Machine Learning

We transfer expert Data Science knowledge to intelligent IT professionals, so they can apply Machine and Deep Learning in the enterprise without spending years in college and without over focusing on math

Learn ML fast

Learning Machine and Deep Learnign Fast

B

DESIRES: Competency in Data Science and Analytic Practices and the ability to apply ML in the enterprise

TOPIC

FORESIGHT (Predictive Analytics)

7 Finalize Your Model
Package and deploy your model
Dev model to a Deployed model

8 Data Science
Use Lime/Shap to define understand WHY your model make predictions
Predictions to Interpretable AI

9 Interactive Web App
Create a UI to present your model to a wider audience
Optimized AI to Usable AI

TRANSFORMATION
("FROM an ACCURATE ML model TO a production ready ML application"

TOPIC

INSIGHT (Model Building)

6 Improve Accuracy
Tune the hyperparameters to increase the accuracy of your model
Good models to Optimized AI

5 Evaluate Algorithms
Fit your data to several models and pick the best
3-5 Models to the BEST model

4 Split and Train
Split your data into train & test sets and FIT (or apply it to a ML model
Data + a Model to a FIT Model

TRANSFORMATION
("FROM a CLEAN dataset TO a model that makes accurate predictions")

TOPIC

HINDSIGHT (Exploratory Data Analysis)

1 Prepare the Problem
Get your data and setup your environment
IDEA to Dev Environment

2 Summarize Your Data
Apply Descriptive Stats to understand your data
Raw Data to an Understanding

3 Prepare Your Data
Wrangle your data to prepare it for ML algorithms
All Data to Clean Relevant Data

TRANSFORMATION
("FROM RAW data TO an Understanding of your problem and your dataset")

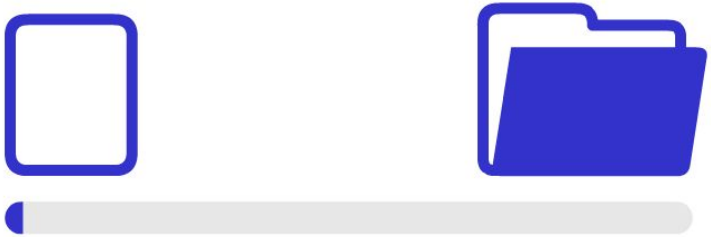
FRUSTRATIONS:
Little to know practical ML knowledge

A

Load Data

Considerations when loading Data

- File Header
- Comments
- Delimiters
- Quotes



Load CSV files with Pandas

```
from urllib.request import urlopen # Load CSV using Pandas

from pandas import read_csv

filename = 'pima-indians-diabetes.data.csv'

names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']

data = read_csv(filename, names=names)

print(data.shape)
```

Load CSV Files from a URL into Pandas

Let's do this!

```
# Load CSV using Pandas from URL

from pandas import read_csv

url = 'https://goo.gl/bDdBiA'

names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']

data = read_csv(url, names=names)

print(data.shape)
```

Understand Your Data with Descriptive Statistics

Understand Your Data with Statistics

1. Take a peek at your raw data.
2. Review the dimensions of your dataset.
3. Review the data types of attributes in your data.
4. Summarize the distribution of instances across classes in your dataset.
5. Summarize your data using descriptive statistics.
6. Understand the relationships in your data using correlations.
7. Review the skew of the distributions of each attribute.

Peek at Your Data

Let's do this!

```
# View first 20 rows
from pandas import read_csv
filename = "pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']
data = read_csv(filename, names=names)
peek = data.head(20)
print(peek)
```

Get the Dimensions of Your Data

Let's do this!

```
# Dimensions of your data
from pandas import read_csv
filename = "pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']
data = read_csv(filename, names=names)
shape = data.shape
print(shape)
```

Get the Data Type for Every Feature

Let's do this!

```
# Data Types for Each Attribute
from pandas import read_csv
filename = "pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']
data = read_csv(filename, names=names)
types = data.dtypes
print(types)
```

Descriptive Statistics

- Count.
- Mean.
- Standard Deviation.
- Minimum Value.
- 25th Percentile.
- 50th Percentile (Median).
- 75th Percentile.
- Maximum Value.

Statistical Summary

Let's do this!

```
from pandas import read_csv

from pandas import set_option

filename = "pima-indians-diabetes.data.csv"

names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']

data = read_csv(filename, names=names)

set_option('display.width', 100)

set_option('precision', 3)

description = data.describe()

print(description)
```

Class Distributions (Classification ONLY)

Let's do this!

```
# Class Distribution
from pandas import read_csv
filename = "pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']
data = read_csv(filename, names=names)
class_counts = data.groupby('class').size()
print(class_counts)
```

Correlations Between Attributes

Let's do this!

```
from pandas import read_csv
from pandas import set_option
filename = "pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi',
'age', 'class']
data = read_csv(filename, names=names)
set_option('display.width', 100)
set_option('precision', 3)
correlations = data.corr(method='pearson')
print(correlations)
```

Skew of Univariate Distributions

Let's do this!

```
# Skew for each attribute
from pandas import read_csv
filename = "pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']
data = read_csv(filename, names=names)
skew = data.skew()
print(skew)
```

Summary

- Peek At Your Data.
- Dimensions of Your Data.
- Data Types.
- Class Distribution.
- Data Summary.
- Correlations.
- Skewness.

