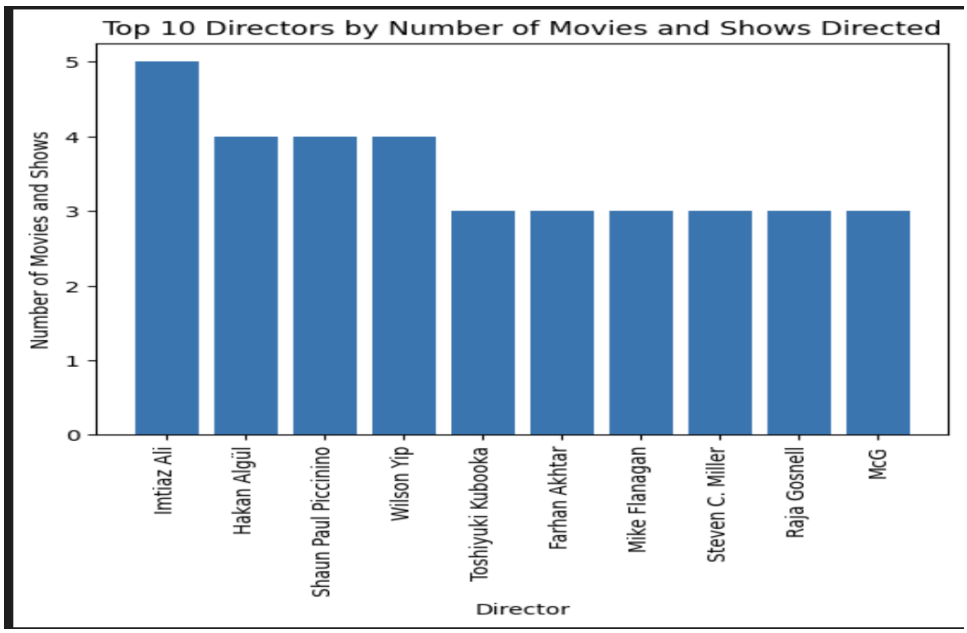
By plotting the Average IMDB Scores and the Release year, we gained insight into the overall trend of movie ratings over time. The highest-rated movies were released around 2007, with ratings gradually declining as we moved toward more recent releases. This information can help Netflix determine which movies and shows to invest in for streaming and prioritize those with high overall ratings.



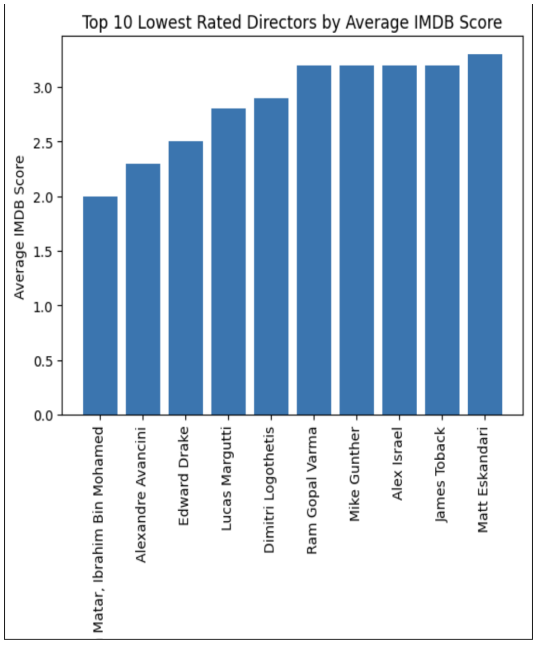
In addition to analyzing the overall trend in ratings, we investigated individual directors' impact on ratings by plotting the top 10 directors based on their IMDB scores. This allowed us to identify directors that Netflix should invest in when producing original content to ensure high ratings.

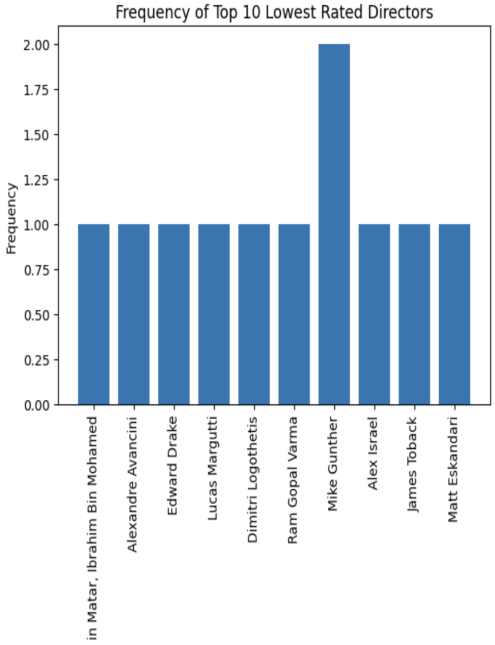


In addition we also investigated the top ten directors by the number of movies and shows they have directed to make sure that the analysis is not skewed due to having a high imdb score for just directing one movie or show.

