Video Game Analysis

January 23, 2024

[117]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
from scipy.stats import probplot
import statsmodels.api as sm
import statsmodels.formula.api as smf
from sklearn.preprocessing import LabelEncoder
from sklearn import metrics
from sklearn import linear_model
from sklearn.linear_model import LinearRegression
from sklearn import metrics
from sklearn.model_selection import cross_val_score
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.stats.api as sms
import statsmodels.stats.outliers_influence as oi
import scipy.stats as stats
from boruta import BorutaPy
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error,mean_squared_error, r2_score
```

1 Import data files

All the data belongs to Kaggle

[118]:
```
video_games_sales = pd.read_csv('video_games_sales.csv')

video_games_sales
```

[118]:
```
        rank                                              name platform  \
0          1                                        Wii Sports      Wii
```

```
1          2                            Super Mario Bros.      NES
2          3                               Mario Kart Wii      Wii
3          4                            Wii Sports Resort      Wii
4          5                     Pokemon Red/Pokemon Blue       GB
…      …                                                …    …
16593  16596               Woody Woodpecker in Crazy Castle 5      GBA
16594  16597                    Men in Black II: Alien Escape       GC
16595  16598  SCORE International Baja 1000: The Official Game      PS2
16596  16599                                       Know How 2       DS
16597  16600                                  Spirits & Spells      GBA

         year         genre   publisher  na_sales  eu_sales  jp_sales  \
0      2006.0        Sports    Nintendo     41.49     29.02      3.77
1      1985.0      Platform    Nintendo     29.08      3.58      6.81
2      2008.0        Racing    Nintendo     15.85     12.88      3.79
3      2009.0        Sports    Nintendo     15.75     11.01      3.28
4      1996.0  Role-Playing    Nintendo     11.27      8.89     10.22
…         …           …         …        …       …       …
16593  2002.0      Platform       Kemco      0.01      0.00      0.00
16594  2003.0       Shooter  Infogrames      0.01      0.00      0.00
16595  2008.0        Racing  Activision      0.00      0.00      0.00
16596  2010.0        Puzzle    7G//AMES      0.00      0.01      0.00
16597  2003.0      Platform     Wanadoo      0.01      0.00      0.00

       other_sales  global_sales
0             8.46         82.74
1             0.77         40.24
2             3.31         35.82
3             2.96         33.00
4             1.00         31.37
…              …            …
16593         0.00          0.01
16594         0.00          0.01
16595         0.00          0.01
16596         0.00          0.01
16597         0.00          0.01

[16598 rows x 11 columns]
```

1.0.1 Video Game Sales

- rank = Sales rank
- name = Name of video game
- platform = Video Game Platform
- year = When game was released
- genre = Game Genre
- publsher = Video Game Publisher
- na_sales = North America Sales, Millions

- eu_sales = European Sales, Millions
- jp_sales = Japan Sales, Millions
- other_sales = Sales in other areas, millions

[119]:
```
data = video_games_sales.copy()
```

2 Clean Data

Check for missing values

- If missing values found, impute or drop them based off data
- In this case, we will drop the missing values becuase you can not impute the year or publisher

[120]:
```
data.isnull().sum()
```

[120]:
```
rank              0
name              0
platform          0
year            271
genre             0
publisher        58
na_sales          0
eu_sales          0
jp_sales          0
other_sales       0
global_sales      0
dtype: int64
```

[121]:
```
data = data.dropna()
data.isnull().sum()
```

[121]:
```
rank            0
name            0
platform        0
year            0
genre           0
publisher       0
na_sales        0
eu_sales        0
jp_sales        0
other_sales     0
global_sales    0
dtype: int64
```

Check for duplicates

- If duplicates found, we drop them
- No duplicates were found

[122]:
```
data.duplicated().sum()
```

[122]: 0

Fix data types

[123]:
```
# Convert the columns below into categorical data
data['genre'] = data['genre'].astype('category')
data['publisher'] = data['publisher'].astype('category')
data['platform'] = data['platform'].astype('category')

# Convert float to datetime year
data['year'] = pd.to_datetime(data['year'], format='%Y', errors='coerce')
data['year'] = data['year'].dt.year
```

[124]:
```
data.rename(columns={'na_sales': 'North America Sales',
                     'eu_sales': 'European Sales',
                     'jp_sales': 'Japan Sales',
                     'other_sales': 'Other Sales',
                     'global_sales': 'Global Sales'}, inplace=True)
```

3 Exploratory Data Analysis & Ad-hoc Analysis

Check data summary

[125]:
```
data.describe()
```

[125]:
```
               rank          year  North America Sales  European Sales  \
count  16291.000000  16291.000000         16291.000000    16291.000000
mean    8290.190228   2006.405561             0.265647        0.147731
std     4792.654450      5.832412             0.822432        0.509303
min        1.000000   1980.000000             0.000000        0.000000
25%     4132.500000   2003.000000             0.000000        0.000000
50%     8292.000000   2007.000000             0.080000        0.020000
75%    12439.500000   2010.000000             0.240000        0.110000
max    16600.000000   2020.000000            41.490000       29.020000

        Japan Sales   Other Sales  Global Sales
count  16291.000000  16291.000000  16291.000000
mean       0.078833      0.048426      0.540910
std        0.311879      0.190083      1.567345
min        0.000000      0.000000      0.010000
25%        0.000000      0.000000      0.060000
50%        0.000000      0.010000      0.170000
75%        0.040000      0.040000      0.480000
max       10.220000     10.570000     82.740000
```

[126]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 16291 entries, 0 to 16597
Data columns (total 11 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   rank                 16291 non-null  int64
 1   name                 16291 non-null  object
 2   platform             16291 non-null  category
 3   year                 16291 non-null  int32
 4   genre                16291 non-null  category
 5   publisher            16291 non-null  category
 6   North America Sales  16291 non-null  float64
 7   European Sales       16291 non-null  float64
 8   Japan Sales          16291 non-null  float64
 9   Other Sales          16291 non-null  float64
 10  Global Sales         16291 non-null  float64
dtypes: category(3), float64(5), int32(1), int64(1), object(1)
memory usage: 1.1+ MB
```

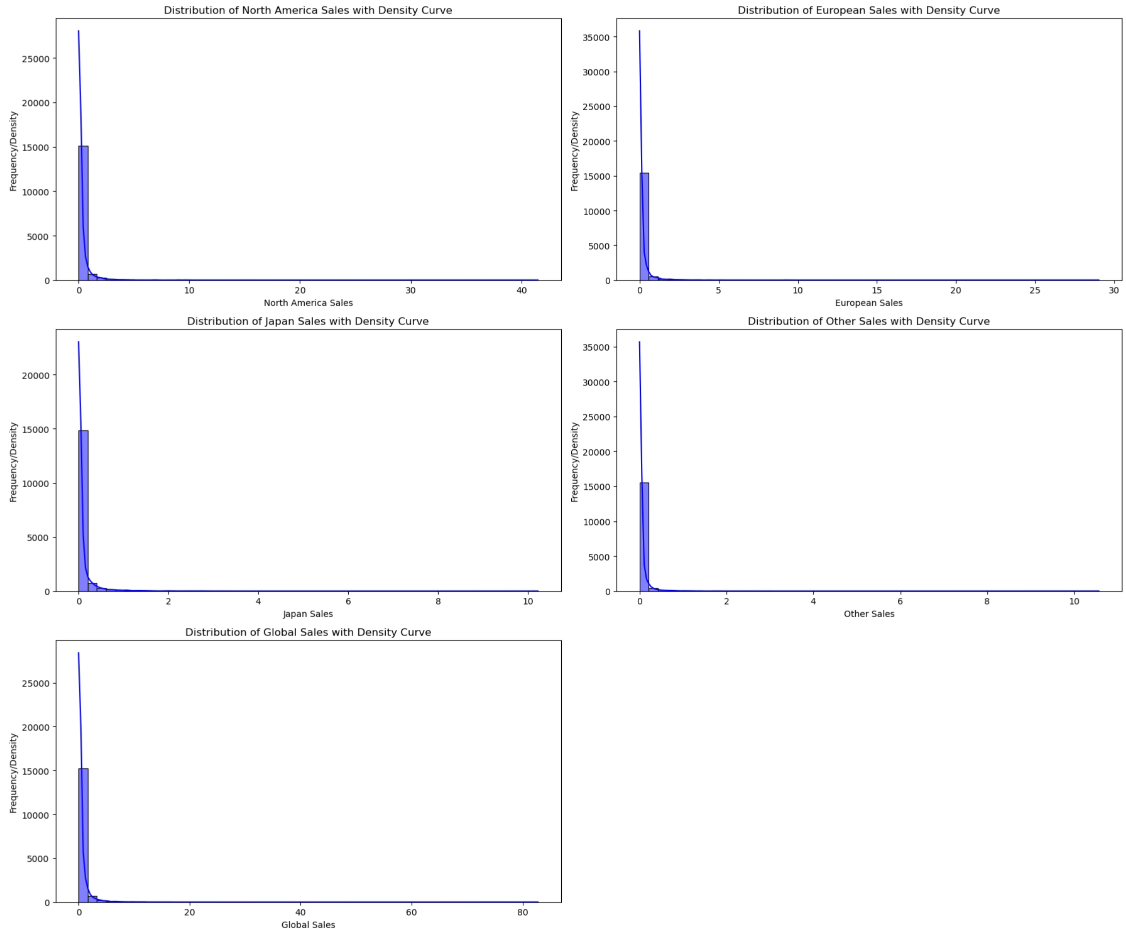
[127]:
```
data.shape
```

[127]: (16291, 11)

