# **IMDb Movies Data Analysis using Python**

#### Content:

- Exploring Dataset:
  - 1. Importing Libraries
  - 2. Importing the dataset, loading in dataframe
  - 3. Studying the structure of the dataset
- · Data Preprocessing:
  - 1. Checking NULL Values
  - 2. Filling NULL Values
  - 3. Checking Duplicates
  - 4. Handling Outliers
  - 5. Data Normalization
- · Data Analysis:
  - 1. Movies per Genre
  - 2. Heatmap
  - 3. Word Cloud for Directors
  - 4. Scatter Plot of Revenue vs. Rating
  - 5. Movies per Director
  - 6. Distribution of Movie Ratings
  - 7. Word cloud of actors
  - 8. Genre Combinations Analysis
  - 9. Revenue Distribution by Genre
  - 10. Rating Distribution by Year
  - 11. Top Actors Analysis
- Time Series Analysis:
  - 1. Times Series Analysis of Movies over Year
  - 2. Time Series Analysis of Average Rating Over Years
  - 3. Time Series Analysis of Revenue Over Years
  - 4. Seasonal Trends in Movie Releases
- Predictive Modeling using Machine Learning Algorithms:
  - 1. For Movie Revenue (Linear Regression)
  - 2. For movie rating category- High/Low (Random Forest)
  - 3. Predicting Movie Success (Binary Classification)
  - 4. Feature Importance Analysis
  - 5. Clustering Movies
- · Visualizations:
  - 1. Interactive Dashboards
  - 2. Sunburst Chart for Genre Distribution
  - 3. Chord Diagram for Director-Actor Collaborations

# **Importing Libraries**

```
In [2]: import numpy as np
        import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns
         import plotly.express as px
         import missingno as msno
         from wordcloud import WordCloud, STOPWORDS
        from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error
        \textbf{from} \  \, \textbf{sklearn.ensemble} \  \, \textbf{import} \  \, \textbf{RandomForestClassifier}
        from sklearn.metrics import classification_report, accuracy_score
         from sklearn.preprocessing import LabelEncoder
         from sklearn.cluster import KMeans
         import warnings
         warnings.filterwarnings("ignore")
```

# **Importing the Dataset**

Out[3]:

	Rank	Genre	Description	Director	Actors	Year	Runtime (Minutes)	Rating	Votes	Revenue (Millions)
Title										
Guardians of the Galaxy	1	Action, Adventure, Sci-Fi	A group of intergalactic criminals are forced	James Gunn	Chris Pratt, Vin Diesel, Bradley Cooper, Zoe S	2014	121	8.1	757074	333.13
Prometheus	2	Adventure, Mystery, Sci-Fi	Following clues to the origin of mankind, a te	Ridley Scott	Noomi Rapace, Logan Marshall- Green, Michael Fa	2012	124	7.0	485820	126.46
Split	3	Horror,Thriller	Three girls are kidnapped by a man with a diag	M. Night Shyamalan	James McAvoy, Anya Taylor-Joy, Haley Lu Richar	2016	117	7.3	157606	138.12
Sing	4	Animation, Comedy, Family	In a city of humanoid animals, a hustling thea	Christophe Lourdelet	Matthew McConaughey,Reese Witherspoon, Seth Ma	2016	108	7.2	60545	270.32
Suicide Squad	5	Action, Adventure, Fantasy	A secret government agency recruits some of th	David Ayer	Will Smith, Jared Leto, Margot Robbie, Viola D	2016	123	6.2	393727	325.02
The Great Wall	6	Action,Adventure,Fantasy	European mercenaries searching for black powde	Yimou Zhang	Matt Damon, Tian Jing, Willem Dafoe, Andy Lau	2016	103	6.1	56036	45.13
La La Land	7	Comedy, Drama, Music	A jazz pianist falls for an aspiring actress i	Damien Chazelle	Ryan Gosling, Emma Stone, Rosemarie DeWitt, J	2016	128	8.3	258682	151.06
Mindhorn	8	Comedy	A has-been actor best known for playing the ti	Sean Foley	Essie Davis, Andrea Riseborough, Julian Barrat	2016	89	6.4	2490	NaN
The Lost City of Z	9	Action,Adventure,Biography	A true-life drama, centering on British explor	James Gray	Charlie Hunnam, Robert Pattinson, Sienna Mille	2016	141	7.1	7188	8.01
Passengers	10	Adventure, Drama, Romance	A spacecraft traveling to a distant colony pla	Morten Tyldum	Jennifer Lawrence, Chris Pratt, Michael Sheen,	2016	116	7.0	192177	100.01

```
In [4]: print("Number of rows:", df.shape[0])
        print("Number of columns:", df.shape[1])
       Number of rows: 1000
       Number of columns: 11
In [5]: df.info()
        df.describe()
       <class 'pandas.core.frame.DataFrame'>
       Index: 1000 entries, Guardians of the Galaxy to Nine Lives
       Data columns (total 11 columns):
                              Non-Null Count Dtype
       # Column
            -----
                                -----
        0
            Rank
                               1000 non-null
                                                int64
                               1000 non-null object
        1
            Genre
            Description
                               1000 non-null object
                               1000 non-null object
        3
            Director
            Actors
                                1000 non-null
                                                object
            Year
                               1000 non-null int64
            Runtime (Minutes) 1000 non-null int64
Rating 1000 non-null float64
        6
           Votes
                               1000 non-null int64
        9 Revenue (Millions) 872 non-null
                                                float64
        10 Metascore
                                936 non-null
                                                float64
       dtypes: float64(3), int64(4), object(4)
       memory usage: 93.8+ KB
Out[5]:
                     Rank
                                  Year Runtime (Minutes)
                                                              Rating
                                                                            Votes Revenue (Millions)
                                                                                                     Metascore
         count 1000.000000 1000.000000
                                              1000.000000 1000.000000 1.000000e+03
                                                                                          872.000000
                                                                                                     936.000000
                500.500000 2012.783000
                                               113.172000
                                                            6.723200 1.698083e+05
                                                                                           82.956376
                                                                                                      58.985043
         mean
                288.819436
                              3.205962
                                               18.810908
                                                            0.945429 1.887626e+05
                                                                                          103.253540
                                                                                                      17.194757
           std
          min
                  1.000000 2006.000000
                                               66.000000
                                                            1.900000 6.100000e+01
                                                                                            0.000000
                                                                                                      11.000000
          25%
                250.750000 2010.000000
                                               100.000000
                                                            6.200000 3.630900e+04
                                                                                           13.270000
                                                                                                      47.000000
```

