# Yang, Steven. Assignment 1

January 22, 2022

# 1 Assignment 1

#### 1.0.1 Steven H. Yang, Minerva University

**January 22nd, 2022**

## 1.1 1. Moore's Law

Use the scripts from here to download a large amount of data relating to CPU specs. The scripts might take as long as an hour, depending on your connection speed. (Pay attention to the line "If you want to skip the steps in this section, you can simply download the aggregated result files from http://preshing.com/files/specdata20120207.zip and extract them to this folder." This will be faster and save you some troubles while providing the same dataset.)

[110]:
```
import pandas as pd



# Read Data
df = pd.read_csv ('data/benchmarks.csv')
df2 = pd.read_csv ('data/summaries.csv')

# Check if the data is loaded correctly
# print (df)
# print(df2)
df2
```

```
/Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-
packages/IPython/core/interactiveshell.py:3444: DtypeWarning: Columns (3) have
mixed types.Specify dtype option on import or set low_memory=False.
  exec(code_obj, self.user_global_ns, self.user_ns)
```

[110]:
```
                         testID             tester  \
0        cpu95-19990104-03254               Dell
1        cpu95-19990104-03256               Dell
2        cpu95-19990118-03257   Siemens, Germany
3        cpu95-19990118-03258   Siemens, Germany
4        cpu95-19990122-03268     Sun, Palo Alto
…                           …                  …
10150  cpu2006-20120102-19311  Intel Corporation
```

```
10151  cpu2006-20120102-19313  Intel Corporation
10152  cpu2006-20120102-19315  Intel Corporation
10153  cpu2006-20120102-19317  Intel Corporation
10154  cpu2006-20120102-19319  Intel Corporation

                                            machine  \
0                 Precision WorkStation 610 (450MHz)
1                 Precision WorkStation 610 (450MHz)
2                                       CELSIUS 2000
3                                       CELSIUS 2000
4                                Sun Enterprise 3500
…                                               …
10150  Intel DH61WW motherboard (Intel Core i3-2130)
10151  Intel DH61WW motherboard (Intel Pentium G840)
10152  Intel DH61WW motherboard (Intel Pentium G840)
10153  Intel DH61WW motherboard (Intel Pentium G840)
10154  Intel DH61WW motherboard (Intel Pentium G840)

                                    cpu     mhz   hwAvail  \
0                 450 MHz Pentium II XEON   450.0  Jan-1999
1                 450 MHz Pentium II XEON   450.0  Jan-1999
2      Pentium II Xeon Processor 450 MHz   450.0  Nov-1998
3      Pentium II Xeon Processor 450 MHz   450.0  Nov-1998
4                    400MHz UltraSPARC II   400.0  Dec-1998
…                                   …     …        …
10150                  Intel Core i3-2130  3400.0  Sep-2011
10151                  Intel Pentium G840  2800.0  May-2011
10152                  Intel Pentium G840  2800.0  May-2011
10153                  Intel Pentium G840  2800.0  May-2011
10154                  Intel Pentium G840  2800.0  May-2011

                                                   os  \
0                          Microsoft Windows NT 4.0 sp3
1                          Microsoft Windows NT 4.0 sp3
2                      Windows NT V4.0 (Service Pack 3)
3                      Windows NT V4.0 (Service Pack 4)
4                                           Solaris 2.7
…                                                  …
10150  Microsoft Windows 7 Ultimate 6.1.7601 Service …
10151  Microsoft Windows 7 Ultimate 6.1.7601 Service …
10152  Microsoft Windows 7 Ultimate 6.1.7601 Service …
10153  Microsoft Windows 7 Ultimate 6.1.7601 Service …
10154  Microsoft Windows 7 Ultimate 6.1.7601 Service …

                                             compiler autoParallel  \
0                         Intel Fortran Compiler 2.4           No
1      Intel C Compiler 2.4 for Windows NT, Microsoft…           No
```

```
2                                Intel C Compiler Plug-In 2.4            No
3                          Intel Fortran Compiler Plug-In 2.4            No
4                                                   Sun C 5.0            No
…                                                          …           …
10150  C/C++: Version 12.1.0.229 of Intel C++ Studio …          Yes
10151  C/C++: Version 12.1.0.229 of Intel C++ Studio …          Yes
10152  C/C++: Version 12.1.0.229 of Intel C++ Studio …          Yes
10153  C/C++: Version 12.1.0.229 of Intel C++ Studio …          Yes
10154  C/C++: Version 12.1.0.229 of Intel C++ Studio …          Yes

      benchType  base  peak
0         CFP95  13.9  15.2
1        CINT95  19.0  19.0
2        CINT95  18.9  18.9
3         CFP95  13.5  15.0
4        CINT95  14.3  17.7
…           …    …     …
10150  CINT2006  39.6  41.2
10151   CFP2006  39.9  40.7
10152  CINT2006  33.5  35.0
10153   CFP2006  35.1  35.9
10154  CINT2006  33.1  34.5

[10155 rows x 12 columns]
```

1-1. Extract the date and base speed for a benchmark of your choice.

[111]:
```python
# Choosing the benchmark of my choice.
# Here I choose 101.tomcatv
df = df[df['benchName']=='101.tomcatv']

# Merge df and df2 with relevant hwAvail dates.
df_final = pd.merge(df, df2[['testID', 'hwAvail']], on = ['testID'])

# Drop all null data.
df_final.dropna(axis=0, how='all', subset = ['base'], inplace=True)
df_final
```

[111]:
```
                   testID    benchName   base  peak   hwAvail
0    cpu95-19990104-03254  101.tomcatv  19.40  27.1  Jan-1999
1    cpu95-19990118-03258  101.tomcatv  19.50  27.5  Nov-1998
2    cpu95-19990122-03281  101.tomcatv  35.30  37.1  Dec-1998
3    cpu95-19990122-03282  101.tomcatv  43.00  49.8  Dec-1998
4    cpu95-19990122-03283  101.tomcatv  63.90  75.0  Dec-1998
..                    …           …    …     …       …
570                  p074  101.tomcatv   3.40  4.66  Jun-1995
571                  p075  101.tomcatv   7.34  8.89  Nov-1995
572                  p076  101.tomcatv   8.46  9.86  Mar-1996
```

```
573                    p077   101.tomcatv   9.45   11.0  Mar-1996
574                    p078   101.tomcatv   4.63   6.68  Aug-1993

[575 rows x 5 columns]
```

[112]:

```python
# Dates are currently in string data type.
# Convert them into numbers so it can be plotted.

import math
def date_to_int(x):
    '''
    This function converts the date data which are in string already to integer.

    Input
    ------
    x, str: hwAvail data from df_final.

    Output
    ------
    converted, int: converted date in integer format.
    '''

    # Make sure the given data is string
    x = str(x)
    # Split the data into month and year.
    x = x.split(" ")[0].split("-")
    # Assign month numbers to the months written in English.
    months = {'Jan': 1, 'Feb': 2, 'Mar': 3, 'Apr': 4, 'May': 5, 'Jun': 6, 'Jul':
 ↪ 7, 'Aug': 8, 'Sep': 9, 'Oct': 10, 'Nov': 11, 'Dec': 12}
    converted = int(months[x[0]])/12+int(x[1])
    return converted

# Apply date_to_int function to the dataframe.
df_final["hwAvail"] = df_final["hwAvail"].apply(date_to_int)

# Convert bases in log format for semi-log plot.
df_final["base"] = df_final["base"].apply(lambda x: math.log2(x))
df_final
```

