Phase 1

In [1]: import numpy as np import pandas as pd

import matplotlib.pyplot as plt

import seaborn as sns

In [2]: df = pd.read_csv("C:\\Users\\Shaun Alex\\Downloads\\archive\\NetflixOrigina

Out[2]:

	Title	Genre	Premiere	Runtime	IMDB Score	Language
0	Enter the Anime	Documentary	August 5, 2019	58	2.5	English/Japanese
1	Dark Forces	Thriller	August 21, 2020	81	2.6	Spanish
2	The App	Science fiction/Drama	December 26, 2019	79	2.6	Italian
3	The Open House	Horror thriller	January 19, 2018	94	3.2	English
4	Kaali Khuhi	Mystery	October 30, 2020	90	3.4	Hindi
579	Taylor Swift: Reputation Stadium Tour	Concert Film	December 31, 2018	125	8.4	English
580	Winter on Fire: Ukraine's Fight for Freedom	Documentary	October 9, 2015	91	8.4	English/Ukranian/Russian
581	Springsteen on Broadway	One-man show	December 16, 2018	153	8.5	English
582	Emicida: AmarElo - It's All For Yesterday	Documentary	December 8, 2020	89	8.6	Portuguese
583	David Attenborough: A Life on Our Planet	Documentary	October 4, 2020	83	9.0	English

584 rows × 6 columns

In [3]: df.info

Out[3]:		nd method Data	aFrame	.info of		
	Title	9		Genre \		
	0				Enter the Ar	nime Documentary
	1				Dark For	rces Thriller
	2				The	App Science fiction/Drama
	3				The Open Ho	ouse Horror thriller
	4				Kaali Kh	nuhi Mystery
						•••
	579	Taylor	Swift	: Reputat	ion Stadium T	our Concert Film
	580				ight for Free	
	581				teen on Broad	
	582	Emicida: A	narElo		ll For Yester	_
	583				fe on Our Pla	
		Prei	niere	Runtime	IMDB Score	Language
	0	August 5,	2019	58	2.5	English/Japanese
	1	August 21,	2020	81	2.6	Spanish
	2	December 26,	2019	79	2.6	Italian
	3	January 19,	2018	94	3.2	English
	4	October 30,	2020	90	3.4	Hindi
						•••
	579	December 31,	2018	125	8.4	English
	580	October 9,	2015	91	8.4	English/Ukranian/Russian
	581	December 16,		153	8.5	English
	582	December 8,		89	8.6	Portuguese
	583	October 4,		83	9.0	English

[584 rows x 6 columns]>

Out[4]:	<box< td=""><td>nd method NDF</td><td>rame.d</td><td>lescribe o</td><td>f</td><td></td></box<>	nd method NDF	rame.d	lescribe o	f	
	Titl	e		Genre \		
	0				Enter the A	nime Documentary
	1				Dark Fo	rces Thriller
	2				The	App Science fiction/Drama
	3				The Open H	ouse Horror thriller
	4				Kaali K	nuhi Mystery
	• •					
	579	Taylor	Swift	: Reputat	ion Stadium	Tour Concert Film
	580	Winter on Fi	re: Uk	raine's F	ight for Fre	edom Documentary
	581				teen on Broa	_
	582				ll For Yeste	-
	583	David Att	enboro	ough: A Li	fe on Our Pl	anet Documentary
		_		.	TUDD 6	
	•		niere	Runtime	IMDB Score	Language
	0	August 5,		58	2.5	English/Japanese
	1	August 21,		81	2.6	Spanish
	2	December 26,		79	2.6	Italian
	3	January 19,		94	3.2	English
	4	October 30,	2020	90	3.4	Hindi
	··	Dagamban 31	2010	125		
	579	December 31,		125	8.4	English
	580	October 9,		91 153	8.4	English/Ukranian/Russian
	581	December 16,		153	8.5	English
	582	December 8,		89	8.6	Portuguese
	583	October 4,	2020	83	9.0	English

[584 rows x 6 columns]>

In [5]: df.rename(columns = {'IMDB Score':'IMDBScore'}, inplace = True)
df

Out[5]:

	Title	Genre	Premiere	Runtime	IMDBScore	Language
0	Enter the Anime	Documentary	August 5, 2019	58	2.5	English/Japanese
1	Dark Forces	Thriller	August 21, 2020	81	2.6	Spanish
2	The App	Science fiction/Drama	December 26, 2019	79	2.6	Italian
3	The Open House	Horror thriller	January 19, 2018	94	3.2	English
4	Kaali Khuhi	Mystery	October 30, 2020	90	3.4	Hindi
579	Taylor Swift: Reputation Stadium Tour	Concert Film	December 31, 2018	125	8.4	English
580	Winter on Fire: Ukraine's Fight for Freedom	Documentary	October 9, 2015	91	8.4	English/Ukranian/Russian
581	Springsteen on Broadway	One-man show	December 16, 2018	153	8.5	English
582	Emicida: AmarElo - It's All For Yesterday	Documentary	December 8, 2020	89	8.6	Portuguese
583	David Attenborough: A Life on Our Planet	Documentary	October 4, 2020	83	9.0	English

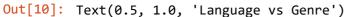
584 rows × 6 columns

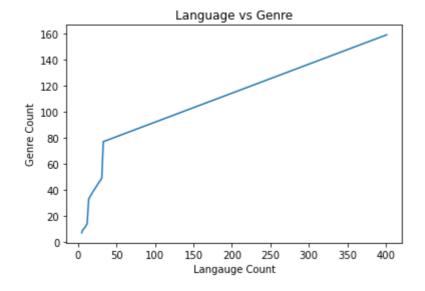
```
In [6]: df.isnull().sum()
```

```
Out[6]: Title 0
Genre 0
Premiere 0
Runtime 0
IMDBScore 0
Language 0
dtype: int64
```

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

```
language=df['Language'].value_counts().sort_values(ascending=False)
In [8]:
          language=language[:10]
          language
Out[8]: English
                         401
          Hindi
                          33
          Spanish
                          31
          French
                          20
          Italian
                          14
          Portuguese
                          12
          Indonesian
                           9
          Korean
                           6
          Japanese
                           6
                           5
          German
          Name: Language, dtype: int64
In [9]:
         Genre=df["Genre"].value_counts().sort_values(ascending=False)
          Genre=Genre[:10]
          Genre
Out[9]: Documentary
                              159
          Drama
                               77
                               49
          Comedy
          Romantic comedy
                               39
          Thriller
                               33
          Comedy-drama
                               14
          Crime drama
                               11
          Biopic
                                9
                                9
          Horror
          Action
          Name: Genre, dtype: int64
In [10]:
         plt.plot(language,Genre)
         plt.xlabel("Langauge Count")
plt.ylabel("Genre Count")
          plt.title("Language vs Genre")
```