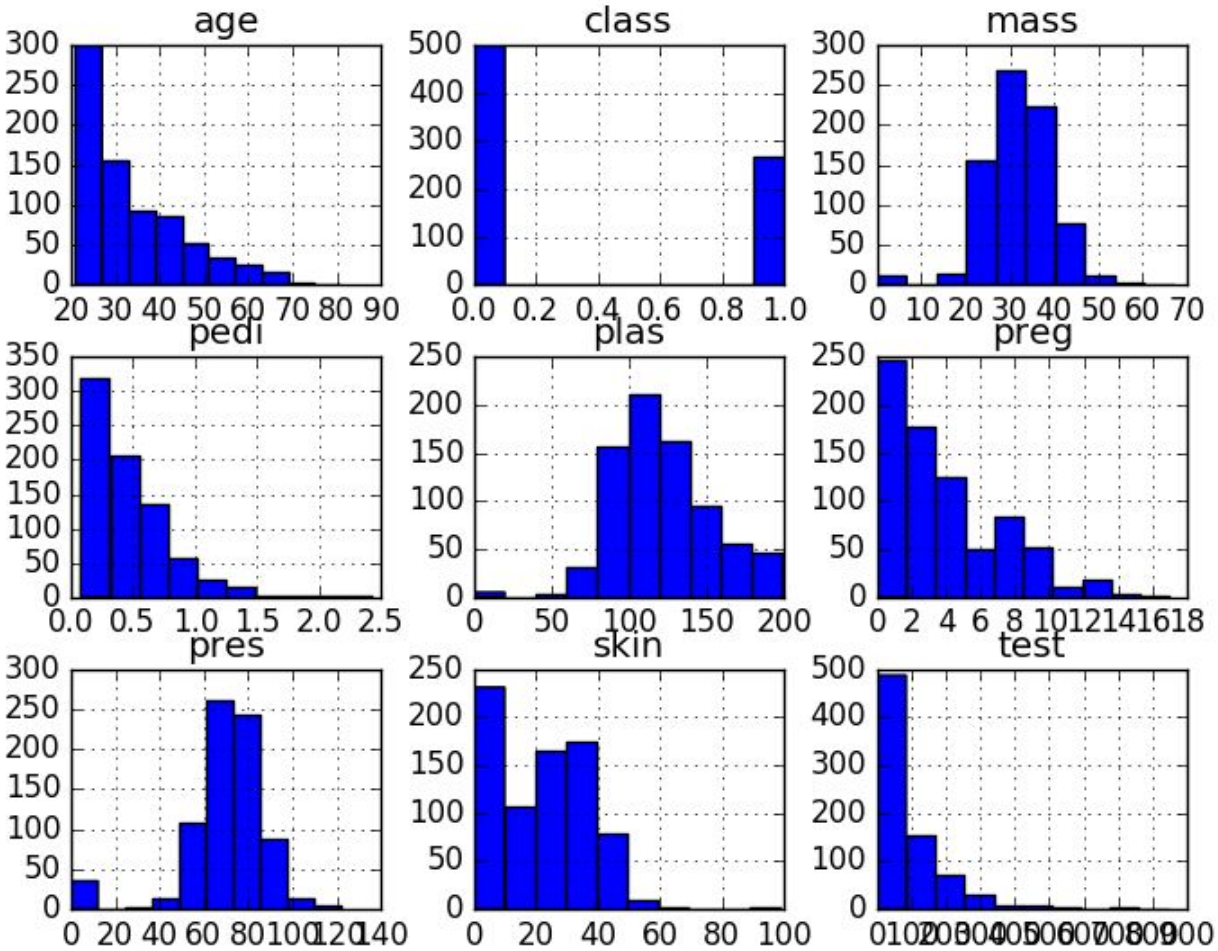
Visualize Your Data

Univariate Plots

- Histograms.
- Density Plots.
- Box and Whisker Plots.

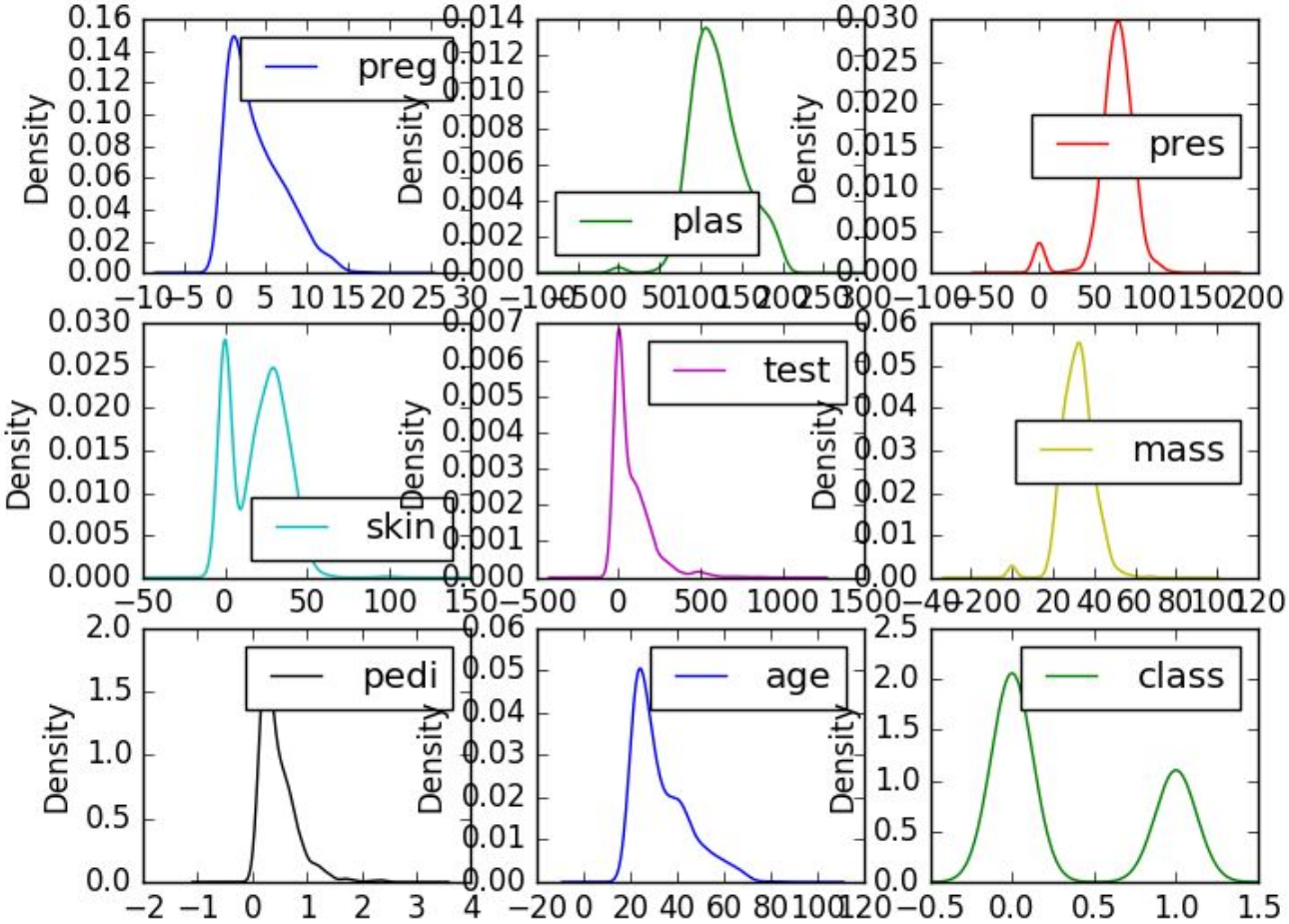
Univariate Histogram

```
from matplotlib import pyplot
from pandas import read_csv
filename = 'pima-indians-diabetes.data.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']
data = read_csv(filename, names=names)
data.hist()
pyplot.show()
```


age
class
mass
pedi
plas
preg
pres
skin
test

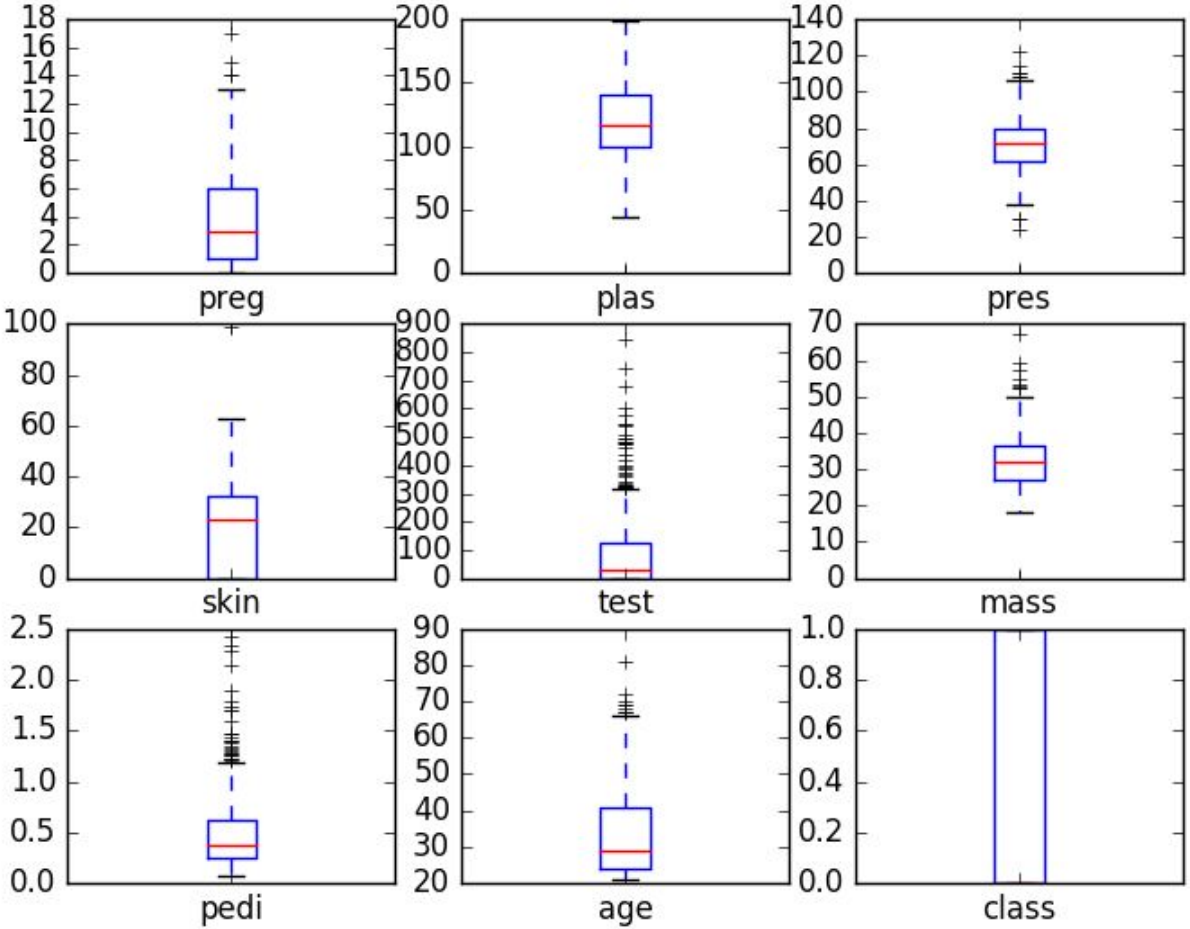
Univariate Density Plots

```
from matplotlib import pyplot

from pandas import read_csv

filename = 'pima-indians-diabetes.data.csv'

names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi',
'age', 'class']

data = read_csv(filename, names=names)

data.plot(kind='density', subplots=True, layout=(3,3),
sharex=False)

pyplot.show()
```


preg
plas
pres
skin
test
mass
pedi
age
class
Density

Box and Whisker Plots

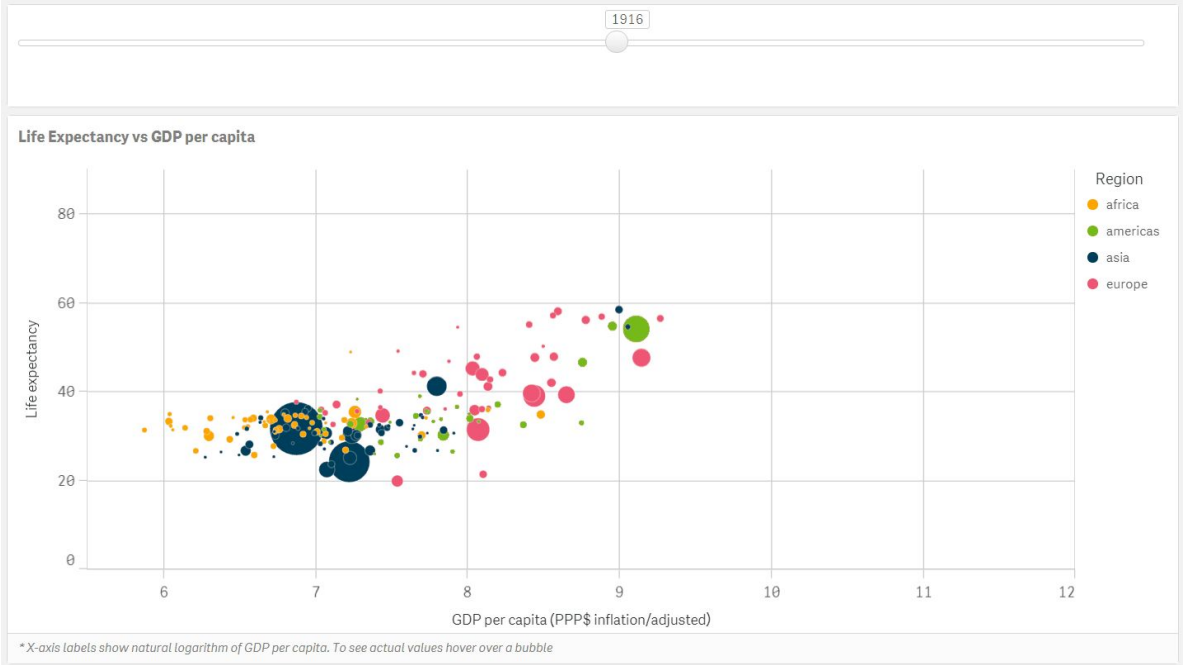
```
from matplotlib import pyplot

from pandas import read_csv

filename = "pima-indians-diabetes.data.csv"

names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi',
'age', 'class']

data = read_csv(filename, names=names)

data.plot(kind='box', subplots=True, layout=(3,3), sharex=False,
sharey=False)

pyplot.show()
```


preg
plas
pres
skin
test
mass
pedi
age
class

Multivariate Visualizations

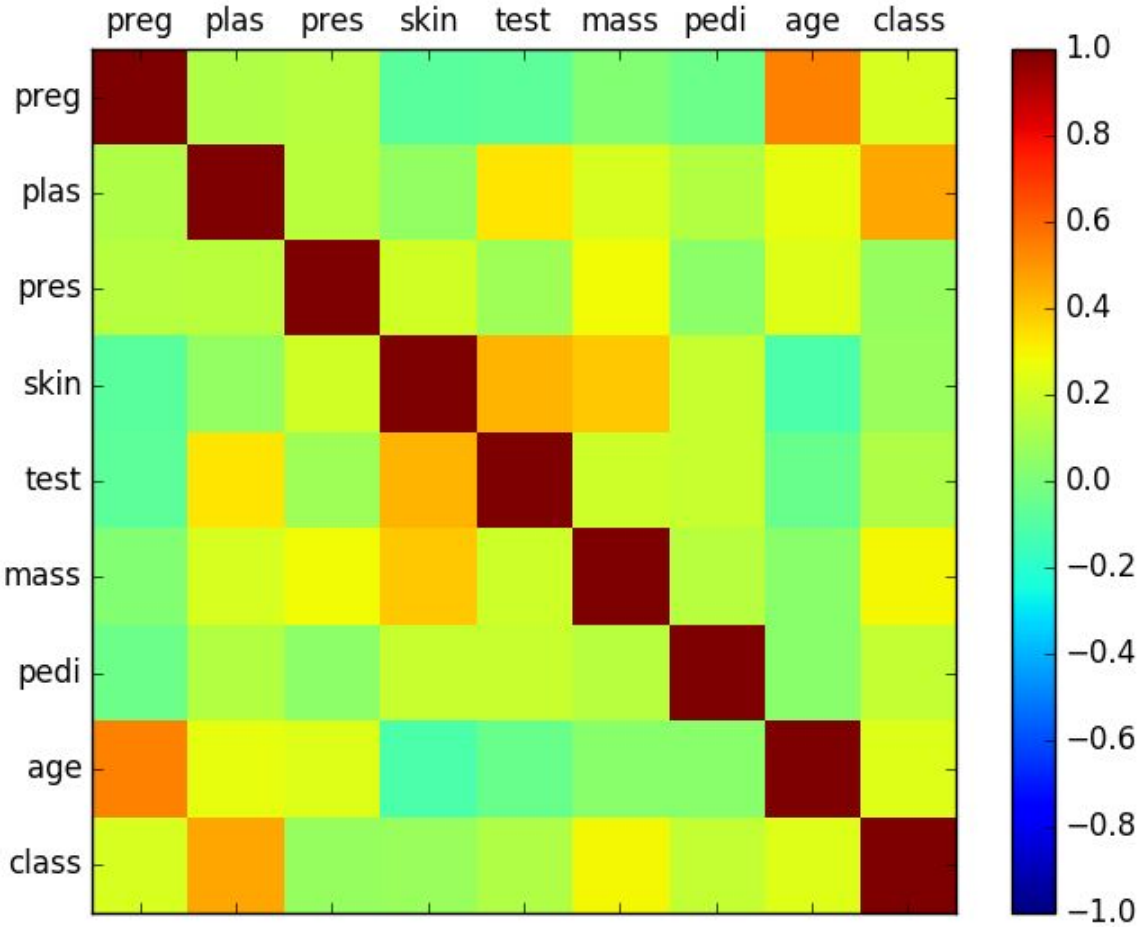
Multivariate Visualizations for ML

- Correlation Matrix Plot.
- Scatter Plot Matrix.



```
from matplotlib import pyplot
from pandas import read_csv
import numpy
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
data = read_csv('pima-indians-diabetes.csv', names=names)
correlations = data.corr()
fig = pyplot.figure()  # plot correlation matrix
ax = fig.add_subplot(111)
cax = ax.matshow(correlations, vmin=-1, vmax=1)
fig.colorbar(cax)
ticks = numpy.arange(0,9,1)
ax.set_xticks(ticks)
ax.set_yticks(ticks)
ax.set_xticklabels(names)
ax.set_yticklabels(names)
pyplot.show()
```

Correlation Matrix : https://bit.ly/jpmcML

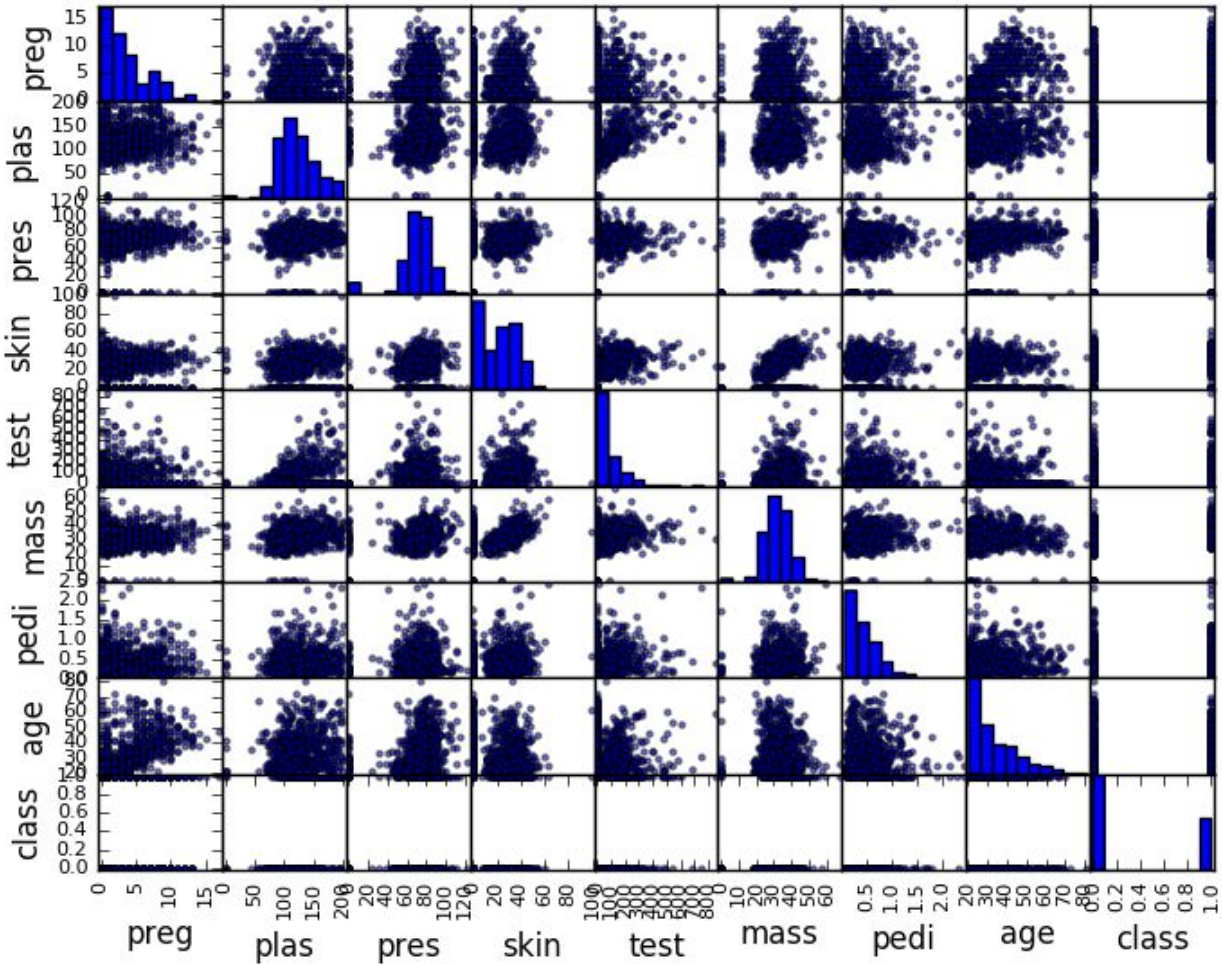

preg
plas
pres
skin
test
mass
pedi
age
class
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4
−0.6
−0.8
−1.0

Generic Correlation Matrix

```
from matplotlib import pyplot

from pandas import read_csv

filename = 'pima-indians-diabetes.data.csv'

names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age',
'class']

data = read_csv(filename, names=names)

correlations = data.corr()

fig = pyplot.figure() # plot correlation matrix

ax = fig.add_subplot(111)

cax = ax.matshow(correlations, vmin=-1, vmax=1)

fig.colorbar(cax)

pyplot.show()
```

Scatter Plot Matrix

```
from matplotlib import pyplot
from pandas import read_csv
from pandas.plotting import scatter_matrix
filename = "pima-indians-diabetes.data.csv"
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass',
'pedi', 'age', 'class']
data = read_csv(filename, names=names)
scatter_matrix(data)
pyplot.show()
```


preg
plas
pres
skin
test
mass
pedi
age
class

Summary

Prepare Your Data

Prepare Your Data

1. Rescale data.
2. Standardize data.
3. Normalize data.
4. Binarize data.

Data Transforms

- Load the dataset
- Split the dataset into the input and output variables for machine learning.
- Apply a pre-processing transform to the input variables.
- Summarize the data to show the change.

Scikit-learn offers two ways to transform data:

1. Fit and Multiple Transform.
2. Combined Fit-And-Transform.

Rescale Data (between 0 and 1)

Neural Networks

KNN

```
from pandas import read_csv
from numpy import set_printoptions
from sklearn.preprocessing import MinMaxScaler
filename = 'pima-indians-diabetes.data.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi',
'age', 'class']
dataframe = read_csv(filename, names=names)
array = dataframe.values
X = array[:,0:8] # separate array into input and output components
Y = array[:,8]
scaler = MinMaxScaler(feature_range=(0, 1))
rescaledX = scaler.fit_transform(X)
set_printoptions(precision=3) # summarize transformed data
print(rescaledX[0:5,:])
```

Standardize Your Data

Linear/Logistic Regression
LDA

```
from sklearn.preprocessing import StandardScaler

from pandas import read_csv

from numpy import set_printoptions

filename = 'pima-indians-diabetes.data.csv'

names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi',
'age', 'class']

dataframe = read_csv(filename, names=names)

array = dataframe.values

X = array[:,0:8]   # separate array into input and output components

Y = array[:,8]

scaler = StandardScaler().fit(X)

rescaledX = scaler.transform(X)

set_printoptions(precision=3)  # summarize transformed data

print(rescaledX[0:5,:])
```

Normalize Your Data KNN

```
from sklearn.preprocessing import Normalizer

from pandas import read_csv

from numpy import set_printoptions

filename = 'pima-indians-diabetes.data.csv'

names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi',
'age', 'class']

dataframe = read_csv(filename, names=names)

array = dataframe.values

X = array[:,0:8]  # separate array into input and output components

Y = array[:,8]

scaler = Normalizer().fit(X)

normalizedX = scaler.transform(X)

set_printoptions(precision=3)  # summarize transformed data

print(normalizedX[0:5,:])
```

Feature Selection

Feature Selection

1. Univariate Selection.
2. Recursive Feature Elimination.
3. Principle Component Analysis.
4. Feature Importance.

Why Feature Selection?

- Reduces Overfitting
- Improves Accuracy
- Reduces Training Time

Univariate Selection

See Lesson 8 Univariate Selection in github

```
# Feature Extraction with Univariate Statistical Tests (Chi-squared for classification)
from pandas import read_csv
from numpy import set_printoptions
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
# load data
filename = 'pima-indians-diabetes.data.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(filename, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
test = SelectKBest(score_func=chi2, k=4)
fit = test.fit(X, Y)
# summarize scores
set_printoptions(precision=3)
print(fit.scores_)
features = fit.transform(X)
# summarize selected features
print(features[0:5,:])
```

Recursive Feature Elimination

See Lesson 8 Recursive Feature Elimination in github

```
# Feature Extraction with RFE
from pandas import read_csv
from sklearn.feature_selection import RFE
from sklearn.linear_model import LogisticRegression
# load data
filename = 'pima-indians-diabetes.data.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(filename, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
model = LogisticRegression(solver='liblinear')
rfe = RFE(model, 3)
fit = rfe.fit(X, Y)
print("Num Features: %d" % fit.n_features_)
print("Selected Features: %s" % fit.support_)
print("Feature Ranking: %s" % fit.ranking_)
```

Principle Component Analysis

```
# Feature Extraction with PCA
from pandas import read_csv
from sklearn.decomposition import PCA
# load data
filename = 'pima-indians-diabetes.data.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(filename, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
pca = PCA(n_components=3)
fit = pca.fit(X)
# summarize components
print("Explained Variance: %s" % fit.explained_variance_ratio_)
print(fit.components_)
```

Feature Importance

```
# Feature Importance with Extra Trees Classifier
from pandas import read_csv
from sklearn.ensemble import ExtraTreesClassifier
# load data
filename = 'pima-indians-diabetes.data.csv'
names = ['preg', 'plas', 'pres', 'skin', 'test', 'mass', 'pedi', 'age', 'class']
dataframe = read_csv(filename, names=names)
array = dataframe.values
X = array[:,0:8]
Y = array[:,8]
# feature extraction
model = ExtraTreesClassifier(n_estimators=100)
model.fit(X, Y)
print(model.feature_importances_)
```

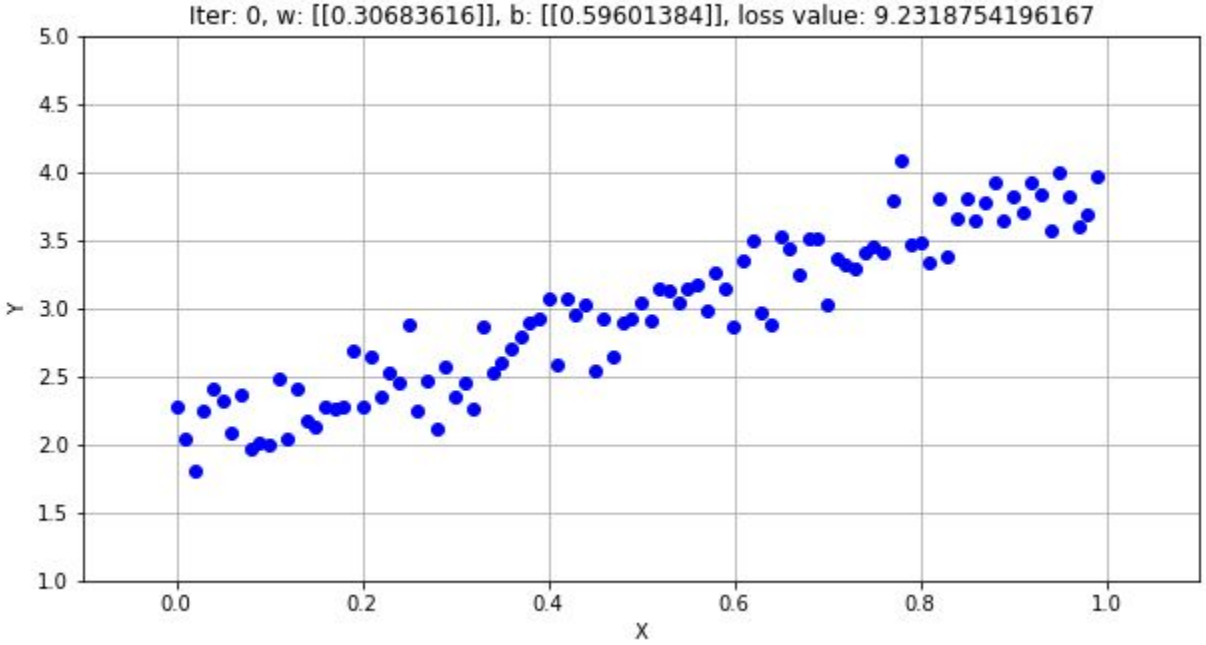
Linear Regression

Professor Ernesto Lee

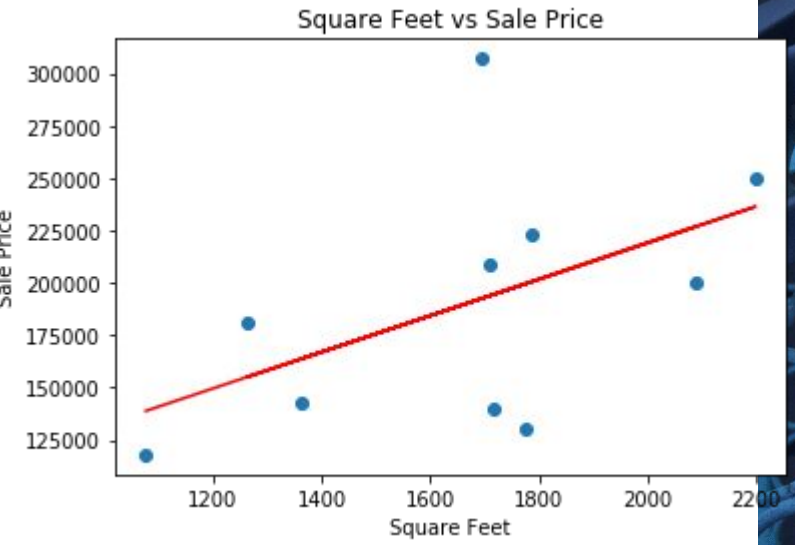
HTTPS://BIT.LY/MLTRAIN

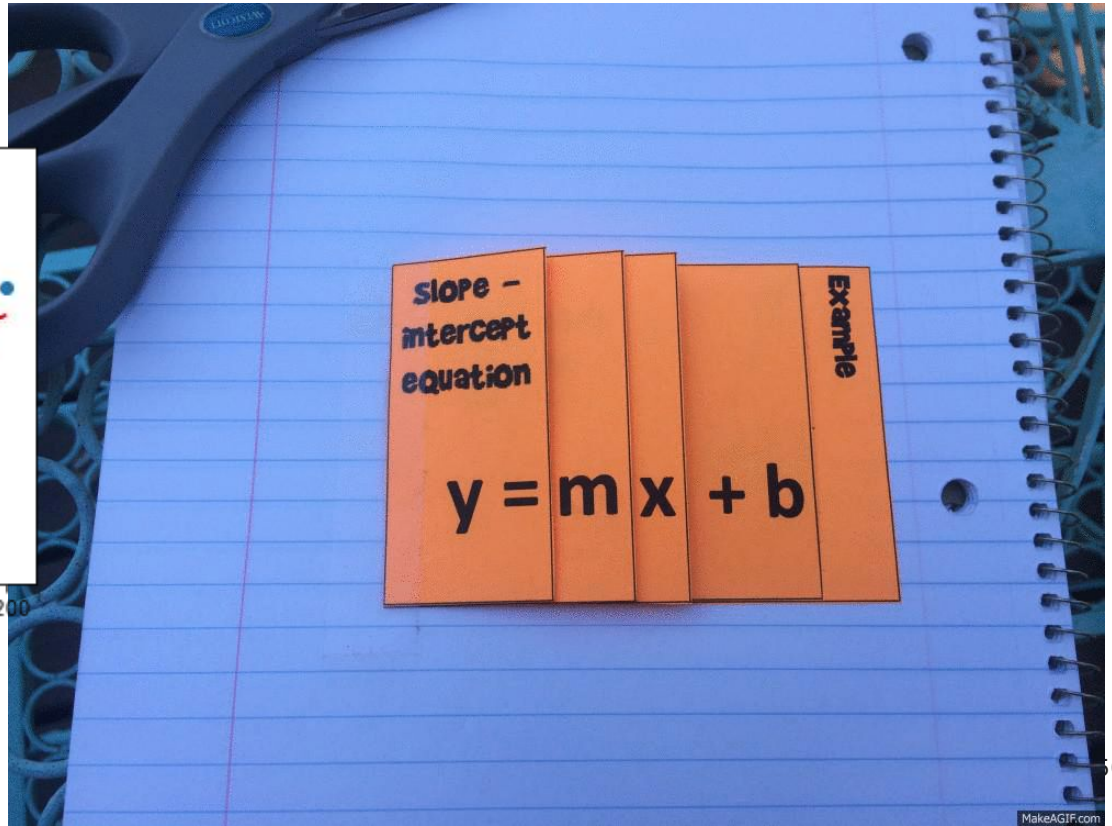
Go here for your LAB ENVIRONMENT

Linear Relationships



Regression Algorithm





Linear Regression with Scikit-Learn

Import Your Libraries

```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn import metrics
```

Pull in Your Data

You can access your data here:
https://bit.ly/21homes

Or here:

https://raw.githubusercontent.com/fenago/pythonml/main/data/HousePrice.csv

---

```
df = pd.read_csv('https://raw.githubusercontent.com/fenago/pythonml/main/data/HousePrice.csv')
```

Putting the Columns You Want In Your Data

```
df2 = df[["open", "close"]] #open and close are the
columns
```

Make sure you have the columns you want and need!

Understand Your Data with SHAPE

df.shape

```
df.shape
```

```
(1460, 2)
```

Understand Your Data: head

df.head()

```
df.head()
```

	SquareFeet	SalePrice
0	1710	208500
1	1262	181500
2	1786	223500
3	1717	140000
4	2198	250000

Understand Your Data: Descriptive Statistics

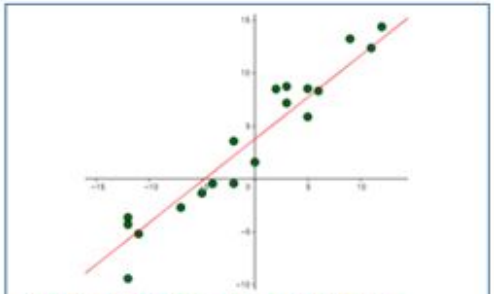
```
df.describe()
```

```
[8] df.describe()
```

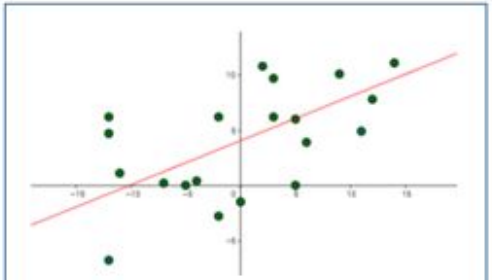
	SquareFeet	SalePrice
count	1460.000000	1460.000000
mean	1515.463699	180921.195890
std	525.480383	79442.502883
min	334.000000	34900.000000
25%	1129.500000	129975.000000
50%	1464.000000	163000.000000
75%	1776.750000	214000.000000
max	5642.000000	755000.000000

Find Your Correlations In your Datasets

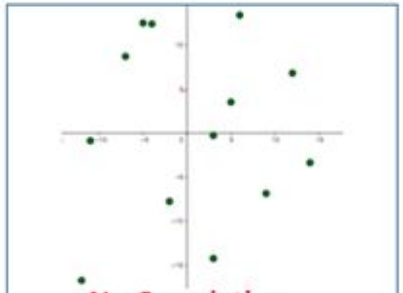
```
# correlation between 2 Specific Columns
print(df['SquareFeet'].corr(df['SalesPrice']))


# pair-wise correlation between all columns

print(df.corr())
```



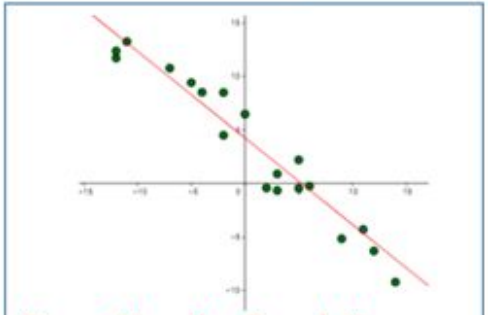
Strong Positive Correlation



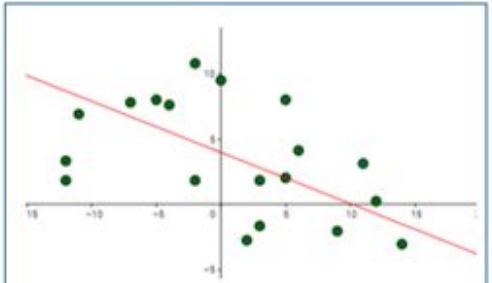
Weak Positive Correlation



No Correlation



Strong Negative Correlation



Weak Negative Correlation

HeatMap

```
# Correlation between different variables
corr = df.corr()
# Set up the matplotlib plot configuration
f, ax = plt.subplots(figsize=(12, 10))
# Generate a mask for upper traingle
mask = np.triu(np.ones_like(corr, dtype=bool))
# Configure a custom diverging colormap
cmap = sns.diverging_palette(230, 20, as_cmap=True)
# Draw the heatmap
sns.heatmap(corr, annot=True, mask = mask, cmap=cmap)
```

Visualize Your Data: PLOT

```
df.plot(x='SquareFeet', y='SalePrice', style='*')
plt.title('Square Feet vs Sale Price')
plt.xlabel('Square Feet')
plt.ylabel('Sale Price')
plt.show()
```

Prepare Your Data: Split Into Training and Test Sets

```
X = df.iloc[:, :-1].values

y = df.iloc[:, 1].values
```

Train Test Split

```
X_train, X_test, y_train, y_test = train_test_split(X,
y, test_size=0.2, random_state=0)
```

Run the Model

```
def get_cv_scores(model):
    scores = cross_val_score(model, X_train, y_train, cv=10, scoring='r2')

    print('CV Mean: ', np.mean(scores))
    print('STD: ', np.std(scores))
    print('\n')

lr = LinearRegression().fit(X_train, y_train)
get_cv_scores(lr)
```

View the Coefficients

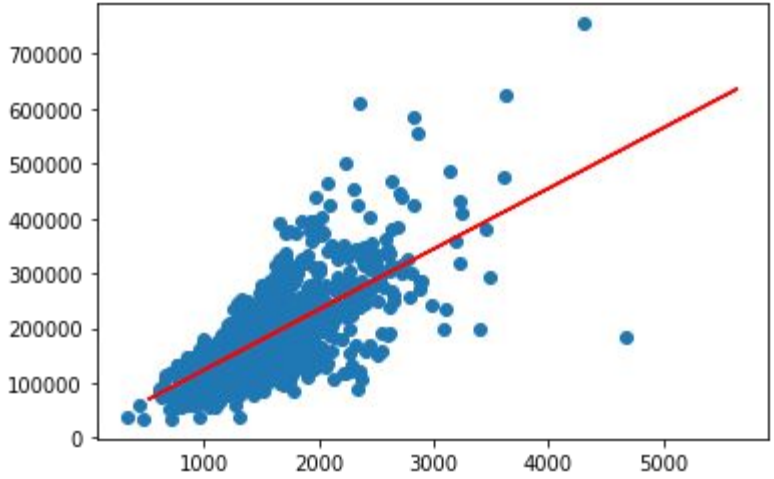
```
print(lr.intercept_)

print(lr.coef_)
```

```
print(lr.intercept_)
print(lr.coef_)
```

```
13330.293444921088
[110.26434426]
```

Predictions

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




```
plt.scatter(X_train, y_train)
plt.plot(X_test, y_pred, color='red')
plt.show()
```

Predict with NEW unseen DATA

```
lr.predict([[2515]])
```

Evaluate Predicted Values from Actuals

```
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})

df.head()
```

```
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})
df.head()
```

	Actual	Predicted
0	200624	290645.119259
1	133000	187327.428687
2	110000	145978.299590
3	192000	236284.797539
4	88000	133738.957377

R-Squared (R2)

```
df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})

df.head()
```

```
print('R-Squared:',metrics.r2_score(df['Actual'],df['Predicted']))
```

Summary Definition

Define R-Squared: Coefficient of determination means a statistical measurement of the correlation between two variables.

https://scikit-learn.org/stable/modules/generated/sklearn.metrics.r2_score.html

Evaluate Your Model

```
print('Mean Absolute Error:',
metrics.mean_absolute_error(y_test, y_pred))

print('Mean Squared Error:',
metrics.mean_squared_error(y_test, y_pred))

print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
```

```
Mean Absolute Error: 39364.76724953735
Mean Squared Error: 3913788296.4027987
Root Mean Squared Error: 62560.277304394986
```

https://scikit-learn.org/

https://github.com/scikit-learn/scikit-learn

Tuning Hyperparameters with Simple Linear Regression

https://bit.ly/ucidata

Hint: To create a new dataframe with selected columns - do this:

```
df2 = df[["open", "close"]] #open and close are the colomns
```

Lab 1

Read in this DATA:

```
pd.read_csv('https://raw.githubusercontent.com/fenago/pythonml/main/data/poverty.txt',sep="\t")
```

Apply what you have learned to create Simple Linear Models.

This dataset of size $n = 51$ are for the 50 states and the District of Columbia in the United States (poverty.txt). The variables are y = year 2002 birth rate per 1000 females 15 to 17 years old and x = poverty rate, which is the percent of the state's population living in households with incomes below the federally defined poverty level. (Data source: *Mind On Statistics*, 3rd edition, Utts and Heckard).

Lab 2

Read in this DATA:

```
pd.read_csv('https://raw.githubusercontent.com/fenago/pythonml/main/data/lungfunction.txt',sep="\t")
```

Apply what you have learned to create Simple Linear Models.

This dataset of size $n = 51$ are for the 50 states and the District of Columbia in the United States (poverty.txt). The variables are y = year 2002 birth rate per 1000 females 15 to 17 years old and x = poverty rate, which is the percent of the state's population living in households with incomes below the federally defined poverty level. (Data source: *Mind On Statistics*, 3rd edition, Utts and Heckard).

