# MLHackathonFinal

November 24, 2019

# 1 Predicting Critic Scores using Video Game Statistics

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## 1.2 Reading Data and Importing Libraries

[1]:
```
import random
from math import *
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.colors
import pandas as pd
import seaborn as sns
%matplotlib inline

from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split


from sklearn.linear_model import Ridge, Lasso, LinearRegression
from sklearn.ensemble import AdaBoostClassifier

from sklearn.metrics import accuracy_score
from sklearn.metrics import mean_squared_error, r2_score
```

[2]:
```
data = pd.read_csv("Video_Games_Sales_as_at_22_Dec_2016.csv")
data.shape
```

[2]:
```
(16719, 16)
```

## 1.3 Data Visualization and Preprocessing

[3]:
```
print(len(data.columns))
data.head(2)
```

```
16
```

[3]:
```
                Name Platform  Year_of_Release     Genre Publisher  NA_Sales  \
0         Wii Sports      Wii           2006.0    Sports  Nintendo     41.36
1  Super Mario Bros.      NES           1985.0  Platform  Nintendo     29.08

   EU_Sales  JP_Sales  Other_Sales  Global_Sales  Critic_Score  Critic_Count  \
0     28.96      3.77         8.45         82.53          76.0          51.0
1      3.58      6.81         0.77         40.24           NaN           NaN

  User_Score  User_Count Developer Rating
0          8       322.0  Nintendo      E
1        NaN         NaN       NaN    NaN
```

**Since we are predicting MetaCritic score for games, we will drop all the data points which do not have a MetaCritic Score.**

[4]:
```python
data = data.dropna(subset=['Critic_Score'])
data.shape
```

[4]: (8137, 16)

[5]:
```python
data.describe()
```

[5]:
```
       Year_of_Release     NA_Sales     EU_Sales     JP_Sales  Other_Sales  \
count      7983.000000  8137.000000  8137.000000  8137.000000  8137.000000
mean       2007.192785     0.352980     0.208311     0.055028     0.072435
std           4.189425     0.896476     0.635622     0.265075     0.249204
min        1985.000000     0.000000     0.000000     0.000000     0.000000
25%        2004.000000     0.050000     0.010000     0.000000     0.010000
50%        2007.000000     0.130000     0.050000     0.000000     0.020000
75%        2010.000000     0.340000     0.180000     0.010000     0.060000
max        2016.000000    41.360000    28.960000     6.500000    10.570000

       Global_Sales  Critic_Score  Critic_Count    User_Count
count   8137.000000   8137.000000   8137.000000   7017.000000
mean       0.689035     68.967679     26.360821    173.432664
std        1.816704     13.938165     18.980495    581.977516
min        0.010000     13.000000      3.000000      4.000000
25%        0.090000     60.000000     12.000000     11.000000
50%        0.240000     71.000000     21.000000     27.000000
75%        0.650000     79.000000     36.000000     89.000000
max       82.530000     98.000000    113.000000  10665.000000
```

**Number of Null values in each column**

[6]:
```python
for i in list(data.columns):
        print (i,":",data[i].isnull().sum())
```

```
Name : 0
Platform : 0
```

```
Year_of_Release : 154
Genre : 0
Publisher : 4
NA_Sales : 0
EU_Sales : 0
JP_Sales : 0
Other_Sales : 0
Global_Sales : 0
Critic_Score : 0
Critic_Count : 0
User_Score : 38
User_Count : 1120
Developer : 6
Rating : 83
```

**None of these columns seems to have more than 20% of their values missing. Therefore, we don't think we should be removing any more columns from the data set**

**Let us see the data type of each column**

[7]:
```python
for i in list(data.columns):
    print(i,":",data[i].dtypes)
```

```
Name : object
Platform : object
Year_of_Release : float64
Genre : object
Publisher : object
NA_Sales : float64
EU_Sales : float64
JP_Sales : float64
Other_Sales : float64
Global_Sales : float64
Critic_Score : float64
Critic_Count : float64
User_Score : object
User_Count : float64
Developer : object
Rating : object
```

**As we can see, every column has the required data type except User_Score which is an object instead of float64**

### 1.3.1 Sampler Function

**When it comes to replacing null values, we can replace them with the mean value of that column, or the median.**

**We can also create a probability distribution based on the given data in that column and can perform Markov Chain Monte Carlo (MCMC) sampling on that distribution to fill the null values.**

**However, the sampler itself is good for generating data but might not perform well for replacing null values**

**Code for MCMC sampling**

[8]:
```
def sampler(s,data):
    d = dict(data[s].value_counts())
    sum1 = sum(d.values())
    m = d.keys()
    prob = [d[x]/float(sum1) for x in d.keys()]
#     print(prob)
    return [d.keys(),prob]

def sample(composite):
    key = list(composite[0])
    prob = composite[1]
    a = random.random()
    sofar = 0
    for i in range(len(key)):
        sofar += prob[i]
        if(a <= sofar):
            return key[i]
    return key[len(key)-1]

def replace_null(s,data):
    composite = sampler(s,data)
    l = list(data[s])
    for i in range(len(l)):
        if(pd.isna(l[i])):
            l[i] = sample(composite)
    data[s]=l
```

#### 1.3.2 Columnwise Analysis

#### 1.3.3 Year of Release

[9]:
```
print(len(data['Year_of_Release'].unique()))
print(sorted(list(data['Year_of_Release'].unique())))
```

```
26
[1985.0, 1988.0, 1992.0, 1994.0, 1996.0, 1997.0, 1998.0, 1999.0, 2000.0, 2001.0,
2002.0, 2003.0, 2004.0, 2005.0, 2006.0, 2007.0, 2008.0, 2009.0, 2010.0, 2011.0,
2012.0, 2013.0, 2014.0, 2015.0, 2016.0, nan]
```

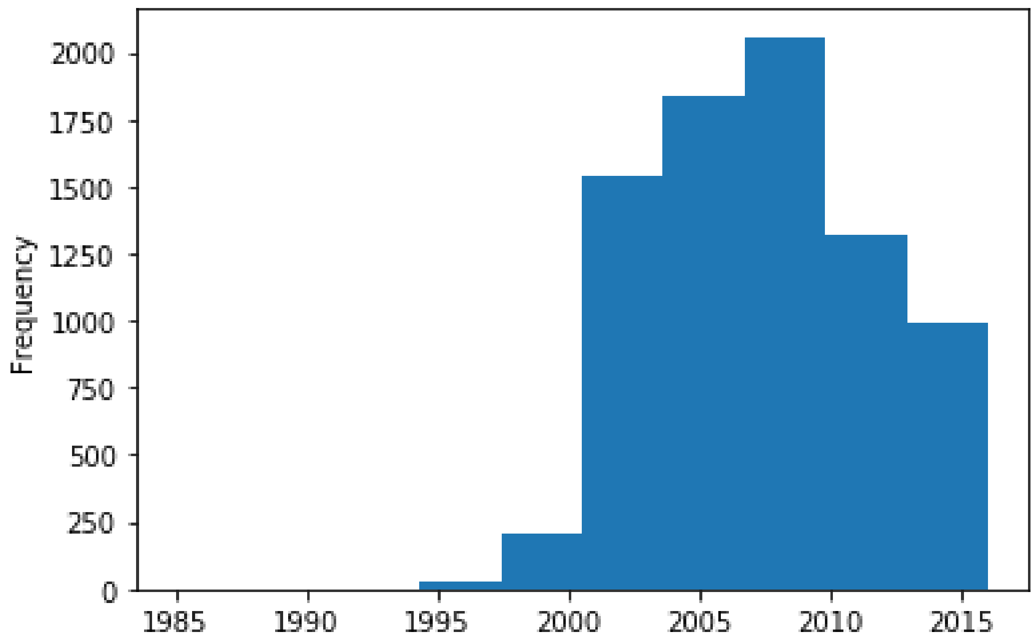
**The year of release might have some importance when it comes to Critic_Score. However, there are 26 values and the order of importance of this feature might not correlate chronologically.**

**We will now populate the nan values in the data set.**

[10]:
```
# replace_null("Year_of_Release",data)
# data['Year_of_Release'] = data['Year_of_Release'].replace(0.0,2002.0)
data['Year_of_Release'] = data['Year_of_Release'].replace(0.
↪0,data['Year_of_Release'].mean())
```

[11]:
```
data['Year_of_Release'].plot(kind='hist')
```

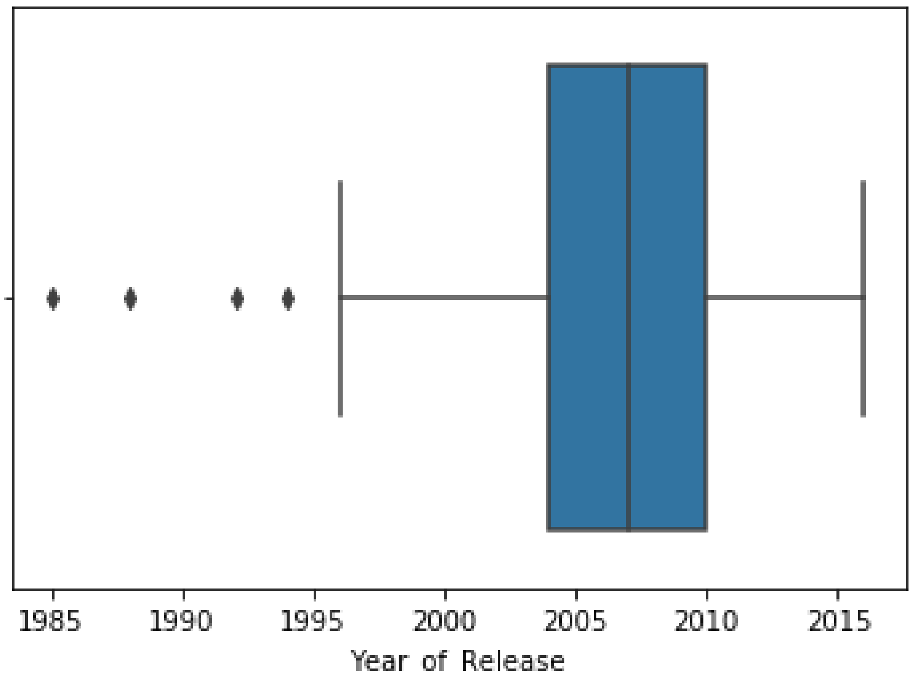
[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5af707e4e0>




