```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# For scaling and encoding
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
```

```
# For modeling and metrics
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error
%matplotlib inline
```

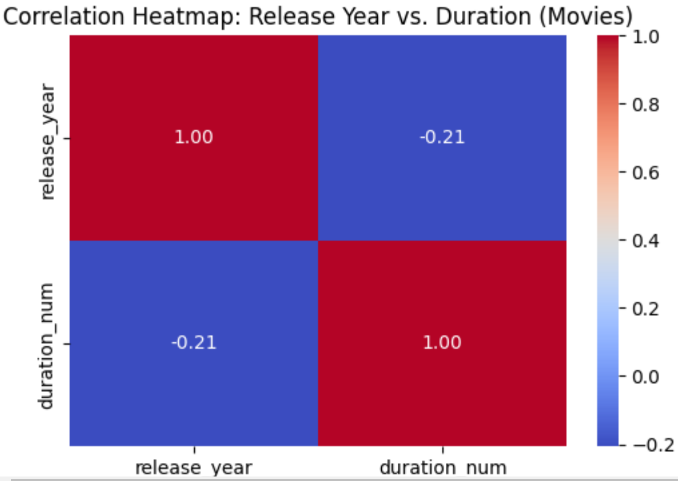
```
# Part1 data loading and initial preprocessing
# Load the Netflix dataset from the attached file (update the file path if needed)
df = pd.read_csv("netflix_titles.csv")
# Clean the 'date_added' column: remove extra spaces and convert to datetime
df['date_added'] = pd.to_datetime(df['date_added'].str.strip(), errors='coerce')
df = df.dropna(subset=['date_added'])  # Remove rows with invalid dates

# Extract the year when the content was added
df['year_added'] = df['date_added'].dt.year

# Display dataset info to verify data cleaning
print("Dataset Information:")
print(df.info())
print(df.head())
```

```
Dataset Information:
<class 'pandas.core.frame.DataFrame'>
Index: 8797 entries, 0 to 8806
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   show_id       8797 non-null   object
 1   type          8797 non-null   object
 2   title         8797 non-null   object
 3   director      6173 non-null   object
 4   cast          7972 non-null   object
 5   country       7967 non-null   object
 6   date_added    8797 non-null   datetime64[ns]
 7   release_year  8797 non-null   int64
 8   rating        8793 non-null   object
 9   duration      8794 non-null   object
 10  listed_in     8797 non-null   object
 11  description   8797 non-null   object
 12  year_added    8797 non-null   int32
dtypes: datetime64[ns](1), int32(1), int64(1), object(10)
memory usage: 927.8+ KB
None
  show_id     type                  title         director  \
0      s1    Movie   Dick Johnson Is Dead  Kirsten Johnson
1      s2  TV Show          Blood & Water              NaN
2      s3  TV Show              Ganglands  Julien Leclercq
3      s4  TV Show  Jailbirds New Orleans              NaN
4      s5  TV Show           Kota Factory              NaN

                                                cast        country  \
0                                                NaN  United States
1  Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...   South Africa
2  Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi...            NaN
3                                                NaN            NaN
4  Mayur More, Jitendra Kumar, Ranjan Raj, Alam K...          India

  date_added  release_year rating   duration  \
0 2021-09-25          2020  PG-13     90 min
1 2021-09-24          2021  TV-MA  2 Seasons
2 2021-09-24          2021  TV-MA   1 Season
3 2021-09-24          2021  TV-MA   1 Season
4 2021-09-24          2021  TV-MA  2 Seasons

                                          listed_in  \
0                                     Documentaries
1   International TV Shows, TV Dramas, TV Mysteries
2  Crime TV Shows, International TV Shows, TV Act...
3                              Docuseries, Reality TV
4  International TV Shows, Romantic TV Shows, TV ...
```

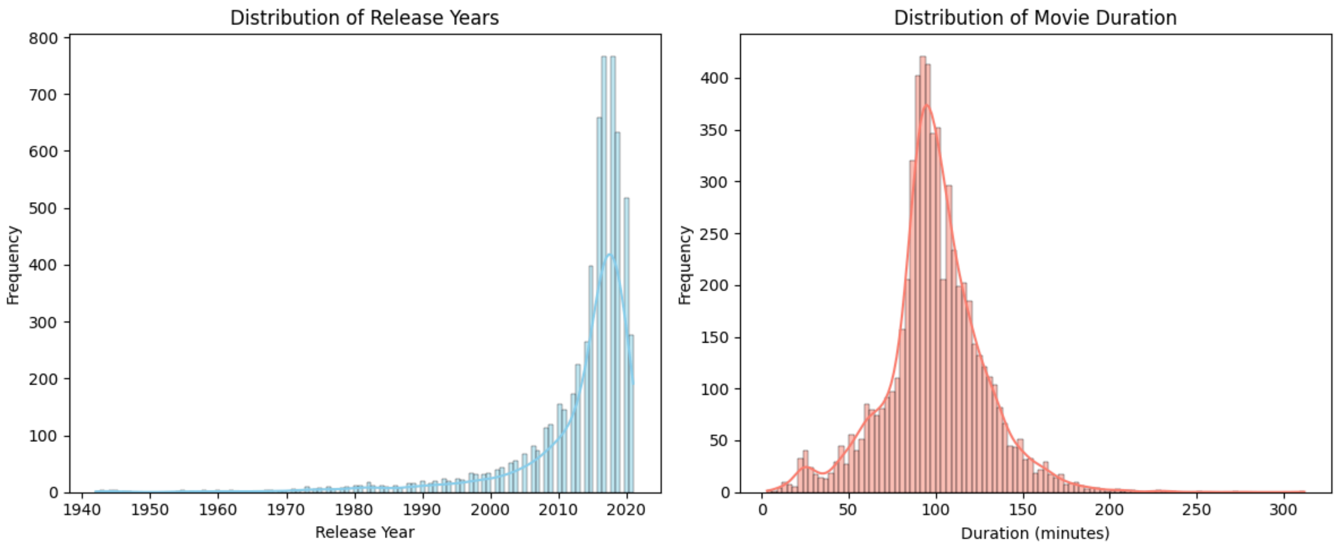
```
                                         description  year_added
0  As her father nears the end of his life, filmm...        2021
1  After crossing paths at a party, a Cape Town t...        2021
2  To protect his family from a powerful drug lor...        2021
3  Feuds, flirtations and toilet talk go down amo...        2021
4  In a city of coaching centers known to train I...        2021
```

```
#part 2 advanced EDA
# Focus on movies for numerical analysis (assumes 'duration' for movies is in format "90 min")
movies = df[df['type'] == 'Movie'].copy()

# Extract numeric duration from the 'duration' column (e.g., "90 min")
movies['duration_num'] = movies['duration'].str.extract('(\d+)').astype(float)
```

```
# Create a correlation matrix for 'release_year' and 'duration_num'
corr_matrix = movies[['release_year', 'duration_num']].corr()

# Plot correlation heatmap
plt.figure(figsize=(6, 4))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation Heatmap: Release Year vs. Duration (Movies)")
plt.show()
```




```
#Enhanced Visualizations: Distribution of Release Year & Duration
plt.figure(figsize=(12, 5))

# Subplot 1: Distribution of Release Years
plt.subplot(1, 2, 1)
sns.histplot(movies['release_year'], kde=True, color='skyblue')
plt.title("Distribution of Release Years")
plt.xlabel("Release Year")
plt.ylabel("Frequency")

# Subplot 2: Distribution of Movie Duration (minutes)
plt.subplot(1, 2, 2)
sns.histplot(movies['duration_num'], kde=True, color='salmon')
plt.title("Distribution of Movie Duration")
plt.xlabel("Duration (minutes)")
plt.ylabel("Frequency")

plt.tight_layout()
plt.show()
```




```
#Scaling Numerical Features
scaler = StandardScaler()
movies['duration_scaled'] = scaler.fit_transform(movies[['duration_num']])
```

```
# One-hot encode the 'rating' column; drop the first category to avoid dummy variable trap
movies_encoded = pd.get_dummies(movies, columns=['rating'], drop_first=True)
```

```
# Clip movie durations to a maximum of 300 minutes
movies['duration_clipped'] = movies['duration_num'].clip(upper=300)
```