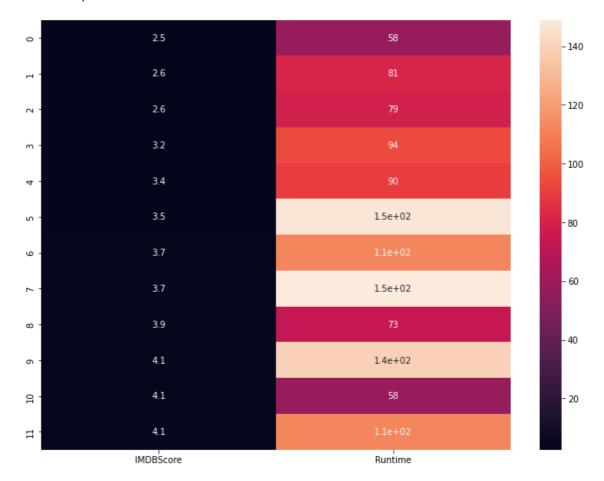
```
In [11]: cols=["IMDBScore","Runtime"]
x=df[cols].head(12)
x.corr()
```

Out[11]:

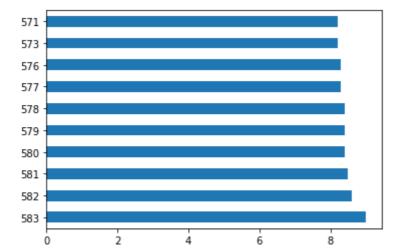
	IMDBScore	Runtime
IMDBScore	1.00000	0.40416
Runtime	0.40416	1.00000

In [12]: plt.figure(figsize=(12,9))
sns.heatmap(x,annot=True)

Out[12]: <AxesSubplot:>

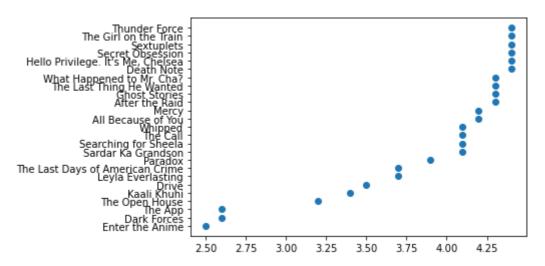


```
In [13]: score=df["IMDBScore"].sort_values(ascending=False)[:10]
score.plot.barh()
plt.show()
```



```
In [14]: plt.scatter(df["IMDBScore"][:25],df["Title"][:25])
    plt.figure(figsize=(30,30))
```

Out[14]: <Figure size 2160x2160 with 0 Axes>



<Figure size 2160x2160 with 0 Axes>

```
In [15]: from sklearn.preprocessing import LabelEncoder
    object_cols = ["Title","Genre"]
    label_encoder = LabelEncoder()
    df2=df.copy()
    for col in object_cols:
        label_encoder.fit(df2[col])
        df2[col] = label_encoder.transform(df2[col])
    df2
```

Out[15]:

	Title	Genre	Premiere	Runtime	IMDBScore	Language
0	147	45	August 5, 2019	58	2.5	English/Japanese
1	120	106	August 21, 2020	81	2.6	Spanish
2	433	93	December 26, 2019	79	2.6	Italian
3	500	63	January 19, 2018	94	3.2	English
4	243	73	October 30, 2020	90	3.4	Hindi
579	425	40	December 31, 2018	125	8.4	English
580	575	45	October 9, 2015	91	8.4	English/Ukranian/Russian
581	410	74	December 16, 2018	153	8.5	English
582	145	45	December 8, 2020	89	8.6	Portuguese
583	121	45	October 4, 2020	83	9.0	English

584 rows × 6 columns

```
In [16]: df2.drop(["Premiere"],axis=1,inplace=True)
```

```
In [17]: df2.drop(["Language"],axis=1,inplace=True)
```

```
In [18]: df2.drop(["IMDBScore"],axis=1,inplace=True)
df2
```

Out[18]:

	Title	Genre	Runtime
0	147	45	58
1	120	106	81
2	433	93	79
3	500	63	94
4	243	73	90
579	425	40	125
580	575	45	91
581	410	74	153
582	145	45	89
583	121	45	83