**Outlier detection**

[12]:
```
sns.boxplot(x=data['Year_of_Release'])
```

[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5af4f6beb8>




#### 1.3.4 Feature Engineering - Year_of_Release

**We will be performing some feature engineering. We will create a new feature which reflect games released in that generation. This is because the exact year seems to be not very related to the score and we do not wish to suppose a**

[13]:
```
#1985 - 1995
data['Year_198595'] = data[data['Year_of_Release'] <= 1995]['Year_of_Release']
data['Year_198595'] = data['Year_198595'].replace(np.nan, 0)
print(sorted(data['Year_198595'].unique()))
for i in sorted(data['Year_198595'].unique()):
    if(i!=0.0):
        data['Year_198595'] = data['Year_198595'].replace(i, 1)
print(sorted(data['Year_198595'].unique()))

#1996 - 2005
data['Year_199505'] = data[data['Year_of_Release'] <= 2005]['Year_of_Release']
data['Year_199505'] = data[data['Year_199505'] > 1995]['Year_199505']
data['Year_199505'] = data['Year_199505'].replace(np.nan, 0)
print(sorted(data['Year_199505'].unique()))
for i in sorted(data['Year_199505'].unique()):
    if(i!=0.0):
        data['Year_199505'] = data['Year_199505'].replace(i, 1)
# print(sorted(data['Year_199505'].unique()))
```

```
#2006 - 2010
data['Year_200510'] = data[data['Year_of_Release'] <= 2010]['Year_of_Release']
data['Year_200510'] = data[data['Year_200510'] > 2005]['Year_200510']
data['Year_200510'] = data['Year_200510'].replace(np.nan, 0)
print(sorted(data['Year_200510'].unique()))
for i in sorted(data['Year_200510'].unique()):
    if(i!=0.0):
        data['Year_200510'] = data['Year_200510'].replace(i, 1)
# print(sorted(data['Year_200510'].unique()))

#2010 - beyond
data['Year_201016'] = data[data['Year_of_Release'] > 2010]['Year_of_Release']
data['Year_201016'] = data['Year_201016'].replace(np.nan, 0)
print(sorted(data['Year_201016'].unique()))
for i in sorted(data['Year_201016'].unique()):
    if(i!=0.0):
        data['Year_201016'] = data['Year_201016'].replace(i, 1)
# print(sorted(data['Year_201016'].unique()))


data.shape
```

```
[0.0, 1985.0, 1988.0, 1992.0, 1994.0]
[0.0, 1.0]
[0.0, 1996.0, 1997.0, 1998.0, 1999.0, 2000.0, 2001.0, 2002.0, 2003.0, 2004.0,
2005.0]
[0.0, 2006.0, 2007.0, 2008.0, 2009.0, 2010.0]
[0.0, 2011.0, 2012.0, 2013.0, 2014.0, 2015.0, 2016.0]
```

[13]:
```
(8137, 20)
```

[14]:
```
# platform_data.mean()

group_by_year = data.groupby(by=['Year_of_Release'])
year_data_avg = group_by_year.mean()
year_data_count = group_by_year.count()


data_count_series = year_data_count.iloc[:,0]

features_of_interest = pd.DataFrame({'Critic_Score':
 ↪year_data_avg['Critic_Score'],'No. Games':data_count_series,})

features_of_interest
```

[14]:
```
                  Critic_Score  No. Games
Year_of_Release
1985.0               59.000000          1
```

```
1988.0              64.000000        1
1992.0              85.000000        1
1994.0              69.000000        1
1996.0              89.875000        8
1997.0              85.294118       17
1998.0              81.821429       28
1999.0              75.769231       39
2000.0              69.349650      143
2001.0              71.414110      326
2002.0              69.046252      627
2003.0              70.181197      585
2004.0              69.393939      561
2005.0              68.819847      655
2006.0              67.338710      620
2007.0              66.180636      692
2008.0              65.904895      715
2009.0              67.554531      651
2010.0              67.482000      500
2011.0              68.692000      500
2012.0              72.984424      321
2013.0              71.278388      273
2014.0              71.065134      261
2015.0              72.871111      225
2016.0              73.155172      232
```

**We still believe that we cannot drop the Year_of_Release feature because it will help with the training. However, the partitions we have made were big turning points in gaming technology as well as general trends in gamer expectations.**

[15]:
```
data.head(2)
```

[15]:
```
             Name Platform  Year_of_Release   Genre Publisher  NA_Sales  \
0      Wii Sports      Wii           2006.0  Sports  Nintendo     41.36
2   Mario Kart Wii      Wii           2008.0  Racing  Nintendo     15.68

   EU_Sales  JP_Sales  Other_Sales  Global_Sales  Critic_Score  Critic_Count  \
0     28.96      3.77         8.45         82.53          76.0          51.0
2     12.76      3.79         3.29         35.52          82.0          73.0

  User_Score  User_Count Developer Rating  Year_198595  Year_199505  \
0          8       322.0  Nintendo      E          0.0          0.0
2        8.3       709.0  Nintendo      E          0.0          0.0

   Year_200510  Year_201016
0          1.0          0.0
2          1.0          0.0
```

### 1.3.5 Platform

[16]:
```python
platform_data = data.groupby(by=['Platform'])
platform_data.count()
```

[16]:
```
          Name  Year_of_Release  Genre  Publisher  NA_Sales  EU_Sales  \
Platform
3DS        168              166    168        168       168       168
DC          14               14     14         14        14        14
DS         717              708    717        717       717       717
GBA        438              430    438        438       438       438
GC         448              437    448        448       448       448
PC         715              699    715        713       715       715
PS         200              196    200        200       200       200
PS2       1298             1275   1298       1297      1298      1298
PS3        820              804    820        819       820       820
PS4        252              252    252        252       252       252
PSP        462              456    462        462       462       462
PSV        120              119    120        120       120       120
Wii        585              568    585        585       585       585
WiiU        90               90     90         90        90        90
X360       916              894    916        916       916       916
XB         725              706    725        725       725       725
XOne       169              169    169        169       169       169

          JP_Sales  Other_Sales  Global_Sales  Critic_Score  Critic_Count  \
Platform
3DS            168          168           168           168           168
DC              14           14            14            14            14
DS             717          717           717           717           717
GBA            438          438           438           438           438
GC             448          448           448           448           448
PC             715          715           715           715           715
PS             200          200           200           200           200
PS2           1298         1298          1298          1298          1298
PS3            820          820           820           820           820
PS4            252          252           252           252           252
PSP            462          462           462           462           462
PSV            120          120           120           120           120
Wii            585          585           585           585           585
WiiU            90           90            90            90            90
X360           916          916           916           916           916
XB             725          725           725           725           725
XOne           169          169           169           169           169

          User_Score  User_Count  Developer  Rating  Year_198595  Year_199505  \
Platform
3DS              168         158        168     167          168          168
```

```
DC                14          14          14       14          14          14
DS               712         469         717      715         717         717
GBA              434         241         438      438         438         438
GC               448         356         448      448         448         448
PC               706         703         714      677         715         715
PS               193         156         200      196         200         200
PS2             1298        1161        1298     1298        1298        1298
PS3              819         790         819      813         820         820
PS4              251         249         252      241         252         252
PSP              461         393         462      461         462         462
PSV              120         119         120      120         120         120
Wii              582         492         585      582         585         585
WiiU              90          89          90       90          90          90
X360             911         881         915      912         916         916
XB               724         581         722      721         725         725
XOne             168         165         169      161         169         169

          Year_200510  Year_201016
Platform
3DS               168          168
DC                 14           14
DS                717          717
GBA               438          438
GC                448          448
PC                715          715
PS                200          200
PS2              1298         1298
PS3               820          820
PS4               252          252
PSP               462          462
PSV               120          120
Wii               585          585
WiiU               90           90
X360              916          916
XB                725          725
XOne              169          169
```

[17]:
```
group_by_platform = data.groupby(by=['Platform'])
platform_data_avg = group_by_platform.mean()
platform_data_count = group_by_platform.count()
```

[18]:
```
data_count_series = platform_data_count.iloc[:,0]

features_of_interest = pd.DataFrame({'Critic_Score':
 ↪platform_data_avg['Critic_Score'],'No. Games':data_count_series,})

features_of_interest
```

[18]:
```
          Critic_Score  No. Games
Platform
3DS          67.101190        168
DC           87.357143         14
DS           63.761506        717
GBA          67.372146        438
GC           69.488839        448
PC           75.928671        715
PS           71.515000        200
PS2          68.727273       1298
PS3          70.382927        820
PS4          72.091270        252
PSP          67.424242        462
PSV          70.791667        120
Wii          62.823932        585
WiiU         70.733333         90
X360         68.616812        916
XB           69.859310        725
XOne         73.325444        169
```

**It might be relevant if we could classify the consoles into four families - Sony, Microsoft, Nintendo, Others. Also we could engineer 3 new features called 'Type' which will specify if the device is a handheld/console/pc.**

**Device Type**

[19]:
```
#Handheld
data['Handheld'] = data[data['Platform'].
 ↪isin(['3DS','DS','GBA','GC','PSP','PSV'])]['Platform']
data['Handheld'] = data['Handheld'].replace(np.nan, 0)
print((data['Handheld'].unique()))
for i in (data['Handheld'].unique()):
    if(i!=0.0):
        data['Handheld'] = data['Handheld'].replace(i, 1)
# print((data['Handheld'].unique()))

#Console
data['Console'] = data[data['Platform'].
 ↪isin(['DC','PS','PS2','PS3','PS4','Wii','WiiU','X360','XB','XOne'])]['Platform']
data['Console'] = data['Console'].replace(np.nan, 0)
print((data['Console'].unique()))
for i in (data['Console'].unique()):
    if(i!=0.0):
        data['Console'] = data['Console'].replace(i, 1)
# print((data['Console'].unique()))

#PC
```

```python
data['PC'] = data[data['Platform'].isin(['PC'])]['Platform']
data['PC'] = data['PC'].replace(np.nan, 0)
print((data['PC'].unique()))
for i in (data['PC'].unique()):
    if(i!=0.0):
        data['PC'] = data['PC'].replace(i, 1)
# print((data['PC'].unique()))
```

```
[0 'DS' '3DS' 'PSP' 'GC' 'GBA' 'PSV']
['Wii' 0 'X360' 'PS3' 'PS2' 'PS4' 'PS' 'XB' 'WiiU' 'XOne' 'DC']
[0 'PC']
```

**Company**

[20]:
```python
#Microsoft
data['Microsoft'] = data[data['Platform'].
 ↪isin(['XB','XOne','X360'])]['Platform']
data['Microsoft'] = data['Microsoft'].replace(np.nan, 0)
print((data['Microsoft'].unique()))
for i in (data['Microsoft'].unique()):
    if(i!=0.0):
        data['Microsoft'] = data['Microsoft'].replace(i, 1)
# print((data['Microsoft'].unique()))

#Sony
data['Sony'] = data[data['Platform'].
 ↪isin(['PS','PS2','PS3','PS4','PSP','PSV'])]['Platform']
data['Sony'] = data['Sony'].replace(np.nan, 0)
print((data['Sony'].unique()))
for i in (data['Sony'].unique()):
    if(i!=0.0):
        data['Sony'] = data['Sony'].replace(i, 1)
# print((data['Sony'].unique()))

#Nintendo
data['Nintendo'] = data[data['Platform'].
 ↪isin(['3DS','DS','GBA','GC','Wii','WiiU'])]['Platform']
data['Nintendo'] = data['Nintendo'].replace(np.nan, 0)
print((data['Nintendo'].unique()))
for i in (data['Nintendo'].unique()):
    if(i!=0.0):
        data['Nintendo'] = data['Nintendo'].replace(i, 1)
# print((data['Nintendo'].unique()))

#PCCom
data['PCCom'] = data[data['Platform'].isin(['PC'])]['Platform']
data['PCCom'] = data['PCCom'].replace(np.nan, 0)
```

```
print((data['PCCom'].unique()))
for i in (data['PCCom'].unique()):
    if(i!=0.0):
        data['PCCom'] = data['PCCom'].replace(i, 1)
# print((data['PCCom'].unique()))
```

```
[0 'X360' 'XB' 'XOne']
[0 'PS3' 'PS2' 'PS4' 'PS' 'PSP' 'PSV']
['Wii' 'DS' 0 '3DS' 'WiiU' 'GC' 'GBA']
[0 'PC']
```

[21]:
```
num=[]
for i in data['Platform'].unique():
    if( isinstance(i, int) == 1 or isinstance(i, float) ==1):
        print(i)
        num.append(i)

#### This shows that there is a 0 in the dataset where there should be a string.
 ↪ We shall replace it with the string 'zero'
for i in num:
    data['Platform'] = data['Platform'].replace(i,"zero")

lc = LabelEncoder()

data['Platform'] = lc.fit_transform(data['Platform'])
```

[22]:
```
data.head(2)
```

[22]:
```
             Name  Platform  Year_of_Release   Genre Publisher  NA_Sales  \
0      Wii Sports        12           2006.0  Sports  Nintendo     41.36
2  Mario Kart Wii        12           2008.0  Racing  Nintendo     15.68

   EU_Sales  JP_Sales  Other_Sales  Global_Sales  ...  Year_199505  \
0     28.96      3.77         8.45         82.53  ...          0.0
2     12.76      3.79         3.29         35.52  ...          0.0

   Year_200510 Year_201016  Handheld Console PC  Microsoft  Sony  Nintendo  \
0          1.0         0.0         0       1  0          0     0         1
2          1.0         0.0         0       1  0          0     0         1

   PCCom
0      0
2      0

[2 rows x 27 columns]
```

### 1.3.6 Genre

[23]:
```
group_by_genre = data.groupby(by=['Genre'])
genre_data_avg = group_by_genre.mean()
genre_data_count = group_by_genre.count()
genre_data_count
```

[23]:
```
              Name  Platform  Year_of_Release  Publisher  NA_Sales  EU_Sales  \
Genre
Action        1890      1890             1851       1890      1890      1890
Adventure      323       323              320        323       323       323
Fighting       409       409              405        408       409       409
Misc           523       523              509        523       523       523
Platform       497       497              490        496       497       497
Puzzle         224       224              220        224       224       224
Racing         742       742              725        742       742       742
Role-Playing   737       737              731        737       737       737
Shooter        944       944              923        944       944       944
Simulation     352       352              348        352       352       352
Sports        1194      1194             1165       1194      1194      1194
Strategy       302       302              296        300       302       302

              JP_Sales  Other_Sales  Global_Sales  Critic_Score  ...  \
Genre                                                           ...
Action            1890         1890          1890          1890  ...
Adventure          323          323           323           323  ...
Fighting           409          409           409           409  ...
Misc               523          523           523           523  ...
Platform           497          497           497           497  ...
Puzzle             224          224           224           224  ...
Racing             742          742           742           742  ...
Role-Playing       737          737           737           737  ...
Shooter            944          944           944           944  ...
Simulation         352          352           352           352  ...
Sports            1194         1194          1194          1194  ...
Strategy           302          302           302           302  ...

              Year_199505  Year_200510  Year_201016  Handheld  Console    PC  \
Genre
Action               1890         1890         1890      1890     1890  1890
Adventure             323          323          323       323      323   323
Fighting              409          409          409       409      409   409
Misc                  523          523          523       523      523   523
Platform              497          497          497       497      497   497
Puzzle                224          224          224       224      224   224
Racing                742          742          742       742      742   742
Role-Playing          737          737          737       737      737   737
Shooter               944          944          944       944      944   944
```

```
Simulation         352        352        352      352      352   352
Sports            1194       1194       1194     1194     1194  1194
Strategy           302        302        302      302      302   302

              Microsoft  Sony  Nintendo  PCCom
Genre
Action             1890  1890      1890   1890
Adventure           323   323       323    323
Fighting            409   409       409    409
Misc                523   523       523    523
Platform            497   497       497    497
Puzzle              224   224       224    224
Racing              742   742       742    742
Role-Playing        737   737       737    737
Shooter             944   944       944    944
Simulation          352   352       352    352
Sports             1194  1194      1194   1194
Strategy            302   302       302    302

[12 rows x 26 columns]
```

[24]:
```python
data_count_series = genre_data_count.iloc[:,0]

features_of_interest = pd.DataFrame({'Critic_Score':
 ↪genre_data_avg['Critic_Score'],'No. Games':data_count_series,})

features_of_interest
```

[24]:
```
              Critic_Score  No. Games
Genre
Action           66.629101       1890
Adventure        65.331269        323
Fighting         69.217604        409
Misc             66.619503        523
Platform         68.058350        497
Puzzle           67.424107        224
Racing           67.963612        742
Role-Playing     72.652646        737
Shooter          70.181144        944
Simulation       68.619318        352
Sports           71.968174       1194
Strategy         72.086093        302
```

**While One Hot Encoding for this feature is very amenable, 12 new features will be added to the data set. It is necessary to check if we can handle such a data set or not**

[25]:
```python
encoded_columns = pd.get_dummies(data['Genre'])
```

```
for i in encoded_columns:
    data[i+"Genre"] = encoded_columns[i]

data = data.drop(columns=['Genre'],axis=1)
data.shape
```

[25]:
```
(8137, 38)
```

[26]:
```
data.head(2)
```

[26]:
```
             Name  Platform  Year_of_Release Publisher  NA_Sales  EU_Sales  \
0      Wii Sports        12           2006.0  Nintendo     41.36     28.96
2  Mario Kart Wii        12           2008.0  Nintendo     15.68     12.76

   JP_Sales  Other_Sales  Global_Sales  Critic_Score  ...  FightingGenre  \
0      3.77         8.45         82.53          76.0  ...              0
2      3.79         3.29         35.52          82.0  ...              0

  MiscGenre  PlatformGenre PuzzleGenre RacingGenre  Role-PlayingGenre  \
0         0              0           0           0                  0
2         0              0           0           1                  0

   ShooterGenre  SimulationGenre  SportsGenre  StrategyGenre
0             0                0            1              0
2             0                0            0              0

[2 rows x 38 columns]
```

### 1.3.7 Publisher

[27]:
```
print("Size of Domain: ",len(data['Publisher'].unique()))
print("Type of Domain: ",data['Publisher'].dtypes)
# print(data['Publisher'].unique())
print("Number of null values: ",data['Publisher'].isnull().sum())
```

```
Size of Domain:  304
Type of Domain:  object
Number of null values:  4
```

**Since we have too many publishers, we shall Label Encode this feature.**

[28]:
```
num=[]
for i in data['Publisher'].unique():
    if( isinstance(i, int) == 1 or isinstance(i, float) ==1):
        print(i)
        num.append(i)
```

```
nan
```

**This shows that there is a 0 in the dataset where there should be a string. We shall replace it with the string 'zero'**

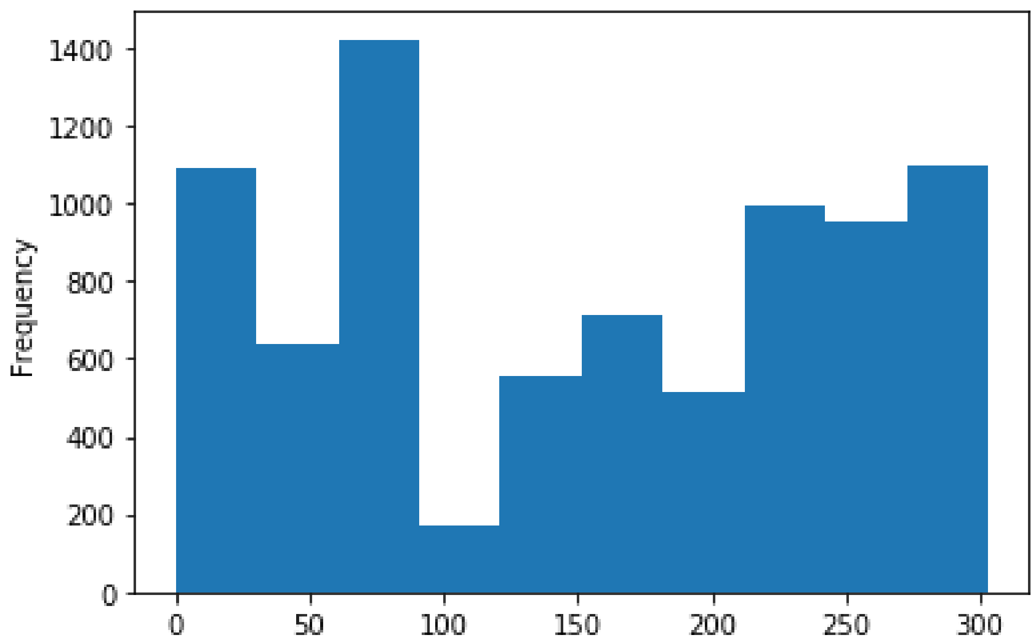
[29]:
```
for i in num:
    data['Publisher'] = data['Publisher'].replace(i,"zero")
```

