Python Tutorial

First, you need to import several important Python packages for data manipulation and scientific computing. The pandas package is helpful for data manipulation and the NumPy package is helpful for scientific computing.

```
import pandas as pd
import numpy as np
```

In Python, comments are indicated in code with a "#" character, and arrays and matrices are zero-indexed.

1 Reading in Data and Basic Statistical Functions

1.1 Read in the data.

The following demonstrate importing data in Python given 3 different data formats. The pandas package is able to read all 3 formats, as well as many others, using Python IO tools.

a) Read the data in as a .csv file.

```
student = pd.read_csv('/Users/class.csv')
```

b) Read the data in as a .xls file.

```
# Notice you must specify the file location, as well as the name of the sheet
# of the .xls file you want to import
student_xls = pd.read_excel(open('/Users/class.xls', 'rb'),
                            sheetname='class')
```

c) Read the data in as a .json file.

```
student_json = pd.read_json('/Users/class.json')
```

1.2 Find the dimensions of the data set.

The dimensions of a DataFrame in Python are known as an attribute of the object. Therefore, you can state the data name followed by ".shape" to return the dimensions of the data.

```
print(student.shape)

## (19, 5)
```

1.3 Find basic information about the data set.

Information about a DataFrame is available by calling the ".info()" function on the data.

```
# Notice that student is a DataFrame object
print(student.info())

## <class 'pandas.core.frame.DataFrame'>
## RangeIndex: 19 entries, 0 to 18
## Data columns (total 5 columns):
## Name      19 non-null object
## Sex       19 non-null object
## Age       19 non-null int64
## Height    19 non-null float64
## Weight    19 non-null float64
## dtypes: float64(2), int64(1), object(2)
## memory usage: 840.0+ bytes
## None
```

1.4 Look at the first 5 observations.

The first 5 observations of a DataFrame are available by calling the ".head()" function on the data. By default, head() returns 5 observations. To return the first *n* observations, pass the integer *n* into the function. The tail() function is analogous and returns the last observations.

```
print(student.head())

##       Name Sex  Age  Height  Weight
## 0   Alfred   M   14    69.0   112.5
## 1    Alice   F   13    56.5    84.0
## 2  Barbara   F   13    65.3    98.0
## 3    Carol   F   14    62.8   102.5
## 4    Henry   M   14    63.5   102.5
```

1.5 Calculate mean of numeric variables.

```
# By default, the mean() function returns the mean of numeric variables of
# the data only
print(student.mean())

## Age        13.315789
## Height     62.336842
## Weight    100.026316
## dtype: float64
```

1.6 Compute summary statistics of the data set.

Summary statistics of a DataFrame are available by calling the ".describe()" function on the data.

```
print(student.describe())

##              Age     Height      Weight
## count  19.000000  19.000000   19.000000
```

```
## mean   13.315789  62.336842  100.026316
## std     1.492672   5.127075   22.773933
## min    11.000000  51.300000   50.500000
## 25%    12.000000  58.250000   84.250000
## 50%    13.000000  62.800000   99.500000
## 75%    14.500000  65.900000  112.250000
## max    16.000000  72.000000  150.000000
```

1.7 Descriptive statistics functions applied to variables of the data set.

```
# Notice the subsetting of student with [] and the name of the variable in
# quotes
print(student["Weight"].std())

## 22.773933493879046

print(student["Weight"].sum())

## 1900.5

print(student["Weight"].count())

## 19

print(student["Weight"].max())

## 150.0

print(student["Weight"].min())

## 50.5

print(student["Weight"].median())

## 99.5
```

1.8 Produce a one-way table to describe the frequency of a variable.

a) Produce a one-way table of a discrete variable.

```
# columns = "count" indicates to make the descriptive portion of the table
# the counts of each level of the index variable
print(pd.crosstab(index=student["Age"], columns="count"))

## col_0  count
## Age
## 11         2
## 12         5
## 13         3
## 14         4
## 15         4
## 16         1
```

b) Produce a one-way table of a categorical variable.

```
print(pd.crosstab(index=student["Sex"], columns="count"))

## col_0  count
## Sex
## F          9
## M         10
```

1.9 Produce a two-way table to describe the frequency of two categorical or discrete variables.

```
# Notice the specification of a variable for the columns argument, instead
# of "count"

## Sex   F  M
## Age
## 11    1  1
## 12    2  3
## 13    2  1
## 14    2  2
## 15    2  2
## 16    0  1
```

crosstab()

1.10 Select a subset of the data that meets a certain criterion.

```
females = student.query('Sex == "F"')
print(females.head())

##        Name Sex  Age  Height  Weight
## 1     Alice   F   13    56.5    84.0
## 2   Barbara   F   13    65.3    98.0
## 3     Carol   F   14    62.8   102.5
## 6      Jane   F   12    59.8    84.5
## 7     Janet   F   15    62.5   112.5
```

query()

1.11 Determine the correlation between two continuous variables.

```
height_weight = pd.concat([student["Height"], student["Weight"]], axis = 1)
print(height_weight.corr(method = "pearson"))

##           Height    Weight
## Height  1.000000  0.877785
## Weight  0.877785  1.000000
```

corr()

---

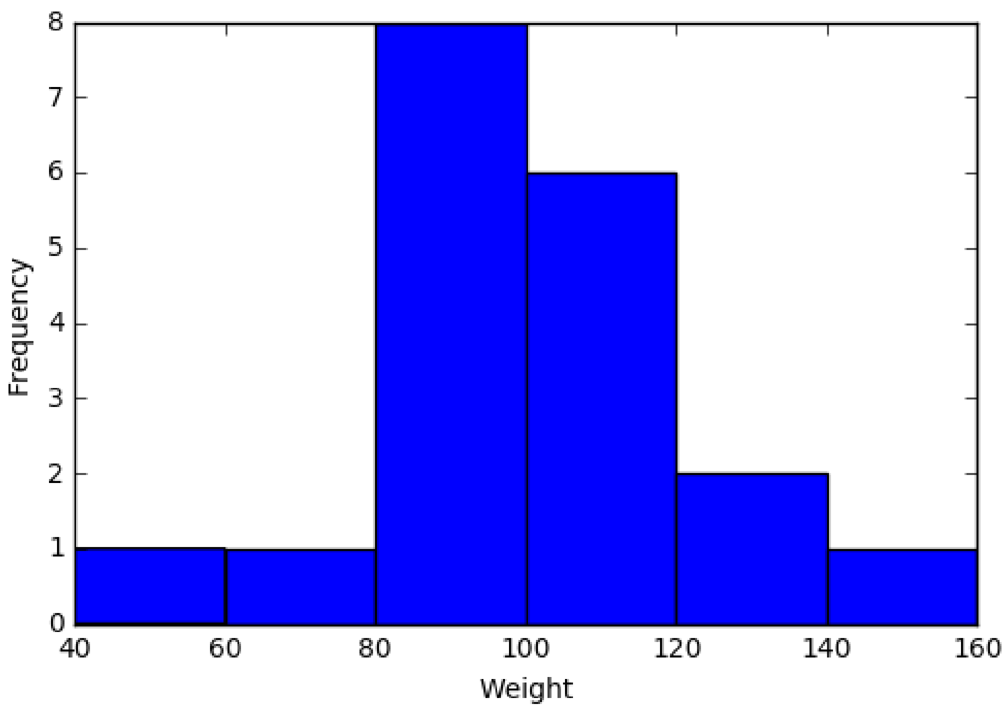
2 Basic Graphing and Plotting Functions

The Matplotlib PyPlot package is a standard Python package to use for plotting. For more information on other Python plotting packages, please see the Appendix Section 2.

```
import matplotlib.pyplot as plt
```

2.1 Visualize a single continuous variable by producing a histogram.

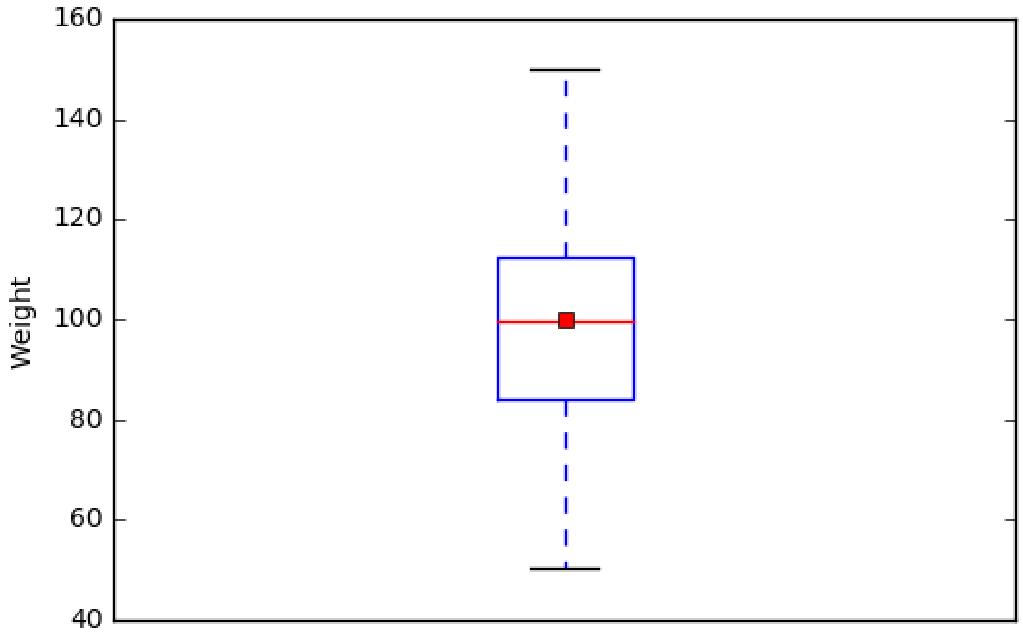
```
# Notice how the bin endpoints are set so the histogram is the same
# as that produced by SAS and R
# Also notice the labeling of the axes
plt.hist(student["Weight"], bins=[40,60,80,100,120,140,160])
plt.xlabel('Weight')
plt.ylabel('Frequency')
plt.show()
```



