If we were to be video game developers, what factors should we consider to maximize global sales?

In [1]:

```
import numpy as np
import pandas as pd
import seaborn as sb; sb.set_theme(color_codes=True)
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.tree import plot_tree
sb.set()
```

In [2]:

```
gamesData = pd.read_csv('sales.csv')
gamesData.head()
```

Out[2]:

	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales	Critic_Score	Critic_Count	User_Sc
0	Wii Sports	Wii	2006.0	Sports	Nintendo	41.36	28.96	3.77	8.45	82.53	76.0	51.0	
1	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	0.77	40.24	NaN	NaN	I
2	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.68	12.76	3.79	3.29	35.52	82.0	73.0	
3	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.61	10.93	3.28	2.95	32.77	80.0	73.0	
4	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.22	1.00	31.37	NaN	NaN	I

We removed games from before 2002 as it might be outdated and irrelevant

In [3]:

```python
gamesData['below2002'] = np.where(gamesData['Year_of_Release']  < 2002.0 ,np.nan , False)
gamesData.dropna(subset=['below2002'], inplace=True)
gamesData.head(10)
```

Out[3]:

	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales	Critic_Score	Critic_Count	User_S
0	Wii Sports	Wii	2006.0	Sports	Nintendo	41.36	28.96	3.77	8.45	82.53	76.0	51.0	
2	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.68	12.76	3.79	3.29	35.52	82.0	73.0	
3	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.61	10.93	3.28	2.95	32.77	80.0	73.0	
6	New Super Mario Bros.	DS	2006.0	Platform	Nintendo	11.28	9.14	6.50	2.88	29.80	89.0	65.0	
7	Wii Play	Wii	2006.0	Misc	Nintendo	13.96	9.18	2.93	2.84	28.92	58.0	41.0	
8	New Super Mario Bros. Wii	Wii	2009.0	Platform	Nintendo	14.44	6.94	4.70	2.24	28.32	87.0	80.0	
10	Nintendogs	DS	2005.0	Simulation	Nintendo	9.05	10.95	1.93	2.74	24.67	NaN	NaN	
11	Mario Kart DS	DS	2005.0	Racing	Nintendo	9.71	7.47	4.13	1.90	23.21	91.0	64.0	
13	Wii Fit	Wii	2007.0	Sports	Nintendo	8.92	8.03	3.60	2.15	22.70	80.0	63.0	
14	Kinect Adventures!	X360	2010.0	Misc	Microsoft Game Studios	15.00	4.89	0.24	1.69	21.81	61.0	45.0	

We filled the empty values with 0 for the quantitative values as to preserve it for use, and N/A for qualitative values

In [4]:

```python
gamesData["Critic_Score"].fillna(value = 0, inplace = True)
gamesData["Critic_Count"].fillna(value = 0, inplace = True)
gamesData["User_Score"].fillna(value = 0, inplace = True)
gamesData['User_Score'].replace('tbd', 0, inplace=True)
gamesData["User_Count"].fillna(value = 0, inplace = True)
```

```
gamesData["Developer"].fillna(value = "N/A", inplace = True)
gamesData["Rating"].fillna(value = "N/A", inplace = True)
gamesData['User_Score'] = gamesData['User_Score'].astype('float')
gamesData.head()
```

Out[4]:

	Name	Platform	Year_of_Release	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales	Critic_Score	Critic_Count	User_Score	U
0	Wii Sports	Wii	2006.0	Sports	Nintendo	41.36	28.96	3.77	8.45	82.53	76.0	51.0	8.0	
2	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.68	12.76	3.79	3.29	35.52	82.0	73.0	8.3	
3	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.61	10.93	3.28	2.95	32.77	80.0	73.0	8.0	
6	New Super Mario Bros.	DS	2006.0	Platform	Nintendo	11.28	9.14	6.50	2.88	29.80	89.0	65.0	8.5	
7	Wii Play	Wii	2006.0	Misc	Nintendo	13.96	9.18	2.93	2.84	28.92	58.0	41.0	6.6	

Removal of outliers from Global Sales

In [35]:

```
gamesData = pd.DataFrame(gamesData[["Genre", "Critic_Score", "Critic_Count", "User_Score", "Global_Sales", "Publisher", "Platform"

# Calculate the quartiles
Q1 = gamesData.quantile(0.25)
Q3 = gamesData.quantile(0.75)

# Rule to identify outliers
rule = ((gamesData < (Q1 - 1.5 * (Q3 - Q1))) | (gamesData > (Q3 + 1.5 * (Q3 - Q1))))

# Count the number of outliers
rule.sum()
```

```
C:\Users\dobin001\AppData\Local\Temp/ipykernel_19060/3248969249.py:8: FutureWarning: Automatic reindexing on DataFrame vs Series c
omparisons is deprecated and will raise ValueError in a future version.  Do `left, right = left.align(right, axis=1, copy=False)`
before e.g. `left == right`
  rule = ((gamesData < (Q1 - 1.5 * (Q3 - Q1))) | (gamesData > (Q3 + 1.5 * (Q3 - Q1))))
```

Out[35]:

```
Critic_Count       302
Critic_Score         0
Genre                0
Global_Sales       458
Platform             0
Publisher            0
User_Score           0
Year_of_Release      0
dtype: int64
```

In [32]:

```
# Find the rows where ANY column is True
outliers = rule.any(axis = 1)   # axis 0 is row, 1 is column

# Check the outliers -- it's a boolean Series
outliers

# How many points are outliers for the two variables combined?
outliers.value_counts()

# Which row indices correspond to outliers in the dataframe?
outlierindices = outliers.index[outliers == True]
outlierindices

# Remove outliers based on the row indices above
gamesData.drop(axis = 0, index = outlierindices, inplace = True)
```

Summary for type of Genres

In [7]:

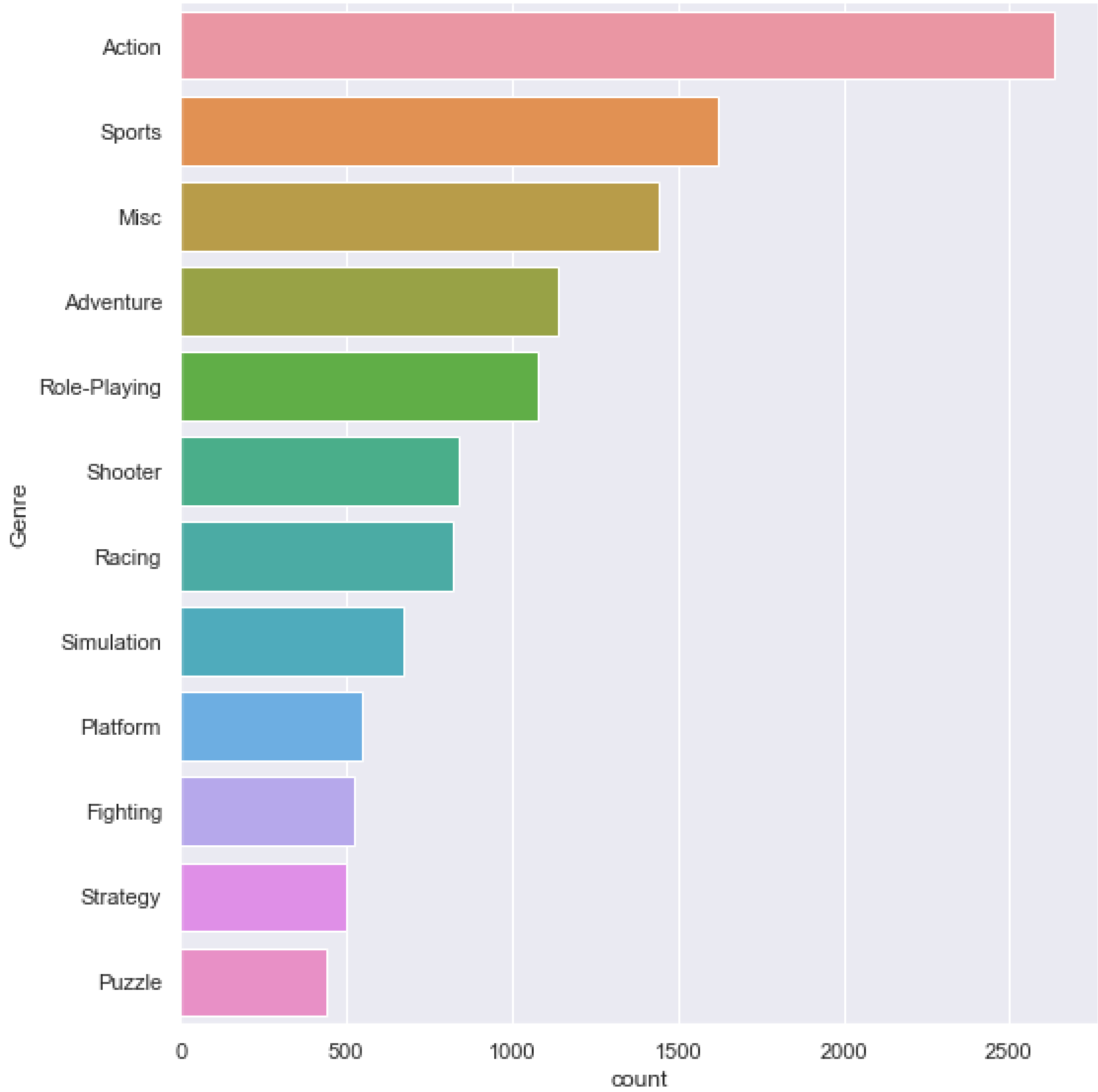
```
print("Number of Genres :", len(gamesData["Genre"].dropna().unique()))

print(gamesData["Genre"].dropna().value_counts())

sb.catplot(y = "Genre", data = gamesData, kind = "count", height = 8, order=gamesData['Genre'].value_counts().index)
```

```
Number of Genres : 12
Action          2636
Sports          1622
```

```
Misc            1442
Adventure       1136
Role-Playing    1079
Shooter          837
Racing           818
Simulation       671
Platform         547
Fighting         524
Strategy         498
Puzzle           436
Name: Genre, dtype: int64
```

Out[7]:

```
<seaborn.axisgrid.FacetGrid at 0x26777271fd0>
```



Top 10 most games published Publishers

In [8]:

```
print("Number of Unique Publisher :", len(gamesData["Publisher"].dropna().unique()))

print(gamesData["Publisher"].dropna().value_counts().head(10))
```

```
Number of Unique Publisher : 434
Electronic Arts                 873
Namco Bandai Games              791
Ubisoft                         744
Activision                      741
Konami Digital Entertainment    600
THQ                             566
Sega                            430
Sony Computer Entertainment     351
Tecmo Koei                      303
Take-Two Interactive            297
Name: Publisher, dtype: int64
```