```
#  Data Preparation for Modeling
# Define features and target. Here we use 'release_year' and 'duration_scaled' as features.
features = ['release_year', 'duration_scaled']
target = 'duration_num'
from sklearn.impute import SimpleImputer
```

```
# Split the data into training and testing sets (80/20 split)
X = movies[features]
y = movies[target]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
# Manually fill NaN values with the mean of each column in the training set
X_train = X_train.fillna(X_train.mean())  # Fill NaNs in X_train
X_test = X_test.fillna(X_train.mean())   # Fill NaNs in X_test using
```

```
# Initialize an imputer for numerical features with a mean strategy
imputer = SimpleImputer(strategy='mean')
```

```
# Fit the imputer on the training data and transform both training and test data
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)
```

```
# Ensure features and target are numeric (before fitting the model)
X_train = X_train.astype(np.float64)  # Convert X_train to float64
X_test = X_test.astype(np.float64)  # Convert X_test to float64
y_train = y_train.astype(np.float64)  # Convert y_train to float64
```

```
y_train = y_train.dropna()  # Remove rows with NaN in y_train
```

```
X_train = X_train.loc[y_train.index]  # Keep only rows in X_train with indices in y_train
```

```
# Baseline Model 1: Linear Regression
lr_model = LinearRegression()
```

```
lr_model.fit(X_train, y_train)
y_pred_lr = lr_model.predict(X_test)
```

```
# Evaluate the Linear Regression model
r2_lr = r2_score(y_test, y_pred_lr)
rmse_lr = np.sqrt(mean_squared_error(y_test, y_pred_lr))
mae_lr = mean_absolute_error(y_test, y_pred_lr)

print("Linear Regression Performance:")
print(f"R²: {r2_lr:.2f}, RMSE: {rmse_lr:.2f}, MAE: {mae_lr:.2f}")
```

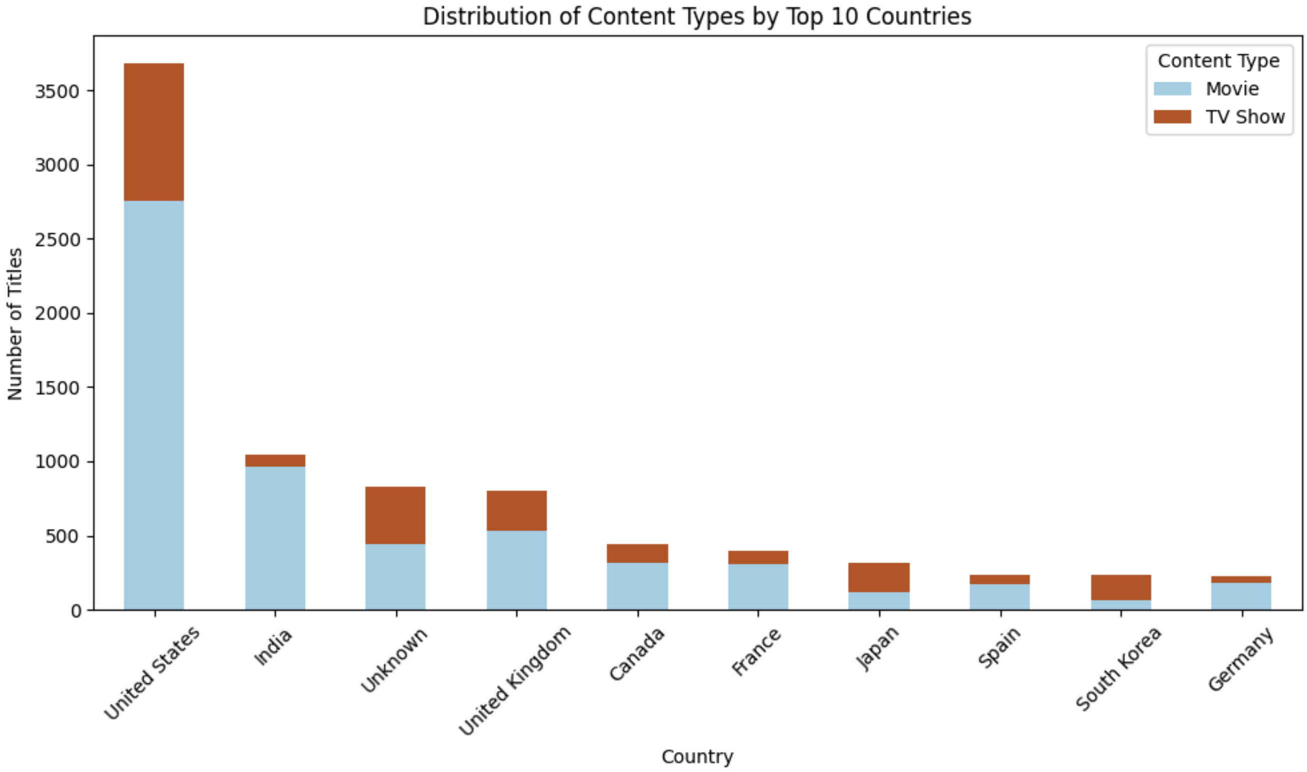
```
Linear Regression Performance:
R²: 1.00, RMSE: 0.00, MAE: 0.00
```

```
# Baseline Model 2: Random Forest Regressor
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)