584 rows × 3 columns

```
In [19]: y=df["IMDBScore"]
Out[19]: 0
                 2.5
         1
                 2.6
         2
                 2.6
         3
                 3.2
         4
                 3.4
         579
                8.4
         580
                8.4
         581
                8.5
         582
                8.6
         583
                9.0
         Name: IMDBScore, Length: 584, dtype: float64
```

```
In [20]: from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
```

```
In [21]: xtrain,xtest,ytrain,ytest=train_test_split(df2,y,test_size=0.2,random_state
```

```
In [23]: print(xtest.shape,ytest.shape)
         (117, 3) (117,)
In [24]: lr=LinearRegression()
In [25]: |lr.fit(xtrain,ytrain)
Out[25]: LinearRegression()
In [26]: |lr.fit(xtest,ytest)
Out[26]: LinearRegression()
In [27]: |lr.score(xtrain,ytrain)
Out[27]: 0.031119103871776743
In [28]: y_pred=lr.predict(xtest)
         x=[[147,45,58]]
         predict=lr.predict(x)
         predict
         C:\Users\Shaun Alex\anaconda3\lib\site-packages\sklearn\base.py:450: UserW
         arning: X does not have valid feature names, but LinearRegression was fitt
         ed with feature names
           warnings.warn(
Out[28]: array([6.3065107])
In [29]: print(lr.score(xtest, ytest))
         0.019033211731675936
In [30]: | # Assuming df2 is your first DataFrame and df is your second DataFrame
         # Filter rows in df2 where 'Title' is equal to 147
         filtered_rows_df2 = df2[df2['Title'] == 147]
         # Get the indices of the filtered rows
         indices = filtered_rows_df2.index
         # Use the indices to access the corresponding rows in df
         resulting rows df = df.loc[indices]
         # Now, resulting_rows_df contains the rows from df where 'Title' is equal t
         resulting_rows_df
Out[30]:
```

```
In [31]: from sklearn.ensemble import RandomForestRegressor
         # create regressor object
         regressor = RandomForestRegressor(n_estimators=100,
                                            random state=0)
         \# fit the regressor with x and y data
         regressor.fit(df2, y)
Out[31]: RandomForestRegressor(random_state=0)
In [32]: Y pred = regressor.predict(xtest)
In [33]: print(regressor.score(xtest, ytest))
         0.8844757926660178
In [34]: |print(regressor.score(xtrain, ytrain))
         0.8848317625613643
In [35]: x=[[147,45,58]]
         predict=regressor.predict(x)
         predict
         C:\Users\Shaun Alex\anaconda3\lib\site-packages\sklearn\base.py:450: UserW
         arning: X does not have valid feature names, but RandomForestRegressor was
         fitted with feature names
           warnings.warn(
Out[35]: array([3.752])
In [36]: | from sklearn.metrics import accuracy_score
```

```
In [37]: import numpy as np
         # Assuming ytest is a Pandas Series
         ytest array = np.array(ytest)
         reshaped_ytest = ytest_array.reshape(-1, 1)
         print(reshaped_ytest)
         ytpred_array = np.array(y_pred)
         reshaped_ypred = ytpred_array.reshape(-1, 1)
         print(reshaped ypred)
          [[6.7]
          [6.9]
          [5.3]
          [7.1]
          [7.4]
          [6.4]
          [5.5]
          [6.2]
          [5.6]
          [6.6]
          [7.6]
          [5.2]
          [7.9]
          [5.8]
          [6.9]
          [6.1]
          [6.]
          [5.4]
           [8.2]
In [38]: from sklearn.metrics import mean_squared_error, mean_squared_log_error,r2_s
In [39]: mse = mean squared error(ytest, y pred)
         # Calculate Root Mean Squared Error (RMSE)
         rmse = np.sqrt(mse)
         r2_score=r2_score(ytest,y_pred) # For the Linear Regression
         print(rmse,mse,r2_score)
         1.0090520571992603 1.0181860541380592 0.019033211731675936
In [40]: Y_pred1 = Y_pred.astype(int)
         Y_pred1
Out[40]: array([6, 6, 5, 6, 7, 6, 5, 5, 5, 6, 7, 5, 7, 5, 6, 6, 5, 5, 8, 6, 7, 5,
                3, 7, 7, 5, 5, 7, 6, 4, 5, 6, 5, 6, 5, 6, 7, 7, 7, 6, 6, 6, 5,
                7, 6, 4, 6, 6, 6, 5, 6, 5, 5, 5, 6, 7, 6, 6, 6, 5, 6, 6, 5, 5, 6,
                5, 7, 6, 5, 6, 6, 5, 5, 6, 6, 5, 5, 6, 7, 6, 4, 5, 6, 7, 5, 6, 7,
                6, 6, 6, 7, 5, 6, 6, 6, 6, 4, 6, 7, 6, 7, 6, 5, 6, 7, 6, 5, 5,
                5, 5, 6, 7, 5, 7, 6])
```

```
In [41]:
          mse = mean_squared_error(ytest, Y_pred1)
          # Calculate Root Mean Squared Error (RMSE)
          rmse = np.sqrt(mse)
          print(rmse,mse)
          0.6717116801102846 0.45119658119658124
In [42]: from sklearn.metrics import r2_score
          # Assuming ytest contains actual labels and Y_pred1 contains predicted labe
          r2 result = r2 score(ytest, Y pred1) # Calculate the R^2 score
          r2_result
Out[42]: 0.565296677031442
In [43]: from sklearn.model selection import train test split, GridSearchCV
          param_grid = {
               'max_depth': [None, 10, 20, 30], # Number of trees
'min_samples_split': [2, 5, 10], # Maximum depth of each tree
'min_samples_leaf': [1, 2, 4] # Minimum samples required to spl
          grid_search = GridSearchCV(estimator=regressor, param_grid=param_grid, cv=5
          grid_search.fit(xtrain, ytrain)
Out[43]: GridSearchCV(cv=5, estimator=RandomForestRegressor(random_state=0),
                         param_grid={'max_depth': [None, 10, 20, 30],
                                       'min_samples_leaf': [1, 2, 4],
                                       'min_samples_split': [2, 5, 10],
                                       'n_estimators': [100, 200, 300]},
                         scoring='neg mean squared error')
```

```
In [44]: best_params = grid_search.best_params_
         print("Best Hyperparameters:", best_params)
         # Train the model with the best hyperparameters
         best rf regressor = grid search.best estimator
         best_rf_regressor.fit(xtrain, ytrain)
         # Make predictions on the test set
         ypred = best_rf_regressor.predict(xtest)
         # Evaluate the model
         mse = mean_squared_error(ytest, ypred)
         rmse = np.sqrt(mse)
         r2 = r2_score(ytest, ypred)
         print("Mean Squared Error:", mse)
         print("Root Mean Squared Error:", rmse)
         print("R-squared:", r2)
         Best Hyperparameters: {'max_depth': 10, 'min_samples_leaf': 4, 'min_sample
         s_split': 10, 'n_estimators': 100}
         Mean Squared Error: 0.7810925200023665
         Root Mean Squared Error: 0.8837943878540792
         R-squared: 0.24745991405688794
```

Phase 2

Neural Network

```
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from tensorflow import keras
from tensorflow.keras import layers
```

```
In [46]: | x = df[['Genre', 'Runtime', 'Language']]
        y = df['IMDBScore']
        # Encode categorical variables (Genre and Language) using one-hot encoding
        x = pd.get_dummies(x, columns=['Genre', 'Language'], drop_first=True)
        # Split the dataset into training and testing sets
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, ra
        # Standardize features (optional but can help neural networks converge fast
        scaler = StandardScaler()
        x train = scaler.fit transform(x train)
        x_test = scaler.transform(x_test)
        # Build the neural network model
        model = keras.Sequential([
            layers.Dense(64, activation='relu', input_shape=(x_train.shape[1],)),
            layers.Dense(32, activation='relu'),
            layers.Dense(1) # Output Layer for regression
        ])
        # Compile the model
        model.compile(optimizer='adam', loss='mean squared error', metrics=['mean a
        # Train the model
        model.fit(x_train, y_train, epochs=100, batch_size=32, validation_split=0.2
        # Evaluate the model on the test set
        loss, mae = model.evaluate(x test, y test)
        print(f"Mean Absolute Error on Test Set: {mae}")
        # Make predictions
        y_pred = model.predict(x_test)
        Epoch 1/100
        12/12 [=============== ] - 1s 18ms/step - loss: 33.8856 -
        mean_absolute_error: 5.6779 - val_loss: 27.4807 - val_mean_absolute_err
        or: 5.0510
        Epoch 2/100
        mean_absolute_error: 4.2941 - val_loss: 18.0831 - val_mean_absolute_err
        or: 3.9985
        Epoch 3/100
        mean absolute error: 3.2651 - val loss: 11.0699 - val mean absolute err
        or: 3.0246
        Epoch 4/100
        12/12 [=============== ] - 0s 5ms/step - loss: 9.1994 - m
        ean_absolute_error: 2.7003 - val_loss: 6.8790 - val_mean_absolute_erro
        r: 2.3458
        Epoch 5/100
        12/12 [================ ] - 0s 5ms/step - loss: 6.3300 - m
        ean absolute error: 2.2119 - val loss: 5.0011 - val mean absolute erro
```

```
In [47]: |y_pred
Out[47]: array([[6.03637
                [5.601603],
                [5.5962715],
                [6.932173],
                [6.819642],
                [7.0490417],
                [5.909452],
                [5.3236194],
                [6.5592623],
                [5.440313],
                [7.1735015],
                [7.0880504],
                [7.0843143],
                [5.3240213],
                [6.6149597],
                [5.327671],
                [4.8287206],
                [5.0816717],
                [7.204135
                           ],
```

Gradient Boosting

```
In [48]: import pandas as pd
         import numpy as np
         from sklearn.model_selection import train_test_split
         from sklearn.ensemble import GradientBoostingRegressor
         from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_scd
         from sklearn.preprocessing import LabelEncoder, StandardScaler
         # Load the dataset
         # data = pd.read_csv("NetflixOriginals.csv")
         # Preprocess the data
         # Assuming you want to use 'Genre', 'Runtime', and 'Language' as features
         X = df[['Genre', 'Runtime', 'Language']]
         y = df['IMDBScore']
         # Encode categorical variables (Genre and Language) using Label Encoding
         label encoders = {}
         for col in ['Genre', 'Language']:
             label encoders[col] = LabelEncoder()
             X[col] = label_encoders[col].fit_transform(X[col])
         # Split the dataset into training and testing sets
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra
         # Standardize features (optional but can help gradient boosting)
         scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X_test = scaler.transform(X_test)
         # Build and train the gradient boosting model
         regressor = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1,
         regressor.fit(X_train, y_train)
         # Make predictions
         y_pred = regressor.predict(X_test)
         # Evaluate the model
         mae = mean_absolute_error(y_test, y_pred)
         mse = mean_squared_error(y_test, y_pred)
         r2 = r2_score(y_test, y_pred)
         print(f"Mean Absolute Error: {mae}")
         print(f"Mean Squared Error: {mse}")
         print(f"R-squared (R2): {r2}")
         Mean Absolute Error: 0.6737418660432508
         Mean Squared Error: 0.7646858702215756
         R-squared (R2): 0.2632668272200527
         C:\Users\Shaun Alex\AppData\Local\Temp\ipykernel_28416\1193338420.py:20: S
         ettingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame.
         Try using .loc[row_indexer,col_indexer] = value instead
         See the caveats in the documentation: https://pandas.pydata.org/pandas-doc
         s/stable/user guide/indexing.html#returning-a-view-versus-a-copy (https://
         pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-
         view-versus-a-copy)
           X[col] = label_encoders[col].fit_transform(X[col])
```

Phase 3

dtype: int64

Data Preprocessing

```
In [49]: from sklearn.preprocessing import StandardScaler
In [50]: data = df2.join(y)
          data
Out[50]:
               Title Genre Runtime IMDBScore
               147
                                         2.5
            0
                       45
                               58
               120
                      106
            1
                               81
                                         2.6
            2
               433
                               79
                                         2.6
                      93
            3
               500
                      63
                               94
                                         3.2
               243
                      73
                               90
            4
                                         3.4
               ...
                              ...
                                         ...
          579
               425
                              125
                      40
                                         8.4
          580
               575
                      45
                               91
                                         8.4
          581
               410
                      74
                              153
                                         8.5
          582
               145
                      45
                               89
                                         8.6
          583
               121
                      45
                               83
                                         9.0
          584 rows × 4 columns
In [51]:
         scaler = StandardScaler()
          model = scaler.fit(data)
          scaled data = model.transform(data)
          scaled data
Out[51]: array([[-0.85712914, -0.30324457, -1.28261511, -3.85494543],
                 [-1.01728476, 2.00257926, -0.45342484, -3.75273959],
                 [0.83933407, 1.51117418, -0.52552834, -3.75273959],
                 [0.70290521, 0.79296676, 2.1423012, 2.27740523],
                 [-0.86899252, -0.30324457, -0.16501084, 2.37961107],
                 [-1.01135307, -0.30324457, -0.38132134, 2.78843445]])
In [52]: data.isnull().sum()
Out[52]: Title
                       0
          Genre
                       0
          Runtime
                       0
          IMDBScore
```

In [53]: data.dropna()

Out[53]:

	Title	Genre	Runtime	IMDBScore
0	147	45	58	2.5
1	120	106	81	2.6
2	433	93	79	2.6
3	500	63	94	3.2
4	243	73	90	3.4
579	425	40	125	8.4
580	575	45	91	8.4
581	410	74	153	8.5
582	145	45	89	8.6
583	121	45	83	9.0

584 rows × 4 columns

In [54]: data.sort_values(by='IMDBScore', ascending = False)

Out[54]:

	Title	Genre	Runtime	IMDBScore
583	121	45	83	9.0
582	145	45	89	8.6
581	410	74	153	8.5
580	575	45	91	8.4
579	425	40	125	8.4
4	243	73	90	3.4
3	500	63	94	3.2
2	433	93	79	2.6
1	120	106	81	2.6
0	147	45	58	2.5
	582 581 580 579 4 3 2	583 121 582 145 581 410 580 575 579 425 4 243 3 500 2 433 1 120	583 121 45 582 145 45 581 410 74 580 575 45 579 425 40 4 243 73 3 500 63 2 433 93 1 120 106	582 145 45 89 581 410 74 153 580 575 45 91 579 425 40 125 4 243 73 90 3 500 63 94 2 433 93 79 1 120 106 81

584 rows × 4 columns

```
In [55]:
          data.sort_values(by='IMDBScore', ascending = False).head()
Out[55]:
                Title Genre Runtime IMDBScore
           583
                121
                        45
                                 83
                                           9.0
           582
                145
                        45
                                 89
                                           8.6
           581
                410
                        74
                                153
                                           8.5
           580
                575
                        45
                                 91
                                           8.4
                425
           579
                        40
                                125
                                           8.4
In [56]:
         data.isna()
Out[56]:
                Title Genre Runtime IMDBScore
             0 False
                      False
                               False
                                          False
                               False
             1 False
                      False
                                          False
             2 False
                      False
                               False
                                          False
               False
                      False
                               False
                                          False
               False
                      False
                               False
                                          False
           579
               False
                      False
                               False
                                          False
           580 False
                      False
                               False
                                          False
           581 False
                      False
                               False
                                          False
           582 False
                      False
                               False
                                          False
           583 False
                      False
                               False
                                          False
          584 rows × 4 columns
In [57]: from sklearn.preprocessing import MinMaxScaler
In [58]:
         scaler1 = MinMaxScaler()
          model1 = scaler1.fit(data)
          scaled_data1 = model.transform(data)
          scaled_data1
Out[58]: array([[-0.85712914, -0.30324457, -1.28261511, -3.85494543],
                  [-1.01728476, 2.00257926, -0.45342484, -3.75273959],
                  [0.83933407, 1.51117418, -0.52552834, -3.75273959],
                  [0.70290521, 0.79296676, 2.1423012, 2.27740523],
                  [-0.86899252, -0.30324457, -0.16501084, 2.37961107],
```

[-1.01135307, -0.30324457, -0.38132134, 2.78843445]])

Univariate Analysis

```
In [59]: column1 = df['Runtime']
         column1
Out[59]: 0
                  58
         1
                  81
          2
                  79
          3
                  94
          4
                  90
          579
                 125
          580
                 91
          581
                 153
          582
                  89
          583
                  83
         Name: Runtime, Length: 584, dtype: int64
In [60]: column1.head()
Out[60]: 0
               58
          1
               81
          2
               79
          3
               94
               90
         Name: Runtime, dtype: int64
In [61]: column1.dropna()
Out[61]: 0
                  58
          1
                  81
                  79
          2
          3
                  94
          4
                  90
                . . .
          579
                 125
          580
                 91
          581
                 153
          582
                  89
                  83
          583
         Name: Runtime, Length: 584, dtype: int64
In [62]: column1.fillna('Nan')
Out[62]: 0
                  58
          1
                  81
                  79
          2
          3
                  94
          4
                  90
          579
                 125
          580
                  91
                 153
          581
          582
                  89
          583
         Name: Runtime, Length: 584, dtype: int64
```

```
In [63]: column1.info()
          <class 'pandas.core.series.Series'>
          RangeIndex: 584 entries, 0 to 583
          Series name: Runtime
          Non-Null Count Dtype
                           int64
          584 non-null
          dtypes: int64(1)
          memory usage: 4.7 KB
In [64]: column1.describe()
Out[64]: count
                   584.000000
                    93.577055
          mean
                    27.761683
          std
          min
                     4.000000
          25%
                    86.000000
                    97.000000
          50%
          75%
                   108.000000
                   209.000000
          {\sf max}
          Name: Runtime, dtype: float64
In [65]: |column11=column1.head(10)
          column11.plot.barh()
Out[65]: <AxesSubplot:>
           7
           6
           5
           4
           3
           2
           1
           0
                  20
                        40
                             60
                                         100
                                               120
                                   80
                                                     140
```

Bivariate Analysis

```
In [66]: df.groupby('Genre').agg({'IMDBScore':'mean'})
```

Out[66]:

IMDBScore

Genre	
Action	5.414286
Action comedy	5.420000
Action thriller	6.400000
Action-adventure	7.300000
Action-thriller	6.133333
War	6.750000
War drama	7.100000
War-Comedy	6.000000
Western	6.066667
Zombie/Heist	5.900000

115 rows × 1 columns

```
In [67]: df.groupby('Runtime').agg({'IMDBScore':'mean'})
```

Out[67]:

IMDBScore

Runtime	
4	4.70
7	6.90
9	6.50
10	5.20
11	7.20
149	6.20
151	6.25
153	8.50
155	6.50
209	7.80

124 rows × 1 columns

```
In [68]: df.groupby('Premiere').agg({'IMDBScore':'mean'})
```

Out[68]:

IMDBScore

Premiere	
April 1, 2021	6.10
April 10, 2020	6.00
April 12, 2019	5.55
April 13, 2018	6.15
April 14, 2017	5.20
 September 4, 2020	6.60
	6.60 6.20
September 4, 2020	
September 4, 2020 September 7, 2018	6.20
September 4, 2020 September 7, 2018 September 7, 2020	6.20 8.10

390 rows × 1 columns

```
In [69]: df.groupby('Title').agg({'IMDBScore':'mean'})
```

Out[69]:

IMDBScore

Title	
#REALITYHIGH	5.2
13th	8.2
13th: A Conversation with Oprah Winfrey & Ava DuVernay	7.1
15 August	5.8
1922	6.3
Yes Day	5.7
You've Got This	5.8
Zion	7.2
iBoy	6.0
Òlòt?ré	5.5

584 rows × 1 columns

```
In [70]: df.groupby('Language').agg({'IMDBScore':'mean'})
```

IMDBScore

Language

Bengali	7.100000
Dutch	5.800000
English	6.380050
English/Akan	7.700000
English/Arabic	7.300000
English/Hindi	7.300000
English/Japanese	4.400000
English/Korean	7.300000
English/Mandarin	7.050000
English/Russian	7.300000
English/Spanish	6.220000
English/Swedish	6.500000
English/Taiwanese/Mandarin	6.500000
English/Ukranian/Russian	8.400000
Filipino	5.100000
French	5.770000
Georgian	6.800000
German	5.640000
Hindi	5.981818
Indonesian	5.844444
Italian	5.542857
Japanese	6.400000
Khmer/English/French	7.200000
Korean	5.916667
Malay	4.200000
Marathi	6.066667
Norwegian	5.100000
Polish	5.166667
Portuguese	6.216667
Spanish	6.303226
Spanish/Basque	5.600000
Spanish/Catalan	6.400000
Spanish/English	7.300000
Swedish	5.500000
Tamil	7.200000
Thai	5.450000
Thia/English	6.700000