Histogram

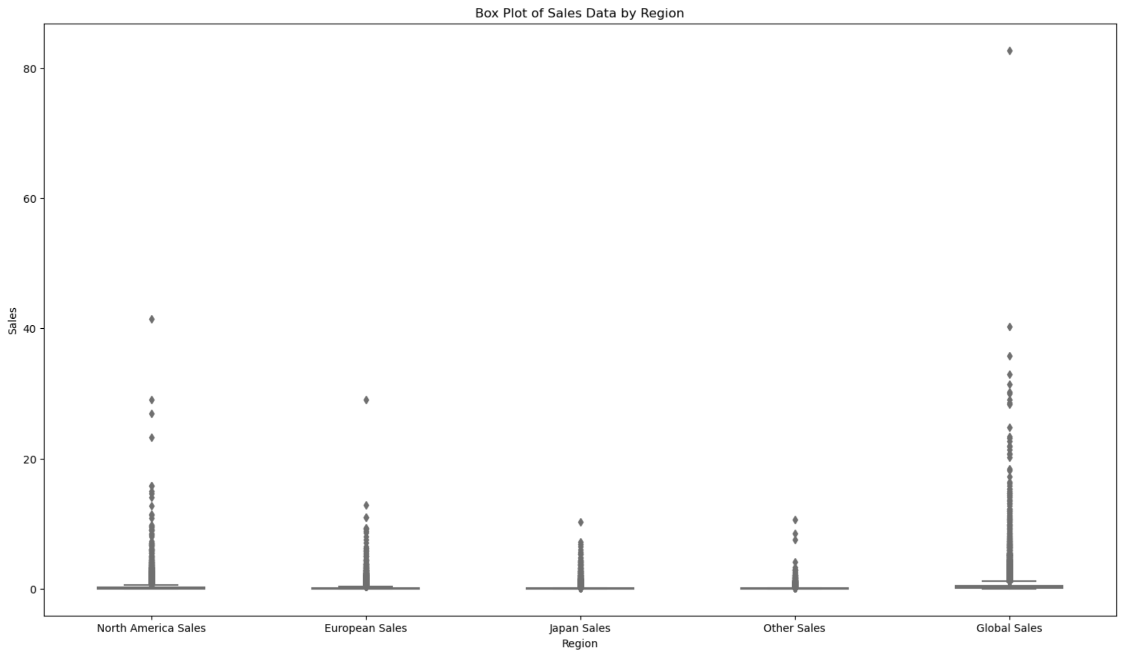
[128]:
```
columns = ['North America Sales', 'European Sales', 'Japan Sales', 'Other␣
↪Sales', 'Global Sales']
```

[129]:
```
plt.figure(figsize=(18, 15))

for i, column in enumerate(columns, 1):
    plt.subplot(3, 2, i)
    sns.histplot(data[column], bins=50, kde=True, color='blue',␣
↪edgecolor='black')
    plt.title(f'Distribution of {column} with Density Curve')
    plt.xlabel(column)
    plt.ylabel('Frequency/Density')

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



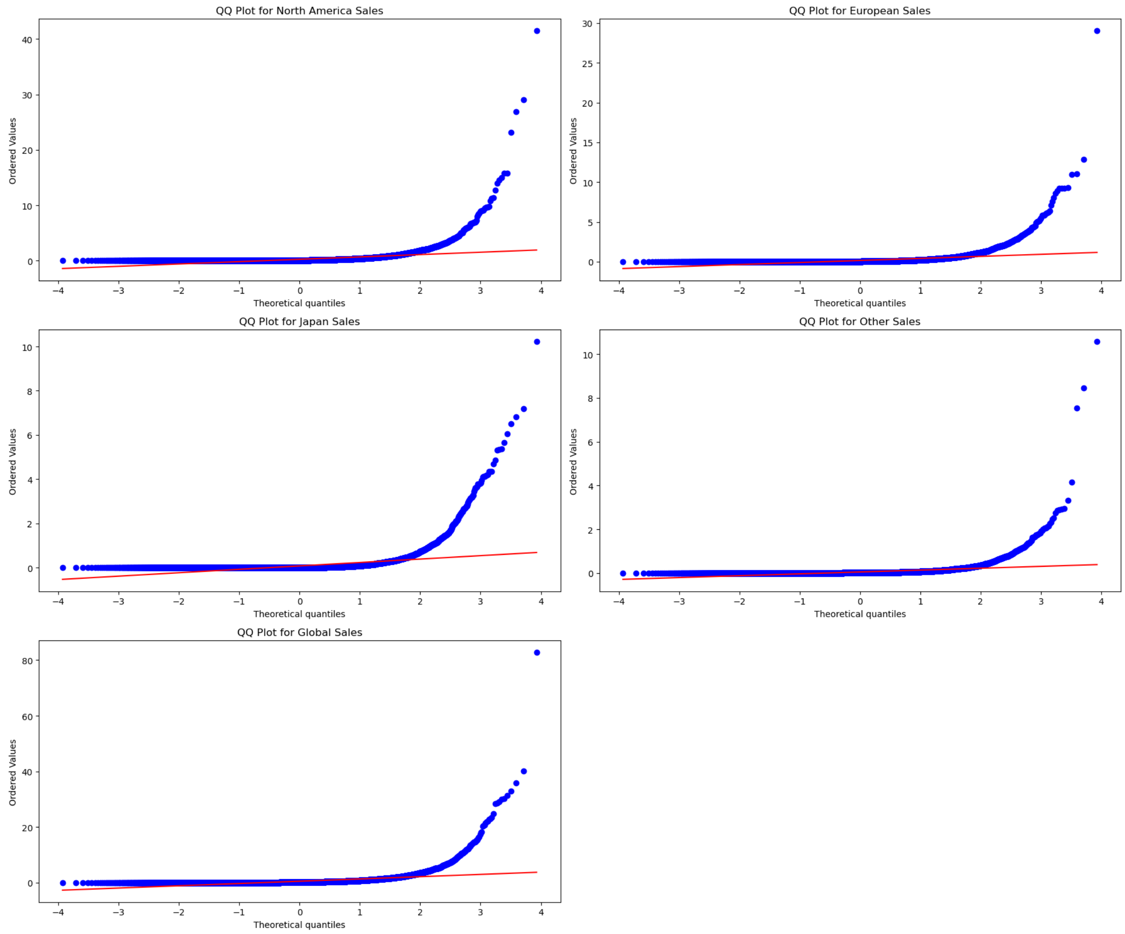
Boxplot

[130]:
```
plt.figure(figsize=(18, 10))



sns.boxplot(data=data[columns], width=0.5, palette='pastel')

