Project Name :- Video Games Sales prediction

I am going to build project of The Machine Learning model to predict future sales of Video Games in gloabal market. We will learn different patterns and relationships between the input Variables or factors that affecting to the video games sales. We analyse data to get meaning information from them and Visualize them to recognise different patterns among them and showing meaning full information that will help us to predict sales data by creating effective machine learning model.

We use Data set which contains the list of video games with sales greater than 16500 games in global market.

Dataset Description

Rank - Ranking of overall sales

Name - The games name

Platform - Platform of the games release (i.e. PC,PS4, etc.)

Year - Year of the game's release

Genre - Genre of the game

Publisher - Publisher of the game

NA_Sales - Sales in North America (in millions)

EU_Sales - Sales in Europe (in millions)

JP_Sales - Sales in Japan (in millions)

Other_Sales - Sales in the rest of the world (in millions)

Global_Sales - Total worldwide sales.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("darkgrid")

from sklearn.metrics import mean_absolute_error as mae, mean_squared_error as mse, r2_score

import warnings
warnings.filterwarnings('ignore')
```

Importing Data set

In [2]:
```
df = pd.read_csv("vgsales.csv")
df.head(5)
```

Out[2]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.77	8.46	82.74
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	0.77	40.24
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.79	3.31	35.82
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.28	2.96	33.00
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	10.22	1.00	31.37

Exploratory Data Analysis

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16598 entries, 0 to 16597
Data columns (total 11 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Rank          16598 non-null  int64  
 1   Name          16598 non-null  object 
 2   Platform      16598 non-null  object 
 3   Year          16327 non-null  float64
 4   Genre         16598 non-null  object 
 5   Publisher     16540 non-null  object 
 6   NA_Sales      16598 non-null  float64
 7   EU_Sales      16598 non-null  float64
 8   JP_Sales      16598 non-null  float64
 9   Other_Sales   16598 non-null  float64
 10  Global_Sales  16598 non-null  float64
dtypes: float64(6), int64(1), object(4)
memory usage: 1.1+ MB
```

As we see, there are 16598 vedio games are there with 11 variables. In the Year and Publisher columns,there will some missing Values

In [5]:
```
df.describe()
```

Out[5]:

	Rank	Year	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
count	16598.000000	16327.000000	16598.000000	16598.000000	16598.000000	16598.000000	16598.000000
mean	8300.605254	2006.406443	0.264667	0.146652	0.077782	0.048063	0.537441
std	4791.853933	5.828981	0.816683	0.505351	0.309291	0.188588	1.555028
min	1.000000	1980.000000	0.000000	0.000000	0.000000	0.000000	0.010000
25%	4151.250000	2003.000000	0.000000	0.000000	0.000000	0.000000	0.060000
50%	8300.500000	2007.000000	0.080000	0.020000	0.000000	0.010000	0.170000
75%	12449.750000	2010.000000	0.240000	0.110000	0.040000	0.040000	0.470000
max	16600.000000	2020.000000	41.490000	29.020000	10.220000	10.570000	82.740000

Handling Missing Values

In [5]:
```
df.isna().sum()
```

Out[5]:
```
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
```

In [6]:
```
df.dropna(inplace=True)
```

In [7]:
```
df.isna().sum()
```

Out[7]:
```
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
```

Knowing about shape and size of dataset

In [10]:
```
df.shape
```

Out[10]:
```
(16291, 11)
```

In [11]:
```
df.size
```

Out[11]:
```
179201
```

In [12]:
```
df.columns
```

Out[12]:
```
Index(['Rank', 'Name', 'Platform', 'Year', 'Genre', 'Publisher', 'NA_Sales',
       'EU_Sales', 'JP_Sales', 'Other_Sales', 'Global_Sales'],
      dtype='object')
```

Unique values present in each feature

In [13]:
```
print("total number Categories/Classes present in Each Variable")
for col in df:
    uni=df[col].nunique()
    print(f" {col} :- {uni}")
```

```
total number Categories/Classes present in Each Variable
 Rank :- 16291
 Name :- 11325
 Platform :- 31
 Year :- 39
 Genre :- 12
 Publisher :- 576
 NA_Sales :- 408
 EU_Sales :- 305
 JP_Sales :- 244
 Other_Sales :- 157
 Global_Sales :- 621
```

Analysis Categorical Features

In [14]:
```
# Creating Categorical DataFrame
df_cat = df.select_dtypes('object')
df_cat.head()
```

Out[14]:

	Name	Platform	Genre	Publisher
0	Wii Sports	Wii	Sports	Nintendo
1	Super Mario Bros.	NES	Platform	Nintendo
2	Mario Kart Wii	Wii	Racing	Nintendo
3	Wii Sports Resort	Wii	Sports	Nintendo
4	Pokemon Red/Pokemon Blue	GB	Role-Playing	Nintendo

checking the top (most repetitive) values.

In [15]:
```
for cat in df_cat.columns:
    print("----------------------------------------------------------------------------------------------------
    print(cat,"\n")
    print(df[cat].value_counts().head())
```

```
----------------------------------------------------------------------------------------------------
Name 

Need for Speed: Most Wanted    12
FIFA 14                         9
Ratatouille                     9
LEGO Marvel Super Heroes        9
The LEGO Movie Videogame        8
Name: Name, dtype: int64
----------------------------------------------------------------------------------------------------
Platform 

DS      2131
PS2     2127
PS3     1304
Wii     1290
X360    1234
Name: Platform, dtype: int64
----------------------------------------------------------------------------------------------------
Genre 

Action          3251
Sports          2304
Misc            1686
Role-Playing    1470
Shooter         1282
Name: Genre, dtype: int64
----------------------------------------------------------------------------------------------------
Publisher 

Electronic Arts                 1339
Activision                       966
Namco Bandai Games               928
Ubisoft                          918
Konami Digital Entertainment     823
Name: Publisher, dtype: int64
```

The game which has highest global sales

In [16]:
```
high = df["Global_Sales"].max()
top_game = df[df["Global_Sales"] == high]
#top_game[["Name","Global_Sales","Year"]]
top_game
```

Out[16]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.77	8.46	82.74

The game which has Lowest global sales

In [17]:
```
low = df["Global_Sales"].min()
low_game = df[df["Global_Sales"] == low]
low_game
```

Out[17]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
15980	15983	Turok	PC	2008.0	Action	Touchstone	0.00	0.01	0.00	0.0	0.01
15981	15984	Coven and Labyrinth of Refrain	PSV	2016.0	Action	Nippon Ichi Software	0.00	0.00	0.01	0.0	0.01
15982	15985	Super Battle For Money Sentouchuu: Kyuukyoku n...	3DS	2016.0	Action	Namco Bandai Games	0.00	0.00	0.01	0.0	0.01
15983	15986	Dragon Zakura DS	DS	2007.0	Misc	Electronic Arts	0.00	0.00	0.01	0.0	0.01
15984	15987	Chameleon: To Dye For!	DS	2006.0	Puzzle	505 Games	0.01	0.00	0.00	0.0	0.01
...	...	...	...	...	...	...	...	...	...	...	...
16593	16596	Woody Woodpecker in Crazy Castle 5	GBA	2002.0	Platform	Kemco	0.01	0.00	0.00	0.0	0.01
16594	16597	Men in Black II: Alien Escape	GC	2003.0	Shooter	Infogrames	0.01	0.00	0.00	0.0	0.01
16595	16598	SCORE International Baja 1000: The Official Game	PS2	2008.0	Racing	Activision	0.00	0.00	0.00	0.0	0.01
16596	16599	Know How 2	DS	2010.0	Puzzle	7G//AMES	0.00	0.01	0.00	0.0	0.01
16597	16600	Spirits & Spells	GBA	2003.0	Platform	Wanadoo	0.01	0.00	0.00	0.0	0.01

600 rows × 11 columns

Data Visualization

Global sales vs No. of games sold

In [3]:
```
plt.hist(df["Global_Sales"],bins=20)
plt.xlabel("Sales in Million",fontsize=15)
plt.xticks(np.arange(0,80,5))
plt.ylabel("No. of games sold")
plt.show()
# in  0 to 5 million range most games are sold
```

In [4]:
```
# Total number of Platform present
df['Platform'].unique()
```

Out[4]:
```
array(['Wii', 'NES', 'GB', 'DS', 'X360', 'PS3', 'PS2', 'SNES', 'GBA',
       '3DS', 'PS4', 'N64', 'PS', 'XB', 'PC', '2600', 'PSP', 'XOne', 'GC',
       'WiiU', 'GEN', 'DC', 'PSV', 'SAT', 'SCD', 'WS', 'NG', 'TG16',
       '3DO', 'GG', 'PCFX'], dtype=object)
```