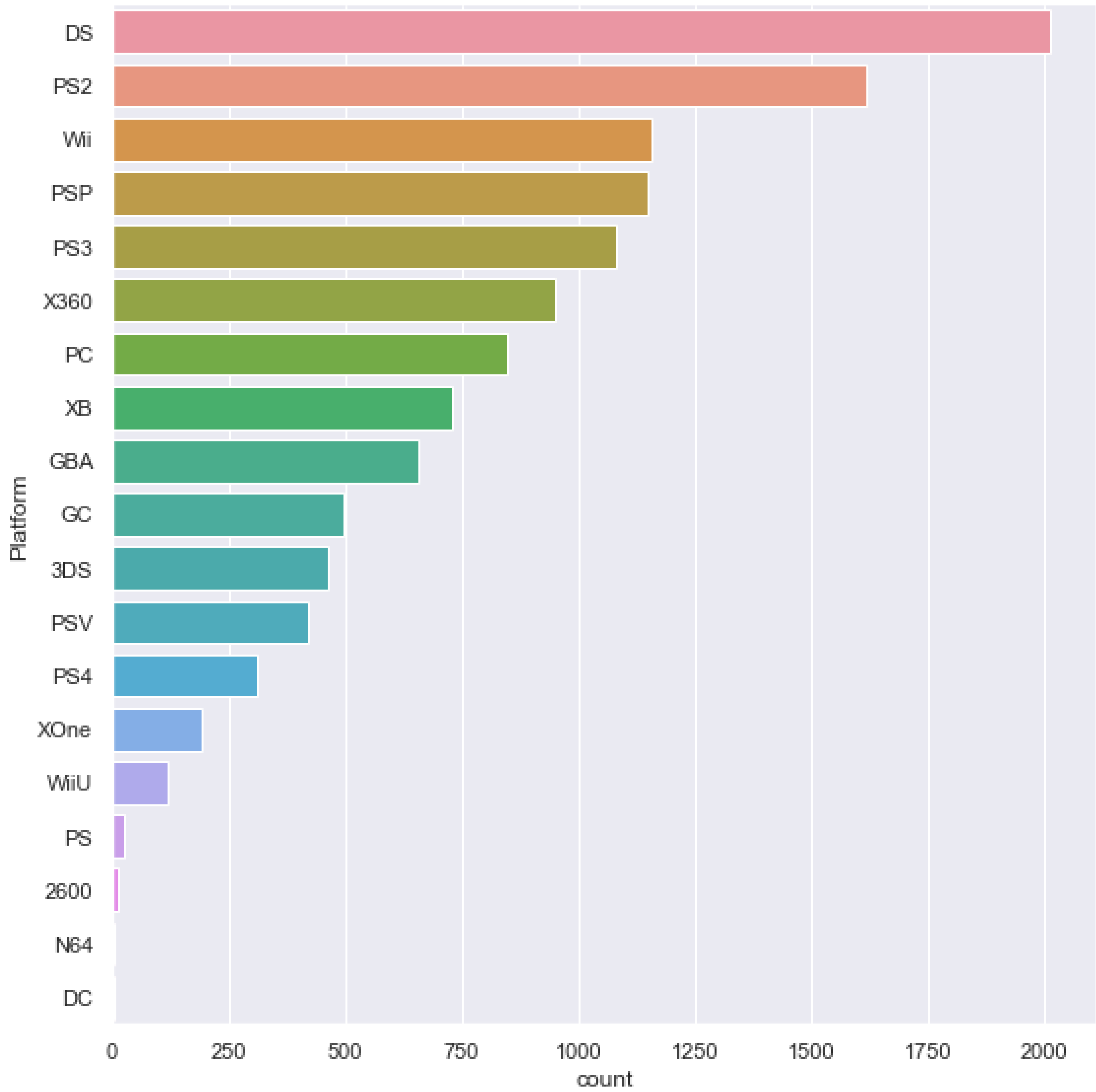
Types of platform

In [9]:

```
print("Number of Unique Platforms :", len(gamesData["Platform"].dropna().unique()))

print(gamesData["Platform"].dropna().value_counts())

sb.catplot(y = "Platform", data = gamesData, kind = "count", height = 8, order=gamesData['Platform'].value_counts().index)
```

```
Number of Unique Platforms : 19
DS      2010
PS2     1620
Wii     1157
PSP     1150
PS3     1079
X360     950
PC       849
XB       731
GBA      659
GC       495
3DS      463
PSV      418
PS4      308
XOne     191
WiiU     120
PS        25
2600      14
N64        4
DC         3
Name: Platform, dtype: int64
```

Out[9]: <seaborn.axisgrid.FacetGrid at 0x267779bf400>



No. of games released per year

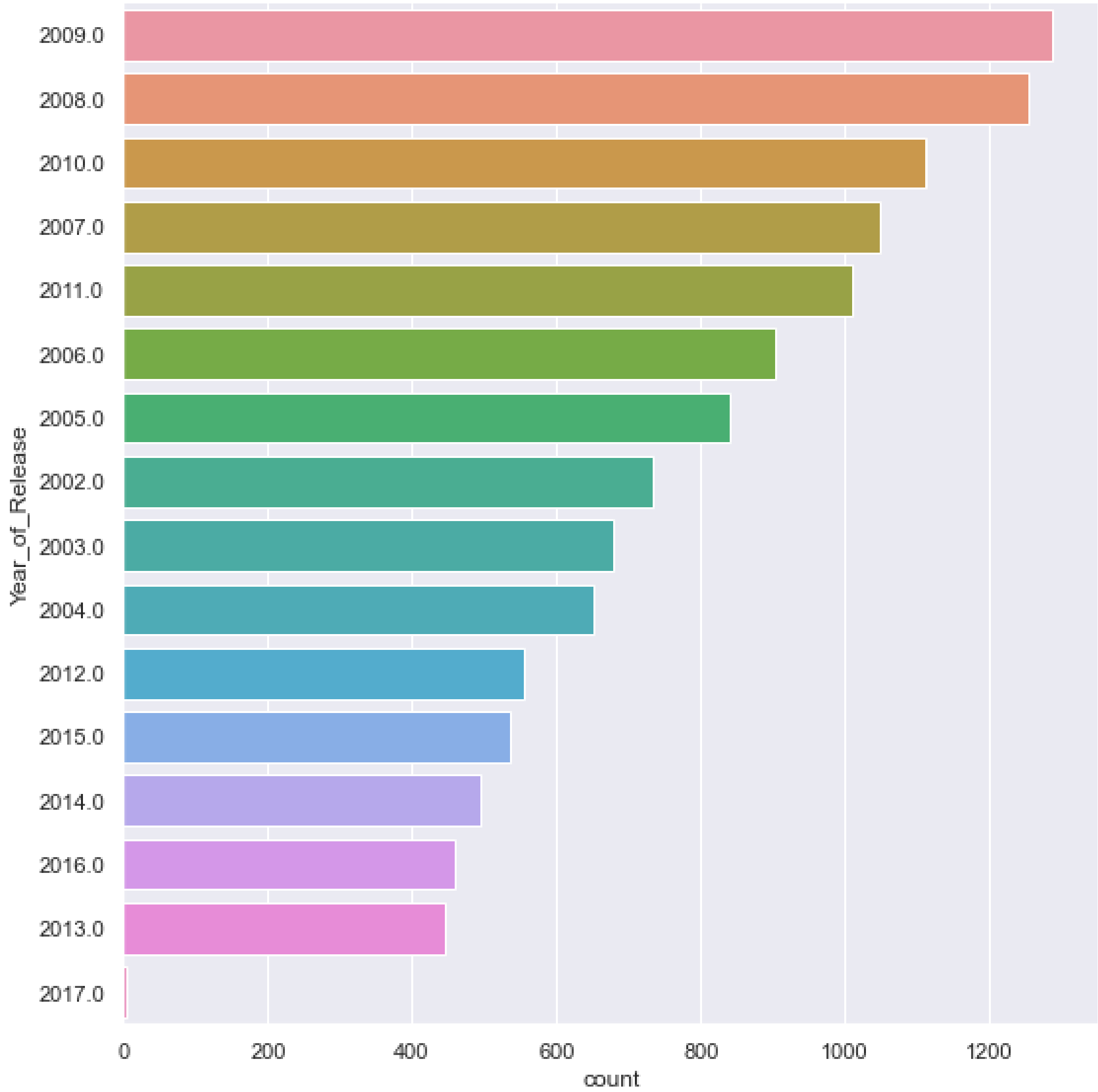
In [10]:

```
print(gamesData["Year_of_Release"].dropna().value_counts())
sb.catplot(y = "Year_of_Release", data = gamesData, kind = "count", height = 8, order=gamesData['Year_of_Release'].value_counts().
```

```
2009.0    1286
2008.0    1253
2010.0    1112
2007.0    1047
2011.0    1010
2006.0     904
2005.0     839
2002.0     733
2003.0     678
2004.0     650
2012.0     555
2015.0     535
2014.0     495
2016.0     459
2013.0     444
2017.0       3
Name: Year_of_Release, dtype: int64
```