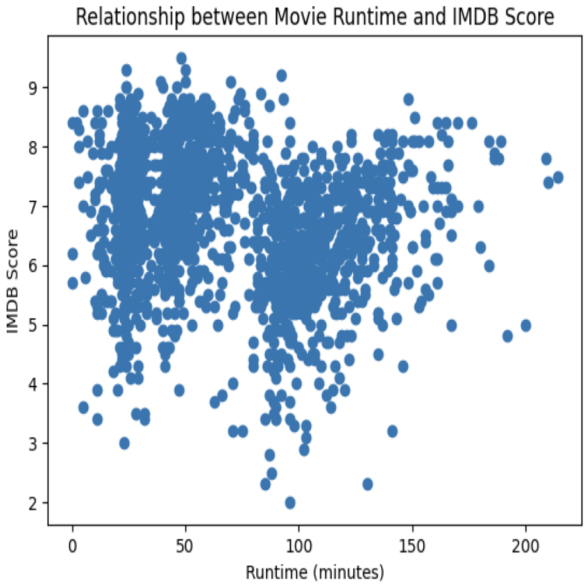


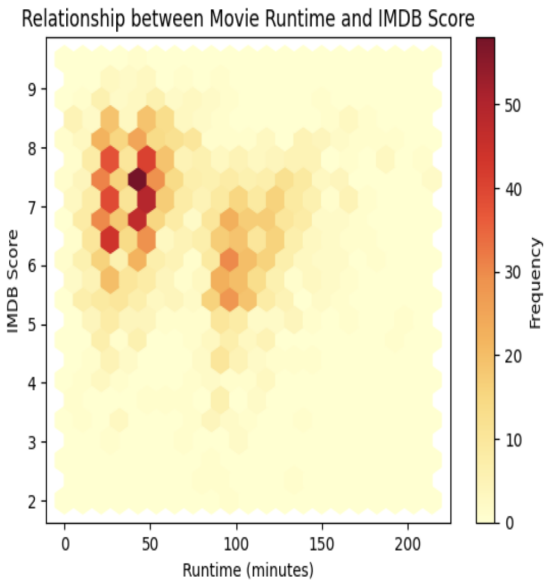
Conversely, we plotted the lowest-rated directors by average IMDB score to identify directors that Netflix should avoid when producing original content. To ensure that our data was not skewed, we also plotted the frequency of each director in our dataset to see how many shows or movies they took part in.



