Import Libraries

In [3]:
```
import pandas as pd
import numpy as np
import warnings
from sklearn.model_selection import train_test_split, cross_val_score, GridSearchCV
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.neighbors import KNeighborsRegressor
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt
from sklearn.inspection import permutation_importance
warnings.filterwarnings('ignore')
```

In [2]:
```
from ydata_profiling import ProfileReport
```

Read Data

In [4]:
```
movie = pd.read_csv("movie_metadata.csv")
```

In [4]:
```
movie.head()
```

Out[4]:

	color	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_name
0	Color	James Cameron	723.0	178.0	0.0	855.0	Joel David Moore
1	Color	Gore Verbinski	302.0	169.0	563.0	1000.0	Orlando Bloom
2	Color	Sam Mendes	602.0	148.0	0.0	161.0	Rory Kinnear
3	Color	Christopher Nolan	813.0	164.0	22000.0	23000.0	Christian Bale
4	NaN	Doug Walker	NaN	NaN	131.0	NaN	Rob Walker

5 rows × 28 columns

In [5]:
```
movie.dtypes
```

Out[5]:
```
color                       object
director_name               object
num_critic_for_reviews     float64
duration                   float64
director_facebook_likes    float64
actor_3_facebook_likes     float64
actor_2_name                object
actor_1_facebook_likes     float64
gross                      float64
genres                      object
actor_1_name                object
movie_title                 object
num_voted_users              int64
cast_total_facebook_likes    int64
actor_3_name                object
facenumber_in_poster       float64
plot_keywords               object
movie_imdb_link             object
num_user_for_reviews       float64
language                    object
country                     object
content_rating              object
budget                     float64
title_year                 float64
actor_2_facebook_likes     float64
imdb_score                 float64
aspect_ratio               float64
movie_facebook_likes         int64
dtype: object
```

Exploratory Data Analysis

In [6]:
```
profile = ProfileReport(movie, title = "Movie Ratings Report")
```

In [7]:
```
profile.to_file("movie_ratings_metadata_profile.html")
```

A Jupyter widget could not be displayed because the widget state could not be found. This could happen if the kernel storing the widget is no longer available, or if the widget state was not saved in the notebook. You may be able to create the widget by running the appropriate cells.

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In [8]:
```
profile
```

Overview

Dataset statistics

Number of variables	28
Number of observations	5043
Missing cells	2698
Missing cells (%)	1.9%
Duplicate rows	45
Duplicate rows (%)	0.9%
Total size in memory	1.1 MiB
Average record size in memory	224.0 B

Variable types

Categorical	3
Text	9
Numeric	16

Alerts

Dataset has 45 (0.9%) duplicate rows	**Duplicates**
`num_critic_for_reviews` is highly overall correlated with `num_voted_users` and 1 other fields (num_voted_users, num_user_for_reviews)	**High correlation**

Out[8]:

Examine and Remove Observations with missing values

In [5]:
```
# Report missing values
print(movie.isnull().sum())
```

```
color                         19
director_name                104
num_critic_for_reviews        50
duration                      15
director_facebook_likes      104
actor_3_facebook_likes        23
actor_2_name                  13
actor_1_facebook_likes         7
gross                        884
genres                         0
actor_1_name                   7
movie_title                    0
num_voted_users                0
cast_total_facebook_likes      0
actor_3_name                  23
facenumber_in_poster          13
plot_keywords                153
movie_imdb_link                0
num_user_for_reviews          21
language                      12
country                        5
content_rating               303
budget                       492
title_year                   108
actor_2_facebook_likes        13
imdb_score                     0
aspect_ratio                 329
movie_facebook_likes           0
dtype: int64
```

In [10]:
```
# Drop columns with missing values
movie = movie.dropna()
```

Check and Drop Duplicates

In [11]:
```
# Check for duplicates
print(movie.duplicated().sum())
```

```
33
```

In [12]:
```
# Remove duplicates
movie = movie.drop_duplicates()
```

Examine Categorical Variables

In [13]:
```
# Check for categorical columns
for col in movie.columns:
    if movie[col].dtype == "object":
        print(col)
```

```
color
director_name
actor_2_name
genres
actor_1_name
movie_title
actor_3_name
plot_keywords
movie_imdb_link
language
country
content_rating
```

Identify and Exclude Highly Correlated Features

In [15]:
```
# Check correlation between variables
correlation_matrix = X.corr()

# Create a mask for highly correlated features
threshold = 0.8  # Set your correlation threshold here
correlation_mask = abs(correlation_matrix) > threshold

# Identify highly correlated pairs
correlation_pairs = []
for i in range(len(correlation_matrix.columns)):
    for j in range(i + 1, len(correlation_matrix.columns)):
        if correlation_mask.iloc[i, j]:
            correlation_pairs.append((correlation_matrix.columns[i], correlation_matrix.columns[j]

print("Highly correlated feature pairs:")
for feature1, feature2 in correlation_pairs:
    print(f"{feature1} - {feature2}")
```

```
Highly correlated feature pairs:
actor_1_facebook_likes - cast_total_facebook_likes
```

In [16]:
```
# Remove one of each correlated pair
filtered_features = set()
for feature1, feature2 in correlation_pairs:
    if feature1 in filtered_features or feature2 in filtered_features:
        continue
    filtered_features.add(feature2)

# Drop highly correlated features from X
X_filtered = X.drop(columns=filtered_features)
```

Define Features and Targets and Training Test Split

In [14]:
```
# Extract features and target variable
X = movie.drop("imdb_score", axis=1)
y = movie["imdb_score"]
```

In [17]:
```
# Split the data into training and testing sets (70-30)
X_train, X_test, y_train, y_test = train_test_split(X_filtered, y, test_size=0.3, random_state=42)
```

Create Transformers for Numerical and Categorical Features

In [18]:
```
# Define numerical and categorical features
numerical_features = X_filtered.select_dtypes(include=[np.number]).columns.tolist()
categorical_features = X_filtered.select_dtypes(include=[object]).columns.tolist()
```

In [19]:
```
numerical_features
```

Out[19]:
```
['num_critic_for_reviews',
 'duration',
 'director_facebook_likes',
 'actor_3_facebook_likes',
 'actor_1_facebook_likes',
 'gross',
 'num_voted_users',
 'facenumber_in_poster',
 'num_user_for_reviews',
 'budget',
 'title_year',
 'actor_2_facebook_likes',
 'aspect_ratio',
 'movie_facebook_likes']
```

In [20]:
```
categorical_features
```

Out[20]:
```
['color',
 'director_name',
 'actor_2_name',
 'genres',
 'actor_1_name',
 'movie_title',
 'actor_3_name',
 'plot_keywords',
 'movie_imdb_link',
 'language',
 'country',
 'content_rating']
```

In [21]:
```
# Preprocessing: Create transformers for numerical and categorical features
numeric_transformer = Pipeline(steps=[('scaler', StandardScaler())])
categorical_transformer = Pipeline(steps=[('onehot', OneHotEncoder(handle_unknown='ignore'))])

preprocessor = ColumnTransformer(
    transformers=[
        ('num', numeric_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])
```

Define Regressor Models

In [22]:
```
# Define models
models = {
    "KNN": KNeighborsRegressor(),
    "Random Forest": RandomForestRegressor(),
    "Gradient Boosting": GradientBoostingRegressor()
}
```

Define Hyperparameters

In [23]:
```
param_grids = {
    "KNN": {
        "model__n_neighbors": [3, 5, 7],
        "model__weights": ['uniform', 'distance'],
        "model__p": [1, 2]  # Manhattan or Euclidean distance
    },
    "Random Forest": {
        "model__n_estimators": [50, 100],
        "model__max_depth": [None, 10, 20],
        "model__min_samples_split": [2, 5, 10],
        "model__min_samples_leaf": [1, 2, 4],
        "model__max_features": ['auto', 'sqrt', 'log2']
    },
    "Gradient Boosting": {
        "model__n_estimators": [50, 100],
        "model__learning_rate": [0.01, 0.1, 0.2],
        "model__max_depth": [3, 5, 7],
        "model__subsample": [0.8, 0.9, 1.0],  # Fraction of samples used for fitting trees
        "model__min_samples_split": [2, 5, 10]
    }
}
```

Model Training and Identifying best Hyperparameters

In [24]:
```
best_models = {}
for model_name, model in models.items():
    pipeline = Pipeline(steps=[('preprocessor', preprocessor), ('model', model)])
    param_grid = param_grids[model_name]
    grid_search = GridSearchCV(pipeline, param_grid, cv=5, scoring='neg_mean_squared_error')
    grid_search.fit(X_train, y_train)
    best_model = grid_search.best_estimator_
    best_models[model_name] = best_model
```

In [27]:
```
best_models
```

```
Out[27]: {'KNN': Pipeline(steps=[('preprocessor',
                                  ColumnTransformer(transformers=[('num',
                                                                   Pipeline(steps=[('scaler',
                                                                                    StandardScaler())]),
                                                                   ['num_critic_for_reviews',
                                                                    'duration',
                                                                    'director_facebook_likes',
                                                                    'actor_3_facebook_likes',
                                                                    'actor_1_facebook_likes',
                                                                    'gross', 'num_voted_users',
                                                                    'facenumber_in_poster',
                                                                    'num_user_for_reviews',
                                                                    'budget', 'title_year',
                                                                    'actor_2_facebook_likes',
                                                                    'aspect_ratio',
                                                                    'movie_facebook_likes']),
                                                                  ('cat',
                                                                   Pipeline(steps=[('onehot',
                                                                                    OneHotEncoder(handle_unknown
='ignore'))]),
                                                                   ['color', 'director_name',
                                                                    'actor_2_name', 'genres',
                                                                    'actor_1_name',
                                                                    'movie_title',
                                                                    'actor_3_name',
                                                                    'plot_keywords',
                                                                    'movie_imdb_link',
                                                                    'language', 'country',
                                                                    'content_rating'])])),
                                 ('model',
                                  KNeighborsRegressor(n_neighbors=7, p=1, weights='distance'))]),
          'Random Forest': Pipeline(steps=[('preprocessor',
                                  ColumnTransformer(transformers=[('num',
                                                                   Pipeline(steps=[('scaler',
                                                                                    StandardScaler())]),
                                                                   ['num_critic_for_reviews',
                                                                    'duration',
                                                                    'director_facebook_likes',
                                                                    'actor_3_facebook_likes',
                                                                    'actor_1_facebook_likes',
                                                                    'gross', 'num_voted_users',
                                                                    'facenumber_in_poster',
                                                                    'num_user_for_reviews',
                                                                    'budget', 'title_year',
                                                                    'actor_2_facebook_likes',
                                                                    'aspect_ratio',
                                                                    'movie_facebook_likes']),
                                                                  ('cat',
                                                                   Pipeline(steps=[('onehot',
                                                                                    OneHotEncoder(handle_unknown
='ignore'))]),
                                                                   ['color', 'director_name',
                                                                    'actor_2_name', 'genres',
                                                                    'actor_1_name',
                                                                    'movie_title',
                                                                    'actor_3_name',
                                                                    'plot_keywords',
                                                                    'movie_imdb_link',
                                                                    'language', 'country',
                                                                    'content_rating'])])),
                                 ('model', RandomForestRegressor(max_features='sqrt'))]),
          'Gradient Boosting': Pipeline(steps=[('preprocessor',
                                  ColumnTransformer(transformers=[('num',
                                                                   Pipeline(steps=[('scaler',
                                                                                    StandardScaler())]),
                                                                   ['num_critic_for_reviews',
                                                                    'duration',
                                                                    'director_facebook_likes',
                                                                    'actor_3_facebook_likes',
```

```
                                                  'actor_1_facebook_likes',
                                                  'gross', 'num_voted_users',
                                                  'facenumber_in_poster',
                                                  'num_user_for_reviews',
                                                  'budget', 'title_year',
                                                  'actor_2_facebook_likes',
                                                  'aspect_ratio',
                                                  'movie_facebook_likes']),
                                                ('cat',
                                                 Pipeline(steps=[('onehot',
                                                                  OneHotEncoder(handle_unknown
='ignore'))]),
                                                 ['color', 'director_name',
                                                  'actor_2_name', 'genres',
                                                  'actor_1_name',
                                                  'movie_title',
                                                  'actor_3_name',
                                                  'plot_keywords',
                                                  'movie_imdb_link',
                                                  'language', 'country',
                                                  'content_rating'])])),
                                ('model',
                                 GradientBoostingRegressor(max_depth=7, subsample=0.8))])}
```

Model Evaluation and Selection

In [43]:
```
eval_results = {}
for model_name, model in best_models.items():
    y_pred = model.predict(X_test)
    rmse = np.sqrt(mean_squared_error(y_test, y_pred))
    r2 = r2_score(y_test, y_pred)
    eval_results[model_name] = (rmse, r2)
```

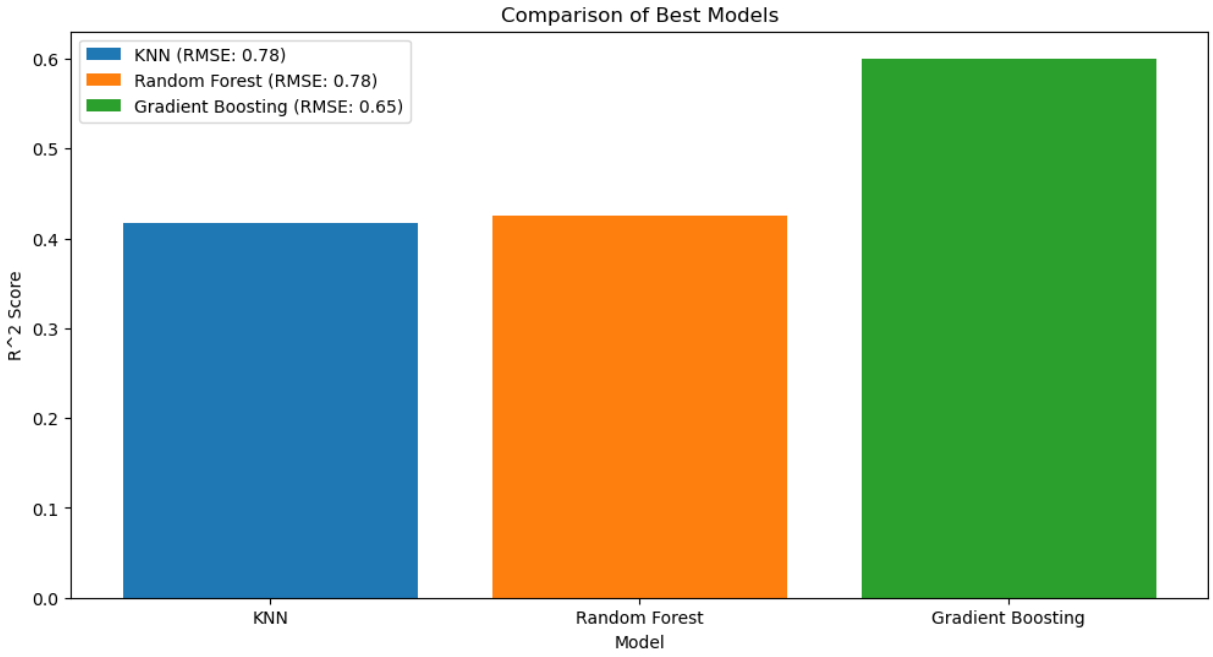
In [44]:
```
eval_results
```

Out[44]:
```
{'KNN': (0.7840421122484241, 0.41734869020343013),
 'Random Forest': (0.7786071384830014, 0.42539856095104045),
 'Gradient Boosting': (0.6491993643125581, 0.6005282070213074)}
```

In [45]:
```
%matplotlib inline
import matplotlib.pyplot as plt
```

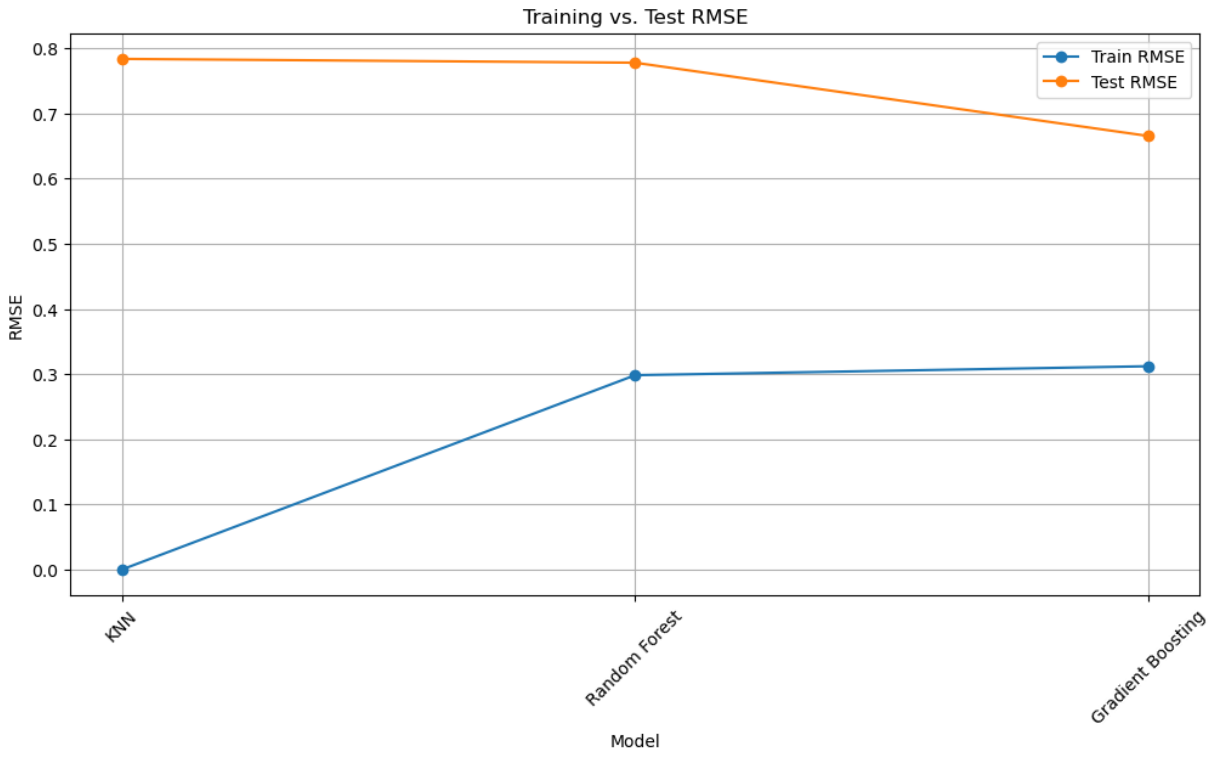
In [46]:

```
# Plot metrics for best models
plt.figure(figsize=(12, 6))
for model_name, (rmse, r2) in eval_results.items():
    plt.bar(model_name, r2, label=f'{model_name} (RMSE: {rmse:.2f})')
plt.xlabel('Model')
plt.ylabel('R^2 Score')
plt.title('Comparison of Best Models')
plt.legend()
plt.show()
```



In [47]:

```
# Train and evaluate models
eval_results = {}
train_rmse_values = []
test_rmse_values = []

for model_name, model in best_models.items():
    model.fit(X_train, y_train)  # Fit on the training data
    y_train_pred = model.predict(X_train)
    y_test_pred = model.predict(X_test)

    rmse_train = np.sqrt(mean_squared_error(y_train, y_train_pred))
    rmse_test = np.sqrt(mean_squared_error(y_test, y_test_pred))

    eval_results[model_name] = (rmse_train, rmse_test)
    train_rmse_values.append(rmse_train)
    test_rmse_values.append(rmse_test)

# Plot training vs. test results as a line graph
plt.figure(figsize=(12, 6))
x_labels = list(eval_results.keys())

plt.plot(x_labels, train_rmse_values, marker='o', label='Train RMSE')
plt.plot(x_labels, test_rmse_values, marker='o', label='Test RMSE')

plt.xlabel('Model')
plt.ylabel('RMSE')
plt.title('Training vs. Test RMSE')
plt.legend()
plt.xticks(rotation=45)
plt.grid(True)
plt.show()
```



Selected Model

In [80]:
```
selected_model_name = "Gradient Boosting"
selected_model = models[selected_model_name]
selected_model
```

Out[80]:
```
GradientBoostingRegressor
GradientBoostingRegressor()
```