6.800000 1.107990e+05

7.400000 2.399098e+05

9.000000 1.791916e+06

47.985000

113.715000

936.630000 100.000000

59.500000

72.000000

## **Data Preprocessing**

500.500000 2014.000000

750.250000 2016.000000

1000.000000 2016.000000

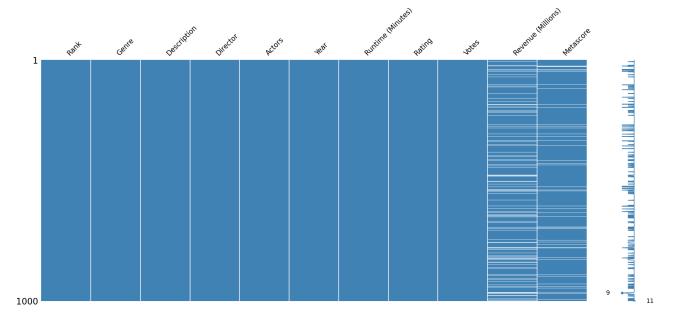
111.000000

123.000000

191.000000

#### 1. Checking NULL Values

```
In [6]: import missingno as msno
         \textbf{import} \ \texttt{matplotlib.pyplot} \ \textbf{as} \ \texttt{plt}
         # Print the count of missing values
         print(df.isnull().sum())
         # Visualize missing data with a colorful matrix
         msno.matrix(df, sparkline=True, color=(0.27, 0.52, 0.72))
         plt.show()
        Rank
       Genre
                                  0
       Description
                                   0
       Director
       Actors
        Runtime (Minutes)
        Rating
                                  0
       Votes
        Revenue (Millions)
                                128
       Metascore
       dtype: int64
```



#### 2. Filling NULL Values

```
In [7]: df['Revenue (Millions)'].fillna(df['Revenue (Millions)'].mean(), inplace=True)
        print(df.isnull().sum())
                              0
       Genre
      Description
                              0
      Director
       Actors
       Year
       Runtime (Minutes)
       Rating
       Votes
                              0
       Revenue (Millions)
                              0
       Metascore
                             64
       dtype: int64
```

#### 3. Checking Duplicates

```
In [8]: duplicates = df[df.duplicated()]
    print(duplicates)

Empty DataFrame
    Columns: [Rank, Genre, Description, Director, Actors, Year, Runtime (Minutes), Rating, Votes, Revenue (Millions), Metascore]
```