Out[10]:

```
<seaborn.axisgrid.FacetGrid at 0x267772b5b80>
```

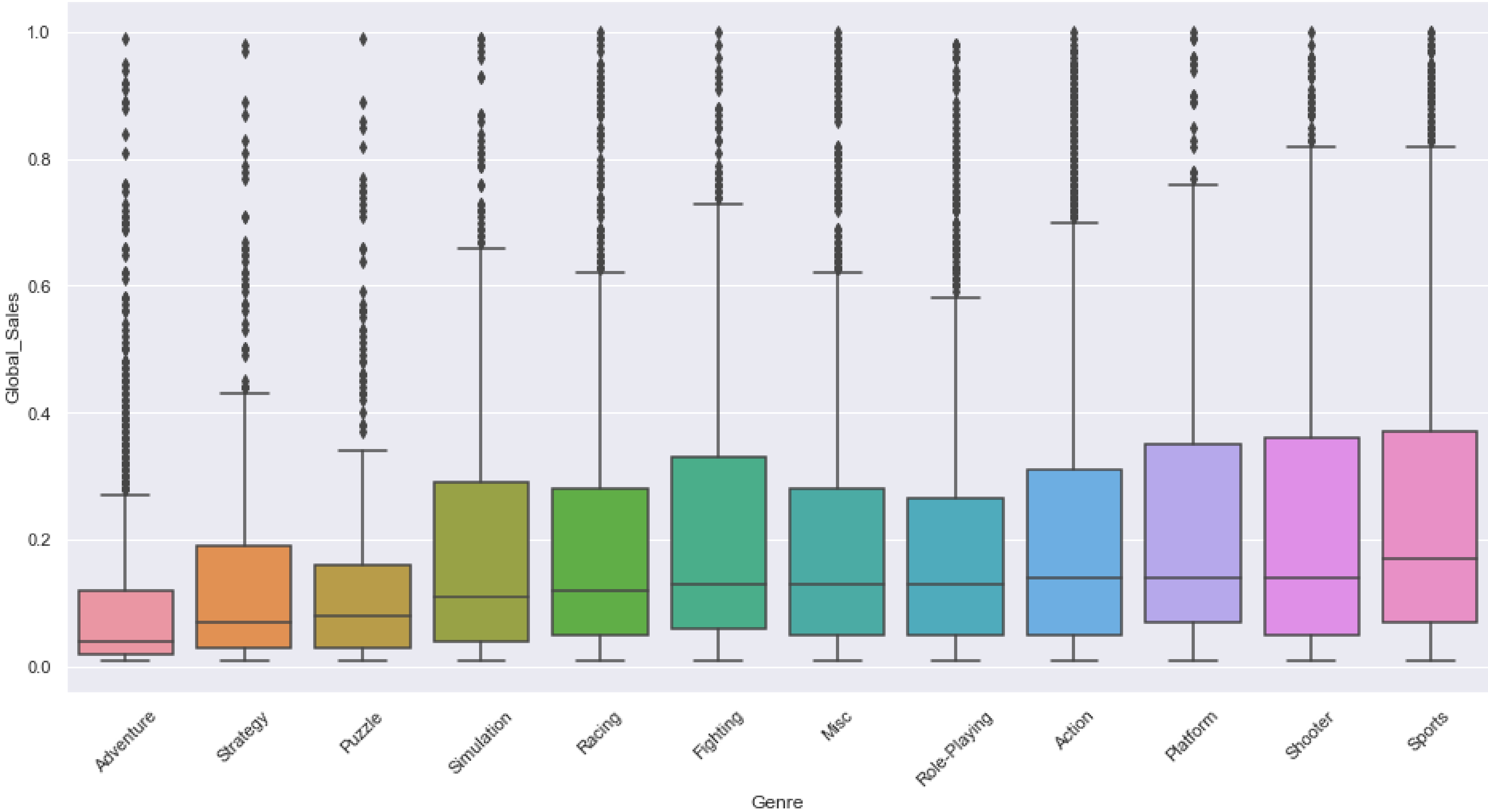


Global Sales based on Genre

In [11]:

```
f = plt.figure(figsize=(16, 8))
sb.boxplot(x = 'Genre', y = 'Global_Sales', data = gamesData,
           order = gamesData.groupby('Genre')['Global_Sales'].median().sort_values().index)
```

```
# Tilt the x-axis labels for better readability
plt.xticks(rotation=45);
```