Output:

2.2 Visualize a single continuous variable by producing a boxplot.

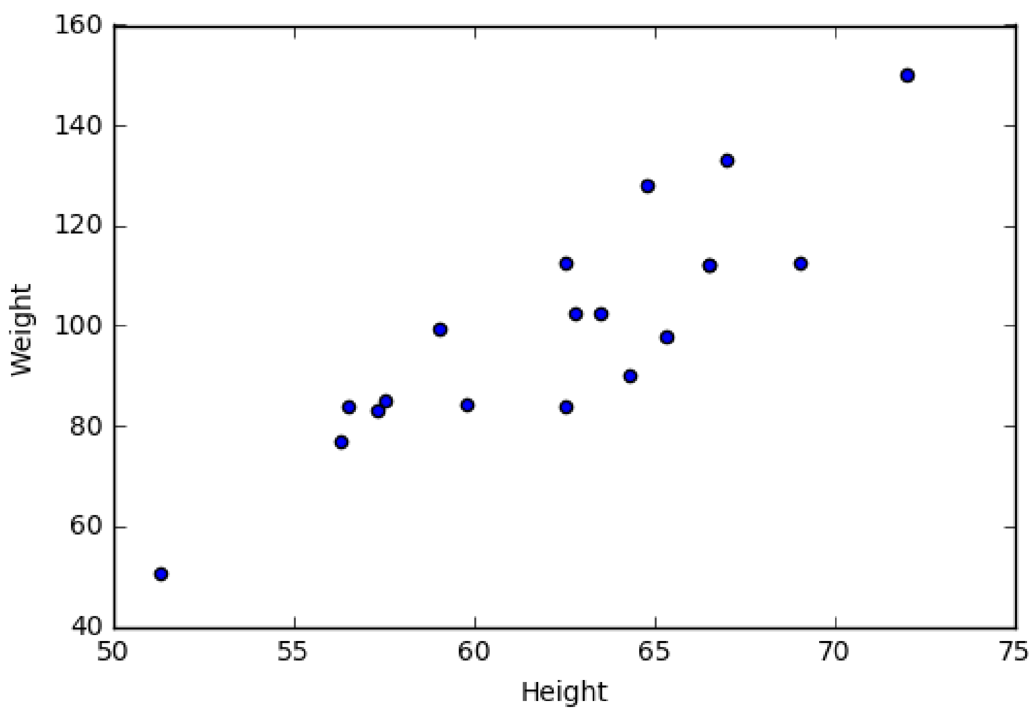
```
# showmeans=True tells Python to plot the mean of the variable on the boxplot
plt.boxplot(student["Weight"], showmeans=True)
 # prevents Python from printing a "1" at the bottom of the boxplot
plt.xticks([]) # prevents Python from printing a "1" at the bottom of the
boxplot
plt.ylabel('Weight')
plt.show()
```



Output:

2.3 Visualize two continuous variables by producing a scatterplot.

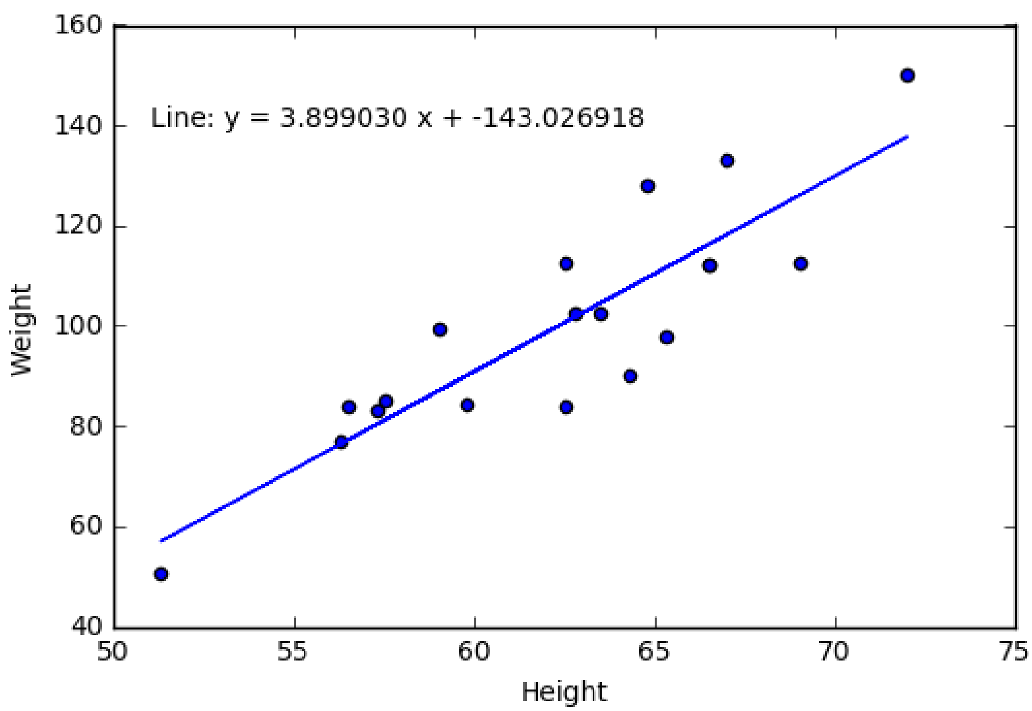
```
# Notice here you specify the x variable first followed by the y variable
plt.scatter(student["Height"], student["Weight"])
plt.xlabel("Height")
plt.ylabel("Weight")
plt.show()
```



Output:

2.4 Visualize a relationship between two continuous variables by producing a scatterplot and a plotted line of best fit.

```
x = student["Height"]
y = student["Weight"]

# np.polyfit() models Weight as a function of Height and returns the
# parameters
m, b = np.polyfit(x, y, 1)
plt.scatter(x, y)

# plt.text() prints the equation of the line of best fit, with the first two
# arguments specifying the x and y locations of the text, respectively
# %f indicates to print a floating point number, that is specified following
# the string
plt.text(51, 140, "Line: y = %f x + %f"% (m,b))
plt.plot(x, m*x + b)
plt.xlabel("Height")
plt.ylabel("Weight")
plt.show()
```



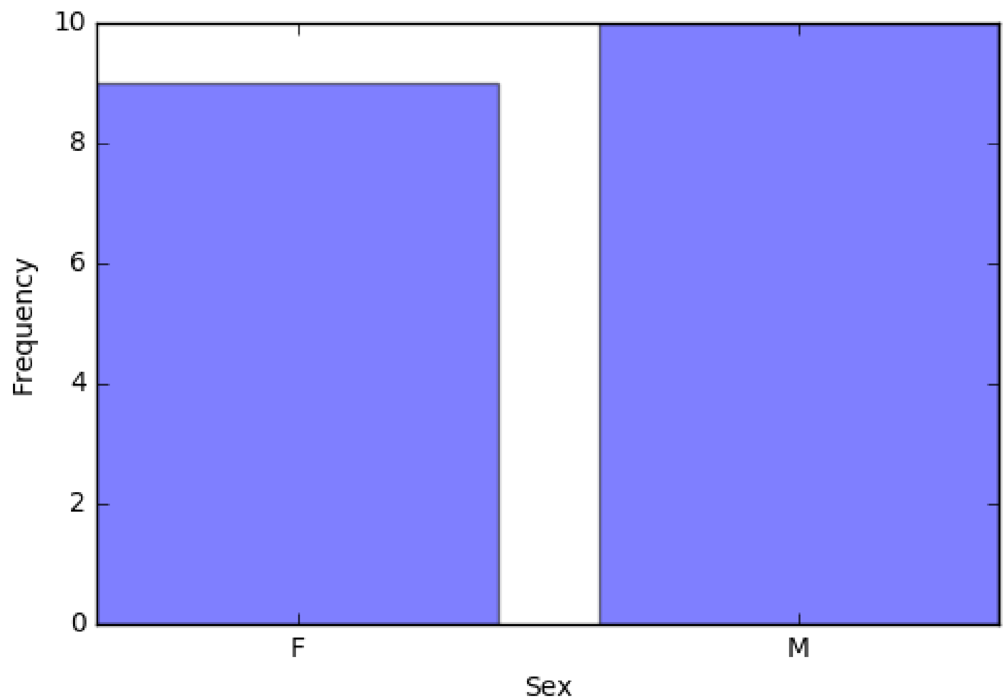
Output:

NumPy polyfit()

2.5 Visualize a categorical variable by producing a bar chart.

```
# Get the counts of Sex
counts = pd.crosstab(index=student["Sex"], columns="count")
```

```
# len() returns the number of categories of Sex (2)
# np.arange() creates a vector of the specified length
num = np.arange(len(counts))
plt.bar(num,counts["count"], align='center', alpha=0.5)

# Set the xticks to be the indices of counts
plt.xticks(num, counts.index)
plt.xlabel("Sex")
plt.ylabel("Frequency")
plt.show()
```



Output:

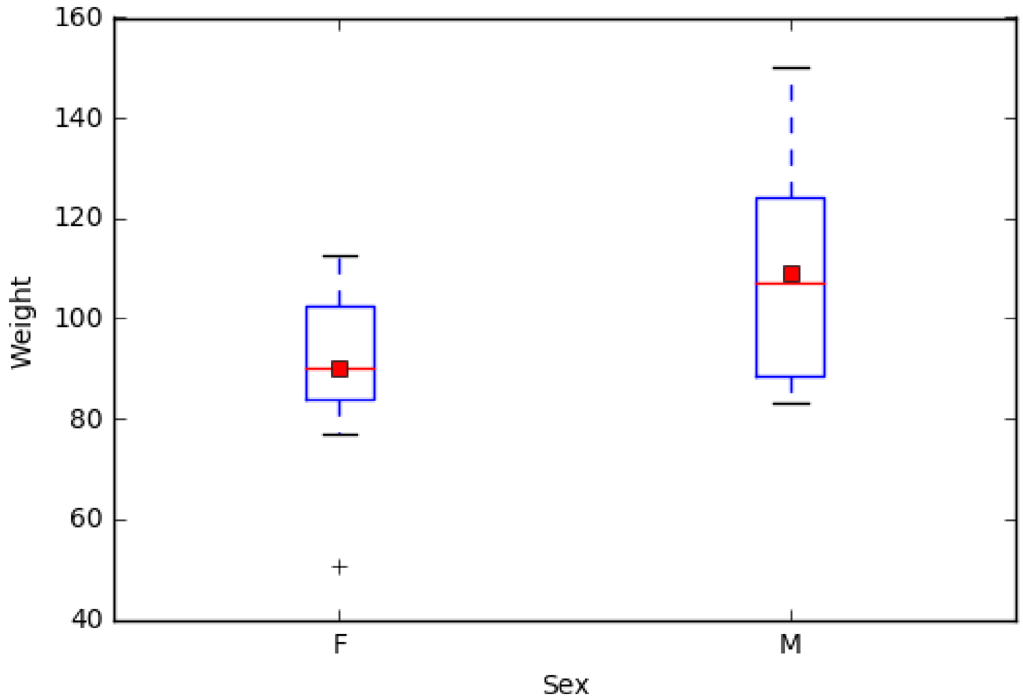
NumPy arange()

2.6 Visualize a continuous variable, grouped by a categorical variable, by producing side-by-side boxplots.

a) Simple side-by-side boxplot without color.

```
# Subset data set to return only female weights, and then only male weights
Weight_F = np.array(student.query('Sex == "F"')["Weight"])
Weight_M = np.array(student.query('Sex == "M"')["Weight"])
Weights = [Weight_F, Weight_M]

# PyPlot automatically plots the two weights side-by-side since Weights
# is a 2D array
plt.boxplot(Weights, showmeans=True, labels=('F', 'M'))
plt.xlabel('Sex')
```

```
plt.ylabel('Weight')
plt.show()
```



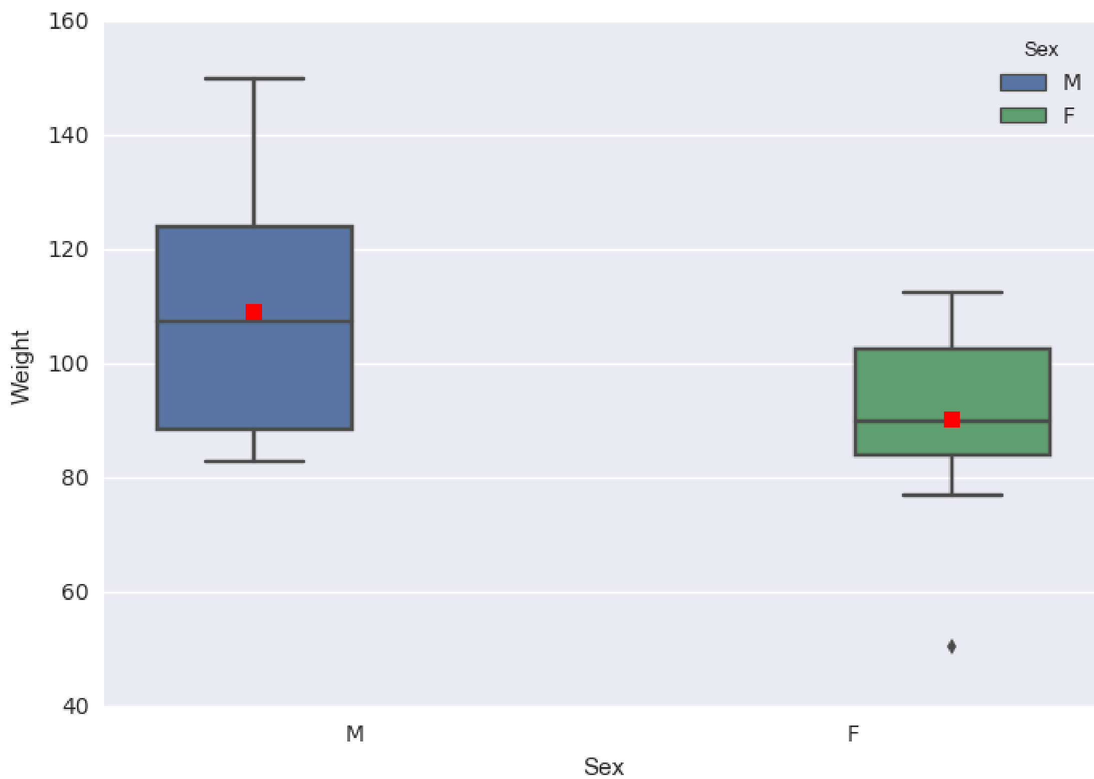
Output:

b) More advanced side-by-side boxplot with color.

```
import seaborn as sns
sns.boxplot(x="Sex", y="Weight", hue="Sex", data = student, showmeans=True)
plt.show()
```

seaborn boxplot

seaborn



Output:

---

3 Basic Data Wrangling and Manipulation

3.1 Create a new variable in a data set as a function of existing variables in the data set.

```
# Notice here how you can create the BMI column in the
# data set just by naming it

student["BMI"] = student["Weight"] / student["Height"]**2 * 703
print(student.head())

##        Name Sex  Age  Height  Weight        BMI
## 0    Alfred   M   14    69.0   112.5  16.611531
## 1     Alice   F   13    56.5    84.0  18.498551
## 2   Barbara   F   13    65.3    98.0  16.156788
## 3     Carol   F   14    62.8   102.5  18.270898
## 4     Henry   M   14    63.5   102.5  17.870296
```

3.2 Create a new variable in a data set using if/else logic of existing variables in the data set.

```
# Notice the use of the np.where() function for a single condition
student["BMI Class"] = np.where(student["BMI"] < 19.0, "Underweight",
```

```
"Healthy")
print(student.head())
NA
```

```
##        Name Sex  Age  Height  Weight        BMI    BMI Class
## 0    Alfred   M   14    69.0   112.5  16.611531  Underweight
## 1     Alice   F   13    56.5    84.0  18.498551  Underweight
## 2   Barbara   F   13    65.3    98.0  16.156788  Underweight
## 3     Carol   F   14    62.8   102.5  18.270898  Underweight
## 4     Henry   M   14    63.5   102.5  17.870296  Underweight
```

NumPy where()

3.3 Create new variables in a data set using mathematical functions applied to existing variables in the data set.

Using the log() function, the exp() function, the sqrt() function, and the abs() function.

```
student["LogWeight"] = np.log(student["Weight"])
student["ExpAge"] = np.exp(student["Age"])
student["SqrtHeight"] = np.sqrt(student["Height"])
student["BMI Neg"] = np.where(student["BMI"] < 19.0, -student["BMI"],
student["BMI"])
student["BMI Pos"] = np.abs(student["BMI Neg"])

# Create a boolean variable
student["BMI Check"] = (student["BMI Pos"] == student["BMI"])
print(student.head())
```

```
##        Name Sex  Age  Height  Weight        BMI    BMI Class  LogWeight  \
## 0    Alfred   M   14    69.0   112.5  16.611531  Underweight   4.722953
## 1     Alice   F   13    56.5    84.0  18.498551  Underweight   4.430817
## 2   Barbara   F   13    65.3    98.0  16.156788  Underweight   4.584967
## 3     Carol   F   14    62.8   102.5  18.270898  Underweight   4.629863
## 4     Henry   M   14    63.5   102.5  17.870296  Underweight   4.629863
##
##          ExpAge  SqrtHeight    BMI Neg    BMI Pos BMI Check
## 0  1.202604e+06    8.306624 -16.611531  16.611531      True
## 1  4.424134e+05    7.516648 -18.498551  18.498551      True
## 2  4.424134e+05    8.080842 -16.156788  16.156788      True
## 3  1.202604e+06    7.924645 -18.270898  18.270898      True
## 4  1.202604e+06    7.968689 -17.870296  17.870296      True
```