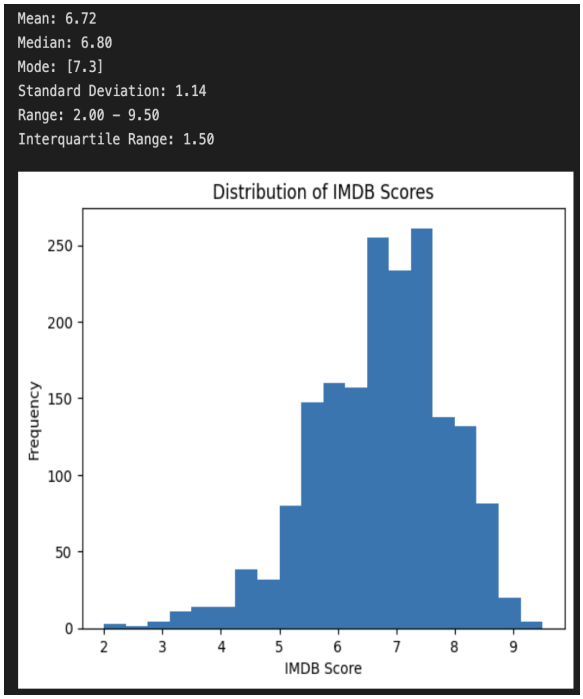


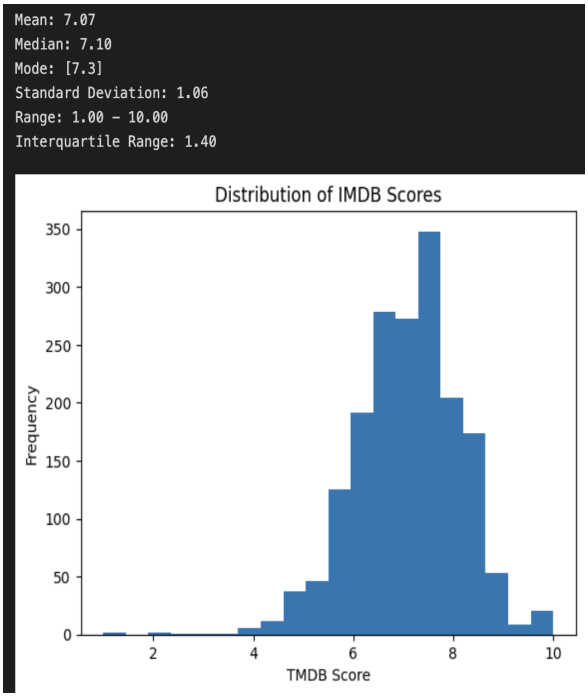
Lastly, we explored the relationship between movie runtime and IMDB score by plotting the data on a scatter plot and heat map. The mixed results indicated that a shorter runtime sometimes leads to higher ratings. However, we found that many movies with short runtimes of around 50 minutes had an average IMDB score of 6-8, whereas as the runtime increased, the IMDB score decreased slightly to approximately 5-7. This information can be used by Netflix to determine the optimal runtime for movies and shows to ensure high ratings.



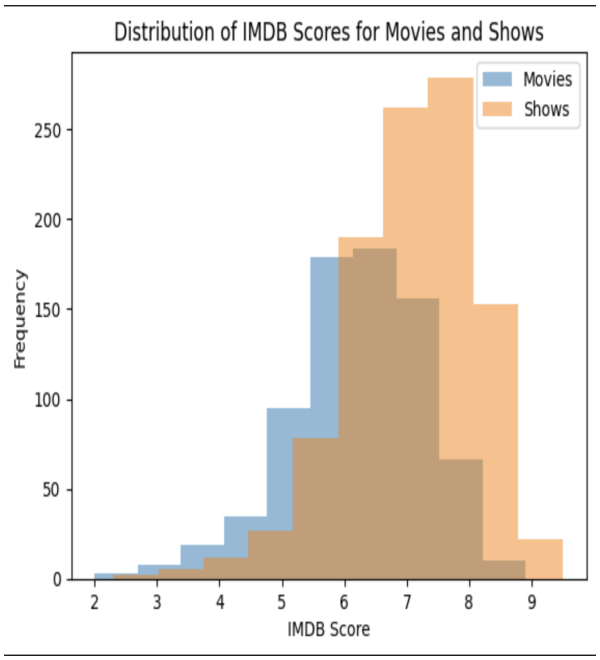


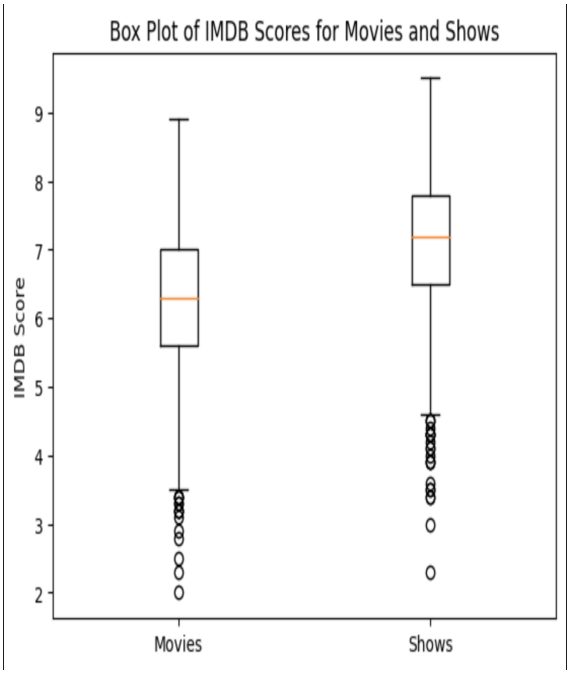
We ensured that our data was reliable and unbiased throughout our analysis by verifying our results and plotting the frequency of directors. In addition to using statistics to describe the data accurately, we used mean, median, mode, standard deviation, and interquartile range. This is shown in our initial figures below the distribution of IMDB Scores and TMDB scores.





One of our final exploratory data analysis we have done is analyzing the IMDB score between movies and shows. Our goal was to find if it is better for Netflix to invest in streaming/creating shows versus streaming/creating movies. This analysis shows that Shows average a higher IMDB score than Movies on Netflix's platform.





The ratings of movies and shows on Netflix were analyzed through various data visualization techniques and statistical measures. Our exploratory data analysis determined accuracy, rating trends over time, and the highest and lowest-rated directors. Using the information from our exploratory data analysis, Netflix can make data-driven decisions to improve its platform and provide a better user experience.

Phase 2

Logistic Regression:

Logistic Regression is a supervised learning algorithm for binary classification tasks, where the goal is to predict a movie or show success based on a threshold IMDB score. We could convert the IMDB scores into a binary format by setting a threshold value where we deem the movie or show successful if the IMDB score >= 7. Logistic Regression is chosen for this problem because it's a simple, interpretable algorithm that can model binary outcomes.

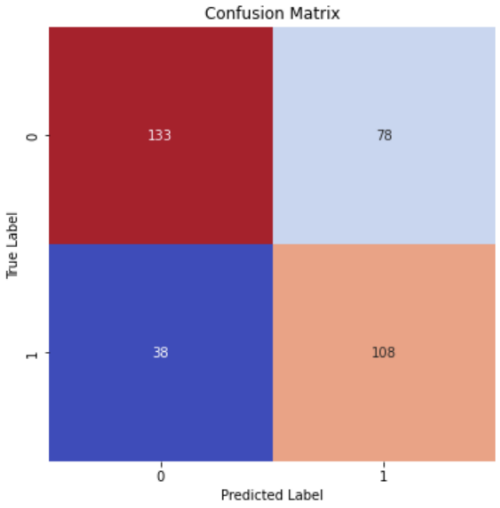
As explained earlier, we converted the IMDB scores into a binary format by setting a threshold value. Then, we split the cleaned dataset into training and testing sets using an 80-20 ratio to train the model. Afterward, we can train the Logistic Regression model using the training set and evaluate its performance on the testing set.

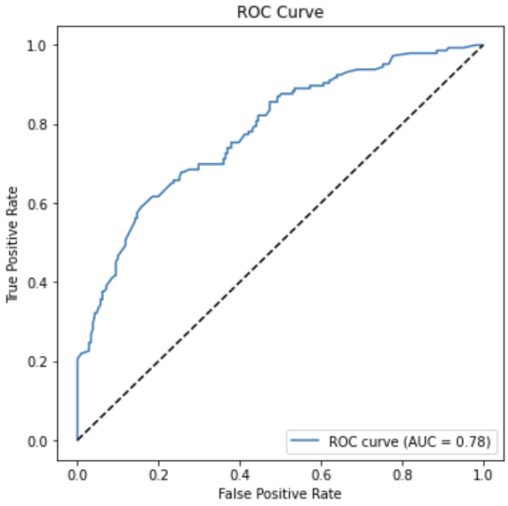
To assess the effectiveness of the Logistic Regression algorithm, we can use metrics such as accuracy, precision, recall, F1-score, and the area under the Receiver Operating Characteristic curve. These metrics help us understand the model's ability to classify movies correctly and shows as successful or not and balance false positive and false pessimistic predictions.

By analyzing the relevant metrics and visualizations, such as a confusion matrix heatmap, we can assess the model's effectiveness and gain insights into the relationships between the features and the binary outcome of the movie or show being successful or not. This intelligence can help us understand which factors contribute to a movie or show's success, make predictions about future productions based on their attributes, and help give insight on a predictive measure to know if the movie or show is a good investment for the company.

Logistic Regression can help Netflix classify movies and shows as successful or not based on a threshold IMDB score where we deem the movie or show to be successful if IMDB score >= 7 and unsuccessful and vice versa. By training a binary classification model on various features, Netflix can predict the probability of success for potential content investments. This can aid Netflix in prioritizing content that is more likely to be watched by its audience, maximizing user watch time, and minimizing the risk of content underperforming.

	precision	recall	f1-score	support
0	0.78	0.63	0.70	211
1	0.58	0.74	0.65	146
accuracy			0.68	357
macro avg	0.68	0.69	0.67	357
weighted avg	0.70	0.68	0.68	357





Linear Regression:

We used a linear regression model to predict the 'imdb_score' based on the 'tmdb_score.' Linear regression is a simple and widely used algorithm for predicting a continuous target variable based on one or more input features. We chose linear regression because it is easy to understand, implement, and interpret, provides insights into the relationship between input features and target variables, and allows quick model training and evaluation.