plt.title('Box Plot of Sales Data by Region')
plt.xlabel('Region')
plt.ylabel('Sales')
plt.show()
```



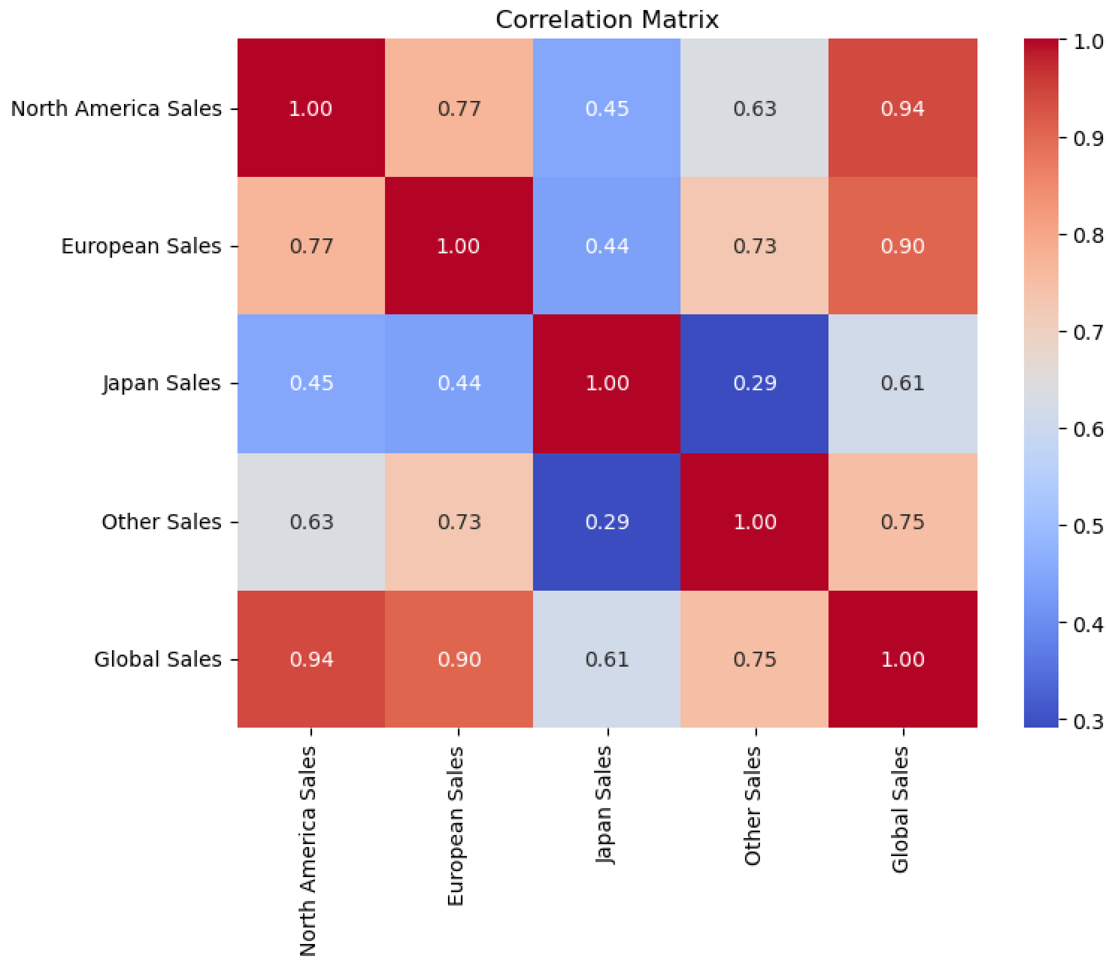
Quantile Plots

[131]:
```
plt.figure(figsize=(18, 15))

for i, column in enumerate(columns, 1):
    plt.subplot(3, 2, i)
    probplot(data[column], plot=plt)
    plt.title(f'QQ Plot for {column}')

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



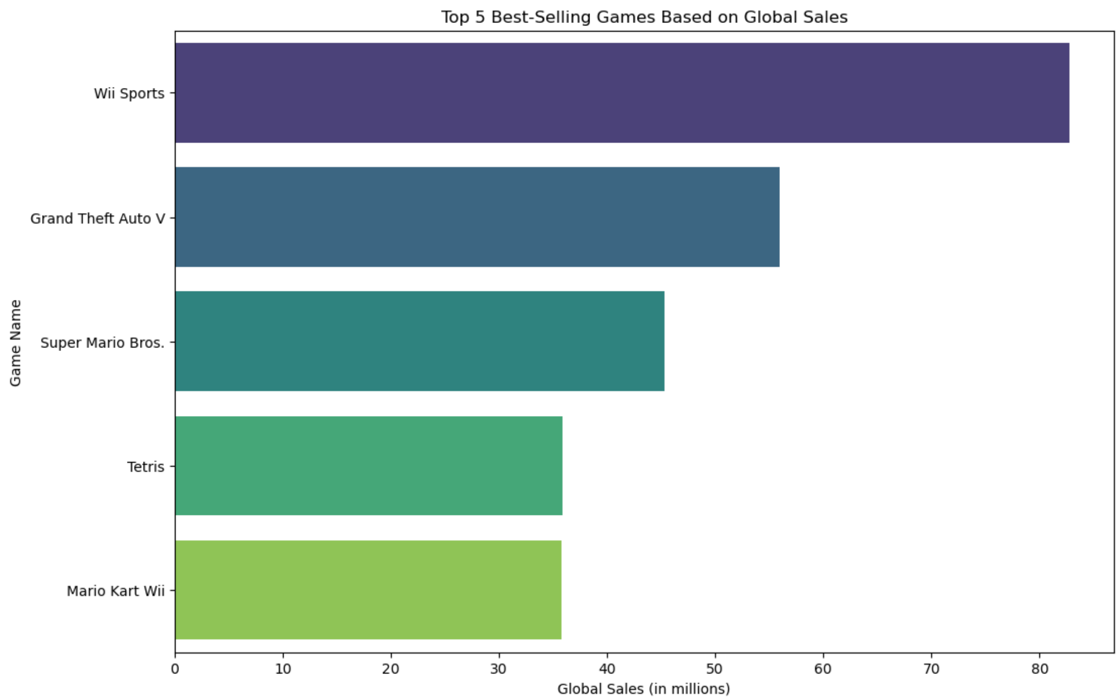
Correlation Matrix

[132]:
```
correlation_matrix = data[['North America Sales', 'European Sales', 'Japan␣
↪Sales', 'Other Sales', 'Global Sales']].corr()

plt.figure(figsize=(8, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix')
plt.show()
```



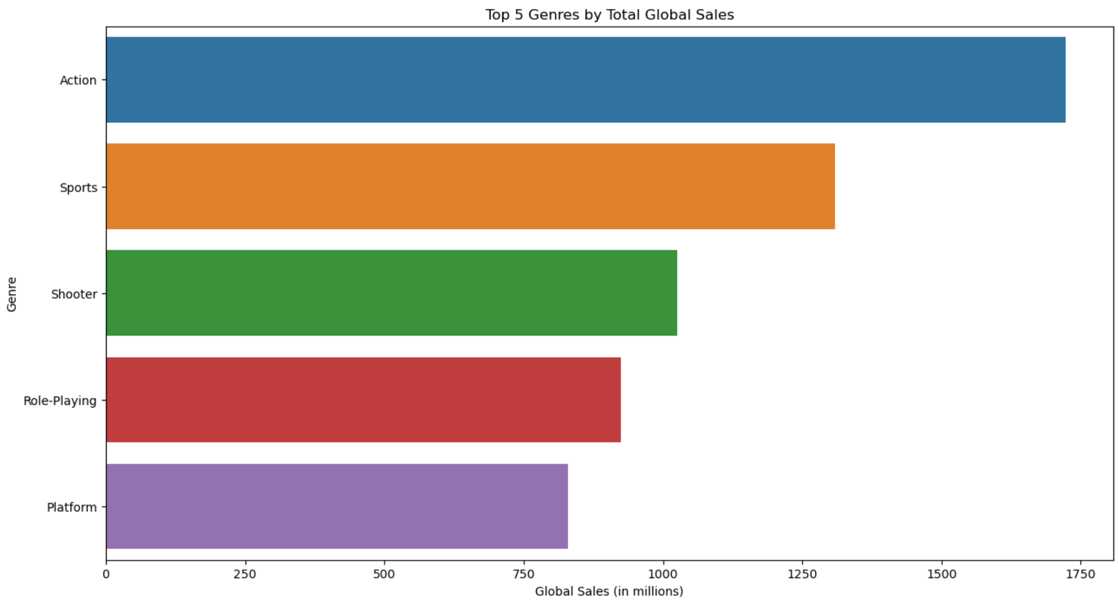
Top 5 Best Seller Games

[133]:
```
top_sellers_combined = data.groupby('name')['Global Sales'].sum().nlargest(5)

plt.figure(figsize=(12, 8))
sns.barplot(x=top_sellers_combined.values, y=top_sellers_combined.index,␣
↪palette='viridis')
plt.title('Top 5 Best-Selling Games Based on Global Sales')
plt.xlabel('Global Sales (in millions)')
plt.ylabel('Game Name')
plt.show()
```



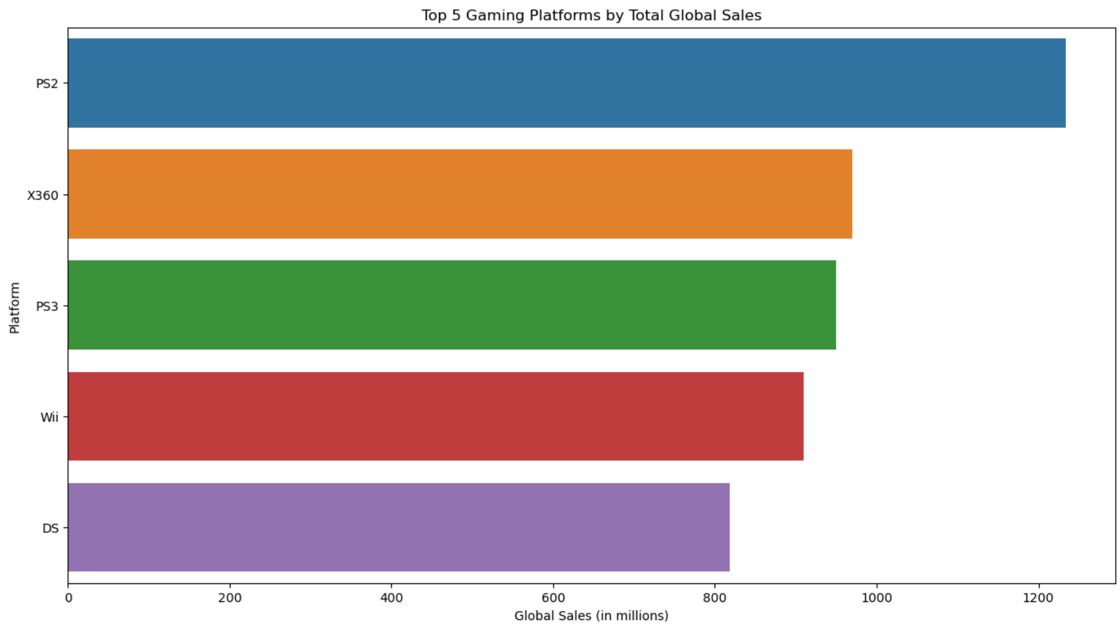
Top 5 genres

[134]:
```
genre_sales = data.groupby('genre')['Global Sales'].sum().nlargest(5)

top_genres = genre_sales.index.tolist()[:5]

plt.figure(figsize=(15, 8))
sns.barplot(x=genre_sales.values, y=genre_sales.index, order=top_genres)
plt.title('Top 5 Genres by Total Global Sales')
plt.xlabel('Global Sales (in millions)')
plt.ylabel('Genre')
plt.show()
```