In [5]:
```
# Top Platforms who released games
df['Platform'].value_counts()
```

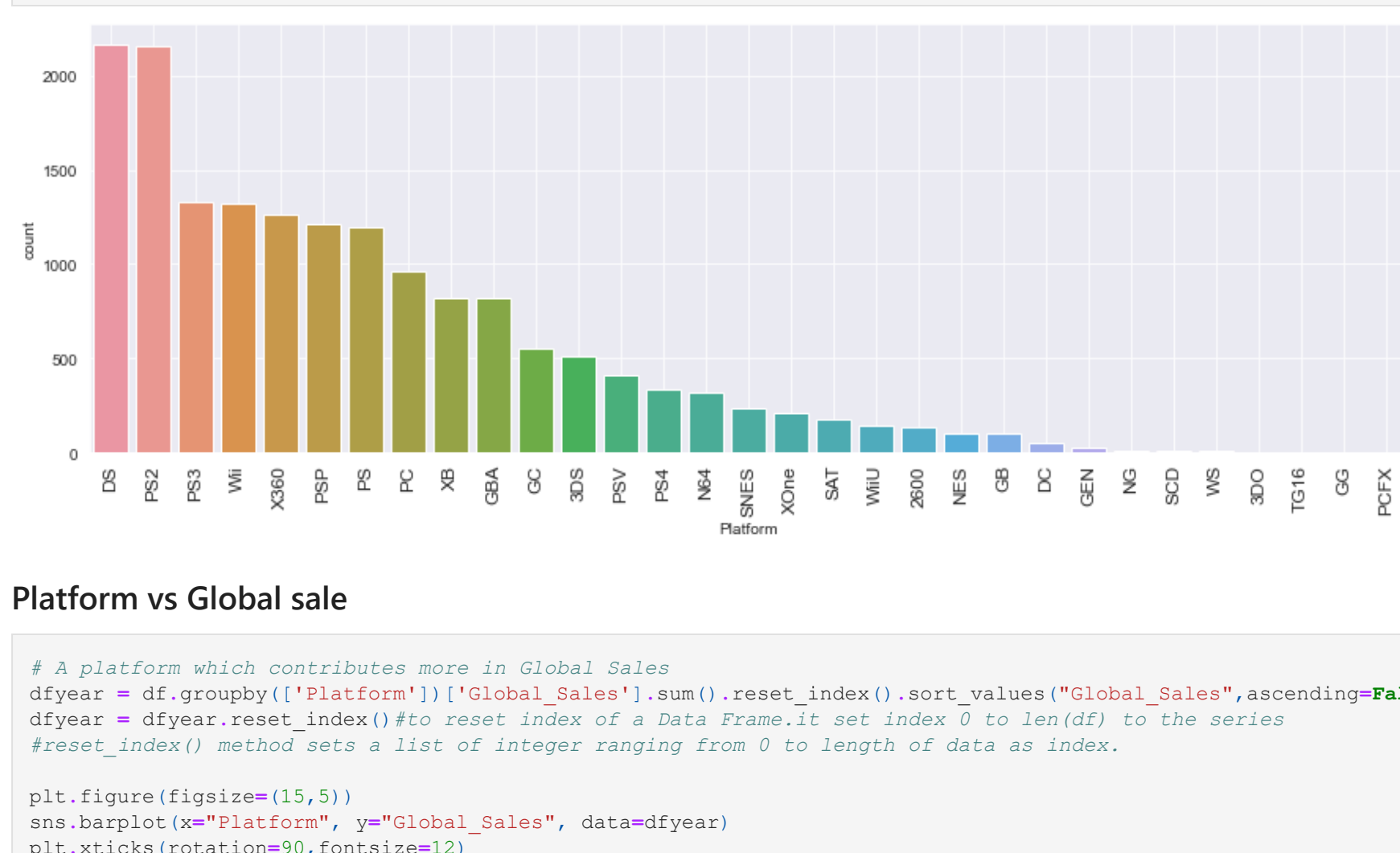
Out[5]:
```
DS      2163
PS2     2161
PS3     1329
Wii     1325
X360    1265
PSP     1213
PS      1196
PC       960
XB       824
GBA      822
GC       556
3DS      509
PSV      413
PS4      336
N64      319
SNES     239
XOne     213
SAT      173
WiiU     143
2600     133
NES       98
GB        98
DC        52
GEN       27
NG        12
SCD        6
WS         6
3DO        3
TG16       2
GG         1
PCFX       1
Name: Platform, dtype: int64
```

Platform vs No. of games released

In [6]:
```
# Platform which released maximum Games
plt.figure(figsize=(15,5))
sns.countplot(x="Platform", data=df, order = df['Platform'].value_counts().index)# unique does not give high to
plt.xticks(rotation=90,fontsize=12)
plt.grid(True)
plt.show()
```

Platform vs Global sale

In [7]:
```
# A platform which contributes more in Global Sales
dfyear = df.groupby(['Platform'])['Global_Sales'].sum().reset_index().sort_values("Global_Sales",ascending=Fals
dfyear = dfyear.reset_index()#to reset index of a Data Frame.it set index 0 to len(df) to the series
#reset_index() method sets a list of integer ranging from 0 to length of data as index.

plt.figure(figsize=(15,5))
sns.barplot(x="Platform", y="Global_Sales", data=dfyear)
plt.xticks(rotation=90,fontsize=12)
plt.xlabel("Platform",fontsize=12)
plt.ylabel("Global Sale",fontsize=12)
plt.grid(True)

plt.show()
# PS2 platform contributes more in Global Sales
```



In [8]:
```
df['Genre'].unique()
```

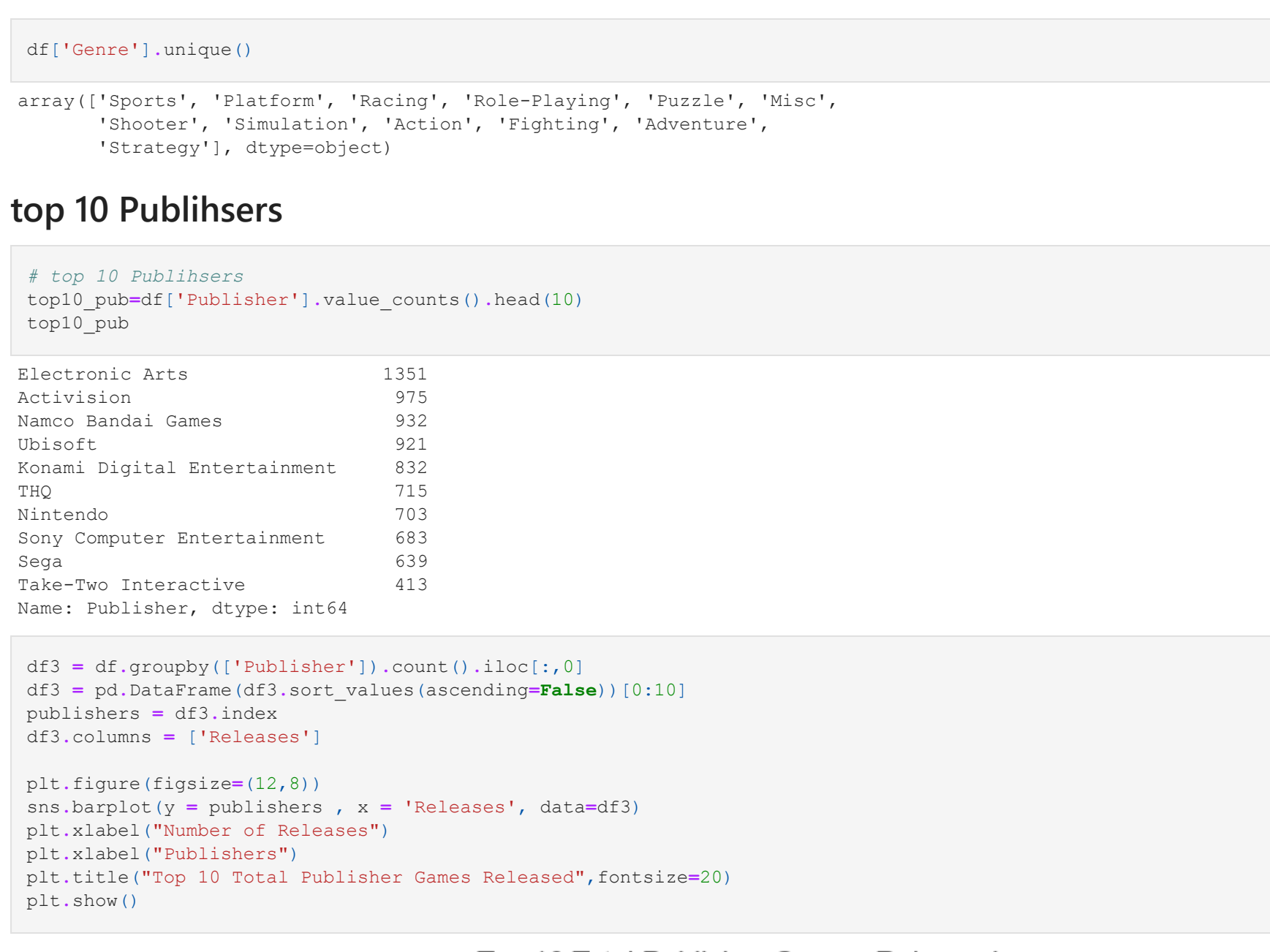
Out[8]:
```
array(['Sports', 'Platform', 'Racing', 'Role-Playing', 'Puzzle', 'Misc',
       'Shooter', 'Simulation', 'Action', 'Fighting', 'Adventure',
       'Strategy'], dtype=object)
```

top 10 Publihsers

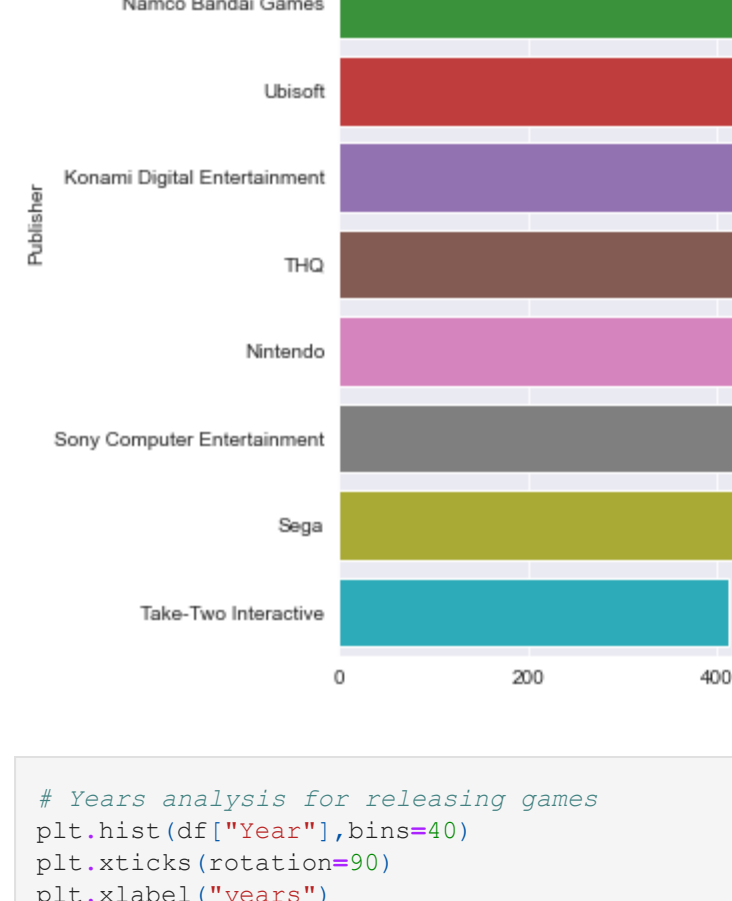
In [9]:
```
# top 10 Publihsers
top10_pub=df['Publisher'].value_counts().head(10)
top10_pub
```

