In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn import neighbors,linear_model
from sklearn.datasets import load_digits
import datetime
```

Part-1

In [2]:

```
bm_data = pd.read_csv("benchmarks.csv")
display(bm_data.head())
```

```
c:\users\os's pc\appdata\local\programs\python\python37-32\lib\site-packages
\IPython\core\interactiveshell.py:3058: DtypeWarning: Columns (3) have mixed
types. Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

	testID	benchName	base	peak
0	cpu95-19990104-03254	101.tomcatv	19.40	27.1
1	cpu95-19990104-03254	102.swim	27.20	34.8
2	cpu95-19990104-03254	103.su2cor	10.10	9.98
3	cpu95-19990104-03254	104.hydro2d	8.58	8.61
4	cpu95-19990104-03254	107.mgrid	8.94	9.44

In [3]:

```
Yearly_testid=[]
bm_data['testID']=bm_data['testID'].str.extract(r'(-[0-9]+-)', expand=False)
bm_data['testID']= bm_data['testID'].str.replace('-', '')
bm_data = bm_data.dropna()
for i in bm_data['testID']:
    Yearly_testid.append(int(i[:4]))
bm_data['Y_testid']=Yearly_testid
bm_data = bm_data[bm_data['benchName'] == '456.hmmer']
bm_data['testID'] = bm_data['testID'].apply(lambda x: pd.to_datetime(x))
display(bm_data.head())
```

	testID	benchName	base	peak	Y_testid
45903	2006-05-13	456.hmmer	8.03	8.03	2006
45990	2006-05-13	456.hmmer	8.32	8.51	2006
46019	2006-05-13	456.hmmer	13.40	18.4	2006
46094	2006-05-13	456.hmmer	12.40	17.1	2006
46106	2006-05-13	456.hmmer	12.50	17.1	2006

In [4]:

```
#Extract the date and base speed for a benchmark of your choice
Y_testid=[]
testid=[]
base=[]
for index, row in bm_data.iterrows():
        testid.append((row["testID"]))
        base.append(float(row["base"]))
        Y_testid.append((row["Y_testid"]))
print(len(base))
```

```
3082
```

In [21]:

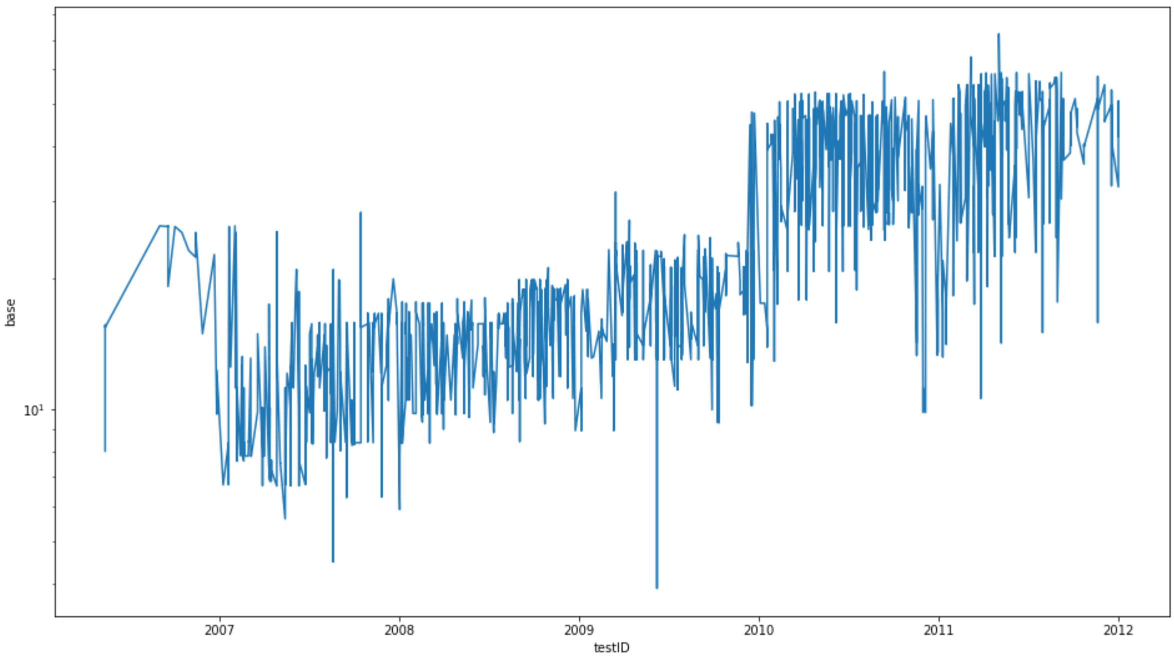
```
base[0]
```

Out[21]:

```
8.03
```

In [141]:

```
#Plot the data in a semi-log plot
plt.figure(figsize=(16,9))
plt.semilogy(testid, base)
plt.xlabel('testID')
plt.ylabel('base')
plt.show()
```



In [5]:

```
#Plot the data in a semi-log plot using scatter plot. With a base of 2 instead of 10
plt.figure(figsize=(16,9))
plt.scatter(testid, base)
plt.yscale('log',basey=2)
plt.xlabel('testID')
plt.ylabel('base')
plt.show()
```

In [6]:

```
#Changing Timestamps into numbers to prepare it for the linear regression model
#for each unique time stamp, the code gives a unique number
d = {ni: indi for indi, ni in enumerate(set(Y_testid))}
coded_testid = [d[ni] for ni in Y_testid]
#print(len(coded_testid))
```

In [61]:

```python
print(coded_testid)
```

```
[0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1,
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6, 6, 6, 6, 6, 6, 6]
```

In [56]:

```
#train a linear model to fit your plot.

import math
from scipy import stats


#X = np.array(coded_testid).reshape(-1, 1)
Y = np.array(np.log2(base)).reshape(-1, 1)
X=bm_data['testID']
X=X.map(datetime.datetime.toordinal)
X = np.array(X).reshape(-1, 1)

regr = linear_model.LinearRegression()
regr.fit(X, Y)

#base_pred = regr.predict(X)
# coefficients
print("Coefficient: ",regr.coef_, "Intercept: ",regr.intercept_)
```

```
Coefficient:  [[0.00134241]] Intercept:  [-980.34786154]
```

In [69]:

```
Moorline=[]
for i in coded_testid:
    z=np.log2(2)*i+np.log2(8.3)
    #print(z)
    z=2**(z)
    Moorline.append(z)
print(Moorline)
```

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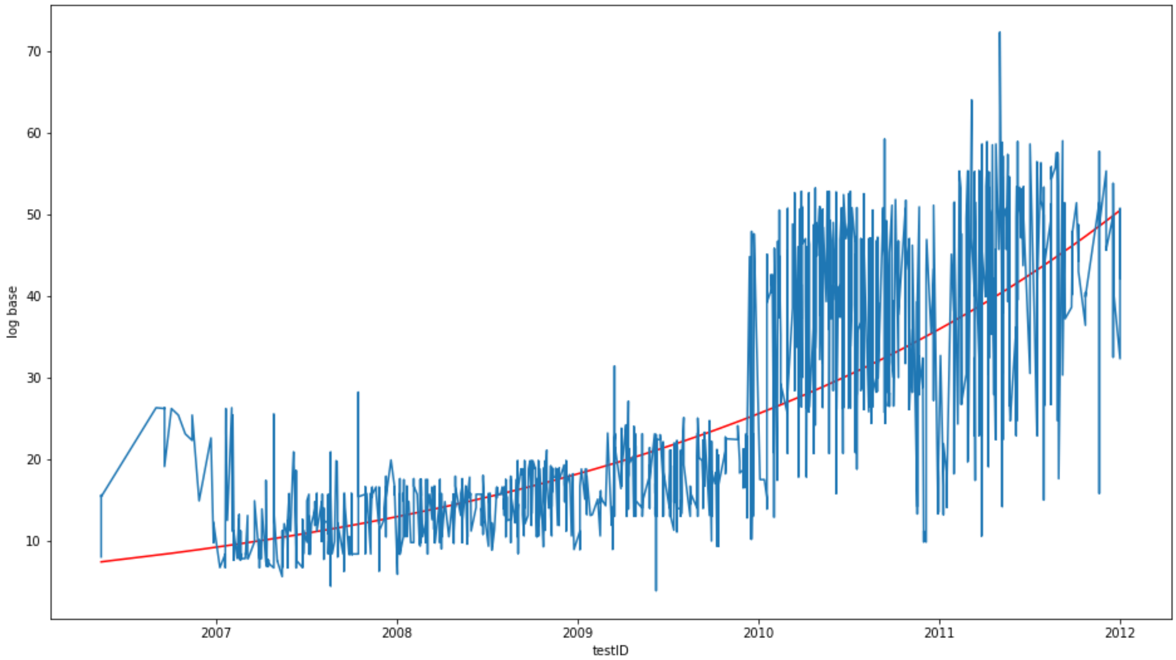
9995, 132.79999999999995, 132.79999999999995, 132.79999999999995, 132.7999
9999999995, 132.79999999999995, 132.79999999999995, 132.79999999999995, 13
2.79999999999995, 132.79999999999995, 132.79999999999995, 132.799999999999
95, 132.79999999999995, 132.79999999999995, 132.79999999999995, 132.799999
99999995, 132.79999999999995, 132.79999999999995, 132.79999999999995, 132.
79999999999995, 132.79999999999995, 132.79999999999995, 132.7999999999999
5, 132.79999999999995, 132.79999999999995, 132.79999999999995, 132.7999999
9999995, 132.79999999999995, 132.79999999999995, 132.79999999999995, 132.7
9999999999995, 132.79999999999995, 132.79999999999995, 132.79999999999995,
132.79999999999995, 132.79999999999995, 132.79999999999995, 132.7999999999
9995, 132.79999999999995, 132.79999999999995, 132.79999999999995, 132.7999
9999999995, 132.79999999999995, 132.79999999999995, 132.79999999999995, 13
2.79999999999995, 132.79999999999995, 132.79999999999995, 132.799999999999
95, 132.79999999999995, 132.79999999999995, 132.79999999999995, 132.799999
99999995, 132.79999999999995, 132.79999999999995, 132.79999999999995, 132.
79999999999995, 132.79999999999995, 132.79999999999995, 132.7999999999999
```

In [75]:

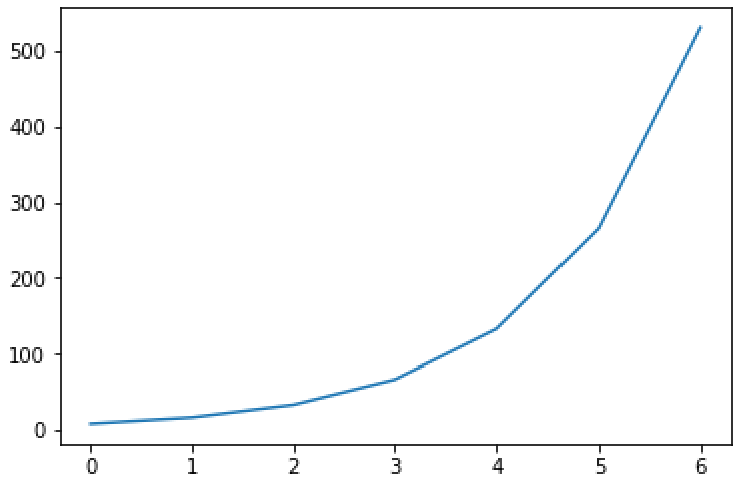
```
line= 2**(regr.coef_*X+regr.intercept_)

plt.figure(figsize=(16,9))
plt.plot(testid, line,color='red')
#plt.plot(testid, base_pred_2,color='red')
plt.plot(testid,base)
#plt.plot(testid,Mooreline)
#plt.plot(testid, line**2, color='red')
#plt.yscale('log',basey=2)
plt.xlabel('testID')
plt.ylabel('log base')
plt.show()
```



In [76]:

```
plt.plot(coded_testid,(Moorline))
plt.show()
```



In my benchName, Moore’s law doesn't hold suffeciently as it increases rapadily with a rule of "np.log2(2)*i+np.log2(first-observation)" which is faster than the speed of the data in my model.

Part-2

In [8]:

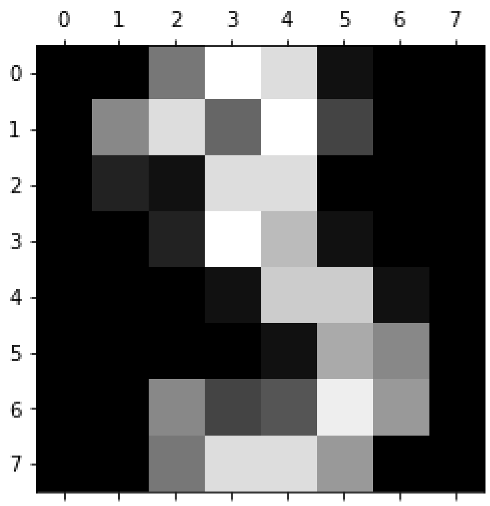
```
#Load Data
digits = load_digits()
print(digits.data.shape)
```

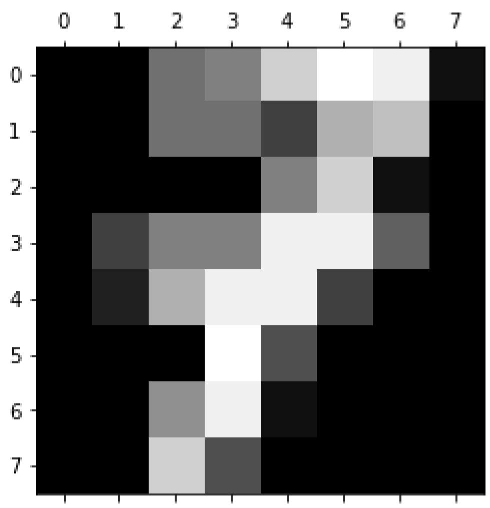
```
(1797, 64)
```

In [10]:

```
#Plot some of the examples.
plt.gray()
plt.matshow(digits.images[3])
plt.matshow(digits.images[7])
plt.show()
```

```
<Figure size 432x288 with 0 Axes>
```





In [11]:

```
#Choose two digit classes (e.g 7s and 3s) , and train a k-nearest neighbor classifier.
x=[]
y=[]
for i in range(len(digits.data)):
    if digits.target[i] == 3 or digits.target[i] == 7:
        x.append(digits.data[i])
        y.append(digits.target[i])
print(len(x))

x_train = x[:-90]
x_test = x[-90:]

y_train = y[:-90]
y_test = y[-90:]

clf = neighbors.KNeighborsClassifier(3, weights='uniform')
clf.fit(x_train, y_train)

y_pred = clf.predict(x_test)
```

```
362
```

In [18]:

```
from sklearn.metrics import mean_squared_error, r2_score
print("Mean squared error: %.2f" % mean_squared_error(y_test, y_pred))
print('Variance score: %.2f' % r2_score(y_test, y_pred))
print("Manual Calculation of the error rate:", (sum(y_test != y_pred) / len(y_test)))
```

```
Mean squared error: 0.16
Variance score: 0.96
Manual Calculation of the error rate: 0.01
```

In [ ]:

```

```