Language

Turkish 5.660000

Phase 4

Feature Engineering

Imputation

```
In [71]: from sklearn.impute import SimpleImputer
In [72]: imputer = SimpleImputer(strategy='mean')
```

In [72]: imputer = SimpleImputer(strategy='mean')
 df_imputed = pd.DataFrame(imputer.fit_transform(df2), columns=df2.columns)
 df_imputed

Out[72]:

	Title	Genre	Runtime
0	147.0	45.0	58.0
1	120.0	106.0	81.0
2	433.0	93.0	79.0
3	500.0	63.0	94.0
4	243.0	73.0	90.0
579	425.0	40.0	125.0
580	575.0	45.0	91.0
581	410.0	74.0	153.0
582	145.0	45.0	89.0
583	121.0	45.0	83.0

584 rows × 3 columns

Outliers

```
In [73]: import numpy as np
         # Sample dataset
         data=df["IMDBScore"]
         # Calculate the first quartile (Q1) and third quartile (Q3)
         Q1 = np.percentile(data, 25)
         Q3 = np.percentile(data, 75)
         # Calculate the interquartile range (IQR)
         IQR = Q3 - Q1
         # Define a lower bound and upper bound to identify outliers
         lower_bound = Q1 - 1.5 * IQR
         upper_bound = Q3 + 1.5 * IQR
         # Detect and handle outliers
         outliers = [x for x in data if x < lower_bound or x > upper_bound]
         # Print the outliers and the modified dataset
         print("Outliers:", outliers)
         data_no_outliers = [x for x in data if lower_bound <= x <= upper_bound]</pre>
         print("Data without outliers:", data_no_outliers)
```

```
Outliers: [2.5, 2.6, 2.6, 3.2, 3.4, 3.5, 3.7, 3.7, 9.0]
Data without outliers: [3.9, 4.1, 4.1, 4.1, 4.1, 4.2, 4.2, 4.3, 4.3, 4.3,
4.6, 4.6, 4.6, 4.6, 4.7, 4.7, 4.7, 4.7, 4.7, 4.8, 4.8, 4.8, 4.8, 4.8,
4.8, 4.8, 4.9, 4.9, 4.9, 4.9, 5.0, 5.0, 5.0, 5.0, 5.0, 5.1, 5.1, 5.1, 5.1,
5.7, 5.7, 5.7, 5.7, 5.7, 5.7, 5.7, 5.8, 5.8, 5.8, 5.8, 5.8, 5.8, 5.8,
6.9,\ 6.9,\ 6.9,\ 6.9,\ 6.9,\ 6.9,\ 6.9,\ 7.0,\ 7.0,\ 7.0,\ 7.0,\ 7.0,\ 7.0,
7.7, 7.7, 7.8, 7.8, 7.8, 7.9, 7.9, 7.9, 7.9, 8.0, 8.1, 8.1, 8.1, 8.2, 8.2,
8.2, 8.2, 8.2, 8.3, 8.3, 8.4, 8.4, 8.4, 8.5, 8.6]
```

Log Transformation

```
In [74]: import numpy as np
         # Sample dataset
         # Apply log transformation
         log_transformed_data = np.log(data)
         # Print original and log-transformed data
         print("Original Data:", data)
         print("Log-Transformed Data:", log_transformed_data)
         Original Data: 0
                              2.5
               2.6
         2
               2.6
         3
               3.2
         4
              3.4
               ...
         579 8.4
         580 8.4
         581 8.5
         582
               8.6
         583
               9.0
         Name: IMDBScore, Length: 584, dtype: float64
         Log-Transformed Data: 0 0.916291
         1
               0.955511
         2
               0.955511
         3
              1.163151
              1.223775
                 . . .
         579 2.128232
         580 2.128232
         581 2.140066
         582
               2.151762
         583
               2.197225
         Name: IMDBScore, Length: 584, dtype: float64
```

One Hot Encoding

```
In [75]: df2=df.copy()
```

```
In [76]: from sklearn.preprocessing import LabelEncoder
    object_cols = ["Title", "Genre"] # doing one hor encoding for Columns Title
    label_encoder = LabelEncoder()
    for col in object_cols:
        label_encoder.fit(df2[col])
        df2[col] = label_encoder.transform(df2[col])
    df2
```

Out[76]:

	Title	Genre	Premiere	Runtime	IMDBScore	Language
0	147	45	August 5, 2019	58	2.5	English/Japanese
1	120	106	August 21, 2020	81	2.6	Spanish
2	433	93	December 26, 2019	79	2.6	Italian
3	500	63	January 19, 2018	94	3.2	English
4	243	73	October 30, 2020	90	3.4	Hindi
579	425	40	December 31, 2018	125	8.4	English
580	575	45	October 9, 2015	91	8.4	English/Ukranian/Russian
581	410	74	December 16, 2018	153	8.5	English
582	145	45	December 8, 2020	89	8.6	Portuguese
583	121	45	October 4, 2020	83	9.0	English

584 rows × 6 columns

Scaling

```
In [77]: import pandas as pd
         from sklearn.preprocessing import MinMaxScaler, StandardScaler
         data1 = data.to_numpy()
         data1=data1.reshape(-1,1)
         # Scaling (Min-Max scaling)
         scaler = MinMaxScaler()
         scaled_data = scaler.fit_transform(data1)
         # Print results
         print("Original DataFrame:")
         print(data1)
         print("\nScaled DataFrame (Min-Max scaling):")
         print(pd.DataFrame(scaled_data1, columns=data1.columns))
         Original DataFrame:
         [[2.5]
          [2.6]
          [2.6]
          [3.2]
          [3.4]
          [3.5]
          [3.7]
          [3.7]
          [3.9]
          [4.1]
          [4.1]
          [4.1]
          [4.1]
          [4.2]
          [4.2]
           [4.3]
           [4.3]
           [4.3]
```