3.4 Drop variables from a data set.

```
# axis = 1 indicates to drop columns instead of rows
student = student.drop(["LogWeight", "ExpAge", "SqrtHeight", "BMI Neg",
                        "BMI Pos", "BMI Check"], axis = 1)
print(student.head())
```

```
##       Name Sex  Age  Height  Weight        BMI    BMI Class
## 0   Alfred   M   14    69.0   112.5  16.611531  Underweight
## 1    Alice   F   13    56.5    84.0  18.498551  Underweight
## 2  Barbara   F   13    65.3    98.0  16.156788  Underweight
## 3    Carol   F   14    62.8   102.5  18.270898  Underweight
## 4    Henry   M   14    63.5   102.5  17.870296  Underweight
```

3.5 Sort a data set by a variable.

a) Sort data set by a continuous variable.

```
# Notice the kind="mergesort" which indicates to use a stable sorting
# algorithm
student = student.sort_values(by="Age", kind = "mergesort")
print(student.head())
```

```
##       Name Sex  Age  Height  Weight        BMI    BMI Class
## 10   Joyce   F   11    51.3    50.5  13.490001  Underweight
## 17  Thomas   M   11    57.5    85.0  18.073346  Underweight
## 5    James   M   12    57.3    83.0  17.771504  Underweight
## 6     Jane   F   12    59.8    84.5  16.611531  Underweight
## 9     John   M   12    59.0    99.5  20.094369      Healthy
```

b) Sort data set by a categorical variable.

```
student = student.sort_values(by="Sex", kind = "mergesort")
# Notice that the data is now sorted first by Sex and then within Sex by Age
print(student.head())
```

```
##        Name Sex  Age  Height  Weight        BMI    BMI Class
## 10    Joyce   F   11    51.3    50.5  13.490001  Underweight
## 6      Jane   F   12    59.8    84.5  16.611531  Underweight
## 12   Louise   F   12    56.3    77.0  17.077695  Underweight
## 1     Alice   F   13    56.5    84.0  18.498551  Underweight
## 2   Barbara   F   13    65.3    98.0  16.156788  Underweight
```

3.6 Compute descriptive statistics of continuous variables, grouped by a categorical variable.

```
print(student.groupby(by = "Sex").mean())
```

```
##            Age     Height      Weight        BMI
## Sex
## F    13.222222  60.588889   90.111111  17.051039
## M    13.400000  63.910000  108.950000  18.594243
```

3.7 Add a new row to the bottom of a data set.

```
# Look at the tail of the data currently
print(student.tail())
```

```
##        Name Sex  Age  Height  Weight        BMI    BMI Class
## 0    Alfred   M   14    69.0   112.5  16.611531  Underweight
```

```
## 4      Henry   M   14    63.5   102.5  17.870296  Underweight
## 16    Ronald   M   15    67.0   133.0  20.828470      Healthy
## 18   William   M   15    66.5   112.0  17.804511  Underweight
## 14    Philip   M   16    72.0   150.0  20.341435      Healthy
```

```
student = student.append({'Name':'Jane', 'Sex':'F', 'Age':14, 'Height':56.3,
                          'Weight':77.0, 'BMI':17.077695,
                          'BMI Class': 'Underweight'},
                         ignore_index=True)

# Notice the change in the indices because of the ignore_index=True option
# which allows for a Series, or one-dimensional DataFrame, to be appended
# to an existing DataFrame
```

```
##         Name Sex  Age  Height  Weight        BMI    BMI Class
## 15     Henry   M   14    63.5   102.5  17.870296  Underweight
## 16    Ronald   M   15    67.0   133.0  20.828470      Healthy
## 17   William   M   15    66.5   112.0  17.804511  Underweight
## 18    Philip   M   16    72.0   150.0  20.341435      Healthy
## 19      Jane   F   14    56.3    77.0  17.077695  Underweight
```

3.8 Create a user defined function and apply it to a variable in the data set to create a new variable in the data set.

```
def toKG(lb):
    return (0.45359237 * lb)

student["Weight KG"] = student["Weight"].apply(toKG)
print(student.head())
```

```
##        Name Sex  Age  Height  Weight        BMI    BMI Class  Weight KG
## 0     Joyce   F   11    51.3    50.5  13.490001  Underweight  22.906415
## 1      Jane   F   12    59.8    84.5  16.611531  Underweight  38.328555
## 2    Louise   F   12    56.3    77.0  17.077695  Underweight  34.926612
## 3     Alice   F   13    56.5    84.0  18.498551  Underweight  38.101759
## 4   Barbara   F   13    65.3    98.0  16.156788  Underweight  44.452052
```

apply()

3.9 Caste a Data Frame to a different object type.

```
student_num = pd.concat([student["Age"], student["Height"],
```

```
##      Age  Height  Weight
## 0   14.0    69.0   112.5
## 1   13.0    56.5    84.0
## 2   13.0    65.3    98.0
## 3   14.0    62.8   102.5
## 4   14.0    63.5   102.5
```

astype()

4 More Advanced Data Wrangling

4.1 Drop observations with missing information.

```
# Notice the use of the fish data set because it has some missing
# observations
fish = pd.read_csv('/Users/fish.csv')

# First sort by Weight, requesting those with NA for Weight first
fish = fish.sort_values(by='Weight', kind='mergesort', na_position='first')
print(fish.head())

##     Species  Weight  Length1  Length2  Length3   Height   Width
## 13    Bream     NaN     29.5     32.0     37.3  13.9129  5.0728
## 40    Roach     0.0     19.0     20.5     22.8   6.4752  3.3516
## 72    Perch     5.9      7.5      8.4      8.8   2.1120  1.4080
## 145   Smelt     6.7      9.3      9.8     10.8   1.7388  1.0476
## 147   Smelt     7.0     10.1     10.6     11.6   1.7284  1.1484
```

--

```
new_fish = fish.dropna()
print(new_fish.head())

##     Species  Weight  Length1  Length2  Length3  Height   Width
## 40    Roach     0.0     19.0     20.5     22.8  6.4752  3.3516
## 72    Perch     5.9      7.5      8.4      8.8  2.1120  1.4080
## 145   Smelt     6.7      9.3      9.8     10.8  1.7388  1.0476
## 147   Smelt     7.0     10.1     10.6     11.6  1.7284  1.1484
## 146   Smelt     7.5     10.0     10.5     11.6  1.9720  1.1600
```

dropna()

4.2 Merge two data sets together on a common variable.

a) First, select specific columns of a data set to create two smaller data sets.

```
# Notice the use of the student data set again, however we want to reload it
# without the changes we've made previously
student = pd.read_csv('/Users/class.csv')
student1 = pd.concat([student["Name"], student["Sex"], student["Age"]],
                    axis = 1)
print(student1.head())
NA

##        Name Sex  Age
## 0    Alfred   M   14
## 1     Alice   F   13
## 2   Barbara   F   13
```

```
## 3     Carol    F    14
## 4     Henry    M    14
```

--

```
student2 = pd.concat([student["Name"], student["Height"], student["Weight"]],
                     axis = 1)
print(student2.head())
```

```
##        Name  Height  Weight
## 0    Alfred    69.0   112.5
## 1     Alice    56.5    84.0
## 2   Barbara    65.3    98.0
## 3     Carol    62.8   102.5
## 4     Henry    63.5   102.5
```

b) Second, we want to merge the two smaller data sets on the common variable.

```
new = pd.merge(student1, student2, on="Name")
print(new.head())
```

```
##        Name Sex  Age  Height  Weight
## 0    Alfred   M   14    69.0   112.5
## 1     Alice   F   13    56.5    84.0
## 2   Barbara   F   13    65.3    98.0
## 3     Carol   F   14    62.8   102.5
## 4     Henry   M   14    63.5   102.5
```

c) Finally, we want to check to see if the merged data set is the same as the original data set.

```
print(student.equals(new))
```

```
## True
```

merge()

4.3 Merge two data sets together by index number only.

a) First, select specific columns of a data set to create two smaller data sets.

```
newstudent1 = pd.concat([student["Name"], student["Sex"], student["Age"]],
                        axis = 1)
print(newstudent1.head())
```

```
##        Name Sex  Age
## 0    Alfred   M   14
## 1     Alice   F   13
## 2   Barbara   F   13
## 3     Carol   F   14
## 4     Henry   M   14
```

```
newstudent2 = pd.concat([student["Height"], student["Weight"]], axis = 1)
print(newstudent2.head())
```

```
##    Height  Weight
## 0    69.0   112.5
## 1    56.5    84.0
## 2    65.3    98.0
## 3    62.8   102.5
## 4    63.5   102.5
```

b) Second, we want to join the two smaller data sets.

```
new2 = newstudent1.join(newstudent2)
print(new2.head())
```

```
##       Name Sex  Age  Height  Weight
## 0   Alfred   M   14    69.0   112.5
## 1    Alice   F   13    56.5    84.0
## 2  Barbara   F   13    65.3    98.0
## 3    Carol   F   14    62.8   102.5
## 4    Henry   M   14    63.5   102.5
```

c) Finally, we want to check to see if the joined data set is the same as the original data set.

```
print(student.equals(new2))
```

```
## True
```

join()