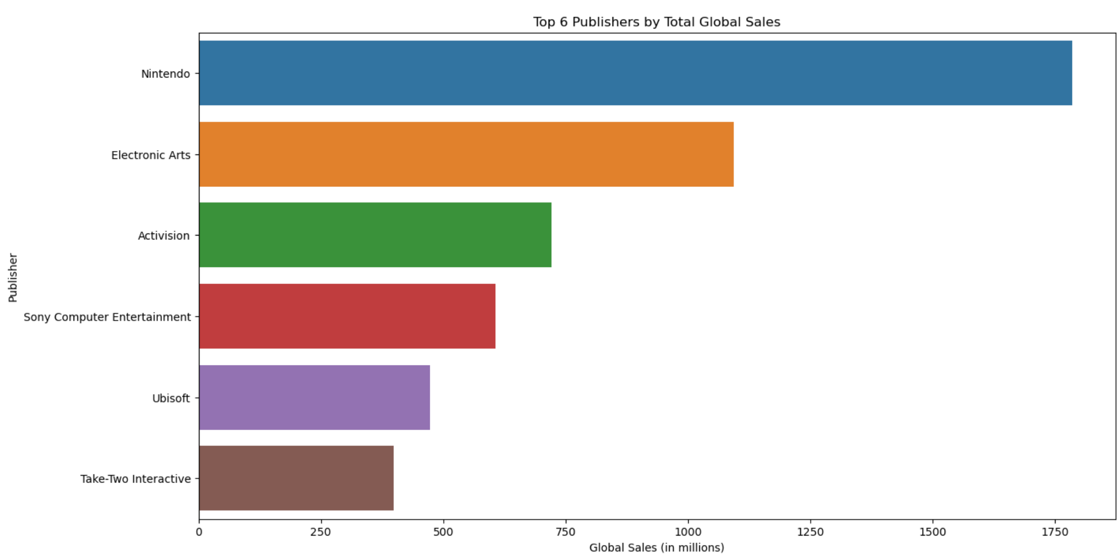
Top 5 Platforms

[135]:
```
platform_sales = data.groupby('platform')['Global Sales'].sum().nlargest(5)
top_platform = platform_sales.index.tolist()[:5]

plt.figure(figsize=(15, 8))
sns.barplot(x=platform_sales.values, y=top_platform, order=top_platform)
plt.title('Top 5 Gaming Platforms by Total Global Sales')
plt.xlabel('Global Sales (in millions)')
plt.ylabel('Platform')
plt.show()
```



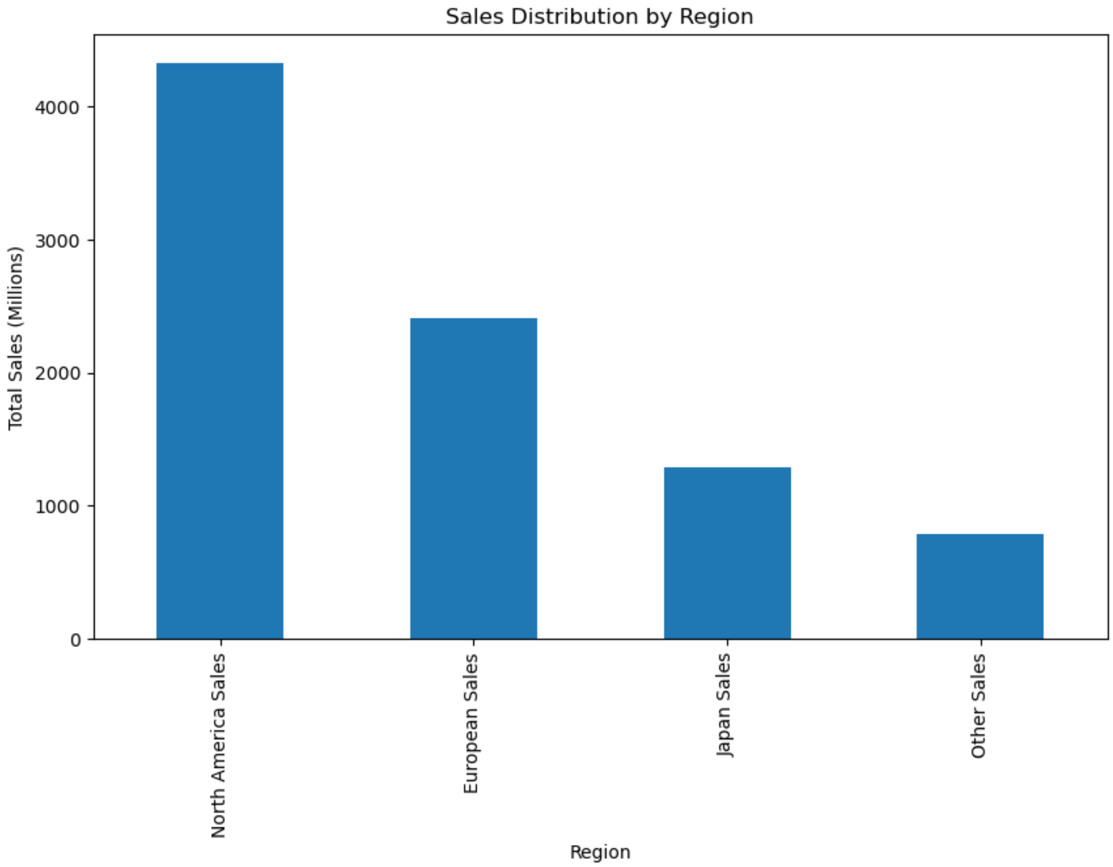
Top 5 publisher

[136]:
```
publisher_sales = data.groupby('publisher')['Global Sales'].sum().nlargest(6)
top_publishers = publisher_sales.index.tolist()[:6]

plt.figure(figsize=(15, 8))
sns.barplot(x=publisher_sales.values, y=top_publishers, order=top_publishers)
plt.title('Top 6 Publishers by Total Global Sales')
plt.xlabel('Global Sales (in millions)')
plt.ylabel('Publisher')
plt.show()
```



Sales Distribution by Region

[137]:
```
regions = ['North America Sales', 'European Sales', 'Japan Sales', 'Other␣
↪Sales']

plt.figure(figsize=(10, 6))
data[regions].sum().plot(kind='bar')
plt.title('Sales Distribution by Region')
plt.xlabel('Region')
plt.ylabel('Total Sales (Millions)')
plt.show()
```