Out[9]:
```
Electronic Arts                 1351
Activision                       975
Namco Bandai Games               932
Ubisoft                          921
Konami Digital Entertainment     832
THQ                              715
Nintendo                         703
Sony Computer Entertainment      683
Sega                             639
Take-Two Interactive             413
Name: Publisher, dtype: int64
```

In [10]:
```
df3 = df.groupby(['Publisher']).count().iloc[:,0]
df3 = pd.DataFrame(df3.sort_values(ascending=False))[0:10]
publishers = df3.index
df3.columns = ['Releases']

plt.figure(figsize=(12,8))
sns.barplot(y = publishers , x = 'Releases', data=df3)
plt.xlabel("Number of Releases")
plt.xlabel("Publishers")
plt.title("Top 10 Total Publisher Games Released",fontsize=20)
plt.show()
```



In [11]:
```
# Years analysis for releasing games
plt.hist(df["Year"],bins=40)
plt.xticks(rotation=90)
plt.xlabel("years")
plt.ylabel("No of games released")
plt.show()
# 2008-10 most games released
```



In [12]:
```
# genres to analysis to how many games have in particalar genre
df['Genre'].value_counts()
```

Out[12]:
```
Action          3316
Sports          2346
Misc            1739
Role-Playing    1488
Shooter         1310
Adventure       1286
Racing          1249
Platform         886
Simulation       867
Fighting         848
Strategy         681
Puzzle           582
Name: Genre, dtype: int64
```

Genre vs No. of games released

In [14]:
```
# Which has released most games
plt.figure(figsize=(9,5))
sns.countplot(x="Genre", data=df, order = df['Genre'].value_counts().index)
plt.xticks(rotation=90,fontsize=12)
plt.xlabel("Genre",fontsize=12)
plt.grid(True)
plt.show()
# most of the people love action and sports game. in action 3251 and in sports 2304 games release.
```

In [29]:
```
x_val=df["Genre"].unique()
x_val.shape
```

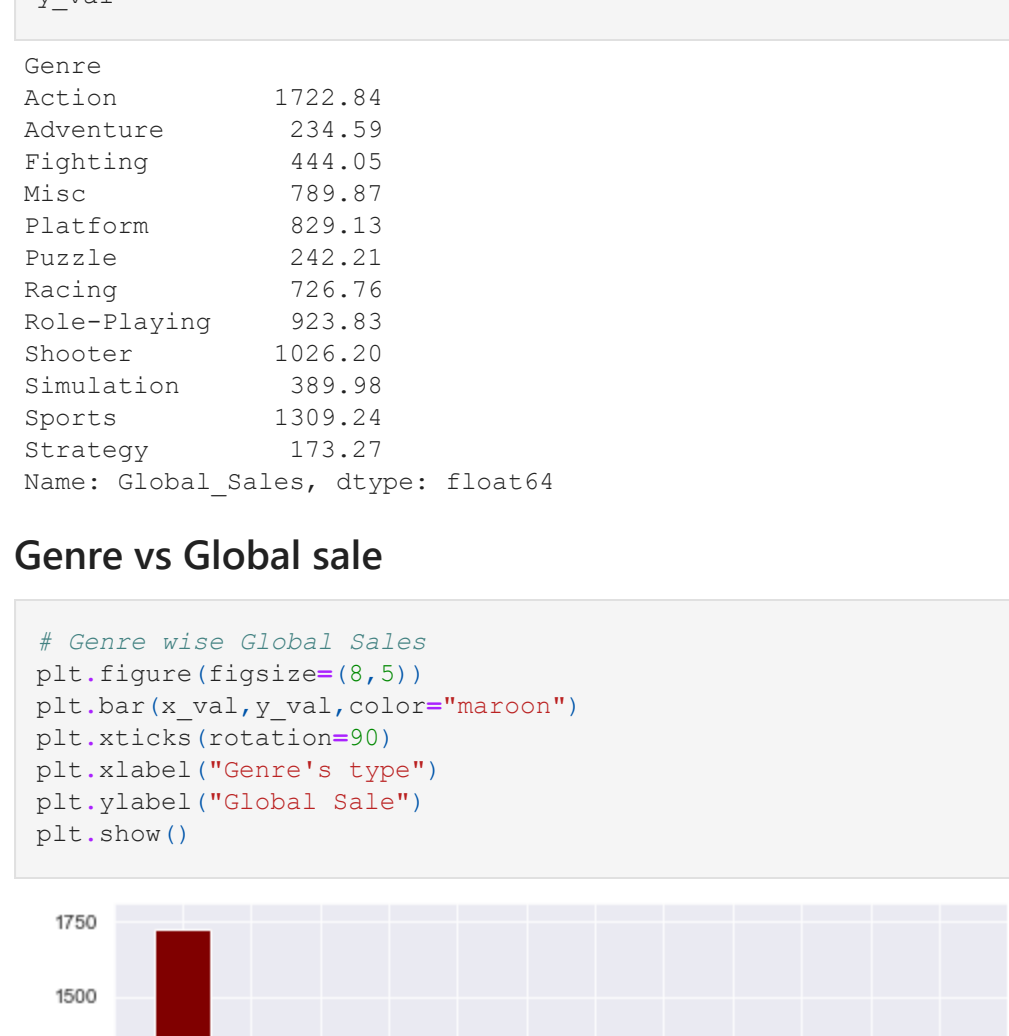
Out[29]:
```
(12,)
```

In [30]:
```
y_val=df.groupby("Genre")["Global_Sales"].sum()
y_val
```

Out[30]:
```
Genre
Action          1722.84
Adventure        234.59
Fighting         444.05
Misc             789.87
Platform         829.13
Puzzle           242.21
Racing           726.76
Role-Playing     923.83
Shooter         1026.20
Simulation       389.98
Sports          1309.24
Strategy         173.27
Name: Global_Sales, dtype: float64
```

Genre vs Global sale

In [31]:
```
# Genre wise Global Sales
plt.figure(figsize=(8,5))
plt.bar(x_val,y_val,color="maroon")
plt.xticks(rotation=90)
plt.xlabel("Genre's type")
plt.ylabel("Global Sale")
plt.show()
```



genrewise regions Sales Comparison

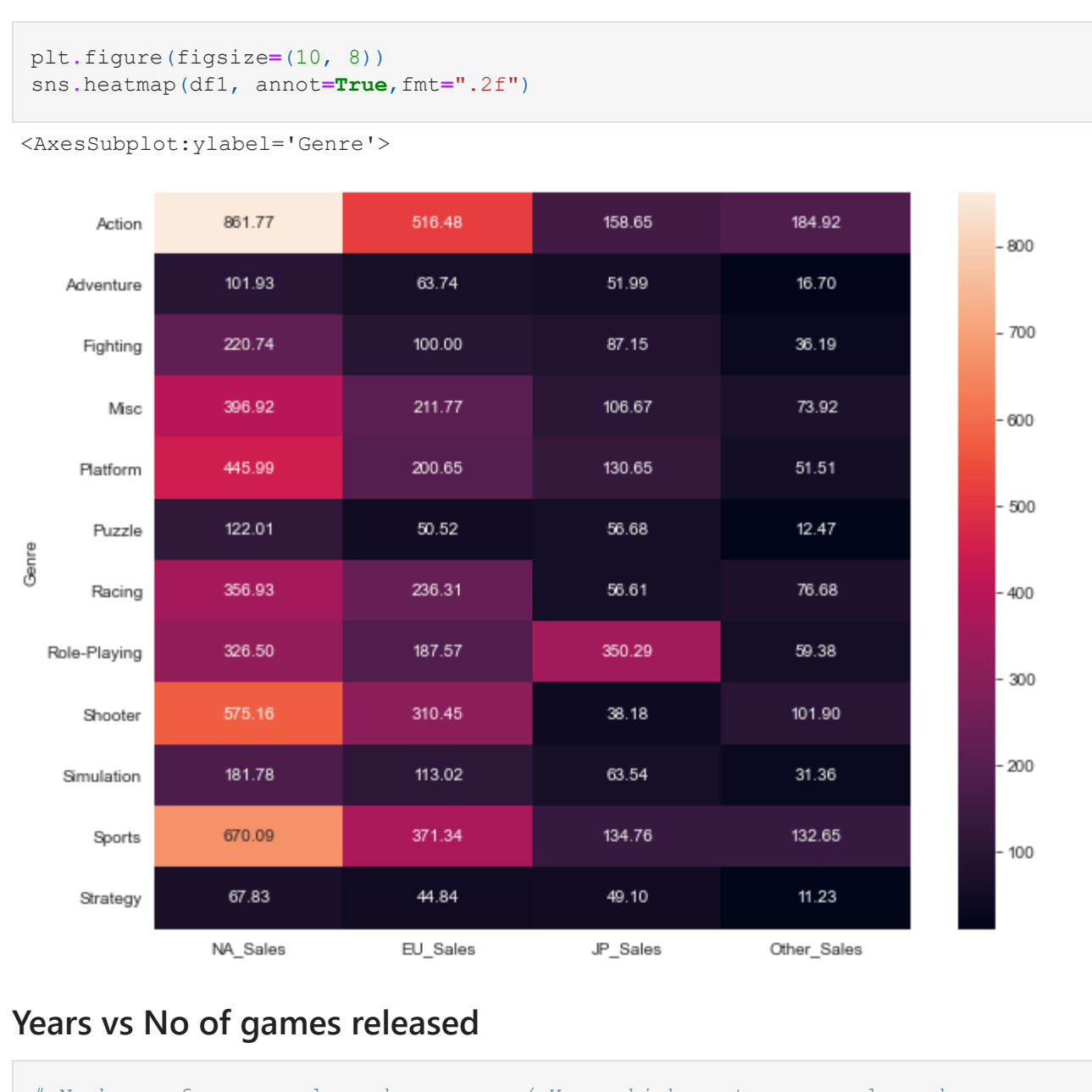
In [32]:
```
# genrewise regions Sales Comparison
df1 = df[['Genre', 'NA_Sales', 'EU_Sales', 'JP_Sales', 'Other_Sales']]
df1 = df1.groupby("Genre").sum()
df1
```

Out[32]:

Genre	NA_Sales	EU_Sales	JP_Sales	Other_Sales
Action	861.77	516.48	158.65	184.92
Adventure	101.93	63.74	51.99	16.70
Fighting	220.74	100.00	87.15	36.19
Misc	396.92	211.77	106.67	73.92
Platform	445.99	200.65	130.65	51.51
Puzzle	122.01	50.52	56.68	12.47
Racing	356.93	236.31	56.61	76.68
Role-Playing	326.50	187.57	350.29	59.38
Shooter	575.16	310.45	38.18	101.90
Simulation	181.78	113.02	63.54	31.36
Sports	670.09	371.34	134.76	132.65
Strategy	67.83	44.84	49.10	11.23

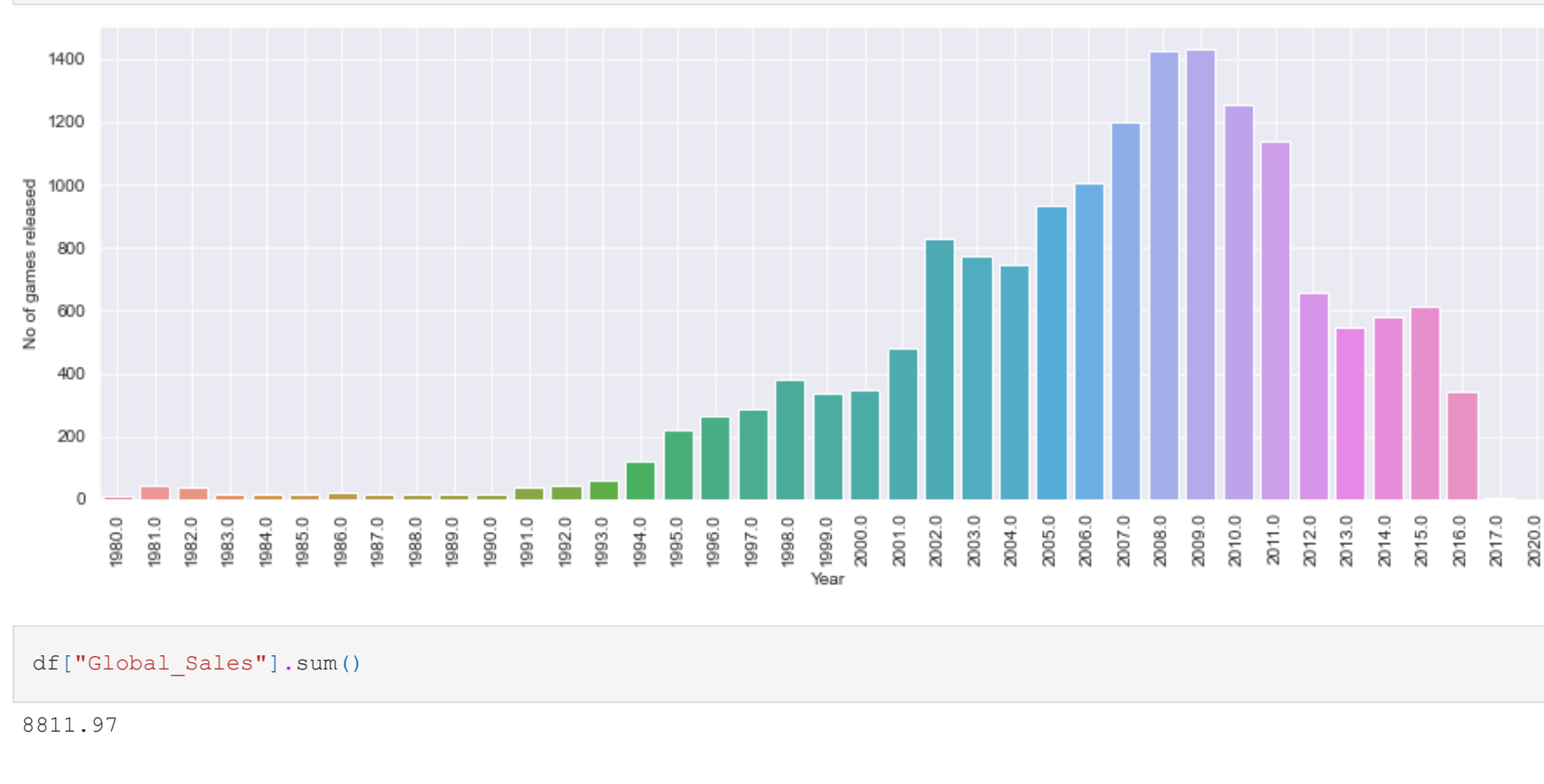
In [33]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(df1, annot=True,fmt=".2f")
```

Out[33]:
```
<AxesSubplot:ylabel='Genre'>
```



Years vs No of games released

In [34]:
```
# Numbers of games released per year / Year which most games released
yrgame = df.groupby('Year')['Name'].count()
plt.figure(figsize=(15,5))
sns.countplot(x="Year", data=df, order=yrgame.index)
plt.xticks(rotation=90)
plt.ylabel("No of games released")
plt.grid(True)

plt.show()
```

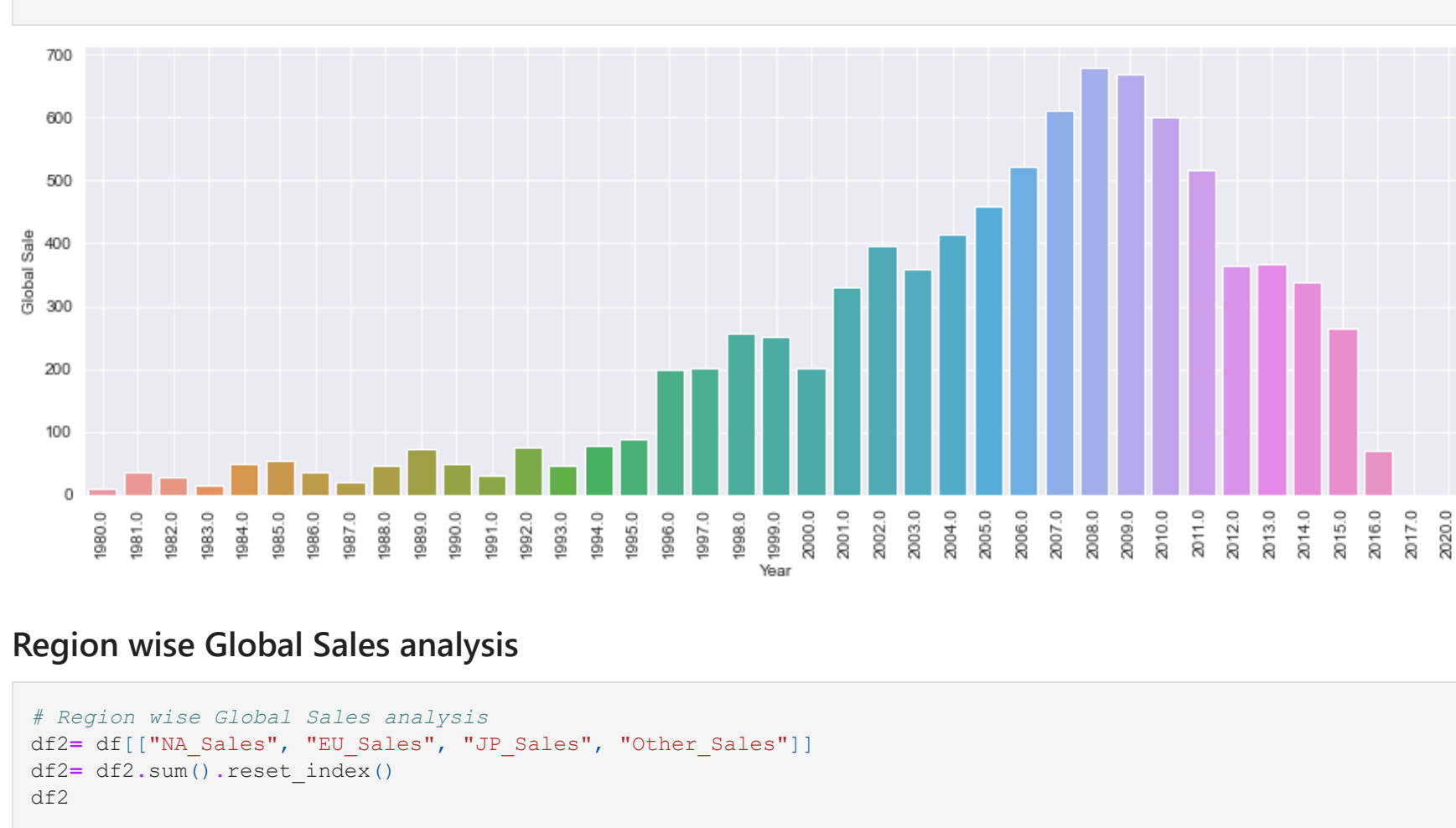


In [35]:
```
df["Global_Sales"].sum()
```

Out[35]:
```
8811.97
```

Year vs Global sale

In [36]:
```
# The year which has Highest Global Sale
dfyear = df.groupby(['Year'])['Global_Sales'].sum() # grouping the data according to the categories and apply a
dfyear = dfyear.reset_index()#to reset index of a Data Frame. reset_index() method sets a list of integer rang

plt.figure(figsize=(15,5))
sns.barplot(x="Year", y="Global_Sales", data=dfyear)
plt.xticks(rotation=90)
plt.ylabel("Global Sale")
plt.grid(True)

plt.show()
```



Region wise Global Sales analysis

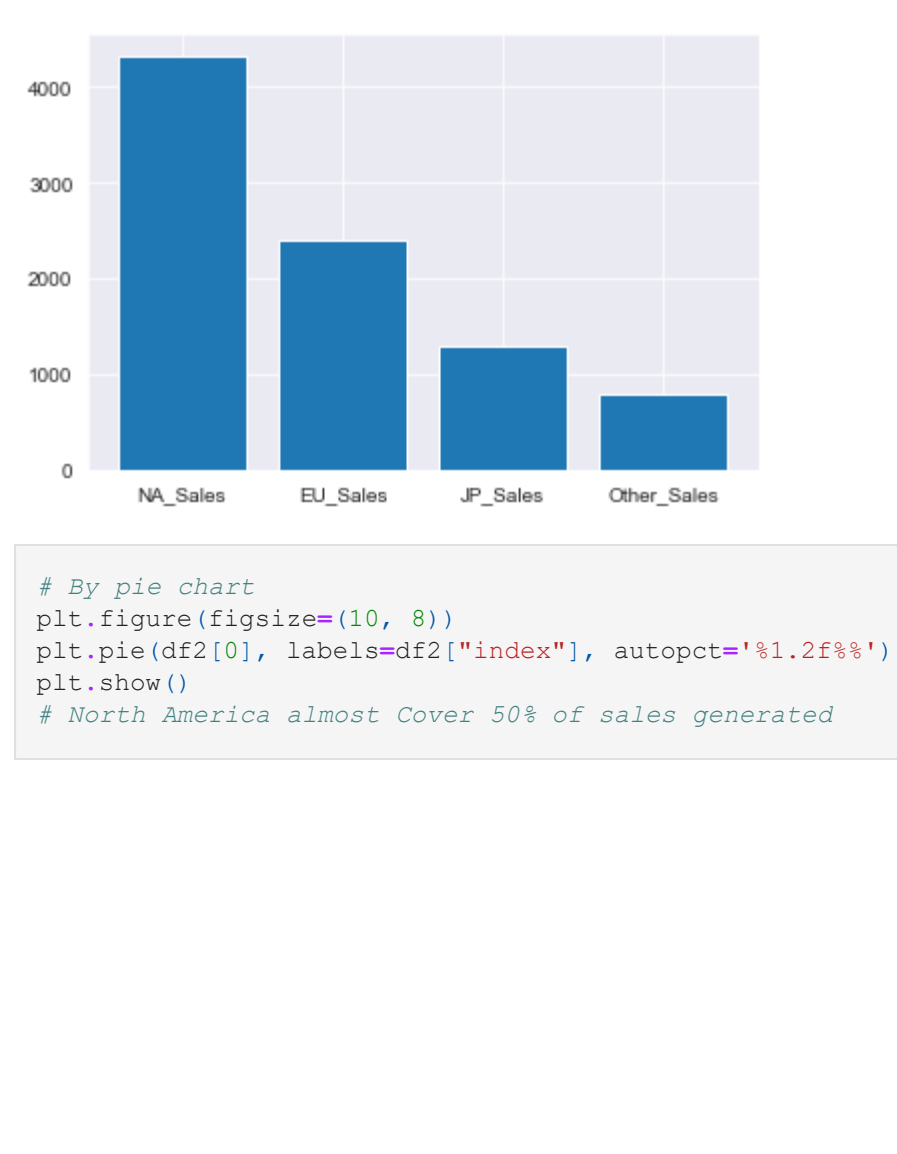
In [37]:
```
# Region wise Global Sales analysis
df2= df[["NA_Sales", "EU_Sales", "JP_Sales", "Other_Sales"]]
df2= df2.sum().reset_index()
df2
```

Out[37]:

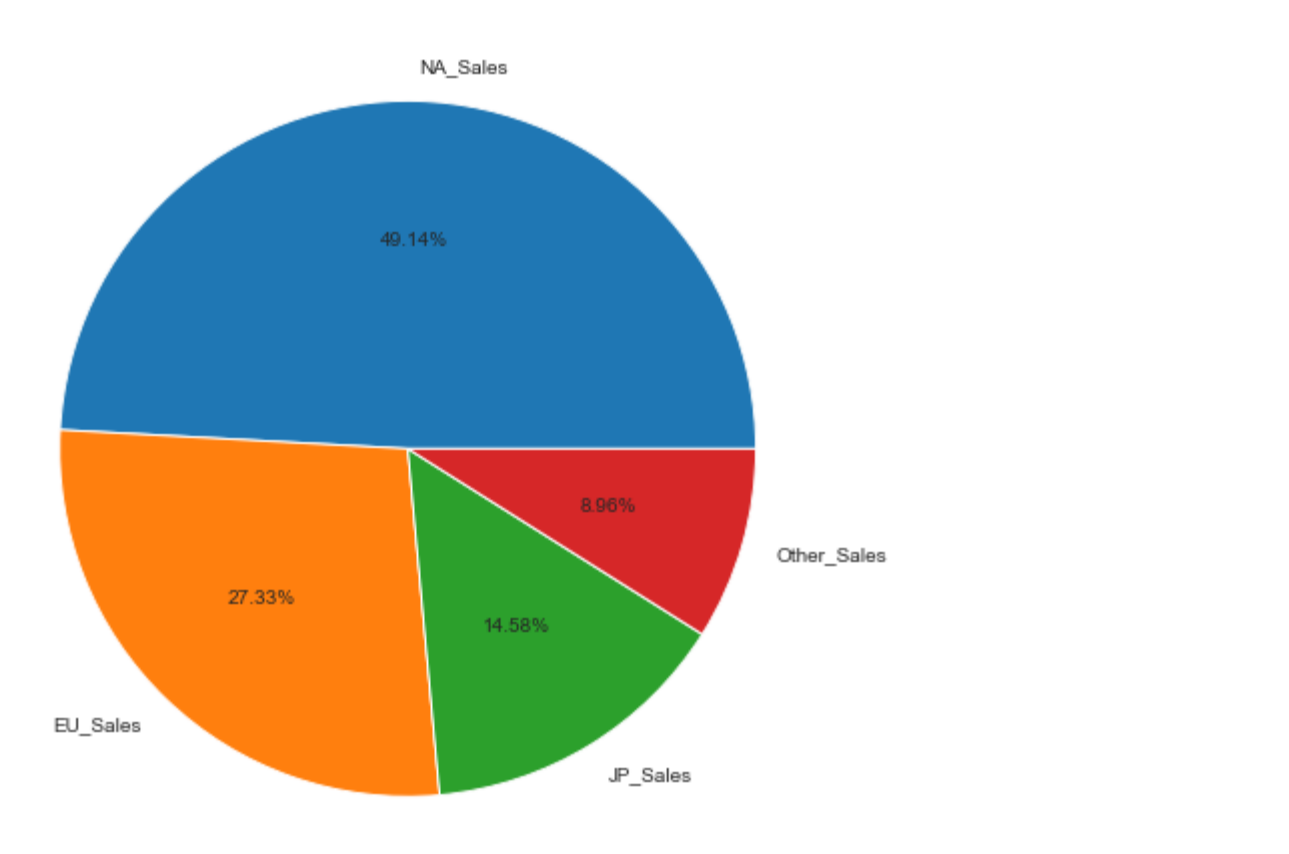
	index	0
0	NA_Sales	4327.65
1	EU_Sales	2406.69
2	JP_Sales	1284.27
3	Other_Sales	788.91

In [38]:
```
# By Bar Graph
plt.bar(df2["index"],df2[0])
```

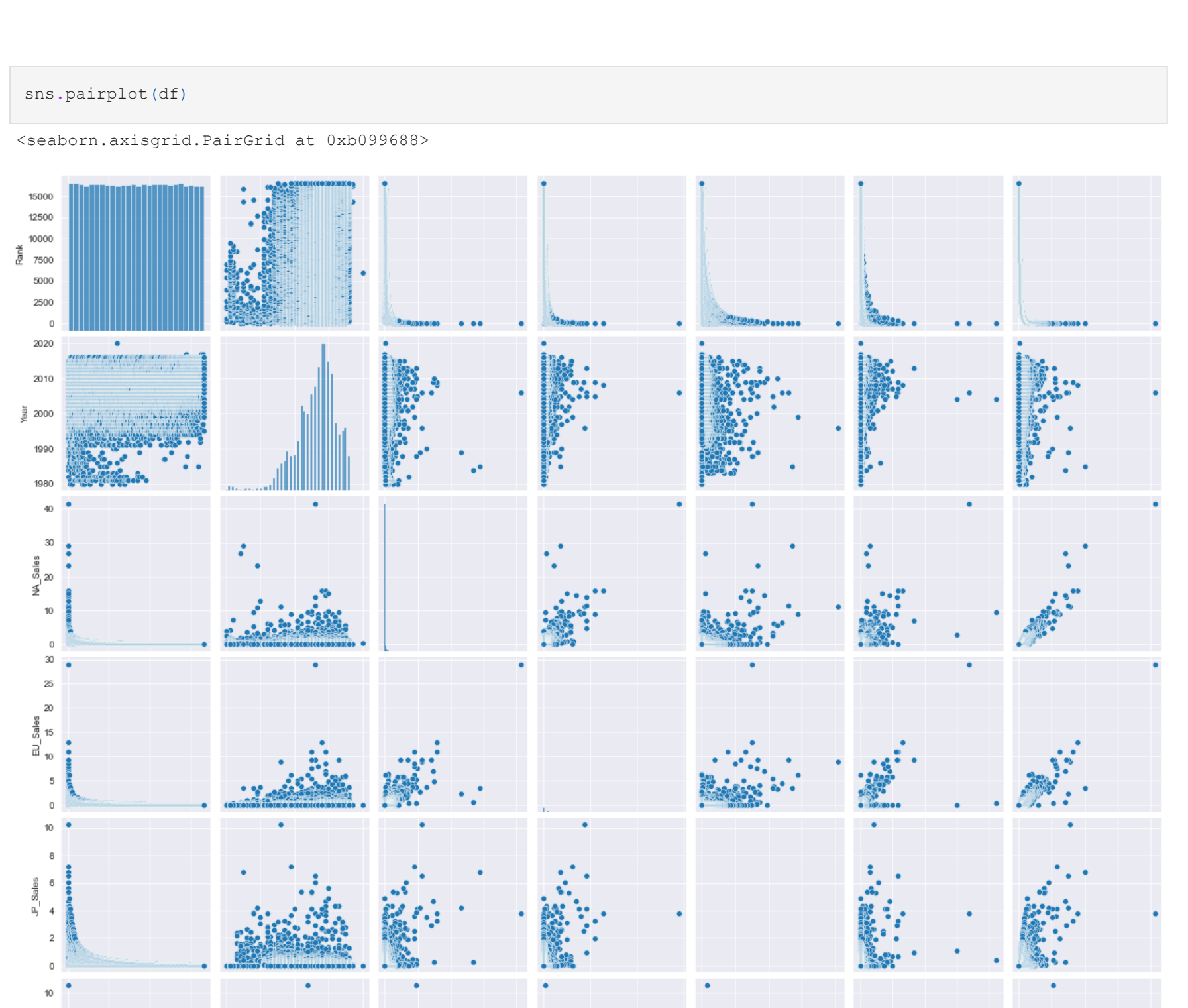
Out[38]:
```
<BarContainer object of 4 artists>
```



In [39]:
```
# By pie chart
plt.figure(figsize=(10, 8))
plt.pie(df2[0], labels=df2["index"], autopct='%1.2f%%')
plt.show()
# North America almost Cover 50% of sales generated
```

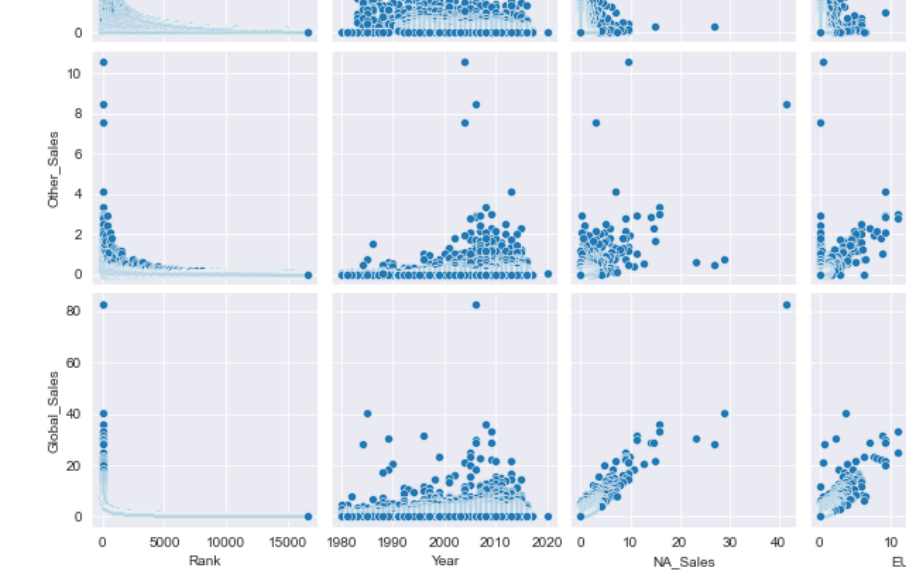


In [40]:
```python
sns.pairplot(df)
```
Out[40]:
```
<seaborn.axisgrid.PairGrid at 0xb099688>
```



Checking Outliers

In [8]:
```python
sns.boxplot(x=df["Global_Sales"],y=df["Genre"],data=df)
```
Out[8]:
```
<AxesSubplot:xlabel='Global_Sales', ylabel='Genre'>
```



Correlation Analysis

In [18]:
```python
plt.figure(figsize=(10,5))
sns.heatmap(df.corr(),annot=True,cmap='RdYlBu_r')
```
Out[18]:
```
<AxesSubplot:>
```

Encoding Categorical Features

In [21]:
```python
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
df["Genre"]=le.fit_transform(df["Genre"])
df["Platform"]=le.fit_transform(df["Platform"])
```

In [22]:
```python
df.head()
```
Out[22]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	Other_Sales	Global_Sales
0	1	Wii Sports	26	2006.0	10	Nintendo	41.49	29.02	3.77	8.46	82.74
1	2	Super Mario Bros.	11	1985.0	4	Nintendo	29.08	3.58	6.81	0.77	40.24
2	3	Mario Kart Wii	26	2008.0	6	Nintendo	15.85	12.88	3.79	3.31	35.82
3	4	Wii Sports Resort	26	2009.0	10	Nintendo	15.75	11.01	3.28	2.96	33.00
4	5	Pokemon Red/Pokemon Blue	5	1996.0	7	Nintendo	11.27	8.89	10.22	1.00	31.37

Standardizaton techniques

- We are not using standardization on our data set but if we have large difference in data points of each feature then we can use this techniques to get better prediction

There Techniques like:

- Min Max scaler
- Standard scaler

steps for standardization

1. from sklearn.preprocessing import StandardScaler
2. sc = StandardScaler()
3. sc.fit_transform(df[[col]]) using for loop on each column

Split the Data into train data and test data

In [23]:
```python
x = df.iloc[:,6:-1].values # Selecting Most correlated features by feature selection using coefiicient of corre
y = df.iloc[:,-1].values
```

In [24]:
```python
x
```
Out[24]:
```
array([[4.149e+01, 2.902e+01, 3.770e+00, 8.460e+00],
       [2.908e+01, 3.580e+00, 6.810e+00, 7.700e-01],
       [1.585e+01, 1.288e+01, 3.790e+00, 3.310e+00],
       ...,
       [0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00],
       [0.000e+00, 1.000e-02, 0.000e+00, 0.000e+00],
       [1.000e-02, 0.000e+00, 0.000e+00, 0.000e+00]])
```

In [25]:
```python
y
```
Out[25]:
```
array([8.274e+01, 4.024e+01, 3.582e+01, ..., 1.000e-02, 1.000e-02,
       1.000e-02])
```

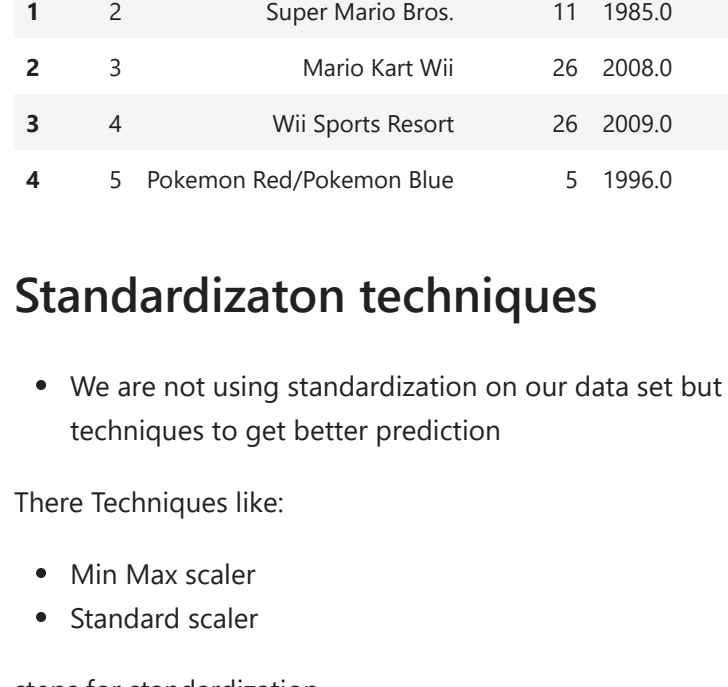
In [26]:
```python
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest = train_test_split(x,y,test_size=0.2,random_state=0)
```

Create Machine Learning Models

Linear Regression

In [27]:
```python
from sklearn.linear_model import LinearRegression

linreg=LinearRegression()
linreg.fit(xtrain,ytrain)
ypred=linreg.predict(xtest)
```

In [28]:
```python
plt.scatter(ytest,ypred)
plt.xlabel('ytest')
plt.ylabel('Predicted Y')
plt.grid(True)
```



In [29]:
```python
print(f"MAE -: {mae(ytest, ypred)}")
print(f"MSE -: {mse(ytest, ypred)}")
print(f"RMSE -: {np.sqrt(mse(ytest, ypred))}")
print(f"R-Squared accuracy -: {r2_score(ytest, ypred)}")
lin_m=r2_score(ytest, ypred)
```
```
MAE -: 0.0028987612559712226
MSE -: 2.695299581184773e-05
RMSE -: 0.005191627472368152
R-Squared accuracy -: 0.999987961673058
```

Sales prediction in million

In [30]:
```python
prd=[[20.2,5,8,14.5]]
```

In [31]:
```python
linreg.predict(prd)
```
Out[31]:
```
array([47.69044386])
```

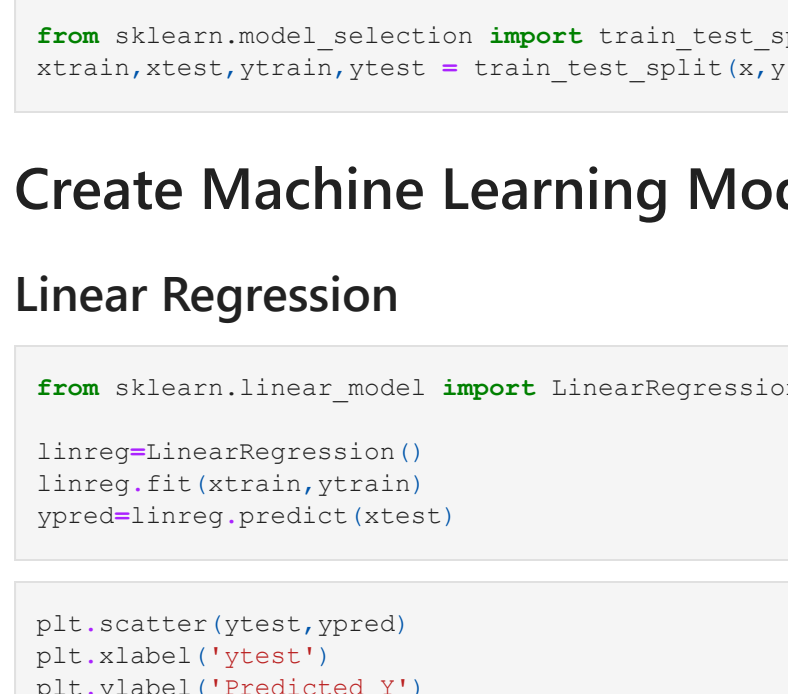
KNN regressor

In [32]:
```python
from sklearn.neighbors import KNeighborsRegressor

knn=KNeighborsRegressor(n_neighbors =4)
knn.fit(xtrain,ytrain)
ypred1=knn.predict(xtest)
```

In [33]:
```python
print(f"MAE -: {mae(ytest, ypred1)}")
print(f"MSE -: {mse(ytest, ypred1)}")
print(f"RMSE -: {np.sqrt(mse(ytest, ypred1))}")
print(f"R-Squared accuracy -: {r2_score(ytest, ypred1)}")
knn_m=r2_score(ytest, ypred1)
```
```
MAE -: 0.020344879518072286
MSE -: 0.013338546686746987
RMSE -: 0.11549262611416794
R-Squared accuracy -: 0.9940424512708272
```

In [34]:
```python
# Hyper Parameter Tunning
k = range(1,15)

accuracy = []
for i in k:
    knn=KNeighborsRegressor(n_neighbors = i)
    knn.fit(xtrain,ytrain)
    ypred1=knn.predict(xtest)
    accuracy.append(r2_score(ytest,ypred1))
```

In [35]:
```python
plt.plot(k, accuracy, linewidth=2, color='blue')
plt.xticks(k)# to show all k values

plt.xlabel('Neighbor Number')
plt.ylabel('r2_Score of KNN')
plt.show()
```



Decision Tree regressor

In [36]:
```python
from sklearn.tree import DecisionTreeRegressor

dt = DecisionTreeRegressor(max_depth=10,random_state=32)
dt.fit(xtrain,ytrain)
ypred2=dt.predict(xtest)
```

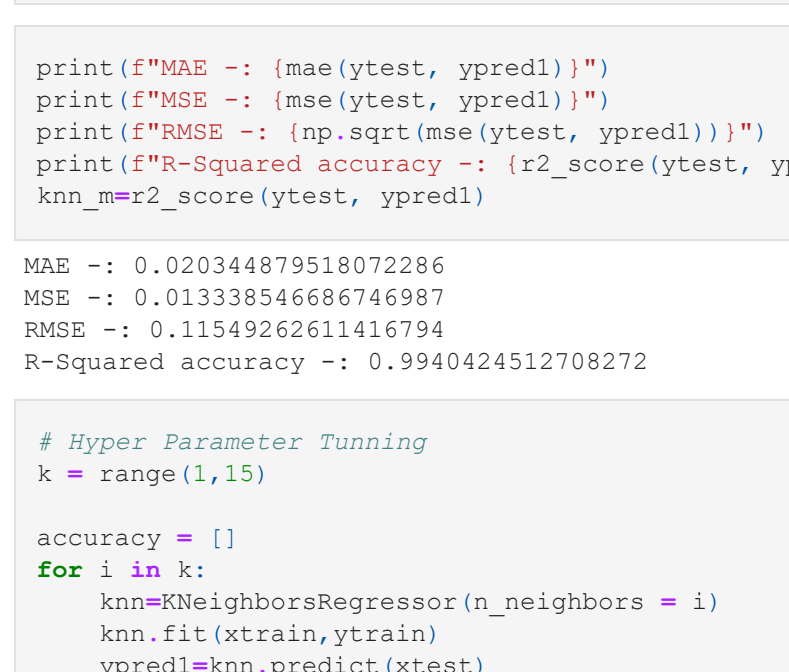
In [37]:
```python
print(f"MAE -: {mae(ytest, ypred2)}")
print(f"MSE -: {mse(ytest, ypred2)}")
print(f"RMSE -: {np.sqrt(mse(ytest, ypred2))}")
print(f"R-Squared accuracy -: {r2_score(ytest, ypred2)}")
dt_m=r2_score(ytest, ypred2)
```
```
MAE -: 0.06617090442659466
MSE -: 0.0990614024787201
RMSE -: 0.3147402142699914
R-Squared accuracy -: 0.9557550649027196
```

In [38]:
```python
# Hyper Parameter Tunning for max depth
md = range(1,15)

accuracy1 = []
for i in md:
    dt = DecisionTreeRegressor(max_depth=i,random_state=1)
    dt.fit(xtrain,ytrain)
    ypred=dt.predict(xtest)
    accuracy1.append(r2_score(ytest,ypred))
```

In [39]:
```python
plt.plot(md, accuracy1, linewidth=2, color='blue')
plt.xticks(md)

plt.xlabel('max depth Number')
plt.ylabel('r2_Score')
plt.show()
```

In [40]:
```python
# Hyper Parameter Tunning for min sample leaf
ms = range(1,15)

accuracy2 = []
for i in ms:
    dt = DecisionTreeRegressor(min_samples_leaf=i,random_state=1)
    dt.fit(xtrain,ytrain)
    ypred=dt.predict(xtest)
    accuracy2.append(r2_score(ytest,ypred))
```

In [41]:
```python
plt.plot(ms, accuracy2, linewidth=2, color='blue')
plt.xticks(ms)

plt.xlabel('min samples leaf')
plt.ylabel('r2_Score')
plt.show()
```



Random Forest Regressor

In [42]:
```python
from sklearn.ensemble import RandomForestRegressor

rf = RandomForestRegressor(random_state= 10)
rf.fit(xtrain,ytrain)
ypred3= rf.predict(xtest)
```

In [43]:
```python
print(f"MAE -: {mae(ytest, ypred3)}")
print(f"MSE -: {mse(ytest, ypred2)}")
print(f"RMSE -: {np.sqrt(mse(ytest, ypred3))}")
print(f"R-Squared accuracy -: {r2_score(ytest, ypred3)}")
rf_m= r2_score(ytest, ypred3)
```
```
MAE -: 0.021355986365877617
MSE -: 0.0990614024787201
RMSE -: 0.1514817393116084
R-Squared accuracy -: 0.9897510433507388
```

Support Vector Regressor

In [44]:
```python
from sklearn.svm import SVR

svrlin = SVR(kernel='linear')

svrrbf = SVR(kernel='rbf')
```

In [45]:
```python
svrlin.fit(xtrain, ytrain)
svrrbf.fit(xtrain, ytrain)

ypred3 = svrlin.predict(xtest)
ypred4 = svrrbf.predict(xtest)

svrlin_m= r2_score(ytest, ypred3)
print("Accuracy by SVR Linear kernel",svrlin_m)
print("Accuracy by SVR rbf kernel",r2_score(ytest, ypred4))
```
```
Accuracy by SVR Linear kernel 0.9970930059437717
Accuracy by SVR rbf kernel 0.7068963986636798
```

Hyper Parameter Tunning using Grid Search Cv

In [46]:
```python
from sklearn.model_selection import GridSearchCV
```

In [47]:
```python
param_grid = {'C' : [0.1, 1, 10, 100, 1000], 'gamma' : [1, 0.1, 0.01, 0.001, 0.0001],"kernel":["linear"]}
```

In [48]:
```python
grid=GridSearchCV(SVR(),param_grid,refit=True,verbose=3)
grid.fit(xtrain,ytrain)
```
```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
[CV] C=0.1, gamma=1, kernel=linear ...................................
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[CV] ....... C=0.1, gamma=1, kernel=linear, score=0.996, total=   0.3s
[CV] C=0.1, gamma=1, kernel=linear ...................................
[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    0.2s remaining:    0.0s
[CV] ....... C=0.1, gamma=1, kernel=linear, score=0.996, total=   0.2s
[CV] C=0.1, gamma=1, kernel=linear ...................................
[Parallel(n_jobs=1)]: Done   2 out of   2 | elapsed:    0.5s remaining:    0.0s
[CV] ....... C=0.1, gamma=1, kernel=linear, score=0.997, total=   0.2s
[CV] C=0.1, gamma=1, kernel=linear ...................................
[CV] ....... C=0.1, gamma=1, kernel=linear, score=0.998, total=   0.3s
[CV] C=0.1, gamma=1, kernel=linear ...................................
[CV] ....... C=0.1, gamma=1, kernel=linear, score=0.998, total=   0.3s
[CV] C=0.1, gamma=0.1, kernel=linear .................................
[CV] ..... C=0.1, gamma=0.1, kernel=linear, score=0.996, total=   0.3s
[CV] C=0.1, gamma=0.1, kernel=linear .................................
[CV] ..... C=0.1, gamma=0.1, kernel=linear, score=0.996, total=   0.3s
[CV] C=0.1, gamma=0.1, kernel=linear .................................
[CV] ..... C=0.1, gamma=0.1, kernel=linear, score=0.997, total=   0.2s
[CV] C=0.1, gamma=0.1, kernel=linear .................................
[CV] ..... C=0.1, gamma=0.1, kernel=linear, score=0.998, total=   0.3s
[CV] C=0.1, gamma=0.1, kernel=linear .................................
[CV] ..... C=0.1, gamma=0.1, kernel=linear, score=0.998, total=   0.2s
[CV] C=0.1, gamma=0.01, kernel=linear ................................
[CV] .... C=0.1, gamma=0.01, kernel=linear, score=0.996, total=   0.3s
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[CV] C=0.1, gamma=0.01, kernel=linear ................................
[CV] .... C=0.1, gamma=0.01, kernel=linear, score=0.998, total=   0.3s
[CV] C=0.1, gamma=0.01, kernel=linear ................................
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[CV] C=0.1, gamma=0.001, kernel=linear ...............................
[CV] ... C=0.1, gamma=0.001, kernel=linear, score=0.996, total=   0.4s
[CV] C=0.1, gamma=0.001, kernel=linear ...............................
[CV] ... C=0.1, gamma=0.001, kernel=linear, score=0.996, total=   0.3s
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[CV] C=0.1, gamma=0.0001, kernel=linear ..............................
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[CV] C=100, gamma=0.0001, kernel=linear ..............................
[CV] .. C=100, gamma=0.0001, kernel=linear, score=0.997, total=   0.2s
[CV] C=100, gamma=0.0001, kernel=linear ..............................
[CV] .. C=100, gamma=0.0001, kernel=linear, score=0.997, total=   0.2s
[CV] C=100, gamma=0.0001, kernel=linear ..............................
[CV] .. C=100, gamma=0.0001, kernel=linear, score=0.998, total=   0.2s
[CV] C=1000, gamma=1, kernel=linear ..................................
[CV] ...... C=1000, gamma=1, kernel=linear, score=0.996, total=   0.2s
[CV] C=1000, gamma=1, kernel=linear ..................................
[CV] ...... C=1000, gamma=1, kernel=linear, score=0.996, total=   0.2s
[CV] C=1000, gamma=1, kernel=linear ..................................
[CV] ...... C=1000, gamma=1, kernel=linear, score=0.997, total=   0.3s
[CV] C=1000, gamma=1, kernel=linear ..................................
[CV] ...... C=1000, gamma=1, kernel=linear, score=0.997, total=   0.3s
[CV] C=1000, gamma=1, kernel=linear ..................................
[CV] ...... C=1000, gamma=1, kernel=linear, score=0.998, total=   0.2s
[CV] C=1000, gamma=0.1, kernel=linear ................................
[CV] .... C=1000, gamma=0.1, kernel=linear, score=0.996, total=   0.3s
[CV] C=1000, gamma=0.1, kernel=linear ................................
[CV] .... C=1000, gamma=0.1, kernel=linear, score=0.996, total=   0.2s
[CV] C=1000, gamma=0.1, kernel=linear ................................
[CV] .... C=1000, gamma=0.1, kernel=linear, score=0.997, total=   0.2s
[CV] C=1000, gamma=0.1, kernel=linear ................................
[CV] .... C=1000, gamma=0.1, kernel=linear, score=0.997, total=   0.3s
[CV] C=1000, gamma=0.1, kernel=linear ................................
[CV] .... C=1000, gamma=0.1, kernel=linear, score=0.998, total=   0.2s
[CV] C=1000, gamma=0.01, kernel=linear ...............................
[CV] ... C=1000, gamma=0.01, kernel=linear, score=0.996, total=   0.3s
[CV] C=1000, gamma=0.01, kernel=linear ...............................
[CV] ... C=1000, gamma=0.01, kernel=linear, score=0.996, total=   0.2s
[CV] C=1000, gamma=0.01, kernel=linear ...............................
[CV] ... C=1000, gamma=0.01, kernel=linear, score=0.997, total=   0.3s
[CV] C=1000, gamma=0.01, kernel=linear ...............................
[CV] ... C=1000, gamma=0.01, kernel=linear, score=0.997, total=   0.3s
[CV] C=1000, gamma=0.01, kernel=linear ...............................
[CV] ... C=1000, gamma=0.01, kernel=linear, score=0.998, total=   0.2s
[CV] C=1000, gamma=0.001, kernel=linear ..............................
[CV] .. C=1000, gamma=0.001, kernel=linear, score=0.996, total=   0.2s
[CV] C=1000, gamma=0.001, kernel=linear ..............................
[CV] .. C=1000, gamma=0.001, kernel=linear, score=0.996, total=   0.2s
[CV] C=1000, gamma=0.001, kernel=linear ..............................
[CV] .. C=1000, gamma=0.001, kernel=linear, score=0.997, total=   0.3s
[CV] C=1000, gamma=0.001, kernel=linear ..............................
[CV] .. C=1000, gamma=0.001, kernel=linear, score=0.997, total=   0.3s
[CV] C=1000, gamma=0.001, kernel=linear ..............................
[CV] .. C=1000, gamma=0.001, kernel=linear, score=0.998, total=   0.2s
[CV] C=1000, gamma=0.0001, kernel=linear .............................
[CV] . C=1000, gamma=0.0001, kernel=linear, score=0.996, total=   0.2s
[CV] C=1000, gamma=0.0001, kernel=linear .............................
[CV] . C=1000, gamma=0.0001, kernel=linear, score=0.996, total=   0.2s
[CV] C=1000, gamma=0.0001, kernel=linear .............................
[CV] . C=1000, gamma=0.0001, kernel=linear, score=0.997, total=   0.2s
[CV] C=1000, gamma=0.0001, kernel=linear .............................
[CV] . C=1000, gamma=0.0001, kernel=linear, score=0.997, total=   0.3s
[CV] C=1000, gamma=0.0001, kernel=linear .............................
[CV] . C=1000, gamma=0.0001, kernel=linear, score=0.998, total=   0.2s
[Parallel(n_jobs=1)]: Done 125 out of 125 | elapsed:   29.9s finished
```
Out[48]:
```
GridSearchCV(estimator=SVR(),
             param_grid={'C': [0.1, 1, 10, 100, 1000],
                         'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
                         'kernel': ['linear']},
             verbose=3)
```

In [49]:
```python
ypred4=grid.predict(xtest)
```

In [50]:
```python
print(f"R-Squared accuracy -: {r2_score(ytest, ypred4)}")
```
```
R-Squared accuracy -: 0.9971435075008018
```

In [51]:
```python
grid.best_params_
```
Out[51]:
```
{'C': 0.1, 'gamma': 1, 'kernel': 'linear'}
```

Hyper Parameter Tunning using Random Search Cv

In [33]:
```python
from sklearn.model_selection import RandomizedSearchCV
```

In [40]:
```python
random = RandomizedSearchCV(SVR(), param_grid, n_iter=500, scoring='neg_mean_absolute_error', n_jobs=-1, cv=5,
random.fit(xtrain,ytrain)
```
Out[40]:
```
RandomizedSearchCV(cv=5, estimator=SVR(), n_iter=500, n_jobs=-1,
                   param_distributions={'C': [0.1, 1, 10, 100, 1000],
                                        'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
                                        'kernel': ['linear']},
                   random_state=1, scoring='neg_mean_absolute_error')
```

In [41]:
```python
ypred5=random.predict(xtest)
```

In [42]:
```python
print(f"R-Squared accuracy -: {r2_score(ytest, ypred5)}")
```
```
R-Squared accuracy -: 0.9967268172157733
```

In [43]:
```python
random.best_params_
```
Out[43]:
```
{'kernel': 'linear', 'gamma': 1, 'C': 0.1}
```

Principal Component Analysis

In [19]:
```python
x
```
Out[19]:
```
array([[2.908e+01, 3.580e+00, 6.810e+00, 7.700e-01],
       [1.585e+01, 1.288e+01, 3.790e+00, 3.310e+00],
       [1.575e+01, 1.101e+01, 3.280e+00, 2.960e+00],
       ...,
       [0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00],
       [0.000e+00, 1.000e-02, 0.000e+00, 0.000e+00],
       [1.000e-02, 0.000e+00, 0.000e+00, 0.000e+00]])
```

In [20]:
```python
y
```
Out[20]:
```
array([4.024e+01, 3.582e+01, 3.300e+01, ..., 1.000e-02, 1.000e-02,
       1.000e-02])
```

In [21]:
```python
from sklearn.decomposition import PCA
pca = PCA(n_components= 4, random_state=1)
```

In [22]:
```python
xtrain, xtest, ytrain, ytest = train_test_split(x,y, test_size=0.3, random_state=1)
```

In [23]:
```python
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

xtrain = sc.fit_transform(xtrain)
xtest = sc.transform(xtest)
```

In [24]:
```python
xtrainpc = pca.fit_transform(xtrain, ytrain)
xtestpc = pca.transform(xtest)
```

In [25]:
```python
xtrainpc[0]
```
Out[25]:
```
array([-0.22330831,  0.13436406, -0.1962463 ,  0.24335034])
```

In [26]:
```python
xtrain[0]
```
Out[26]:
```
array([ 0.14064711, -0.2730571 , -0.24817691, -0.09858361])
```

In [29]:
```python
linreg = LinearRegression()
linreg.fit(xtrainpc, ytrain)
```
Out[29]:
```
LinearRegression()
```

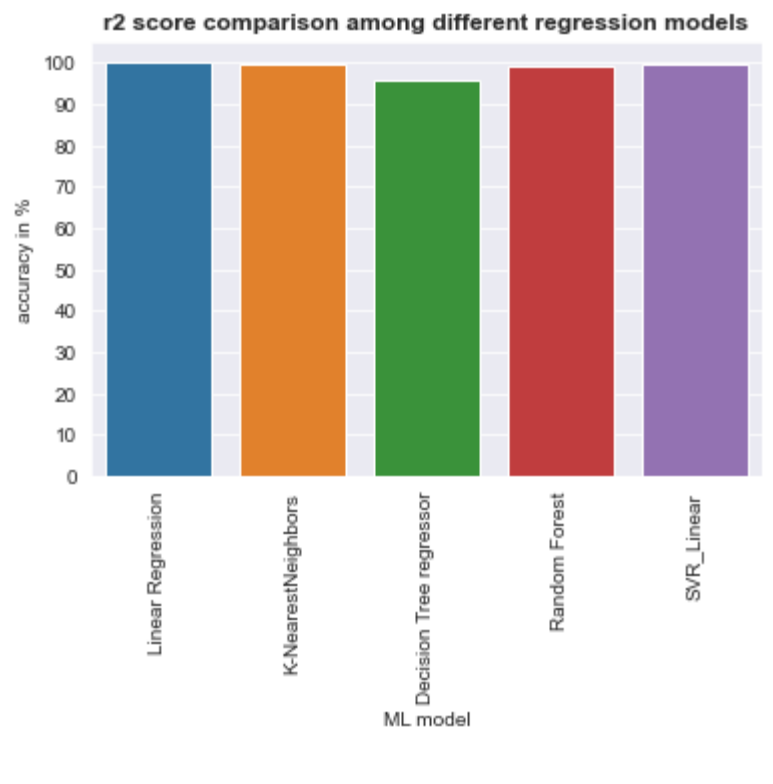
In [30]:
```python
linreg.score(xtestpc, ytest)
```
Out[30]:
```
0.9999853830305152
```

We can use another methods also such Kernel PCA, LDA etc

Comparing the Accuracy of different models

In [52]:
```python
models = ["Linear Regression","K-NearestNeighbors","Decision Tree regressor","Random Forest","SVR_Linear"]
accuracy = [lin_m,knn_m,dt_m,rf_m,svrlin_m]
for i in range(0,len(accuracy)):
    accuracy[i]=np.round(accuracy[i]*100,decimals=3)
print(accuracy)
```
```
[99.999, 99.404, 95.576, 98.975, 99.709]
```

In [53]:
```python
compare = sns.barplot(x=models,y=accuracy)
plt.yticks(np.arange(0,101,10))
plt.xticks(rotation=90,fontsize=10)
plt.xlabel("ML model")
plt.ylabel("accuracy in %")
plt.title('r2 score comparison among different regression models',fontweight='bold')
plt.show()
```



Conclusion

- Sales prediction is a playing vital role while developing marketing techniques and and strategic planning by any company. It allows a company to forecast how the company will perform in the future. Sales prediction is als important to make decission on which area we have to focus and which techniques or methods needs to implement to increase sales.
- So that we have concluded that, In sales prediction of video games we observed which game has more sales in the market globally and which has less sales.we also analyse which Genre , Publishers and platforms contributes more and less in global sales.
- To predict sales we implement some Supervised Machine Learning Techniques and Create better model by Different Algorithms such as Linear regression, Random Forest, Decision tree, Support vector regression,kneighbors regressor. Among all these algorithms Linear regression, Random Forest,Support Vector Regressor with Linear gave us the best accurate result with minimum error rate.

Thank You !!!