#### 4. Handling Outliers

```
In [9]: def detect_outliers(data):
            Q1 = data.quantile(0.25)
            Q3 = data.quantile(0.75)
            IQR = Q3 - Q1
            outliers = ((data < (Q1 - 1.5 * IQR)) | (data > (Q3 + 1.5 * IQR)))
            return outliers
        outliers = df[['Revenue (Millions)', 'Runtime (Minutes)', 'Rating', 'Votes']].apply(detect_outliers)
        print(outliers.sum())
       Revenue (Millions)
                            82
       Runtime (Minutes)
       Rating
                            19
       Votes
                             45
       dtype: int64
```

#### 5. Data Normalization

```
In [10]: from sklearn.preprocessing import MinMaxScaler

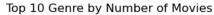
# Normalizing numerical features
```

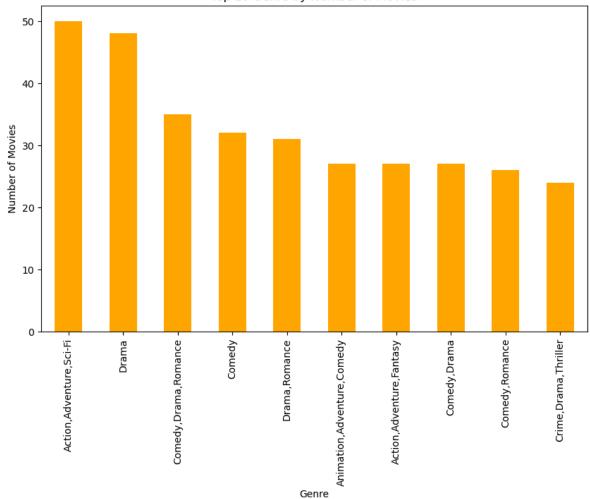
```
scaler = MinMaxScaler()
df[['Revenue (Millions)', 'Runtime (Minutes)', 'Rating', 'Votes']] = scaler.fit_transform(df[['Revenue (Millions)', 'Runtime
```

### **Data Analysis**

#### 1. Movies per Genre

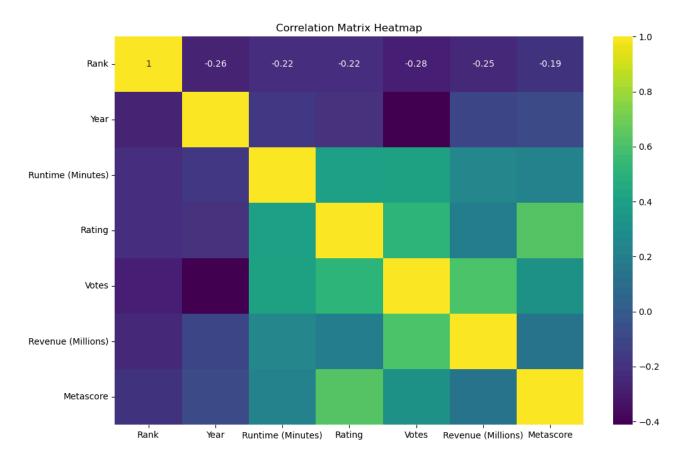
```
In [11]: top_10_genres = df['Genre'].value_counts().nlargest(10)
    plt.figure(figsize=(10, 6))
    top_10_genres.plot(kind='bar', color='Orange')
    plt.title('Top 10 Genre by Number of Movies')
    plt.xlabel('Genre')
    plt.ylabel('Number of Movies')
    plt.xticks(rotation=90)
    plt.show()
```





#### 2. Heatmap

```
In [12]: numeric_df = df.select_dtypes(include=['float64', 'int64'])
plt.figure(figsize=(12, 8))
sns.heatmap(numeric_df.corr(), annot=True, cmap='viridis')
plt.title('Correlation Matrix Heatmap')
plt.show()
```



#### 3. Word Cloud for Directors

```
In [13]: text = ''
for i in df['Director']:
    value = i.strip()
    value = value.replace(" ", "_")
    text = text + " " + value

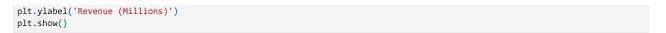
text = text.strip()

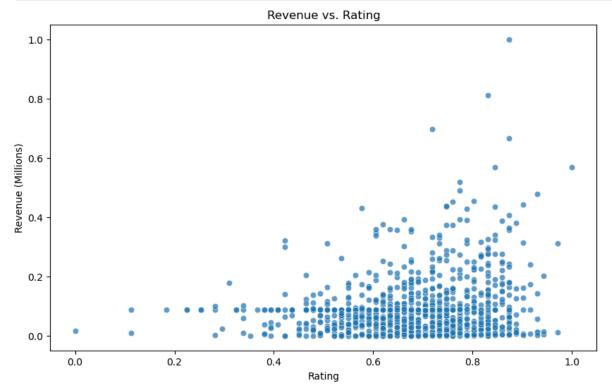
wordcloud = WordCloud(stopwords=STOPWORDS, background_color="white").generate(text)
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.title('Word Cloud of Directors')
plt.show()
```

