数据挖掘互评作业三：分类与预测

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[仓库地址: (https://github.com/liucc1997/DMC/tree/master/assignment3)](https://github.com/liucc1997/DMC/tree/master/assignment3)

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1. 问题描述 ¶

数据集：Video Game Sales

该数据集包含游戏名称、类型、发行时间、发布者以及在全球各地的销售额数据。

数据量：11列共1.66W数据。

基于这个数据集，可进行以下问题的探索：

- 电子游戏市场分析：受欢迎的游戏、类型、发布平台、发行人等；
- 预测每年电子游戏销售额。
- 可视化应用：如何完整清晰地展示这个销售故事。

也可以自行发现其他问题，并进行相应的挖掘。

2. 数据处理

首先导入数据集，查看数据概要，并对数据集中的缺失值进行处理

In [1]:

```
import matplotlib
import numpy as np
import pandas as pd
%matplotlib inline
dataset_path = "data/vgsales.csv"
dataset = pd.read_csv(dataset_path)
dataset_origin = pd.read_csv(dataset_path)
```

Video Game Sales数据集的的属性包括：

- Rank 游戏销量排名
- Name 游戏名
- Year 发布年份
- Platform 游戏平台/发布平台
- Genre 游戏类型
- Publisher 游戏厂商/发行人
- NA_Sales EU_Sales JP_Sales Other_Sales Global_Sales 北美销量 欧洲销量 日本销量 其它地区销量 全球销量

Video Game Sales数据集的概要如下所示:

In [2]:

```
dataset
```

Out[2]:

	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales	EU_Sales	JP_
0	1	Wii Sports	Wii	2006.0	Sports	Nintendo	41.49	29.02	
1	2	Super Mario Bros.	NES	1985.0	Platform	Nintendo	29.08	3.58	
2	3	Mario Kart Wii	Wii	2008.0	Racing	Nintendo	15.85	12.88	
3	4	Wii Sports Resort	Wii	2009.0	Sports	Nintendo	15.75	11.01	
4	5	Pokemon Red/Pokemon Blue	GB	1996.0	Role-Playing	Nintendo	11.27	8.89	
...	...	...	...	...	...	...	...	...	
16593	16596	Woody Woodpecker in Crazy Castle 5	GBA	2002.0	Platform	Kemco	0.01	0.00	
16594	16597	Men in Black II: Alien Escape	GC	2003.0	Shooter	Infogrames	0.01	0.00	
16595	16598	SCORE International Baja 1000: The Official Game	PS2	2008.0	Racing	Activision	0.00	0.00	
16596	16599	Know How 2	DS	2010.0	Puzzle	7G//AMES	0.00	0.01	
16597	16600	Spirits & Spells	GBA	2003.0	Platform	Wanadoo	0.01	0.00	

16598 rows × 11 columns

查看数据集中存在的缺失值:

In [3]:

```
dataset.isnull().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
```

Year和Publisher属性存在缺失，删除空值所在的行。

In [4]:

```
dataset.dropna(inplace=True)
```

3. 问题探索

3.1 电子游戏市场分析

最受欢迎的游戏

不同游戏按照不同平台、不同发行年份统计销量，区分平台和年份的话，最受欢迎的游戏是2006年Wii的Wii Sports，全球销量达到了82.74

In [5]:

```
print(dataset.iloc[0,:])
```

```
Rank                      1
Name             Wii Sports
Platform                Wii
Year                   2006
Genre                Sports
Publisher          Nintendo
NA_Sales              41.49
EU_Sales              29.02
JP_Sales               3.77
Other_Sales            8.46
Global_Sales          82.74
Name: 0, dtype: object
```

不区分平台和年份的情况，依然是Wii Sports

In [6]:

```
dataset.groupby("Name").sum()["Global_Sales"].idxmax(axis=0,skipna=True)
```