4.4 Create a pivot table to summarize information about a data set.

```
# Notice we are using a new data set that needs to be read into the
# environment
price = pd.read_csv('/Users/price.csv')

# The following code is used to remove the ',' and '$' characters from
# the ACTUAL colum so that the values can be summed
from re import sub
from decimal import Decimal
def trim_money(money):
    return(float(Decimal(sub(r'[^\d.]', '', money))))

price["REVENUE"] = price["ACTUAL"].apply(trim_money)
table = pd.pivot_table(price, index=["COUNTRY", "STATE", "PRODTYPE",
                                     "PRODUCT"], values="REVENUE",
aggfunc=np.sum)
print(table.head())
```

```
## COUNTRY  STATE             PRODTYPE   PRODUCT
## Canada   British Columbia  FURNITURE  BED        197706.6
##                                       SOFA       216282.6
```

```
##                            OFFICE     CHAIR      200905.2
##                                       DESK       186262.2
##          Ontario           FURNITURE  BED        194493.6
## Name: REVENUE, dtype: float64
```

sub

Decimal

pivot_table() for more information on the pandas pivot_table() function

pivot()

---

5 Regression & Modeling

The following sections focus on the Python sklearn package.

5.1 Pre-process a data set using principal component analysis.

```
from sklearn.decomposition import PCA

# Notice we are using a new data set that needs to be read into the
# environment
iris = pd.read_csv('/Users/iris.csv')
features = iris.drop(["Target"], axis = 1)

pca = PCA(n_components = 4)
pca = pca.fit(features)
print(np.transpose(pca.components_))
```

```
## [[ 0.36158968  0.65653988 -0.58099728  0.31725455]
##  [-0.08226889  0.72971237  0.59641809 -0.32409435]
##  [ 0.85657211 -0.1757674   0.07252408 -0.47971899]
##  [ 0.35884393 -0.07470647  0.54906091  0.75112056]]
```

PCA

5.2 Split data into training and testing data and export as a .csv file.

```
from sklearn.model_selection import train_test_split

target = iris["Target"]

# The following code splits the iris data set into 70% train and 30% test
X_train, X_test, Y_train, Y_test = train_test_split(features, target,
                                                    test_size = 0.3,
                                                    random_state = 29)
train_x = pd.DataFrame(X_train)
train_y = pd.DataFrame(Y_train)
```

```
test_x = pd.DataFrame(X_test)
test_y = pd.DataFrame(Y_test)

train = pd.concat([train_x, train_y], axis = 1)
test = pd.concat([test_x, test_y], axis = 1)

train.to_csv('/Users/iris_train.csv', index = False)
test.to_csv('/Users/iris_test.csv', index = False)
```

train_test_split

5.3 Fit a logistic regression model.

```
# Notice we are using a new data set that needs to be read into the
# environment
tips = pd.read_csv('/Users/tips.csv')

# The following code is used to determine if the individual left more
# than a 15% tip
tips["fifteen"] = 0.15 * tips["total_bill"]
tips["greater15"] = np.where(tips["tip"] > tips["fifteen"], 1, 0)

import statsmodels.api as sm

# Notice the syntax of greater15 as a function of total_bill
res = sm.formula.glm("greater15 ~ total_bill", family=sm.families.Binomial(),
                     data=tips).fit()
print(res.summary())

##                  Generalized Linear Model Regression Results
##
==============================================================================
=
## Dep. Variable:              greater15   No. Observations:
244
## Model:                            GLM   Df Residuals:
242
## Model Family:                Binomial   Df Model:
1
## Link Function:                  logit   Scale:
1.0
## Method:                          IRLS   Log-Likelihood:                -
156.87
## Date:                Wed, 07 Jun 2017   Deviance:
313.74
## Time:                        16:27:29   Pearson chi2:
247.
## No. Iterations:                     6
##
==============================================================================
```

```
=
##                   coef    std err          z      P>|z|      [95.0% Conf.
Int.]
## -----------------------------------------------------------------------------
----
## Intercept      1.6477      0.355      4.646      0.000         0.953
2.343
## total_bill    -0.0725      0.017     -4.319      0.000        -0.105    -
0.040
##
================================================================================
=
```

A logistic regression model can be implemented using sklearn, however statsmodels.api provides a helpful summary about the model, so it is preferable for this example.

5.4 Fit a linear regression model on training data and assess against testing data.

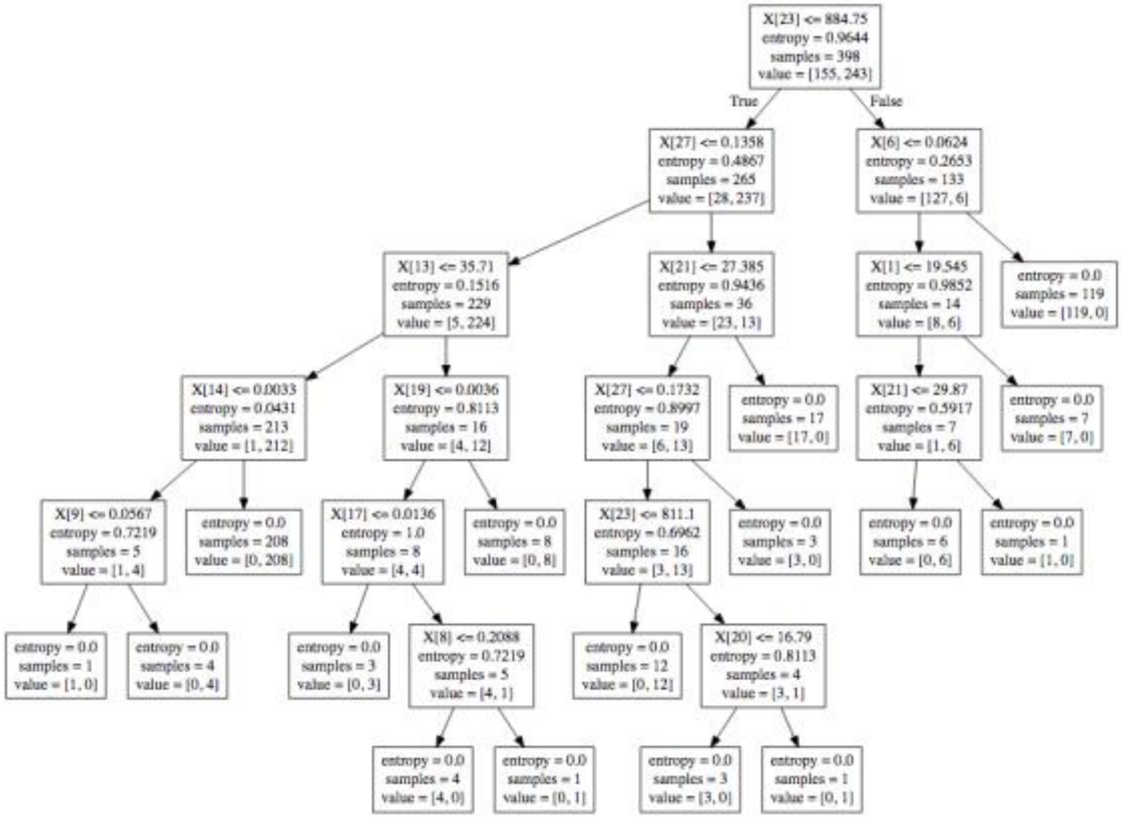
```
# Notice we are using new data sets that need to be read into the environment
train = pd.read_csv('/Users/tips_train.csv')
test = pd.read_csv('/Users/tips_test.csv')

# Fit a linear regression model of tip by total_bill on the training data
from sklearn import linear_model
regr = linear_model.LinearRegression()
# If your data has one feature, you need to reshape the 1D array
model = regr.fit(train["total_bill"].reshape(-1,1), train["tip"])

# Predict the tip based on the total_bill given in the testing data
prediction = pd.DataFrame()
prediction["tip_hat"] = regr.predict(test["total_bill"].reshape(-1,1))

# Compute the squared difference between predicted tip and actual tip
prediction["diff"] = (prediction["tip_hat"] - test["tip"])**2

# Compute the mean of the squared differences (mean squared error)
# as an assessment of the model
mean_sq_error = np.mean(prediction["diff"])
print(mean_sq_error)

## 1.08759363430702
```