# Word Cloud of Directors | Solution | Control | Control

#### 4. Scatter Plot of Revenue vs. Rating

```
In [14]: plt.figure(figsize=(10, 6))
sns.scatterplot(x='Rating', y='Revenue (Millions)', data=df, alpha=0.7)
plt.title('Revenue vs. Rating')
plt.xlabel('Rating')
```





# 5. Movies per Director

```
In [15]: top_directors = df['Director'].value_counts().nlargest(10)
    plt.figure(figsize=(10, 6))
    top_directors.plot(kind='bar', color='Orange')
    plt.title('Top 10 Directors by Number of Movies')
    plt.xlabel('Director')
    plt.ylabel('Number of Movies')
    plt.xticks(rotation=90)
    plt.show()
```

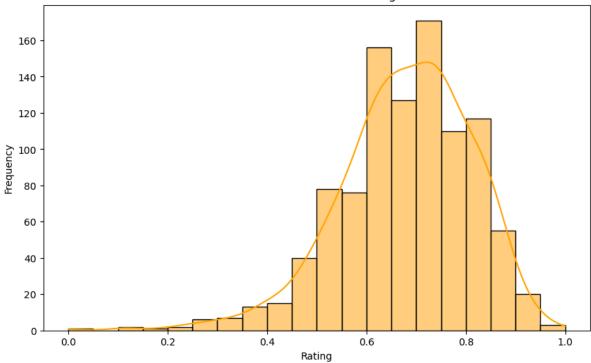
Top 10 Directors by Number of Movies 8 7 6 Number of Movies 4 2 1 Ridley Scott David Yates Michael Bay Zack Snyder Danny Boyle M. Night Shyamalan Paul W.S. Anderson Denis Villeneuve Woody Allen Peter Berg

# 6. Distribution of Movie Ratings

```
In [16]: plt.figure(figsize=(10, 6))
    sns.histplot(df['Rating'], bins=20, kde=True, color='Orange')
    plt.title('Distribution of Movie Ratings')
    plt.xlabel('Rating')
    plt.ylabel('Frequency')
    plt.show()
```

Director

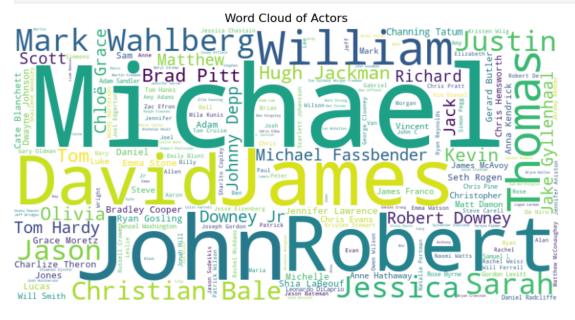
#### Distribution of Movie Ratings



#### 7. Word Cloud of Actors

```
In [17]: actors_text = ' '.join(df['Actors'].str.replace(',', '').values)
    wordcloud = WordCloud(width=800, height=400, background_color='white').generate(actors_text)

plt.figure(figsize=(10, 6))
    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title('Word Cloud of Actors')
    plt.axis('off')
    plt.show()
```

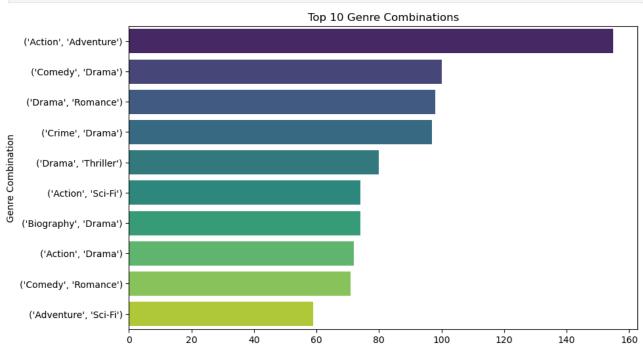


#### 8. Genre Combinations Analysis

```
In [18]:
    from itertools import combinations
    from collections import Counter

genre_combinations = df['Genre'].str.split(',').apply(lambda x: list(combinations(x, 2)))
    genre_combinations_flat = [item for sublist in genre_combinations for item in sublist]
    genre_combinations_counter = Counter(genre_combinations_flat)
```