We first split the cleaned dataset into training and testing sets using an 80-20 ratio to train the model. We then used the training set to fit the linear regression model and evaluated its performance on the testing set.

We analyzed how well the linear regression model performs by looking at both metrics, the mean squared error (MSE) and the R-squared score. We used both metrics to determine how well our model predicts the IMDB scores using the TMDB scores. We can consider trying different algorithms if the model's performance isn't up to par. The MSE helps us understand the average squared difference between the predicted and actual values. A lower MSE means that our model is better fitting the data. The R-squared score shows the percentage of the variation in the target variable that can be explained by our model's input features. It ranges from 0 to 1, with a higher value indicating a better fit.

The linear regression model helps address the problem statement by identifying the relationship between features such as 'tmdb_score' and the target variable 'imdb_score.' By analyzing user ratings and understanding the impact of various factors on the scores, the model can provide insights informing Netflix's investment decisions for creating, acquiring, or streaming TV shows and movies. This, in turn, can help Netflix make data-driven decisions to satisfy and attract consumers, ultimately preventing significant revenue losses and optimizing its content portfolio.

The linear regression model can help Netflix by uncovering the relationships between various features, such as user ratings or content attributes, and the target variable, like IMDB scores. By analyzing these relationships, Netflix can identify trends and patterns that are associated with successful and well-received content. This knowledge can guide the company in making more informed investment decisions regarding the creation, acquisition, or streaming of TV shows and movies. Moreover, the model can help Netflix optimize its content portfolio and tailor its offerings to better match viewer preferences, which can lead to increased user satisfaction, higher viewer retention, and ultimately, improved business performance. The simplicity and interpretability of the linear regression model make it an effective starting point for exploring these relationships and extracting valuable insights from the available data.

As a result, the linear regression algorithm provides a simple and interpretable way to explore the relationship between the 'tmdb_score' and 'imdb_score.' While there may be more powerful or accurate algorithms for this problem, it is a helpful starting point for understanding the data and guiding further analysis. By evaluating the model's effectiveness using relevant metrics, we can decide whether to refine the current model or explore other algorithms to improve predictions.

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Mean Squared Error: 0.93
R-squared: 0.24
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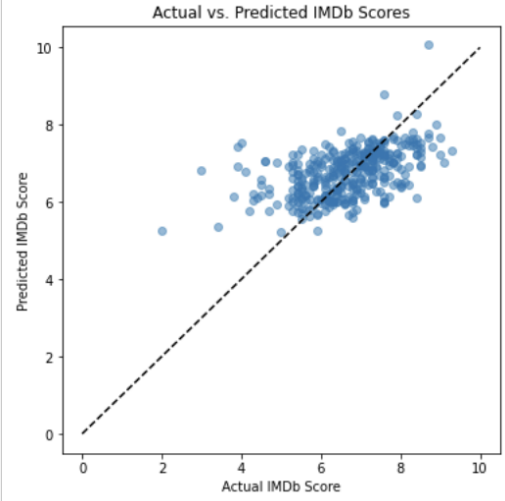


K-means:

The K-means algorithm is used for clustering tasks where the goal is to identify groups or patterns in the data. For our situation, we grouped of movies and shows with similar features, such as runtime, release year, and genre, to understand the relationships between these features and their performance in IMDB scores.

K-Means Clustering can help Netflix group similar movies and shows based on their features. By identifying clusters of content with similar characteristics, Netflix can gain insights into audience preferences and identify trends or patterns in successful content. This information can guide Netflix's content acquisition and production decisions, as well as help them make more targeted recommendations to users, which can enhance user satisfaction and engagement.