LinearRegression

5.5 Fit a decision tree model on training data and assess against testing data.

a) Build a model, assess the model against the training data, plot the tree, and determine variable importance.

```
# Notice we are using new data sets that need to be read into the environment
train = pd.read_csv('/Users/breastcancer_train.csv')
test = pd.read_csv('/Users/breastcancer_test.csv')

from sklearn import tree

# random_state is used to specify a seed for a random integer so that the
# results are reproducible
clf = tree.DecisionTreeClassifier(criterion='entropy', random_state=29)
clf = clf.fit(train.drop(["Target"], axis = 1), train["Target"])

# Prediction on training data
scored = pd.DataFrame(clf.predict(train.drop(["Target"], axis = 1)))
scored["Target"] = train["Target"]

# Determine how many were correctly classified
scored["correct"] = (scored["Target"] == scored[0])

## col_0    count
## correct
## True       398
```



Output:

```
# Determine variable importance
var_import = clf.feature_importances_
var_import = pd.DataFrame(var_import)
var_import = var_import.rename(columns = {0:'Importance'})
var_import = var_import.sort_values(by="Importance", kind = "mergesort",
                                    ascending = False)
print(var_import.head())

##      Importance
## 23     0.592658
## 27     0.172561
## 6      0.055977
## 21     0.054751
## 13     0.032737
```

b) Assess the model against the testing data.

```
# Prediction on testing data
scored = pd.DataFrame(clf.predict(test.drop(["Target"], axis = 1)))
scored["Target"] = test["Target"]

# Determine how many were correctly classified
scored["correct"] = (scored["Target"] == scored[0])
print(pd.crosstab(index=scored["correct"], columns="count"))
```

```
## col_0    count
## correct
## False        9
## True       162
```

DecisionTreeClassifier

5.6 Fit a random forest classification model on training data and assess against testing data.

a) Build a model, assess the model against the training data, and determine variable importance.

```
# Notice we are using new data sets that need to be read into the environment
train = pd.read_csv('/Users/iris_train.csv')
test = pd.read_csv('/Users/iris_test.csv')

from sklearn.ensemble import RandomForestClassifier

clf = RandomForestClassifier(random_state=29)
clf = clf.fit(train.drop(["Target"], axis = 1), train["Target"])

# Prediction on training data
scored = pd.DataFrame(clf.predict(train.drop(["Target"], axis = 1)))
scored["Target"] = train["Target"]

# Determine how many were correctly classified
scored["correct"] = (scored["Target"] == scored[0])
print(pd.crosstab(index=scored["correct"], columns="count"))

## col_0    count
## correct
## True       105
```

--

```
# Determine variable importance
var_import = clf.feature_importances_
var_import = pd.DataFrame(var_import)
var_import = var_import.rename(columns = {0:'Importance'})
var_import = var_import.sort_values(by="Importance", kind = "mergesort",
                                    ascending = False)
print(var_import.head())

##    Importance
## 2    0.515197
## 3    0.388860
## 0    0.080865
## 1    0.015078
```

b) Assess the model against the testing data.

```
# Prediction on testing data
scored = pd.DataFrame(clf.predict(test.drop(["Target"], axis = 1)))
scored["Target"] = test["Target"]

# Determine how many were correctly classified
scored["correct"] = (scored["Target"] == scored[0])
print(pd.crosstab(index=scored["correct"], columns="count"))
```

```
## col_0    count
## correct
## False        3
## True        42
```

RandomForestClassifier

5.7 Fit a random forest regression model on training data and assess against testing data.

a) Build a model and assess the model against the training data.

```
# Notice we are re-using data sets but it is good to re-read the original
# version back into the environment
train = pd.read_csv('/Users/tips_train.csv')
test = pd.read_csv('/Users/tips_test.csv')

from sklearn.ensemble import RandomForestRegressor

clf = RandomForestRegressor(random_state=29)
clf = clf.fit(train.drop(["tip"], axis = 1), train["tip"])

# Prediction on training data
scored = pd.DataFrame(clf.predict(train.drop(["tip"], axis = 1)))
scored["Target"] = train["tip"]

# Determine mean squared error
scored["diff"] = (scored["Target"] - scored[0])**2
print(scored["diff"].mean())
```

```
## 0.2177569846153845
```

b) Assess the model against the testing data.

```
# Prediction on testing data
scored = pd.DataFrame(clf.predict(test.drop(["tip"], axis = 1)))
scored["Target"] = test["tip"]

# Determine mean squared error
scored["diff"] = (scored["Target"] - scored[0])**2
print(scored["diff"].mean())
```

```
## 1.182229489795918
```

RandomForestRegressor

5.8 Fit a gradient boosting model on training data and assess against testing data.

a) Build a model and assess the model against the training data.

```
# Notice we are re-using data sets but it is good to re-read the original
# version back into the environment
train = pd.read_csv('/Users/breastcancer_train.csv')
test = pd.read_csv('/Users/breastcancer_test.csv')

from sklearn.ensemble import GradientBoostingClassifier

# n_estimators = total number of trees to fit which is analogous to the
# number of iterations
# learning_rate = shrinkage or step-size reduction, whereas a lower
# learning rate requires more iterations
# min_samples_leaf = minimum number of observations in the trees
# terminal nodes

clf = GradientBoostingClassifier(random_state = 29, learning_rate = .01,
min_samples_leaf = 20, n_estimators = 2500)
clf = clf.fit(train.drop(["Target"], axis = 1), train["Target"])

# Prediction on training data
scored = pd.DataFrame(clf.predict(train.drop(["Target"], axis = 1)))
scored["Target"] = train["Target"]

# Determine how many were correctly classified
scored["correct"] = (scored["Target"] == scored[0])
print(pd.crosstab(index = scored["correct"], columns = "count"))

## col_0    count
## correct
## True       398
```

b) Assess the model against the testing data.

```
# Prediction on testing data
scored = pd.DataFrame(clf.predict(test.drop(["Target"], axis = 1)))
scored["Target"] = test["Target"]

# Determine how many were correctly classified
scored["correct"] = (scored["Target"] == scored[0])

## col_0    count
## correct
```

```
## False        4
## True       167
```

GradientBoostingClassifier

5.9 Fit a support vector classification model.

a) Build a model and assess the model against the training data.

```
# Notice we are re-using data sets but it is good to re-read the original
# version back into the environment
train = pd.read_csv('/Users/breastcancer_train.csv')
test = pd.read_csv('/Users/breastcancer_test.csv')

# First we need to scale the data
from sklearn.preprocessing import StandardScaler

train_features = train.drop(["Target"], axis = 1)
scaler = StandardScaler().fit(np.array(train_features))
train_scaled = scaler.transform(np.array(train_features))
train_scaled = pd.DataFrame(train_scaled)
train_scaled["Target"] = train["Target"]

test_features = test.drop(["Target"], axis = 1)
scaler = StandardScaler().fit(np.array(test_features))
test_scaled = scaler.transform(np.array(test_features))
test_scaled = pd.DataFrame(test_scaled)
test_scaled["Target"] = test["Target"]

# Fit a support vector classification model
from sklearn.svm import SVC
clf = SVC(random_state = 29, kernel = 'linear')
clf = clf.fit(train_scaled.drop(["Target"], axis = 1),
train_scaled["Target"])

# Evaluation on training data
predictions = pd.DataFrame()
predictions["predY"] = clf.predict(train_scaled.drop(["Target"], axis = 1))

# Determine how many were correctly classified
predictions["actual"] = train_scaled["Target"]
predictions["correct"] = (predictions["actual"] == predictions["predY"])
print(pd.crosstab(index = predictions["correct"], columns = "count"))

## col_0    count
## correct
## False        6
## True       392
```

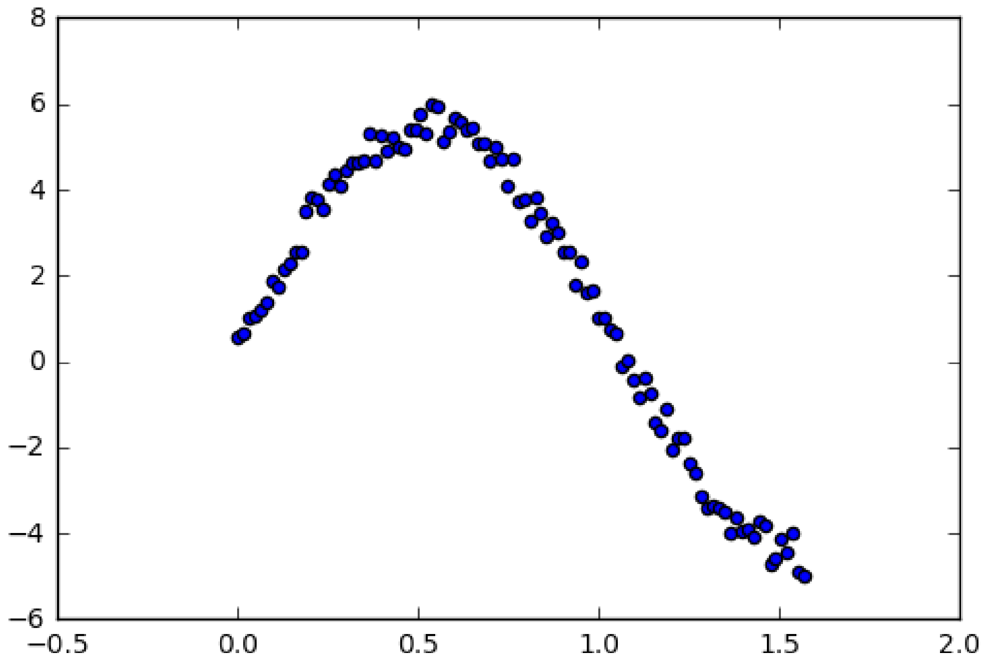
b) Assess the model against the testing data.

```
# Evaluation on testing data
predictions = pd.DataFrame()
predictions["predY"] = clf.predict(test_scaled.drop(["Target"], axis = 1))

# Determine how many were correctly classified
predictions["actual"] = test_scaled["Target"]
predictions["correct"] = (predictions["actual"] == predictions["predY"])
print(pd.crosstab(index = predictions["correct"], columns = "count"))

## col_0    count
## correct
## False        7
## True       164
```