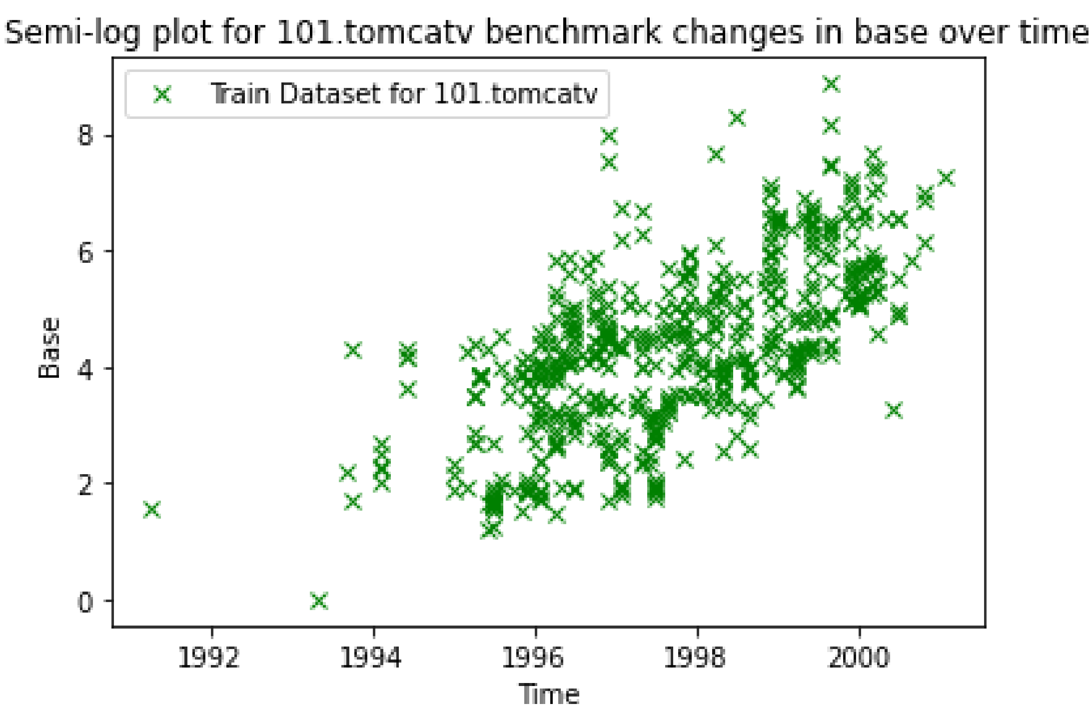
[112]:

```
                   testID    benchName      base  peak      hwAvail
0    cpu95-19990104-03254  101.tomcatv  4.277985  27.1  1999.083333
1    cpu95-19990118-03258  101.tomcatv  4.285402  27.5  1998.916667
2    cpu95-19990122-03281  101.tomcatv  5.141596  37.1  1999.000000
3    cpu95-19990122-03282  101.tomcatv  5.426265  49.8  1999.000000
4    cpu95-19990122-03283  101.tomcatv  5.997744  75.0  1999.000000
..                    …            …         …     …            …
570                  p074  101.tomcatv  1.765535  4.66  1995.500000
```

```
571                    p075  101.tomcatv  2.875780  8.89  1995.916667
572                    p076  101.tomcatv  3.080658  9.86  1996.250000
573                    p077  101.tomcatv  3.240314  11.0  1996.250000
574                    p078  101.tomcatv  2.211012  6.68  1993.666667

[575 rows x 5 columns]
```

1-2. Plot the data in a semi-log plot.

[113]:
```
import matplotlib.pyplot as plt
plt.plot(df_final["hwAvail"], df_final['base'], 'x', color='green', label =
 ↪"Train Dataset for 101.tomcatv")

# Title for the plot
plt.title('Semi-log plot for 101.tomcatv benchmark changes in base over time')

# X label
plt.xlabel('Time')

# Y label
plt.ylabel('Base')

# Show the legend
plt.legend()
plt.show()
```

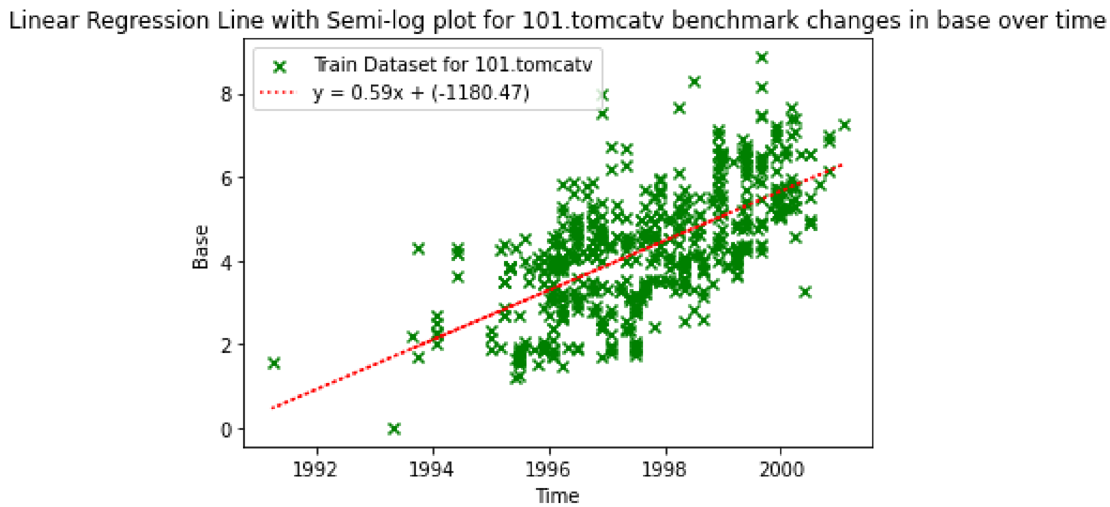


1-3. Now train a linear model to fit your plot.

[114]:
```
# This code cell is written after looking at the documentation:
# https://scikit-learn.org/stable/auto_examples/linear_model/plot_ols.html

from sklearn.linear_model import LinearRegression
import numpy
from numpy import array
# Checking the dimension of the current df_final
print(df_final.ndim)

# Reshape the data to change the dimension of the df_final
# Referenece: https://towardsdatascience.com/get-into-shape-14637fe1cd32
X = df_final["hwAvail"].values.reshape(-1, 1)
y = df_final["base"].values.reshape(-1, 1)

linear_model = LinearRegression()
linear_model.fit(X, y)

plt.scatter(X, y, marker = 'x', color='green', label = "Train Dataset for 101.
 ↪tomcatv")



# Getting coefficient and y_intercept for the linearn regression line.
# Round up to two digits.
coef = round(float(linear_model.coef_[0]),2)
y_intercept = round(float(linear_model.intercept_),2)

# Plot the Linear Regerssion Line
plt.plot(X, linear_model.predict(X),color='red', label = f"y = {coef}x +␣
 ↪({y_intercept})",  linewidth = 1.5, linestyle=':')
plt.legend()

# Title
plt.title('Linear Regression Line with Semi-log plot for 101.tomcatv benchmark␣
 ↪changes in base over time')

# X label
plt.xlabel('Time')

# Y label
plt.ylabel('Base')

plt.show()
```

```
# This R2 score does NOT compare with the trained and test data due to the␣
↪missing of test data.
# However, this still shows how scores how much good that this regression line␣
↪is represented.
print('R2 score of the model:', linear_model.score(X,y))
```

2




```
R2 score of the model: 0.4218725529134727
```

1-4. How well is Moore's Law holding up?

Moore's law states that the number of transistors in IC (integrated circuit) doubles about every two years. This is based on the observation and basically tells us that how CPU industry can changes over the time.

As I found above relationship, there's a linear regression line found, which tells us there's a linear relationship. As I mentioned in the code cell as a comment, the R2 score that I have here does not compare with the test data with this current trained data due to the lack of test data; however, it tells us how good enough this linear regression line is representing the current data set. Based on the R2 score I got, I can tell there is a weak linear relationship observed in this case.

To improve this, one can consider splitting current data into train and test data; however, one should be aware of having too less train data. After that if one observes a regression line with good accuracy, that might be a better model than this.

## 1.2 2. MNIST Digits

No machine learning course would be complete without using the MNIST dataset. This dataset was a hugely influential dataset of handwriting digits (0-9).

2-1. Using scikit-learn, load the MNIST digits (see here).

[115]:
```python
from sklearn.datasets import load_digits
digits = load_digits()

# Check if the data is loaded successfully.
digits
```

[115]:
```
{'data': array([[ 0.,  0.,  5., …,  0.,  0.,  0.],
        [ 0.,  0.,  0., …, 10.,  0.,  0.],
        [ 0.,  0.,  0., …, 16.,  9.,  0.],
        …,
        [ 0.,  0.,  1., …,  6.,  0.,  0.],
        [ 0.,  0.,  2., …, 12.,  0.,  0.],
        [ 0.,  0., 10., …, 12.,  1.,  0.]]),
 'target': array([0, 1, 2, …, 8, 9, 8]),
 'frame': None,
 'feature_names': ['pixel_0_0',
  'pixel_0_1',
  'pixel_0_2',
  'pixel_0_3',
  'pixel_0_4',
  'pixel_0_5',
  'pixel_0_6',
  'pixel_0_7',
  'pixel_1_0',
  'pixel_1_1',
  'pixel_1_2',
  'pixel_1_3',
  'pixel_1_4',
  'pixel_1_5',
  'pixel_1_6',
  'pixel_1_7',
  'pixel_2_0',
  'pixel_2_1',
  'pixel_2_2',
  'pixel_2_3',
  'pixel_2_4',
  'pixel_2_5',
  'pixel_2_6',
  'pixel_2_7',
  'pixel_3_0',
  'pixel_3_1',
  'pixel_3_2',
  'pixel_3_3',
  'pixel_3_4',
  'pixel_3_5',
  'pixel_3_6',
  'pixel_3_7',
```

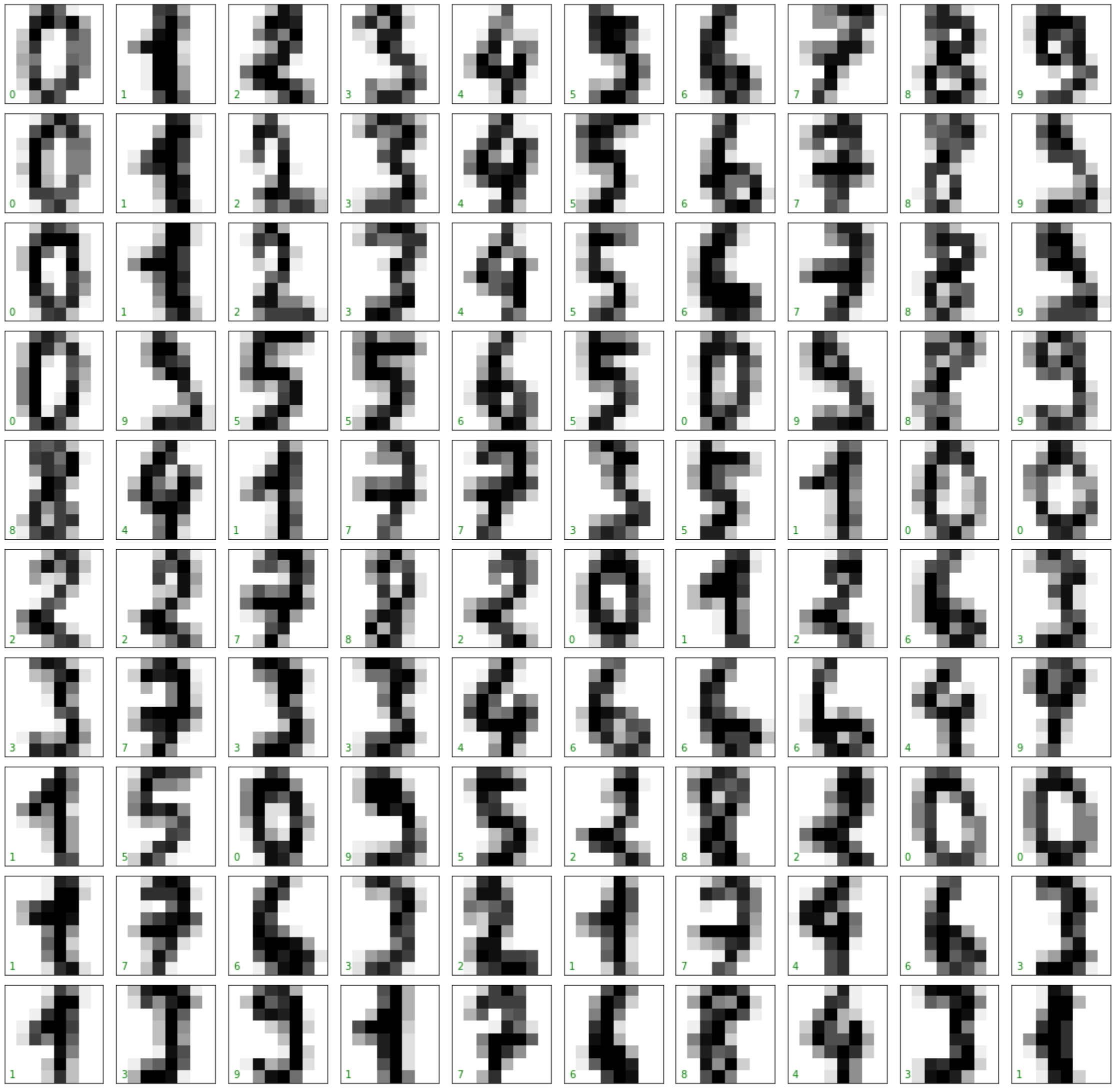
```
 'pixel_4_0',
 'pixel_4_1',
 'pixel_4_2',
 'pixel_4_3',
 'pixel_4_4',
 'pixel_4_5',
 'pixel_4_6',
 'pixel_4_7',
 'pixel_5_0',
 'pixel_5_1',
 'pixel_5_2',
 'pixel_5_3',
 'pixel_5_4',
 'pixel_5_5',
 'pixel_5_6',
 'pixel_5_7',
 'pixel_6_0',
 'pixel_6_1',
 'pixel_6_2',
 'pixel_6_3',
 'pixel_6_4',
 'pixel_6_5',
 'pixel_6_6',
 'pixel_6_7',
 'pixel_7_0',
 'pixel_7_1',
 'pixel_7_2',
 'pixel_7_3',
 'pixel_7_4',
 'pixel_7_5',
 'pixel_7_6',
 'pixel_7_7'],
'target_names': array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9]),
'images': array([[[ 0.,  0.,  5., …,  1.,  0.,  0.],
        [ 0.,  0., 13., …, 15.,  5.,  0.],
        [ 0.,  3., 15., …, 11.,  8.,  0.],
        …,
        [ 0.,  4., 11., …, 12.,  7.,  0.],
        [ 0.,  2., 14., …, 12.,  0.,  0.],
        [ 0.,  0.,  6., …,  0.,  0.,  0.]],

       [[ 0.,  0.,  0., …,  5.,  0.,  0.],
        [ 0.,  0.,  0., …,  9.,  0.,  0.],
        [ 0.,  0.,  3., …,  6.,  0.,  0.],
        …,
        [ 0.,  0.,  1., …,  6.,  0.,  0.],
        [ 0.,  0.,  1., …,  6.,  0.,  0.],
```

```
         [ 0.,  0.,  0., …, 10.,  0.,  0.]],

        [[ 0.,  0.,  0., …, 12.,  0.,  0.],
         [ 0.,  0.,  3., …, 14.,  0.,  0.],
         [ 0.,  0.,  8., …, 16.,  0.,  0.],
         …,
         [ 0.,  9., 16., …,  0.,  0.,  0.],
         [ 0.,  3., 13., …, 11.,  5.,  0.],
         [ 0.,  0.,  0., …, 16.,  9.,  0.]],

        …,

        [[ 0.,  0.,  1., …,  1.,  0.,  0.],
         [ 0.,  0., 13., …,  2.,  1.,  0.],
         [ 0.,  0., 16., …, 16.,  5.,  0.],
         …,
         [ 0.,  0., 16., …, 15.,  0.,  0.],
         [ 0.,  0., 15., …, 16.,  0.,  0.],
         [ 0.,  0.,  2., …,  6.,  0.,  0.]],

        [[ 0.,  0.,  2., …,  0.,  0.,  0.],
         [ 0.,  0., 14., …, 15.,  1.,  0.],
         [ 0.,  4., 16., …, 16.,  7.,  0.],
         …,
         [ 0.,  0.,  0., …, 16.,  2.,  0.],
         [ 0.,  0.,  4., …, 16.,  2.,  0.],
         [ 0.,  0.,  5., …, 12.,  0.,  0.]],

        [[ 0.,  0., 10., …,  1.,  0.,  0.],
         [ 0.,  2., 16., …,  1.,  0.,  0.],
         [ 0.,  0., 15., …, 15.,  0.,  0.],
         …,
         [ 0.,  4., 16., …, 16.,  6.,  0.],
         [ 0.,  8., 16., …, 16.,  8.,  0.],
         [ 0.,  1.,  8., …, 12.,  1.,  0.]]]]),
 'DESCR': ".. _digits_dataset:\n\nOptical recognition of handwritten digits
dataset\n--------------------------------------------------\n\n**Data Set
Characteristics:**\n\n    :Number of Instances: 1797\n    :Number of Attributes:
64\n    :Attribute Information: 8x8 image of integer pixels in the range
0..16.\n    :Missing Attribute Values: None\n    :Creator: E. Alpaydin (alpaydin
'@' boun.edu.tr)\n    :Date: July; 1998\n\nThis is a copy of the test set of the
UCI ML hand-written digits datasets\nhttps://archive.ics.uci.edu/ml/datasets/Opt
ical+Recognition+of+Handwritten+Digits\n\nThe data set contains images of hand-
written digits: 10 classes where\neach class refers to a digit.\n\nPreprocessing
programs made available by NIST were used to extract\nnormalized bitmaps of
handwritten digits from a preprinted form. From a\ntotal of 43 people, 30
contributed to the training set and different 13\nto the test set. 32x32 bitmaps
```

```
are divided into nonoverlapping blocks of\n4x4 and the number of on pixels are
counted in each block. This generates\nan input matrix of 8x8 where each element
is an integer in the range\n0..16. This reduces dimensionality and gives
invariance to small\ndistortions.\n\nFor info on NIST preprocessing routines,
see M. D. Garris, J. L. Blue, G.\nT. Candela, D. L. Dimmick, J. Geist, P. J.
Grother, S. A. Janet, and C.\nL. Wilson, NIST Form-Based Handprint Recognition
System, NISTIR 5469,\n1994.\n\n.. topic:: References\n\n  - C. Kaynak (1995)
Methods of Combining Multiple Classifiers and Their\n    Applications to
Handwritten Digit Recognition, MSc Thesis, Institute of\n    Graduate Studies in
Science and Engineering, Bogazici University.\n  - E. Alpaydin, C. Kaynak (1998)
Cascading Classifiers, Kybernetika.\n  - Ken Tang and Ponnuthurai N. Suganthan
and Xi Yao and A. Kai Qin.\n    Linear dimensionalityreduction using relevance
weighted LDA. School of\n    Electrical and Electronic Engineering Nanyang
Technological University.\n    2005.\n  - Claudio Gentile. A New Approximate
Maximal Margin Classification\n    Algorithm. NIPS. 2000.\n"}
```