# Evaluate the Random Forest model
r2_rf = r2_score(y_test, y_pred_rf)
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))
mae_rf = mean_absolute_error(y_test, y_pred_rf)

print("Random Forest Regressor Performance:")
print(f"R²: {r2_rf:.2f}, RMSE: {rmse_rf:.2f}, MAE: {mae_rf:.2f}")

# Feature Importance Analysis (Random Forest)
feature_importances = pd.Series(rf_model.feature_importances_, index=features)
print("Random Forest Feature Importances:")
print(feature_importances.sort_values(ascending=False))
```

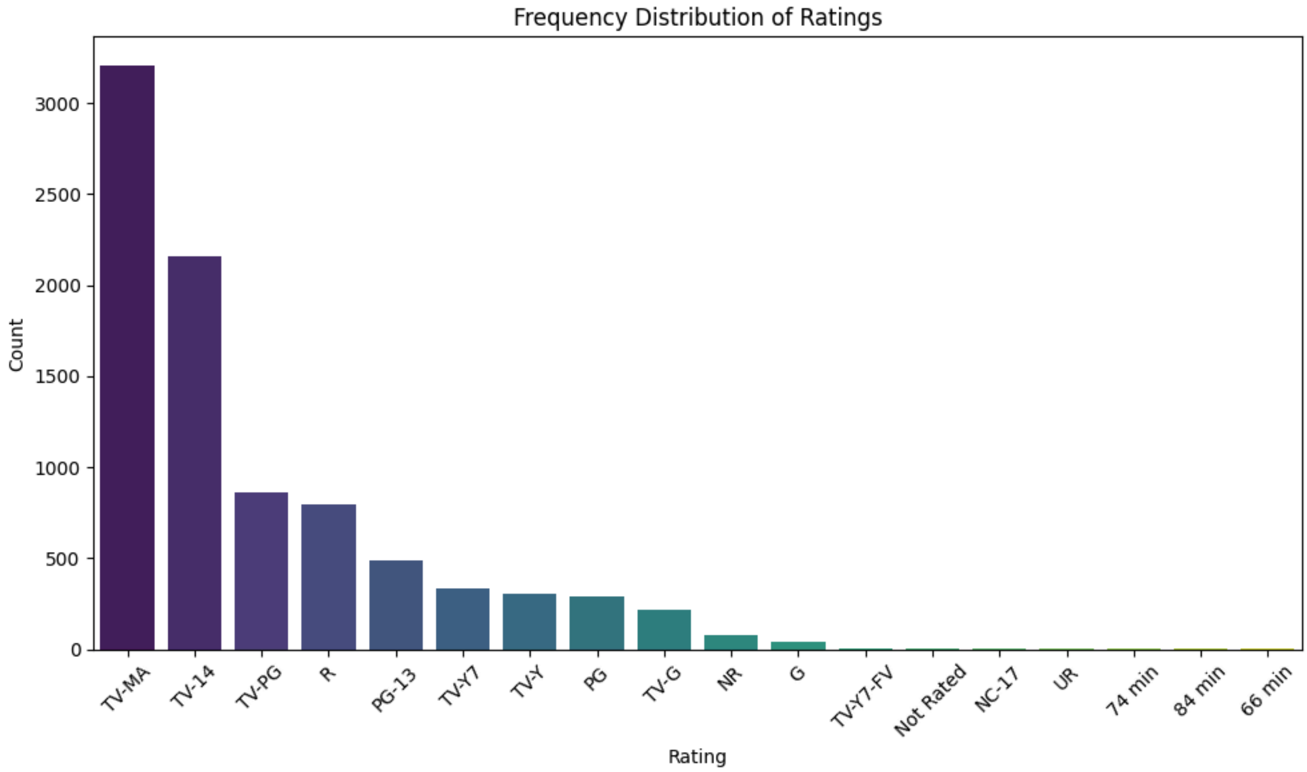
```
Random Forest Regressor Performance:
R²: 1.00, RMSE: 0.49, MAE: 0.02
Random Forest Feature Importances:
duration_scaled    0.999598
release_year       0.000402
dtype: float64
```

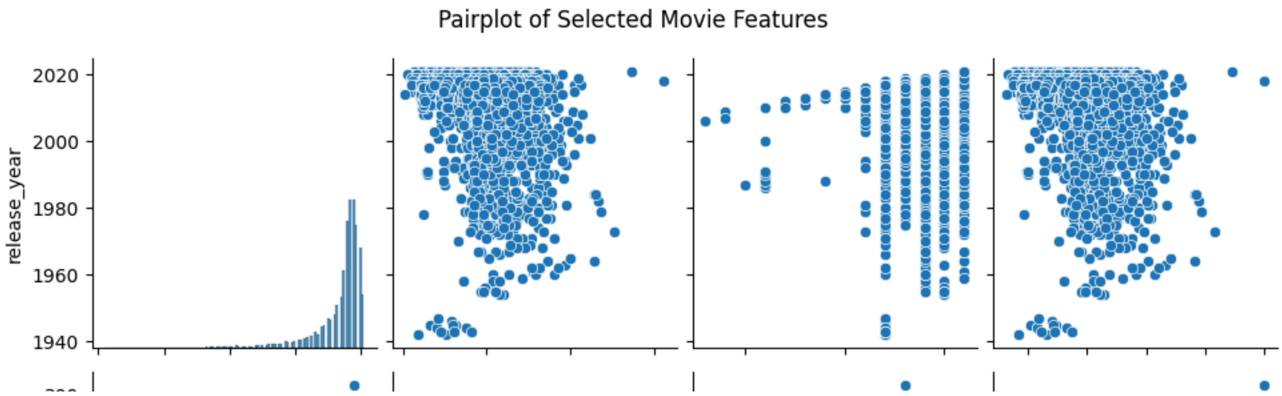
```
# ============================================================================
# Extended Analytics: Additional Exploratory Data Analysis on Netflix Dataset
# ============================================================================

# ----------------------------------------------------------------------------
# 1. Distribution of Content Types by Country
# ----------------------------------------------------------------------------
# Count the number of movies and TV shows available by country.
# Since a title can be associated with multiple countries, we first split the 'country' column.
df ['country'] = df ['country'].fillna('Unknown')  # Replace missing countries with 'Unknown'
df ['country_list'] = df ['country'].str.split(', ')

# Explode the dataframe to have one country per row
df_exploded = df.explode('country_list')

# Group by country and type, then count titles
country_content = df_exploded.groupby(['country_list', 'type']).size().unstack(fill_value=0)

# Plot a bar chart for the top 10 countries by total number of titles
top_countries = country_content.sum(axis=1).nlargest(10).index
country_content_top = country_content.loc[top_countries]

country_content_top.plot(kind='bar', stacked=True, figsize=(10, 6), colormap='Paired')
plt.title("Distribution of Content Types by Top 10 Countries")
plt.xlabel("Country")
plt.ylabel("Number of Titles")
plt.legend(title="Content Type")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# ----------------------------------------------------------------------------
# Text Box (Extended Analytics):
# ----------------------------------------------------------------------------
# Here, we analyzed the distribution of content types (Movies vs. TV Shows) across the top 10 countries.
# This helps identify which regions have a more balanced or skewed mix of content, supporting strategic
# decisions in content acquisition and localization.

# ----------------------------------------------------------------------------
# 2. Rating Frequency Analysis
```