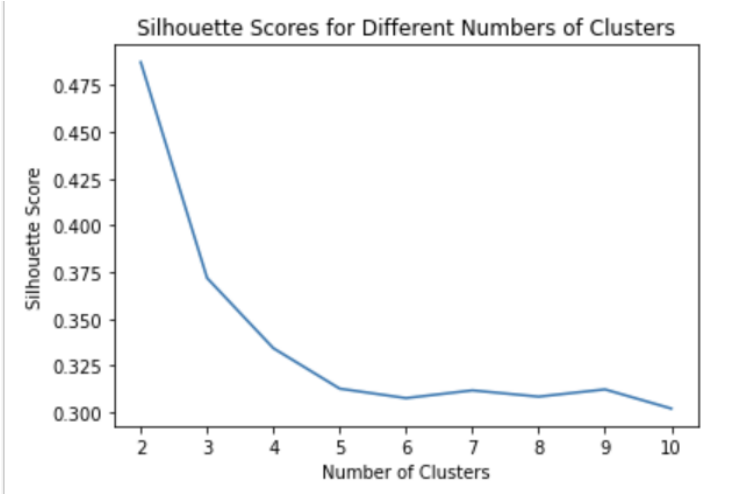
One reason we chose the K-means algorithm is due to it's simplicity and scalability, making it suitable for large datasets. Additionally, it can help us uncover hidden patterns and structures in the data. We first need to preprocess the dataset to train and tune the K-means model. This involves selecting appropriate features, encoding categorical variables, and scaling numerical variables. We then determine the optimal number of clusters (K) using techniques like the elbow method or silhouette score, which involves running the K-means algorithm with different K values and evaluating the within-cluster sum of squares (WCSS) or average silhouette score.

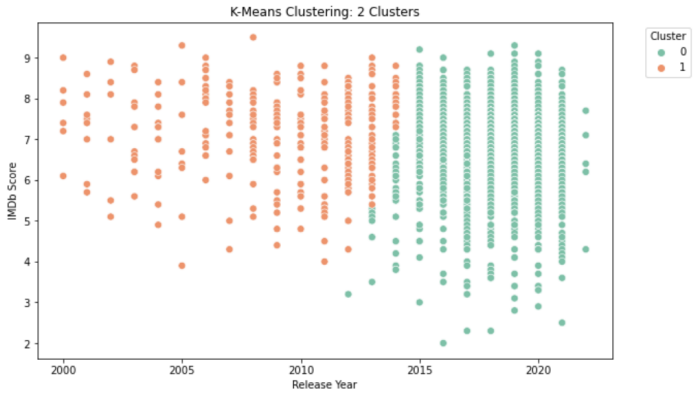
After finding the optimal K value, we train the K-means model and assign each data point to the nearest cluster. We can then analyze the cluster centroids and the distribution of data points within each cluster to gain insights into the characteristics of different groups of movies and shows.

We can use metrics such as WCSS or silhouette score to assess the effectiveness of the K-means algorithm. Lower WCSS values or higher silhouette scores indicate better clustering performance. However, these metrics are not directly related to our problem statement (predicting IMDB scores) but can give us an idea of how well the algorithm has grouped similar movies and shows together.

By applying the K-means algorithm to our data, we can gain intelligence about the relationships between the features and the IMDB scores indirectly through the analysis of clusters. We can study the characteristics of each cluster to understand which features tend to be associated with higher or lower IMDB scores and use this information to inform our decision-making process, such as recommending movies or shows, targeting marketing efforts, or making production decisions.

The K-means analysis is not designed to predict target variables such as IMDB scores directly, but uncover patterns and relationships within the data that can be further analyzed to gain insights. If the primary goal is to predict IMDB scores, a supervised learning algorithm like Linear Regression, as discussed earlier, might be more appropriate.





K-NN:

The k-Nearest Neighbors (k-NN) algorithm is a supervised learning method that can be used for both classification and regression tasks. It is based on the idea that data points with similar features will likely have identical target values. We aim to predict the IMDB scores of movies and shows based on their attributes, making k-NN a potential candidate for our problem.

K-NN can be used by Netflix to make recommendations based on content similarity. By finding the "nearest neighbors" of a given movie or show based on their features, Netflix can recommend similar content to users who enjoyed a particular title. This can improve the user experience on the platform by providing more accurate and tailored recommendations, which in turn can increase user engagement and satisfaction.

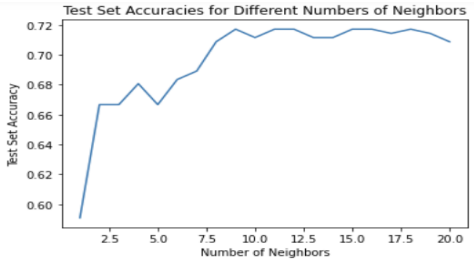
One reason to choose k-NN is its simplicity and ease of implementation. It is a non-parametric, instance-based learning algorithm that does not require any assumptions about the underlying data distribution. This can be particularly beneficial when dealing with complex, non-linear relationships between features and target values.
Training and tuning the k-NN model involved selecting appropriate features, encoding categorical variables, and scaling numerical variables. We then split the dataset into training and testing sets to train the model and evaluate its performance.