5.10 Fit a support vector regression model.

a) Generate random data based on a sine curve.

```
# Generate the time variable
t = np.linspace(start = 0, stop = 0.5*np.pi, num = 100)

# Generate the sine curve with uniform noise
y1 = 5*np.sin(3*t) + np.random.uniform(size=100)

# Create a data frame for the generated data
random_data = pd.DataFrame()
random_data["X"] = t
random_data["Y"] = y1

# Plot the generated data
```

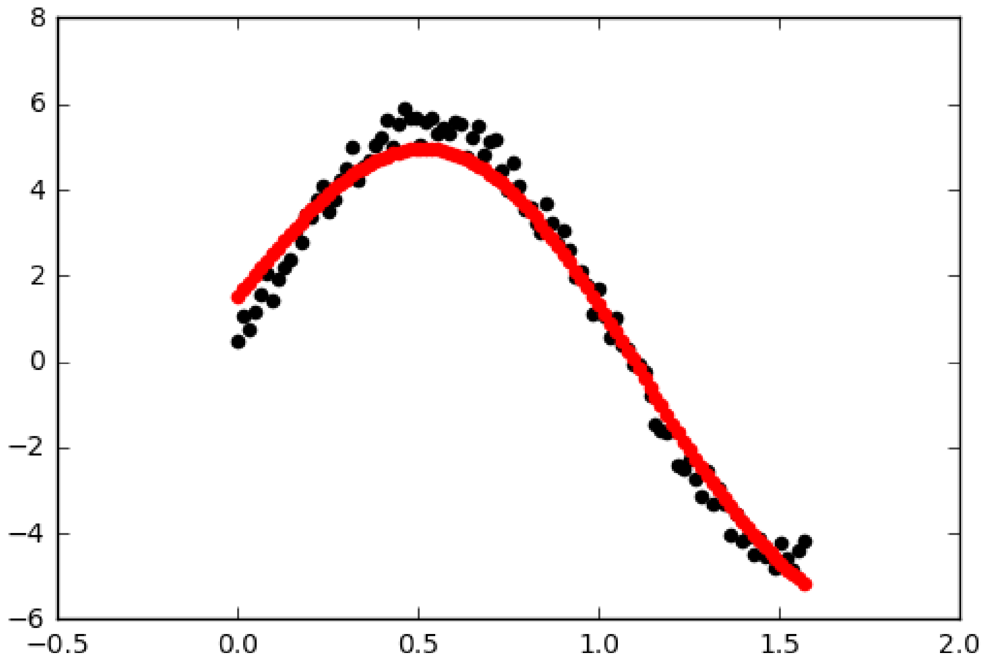


Output:

np.linspace() np.sin() np.random.uniform()

b) Fit a support vector regression model to the data.

```
from sklearn.svm import SVR
clf = SVR()
clf = clf.fit(random_data["X"].reshape(-1,1),random_data["Y"])
predictions = pd.DataFrame()
predictions["predY"] = clf.predict(random_data["X"].reshape(-1,1))

plt.scatter(t,y1,color="black")
plt.scatter(t,predictions["predY"],color="r")
plt.show()
```



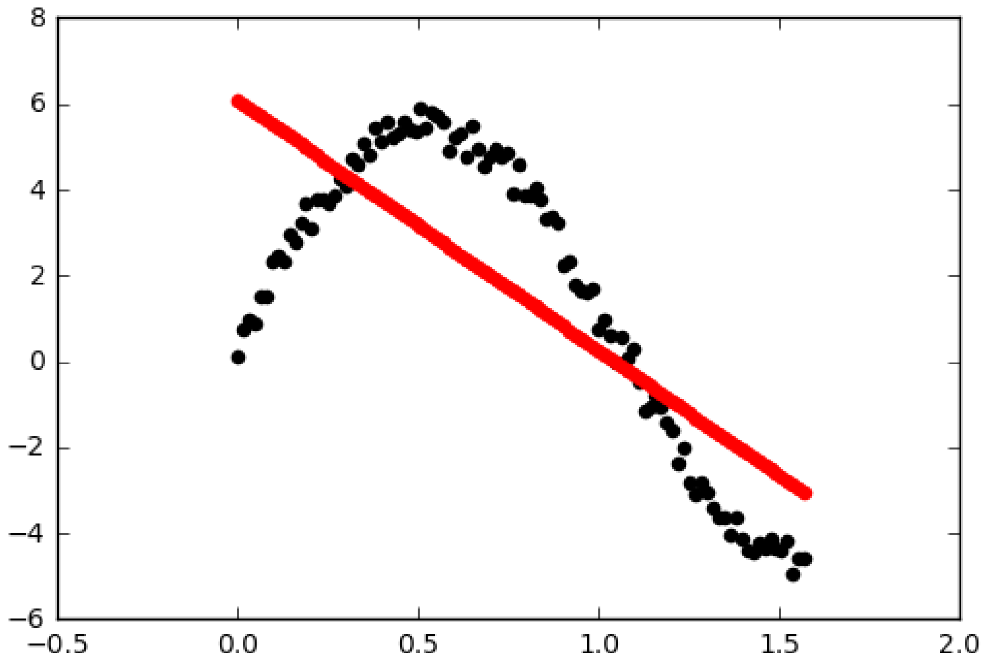
Output:

SVR

```
predictions["actual"] = random_data["Y"]
predictions["sq_diff"] = (predictions["predY"] - predictions["actual"])**2
print(predictions["sq_diff"].mean())

## 0.20626922373052764
```

c) Fit a linear regression model to the data.

```
from sklearn import linear_model
linMod = linear_model.LinearRegression()
linMod = linMod.fit(random_data["X"].reshape(-1,1),  random_data["Y"])
predictions = pd.DataFrame()
predictions["predY"] = linMod.predict(random_data["X"].reshape(-1,1))

plt.scatter(t,y1,color="black")
plt.scatter(t,predictions["predY"],color="r")
plt.show()
```



Output:

LinearRegression

```
predictions["actual"] = random_data["Y"]
predictions["sq_diff"] = (predictions["predY"] - predictions["actual"])**2
print(predictions["sq_diff"].mean())

## 4.753313156881628
```

---

6 Model Evaluation & Selection

6.1 Evaluate the accuracy of regression models.

a) Evaluation on training data.

```
# Notice we are re-using data sets but it is good to re-read the original
# version back into the environment
train = pd.read_csv('/Users/tips_train.csv')
test = pd.read_csv('/Users/tips_test.csv')

# 1. Linear Regression Model
from sklearn.metrics import r2_score
from sklearn import linear_model
linMod = linear_model.LinearRegression()
linMod = linMod.fit(train.drop(["tip"], axis = 1),  train["tip"])

# Evaluation on training data
```

```
pred_lin = linMod.predict(train.drop(["tip"], axis = 1))

# Determine coefficient of determination score
r2_lin = r2_score(train["tip"], pred_lin)
print("Linear regression model r^2 score (coefficient of determination): %f"
% r2_lin)

## Linear regression model r^2 score (coefficient of determination): 0.496730
```

--

```
# 2. Random Forest Regression Model
from sklearn.ensemble import RandomForestRegressor
rfMod = RandomForestRegressor(random_state=29)
rfMod = rfMod.fit(train.drop(["tip"], axis = 1), train["tip"])

# Evaluation on training data
pred_rf = rfMod.predict(train.drop(["tip"], axis = 1))

# Determine coefficient of determination score
r2_rf = r2_score(train["tip"], pred_rf)
print("Random forest regression model r^2 score (coefficient of
determination): %f" % r2_rf)

## Random forest regression model r^2 score (coefficient of determination):
0.892204
```

b) Evaluation on testing data.

```
# 1. Linear Regression Model (linMod)

# Evaluation on testing data
pred_lin = linMod.predict(test.drop(["tip"], axis = 1))

# Determine coefficient of determination score
r2_lin = r2_score(test["tip"], pred_lin)
print("Linear regression model r^2 score (coefficient of determination): %f"
% r2_lin)

## Linear regression model r^2 score (coefficient of determination): 0.270945
```

--

```
# 2. Random Forest Regression Model (rfMod)

# Evaluation on testing data
pred_rf = rfMod.predict(test.drop(["tip"], axis = 1))

# Determine coefficient of determination score
r2_rf = r2_score(test["tip"], pred_rf)
```

```
print("Random forest regression model r^2 score (coefficient of
determination): %f" % r2_rf)

## Random forest regression model r^2 score (coefficient of determination):
0.163330
```

The sklearn metric r2_score is only one option for assessing a regression model. Please go here for more information about other sklearn regression metrics.