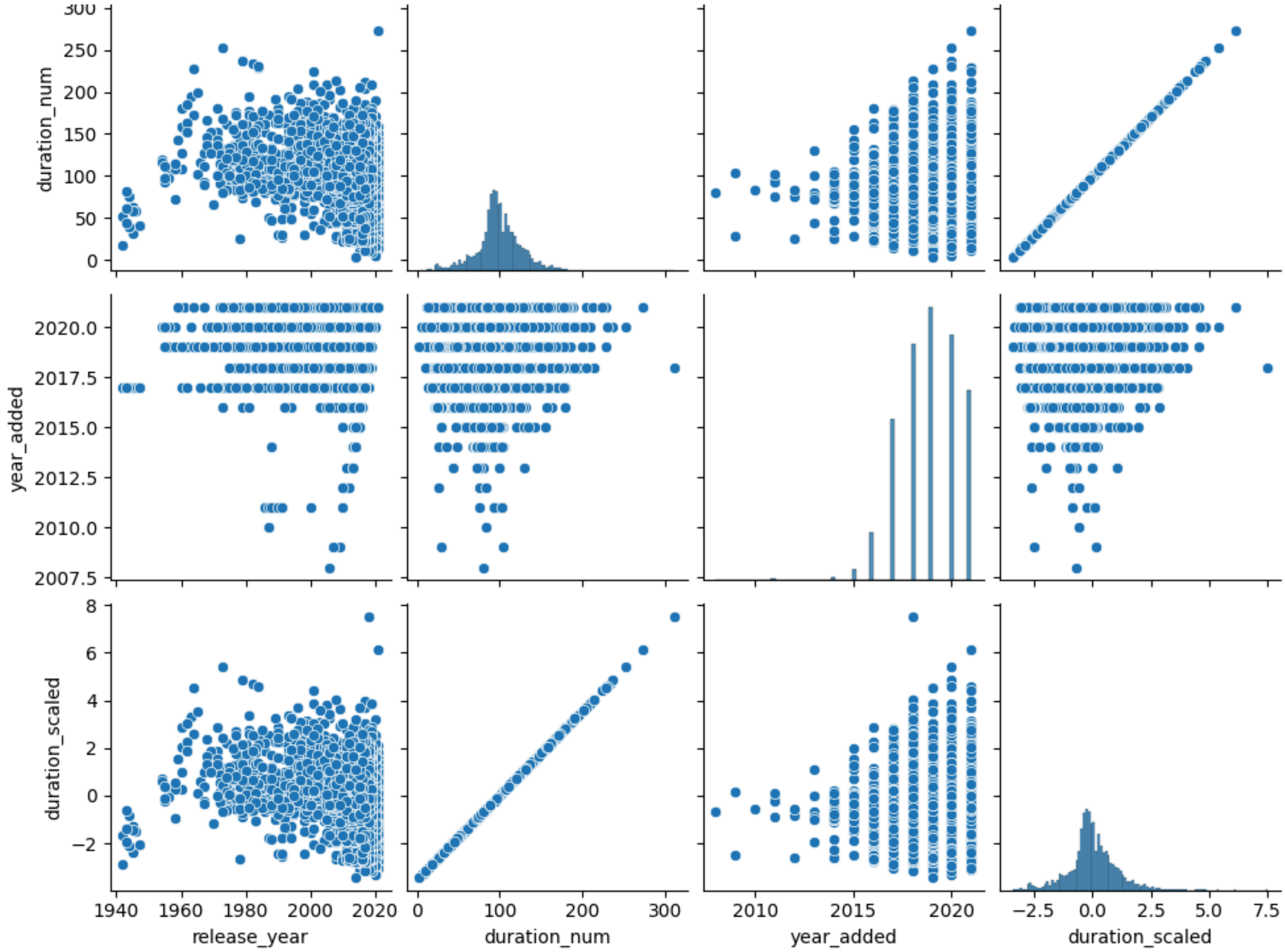
```
# ---------------------------------------------------------------------------
# Analyze the frequency distribution of ratings across the dataset.
# Replace missing ratings with 'Not Rated' for visualization purposes.
df['rating'] = df['rating'].fillna('Not Rated')
rating_counts = df['rating'].value_counts()

plt.figure(figsize=(10, 6))
sns.barplot(x=rating_counts.index, y=rating_counts.values, palette='viridis')
plt.title("Frequency Distribution of Ratings")
plt.xlabel("Rating")
plt.ylabel("Count")
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()

# ---------------------------------------------------------------------------
# Text Box (Extended Analytics):
# ---------------------------------------------------------------------------
# This bar chart shows how content is rated on Netflix. It highlights which ratings are most common,
# thereby offering insight into the audience the platform caters to (e.g., prevalence of mature content vs. family-friendly content).

# ---------------------------------------------------------------------------
# 3. Pairplot of Selected Features
# ---------------------------------------------------------------------------
# For deeper insight, we can create a pairplot to observe relationships among several numeric features.
# We use movies for this analysis, considering features such as 'release_year', 'duration_num', and 'year_added'.
# We'll add the scaled duration feature as well.
sns.pairplot(movies[['release_year', 'duration_num', 'year_added', 'duration_scaled']])
plt.suptitle("Pairplot of Selected Movie Features", y=1.02)
plt.show()

# ---------------------------------------------------------------------------
# Text Box (Extended Analytics):
# ---------------------------------------------------------------------------
# The pairplot visualizes pairwise relationships between key numerical features.
# It aids in detecting patterns or correlations that might not be evident from simple correlation matrices alone.

# ---------------------------------------------------------------------------
# 4. Temporal Trend by Content Type (Extended Analysis)
# ---------------------------------------------------------------------------
# Analyze the trend of content additions over time, broken down by both movies and TV shows.
# Group by year_added and type.
content_trend_all = df.groupby(['year_added', 'type']).size().unstack(fill_value=0)

plt.figure(figsize=(12, 6))
content_trend_all.plot(kind='line', marker='o', colormap='tab10', linewidth=2)
plt.title("Temporal Trend of Content Additions by Type")
plt.xlabel("Year Added")
plt.ylabel("Number of Titles")
plt.legend(title="Content Type")
plt.grid(True, linestyle="--", alpha=0.5)
plt.tight_layout()
plt.show()

# ---------------------------------------------------------------------------
# Text Box (Extended Analytics):
# ---------------------------------------------------------------------------
# This line plot provides a temporal analysis of content additions to Netflix,
# segmented by content type. It further supports the understanding of content expansion
# strategies over time and can be pivotal for forecasting future trends.

# ===========================================================================
# End of Extended Analytics Section
# ===========================================================================
```




```
<ipython-input-33-649fc9210a1d>:48: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.barplot(x=rating_counts.index, y=rating_counts.values, palette='viridis')
```








```
<Figure size 1200x600 with 0 Axes>
```