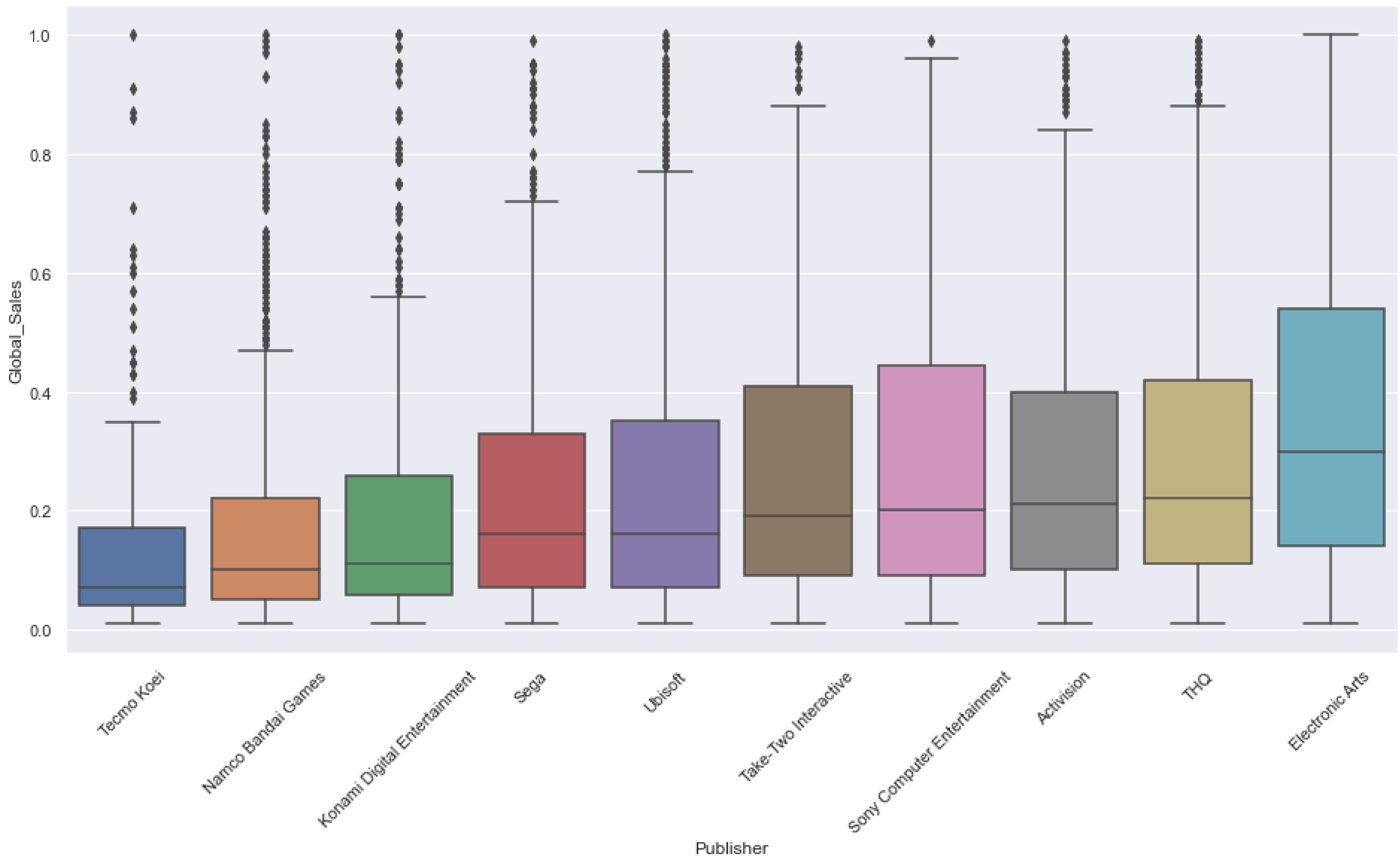


Global sales based on Publisher

In [12]:

```
pubData = pd.DataFrame(gamesData[["Publisher","Global_Sales"]]).copy()

pubData["Top"] = np.where((pubData['Publisher'] == 'Electronic Arts') | (pubData['Publisher'] == 'Namco Bandai Games')
                          | (pubData['Publisher'] == 'Ubisoft') | (pubData['Publisher'] == 'Activision')
```

```
                                   | (pubData['Publisher'] == 'Konami Digital Entertainment') | (pubData['Publisher'] == 'THQ')
                                   | (pubData['Publisher'] == 'Sega') | (pubData['Publisher'] == 'Sony Computer Entertainment')
                                   | (pubData['Publisher'] == 'Tecmo Koei') | (pubData['Publisher'] == 'Take-Two Interactive'),True, np.nan

pubData.dropna(subset=["Top"], inplace=True)

f = plt.figure(figsize=(16, 8))
sb.boxplot(x = 'Publisher', y = 'Global_Sales', data = pubData,
           order = pubData.groupby('Publisher')['Global_Sales'].median().sort_values().index)

# Tilt the x-axis labels for better readability
plt.xticks(rotation=45);
```

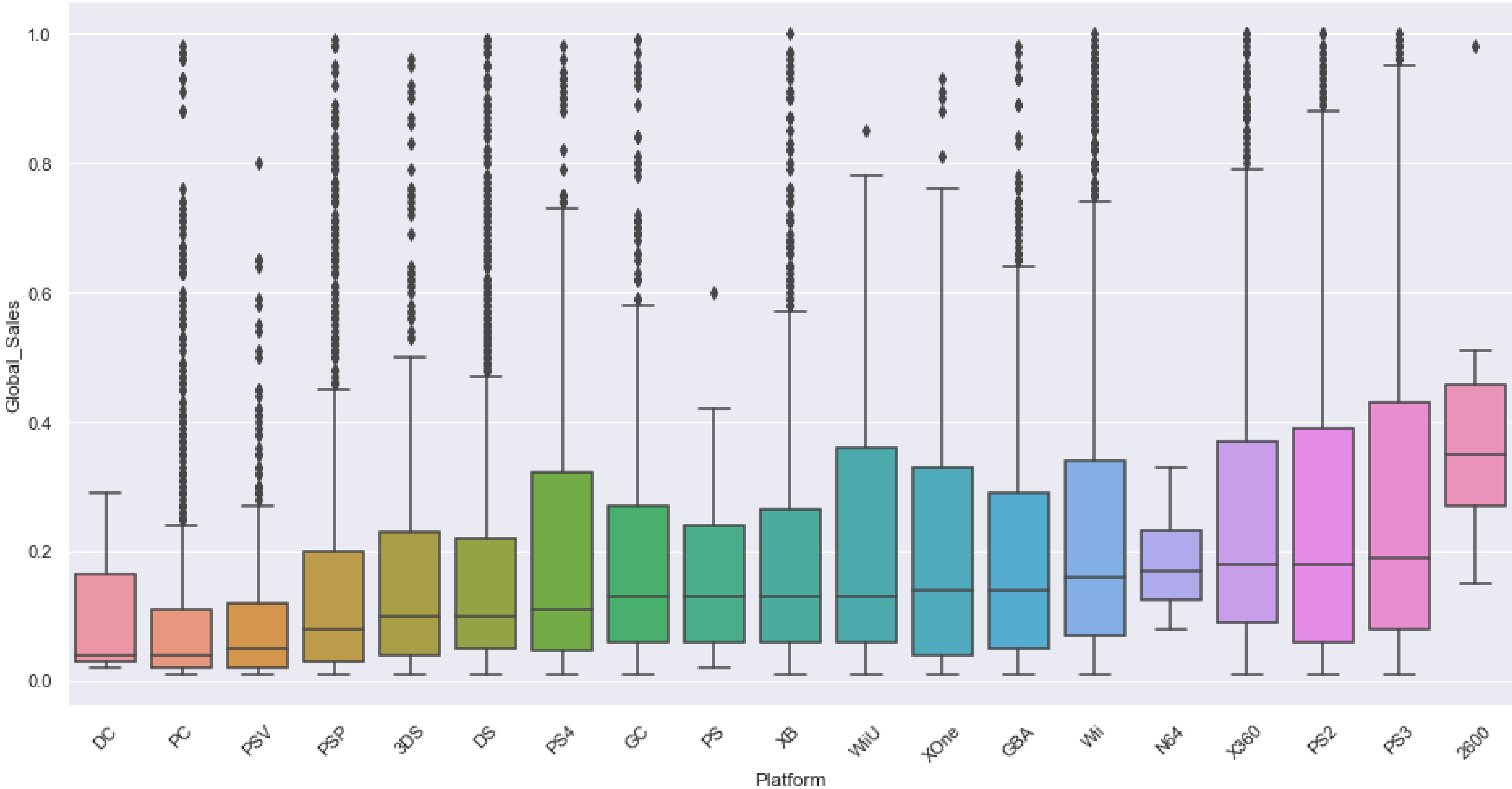


Global Sales based on Platform

In [13]:

```
f = plt.figure(figsize=(16, 8))
sb.boxplot(x = 'Platform', y = 'Global_Sales', data = gamesData,
           order = gamesData.groupby('Platform')['Global_Sales'].median().sort_values().index)
```

```python
# Tilt the x-axis labels for better readability
plt.xticks(rotation=45);
```