The primary hyperparameter to tune in a k-NN model is the number of neighbors (k). By varying the value of k, we can control the trade-off between model complexity and smoothness. A

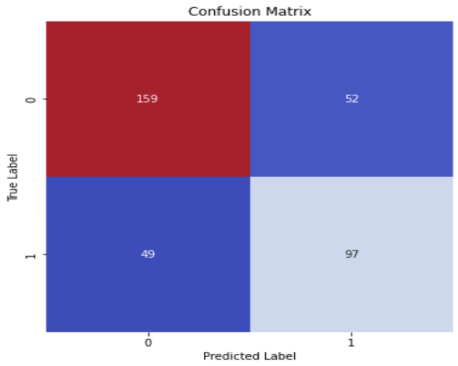
smaller value of k can result in a more flexible model that captures local patterns, while a larger value of k can lead to a smoother decision boundary that is less sensitive to noise.

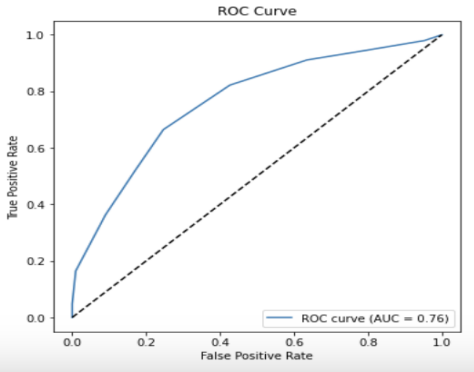
To find the optimal value of k, we used techniques like validation set to compare the performance of different k values and chose the one with the best results. When applied to our dataset, the effectiveness of the k-NN algorithm depended on its ability to capture the relationships between the input features and the IMDB scores. The algorithm had subpar accuracy in predicting the IMDB scores based on the given features. This was able to help us answer questions related to our problem statement and gain insights into the factors influencing the success of movies and shows.

In summary, the k-NN algorithm can be an appropriate choice for our problem due to its simplicity and ability to handle non-linear relationships. By tuning the model's hyperparameters and evaluating its performance using relevant metrics, we can assess its effectiveness and derive valuable intelligence from applying the algorithm to our dataset.



	precision	recall	f1-score	supp
0	0.76	0.75	0.76	
1	0.65	0.66	0.66	
accuracy			0.72	
macro avg	0.71	0.71	0.71	
weighted avg	0.72	0.72	0.72	





Decision Tree:

The Decision Tree algorithm is a versatile supervised learning method for classification and regression tasks. It recursively splits the dataset into subsets based on the most informative feature at each step, resulting in a tree-like structure with decision nodes and leaf nodes representing the predicted target variable. Choosing a Decision Tree algorithm for predicting IMDB scores offers several advantages, including interpretability, non-linearity, and minimal data preprocessing. Decision Trees are easy to understand and visualize, enabling users to gain insights into feature-target relationships. They can handle non-linear relationships in complex

datasets and simplify the preprocessing step by accommodating missing values without requiring feature scaling or encoding.

To train and tune a Decision Tree model for our problem, we first preprocess the data by selecting relevant features, encoding categorical variables, scaling numerical variables, and handling missing values using imputation or other techniques. Next, we split the dataset into training and testing sets for model training and performance evaluation. We then create and train a Decision Tree model by fitting it to the training data, which involves recursively splitting the data and constructing the tree structure. Since Decision Trees can be prone to overfitting, we adjust hyperparameters such as the maximum depth, minimum samples per split, and minimum samples per leaf to balance model complexity and performance. Finally, we evaluate the model by predicting IMDB scores for the test dataset and comparing these predictions to the actual IMDB scores, assessing the model's effectiveness using relevant metrics like mean squared error (MSE) for regression tasks, or accuracy, precision, recall, and F1 score for classification tasks.