[30]:
```
lc = LabelEncoder()

data['Publisher'] = lc.fit_transform(data['Publisher'])
```

[31]:
```
data['Publisher'].plot(kind='hist')
```

[31]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5af48339b0>
```




### 1.3.8 Developer

[32]:
```
print("Size of Domain: ",len(data['Developer'].unique()))
print("Type of Domain:",data['Developer'].dtypes)
# print(data['Publisher'].unique())
print("Number of null values: ",data['Developer'].isnull().sum())
```

```
Size of Domain:  1467
Type of Domain: object
Number of null values:  6
```

**We see that we need to do something very similar to what we did for Publisher, which is Label Encoding**

[33]:
```
num=[]
for i in data['Developer'].unique():
    if( isinstance(i, int) == 1 or isinstance(i, float) ==1):
        print(i)
        num.append(i)
```

```
nan
```

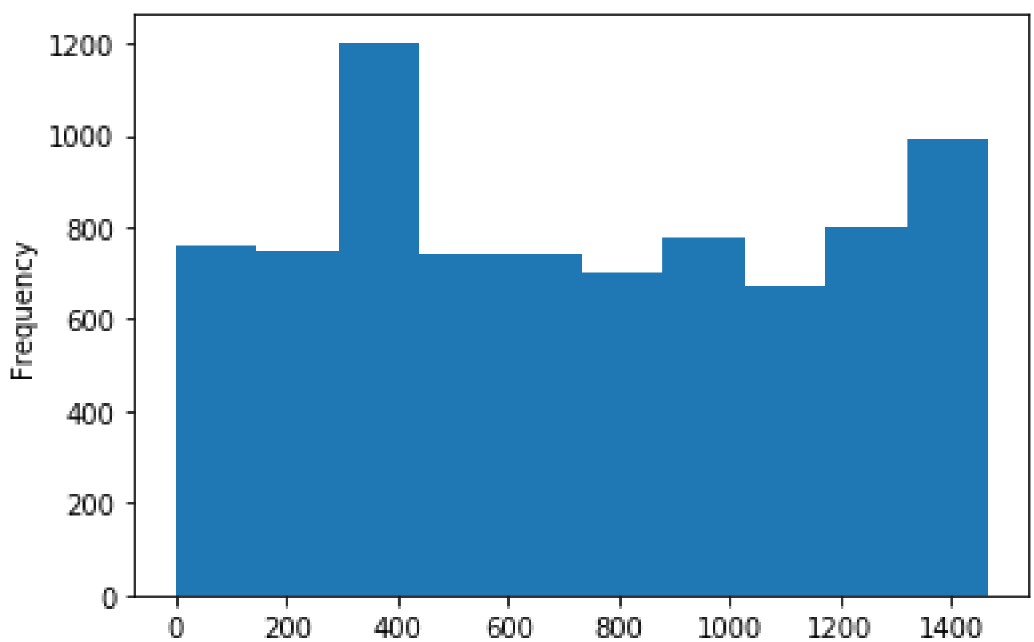
[34]:
```
for i in num:
    data['Developer'] = data['Developer'].replace(i,"zero")
```

[35]:
```
lc = LabelEncoder()

data['Developer'] = lc.fit_transform(data['Developer'])
```

[36]:
```
data['Developer'].plot(kind='hist')
```

[36]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5af47c0128>
```




### 1.3.9 Rating

[37]:
```
print(data['Rating'].unique())
data['Rating'].dtypes
```

```
['E' 'M' 'T' 'E10+' nan 'AO' 'K-A' 'RP']
```

[37]: dtype('O')

[38]:
```
group_by_rating = data.groupby(by=['Rating'])
rating_data_avg = group_by_rating.mean()
rating_data_count = group_by_rating.count()
rating_data_count
```

[38]:
```
        Name  Platform  Year_of_Release  Publisher  NA_Sales  EU_Sales  \
Rating
AO         1         1                1          1         1         1
E       2808      2808             2756       2808      2808      2808
E10+    1118      1118             1097       1118      1118      1118
K-A        1         1                1          1         1         1
M       1483      1483             1457       1483      1483      1483
RP         3         3                1          3         3         3
T       2640      2640             2589       2640      2640      2640

        JP_Sales  Other_Sales  Global_Sales  Critic_Score  ...  FightingGenre  \
Rating                                                     ...
AO             1            1             1             1  ...              1
E           2808         2808          2808          2808  ...           2808
E10+        1118         1118          1118          1118  ...           1118
K-A            1            1             1             1  ...              1
M           1483         1483          1483          1483  ...           1483
RP             3            3             3             3  ...              3
T           2640         2640          2640          2640  ...           2640

        MiscGenre  PlatformGenre  PuzzleGenre  RacingGenre  Role-PlayingGenre  \
Rating
AO              1              1            1            1                  1
E            2808           2808         2808         2808               2808
E10+         1118           1118         1118         1118               1118
K-A             1              1            1            1                  1
M            1483           1483         1483         1483               1483
RP              3              3            3            3                  3
T            2640           2640         2640         2640               2640

        ShooterGenre  SimulationGenre  SportsGenre  StrategyGenre
Rating
AO                 1                1            1              1
E               2808             2808         2808           2808
E10+            1118             1118         1118           1118
K-A                1                1            1              1
M               1483             1483         1483           1483
RP                 3                3            3              3
T               2640             2640         2640           2640

[7 rows x 37 columns]
```

[39]:
```
data_count_series = rating_data_count.iloc[:,0]

features_of_interest = pd.DataFrame({'Critic_Score':
 ↪rating_data_avg['Critic_Score'],'No. Games':data_count_series})

features_of_interest
```

[39]:
```
        Critic_Score  No. Games
Rating
AO         93.000000          1
E          68.484687       2808
E10+       66.759392       1118
K-A        92.000000          1
M          71.797033       1483
RP         62.000000          3
T          68.828409       2640
```

**Encoding: Since the size of the domain is less, we can safely One Hot Encode this data.**

[40]:
```
num=[]
for i in data['Rating'].unique():
    if( isinstance(i, int) == 1 or isinstance(i, float) ==1):
        print(i)
        num.append(i)
```

```
nan
```

[41]:
```
for i in num:
    data['Rating'] = data['Rating'].replace(i,"zero")
```

[42]:
```
encoded_columns = pd.get_dummies(data['Rating'])

for i in encoded_columns:
    data[i] = encoded_columns[i]
data = data.drop(columns=['Rating'],axis=1)
data.shape
```

[42]:
```
(8137, 45)
```

### 1.3.10 User Score

[43]:
```
data['User_Score'].unique()
```

[43]:
```
array(['8', '8.3', '8.5', '6.6', '8.4', '8.6', '7.7', '6.3', '7.4', '8.2',
       '9', '7.9', '8.1', '8.7', '7.1', '3.4', '5.3', '4.8', '3.2', '8.9',
       '6.4', '7.8', '7.5', '2.6', '7.2', '9.2', '7', '7.3', '4.3', '7.6',
       '5.7', '5', '9.1', '6.5', '8.8', '6.9', '9.4', '6.8', '6.1', '6.7',
       '5.4', nan, '4', '9.3', '6.2', '4.2', '6', 'tbd', '4.9', '3.7',
       '4.1', '5.8', '5.6', '5.5', '4.4', '4.6', '5.9', '3.9', '3.1',
```

```
'2.9', '5.2', '3.3', '4.5', '5.1', '3.5', '2.5', '1.9', '2.2', '2',
'9.5', '4.7', '2.1', '3.6', '1.8', '3.8', '3', '9.6', '2.8', '1.7',
'2.7', '2.4', '1.5', '1.2', '2.3', '0.5', '0.6', '0.9', '1', '1.4',
'1.3', '0.7'], dtype=object)
```

**We can see that except for nan, 'tbd' the rest of the values are all numbers.**

[44]:
```
print(data['User_Score'].isnull().sum())
```

```
38
```

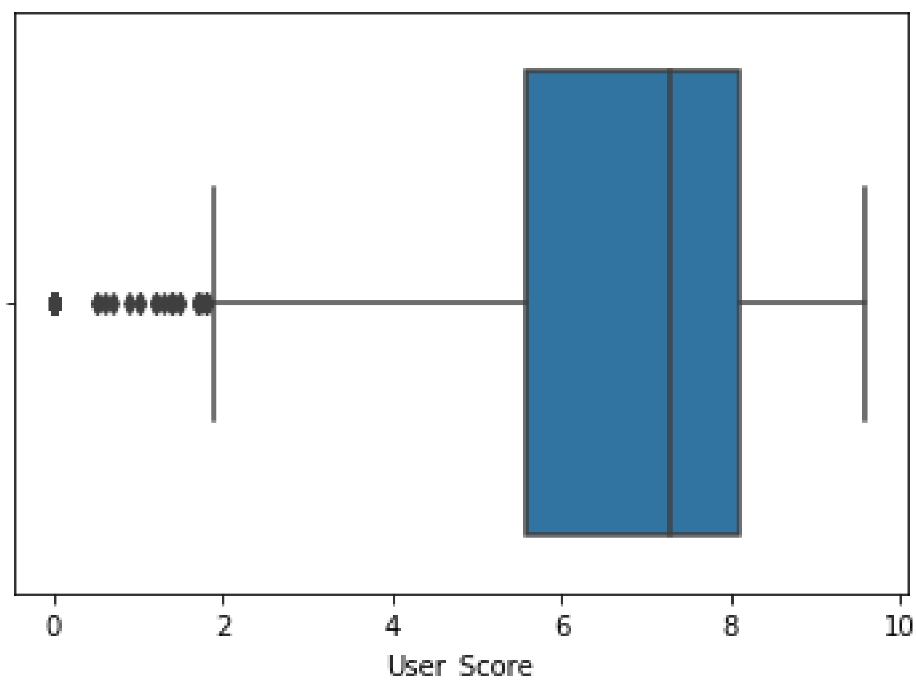
**We can convert User_Score column into a numerical column. We replace the illegal values with mean as there are very few values.**

[45]:
```
data['User_Score'] = pd.to_numeric(data['User_Score'], errors='coerce')

data['User_Score'] = data['User_Score'].replace(np.nan, 0 , regex=True)
data['User_Score'] = data['User_Score'].astype(float)
```

[46]:
```
sns.boxplot(x=data['User_Score'])
```

[46]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5af474d9b0>
```




[47]:
```
data.head(2)
```

[47]:
```
               Name  Platform  Year_of_Release  Publisher  NA_Sales  EU_Sales  \
0        Wii Sports        12           2006.0        185     41.36     28.96
```

```
2  Mario Kart Wii        12           2008.0        185      15.68      12.76

   JP_Sales  Other_Sales  Global_Sales  Critic_Score  ...  SportsGenre  \
0      3.77         8.45         82.53          76.0  ...            1
2      3.79         3.29         35.52          82.0  ...            0

   StrategyGenre  AO  E  E10+  K-A  M  RP  T  zero
0              0   0  1     0    0  0   0  0     0
2              0   0  1     0    0  0   0  0     0

[2 rows x 45 columns]
```

#### 1.3.11 Other Numerical features - Global_Sales, EU_Sales ...

[48]:
```
data['Platform'].unique()
```

[48]:
```
array([12,  2, 14,  8,  7,  0,  9,  6, 15,  5, 10, 13,  4,  3, 16, 11,  1])
```

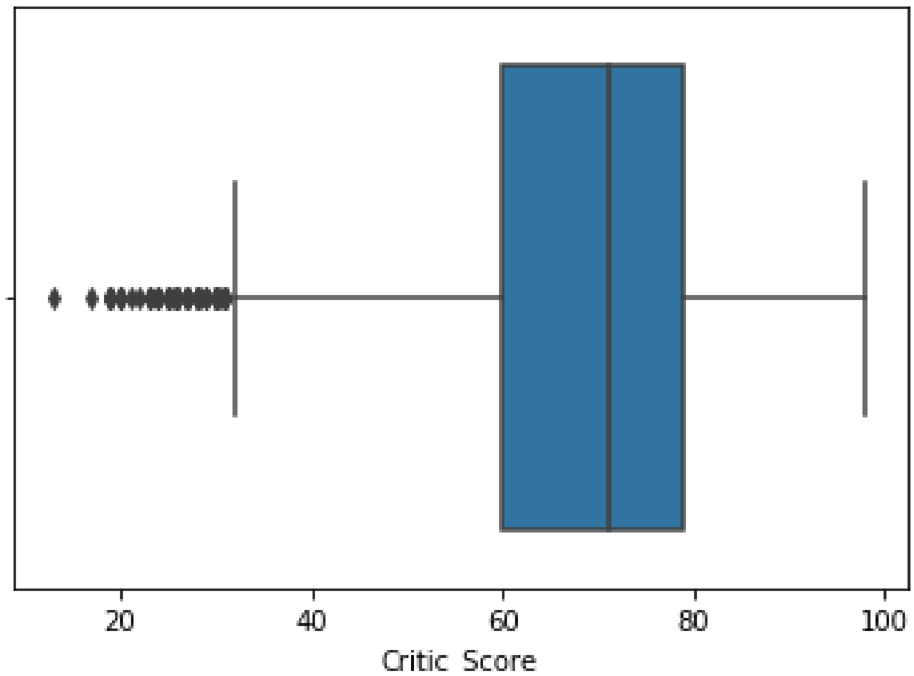
**We can also use our sampler/mean to fill the missing values in all the numerical columns**

[49]:
```
# Using Sampler/mean for each column

for i in list(data.columns):
    if(data[i].dtypes != 'object'):
        data[i] = data[i].fillna(data[i].mean())
#         replace_null(i,data)
```

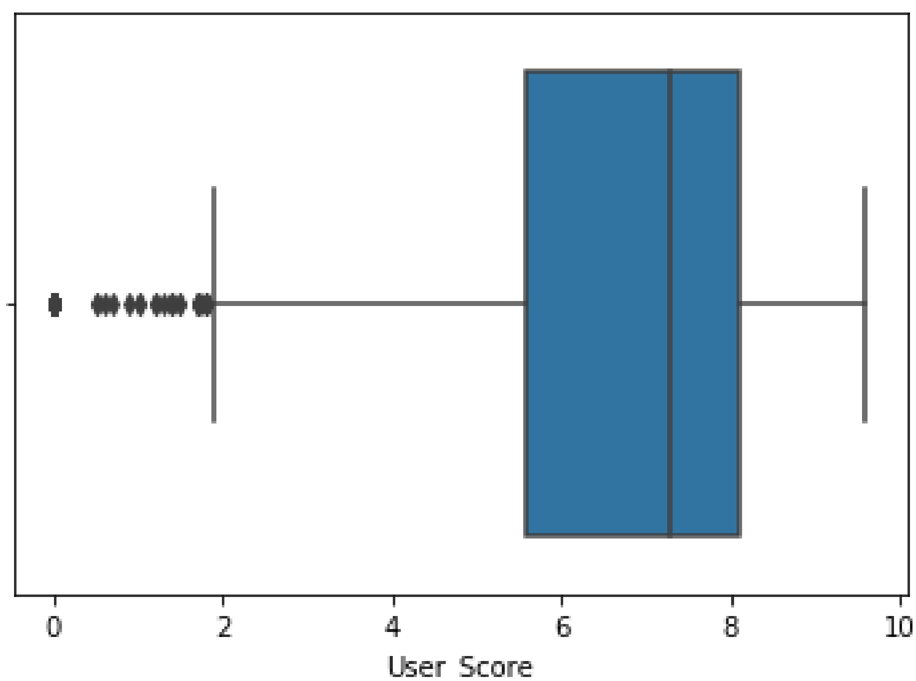
[50]:
```
sns.boxplot(x=data['Critic_Score'])
```

[50]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5af46b42b0>
```




[51]:
```
sns.boxplot(x=data['User_Score'])
```

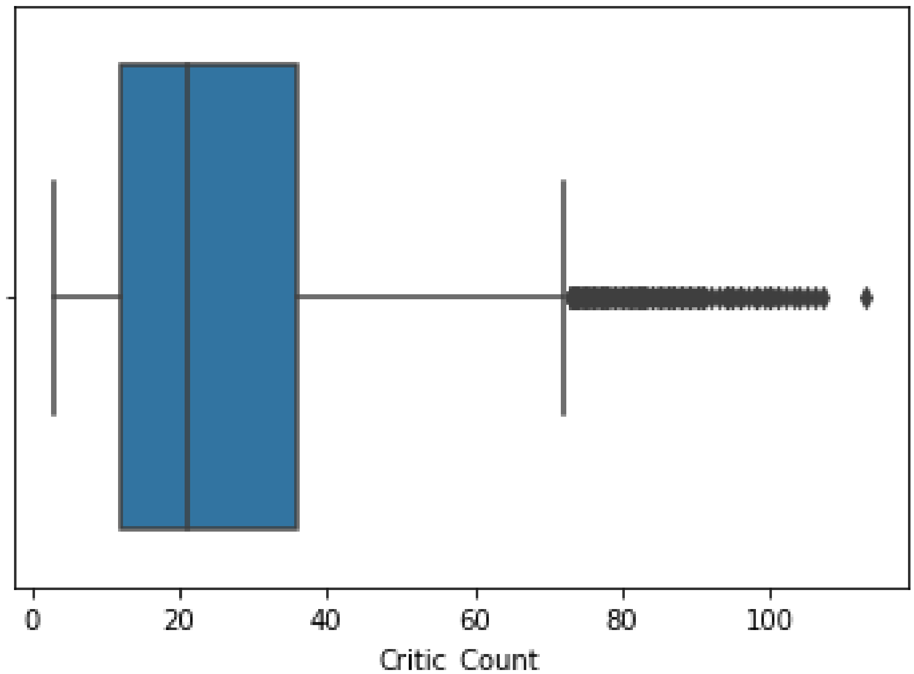
[51]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5af4694f98>



**It can be seen that generally people are a little more generous with their scores compared to critics.**

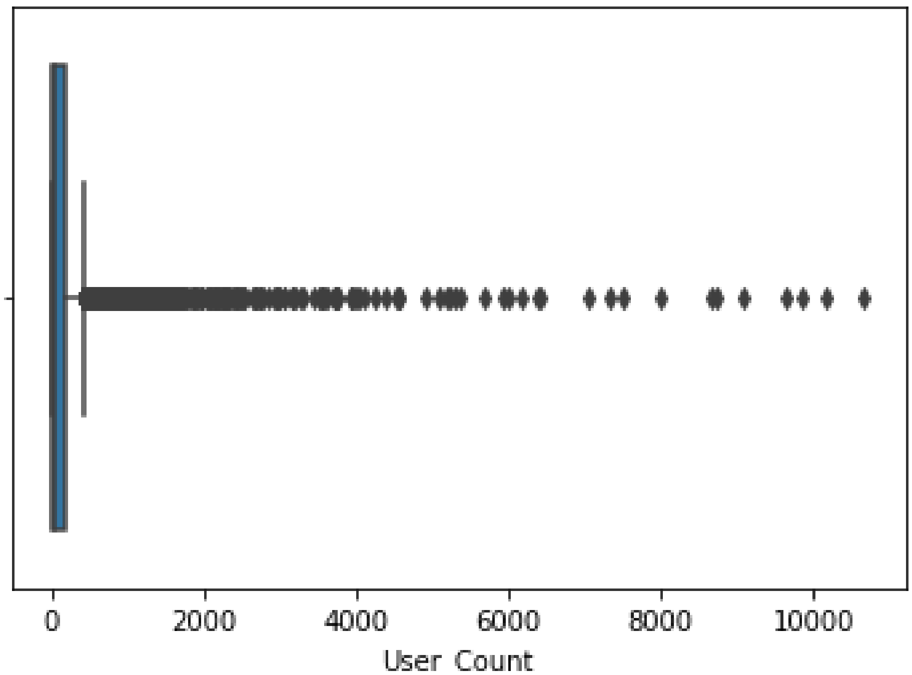
[52]:
```
sns.boxplot(x=data['Critic_Count'])
```