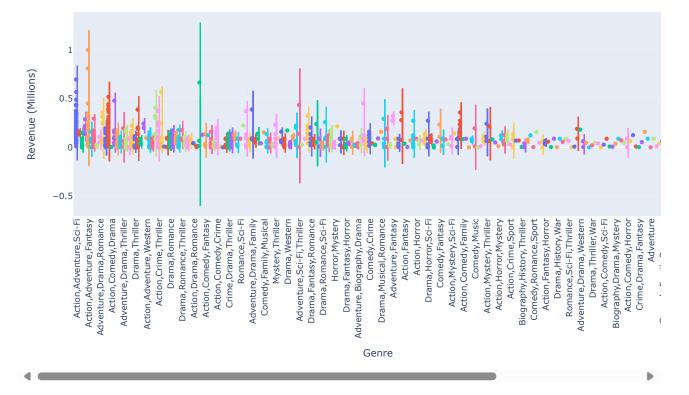
```
# Plot the most common genre combinations
common_combinations = pd.DataFrame(genre_combinations_counter.most_common(10), columns=['Combination', 'Count'])
plt.figure(figsize=(10, 6))
sns.barplot(x='Count', y='Combination', data=common_combinations, palette='viridis')
plt.title('Top 10 Genre Combinations')
plt.xlabel('Count')
plt.ylabel('Genre Combination')
plt.show()
```



Count

#### 9. Revenue Distribution by Genre

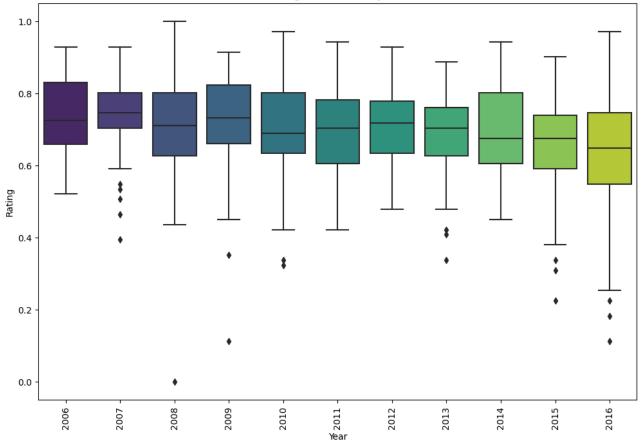
#### Revenue Distribution by Genre



#### 10. Rating Distribution by Year

```
In [20]: plt.figure(figsize=(12, 8))
    sns.boxplot(x='Year', y='Rating', data=df, palette='viridis')
    plt.title('Rating Distribution by Year')
    plt.xlabel('Year')
    plt.ylabel('Rating')
    plt.xticks(rotation=90)
    plt.show()
```

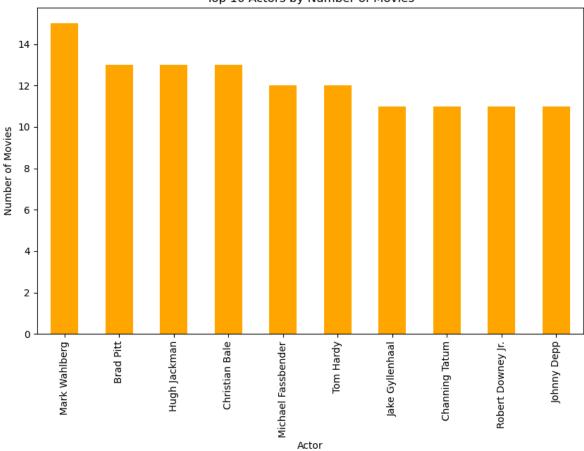




# 11. Top Actors Analysis

```
In [21]: actors_list = df['Actors'].str.split(', ').explode()
    top_actors = actors_list.value_counts().nlargest(10)
    plt.figure(figsize=(10, 6))
    top_actors.plot(kind='bar', color='Orange')
    plt.title('Top 10 Actors by Number of Movies')
    plt.xlabel('Actor')
    plt.ylabel('Number of Movies')
    plt.xticks(rotation=90)
    plt.show()
```