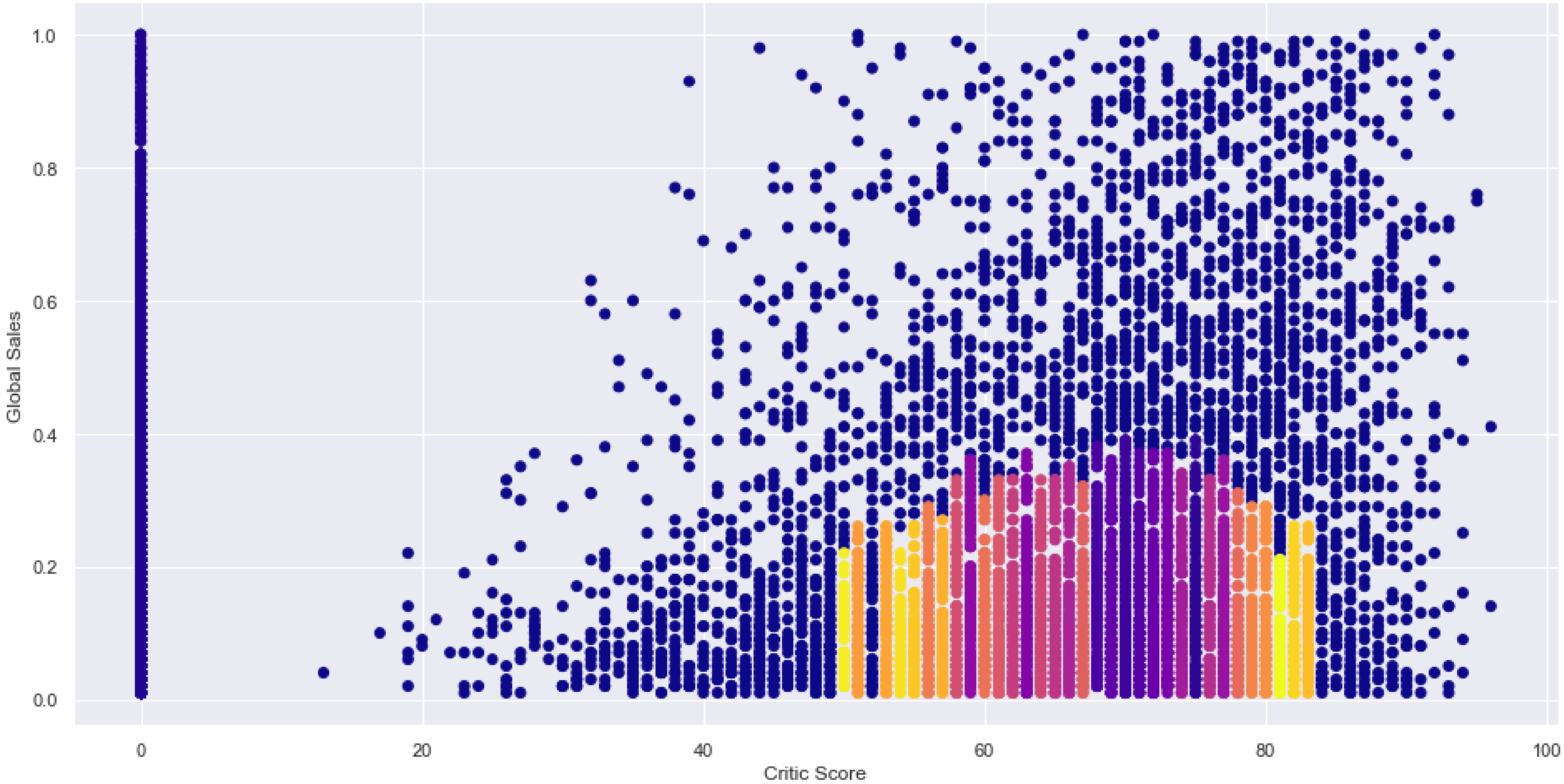


Critic Score vs Global Sales

In [14]:

```python
from sklearn.neighbors import NearestNeighbors # importing the library
from sklearn.cluster import DBSCAN

f, axes = plt.subplots(1, 1, figsize=(16, 8))
```

```python
x = gamesData.loc[:, ['Critic_Score','Global_Sales']].values

neighb = NearestNeighbors(n_neighbors=2) # creating an object of the NearestNeighbors class
nbrs=neighb.fit(x) # fitting the data to the object
distances,indices=nbrs.kneighbors(x) # finding the nearest neighbours

# cluster the data into five clusters
dbscan = DBSCAN(eps = 0.1, min_samples = 50).fit(x) # fitting the model
labels = dbscan.labels_ # getting the labels

# Plot the clusters
plt.scatter(x[:, 0], x[:,1], c = labels, cmap= "plasma") # plotting the clusters
plt.xlabel("Critic Score") # X-axis label
plt.ylabel("Global Sales") # Y-axis label
plt.show() # showing the plot

n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
n_noise_ = list(labels).count(-1)

print('Estimated number of clusters: %d' % n_clusters_)
print('Estimated number of noise points: %d' % n_noise_)
```




```
Estimated number of clusters: 34
Estimated number of noise points: 2674
```

User_Score & Critic_Score VS Global_Sales using Machine Learning

In [15]:

```
rawData = pd.read_csv('sales.csv')
naDropped = rawData.dropna(subset=["Name", "Platform", "Year_of_Release", "Genre", "Publisher", "NA_Sales",
                                   "EU_Sales", "JP_Sales", "Other_Sales", "Global_Sales", "Critic_Score",
                                   "Critic_Count", "User_Score", "User_Count", "Developer", "Rating"])
```

In [16]:

```
netData = pd.DataFrame(naDropped[["Critic_Score", "Critic_Count", "User_Score", "User_Count", "Global_Sales"]]).copy()
```

```python
Q1 = netData.quantile(0.25)
Q3 = netData.quantile(0.75)
rule = ((netData < (Q1 - 1.5 * (Q3 - Q1))) | (netData > (Q3 + 1.5 * (Q3 - Q1))))
outliers = rule.any(axis = 1)
outliers.value_counts()
outlierindices = outliers.index[outliers == True]
netData.drop(axis = 0, index = outlierindices, inplace = True)

s = netData['Global_Sales'].quantile(0.85)
netData['Successful'] = (netData['Global_Sales'] >= s)

netData.head(810)
```

```
C:\Users\dobin001\AppData\Local\Temp/ipykernel_19060/3607325086.py:5: FutureWarning: Automatic reindexing on DataFrame vs Series c
omparisons is deprecated and will raise ValueError in a future version.  Do `left, right = left.align(right, axis=1, copy=False)`
before e.g. `left == right`
  rule = ((netData < (Q1 - 1.5 * (Q3 - Q1))) | (netData > (Q3 + 1.5 * (Q3 - Q1))))
```

Out[16]:

	Critic_Score	Critic_Count	User_Score	User_Count	Global_Sales	Successful
1042	89.0	25.0	8.9	43.0	1.71	True
1043	84.0	57.0	9.1	81.0	1.71	True
1044	83.0	25.0	8.7	35.0	1.71	True
1053	87.0	18.0	8.6	23.0	1.70	True
1054	74.0	17.0	5.3	77.0	1.70	True
...	...	...	...	...	...	...
2742	59.0	42.0	6.5	61.0	0.75	True
2743	80.0	47.0	6.9	106.0	0.75	True
2746	54.0	45.0	7.1	57.0	0.74	False
2747	76.0	45.0	5.7	9.0	0.74	False
2748	79.0	25.0	7.7	33.0	0.74	False

810 rows × 6 columns

In [17]:
```python
# Extracting Response and Predictors
p = pd.DataFrame(netData[["Critic_Score", "User_Score"]])
r = pd.DataFrame(netData["Successful"])
test = pd.DataFrame(netData["Global_Sales"])
test.describe()
```

Out[17]:

	Global_Sales
count	5374.000000
mean	0.372657
std	0.369865
min	0.010000
25%	0.100000
50%	0.240000
75%	0.520000
max	1.710000

In [18]:
```python
# Create a Decision Tree Classifier object
dectree = DecisionTreeClassifier(max_depth = 3)

# Split the Dataset into Train and Test
p_train, p_test, r_train, r_test = train_test_split(p, r, test_size = 0.33)

# Check the sample sizes
print("Train Set :", r_train.shape, p_train.shape)
print("Test Set  :", r_test.shape, p_test.shape)
```

```
Train Set : (3600, 1) (3600, 2)
Test Set  : (1774, 1) (1774, 2)
```

In [19]:
```python
# Summary Statistics for Response
r_train["Successful"].value_counts()
```

Out[19]:
```
False    3050
True      550
Name: Successful, dtype: int64
```

In [20]:

```python
# Summary Statistics for Predictors
p_train.describe(include = 'all')
```

Out[20]:

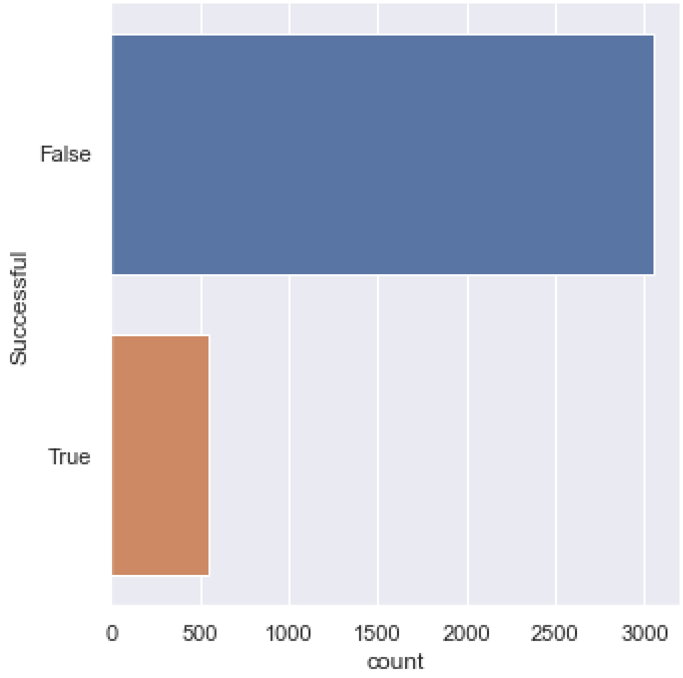
	Critic_Score	User_Score
count	3600.000000	3600
unique	NaN	82
top	NaN	7.8
freq	NaN	163
mean	68.447500	NaN
std	12.372473	NaN
min	35.000000	NaN
25%	60.000000	NaN
50%	70.000000	NaN
75%	78.000000	NaN
max	98.000000	NaN

In [21]:

```python
# Draw the distribution of Response
sb.catplot(y = "Successful", data = r_train, kind = "count")
```

Out[21]:

```
<seaborn.axisgrid.FacetGrid at 0x26778e71e80>
```



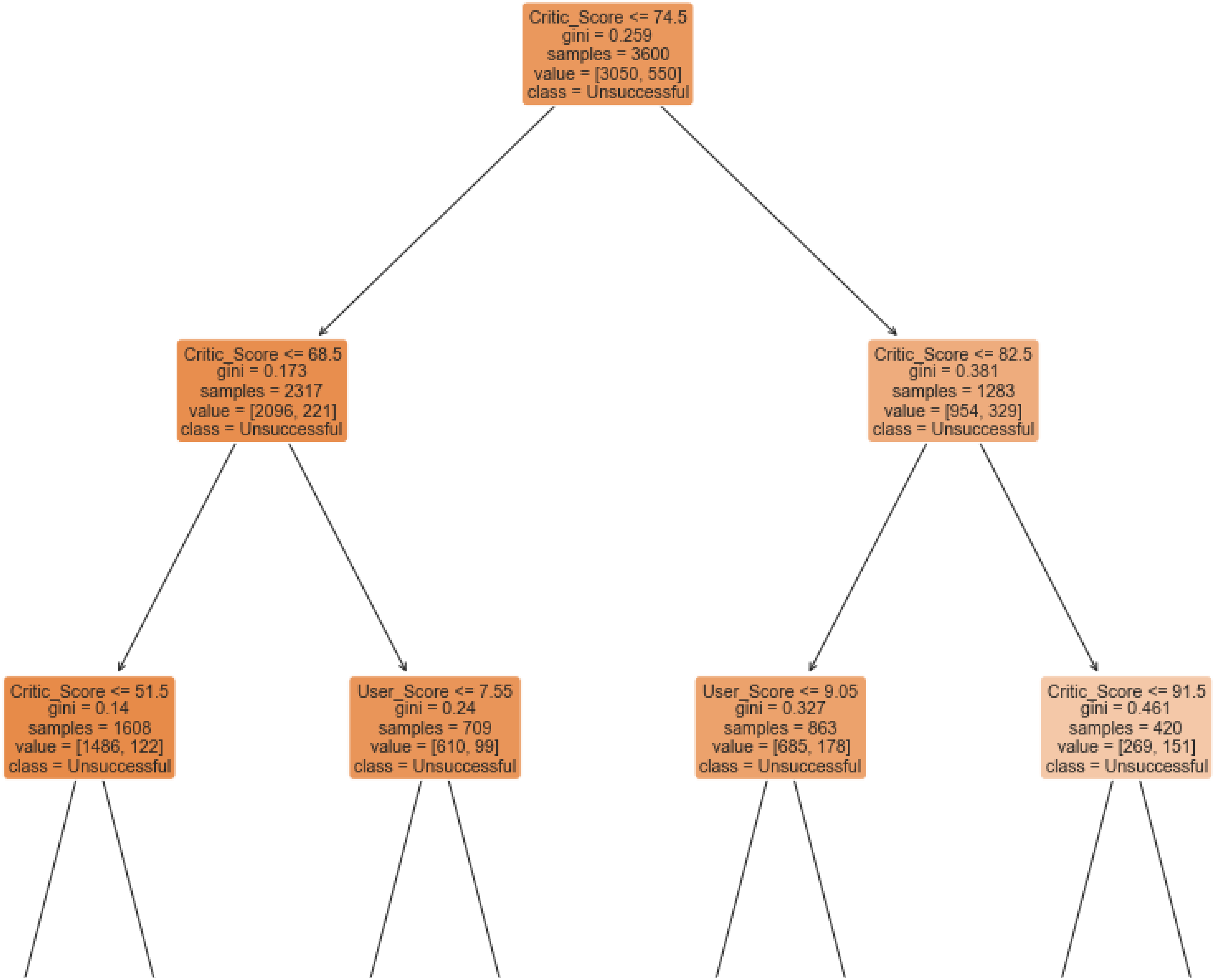
In [22]:

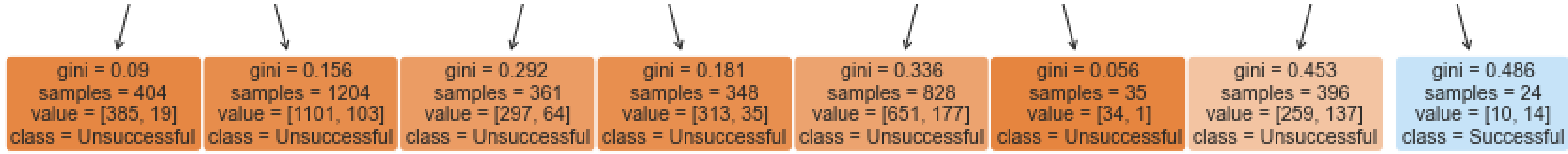
```
dectree.fit(p_train, r_train)                      # train the decision tree model

# Plot the trained Decision Tree
f = plt.figure(figsize=(15,15))
plot_tree(dectree, filled=True, rounded=True,
          feature_names=p_train.columns,
          class_names=["Unsuccessful","Successful"])
```

Out[22]:

```
[Text(418.5, 713.475, 'Critic_Score <= 74.5\ngini = 0.259\nsamples = 3600\nvalue = [3050, 550]\nclass = Unsuccessful'),
 Text(209.25, 509.625, 'Critic_Score <= 68.5\ngini = 0.173\nsamples = 2317\nvalue = [2096, 221]\nclass = Unsuccessful'),
 Text(104.625, 305.775, 'Critic_Score <= 51.5\ngini = 0.14\nsamples = 1608\nvalue = [1486, 122]\nclass = Unsuccessful'),
 Text(52.3125, 101.92499999999995, 'gini = 0.09\nsamples = 404\nvalue = [385, 19]\nclass = Unsuccessful'),
 Text(156.9375, 101.92499999999995, 'gini = 0.156\nsamples = 1204\nvalue = [1101, 103]\nclass = Unsuccessful'),
 Text(313.875, 305.775, 'User_Score <= 7.55\ngini = 0.24\nsamples = 709\nvalue = [610, 99]\nclass = Unsuccessful'),
 Text(261.5625, 101.92499999999995, 'gini = 0.292\nsamples = 361\nvalue = [297, 64]\nclass = Unsuccessful'),
 Text(366.1875, 101.92499999999995, 'gini = 0.181\nsamples = 348\nvalue = [313, 35]\nclass = Unsuccessful'),
 Text(627.75, 509.625, 'Critic_Score <= 82.5\ngini = 0.381\nsamples = 1283\nvalue = [954, 329]\nclass = Unsuccessful'),
 Text(523.125, 305.775, 'User_Score <= 9.05\ngini = 0.327\nsamples = 863\nvalue = [685, 178]\nclass = Unsuccessful'),
 Text(470.8125, 101.92499999999995, 'gini = 0.336\nsamples = 828\nvalue = [651, 177]\nclass = Unsuccessful'),
 Text(575.4375, 101.92499999999995, 'gini = 0.056\nsamples = 35\nvalue = [34, 1]\nclass = Unsuccessful'),
```

```
Text(732.375, 305.775, 'Critic_Score <= 91.5\ngini = 0.461\nsamples = 420\nvalue = [269, 151]\nclass = Unsuccessful'),
Text(680.0625, 101.92499999999995, 'gini = 0.453\nsamples = 396\nvalue = [259, 137]\nclass = Unsuccessful'),
Text(784.6875, 101.92499999999995, 'gini = 0.486\nsamples = 24\nvalue = [10, 14]\nclass = Successful')]
```





In [23]:

```
# Extract Response and Predictors
predictors = ["Critic_Score", "User_Score"]

r = pd.DataFrame(netData['Successful'])
p = pd.DataFrame(netData[predictors])

# Split the Dataset into Train and Test
p_train, p_test, r_train, r_test = train_test_split(p, r, test_size = 0.25)

# Decision Tree using Train Data
dectree = DecisionTreeClassifier(max_depth = 3)  # create the decision tree object
dectree.fit(p_train, r_train)                    # train the decision tree model

# Predict Response corresponding to Predictors
r_train_pred = dectree.predict(p_train)
r_test_pred = dectree.predict(p_test)

# Extract Predictors for Prediction
p_pred = pd.DataFrame(netData[predictors])

# Predict Response corresponding to Predictors
r_pred = dectree.predict(p_pred)
r_pred
```

Out[23]:

```
array([False, False, False, ..., False, False, False])
```

In [24]:

```
# Summarize the Actuals and Predictions
r_pred = pd.DataFrame(r_pred, columns = ["Pred_Successful"], index = netData.index)
netData_acc = pd.concat([netData[["Critic_Score", "User_Score", "Successful"]], r_pred], axis = 1)
```

```python
netData_acc['Correct Guess'] = (netData_acc["Successful"] == netData_acc["Pred_Successful"])
netData_acc
```

Out[24]:

	Critic_Score	User_Score	Successful	Pred_Successful	Correct Guess
1042	89.0	8.9	True	False	False
1043	84.0	9.1	True	False	False
1044	83.0	8.7	True	False	False
1053	87.0	8.6	True	False	False
1054	74.0	5.3	True	False	False
...	...	...	...	...	...
16654	81.0	8.5	False	False	True
16665	46.0	2.4	False	False	True
16675	81.0	8.8	False	False	True
16698	61.0	5.8	False	False	True
16704	60.0	7.2	False	False	True

5374 rows × 5 columns

In [25]:

```python
netData_acc['Correct Guess'].value_counts()
```

Out[25]:

```
True     4569
False     805
Name: Correct Guess, dtype: int64
```

In [27]:

```python
print(4569/(4569 + 805), "% of predictions were correct.")
```

```
0.8502046892445106 % of predictions were correct.
```

In [ ]: