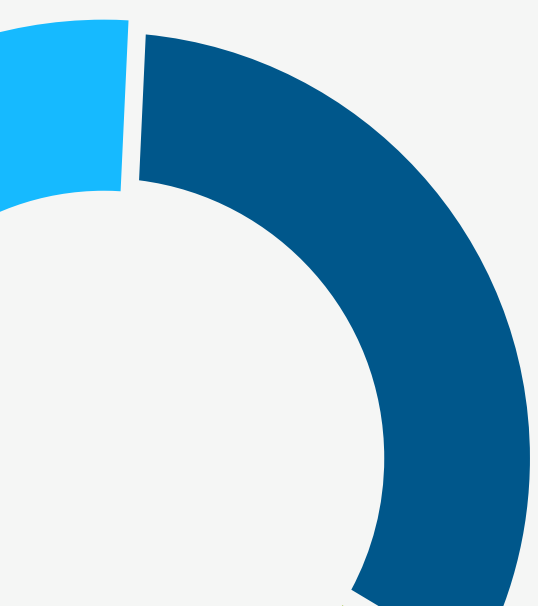





MARVEL MOVIES CLASSIFICATION



Objectives

- Predicting Success: Classification can help determine whether a movie will be a box office success based on various features such as budget, genre, director, and critic scores.
 - Understanding Influential Factors: By identifying which features contribute most significantly to a movie's success or failure, stakeholders can make informed decisions about future projects.
- 
- 



Introduction



This analysis focuses on the Marvel Movies dataset, which includes information about films from the Marvel Cinematic Universe, such as titles, directors, budgets, and performance metrics like IMDb ratings and box office gross.

The primary goal is to conduct Exploratory Data Analysis (EDA) to uncover trends and patterns in the data, including visualizing rating distributions and the relationship between budgets and earnings.

Following the EDA, we will develop a classification model to predict the success of future Marvel movies based on historical data, categorizing them as "blockbuster" or "average performer."


Ultimately, this analysis aims to provide insights into the factors influencing movie performance, aiding strategic planning in the film industry.



EXPLORATORY DATA AND ANAYLISIS (EDA)

Data Info: This command prints a summary of the DataFrame, including the number of entries, column names, data types, and memory usage.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 34 entries, 0 to 33
Data columns (total 14 columns):
#   Column                                                                 Non-Null Count  Dtype
---  -
0   Index                                                                34 non-null    int64
1   Title                                                                34 non-null    object
2   Director (1)                                                         34 non-null    object
3   Director (2)                                                         5 non-null     object
4   Release Date (DD-MM-YYYY)                                           34 non-null    object
5   IMDb (scored out of 10)                                             34 non-null    float64
6   IMDB Metascore (scored out of 100)                                  34 non-null    int64
7   Rotten Tomatoes - Critics (scored out of 100%)                    34 non-null    int64
8   Rotten Tomatoes - Audience (scored out of 100%)                   34 non-null    int64
9   Letterboxd (scored out of 5)                                        34 non-null    float64
10  CinemaScore (grades A+ to F)                                        34 non-null    object
11  Budget (in million $)                                              34 non-null    float64
12  Domestic Gross (in million $)                                       34 non-null    float64
13  Worldwide Gross (in million $)                                       34 non-null    float64
dtypes: float64(5), int64(4), object(5)
memory usage: 3.8+ KB
None
```





EXPLORATORY DATA AND ANAYLISIS (EDA)

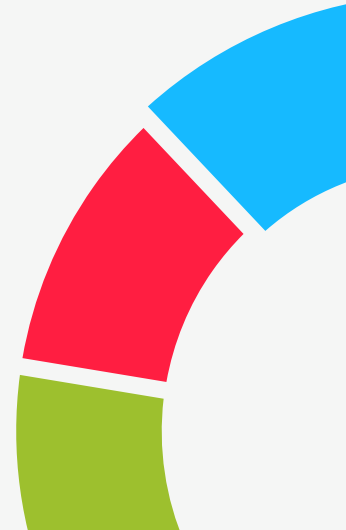
Descriptive Statistics: This prints summary statistics for numerical columns, such as count, mean, standard deviation, min, and max values.

```
Index IMDb (scored out of 10) IMDB Metascore (scored out of 100)
count 34.000000 34.000000 34.000000
mean 16.500000 7.244118 65.97058
std 9.958246 0.692029 8.85740
min 0.000000 5.500000 48.00000
25% 8.250000 6.825000 60.25000
50% 16.500000 7.300000 67.00000
75% 24.750000 7.800000 71.00000
max 33.000000 8.400000 88.00000

Rotten Tomatoes - Critics (scored out of 100%) \
count 34.000000
mean 80.882353
std 12.727362
min 46.000000
25% 76.250000
50% 83.500000
75% 91.000000
max 96.000000

Rotten Tomatoes - Audience (scored out of 100%) \
count 34.000000
mean 84.205882
std 10.446920
min 45.000000
25% 78.250000
50% 86.500000
75% 91.750000
max 98.000000

Letterboxd (scored out of 5) Budget (in million $) \
count 34.000000 34.000000
mean 3.235294 229.523529
std 0.519255 69.004243
min 2.000000 140.000000
```



MACHINE LEARNING MODEL

- Import Machine Learning Libraries: This imports necessary functions from scikit-learn for splitting the dataset, creating a linear regression model, and evaluating model performance.
- Data Cleaning: This line removes unnecessary columns that are not useful for modeling, such as the index, title of the movie, directors, and release date.
- Convert Categorical Variables: This converts categorical variables into dummy/indicator variables, which are necessary for modeling. The `drop_first=True` argument avoids multicollinearity.

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

df_cleaned = df.drop(columns=['Index', 'Title', 'Director (1)', 'Director (2)', 'Release Date (DD-MM-YYYY)'])
df_cleaned = pd.get_dummies(df_cleaned, drop_first=True)

X = df_cleaned.drop('Worldwide Gross (in million $)', axis=1)
y = df_cleaned['Worldwide Gross (in million $)']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = LinearRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
print('R2 Score:', r2_score(y_test, y_pred))
```



MACHINE LEARNING MODEL

- Define Features and Target: Here, X contains all the feature columns while y is the target variable (Worldwide Gross).
- Split Dataset: This line splits the dataset into training and testing sets, with 20% of the data reserved for testing.
- Create and Train Model: This creates a linear regression model and fits it to the training data
- Make Predictions: This line uses the trained model to predict the target variable (Worldwide Gross) for the test set.
- Evaluate Model Performance: This prints the Mean Squared Error (MSE) and R^2 score to assess the model's accuracy. A lower MSE indicates better fit, and R^2 indicates the proportion of variance explained by the model.

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

df_cleaned = df.drop(columns=['Index', 'Title', 'Director (1)', 'Director (2)', 'Release Date (DD-MM-YYYY)'])
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X = df_cleaned.drop('Worldwide Gross (in million $)', axis=1)
y = df_cleaned['Worldwide Gross (in million $)']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

model = LinearRegression()
model.fit(X_train, y_train)

y_pred = model.predict(X_test)

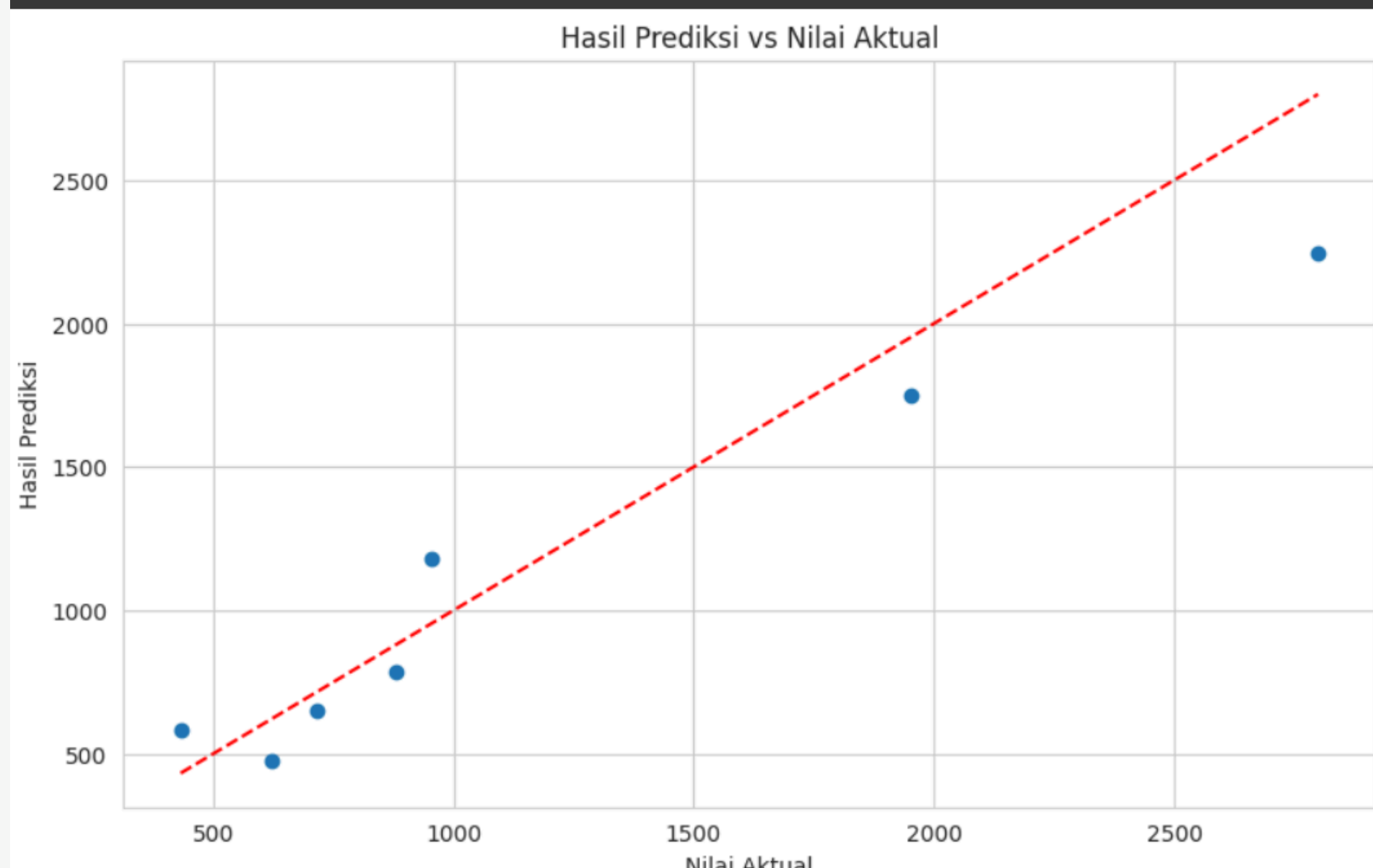
print('Mean Squared Error:', mean_squared_error(y_test, y_pred))
print('R2 Score:', r2_score(y_test, y_pred))
```



DATA VISUALIZATION

```
plt.figure(figsize=(10, 6))  
plt.scatter(y_test, y_pred)  
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], '--r')  
plt.title('Hasil Prediksi vs Nilai Aktual')  
plt.xlabel('Nilai Aktual')  
plt.ylabel('Hasil Prediksi')  
plt.show()
```

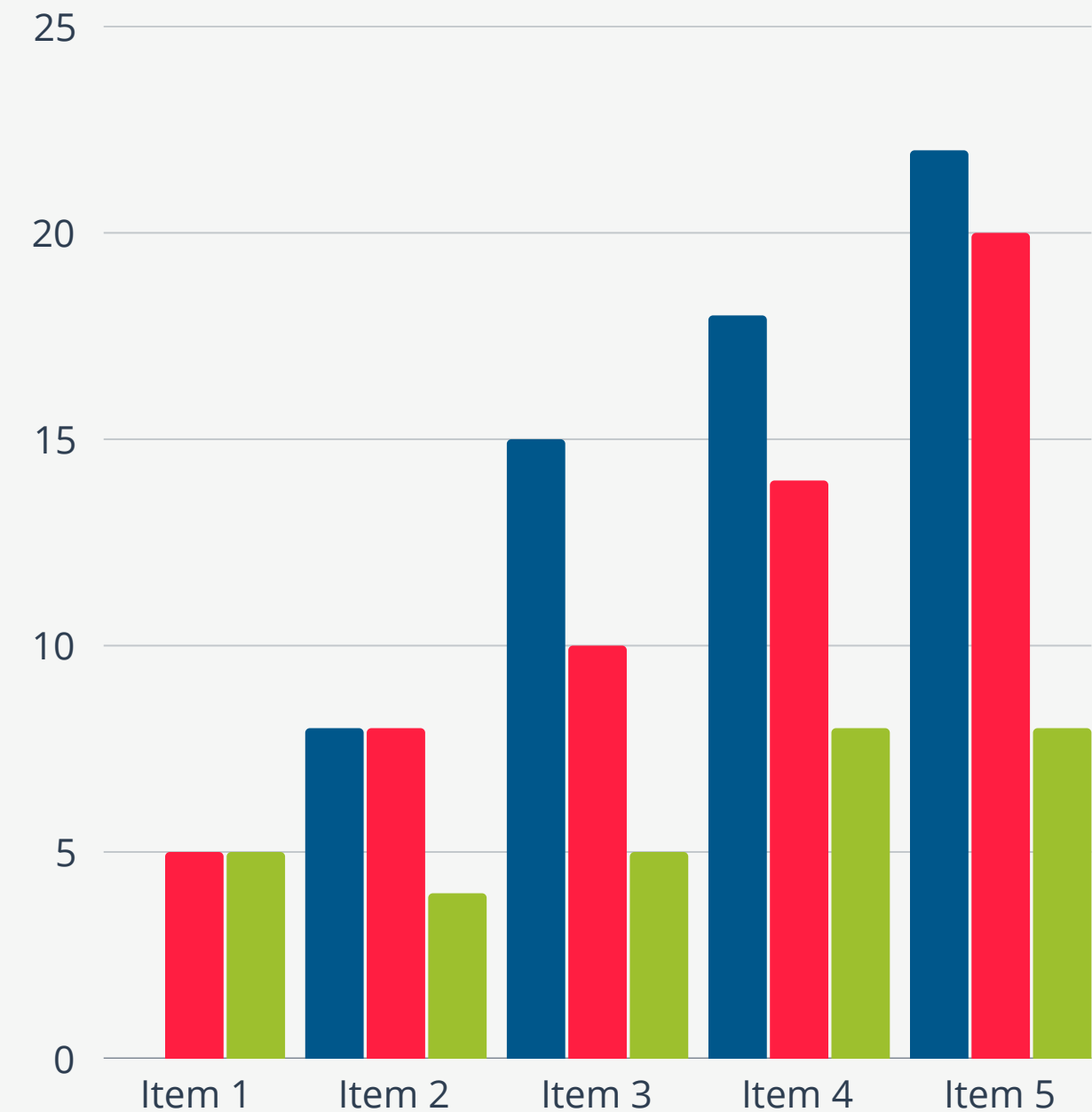
Predicted vs. Actual Values: This scatter plot compares the predicted values against the actual values of Worldwide Gross. The red dashed line represents the ideal scenario where predicted values match actual values perfectly.

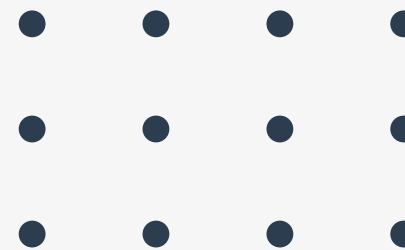




CONCLUSION

These steps provide a comprehensive approach to analyzing the Marvel Movies dataset, building a predictive model, and visualizing results, helping derive insights from the data effectively.





CONTACT ME

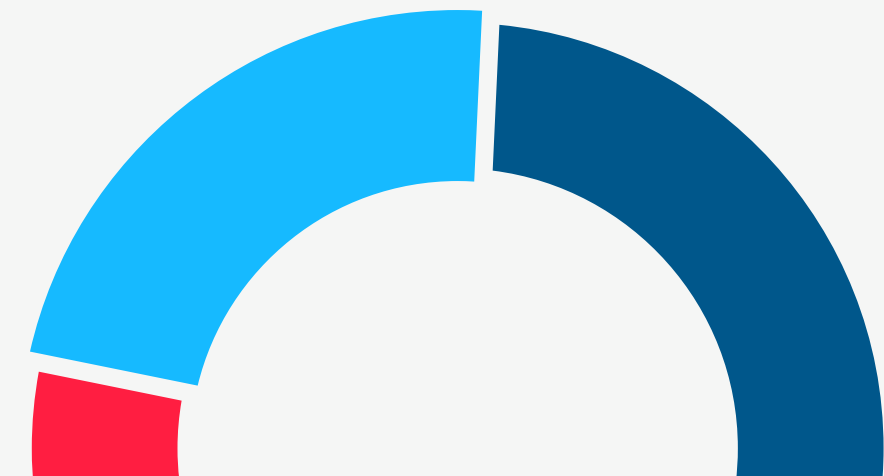
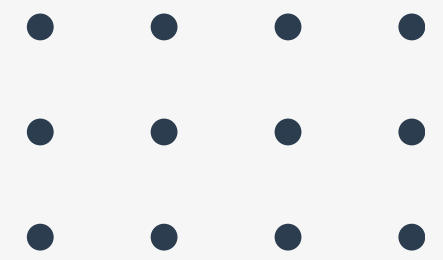
FOR INQUIRIES

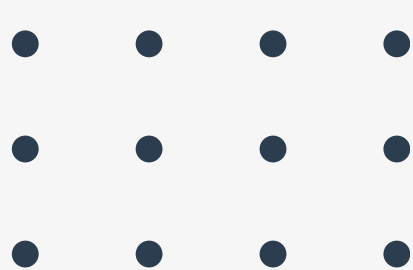
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Thank you!