[52]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5af45f7240>




[53]:
```
sns.boxplot(x=data['User_Count'])
```

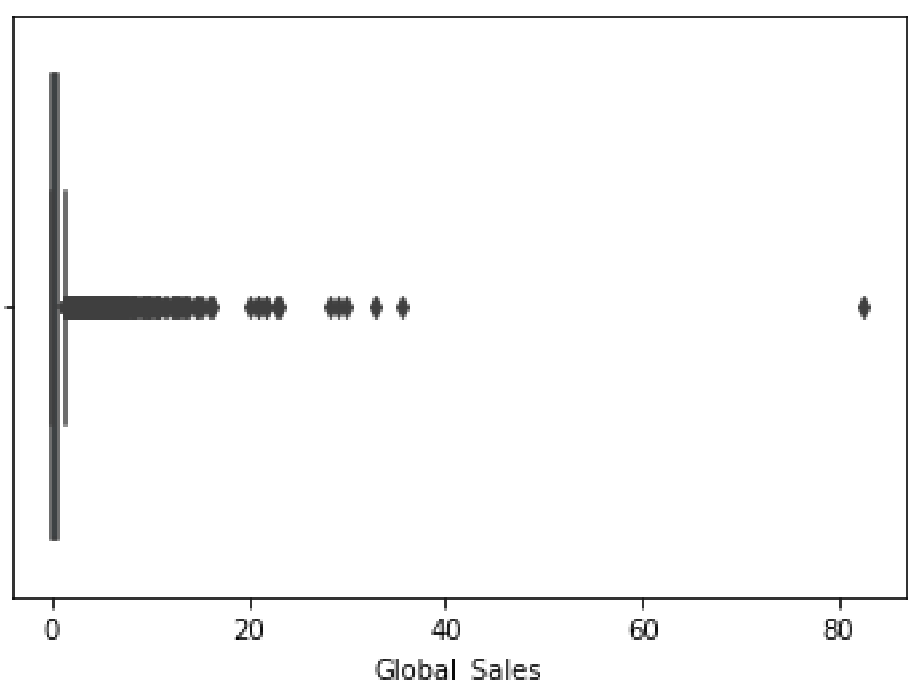
[53]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5af45c04a8>




### 1.3.12 Illegal value analysis for features

[54]:
```
sns.boxplot(x=data['Global_Sales'])
```

[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5af45372b0>



[55]:
```
data[data['Global_Sales'] > 60]
```

[55]:
```
          Name  Platform  Year_of_Release  Publisher  NA_Sales  EU_Sales  \
0   Wii Sports        12           2006.0        185     41.36     28.96

   JP_Sales  Other_Sales  Global_Sales  Critic_Score  ...  SportsGenre  \
0      3.77         8.45         82.53          76.0  ...            1

   StrategyGenre  AO  E  E10+  K-A  M  RP  T  zero
0              0   0  1     0    0  0   0  0     0

[1 rows x 45 columns]
```

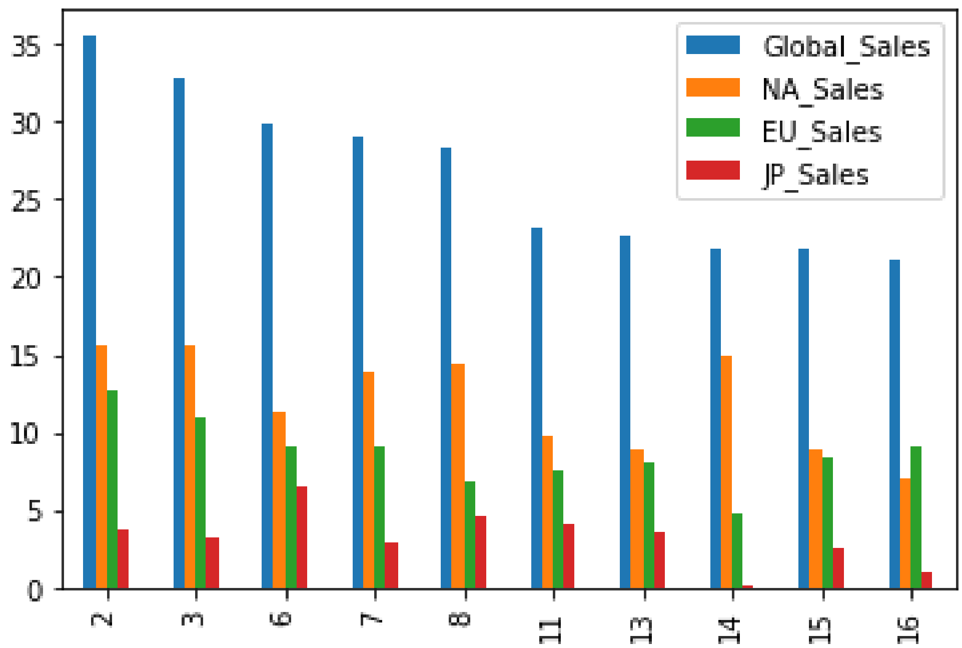
**This game is a special case as it was given for free to all customers who bought the Wii console (which is one of the most popular consoles of all time). It is an outlier.**

[56]:
```
indexNames = data[ data['Global_Sales'] > 60 ].index

# Delete these row indexes from dataFrame
data.drop(indexNames , inplace=True)
```

[57]:
```
plotting = pd.DataFrame(data['Global_Sales'])
plotting['NA_Sales'] = data['NA_Sales']
plotting['EU_Sales'] = data['EU_Sales']
plotting['JP_Sales'] = data['JP_Sales']
plotting.head(10).plot(kind='bar')
```

[57]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5af45197f0>



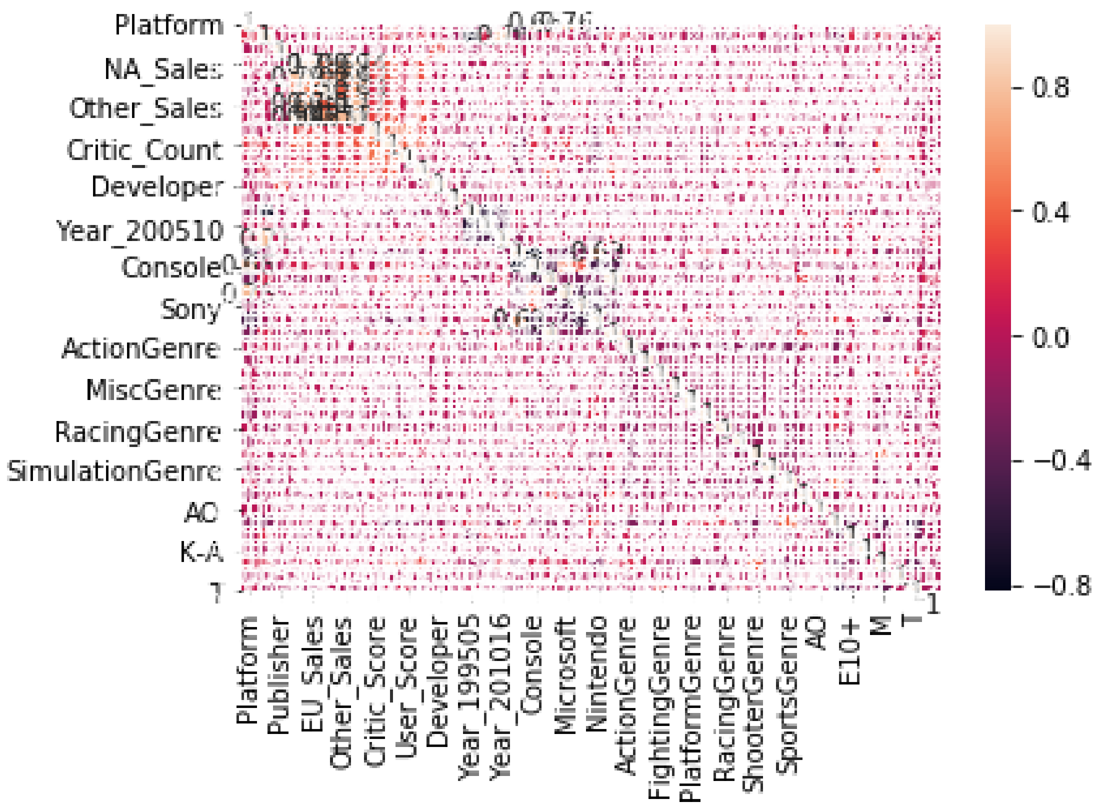
### 1.3.13 Correlation matrix and heat maps

[58]:
```
corr = data.corr()
corr.style.background_gradient(cmap='coolwarm')
```

[58]: <pandas.io.formats.style.Styler at 0x7f5af44562e8>

[59]:
```
sns.heatmap(data.corr(), annot=True)
```

[59]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5af40d95f8>




### 1.3.14 Train Test Split for Critic Score

[60]:
```
train, test = train_test_split(data, test_size=0.33,random_state=6)
```