Normalization

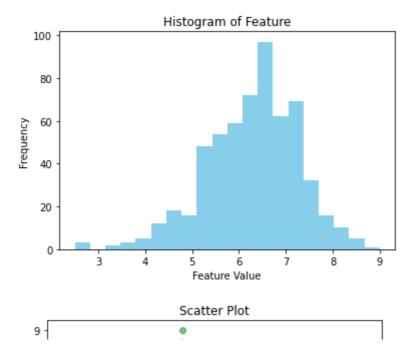
```
In [78]:
        data=df["IMDBScore"].to_numpy()
         # Sample data
         data = data.reshape(-1, 1)
         # Initialize the StandardScaler
         scaler = StandardScaler()
         # Fit and transform the data to normalize it
         normalized_data = scaler.fit_transform(data)
         # Print the normalized data
         print(normalized_data)
         [[-3.85494543]
          [-3.75273959]
          [-3.75273959]
          [-3.13950452]
          [-2.93509283]
          [-2.83288699]
          [-2.6284753]
          [-2.6284753]
          [-2.42406361]
          [-2.21965192]
          [-2.21965192]
          [-2.21965192]
          [-2.21965192]
          [-2.11744608]
          [-2.11744608]
          [-2.01524024]
          [-2.01524024]
          [-2.01524024]
          [-2.01524024]
```

Standardization

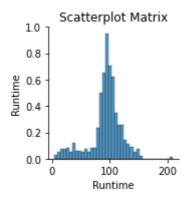
```
In [79]: # Sample data
         # Initialize the StandardScaler
         scaler = StandardScaler()
         # Fit and transform the data to standardize it
         standardized_data = scaler.fit_transform(data)
         # Print the standardized data
         print(standardized_data)
         [[-3.85494543]
          [-3.75273959]
          [-3.75273959]
          [-3.13950452]
          [-2.93509283]
          [-2.83288699]
          [-2.6284753]
          [-2.6284753]
          [-2.42406361]
          [-2.21965192]
          [-2.21965192]
          [-2.21965192]
          [-2.21965192]
          [-2.11744608]
          [-2.11744608]
          [-2.01524024]
          [-2.01524024]
          [-2.01524024]
          [-2.01524024]
```

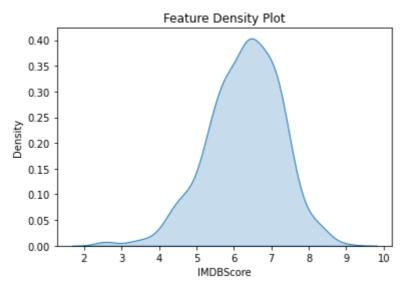
Plot for Feature Engineering

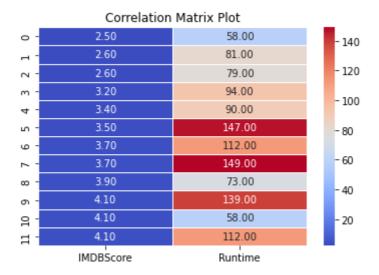
```
In [84]:
         import pandas as pd
         import matplotlib.pyplot as plt
         # Assuming you have a DataFrame 'df' with your data
         # 1. Histogram
         plt.hist(df2['IMDBScore'], bins=20, color='skyblue')
         plt.xlabel('Feature Value')
         plt.ylabel('Frequency')
         plt.title('Histogram of Feature')
         plt.show()
         # 2. Scatter Plot
         plt.scatter(df2['Genre'], df2['IMDBScore'], alpha=0.5, c='green')
         plt.xlabel('Feature 1')
         plt.ylabel('Feature 2')
         plt.title('Scatter Plot')
         plt.show()
         # 3. Box Plot
         plt.boxplot(df2['Genre'])
         plt.xlabel('Feature')
         plt.title('Box Plot')
         plt.show()
         # 5. Bar Plot for Categorical Data
         plt.bar(df2['Genre'], df['IMDBScore'], color='orange')
         plt.xlabel('Category')
         plt.ylabel('Count')
         plt.title('Bar Plot for Categorical Data')
         plt.show()
         # 6. Time Series Plot (assuming a time-series dataset)
         plt.plot(df['Runtime'], df['IMDBScore'], color='purple')
         plt.xlabel('Timestamp')
         plt.ylabel('Value')
         plt.title('Time Series Plot')
         plt.show()
         # 7. Pair Plot (for a selection of features)
         import seaborn as sns
         features = ['Genre', 'Runtime', 'IMDBScore']
         sns.pairplot(df[features])
         plt.title('Pair Plot')
         plt.show()
```



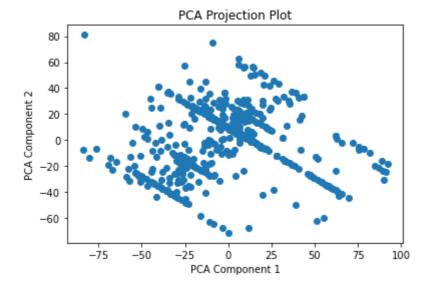
```
In [86]:
         import pandas as pd
         import matplotlib.pyplot as plt
         import seaborn as sns # Import Seaborn for scatter plots
         # Assuming you have a DataFrame 'df' with your data
         # 1. Scatterplot Matrix
         features = ['Genre', 'Runtime'] # Replace with your feature names
         sns.pairplot(df[features])
         plt.title('Scatterplot Matrix')
         plt.show()
         # 2. Feature Density Plot
         feature = 'IMDBScore' # Replace with your feature name
         sns.kdeplot(df2[feature], shade=True)
         plt.title('Feature Density Plot')
         plt.show()
         # 3. Correlation Matrix Plot
         x=df[cols].head(12)
         sns.heatmap(x, annot=True, fmt=".2f", cmap='coolwarm', linewidths=0.5)
         plt.title('Correlation Matrix Plot')
         plt.show()
```







```
In [87]: from sklearn.decomposition import PCA
         # Assuming you have a DataFrame 'df' with your data
         # Specify the features you want to include in the PCA
         features = ['Genre', 'Runtime'] # Replace with your feature names
         # Standardize the data (if necessary)
         # You can use a StandardScaler from scikit-learn
         # from sklearn.preprocessing import StandardScaler
         # scaler = StandardScaler()
         # df[features] = scaler.fit_transform(df[features])
         # Create a PCA model and fit it to your data
         pca = PCA(n_components=2) # You can choose the number of components
         pca_result = pca.fit_transform(df2[features])
         plt.scatter(pca_result[:, 0], pca_result[:, 1])
         plt.xlabel('PCA Component 1')
         plt.ylabel('PCA Component 2')
         plt.title('PCA Projection Plot')
         plt.show()
```