2-2. Plot some of the examples.

[116]:
```python
import matplotlib.pyplot as plt

fig, axes = plt.subplots(10, 10, figsize=(20, 20),
                         subplot_kw={'xticks':[], 'yticks':[]},
                         gridspec_kw=dict(hspace=0.1, wspace=0.1))
for i, ax in enumerate(axes.flat):
    ax.imshow(digits.images[i], cmap='binary', interpolation='nearest')
    ax.text(0.05, 0.05, str(digits.target[i]),
            transform=ax.transAxes, color='green')
```



2-3. Choose two digit classes (e.g. 7s and 3s), and train a k-nearest neighbor classifier.

(Note: Here, I wanted to see all digits, so I do this for every digit)

[117]:
```
import numpy as np
import pandas as pd
import pprint
from sklearn.datasets import load_digits
from IPython.display import display, HTML
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split

# Initialize data and target
```

```python
X = digits.data
y = digits.target

# Split train and test data.
# I use 30% of data as train data.
trainData,testData,trainLabel,testLabel = train_test_split(X, y, test_size=0.
 ↪30, random_state=123)
```

2-4. Report your error rates on a held out part of the data.

Here, I use 30% of data as train data. I wanted to have a model that makes a good prediction for the majority of data but with smallest sample possible. To avoid having too less sample, I avoid going lower than 25% but to avoid having too many ample, I avoid going over 50%. In between, I tried different values and choose the one gives the best accuracy.

