In [47]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import LabelEncoder
from sklearn import linear_model
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from subprocess import check_output
from sklearn.model_selection import train_test_split
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.svm import SVR
df = pd.read_csv(r"C:\Users\Brent\Documents\GitHub\DataScience\Challenges\Personal
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 16598 entries, 0 to 16597
Data columns (total 11 columns):
                16598 non-null int64
                16598 non-null object
Name
Platform
                16598 non-null object
                16327 non-null float64
Year
Genre
               16598 non-null object
Publisher 16540 non-null object NA_Sales 16598 non-null float64
NA Sales
               16598 non-null float64
EU Sales
JP Sales
               16598 non-null float64
Other_Sales 16598 non-null float64
Global_Sales 16598 non-null float64
dtypes: float64(6), int64(1), object(4)
memory usage: 1.4+ MB
```

In [2]:

df.head(10)

Out[2]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_Sales	C
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	3.77	
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	6.81	
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	3.79	
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	3.28	
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role- Playing	Nintendo	11.27	8.89	10.22	
5	6	Tetris	GB	1989.0	Puzzle	Nintendo	23.20	2.26	4.22	
6	7	New Super Mario Bros.	DS	2006.0	Platform	Nintendo	11.38	9.23	6.50	
7	8	Wii P l ay	Wii	2006.0	Misc	Nintendo	14.03	9.20	2.93	
8	9	New Super Mario Bros. Wii	Wii	2009.0	Platform	Nintendo	14.59	7.06	4.70	
9	10	Duck Hunt	NES	1984.0	Shooter	Nintendo	26.93	0.63	0.28	
4										•

In [3]:

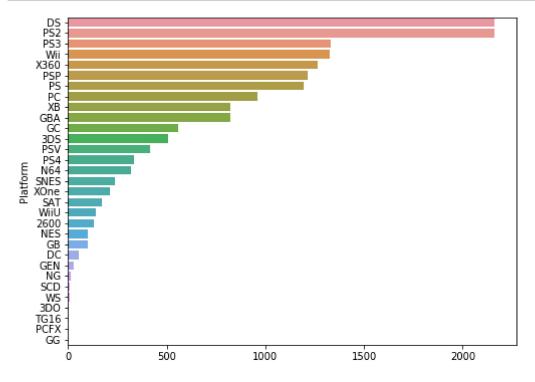
df.isna().sum()

Out[3]:

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	

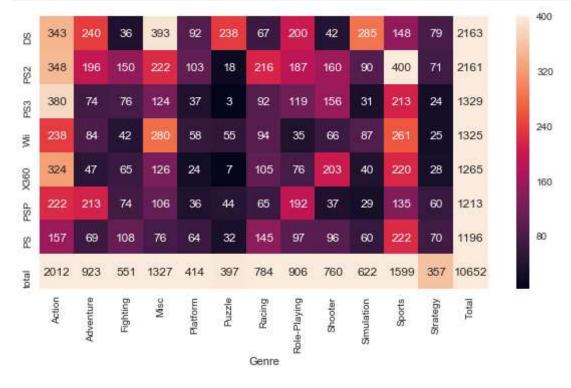
In [4]:

```
## I want to know how many games each platform has. i found a function called cross
## me with visualizing this.
platGenre = pd.crosstab(df.Platform,df.Genre)
platGenreTotal = platGenre.sum(axis=1).sort_values(ascending = False)
plt.figure(figsize=(8,6))
sns.barplot(y = platGenreTotal.index, x = platGenreTotal.values, orient='h')
plt.ylabel = "Platform"
plt.xlabel = "The amount of games"
plt.show()
```



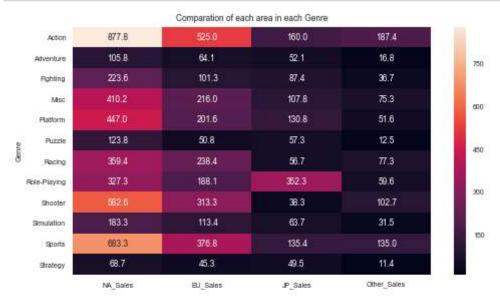
In [5]:

```
## Now i want to focus on the platforms that have 1000 or more games.
platGenre['Total'] = platGenre.sum(axis=1)
popPlatform = platGenre[platGenre['Total']>1000].sort_values(by='Total', ascending
neededdata = popPlatform.loc[:,:'Strategy']
maxi = neededdata.values.max()
mini = neededdata.values.min()
popPlatformfinal = popPlatform.append(pd.DataFrame(popPlatform.sum(), columns=['tot
sns.set(font_scale=1.0)
plt.figure(figsize=(10,5))
sns.heatmap(popPlatformfinal, vmin = mini, vmax = maxi, annot=True, fmt="d")
plt.xticks(rotation = 90)
plt.show()
```



In [6]:

```
GenreGroup = df.groupby(['Genre']).sum().loc[:, 'NA_Sales':'Global_Sales']
GenreGroup['NA_Sales%'] = GenreGroup['NA_Sales']/GenreGroup['Global_Sales']
GenreGroup['EU_Sales%'] = GenreGroup['EU_Sales']/GenreGroup['Global_Sales']
GenreGroup['JP_Sales%'] = GenreGroup['JP_Sales']/GenreGroup['Global_Sales']
GenreGroup['Other_Sales%'] = GenreGroup['Other_Sales']/GenreGroup['Global_Sales']
plt.figure(figsize=(8, 10))
sns.set(font_scale=0.7)
plt.subplot(211)
sns.heatmap(GenreGroup.loc[:, 'NA_Sales':'Other_Sales'], annot=True, fmt = '.1f')
plt.title("Comparation of each area in each Genre")
plt.subplot(212)
sns.heatmap(GenreGroup.loc[:,'NA_Sales%':'Other_Sales%'], vmax =1, vmin=0, annot=Tr
plt.title("Comparation of each area in each Genre(Pencentage)")
plt.show()
```





```
In [7]:
```

```
li = ['NA_Sales', 'EU_Sales', 'JP_Sales', 'Other_Sales', 'Global_Sales']

for i in li:
    print(i, end=" -->> ")
    print(df[i].mean(), end=" million")
    print("\n")

NA_Sales -->> 0.26466742981084057 million

EU_Sales -->> 0.1466520062658483 million
```

```
EU_Sales -->> 0.1466520062658483 million

JP_Sales -->> 0.07778166044101108 million

Other_Sales -->> 0.048063019640913515 million

Global_Sales -->> 0.53744065550074 million
```

Type $\mathit{Markdown}$ and LaTeX : α^2

Finding Correlations

First i want to group up the publishers and platforms that don't have a lot of games. In my opinion, this will make the visualizations cleaner and analyzing more easier.

```
In [8]:
```

```
for i in df['Publisher'].unique():
    if df['Publisher'][df['Publisher'] == i].count() < 50:</pre>
        df['Publisher'][df['Publisher'] == i] = 'Other'
for i in df['Platform'].unique():
    if df['Platform'][df['Platform'] == i].count() < 100:</pre>
        df['Platform'][df['Platform'] == i] = 'Other'
E:\Anaconda\lib\site-packages\ipykernel launcher.py:3: SettingWithCopy
Warning:
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy (http://pandas.pyd
ata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
  This is separate from the ipykernel package so we can avoid doing im
ports until
E:\Anaconda\lib\site-packages\ipykernel launcher.py:7: SettingWithCopy
A value is trying to be set on a copy of a slice from a DataFrame
See the caveats in the documentation: http://pandas.pydata.org/pandas-
docs/stable/indexing.html#indexing-view-versus-copy (http://pandas.pyd
ata.org/pandas-docs/stable/indexing.html#indexing-view-versus-copy)
  import sys
```

In [9]:

18-11-2018

```
df['Publisher'].value_counts()
```

Out[9]:		
Other	3342	
Electronic Arts	1351	
Activision	975	
Namco Bandai Games	932	
Ubisoft	921	
Konami Digital Entertainment	832	
THO	715	
Nintendo	703	
Sony Computer Entertainment	683	
Sega	639	
Take-Two Interactive	413	
Capcom	381	
Atari	363	
Tecmo Koei	338	
Square Enix	233	
Warner Bros. Interactive Entertainment	232	
Disney Interactive Studios	218	
Unknown	203	
Eidos Interactive	198	
Midway Games	198	
505 Games	192	
Microsoft Game Studios	189	
Acclaim Entertainment	184	
D3Publisher	184	
Vivendi Games	164	
Codemasters	152	
Idea Factory	129	
Deep Silver	122	
Nippon Ichi Software	105	
Zoo Digital Publishing	104	
Majesco Entertainment	92	
LucasArts	90	
Rising Star Games	86	
Hudson Soft	81	
Banpresto	73	
Bethesda Softworks	71	
Crave Entertainment	71	
Atlus	67	
Infogrames	62	
Virgin Interactive	62	
5pb	61	
Ignition Entertainment	61	
Focus Home Interactive	58	
Marvelous Interactive	56	
SquareSoft	52	
Empire Interactive	52	
Kadokawa Shoten	50	
Name: Publisher, dtype: int64		
, <u> </u>		

```
In [10]:
```

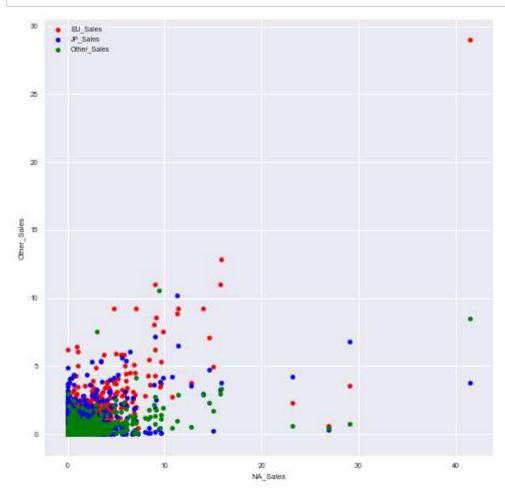
```
df['Platform'].value counts()
Out[10]:
DS
         2163
         2161
PS2
PS3
         1329
         1325
Wii
X360
         1265
         1213
PSP
         1196
PS
РC
          960
          824
ΧB
GBA
          822
          556
GC
3DS
          509
PSV
          413
          336
PS4
N64
          319
          306
Other
          239
SNES
          213
XOne
SAT
          173
          143
WiiU
2600
          133
Name: Platform, dtype: int64
```

Much cleaner lists in my opinion just by grouping up the publishers and platforms with not a lot of games.

```
In [ ]:
```

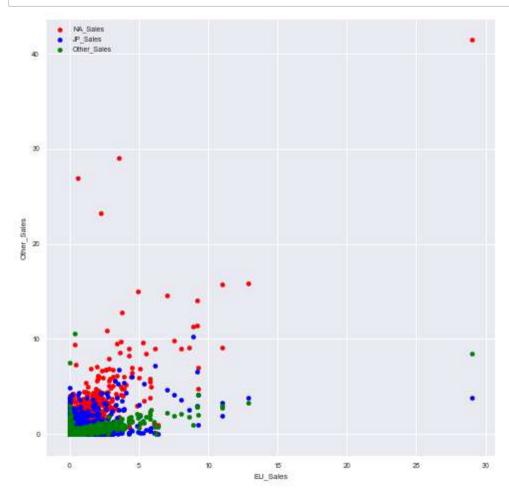
In [11]:

ax = df.plot(kind='scatter',x='NA_Sales',y='EU_Sales',color='red',label='EU_Sales',
df.plot(kind='scatter',x='NA_Sales',y='JP_Sales',ax=ax,color='blue',label='JP_Sales
df.plot(kind='scatter',x='NA_Sales',y='Other_Sales',ax=ax,color='green',label='Othe
plt.show()



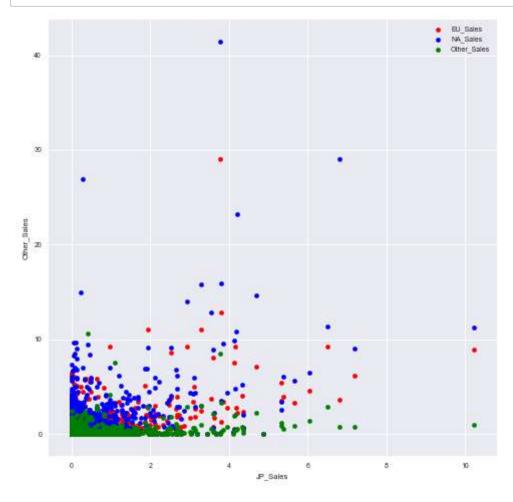
In [12]:

ax = df.plot(kind='scatter', x='EU_Sales', y='NA_Sales', color='red', label='NA_Sales',
df.plot(kind='scatter', x='EU_Sales', y='JP_Sales', ax=ax, color='blue', label='JP_Sales
df.plot(kind='scatter', x='EU_Sales', y='Other_Sales', ax=ax, color='green', label='Othe
plt.show()



In [13]:

ax = df.plot(kind='scatter',x='JP_Sales',y='EU_Sales',color='red',label='EU_Sales',
df.plot(kind='scatter',x='JP_Sales',y='NA_Sales',ax=ax,color='blue',label='NA_Sales
df.plot(kind='scatter',x='JP_Sales',y='Other_Sales',ax=ax,color='green',label='Othe
plt.show()



In [14]:

Out[14]:

	Corr_1	Corr_2	Correlation
0	NA_Sales	NA_Sales	1.000000
1	NA_Sales	EU_Sales	0.767727
2	NA_Sales	JP_Sales	0.449787
3	NA_Sales	Other_Sales	0.634737
4	NA_Sales	Global_Sales	0.941047
5	EU_Sales	NA_Sales	0.767727
6	EU_Sales	EU_Sales	1.000000
7	EU_Sales	JP_Sales	0.435584
8	EU_Sales	Other_Sales	0.726385
9	EU_Sales	Global_Sales	0.902836
10	JP_Sales	NA_Sales	0.449787
11	JP_Sales	EU_Sales	0.435584
12	JP_Sales	JP_Sales	1.000000
13	JP_Sales	Other_Sales	0.290186
14	JP_Sales	Global_Sales	0.611816
15	Other_Sales	NA_Sales	0.634737
16	Other_Sales	EU_Sales	0.726385
17	Other_Sales	JP_Sales	0.290186
18	Other_Sales	Other_Sales	1.000000
19	Other_Sales	Global_Sales	0.748331
20	Global_Sales	NA_Sales	0.941047
21	Global_Sales	EU_Sales	0.902836
22	Global_Sales	JP_Sales	0.611816
23	Global_Sales	Other_Sales	0.748331
24	Global_Sales	Global_Sales	1.000000

In [15]:

```
corr_data = corr_data.pivot(values='Correlation',index='Corr_1',columns='Corr_2')
corr_data
```

Out[15]:

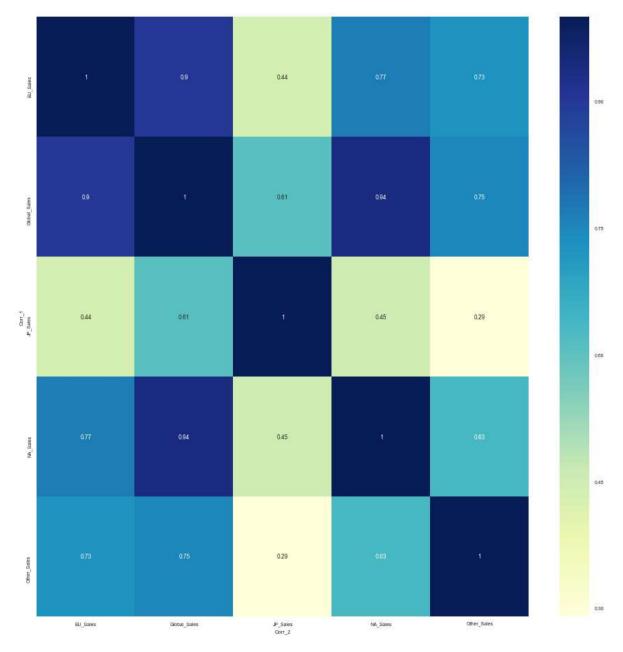
Corr_2	EU_Sales	Global_Sales	JP_Sales	NA_Sales	Other_Sales
Corr_1					
EU_Sales	1.000000	0.902836	0.435584	0.767727	0.726385
Global_Sales	0.902836	1.000000	0.611816	0.941047	0.748331
JP_Sales	0.435584	0.611816	1.000000	0.449787	0.290186
NA_Sales	0.767727	0.941047	0.449787	1.000000	0.634737
Other_Sales	0.726385	0.748331	0.290186	0.634737	1.000000

In [16]:

```
plt.figure(figsize=(16,16))
sns.heatmap(corr_data,cmap = "YlGnBu", annot=True)
```

Out[16]:

<matplotlib.axes._subplots.AxesSubplot at 0x2a1e6df9278>

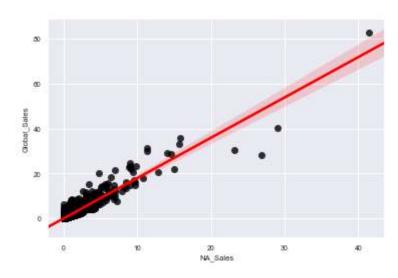


```
In [17]:
```

```
sns.regplot(x="NA_Sales", y="Global_Sales", data=df, scatter_kws={"color": "black"}
```

Out[17]:

<matplotlib.axes. subplots.AxesSubplot at 0x2a1e6e2a9b0>



Training

I want to predict something useing NA sales and Global sales as these have the highest correlation. These are columns 6 and 10 in my dataframe.

```
In [56]:
```

```
X = df.iloc[:, 6].values
y = df.iloc[:, 10].values
```

In [57]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.10, random_
```

In [59]:

```
#I have to reshape these in order to run the regressor.
X_train = X_train.reshape((14938,1))
y_train = y_train.reshape((14938,1))
X_test = X_test.reshape((1660,1))
y_test = y_test.reshape((1660,1))
```

In [60]:

```
regressor = LinearRegression()
regressor.fit(X_test, y_test)
```

Out[60]:

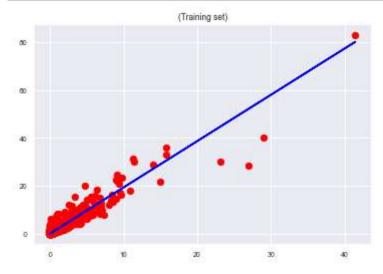
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=
False)
```

```
In [25]:
```

```
y_pred = regressor.predict(X_test)
```

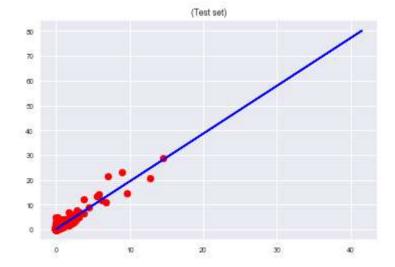
In [32]:

```
#For some reason i can't set labels to the axi. Errormessage: 'str' object is not c
# X-axis = North America sales, Y-axis = Global Sales
plt.scatter(X_train, y_train,color='red')
plt.plot(X_train, regressor.predict(X_train), color='blue')
plt.title('(Training set)')
plt.show()
```



In [31]:

```
plt.scatter(X_test, y_test,color='red')
plt.plot(X_train, regressor.predict(X_train), color='blue')
plt.title('(Test set)')
plt.show()
```



In [36]:

```
print("Training set score: {:.2f}".format(regressor.score(X_train,y_train)))
print("Test set score: {:.2f}".format(regressor.score(X_test,y_test)))
```

Training set score: 0.88 Test set score: 0.90

Pretty good scores for the Linear regressor. Now i'm going to try a decision tree.

```
In [38]:
```

```
X = X.reshape((16598,1))
y = y.reshape((16598,1))

TreeReg = DecisionTreeRegressor(random_state=0)
TreeReg.fit(X,y)
```

Out[38]:

In [40]:

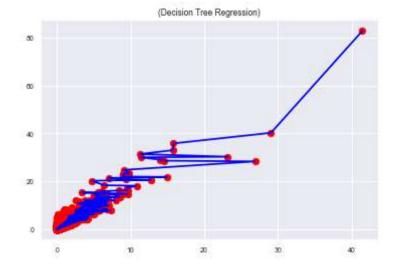
```
y_pred = TreeReg.predict(6.5)
y_pred
```

Out[40]:

array([18.36])

In [48]:

```
#Same as with the linear regression, i can't set labels to the axi.
plt.scatter(X, y, color = 'red')
plt.plot(X, TreeReg.predict(X), color = 'blue')
plt.title('(Decision Tree Regression)')
plt.show()
```



In []:

In [49]:

```
print("Decision tree score: {:.2f}".format(TreeReg.score(X,y)))
```

Decision tree score: 0.95

0.95 is very good, but can SVR do better?

```
In [50]:
```

```
SVRregressor = SVR(kernel = 'rbf')
SVRregressor.fit(X,y)
```

E:\Anaconda\lib\site-packages\sklearn\utils\validation.py:578: DataCon versionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example using ravel().

y = column or 1d(y, warn=True)

Out[50]:

SVR(C=1.0, cache_size=200, coef0=0.0, degree=3, epsilon=0.1, gamma='au
to',
 kernel='rbf', max iter=-1, shrinking=True, tol=0.001, verbose=False)

In [51]:

```
sc_X = StandardScaler()
sc_y = StandardScaler()
X = sc_X.fit_transform(X)
y = sc_y.fit_transform(y)
```

In [52]:

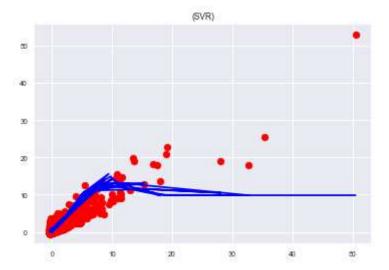
```
y_pred = sc_y.inverse_transform(SVRregressor.predict(sc_X.transform(np.array([[6.5]
y_pred
```

Out [52]:

array([18.12001474])

In [54]:

```
plt.scatter(X, y, color = 'red')
plt.plot(X, SVRregressor.predict(X), color = 'blue')
plt.title('(SVR)')
plt.show()
```



```
In [55]:
print("SVR score: {:.2f}".format(SVRregressor.score(X,y)))
SVR score: 0.31
```

SVR doesn't seem to have a good score, so i'll use the decision tree and linear regression to draw a conclusion.

In []:		