Out[6]:

```
'Wii Sports'
```

最受欢迎的游戏类型

In [7]:

```
dataset.groupby("Genre").sum()["Global_Sales"].idxmax(axis=0,skipna=True)
```

Out[7]:

```
'Action'
```

最受欢迎的发布平台

In [8]:

```
dataset.groupby("Platform").sum()["Global_Sales"].idxmax(axis=0,skipna=True)
```

Out[8]:

```
'PS2'
```

最受欢迎的发行人

In [9]:

```
dataset.groupby("Publisher").sum()["Global_Sales"].idxmax(axis=0,skipna=True)
```

Out[9]:

```
'Nintendo'
```

3.2 预测电子游戏销售额

预测每年全球电子游戏销售额

由于该数据更新于4年前，所以删除2015年之后的数据，然后绘制历年全球电子游戏销售额的散点图

In [10]:

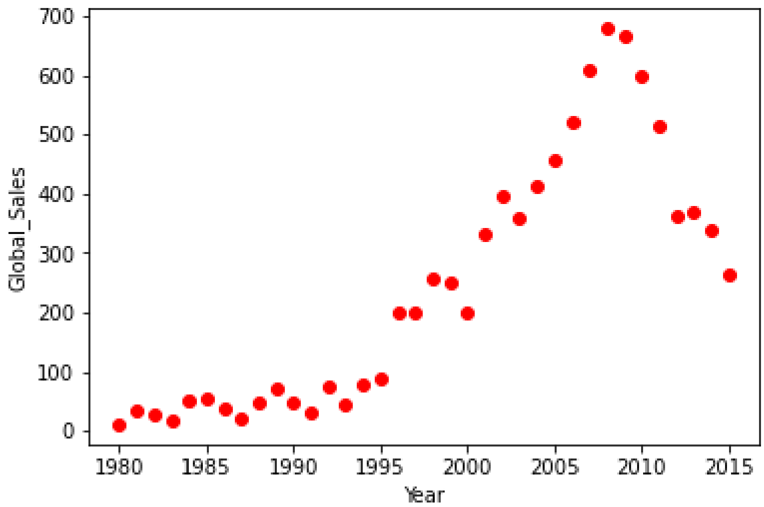
```
total_sales = dataset.drop(dataset[dataset["Year"]>2015].index).groupby("Year").sum()["Global_Sa
les"]
```

In [11]:

```
import  matplotlib.pyplot as plt
plt.xlabel('Year')
plt.ylabel('Global_Sales')
plt.scatter(total_sales.keys(),total_sales,c='r')
```

Out[11]:

<matplotlib.collections.PathCollection at 0x111bf5b0>



然后建立回归模型

In [12]:

```
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
X = []
y = []
for i in total_sales.keys():
    X.append([i])
    y.append(total_sales[i])

polynomial  = PolynomialFeatures(degree = 3)
x_transformed = polynomial.fit_transform(X)

poly_linear_model = LinearRegression()
poly_linear_model.fit(x_transformed, y)
```

Out[12]:

LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)