[61]:
```
x_train = train.
 ↪drop(['Name','User_Score','Global_Sales','NA_Sales','EU_Sales','JP_Sales','Other_Sales'],ax
y_train1 = train['User_Score']
y_train2 = train['Global_Sales']
y_train3 = train['NA_Sales']
```

```
y_train4 = train['EU_Sales']
y_train5 = train['JP_Sales']

x_test = test.
 ↪drop(['Name','User_Score','Global_Sales','NA_Sales','EU_Sales','JP_Sales','Other_Sales'],ax
y_test1 = test['User_Score']
y_test2 = test['Global_Sales']
y_test3 = test['NA_Sales']
y_test4 = test['EU_Sales']
y_test5 = test['JP_Sales']
```

#### 1.3.15 Scaling the Data set

**If we perform only Linear Regression, it is not necessary to scale the feature set, however, it is very useful for interpretability fo the data**

[62]:
```
scaler = StandardScaler()

scaler.fit(x_train)

x_train = scaler.transform(x_train)

x_test = scaler.transform(x_test)
```

### 1.4 Model Training and Error Evaluation

[63]:
```
#Creating model
modellir = Ridge()

# Fitting the model with prepared data
modellir.fit(x_train,y_train1)
y_predlir = modellir.predict(x_test)
```

[64]:
```
print("Ridge Regression RMSE (User Score):",␣
 ↪sqrt(mean_squared_error(y_test1,y_predlir)))
print("Ridge Regression R2 Score (User Score):", r2_score(y_test1,y_predlir))
```

```
Ridge Regression RMSE (User Score): 2.315152146049301
Ridge Regression R2 Score (User Score): 0.33406573955813257
```

[65]:
```
modellir.fit(x_train,y_train2)
y_predlir = modellir.predict(x_test)
```

[66]:
```
print("Ridge Regression RMSE (Global Sales):",␣
 ↪sqrt(mean_squared_error(y_test2,y_predlir)))
print("Ridge Regression R2 Score (Global Sales):", r2_score(y_test2,y_predlir))
```

```
Ridge Regression RMSE (Global Sales): 1.5462780504537277
Ridge Regression R2 Score (Global Sales): 0.1913534332277942
```

[67]:
```python
modellir.fit(x_train,y_train3)
y_predlir = modellir.predict(x_test)

print("Linear Regression RMSE (NA Sales):",␣
 ↪sqrt(mean_squared_error(y_test3,y_predlir)))
print("Linear Regression R2 Score (NA Sales):", r2_score(y_test3,y_predlir))
```

```
Linear Regression RMSE (NA Sales): 0.7323070083231055
Linear Regression R2 Score (NA Sales): 0.1874498909918716
```

[68]:
```python
modellir.fit(x_train,y_train4)
y_predlir = modellir.predict(x_test)

print("Ridge Regression RMSE (EU Sales):",␣
 ↪sqrt(mean_squared_error(y_test4,y_predlir)))
print("Ridge Regression R2 Score (EU Sales):", r2_score(y_test4,y_predlir))
```

```
Ridge Regression RMSE (EU Sales): 0.5424499796923218
Ridge Regression R2 Score (EU Sales): 0.16369286009323802
```

[69]:
```python
modellir.fit(x_train,y_train5)
y_predlir = modellir.predict(x_test)

print("Ridge Regression RMSE (JP Sales):",␣
 ↪sqrt(mean_squared_error(y_test5,y_predlir)))
print("Ridge Regression R2 Score (JP Sales):", r2_score(y_test5,y_predlir))
```

```
Ridge Regression RMSE (JP Sales): 0.2780761804057319
Ridge Regression R2 Score (JP Sales): 0.0978042005200237
```

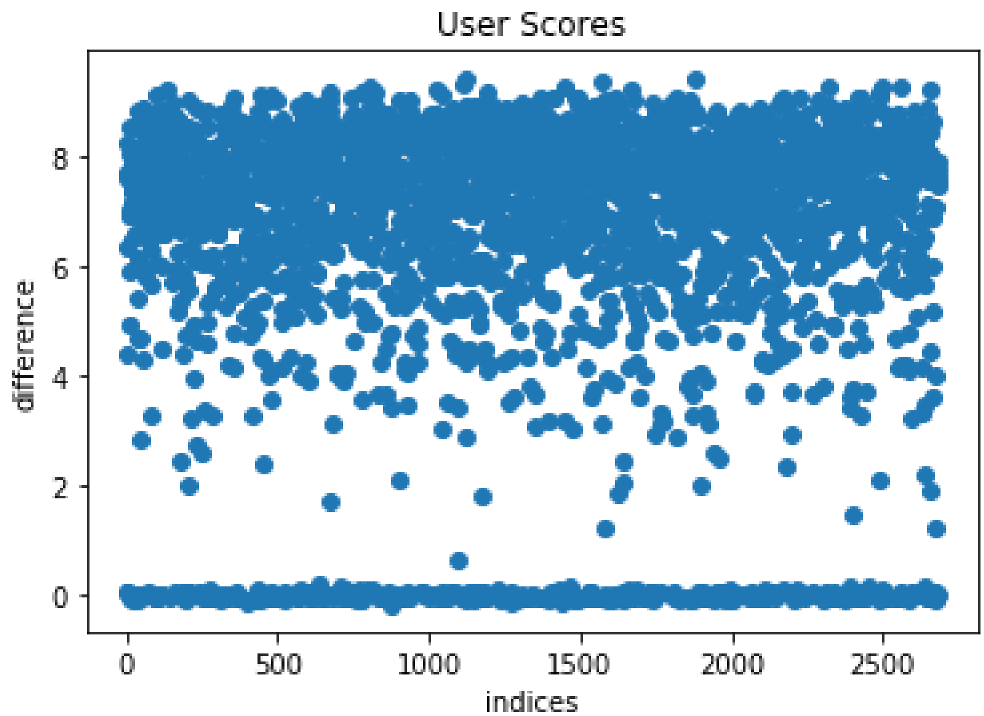
### 1.4.1 Residual Plot

[70]:
```python
plt.scatter(range(0,len(y_test1-y_predlir)),(y_test1-y_predlir))

plt.xlabel('indices')
plt.ylabel('difference')

plt.title('User Scores')

plt.show()
```

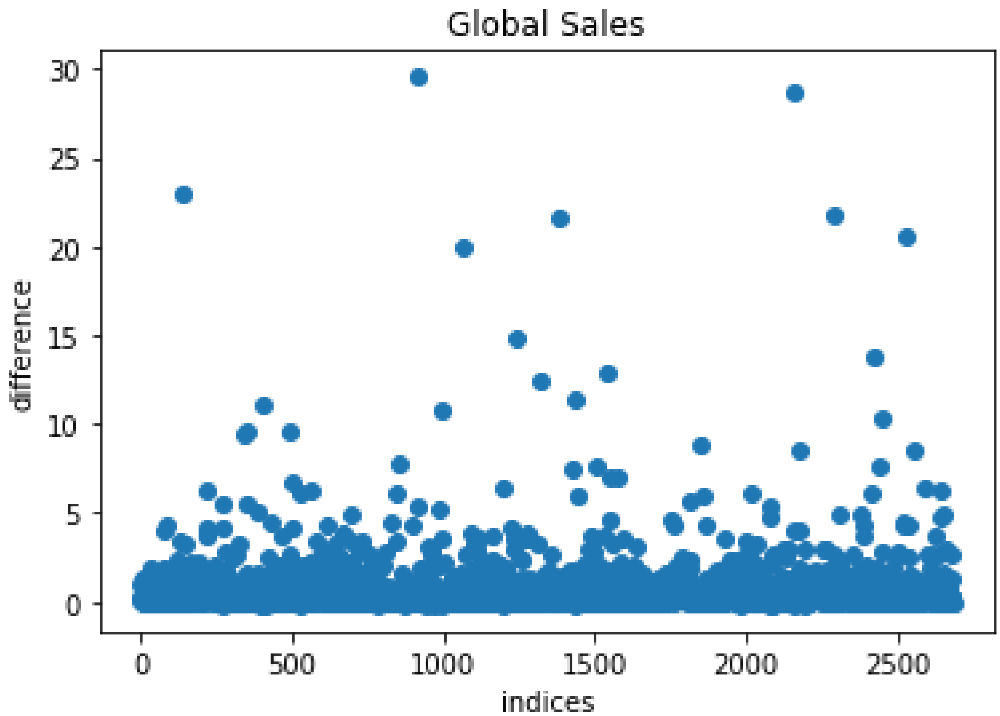



[71]:
```
plt.scatter(range(0,len(y_test2-y_predlir)),(y_test2-y_predlir))

plt.xlabel('indices')
plt.ylabel('difference')

plt.title('Global Sales')

plt.show()
```

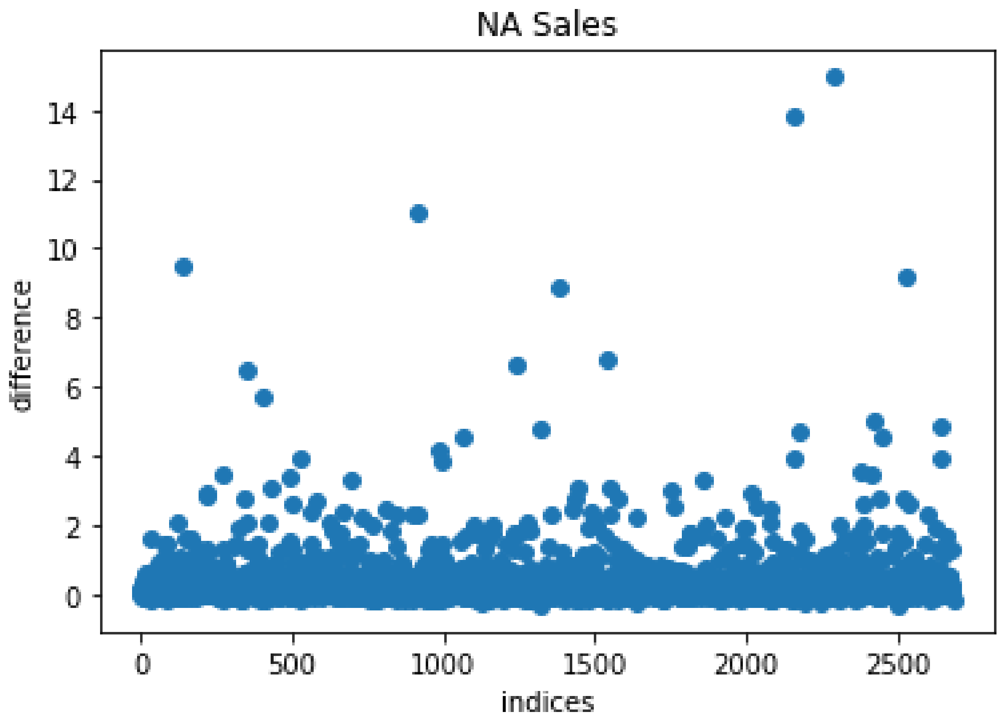



[72]:
```
plt.scatter(range(0,len(y_test3-y_predlir)),(y_test3-y_predlir))

plt.xlabel('indices')
plt.ylabel('difference')

plt.title('NA Sales')

plt.show()
```