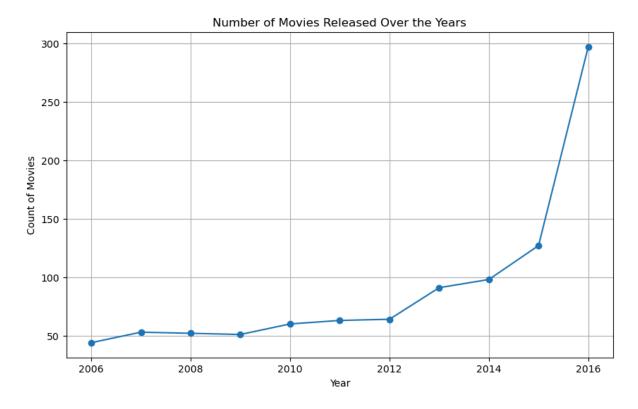
Top 10 Actors by Number of Movies



# **Time Series Analysis**

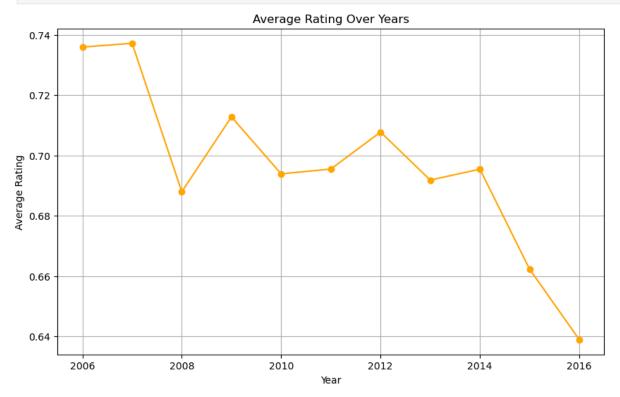
#### 1. Time Series Analysis of Movies over Year

```
In [22]: movie_over_years = df['Year'].value_counts().sort_index()
    plt.figure(figsize=(10, 6))
    plt.plot(movie_over_years, marker='o')
    plt.xlabel('Year')
    plt.ylabel('Count of Movies')
    plt.grid(True)
    plt.title('Number of Movies Released Over the Years')
    plt.show()
```



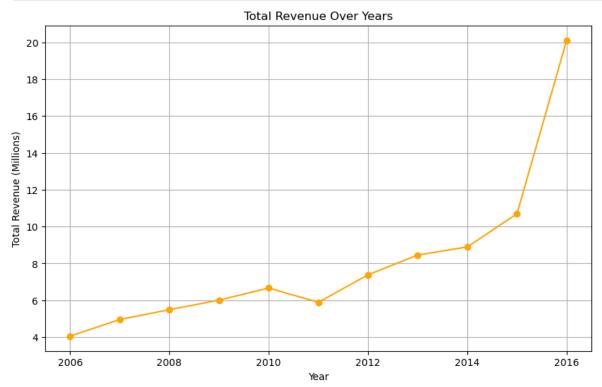
# 2. Time Series Analysis of Average Rating Over Years

```
In [23]: ratings_over_years = df.groupby('Year')['Rating'].mean()
    plt.figure(figsize=(10, 6))
    ratings_over_years.plot(marker='o', color='orange')
    plt.title('Average Rating Over Years')
    plt.xlabel('Year')
    plt.ylabel('Average Rating')
    plt.grid(True)
    plt.show()
```



#### 3. Time Series Analysis of Revenue Over Years

```
In [24]: revenue_over_years = df.groupby('Year')['Revenue (Millions)'].sum()
plt.figure(figsize=(10, 6))
revenue_over_years.plot(marker='o', color='orange')
plt.title('Total Revenue Over Years')
plt.xlabel('Year')
plt.ylabel('Total Revenue (Millions)')
plt.grid(True)
plt.show()
```



# **Predictive Modeling using Machine Learning Algorithms**

#### 1. For Movie Revenue (Linear Regression)

Test RMSE: 0.09808285077921733

```
In [25]: features = ['Rating', 'Runtime (Minutes)', 'Metascore', 'Year']
         X = df[features].fillna(0)
         y = df['Revenue (Millions)'].fillna(0)
         # Split data into train and test sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
         # Train linear regression model
         model = LinearRegression()
         model.fit(X_train, y_train)
         # Predictions using the model
         y_pred_train = model.predict(X_train)
         y_pred_test = model.predict(X_test)
         # Evaluation of the model
         train_rmse = np.sqrt(mean_squared_error(y_train, y_pred_train))
         test_rmse = np.sqrt(mean_squared_error(y_test, y_pred_test))
         print("Train RMSE:", train_rmse)
         print("Test RMSE:", test_rmse)
       Train RMSE: 0.09896805404834702
```

#### 2. For Movie Rating Category- High/Low (Random Forest)

```
In [26]: rating_threshold = df['Rating'].quantile(0.75)
         df['Rating_Category'] = df['Rating'].apply(lambda x: 'High' if x >= rating_threshold else 'Low')
         # Feature Engineering
        features = ['Genre', 'Director', 'Actors', 'Runtime (Minutes)', 'Year']
         X = df[features]
         y = df['Rating_Category']
        # Encode categorical features
         label_encoders = {}
         for column in ['Genre', 'Director', 'Actors']:
            label_encoders[column] = LabelEncoder()
            X[column] = label_encoders[column].fit_transform(X[column])
         # Handle missing values
         X.fillna(0, inplace=True)
         # Model Training
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
         clf = RandomForestClassifier(n_estimators=100, random_state=42)
         clf.fit(X_train, y_train)
         # Make predictions
        y_pred = clf.predict(X_test)
         # Model Evaluation
         print("Accuracy:", accuracy_score(y_test, y_pred))
        print("Classification Report:\n", classification_report(y_test, y_pred))
       Accuracy: 0.81
       Classification Report:
                      precision recall f1-score support
               High
                         0.66
                                0.44 0.53
                                                        18
                Low
                         0.84
                                  0.93
                                            0.88
                                                       152
           accuracy
                                             0.81
                                                      200
          macro avg
                         0.75
                                   0.68
                                            0.70
                                                       200
       weighted avg
                         0.80
                                   0.81
                                             0.80
                                                       200
```