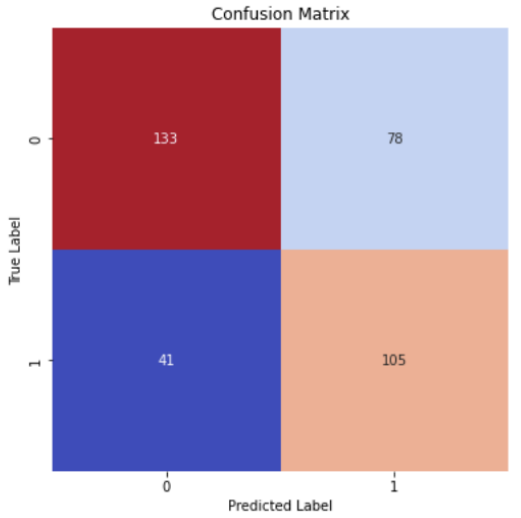
When applied to our data, the Decision Tree algorithm can help us answer questions related to our problem statement by providing an interpretable model that captures the relationships between the input features and the target variable (IMDB scores). By analyzing the relevant metrics and visualizing the decision tree structure, we can learn which features have the most significant impact on IMDB scores and how these features interact.

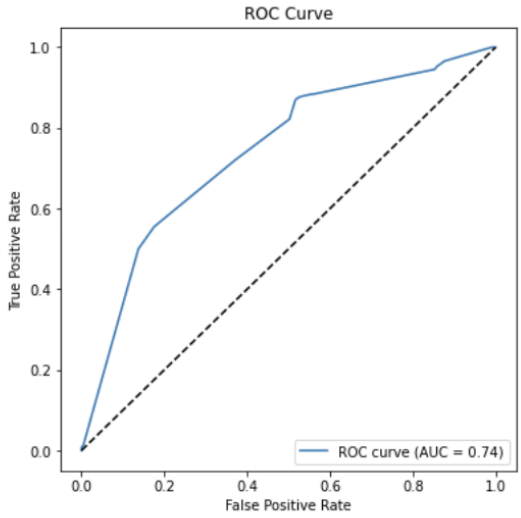
A Decision Tree model is a robust and interpretable machine learning algorithm that can help address the problem statement by predicting the success of TV shows and movies based on various features. Here's how the Decision Tree model can help with each part of the problem statement:

By training a Decision Tree model on historical data, Netflix can identify which features contribute most to the success of a TV show or movie. The model can help predict the potential success of a new production based on factors such as genre, production budget, cast, director, and more. This information can guide Netflix in making informed decisions about which projects to invest in and which to avoid, thereby maximizing return on investment.

In summary, the Decision Tree algorithm is suitable for our problem due to its interpretability, ability to handle non-linearity, and minimal data preprocessing requirements. By tuning and training the model effectively, we can gain valuable insights into the factors influencing IMDB scores and make accurate predictions.

	precision	recall	f1-score	support
0	0.76	0.63	0.69	211
1	0.57	0.72	0.64	146
accuracy			0.67	357
macro avg	0.67	0.67	0.66	357
weighted avg	0.69	0.67	0.67	357





Citation: Scikit-learn: Machine Learning in Python, Pedregosa et al., JMLR 12, pp. 2825-2830, 2011.

Phase 3

Instructions to run our Web App:

1) **Make sure you have Python Installed**
2) **Download the zip file.**
3) **Open a terminal app and navigate through the unzipped file to the src file**
4) **Within the src file, run pip install -r requirements.txt**
5) **After, run the command python app.py**
6) **After running this command, go to your web browser and navigate to http://127.0.0.1:5000/**
7) **Enjoy using our application!**

Models:

We have used three models from phase 1 and 2, those models include, We had to tune these algorithms to accept user input instead of hard coded columns:

- Histogram Frequency
  - Histogram Frequency accepts one input, **it can be any column that contains only floats or integers.**

- Line Plot Comparison
  - Line Plot Comparison accepts two inputs, and **the first input must be a column of integers or floats, and the second must be a column of floats or integers.**

- Top Value Bar Plot
  - Top Value Bar Plot accepts two inputs, **the first input must be a column of strings, and the second must be a column of floats or integers.**

- Linear Regression
  - Linear Regression accepts two inputs, **the first input must be a column of integers or floats, and the second must be a column of floats or integers.**

- K-NN Algorithm
  - K-NN Algorithm accepts three inputs, **the first input must be a column of integers or floats, the second must be a column of floats or integers, the third input represents the threshold so you can manually put any integer or float.**

- Decision Tree Algorithm
  - Decision Tree Algorithm accepts three inputs, **the first input must be a column of integers or floats, the second must be a column of floats**

or integers, the third input represents the threshold so you can manually put any integer or float.