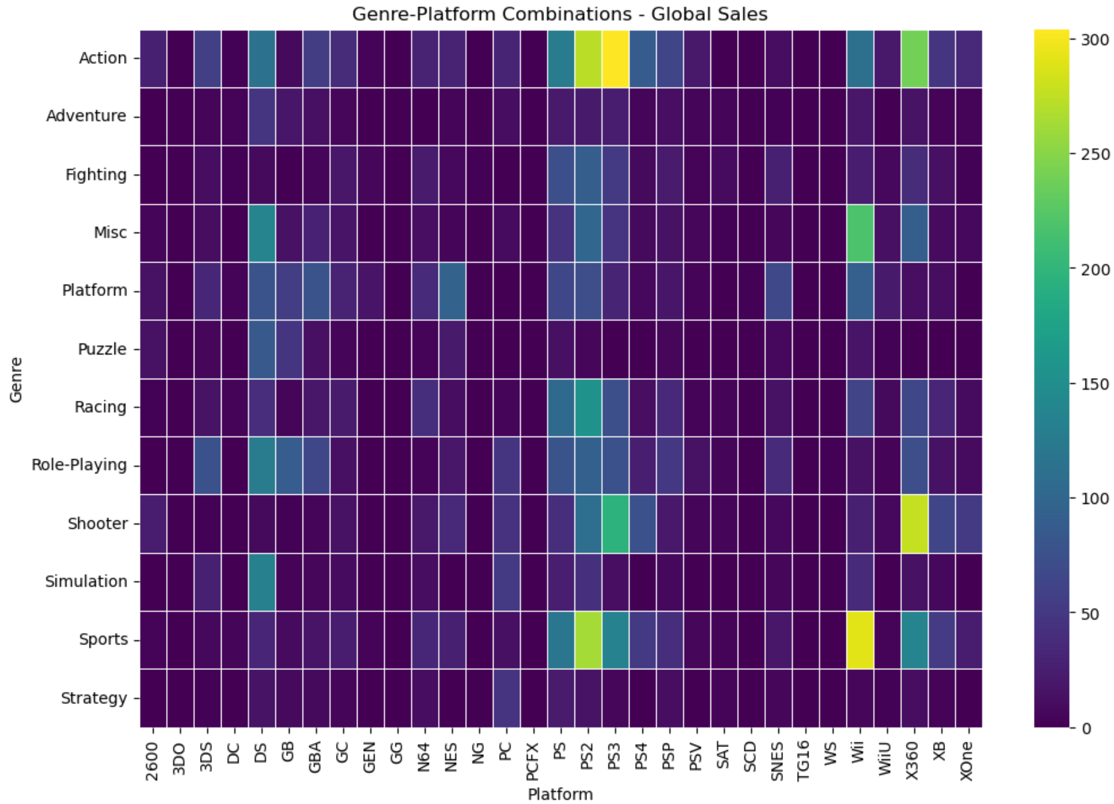
Yearly Trends

[138]:
```
plt.figure(figsize=(12, 6))
data.groupby('year')['Global Sales'].sum().plot(kind='line', marker='o',␣
↪color='purple')
plt.title('Global Sales Trend 1997-2016')
```

```
plt.xlabel('Year')
plt.ylabel('Total Global Sales (Millions)')
plt.show()
```

Genre-Platform Combinations

[139]:
```
genre_platform_combinations = data.pivot_table(index='genre',␣
↪columns='platform', values='Global Sales', aggfunc='sum')

plt.figure(figsize=(12, 8))
sns.heatmap(genre_platform_combinations, cmap='viridis', fmt='.1f', linewidths=.
↪5)
plt.title('Genre-Platform Combinations - Global Sales')
plt.xlabel('Platform')
plt.ylabel('Genre')
plt.show()
```



[140]:

```
genre_platform_combinations = data.pivot_table(index='genre',␣
↪columns='platform', values='Global Sales', aggfunc='sum')

top_combinations = genre_platform_combinations.stack().idxmax()

print("Most Successful Genre-Platform Combinations:")
print(top_combinations)
```

```
Most Successful Genre-Platform Combinations:
('Action', 'PS3')
```

4 A/B Testing

Platform Impact Hypothesis

[141]:

```
platform_1_name = 'PS2'
platform_2_name = 'X360'

platform_1_sales = data[data['platform'] == platform_1_name]['Global Sales']
platform_2_sales = data[data['platform'] == platform_2_name]['Global Sales']

t_stat, p_value = stats.ttest_ind(platform_1_sales, platform_2_sales)
```

```
alpha = 0.05

if p_value < alpha:
    print(f"Reject the null hypothesis. There is a significant difference in␣
↪global sales between {platform_1_name} and {platform_2_name}.")
else:
    print(f"Fail to reject the null hypothesis. There is no significant␣
↪difference in global sales between {platform_1_name} and {platform_2_name}.")
```

```
Reject the null hypothesis. There is a significant difference in global sales
between PS2 and X360.
```

Genre Impact Hypothesis:

[142]:
```
genre_1_name = 'Action'
genre_2_name = 'Shooter'

genre_1_sales = data[data['genre'] == genre_1_name]['Global Sales']
genre_2_sales = data[data['genre'] == genre_2_name]['Global Sales']

t_stat_genre, p_value_genre = stats.ttest_ind(genre_1_sales, genre_2_sales)



alpha = 0.05

if p_value_genre < alpha:
    print(f"Reject the null hypothesis. There is a significant difference in␣
↪global sales between {genre_1_name} and {genre_2_name}.")
else:
    print(f"Fail to reject the null hypothesis. There is no significant␣
↪difference in global sales between {genre_1_name} and {genre_2_name}.")
```

```
Reject the null hypothesis. There is a significant difference in global sales
between Action and Shooter.
```

Publisher Impact Hypothesis:

[143]:
```
publisher_1_name = 'Take-Two Interactive'
publisher_2_name = 'Activision'

publisher_1_sales = data[data['publisher'] == publisher_1_name]['Global Sales']
publisher_2_sales = data[data['publisher'] == publisher_2_name]['Global Sales']

t_stat_publisher, p_value_publisher = stats.ttest_ind(publisher_1_sales,␣
↪publisher_2_sales)

alpha = 0.05
```

```
if p_value_publisher < alpha:
    print(f"Reject the null hypothesis. There is a significant difference in␣
↪global sales between {publisher_1_name} and {publisher_2_name}.")
else:
    print(f"Fail to reject the null hypothesis. There is no significant␣
↪difference in global sales between {publisher_1_name} and {publisher_2_name}.
↪")
```

```
Reject the null hypothesis. There is a significant difference in global sales
between Take-Two Interactive and Activision.
```

5 Model Building

5.0.1 Fit the model

[144]:
```
label_encoder = LabelEncoder()

data['genre_encoded'] = label_encoder.fit_transform(data['genre'])
data['publisher_encoded'] = label_encoder.fit_transform(data['publisher'])
data['platform_encoded'] = label_encoder.fit_transform(data['platform'])
```

[145]:
```
X = data[['genre_encoded', 'publisher_encoded', 'platform_encoded']]

y = data['Global Sales']
```

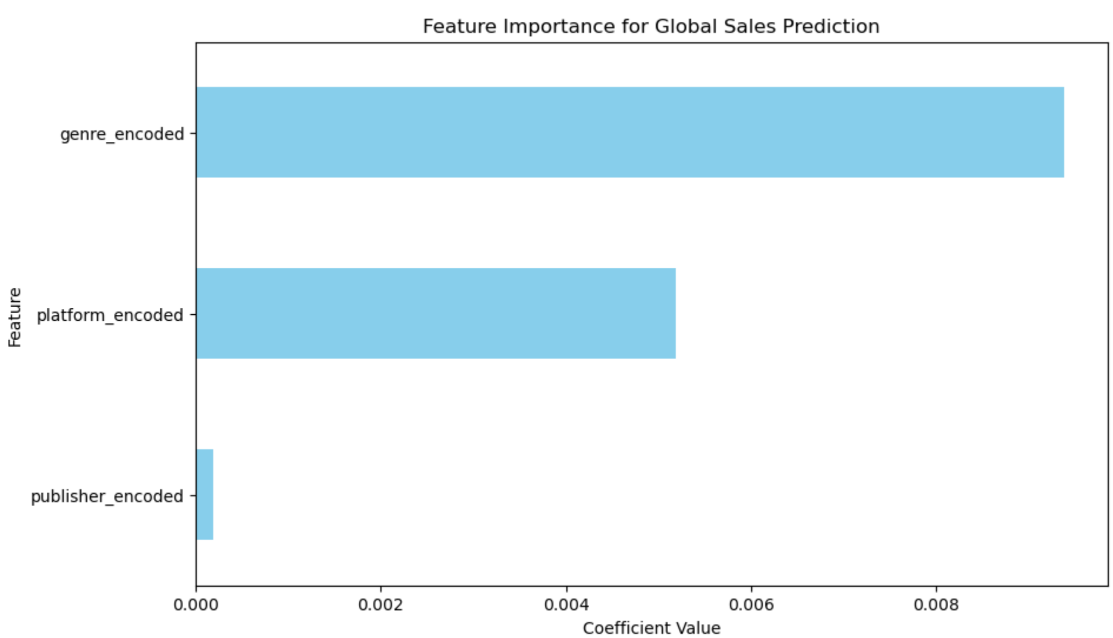
[146]:
```
X = sm.add_constant(X)

model = sm.OLS(y, X).fit()

print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Global Sales   R-squared:                       0.002
Model:                            OLS   Adj. R-squared:                  0.001
Method:                 Least Squares   F-statistic:                     9.146
Date:                Tue, 23 Jan 2024   Prob (F-statistic):           4.82e-06
Time:                        16:56:42   Log-Likelihood:                -30423.
No. Observations:               16291   AIC:                         6.085e+04
Df Residuals:                   16287   BIC:                         6.088e+04
Df Model:                           3
Covariance Type:            nonrobust
================================================================================
=====
                        coef    std err          t      P>|t|      [0.025
0.975]
--------------------------------------------------------------------------------
-----
```

```
const                   0.3581      0.037      9.606      0.000       0.285
0.431
genre_encoded           0.0094      0.003      2.876      0.004       0.003
0.016
publisher_encoded       0.0002   6.96e-05      2.681      0.007    5.01e-05
0.000
platform_encoded        0.0052      0.001      3.537      0.000       0.002
0.008
==============================================================================
Omnibus:                33706.268   Durbin-Watson:                   0.050
Prob(Omnibus):              0.000   Jarque-Bera (JB):        241118304.225
Skew:                      17.294   Prob(JB):                         0.00
Kurtosis:                 597.996   Cond. No.                     1.04e+03
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.04e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[147]:

```python
feature_importance = model.params.drop("const")

plt.figure(figsize=(10, 6))
feature_importance.sort_values().plot(kind='barh', color='skyblue')
plt.title('Feature Importance for Global Sales Prediction')
plt.xlabel('Coefficient Value')
plt.ylabel('Feature')
plt.show()
```



5.0.2 Make Predictions for Global Sales

Predictions at Random

[148]:
```
genre_range = data['genre_encoded'].max() - data['genre_encoded'].min()
publisher_range = data['publisher_encoded'].max() - data['publisher_encoded'].
  ↪min()
platform_range = data['platform_encoded'].max() - data['platform_encoded'].min()

random_genre_encoded = np.random.randint(data['genre_encoded'].min(),␣
  ↪data['genre_encoded'].min() + genre_range + 1)
random_publisher_encoded = np.random.randint(data['publisher_encoded'].min(),␣
  ↪data['publisher_encoded'].min() + publisher_range + 1)
random_platform_encoded = np.random.randint(data['platform_encoded'].min(),␣
  ↪data['platform_encoded'].min() + platform_range + 1)

new_random_data = {
    'genre_encoded': random_genre_encoded,
    'publisher_encoded': random_publisher_encoded,
    'platform_encoded': random_platform_encoded,
    'const': 1
}

new_random_data_df = pd.DataFrame([new_random_data])

actual_random_genre = data[data['genre_encoded'] ==␣
  ↪new_random_data['genre_encoded']]['genre'].iloc[0]
actual_random_publisher = data[data['publisher_encoded'] ==␣
  ↪new_random_data['publisher_encoded']]['publisher'].iloc[0]
actual_random_platform = data[data['platform_encoded'] ==␣
  ↪new_random_data['platform_encoded']]['platform'].iloc[0]

print("Actual Random Genre:", actual_random_genre)
print("Actual Random Publisher:", actual_random_publisher)
print("Actual Random Platform:", actual_random_platform)

predicted_random_global_sales = model.predict(new_random_data_df)

print("Predicted Random Global Sales:", predicted_random_global_sales.iloc[0])
```

```
Actual Random Genre: Shooter
Actual Random Publisher: Marvelous Entertainment
Actual Random Platform: PS2
Predicted Random Global Sales: 5.6818253263882585
```

Predictons made manually

[149]:
```python
new_data = {
    'genre_encoded': 10,
    'publisher_encoded': 359,
    'platform_encoded': 26,
    'const': 1
}

new_data_df = pd.DataFrame([new_data])

# Get the original names for the encoded values
actual_genre = data[data['genre_encoded'] ==␣
↪new_data['genre_encoded']]['genre'].iloc[0]
actual_publisher = data[data['publisher_encoded'] ==␣
↪new_data['publisher_encoded']]['publisher'].iloc[0]
actual_platform = data[data['platform_encoded'] ==␣
↪new_data['platform_encoded']]['platform'].iloc[0]

# Print the actual categories
print("Actual Genre:", actual_genre)
print("Actual Publisher:", actual_publisher)
print("Actual Platform:", actual_platform)

# Make predictions
predicted_global_sales = model.predict(new_data_df)

print("Predicted Global Sales:", predicted_global_sales.iloc[0])
```

```
Actual Genre: Sports
Actual Publisher: Nintendo
Actual Platform: Wii
Predicted Global Sales: 6.963548397872952
```

5.0.3 Statistical Analysis

Test for multicollinearity

- All VIF values are well below 5, which is a good sign. It suggests that there is no severe multicollinearity among the features.

[150]:
```python
vif_data = pd.DataFrame()
vif_data["feature"] = X.columns

vif_data["VIF"] = [variance_inflation_factor(X.values, i)
                          for i in range(len(X.columns))]

print(vif_data)
```

```
             feature       VIF
0              const  9.231023
```

```
1      genre_encoded  1.003293
2  publisher_encoded  1.002902
3   platform_encoded  1.000987
```

Test for heteroskedasticity

- Since the p-value (0.1400) is greater than the typical significance level (e.g., 0.05), we do not have sufficient evidence to reject the null hypothesis.
- This suggests that there is no strong evidence of heteroskedasticity in our model.

[151]:
```
# Heteroskedasticity: Breush-Pagan --> Ho: var = constant

name = ["Lagrange multiplier statistic", "p-value", "f-value", "f p-value"]
test = sms.het_breuschpagan(model.resid, model.model.exog)
print(("BP Results:",['bold']))
print(list(zip(name, test)))
```

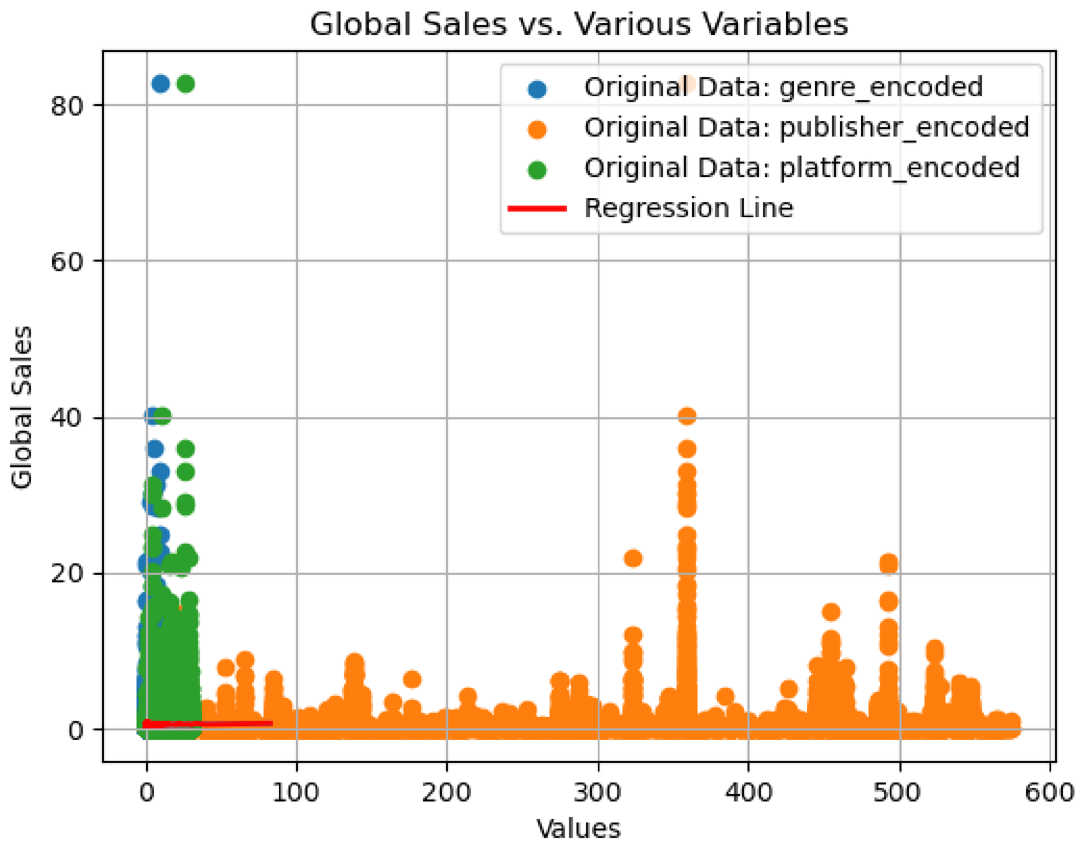
```
('BP Results:', ['bold'])
[('Lagrange multiplier statistic', 5.476703548157174), ('p-value',
0.1400386619168625), ('f-value', 1.8257333842887522), ('f p-value',
0.14005412400102765)]
```

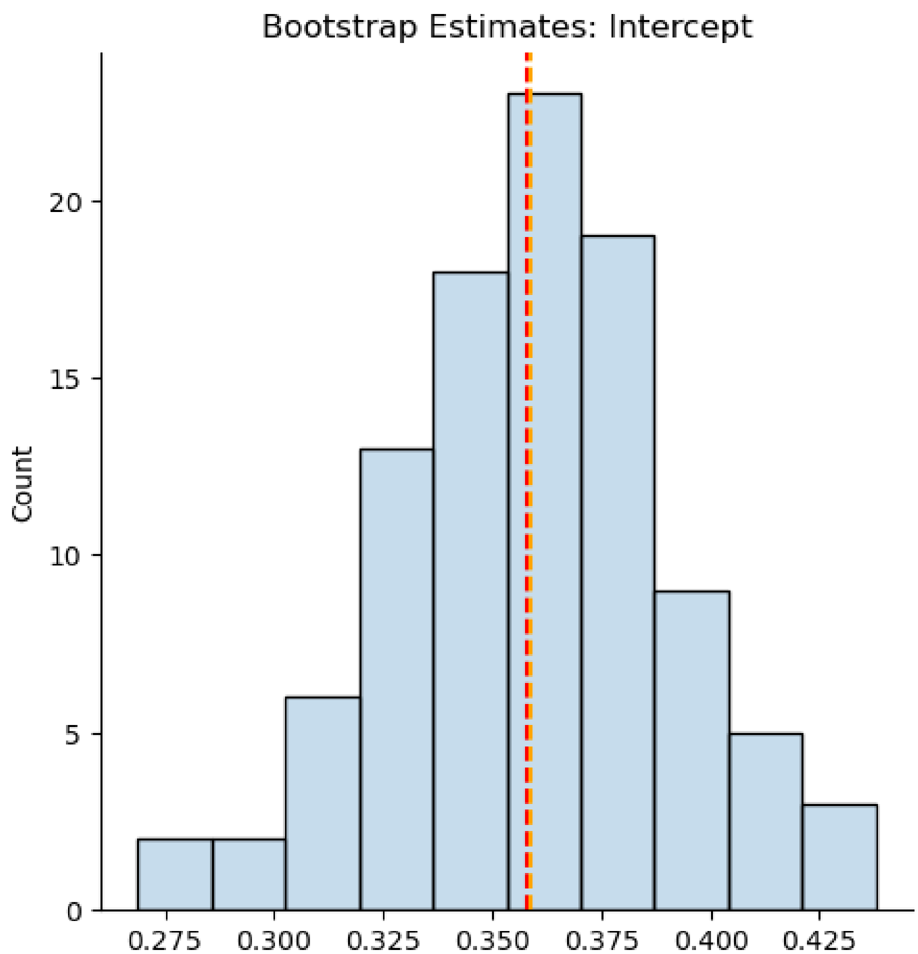
Evaluate the robustness of your coefficient estimates by bootstrapping model

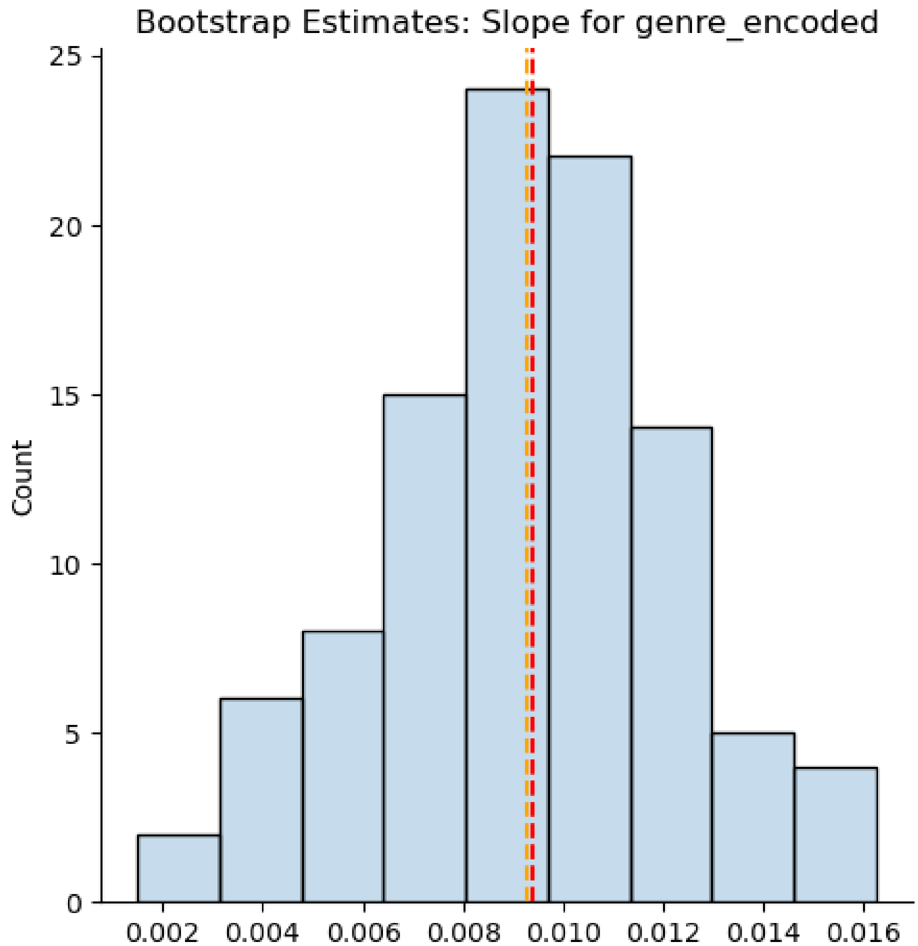
[152]:
```
ols_mod = sm.OLS(y, X).fit()

boot_slope_genre = []
boot_slope_publisher = []
boot_slope_platform = []
boot_interc = []
boot_adjR2 = []

n_boots = 100
n_points = data.shape[0]

plt.figure()

for _ in range(n_boots):
    sample_df = data.sample(n=n_points, replace=True)

    X_temp = sm.add_constant(sample_df[['genre_encoded', 'publisher_encoded',␣
 ↪'platform_encoded']])
    y_temp = sample_df['Global Sales']

    ols_model_temp = sm.OLS(y_temp, X_temp).fit()

    boot_interc.append(ols_model_temp.params[0])
    boot_slope_genre.append(ols_model_temp.params[1])
    boot_slope_publisher.append(ols_model_temp.params[2])
```

```
    boot_slope_platform.append(ols_model_temp.params[3])
    boot_adjR2.append(ols_model_temp.rsquared_adj)

    y_pred_temp = ols_model_temp.predict(X_temp)
    plt.plot(sample_df['Global Sales'], y_pred_temp, color='grey', alpha=0.2)

y_pred = ols_mod.predict(X)

plt.scatter(data['genre_encoded'], data['Global Sales'], label='Original Data:␣
↪genre_encoded')
plt.scatter(data['publisher_encoded'], data['Global Sales'], label='Original␣
↪Data: publisher_encoded')
plt.scatter(data['platform_encoded'], data['Global Sales'], label='Original␣
↪Data: platform_encoded')

plt.plot(data['Global Sales'], y_pred, linewidth=2, color='red',␣
↪label='Regression Line')
plt.grid(True)
plt.xlabel('Values')
plt.ylabel('Global Sales')
plt.title('Global Sales vs. Various Variables')
plt.legend()
plt.show()

sns.displot(boot_interc, alpha=0.25)
plt.axvline(x=ols_mod.params[0], color='red', linestyle='--')
plt.axvline(x=np.mean(boot_interc), color='orange', linestyle='--')
plt.title('Bootstrap Estimates: Intercept')
plt.show()

sns.displot(boot_slope_genre, alpha=0.25)
plt.axvline(x=ols_mod.params[1], color='red', linestyle='--')
plt.axvline(x=np.mean(boot_slope_genre), color='orange', linestyle='--')
plt.title('Bootstrap Estimates: Slope for genre_encoded')
plt.show()

sns.displot(boot_slope_publisher, alpha=0.25)
plt.axvline(x=ols_mod.params[2], color='red', linestyle='--')
plt.axvline(x=np.mean(boot_slope_publisher), color='orange', linestyle='--')
plt.title('Bootstrap Estimates: Slope for publisher_encoded')
plt.show()