6.2 Evaluate the accuracy of classification models.

a) Evaluation on training data.

```
# Notice we are re-using data sets but it is good to re-read the original
# version back into the environment
train = pd.read_csv('/Users/breastcancer_train.csv')
test = pd.read_csv('/Users/breastcancer_test.csv')

# 1. Decision Tree Classification Model
from sklearn import tree
from sklearn.metrics import accuracy_score
treeMod = tree.DecisionTreeClassifier(criterion='entropy', random_state=29)
treeMod = treeMod.fit(train.drop(["Target"], axis = 1), train["Target"])

# Evaluation on training data
scored = pd.DataFrame(treeMod.predict(train.drop(["Target"], axis = 1)))
scored["Target"] = train["Target"]

# Determine accuracy score
accuracy_tree = accuracy_score(scored["Target"], scored[0])
print("Decision tree model accuracy: %f" % accuracy_tree)

## Decision tree model accuracy: 1.000000
```

--

```
# 2. Random Forest Classification Model
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
rfMod = RandomForestClassifier(random_state=29)
rfMod = rfMod.fit(train.drop(["Target"], axis = 1), train["Target"])

# Evaluation on training data
scored = pd.DataFrame(rfMod.predict(train.drop(["Target"], axis = 1)))
scored["Target"] = train["Target"]

# Determine accuracy score
accuracy_rf = accuracy_score(scored["Target"], scored[0])
print("Random forest model accuracy: %f" % accuracy_rf)

## Random forest model accuracy: 0.997487
```

--

```
# 3. Gradient Boosting Classifcation Model
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import accuracy_score
gbmMod = GradientBoostingClassifier(random_state = 29, learning_rate = .01,
min_samples_leaf = 20, n_estimators = 2500)
gbmMod = gbmMod.fit(train.drop(["Target"], axis = 1), train["Target"])

# Evaluation on training data
scored = pd.DataFrame(gbmMod.predict(train.drop(["Target"], axis = 1)))
scored["Target"] = train["Target"]

# Determine accuracy score
accuracy_gbm = accuracy_score(scored["Target"], scored[0])
print("Gradient boosting model accuracy: %f" % accuracy_gbm)

## Gradient boosting model accuracy: 1.000000
```

b) Evaluation on testing data.

```
# 1. Decision Tree Classification Model (treeMod)

# Evaluation on testing data
scored = pd.DataFrame(treeMod.predict(test.drop(["Target"], axis = 1)))
scored["Target"] = test["Target"]

# Determine accuracy score
accuracy_tree = accuracy_score(scored["Target"], scored[0])
print("Decision tree model accuracy: %f" % accuracy_tree)

## Decision tree model accuracy: 0.947368
```

--

```
# 2. Random Forest Classification Model (rfMod)

# Evaluation on testing data
scored = pd.DataFrame(rfMod.predict(test.drop(["Target"], axis = 1)))
scored["Target"] = test["Target"]

# Determine accuracy score
accuracy_rf = accuracy_score(scored["Target"], scored[0])
print("Random forest model accuracy: %f" % accuracy_rf)

## Random forest model accuracy: 0.964912
```

--

```
# 3. Gradient Boosting Classifcation Model (gbmMod)

# Evaluation on testing data
```

```
scored = pd.DataFrame(gbmMod.predict(test.drop(["Target"], axis = 1)))
scored["Target"] = test["Target"]

# Determine accuracy score
accuracy_gbm = accuracy_score(scored["Target"], scored[0])
print("Gradient boosting model accuracy: %f" % accuracy_gbm)

## Gradient boosting model accuracy: 0.976608
```

Note: The sklearn metric accuracy_score is only one option for assessing a classification model. Please go here for more information about other sklearn classification metrics.

6.3 Evaluation with cross validation.

a) KFold

```
# Notice we are using a new data set that need to be read into the
# environment
breastcancer = pd.read_csv('/Users/breastcancer.csv')

from sklearn import model_selection
from sklearn.ensemble import RandomForestClassifier

X = breastcancer.drop(["Target"], axis = 1)
Y = breastcancer["Target"]

kfold = model_selection.KFold(n_splits = 5, random_state = 29)
model = RandomForestClassifier(random_state = 29)
results = model_selection.cross_val_score(model, X, Y, cv = kfold)

print("Accuracy: %.2f%% +/- %.2f%%" % (results.mean()*100,
                                       results.std()*100))

## Accuracy: 94.38% +/- 2.39%
```

b) ShuffleSplit

```
shuffle = model_selection.ShuffleSplit(n_splits = 5, random_state = 29)
model = RandomForestClassifier(random_state = 29)
results = model_selection.cross_val_score(model, X, Y, cv = shuffle)

print("Accuracy: %.2f%% +/- %.2f%%" % (results.mean()*100,
                                       results.std()*100))

## Accuracy: 95.09% +/- 0.70%
```

Appendix

1 Built-in Python Data Types

- Boolean

Numeric types:

- int
- long
- float
- complex

Sequences:

- str
- bytes
- byte array
- list
- tuple

Sets:

- set
- frozen set

Mapping:

- dictionary

2 Python Plotting Packages

Bokeh

PyPlot

Seaborn

Alphabetical Index

Array

A NumPy array is a data type implemented by the NumPy package in which the elements of the array are all of the same type. Please see the following example of array creation and access:

```
import numpy as np
my_array = np.array([1, 2, 3, 4])
print(my_array)

## [1 2 3 4]

print(my_array[3])

## 4
```

For more information, please see NumPy Arrays.

Bokeh

Bokeh is a Python package which is useful for interactive visualizations and is optimized for web browser presentations.

Boolean

A Boolean value is either True or False, and represents the truth of an expression or statement.

Bytes & Byte arrays

A byte is a sequence of integers which is immutable, whereas a byte array is its mutable counterpart.

---

complex

A complex number includes a real part and an imaginary part, both of which are floating point numbers.

Data Frame

A Pandas Data Frame is a two-dimensional tabular structure with labeled axes (rows and columns), where data observations are represented by rows and data variables are represented by columns.

---

datetime

The datetime Python module includes tools for manipulating data and time objects.

Decimal

Decimal is a Python package which provides tools for decimal floating point arithmetic.

Dictionary

A dictionary is an associative array which is indexed by keys which map to values. Therefore, a dictionary is an unordered set of key:value pairs where each key is unique. Please see the following example of dictionary creation and access:

```
import pandas as pd
student = pd.read_csv('/Users/class.csv')
for_dict = pd.concat([student["Name"], student["Age"]], axis = 1)
class_dict = for_dict.set_index('Name').T.to_dict('list')
print(class_dict.get('James'))

## [12]
```

---

float

A float is a decimal point number.

---

int

An int is a natural number. In Python, you can convert to an int from a float by using the int() function. Python stores ints with at least 32 bits of precision.

List

A list is a sequence of comma-separated objects that need not be of the same type. Please see the following example of list creation and access:

```
list1 = ['item1', 102]
print(list1)

## ['item1', 102]
```

```
print(list1[1])

## 102
```

Python also has what are known as "Tuples", which are immutable lists created in the same way as lists, except with paranthesis instead of brackets.

Long

A long is a type of integer with unlimited precision. In Python, you can convert to a long using the long() function.

NumPy

NumPy is a Python package which is useful for scientific and mathematical computing.

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pandas

pandas is a Python package which is useful for working with data structures and performing data analysis.

PyPlot

PyPlot is a Python package which is useful data plotting and visualization.

Seaborn

Seaborn is another Python package which is useful for data plotting and visualization. In particular, Seaborn includes tools for drawing attractive statistical graphics.

Series

A Pandas Series is a one-dimensional data frame, which is also called an array in R. Please see the following example of Series creation and access:

```
import pandas as pd
my_array = pd.Series([1, 3, 5, 9])
print(my_array)
```

```
## 0    1
## 1    3
## 2    5
## 3    9
## dtype: int64
```

```
print(my_array[1])
```

```
## 3
```

Sets & Frozen Sets

A set is a unordered collection of immutable objects. The difference between a set and a frozen set is that the former is mutable, while the latter is immutable. Please see the following example of set and frozen set creation and access:

```
s = set(["1", "2", "3"])
print(s)
# s is a set, which means you can add or delete elements from s
```

```
## {'3', '1', '2'}
```

```
fs = frozenset(["1", "2", "3"])
print(fs)
# fs is a frozenset, which means you cannot add or delete elements from fs
```

```
## frozenset({'2', '3', '1'})
```

---

sklearn

scikit-learn, or more commonly known as sklearn, is a Python package which is useful for basic and advanced data mining, machine learning, and data analysis. sklearn includes tools for classification, regression, clustering, dimensionality reduction, model selection, and data pre-processing.

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str

Strings are a list of characters, though characters are not a type in Python, but rather a string of length 1. Strings are indexable like arrays. Please see the following example of String creation and access:

```
s = 'My first string!'
print(s)
```

```
## My first string!
```

```
print(s[5])

## r
```

Please go here for more information on the str() function.

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sub

sub is a function of the re Python package useful for replacing a pattern in a string.

For more information on Python packages and functions, along with helpful examples, please see Python.