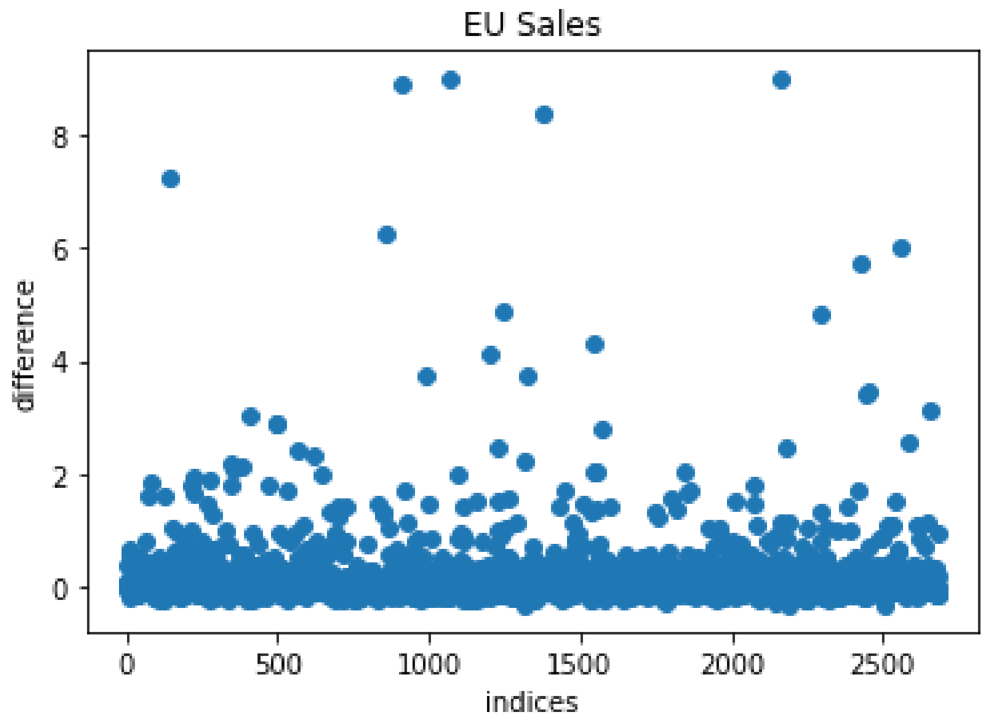



[73]:
```
plt.scatter(range(0,len(y_test4-y_predlir)),(y_test4-y_predlir))

plt.xlabel('indices')
plt.ylabel('difference')

plt.title('EU Sales')

plt.show()
```

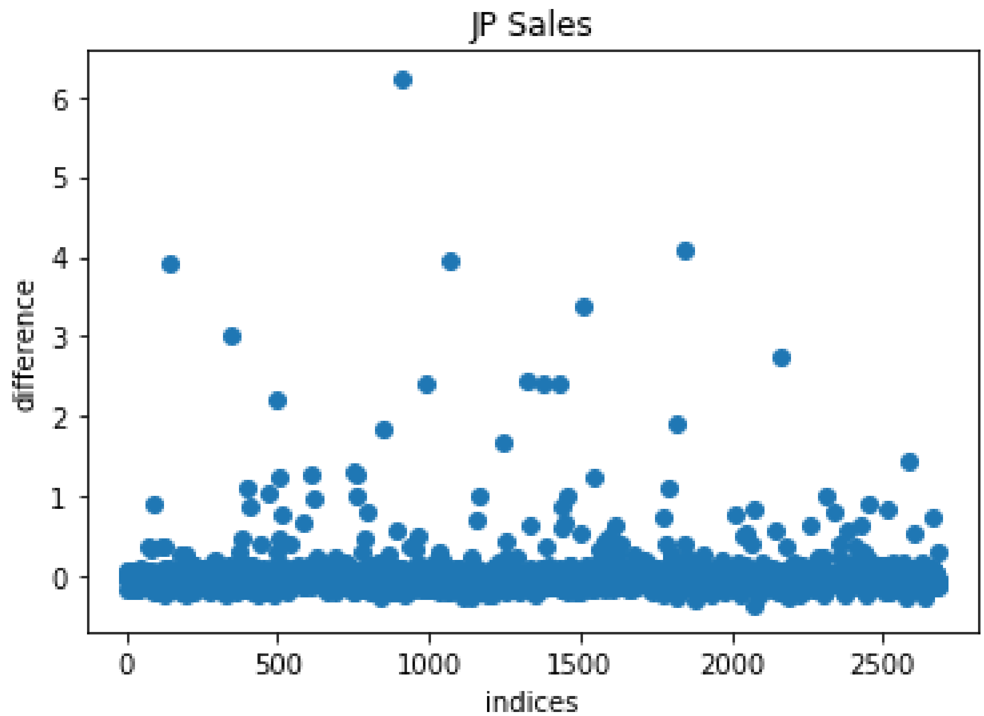



[74]:
```
plt.scatter(range(0,len(y_test5-y_predlir)),(y_test5-y_predlir))

plt.xlabel('indices')
plt.ylabel('difference')

plt.title('JP Sales')

plt.show()
```




**This plot gives us a much better idea as to how large a difference the errors are.**

## 1.5 The END

### 1.5.1 Creating Pickle file

[75]:
```
import pickle

file_Name = "model"

fileObject = open(file_Name, 'wb')

pickle.dump(modellir, fileObject)

fileObject.close()
```

## 1.6 EXTRA:

### 1.6.1 Error Evaluation without Feature Engineering and Preprocessing

[76]:
```
# data = pd.read_csv("Video_Games_Sales_as_at_22_Dec_2016.csv")

# data = data.dropna(subset=['Critic_Score'])

# for i in list(data.columns):
#     if(data[i].dtypes != 'object'):
#         data[i].fillna(data[i].mean())

# data['User_Score'] = pd.to_numeric(data['User_Score'], errors='coerce')

# data = data.replace(np.nan, 0 , regex=True)
# data['User_Score'] = data['User_Score'].astype(float)

# data['User_Score'].dtypes

# for s in list(data.columns):
#     if(data[s].dtypes == 'object'):
#         num=[]
#         for i in data[s].unique():
#             if( isinstance(i, int) == 1 or isinstance(i, float) ==1):
# #                 print(i)
#                 num.append(i)

# #### This shows that there is a 0 in the dataset where there should be a␣
↪string. We shall replace it with the string 'zero'

#         for i in num:
#             data[s] = data[s].replace(i,"zero")




# lc = LabelEncoder()
# for s in list(data.columns):
#     if(data[s].dtypes == 'object'):
# #         print(data[s])
#         data[s] = lc.fit_transform(data[s])

# train, test = train_test_split(data, test_size=0.33,random_state=6)

# x_train = train.
↪drop(['Name','User_Score','Global_Sales','NA_Sales','EU_Sales','JP_Sales','Other_Sales'],ax
# y_train1 = train['User_Score']
# y_train2 = train['Global_Sales']
```

```
# y_train3 = train['NA_Sales']
# y_train4 = train['EU_Sales']
# y_train5 = train['JP_Sales']

# x_test = test.
↪drop(['Name','User_Score','Global_Sales','NA_Sales','EU_Sales','JP_Sales','Other_Sales'],ax
# y_test1 = test['User_Score']
# y_test2 = test['Global_Sales']
# y_test3 = test['NA_Sales']
# y_test4 = test['EU_Sales']
# y_test5 = test['JP_Sales']
# scaler = StandardScaler()

# scaler.fit(x_train)

# x_train = scaler.transform(x_train)

# x_test = scaler.transform(x_test)

# ## Model Training and Error Evaluation

# #Creating model
# modellir = Lasso()

# # Fitting the model with prepared data
# modellir.fit(x_train,y_train1)
# y_predlir = modellir.predict(x_test)


# print("Linear Regression RMSE (User Score):",␣
↪sqrt(mean_squared_error(y_test1,y_predlir)))
# print("Linear Regression R2 Score (User Score):",␣
↪r2_score(y_test1,y_predlir))

# modellir.fit(x_train,y_train2)
# y_predlir = modellir.predict(x_test)

# print("Linear Regression RMSE (Global Sales):",␣
↪sqrt(mean_squared_error(y_test2,y_predlir)))
# print("Linear Regression R2 Score (Global Sales):",␣
↪r2_score(y_test2,y_predlir))

# modellir.fit(x_train,y_train3)
# y_predlir = modellir.predict(x_test)

# print("Linear Regression RMSE (NA Sales):",␣
↪sqrt(mean_squared_error(y_test3,y_predlir)))
```

```
# print("Linear Regression R2 Score (NA Sales):", r2_score(y_test3,y_predlir))

# modellir.fit(x_train,y_train4)
# y_predlir = modellir.predict(x_test)

# print("Linear Regression RMSE (EU Sales):",␣
↪sqrt(mean_squared_error(y_test4,y_predlir)))
# print("Linear Regression R2 Score (EU Sales):", r2_score(y_test4,y_predlir))

# modellir.fit(x_train,y_train5)
# y_predlir = modellir.predict(x_test)

# print("Linear Regression RMSE (JP Sales):",␣
↪sqrt(mean_squared_error(y_test5,y_predlir)))
# print("Linear Regression R2 Score (JP Sales):", r2_score(y_test5,y_predlir))
```

[ ]:

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