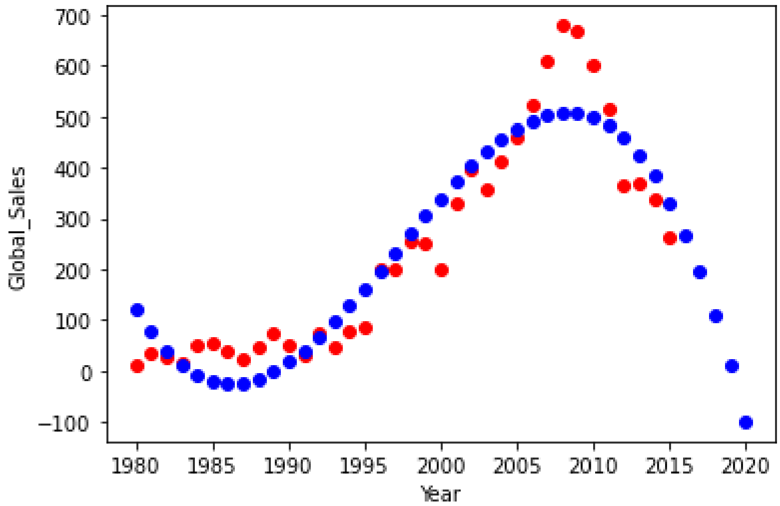
预测游戏销售额，显示可视化结果

In [13]:

```
predict_x = [[2016],[2017],[2018],[2019],[2020]]
predict_x_tran = polynomial.fit_transform(predict_x)
predict_y = poly_linear_model.predict(predict_x_tran)
test_y = poly_linear_model.predict(polynomial.fit_transform(X))
plt.xlabel('Year')
plt.ylabel('Global_Sales')
plt.scatter(total_sales.keys(),total_sales,label='real',c='r')
plt.scatter(X,test_y,label='predict',c='b')
plt.scatter(predict_x,predict_y,label='predict',c='b')
```

Out[13]:

```
<matplotlib.collections.PathCollection at 0x1dcc3988>
```



In [14]:

```
predict_y
```

Out[14]:

```
array([268.61451471, 195.00840974, 109.71814442,  12.15264106,
       -98.27917337])
```

预测某一款游戏的全球销售额

这里以Animal Crossing: New Horizons为例，预测其销售量。

Animal Crossing: New Horizons于2020-03-20由Nintendo发行，发行平台Nintendo Switch，模拟经营类（Simulation）游戏。

In [133]:

```python
example = {"Name":"Animal Crossing: New Horizons",
           "name1":"Animal",
           "name2":"Crossing:",
           "name3":"New",
           "Platform":"Nintendo Switch",
           "year":2020.0,
           "Publisher":"Nintendo",
           "Genre":"Simulation"
          }
```

选取数据集80%的游戏的销售情况作为训练集，建立决策树预测模型

首先准备训练数据

In [168]:

```
dataset_train = dataset.drop(["Rank","NA_Sales","EU_Sales","JP_Sales","Other_Sales"],axis = 1)
dataset_train_baka = dataset_train.copy(deep=True)
#print(dataset_train_baka)
name1,name2,name3 = [],[],[]
for index, row in dataset_train.iterrows():
    array = row[0].split(" ")
    name1.append(array[0])
    name2.append("NaN" if len(array) < 2 else array[1])
    name3.append("NaN" if len(array) < 3 else array[2])
from sklearn import preprocessing
le = preprocessing.LabelEncoder()

dataset_train["Platform"] = le.fit_transform(dataset_train["Platform"].values)
dataset_train["Genre"] = le.fit_transform(dataset_train["Genre"].values)
dataset_train["Publisher"] = le.fit_transform(dataset_train["Publisher"].values)

dataset_train["name1"] = le.fit_transform(name1)
dataset_train["name2"] = le.fit_transform(name2)
dataset_train["name3"] = le.fit_transform(name3)
dataset_train = dataset_train.drop(["Name"],axis = 1)
dataset_train
```

Out[168]:

	Platform	Year	Genre	Publisher	Global_Sales	name1	name2	name3
0	26	2006.0	10	359	82.74	3674	2850	1799
1	11	1985.0	4	359	40.24	3267	1924	455
2	26	2008.0	6	359	35.82	2060	1706	2883
3	26	2009.0	10	359	33.00	3674	2850	2186
4	5	1996.0	7	359	31.37	2588	2492	422
...	...	...	...	...	...	...	...	...
16593	6	2002.0	4	269	0.01	3699	3299	3012
16594	7	2003.0	8	241	0.01	2115	3398	408
16595	16	2008.0	6	21	0.01	2897	1594	348
16596	4	2010.0	5	8	0.01	1848	1533	71
16597	6	2003.0	4	544	0.01	3175	3	2472

16291 rows × 8 columns

训练模型

In [169]:

```
X = []
y = []
X_test,y_test = [],[]
X_train,y_train = [],[]
X = list(zip(dataset_train["Platform"],dataset_train["Year"],dataset_train["Publisher"],dataset_train["name1"],dataset_train["name2"],\
    dataset_train["name3"]))
y = list(dataset_train["Global_Sales"])
y = list(map(int,y))
# print(len(X))
# print(len(y))
for i in range(0,len(X)):
    if i%5 == 0:
        X_test.append(X[i])
        y_test.append(y[i])
    else:
        X_train.append(X[i])
        y_train.append(y[i])
from sklearn import tree
dtree = tree.DecisionTreeClassifier()
dtree.fit(X_train,y_train)
```

Out[169]:

```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=None, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

可视化地展示测试集结果的误差:

In [170]:

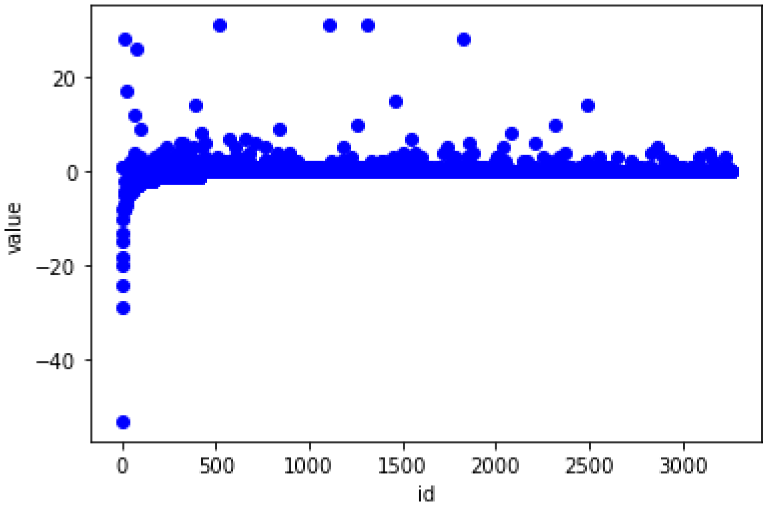
```
y_predict = dtree.predict(X_test)
```

In [171]:

```
plt.xlabel('id')
plt.ylabel('value')
xarary = list(range(0,len(X_test)))
plt.scatter(xarary,y_predict-y_test,c='b')
```

Out[171]:

<matplotlib.collections.PathCollection at 0x1ded1220>



模型的预测准确率为：

In [172]:

```
dtree.score(X_test,y_test)
```

Out[172]:

0.7999386314820497

然后预测Animal Crossing: New Horizons的销量

In [193]:

```
example = {"Name":"Animal Crossing: New Horizons",
           "name1":"Animal",
           "name2":"Crossing:",
           "name3":"New",
           "Platform":"NS",
           "Year":2020.0,
           "Publisher":"Nintendo",
           "Genre":"Simulation"
          }
dataset_train_baka["name1"] = name1
dataset_train_baka["name2"] = name2
dataset_train_baka["name3"] = name3

platform_dict = dict(zip(dataset_train_baka["Platform"].values, dataset_train["Platform"].values
))
gen_dict = dict(zip(dataset_train_baka["Genre"].values, dataset_train["Genre"].values))
pub_dict = dict(zip(dataset_train_baka["Publisher"].values, dataset_train["Publisher"].values))
name1_dict = dict(zip(dataset_train_baka["name1"].values, dataset_train["name1"].values))
name2_dict = dict(zip(dataset_train_baka["name2"].values, dataset_train["name2"].values))
name3_dict = dict(zip(dataset_train_baka["name3"].values, dataset_train["name3"].values))

example_array = [[platform_dict.get(example["Platform"]),
                  example["Year"],
                  pub_dict.get(example["Publisher"]),
                  name1_dict.get(example["name1"]),
                  name2_dict.get(example["name2"]),
                  name3_dict.get(example["name3"]),
                 ]]
#platform_dict
example_array
```

Out[193]:

```
[[None, 2020.0, 359, 165, 791, 1831]]
```

预测结果为:

In [201]:

```
x =  dataset_train["Platform"].mode()[0]
example_array[0][0] = x
print(dtree.predict(example_array))
```

```
[9]
```

4. 可视化应用

如何开发一款可能更受欢迎的游戏?

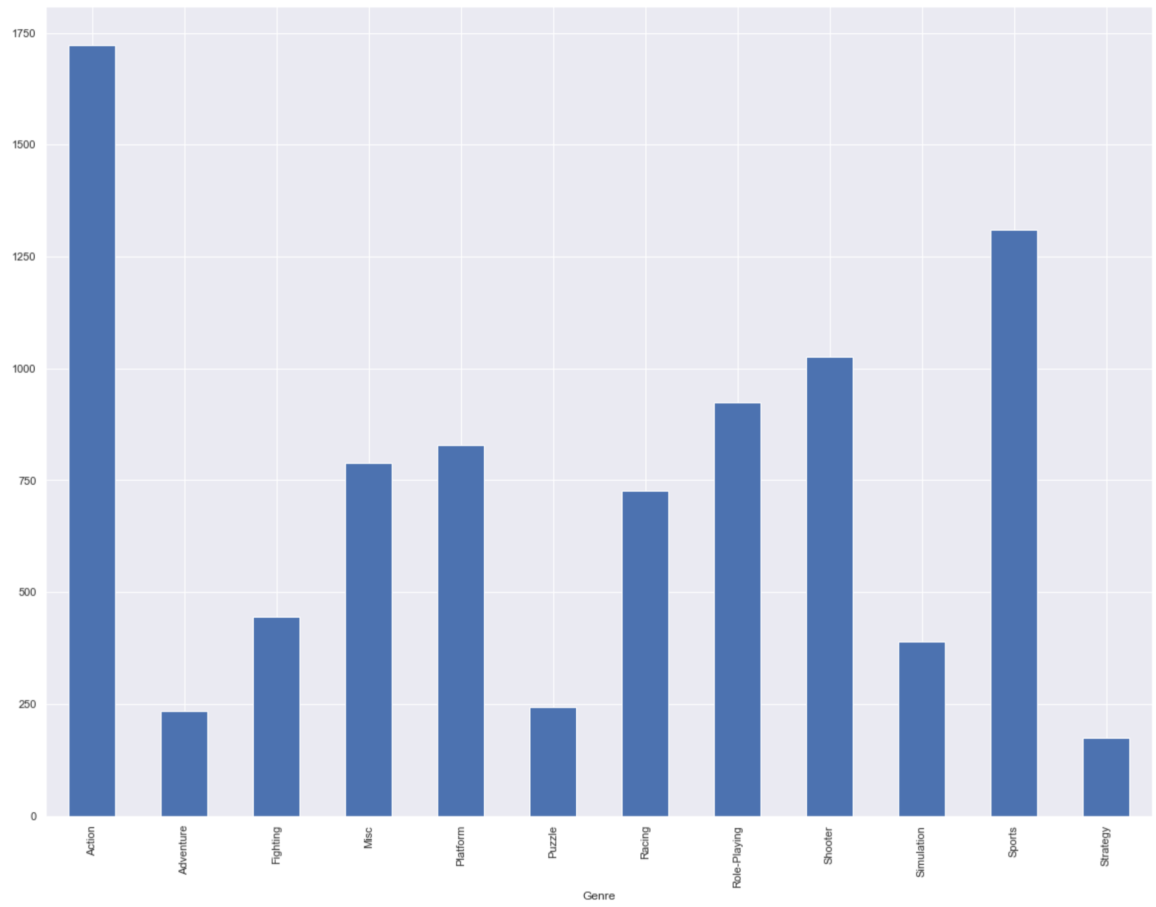
首先选择做什么类型的游戏

In [233]:

```
dataset.groupby("Genre").sum()["Global_Sales"].plot(kind='bar',figsize=(20,15))
```

Out[233]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x238768f8>
```



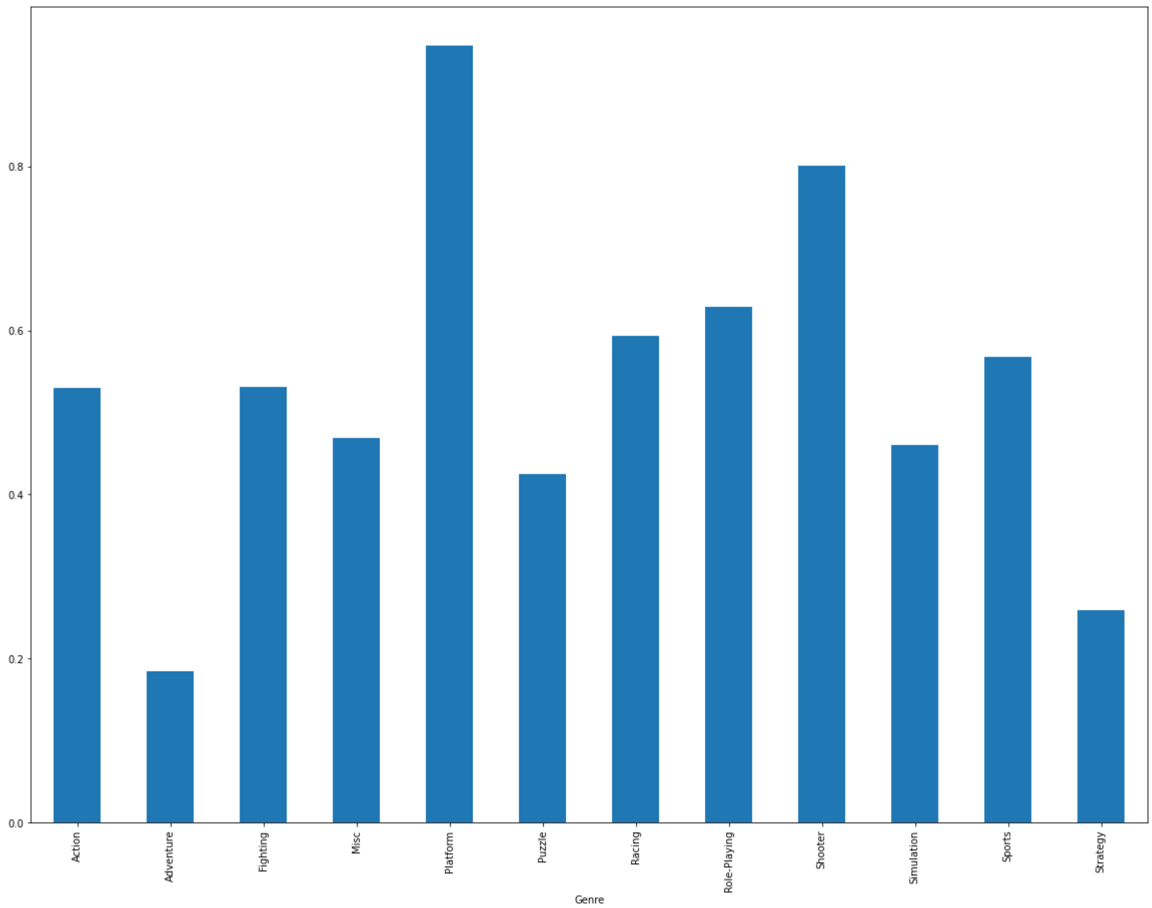
由此看出，选择动作类和体育类的游戏占据了比较大的市场,然后我们看不同类型游戏的销量均值：

In [214]:

```
dataset.groupby("Genre").mean()["Global_Sales"].plot(kind='bar',figsize=(20,15))
```

Out[214]:

<matplotlib.axes._subplots.AxesSubplot at 0x228db0b8>



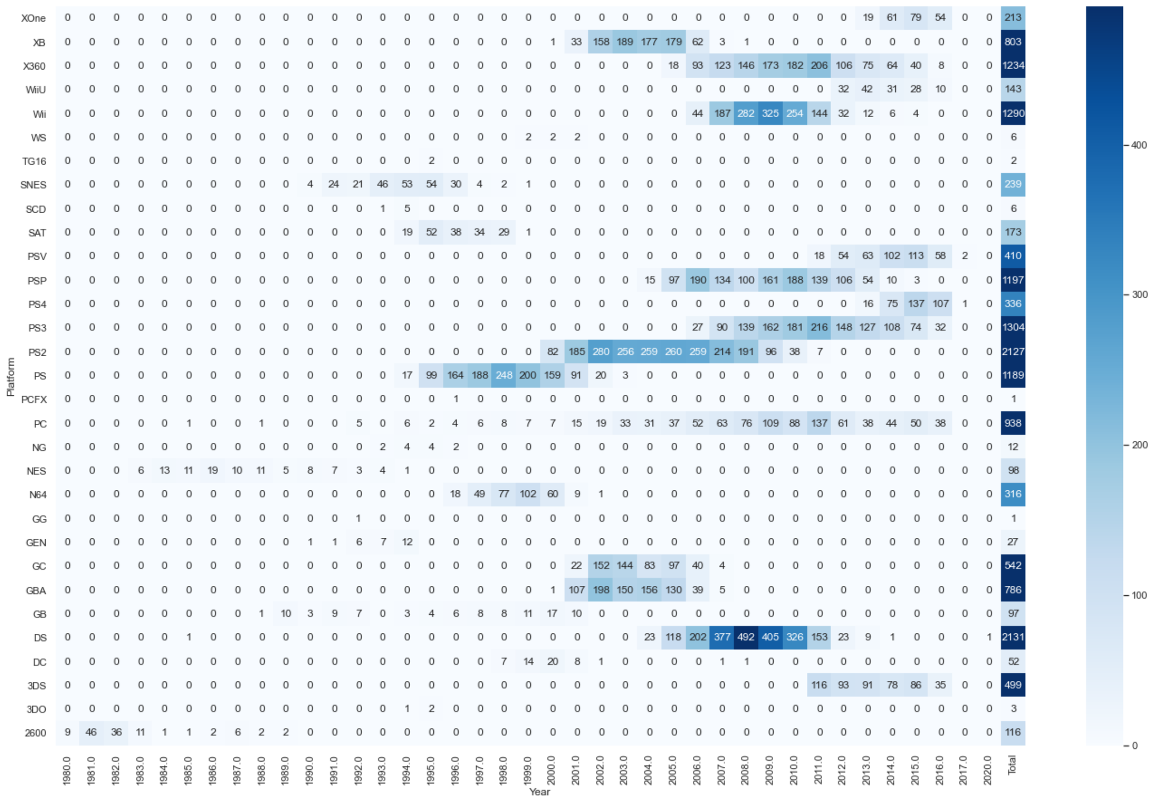
这里看出，虽然动作类和体育类的游戏占据了比较大的市场，但是就平均销量而言，平台类和射击类游戏的的销量更高。综合两个图来看，冒险类和策略类游戏的总销量和平均销量都是最后两位，所以开发这两种的类型的游戏可能对销量造成一定的影响。

然后考虑游戏平台

下图显示了历年来不同平台的总销售量。

In [230]:

```
import seaborn
f = pd.crosstab(dataset.Platform,dataset.Year).sort_values(by="Platform",ascending = False)
max = f.values.max()
min = f.values.min()
f['Total'] = f.sum(axis=1)
plt.figure(figsize=(24,15))
seaborn.heatmap(f, vmin = min, vmax = max, annot=True,cmap='Blues', fmt="d")
plt.xticks()
plt.show()
```



可以看到，PS系列已知以来是来比较热门的游戏主机，此外近年来比较游戏销量比较高的平台还有X360、3DS、Wii和PC。

最后考虑合作的游戏厂商或者是作为参照的厂商

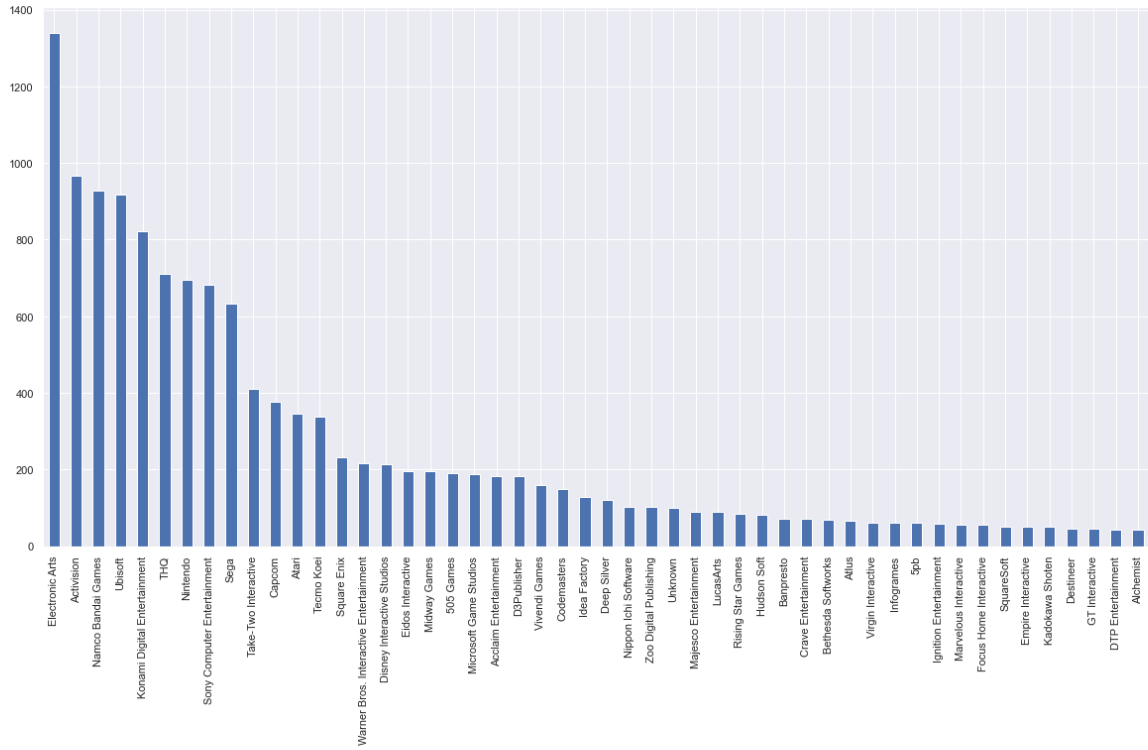
下面的图列出来历年来前50位的不同厂商游戏的累计销量。

In [255]:

```
dataset["Publisher"].value_counts()[:50].plot(kind='bar',figsize=(20,10))
```

Out[255]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x285de448>
```



由此看出，考虑合作的游戏厂商或者是作为参照的厂商可以从Electronics Ats、Activision、Namco Bandai Games、Ubisoft、Konami Digital Entertainment、THQ、Nintendo、Sony Computer Entertainment等厂商中选择。

In [257]:

```
dataset["Publisher"].value_counts()[:8]
```

Out[257]:

```
Electronic Arts                 1339
Activision                       966
Namco Bandai Games               928
Ubisoft                          918
Konami Digital Entertainment     823
THQ                              712
Nintendo                         696
Sony Computer Entertainment      682
Name: Publisher, dtype: int64
```