#### 3. Predicting Movie Success (Binary Classification)

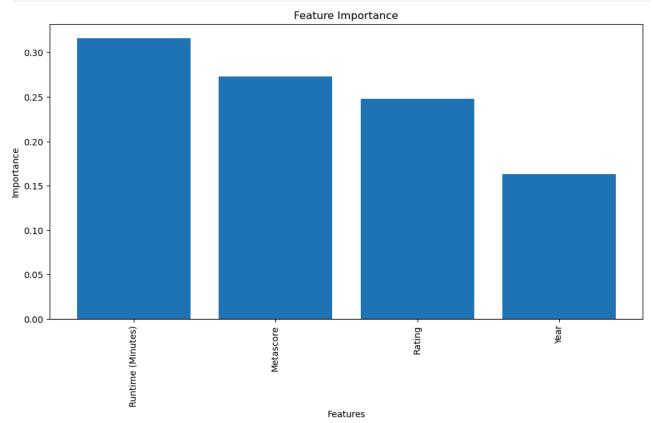
```
In [27]: success_threshold = df['Revenue (Millions)'].quantile(0.75)
         df['Success'] = df['Revenue (Millions)'].apply(lambda x: 1 if x >= success_threshold else 0)
         # Feature Engineering
         features = ['Rating', 'Runtime (Minutes)', 'Metascore', 'Year']
         X = df[features].fillna(0)
         y = df['Success']
         # Split data into train and test sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
         # Train Logistic regression model
         \textbf{from} \ \textbf{sklearn.linear\_model import} \ \textbf{LogisticRegression}
         log_reg = LogisticRegression()
         log_reg.fit(X_train, y_train)
         # Make predictions
         y_pred = log_reg.predict(X_test)
         # Model Evaluation
         print("Accuracy:", accuracy_score(y_test, y_pred))
         print("Classification Report:\n", classification_report(y_test, y_pred))
        Accuracy: 0.76
        Classification Report:
                       precision
                                   recall f1-score support
                   0
                           0.76
                                     1.00
                                                0.86
                                                           152
                           0.00
                                     0.00
                                                0.00
                                                            48
            accuracy
                                                0.76
                                                           200
                           0.38
                                     0.50
                                                           200
           macro avg
                                                0.43
        weighted avg
                           0.58
                                     0.76
                                                0.66
                                                           200
```

#### 4. Feature Importance Analysis

```
In [28]: clf = RandomForestClassifier(n_estimators=100, random_state=42)
    clf.fit(X_train, y_train)

# Plot feature importance
    importances = clf.feature_importances_
    indices = np.argsort(importances)[::-1]
    feature_names = [features[i] for i in indices]

plt.figure(figsize=(12, 6))
    plt.title('Feature Importance')
    plt.bar(range(X_train.shape[1]), importances[indices], align='center')
    plt.xticks(range(X_train.shape[1]), feature_names, rotation=90)
    plt.xlabel('Features')
    plt.ylabel('Importance')
    plt.show()
```

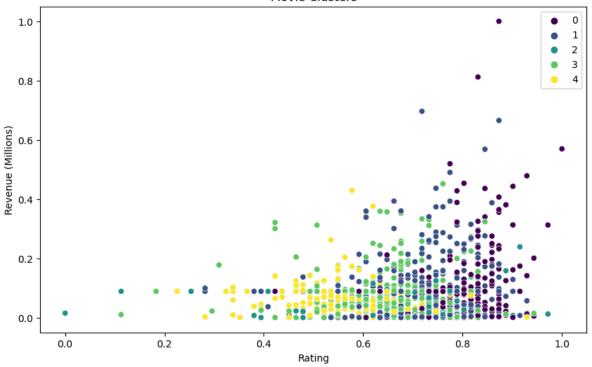


#### 5. Clustering Movies

```
In [29]: kmeans = KMeans(n_clusters=5, random_state=42)
df['Cluster'] = kmeans.fit_predict(X)

# Visualize clusters
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Rating', y='Revenue (Millions)', hue='Cluster', data=df, palette='viridis')
plt.title('Movie Clusters')
plt.xlabel('Rating')
plt.ylabel('Rating')
plt.ylabel('Revenue (Millions)')
plt.legend()
plt.show()
```