sns.displot(boot_slope_platform, alpha=0.25)
plt.axvline(x=ols_mod.params[3], color='red', linestyle='--')
plt.axvline(x=np.mean(boot_slope_platform), color='orange', linestyle='--')
plt.title('Bootstrap Estimates: Slope for platform_encoded')
plt.show()
```

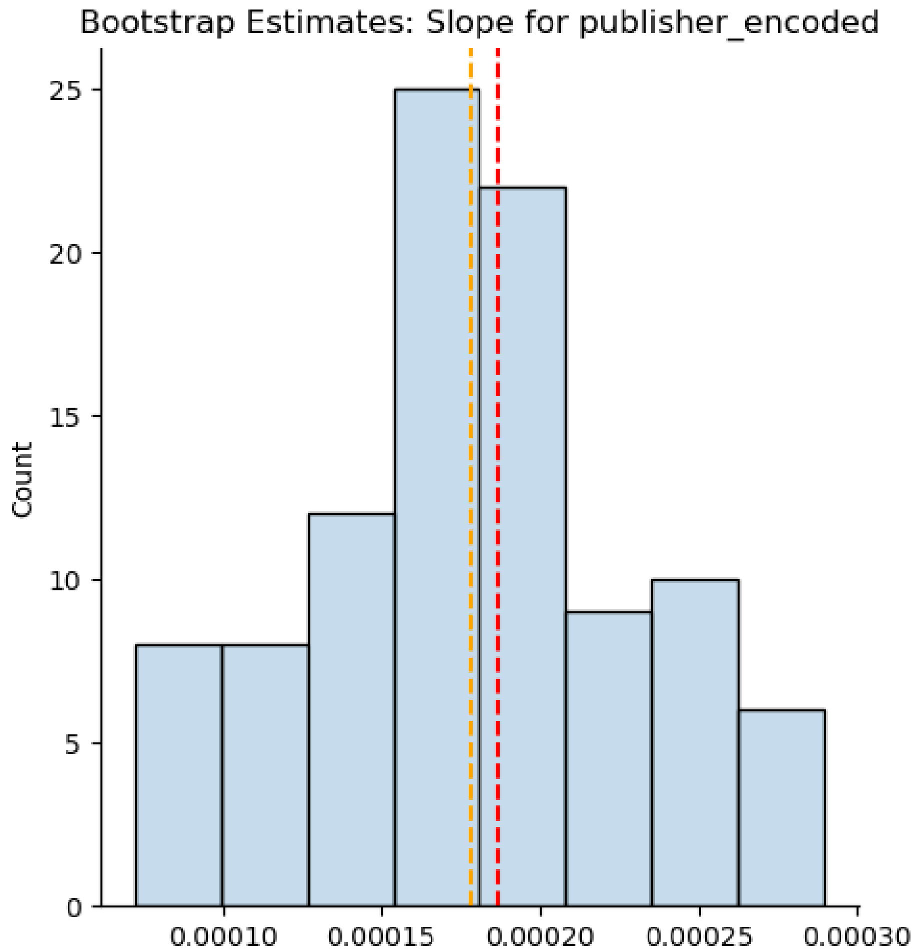
```
sns.displot(boot_adjR2, alpha=0.25)
plt.axvline(x=ols_mod.rsquared_adj, color='red', linestyle='--')
plt.axvline(x=np.mean(boot_adjR2), color='orange', linestyle='--')
plt.title('Bootstrap Estimates: Adjusted R-squared')
plt.show()
```

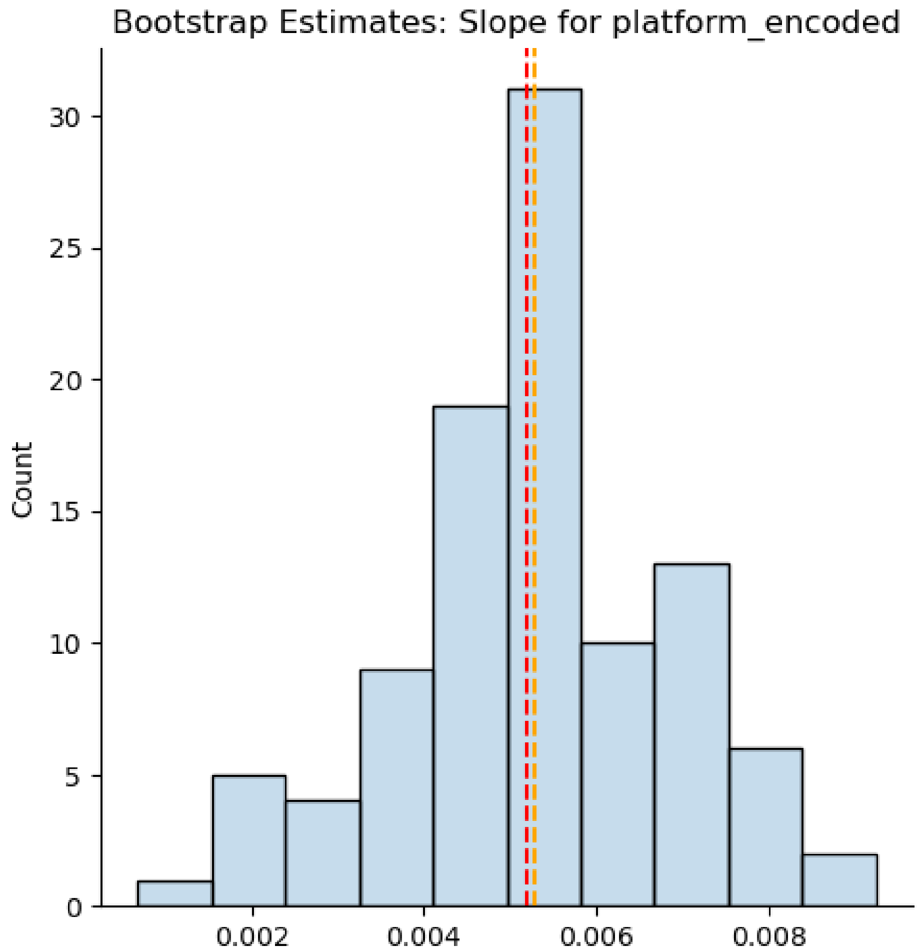


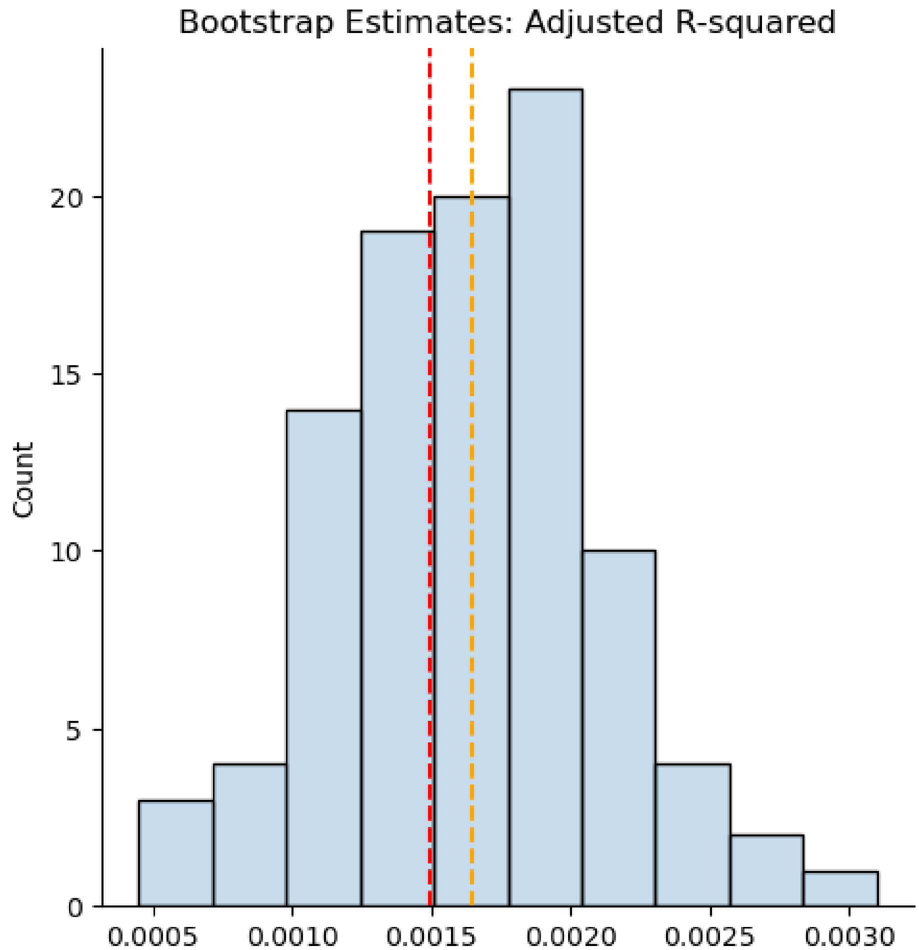

Bootstrap Estimates: Intercept
Count
0
5
10
15
20
0.275
0.300
0.325
0.350
0.375
0.400
0.425



Bootstrap Estimates: Slope for genre_encoded
Count
0
5
10
15
20
25
0.002
0.004
0.006
0.008
0.010
0.012
0.014
0.016


Bootstrap Estimates: Slope for publisher_encoded
Count
0
5
10
15
20
25
0.00010
0.00015
0.00020
0.00025
0.00030


Bootstrap Estimates: Slope for platform_encoded
Count
0
5
10
15
20
25
30
0.002
0.004
0.006
0.008



Use cross-validation to evaluate your model's performance

[153]:
```
regr = LinearRegression()
model_val = regr.fit(X,y)
regr.coef_
regr.intercept_


x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
    ↪random_state=0)


regr = LinearRegression()
regr.fit(x_train, y_train)


y_pred = regr.predict(x_test)
```

```
print('MAE:', metrics.mean_absolute_error(y_test, y_pred))
print('MSE:', metrics.mean_squared_error(y_test, y_pred))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))



regr = linear_model.LinearRegression()
scores = cross_val_score(regr, X, y, cv=5,␣
 ↪scoring='neg_root_mean_squared_error')
print('5-Fold CV RMSE Scores:', scores)
```

```
MAE: 0.5924579386055017
MSE: 1.9563671461045857
RMSE: 1.398701950418525
5-Fold CV RMSE Scores: [-3.58691194 -0.22708645 -0.47090875 -0.57687974
-0.63498612]
```

[ ]:

```

```