[118]:
```python
# Define KNN's k. The number of neighbors.
model = KNeighborsClassifier(n_neighbors=3)
# I tried multiple values of k, and seems k=3 performs the best.

# Fit the model
model.fit(trainData,trainLabel)

predictions = model.predict(testData)
print(classification_report(testLabel,predictions))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        59
           1       0.92      1.00      0.96        56
           2       1.00      0.98      0.99        53
           3       0.94      1.00      0.97        46
           4       0.98      1.00      0.99        61
           5       1.00      0.96      0.98        57
           6       1.00      1.00      1.00        57
           7       1.00      1.00      1.00        50
           8       0.98      0.92      0.95        48
           9       0.96      0.91      0.93        53

    accuracy                           0.98       540
   macro avg       0.98      0.98      0.98       540
weighted avg       0.98      0.98      0.98       540
```

As it has 0.98 accuracy, the error rate here is 1=0.98 = 0.02, which is 2%.

2-5. (Optional) Test your model on the full dataset (available from http://yann.lecun.com/exdb/mnist/)

[124]:
```python
import gzip
import shutil
with gzip.open('train-labels-idx1-ubyte.gz', 'rb') as f_in:
    with open('train-labels-idx1-ubyte', 'wb') as f_out:
        shutil.copyfileobj(f_in, f_out)
with gzip.open('train-images-idx3-ubyte.gz', 'rb') as f_in:
    with open('train-images-idx3-ubyte', 'wb') as f_out:
        shutil.copyfileobj(f_in, f_out)
with gzip.open('t10k-labels-idx1-ubyte.gz', 'rb') as f_in:
    with open('t10k-labels-idx1-ubyte', 'wb') as f_out:
        shutil.copyfileobj(f_in, f_out)
with gzip.open('t10k-images-idx3-ubyte.gz', 'rb') as f_in:
    with open('t10k-images-idx3-ubyte', 'wb') as f_out:
        shutil.copyfileobj(f_in, f_out)
```

[125]:
```python
# Reference for this code can be found here: https://github.com/egcode/
↪MNIST-to-CSV

def convert(imgf, labelf, outf, n):
    f = open(imgf, "rb")
    o = open(outf, "w")
    l = open(labelf, "rb")

    f.read(16)
    l.read(8)
    images = []

    for i in range(n):
        image = [ord(l.read(1))]
        for j in range(28*28):
            image.append(ord(f.read(1)))
        images.append(image)

    for image in images:
        o.write(",".join(str(pix) for pix in image)+"\n")
    f.close()
    o.close()
    l.close()
    print('Conversion Finished.')

convert("train-images-idx3-ubyte", "train-labels-idx1-ubyte",
"mnist_train.csv", 60000)
convert("t10k-images-idx3-ubyte", "t10k-labels-idx1-ubyte",
"mnist_test.csv", 10000)
```

```
Conversion Finished.
Conversion Finished.
```

[126]:

```
# Import csv data sets.
df = pd.read_csv ('mnist_train.csv', header = None)
df2 = pd.read_csv('mnist_test.csv', header = None)
trainData2,trainLabel2 = df.loc[:, df.columns!= 0], df[0]

# Define KNN's k. The number of neighbors.
model2 = KNeighborsClassifier(n_neighbors=3)
# Keep use 3 as above for consistency.

# Fit the model.
model2.fit(trainData2,trainLabel2)



testLabel2 = df2[0]
predictions2 = model2.predict(df2.loc[:, df2.columns!= 0])
print(classification_report(testLabel,predictions))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        59
           1       0.92      1.00      0.96        56
           2       1.00      0.98      0.99        53
           3       0.94      1.00      0.97        46
           4       0.98      1.00      0.99        61
           5       1.00      0.96      0.98        57
           6       1.00      1.00      1.00        57
           7       1.00      1.00      1.00        50
           8       0.98      0.92      0.95        48
           9       0.96      0.91      0.93        53

    accuracy                           0.98       540
   macro avg       0.98      0.98      0.98       540
weighted avg       0.98      0.98      0.98       540
```