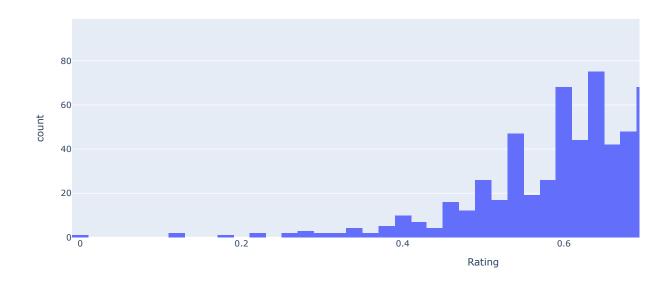
#### Visualizations

#### 1. Interactive Dashboards

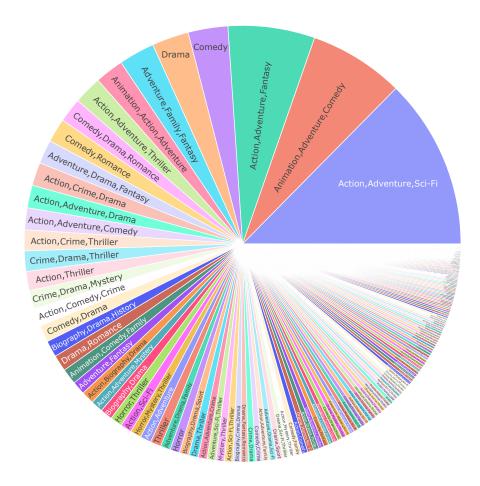
```
In [30]: # Example using Plotly Dash (Please run this as a separate script)
        import dash
        import dash_core_components as dcc
        import dash_html_components as html
        from dash.dependencies import Input, Output
        app = dash.Dash(__name__)
        app.layout = html.Div([
            html.H1("IMDb Movies Analysis Dashboard"),
           ], value='Rating'),
           dcc.Graph(id='feature-graph')
        ])
        @app.callback(
           Output('feature-graph', 'figure'),
            [Input('feature-dropdown', 'value')]
        def update_graph(selected_feature):
           fig = px.histogram(df, x=selected_feature)
            return fig
        if __name__ == '__main__':
           app.run_server(debug=True)
```

# **IMDb Movies Analysis Dashboard**





#### 2. Sunburst Chart for Genre Distribution



#### 3. Chord Diagram for Director-Actor Collaborations

```
In [32]: import plotly.graph_objects as go
         # Prepare data for chord diagram
         director_actor_pairs = df[['Director', 'Actors']].dropna()
         director_actor_pairs['Actors'] = director_actor_pairs['Actors'].str.split(', ')
         pairs = director_actor_pairs.explode('Actors')
         # Count the number of collaborations
         collaborations = pairs.groupby(['Director', 'Actors']).size().reset_index(name='Count')
         # Get the top 5 directors by the number of collaborations
         top_3_directors = collaborations['Director'].value_counts().nlargest(3).index.tolist()
         top_director_collaborations = collaborations[collaborations['Director'].isin(top_3_directors)]
         # Create a list of unique directors and actors
         directors = top_director_collaborations['Director'].unique().tolist()
         actors = top_director_collaborations['Actors'].unique().tolist()
         # Create a combined list of nodes
         nodes = directors + actors
         # Create a dictionary to index nodes
         node_indices = {node: idx for idx, node in enumerate(nodes)}
         # Create the links for the chord diagram
         links = []
         for _, row in top_director_collaborations.iterrows():
```

```
source = node_indices[row['Director']]
    target = node_indices[row['Actors']]
    value = row['Count']
   links.append({'source': source, 'target': target, 'value': value})
# Create the node colors
colors = ['#636EFA'] * len(directors) + ['#EF553B'] * len(actors)
# Create the Plotly figure
fig = go.Figure(data=[go.Sankey(
    node=dict(
         pad=15,
         thickness=20,
        line=dict(color="black", width=0.5),
        label=nodes,
        color=colors
    link=dict(
        source=[link['source'] for link in links],
target=[link['target'] for link in links],
value=[link['value'] for link in links]
)])
# Update the layout to make the figure larger
fig.update_layout(
    title_text="Director-Actor Collaborations (Top 3 Director)",
    font_size=10,
    width=1000, # Set the width
    height=1000 # Set the height
# Show the figure
fig.show()
```