Model Training

Linear Regression

```
In [88]: # Import necessary libraries
         import pandas as pd
         from sklearn.model_selection import train_test_split
         from sklearn.linear_model import LinearRegression
         from sklearn.metrics import mean_squared_error, r2_score
         X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, ra
         X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0
         # Create and train the model (linear regression in this case)
         model = LinearRegression()
         model.fit(X_train, y_train)
         # Make predictions on the validation set
         y_val_pred = model.predict(X_val)
         # Evaluate the model
         mse = mean_squared_error(y_val, y_val_pred)
         r2 = r2_score(y_val, y_val_pred)
         print(f"Mean Squared Error: {mse}")
         print(f"R-squared: {r2}")
```

Mean Squared Error: 0.8778747725462929

R-squared: 0.027707099323870277

Decision Tree

```
In [89]: # Import necessary libraries
         import pandas as pd
         from sklearn.model selection import train test split
         from sklearn.tree import DecisionTreeRegressor
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import mean_squared_error, r2_score
         X train, X temp, y train, y temp = train test split(X, y, test size=0.3, ra
         X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0
         # Feature scaling
         scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X val = scaler.transform(X val)
         # Create and train the decision tree model with adjusted hyperparameters
         model = DecisionTreeRegressor(max_depth=5, min_samples_split=5, min_samples
         model.fit(X_train, y_train)
         # Make predictions on the validation set
         y_val_pred = model.predict(X_val)
         # Evaluate the model
         mse = mean_squared_error(y_val, y_val_pred)
         r2 = r2_score(y_val, y_val_pred)
         print(f"Mean Squared Error: {mse}")
         print(f"R-squared: {r2}")
```

Mean Squared Error: 0.8258483907246518

R-squared: 0.08532907830650449

Random Forest

```
In [90]: # Import necessary libraries
         import pandas as pd
         from sklearn.model selection import train test split
         from sklearn.ensemble import RandomForestRegressor
         from sklearn.metrics import mean_squared_error, r2_score
         X_train, X_temp, y_train, y_temp = train_test_split(X, y, test_size=0.3, ra
         X_val, X_test, y_val, y_test = train_test_split(X_temp, y_temp, test_size=0
         # Create and train the Random Forest model
         model = RandomForestRegressor(n_estimators=100, random_state=42) # You can
         model.fit(X_train, y_train)
         # Make predictions on the validation set
         y_val_pred = model.predict(X_val)
         # Evaluate the model
         mse = mean_squared_error(y_val, y_val_pred)
         r2 = r2_score(y_val, y_val_pred)
         print(f"Mean Squared Error: {mse}")
         print(f"R-squared: {r2}")
```

Mean Squared Error: 0.8215188404881246

R-squared: 0.09012428496893776

Gradient boosting model

```
In [91]:
        from sklearn.ensemble import GradientBoostingRegressor
         from sklearn.metrics import mean_squared_error, r2_score,mean_absolute_error
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra
         # Standardize features (optional but can help gradient boosting)
         scaler = StandardScaler()
         X_train = scaler.fit_transform(X_train)
         X test = scaler.transform(X test)
         # Build and train the gradient boosting model
         regressor = GradientBoostingRegressor(n_estimators=100, learning_rate=0.1,
         regressor.fit(X_train, y_train)
         # Make predictions
         y_pred = regressor.predict(X_test)
         # Evaluate the model
         mae = mean_absolute_error(y_test, y_pred)
         mse = mean_squared_error(y_test, y_pred)
         r2 = r2_score(y_test, y_pred)
         print(f"Mean Absolute Error: {mae}")
         print(f"Mean Squared Error: {mse}")
         print(f"R-squared (R2): {r2}")
         Mean Absolute Error: 0.6737418660432508
         Mean Squared Error: 0.7646858702215756
         R-squared (R2): 0.2632668272200527
         Evaluation
```

```
In [92]: mse = mean_squared_error(ytest, y_pred)
         # Calculate Root Mean Squared Error (RMSE)
         rmse = np.sqrt(mse)
         r2_score=r2_score(ytest,y_pred) # For the Linear Regression
         print(rmse,mse,r2 score)
         0.8744631897464727 0.7646858702215756 0.2632668272200527
In [93]: | mse = mean squared error(ytest, Y pred1)
         # Calculate Root Mean Squared Error (RMSE)
         rmse = np.sqrt(mse)
         print(rmse,mse)
```

0.6717116801102846 0.45119658119658124

```
In [94]: from sklearn.metrics import r2_score
         # Assuming ytest contains actual labels and Y_pred1 contains predicted labe
         r2_result = r2_score(ytest, Y_pred1) # Calculate the R^2 score
         r2 result
Out[94]: 0.565296677031442
In [95]: best_params = grid_search.best_params_
         print("Best Hyperparameters:", best_params)
         # Train the model with the best hyperparameters
         best_rf_regressor = grid_search.best_estimator_
         best_rf_regressor.fit(xtrain, ytrain)
         # Make predictions on the test set
         ypred = best_rf_regressor.predict(xtest)
         # Evaluate the model
         mse = mean_squared_error(ytest, ypred)
         rmse = np.sqrt(mse)
         r2 = r2_score(ytest, ypred)
         print("Mean Squared Error:", mse)
         print("Root Mean Squared Error:", rmse)
         print("R-squared:", r2)
         Best Hyperparameters: {'max_depth': 10, 'min_samples_leaf': 4, 'min_sample
```

Best Hyperparameters: {'max_depth': 10, 'min_samples_leaf': 4, 'min_samples_s_split': 10, 'n_estimators': 100}
Mean Squared Error: 0.7810925200023665
Root Mean Squared Error: 0.8837943878540792
R-squared: 0.24745991405688794

```
In [96]: rmse = np.sqrt(mse)

# Create a bar chart to visualize the errors
errors = [mae, mse, rmse, r2]
error_labels = ['MAE', 'MSE', 'RMSE', 'R2']

plt.bar(error_labels, errors, color=['blue', 'green', 'orange', 'red'])
plt.xlabel('Error Metric')
plt.ylabel('Error Value')
plt.title('Error Metrics for the Model')
plt.show()
```