Multivariate Linear Regression

Our Dataset

Data Dictionary:

http://people.sc.fsu.edu/~jburkardt/datasets/regression/x16.txt

Dataset:

pd.read_csv("https://raw.githubusercontent.com/fenago/pythonml/main/data/petrol_consumption.csv")

Load the Libraries

```
import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

%matplotlib inline
```

Load the Data

```
df =
pd.read_csv("https://raw.githubusercontent.com/fenago/python
ml/main/data/petrol_consumption.csv")

df.head()

df.describe()
```

Find Your Correlations In your Datasets

```
# correlation between 2 Specific Columns
print(df['Petrol_tax'].corr(df['Petrol_Consumption']))


# pair-wise correlation between all columns

print(df.corr())
```

Prepare the Data

```
X = dataset[['Petrol_tax', 'Average_income',
'Paved_Highways','Population_Driver_licence(%)']]

y = dataset['Petrol_Consumption']


#Execute below to divide into train/test sets

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=0)
```

Train the Algorithm as Before

```
from sklearn.linear_model import LinearRegression

regressor = LinearRegression()

regressor.fit(X_train, y_train)
```

What Coefficients Did it Find?

```
coeff_df = pd.DataFrame(regressor.coef_, X.columns,
columns=['Coefficient'])
```

```
coeff_df
```

	Coefficient
Petrol_tax	-24.196784
Average_income	-0.81680
Paved_Highways	-0.000522
Population_Driver_license(%)	1324.675464

Predictions

```
y_pred = regressor.predict(X_test)

df = pd.DataFrame({'Actual': y_test, 'Predicted': y_pred})

df
```

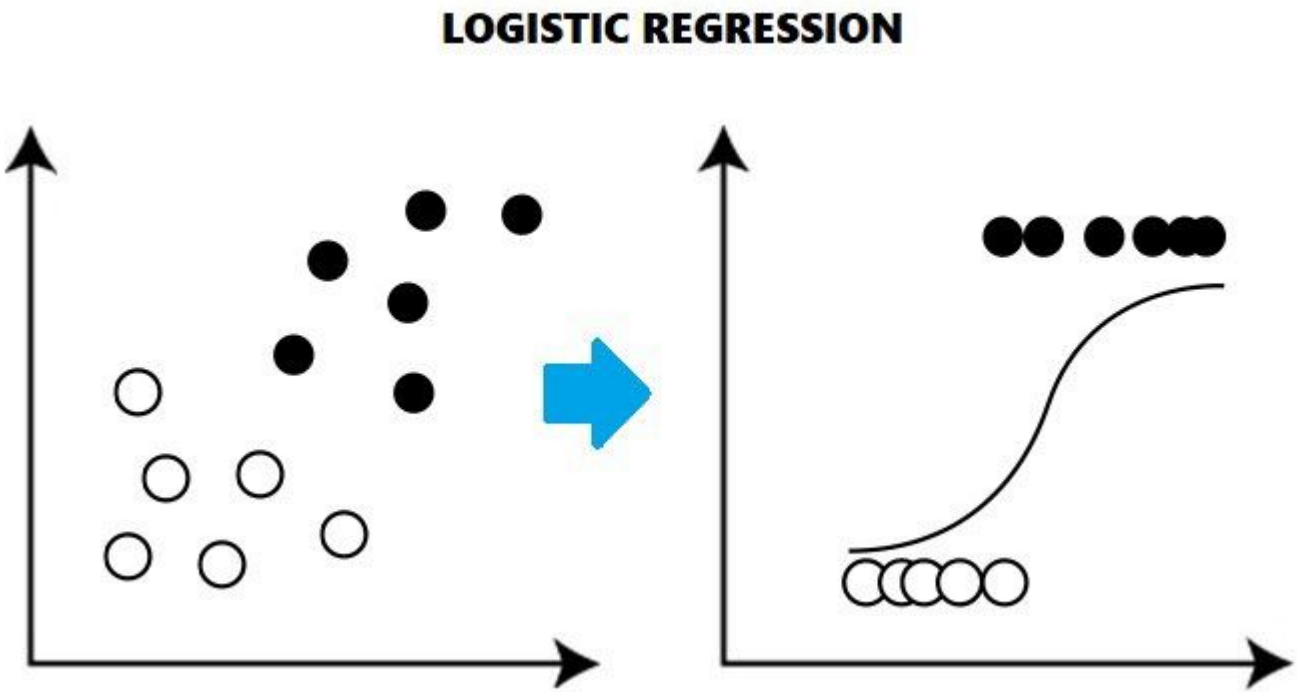
	Actual	Predicted
36	640	643.176639
22	464	411.950913
20	649	683.712762
38	648	728.049522
18	865	755.473801

Evaluate the Algorithm

```
from sklearn import metrics

print('Mean Absolute Error:',
metrics.mean_absolute_error(y_test, y_pred))

print('Mean Squared Error:',
metrics.mean_squared_error(y_test, y_pred))

print('Root Mean Squared Error:',
np.sqrt(metrics.mean_squared_error(y_test, y_pred)))

print('R-Squared:',metrics.r2_score(df['Actual'],
df['Predicted']))
```

Logistic Regression

Logistic Regression

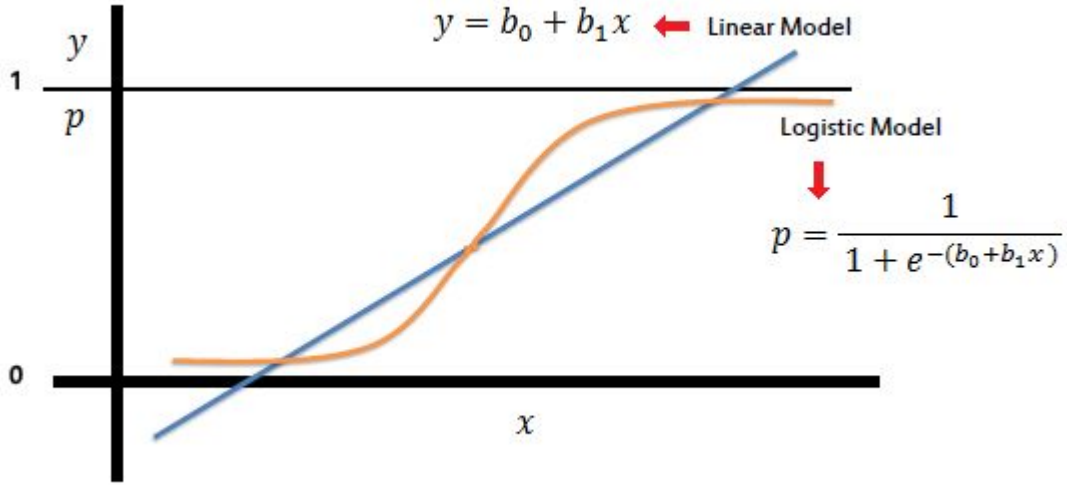


Logistic Regression

when b0+b1X == 0, then the p will be 0.5,

similarly,b0+b1X > 0, then the p will be going towards 1 and

b0+b1X < 0, then the p will be going towards 0.

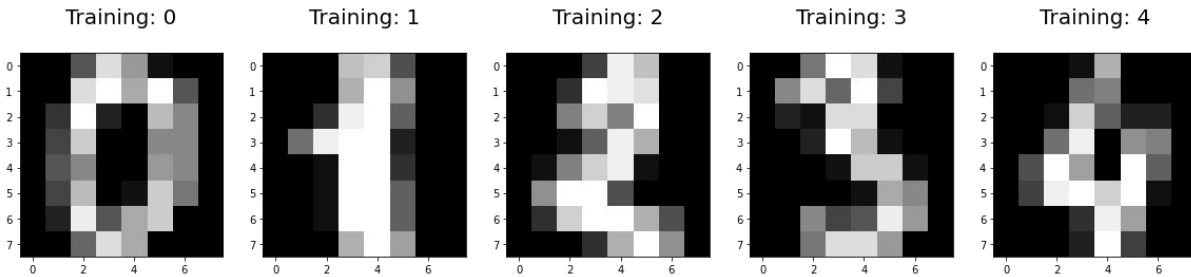


Loading the Data

```
from sklearn.datasets import load_digits

digits = load_digits()
```

Showing the Images and Labels

```
import numpy as np

import matplotlib.pyplot as plt


plt.figure(figsize=(20,4))


for index, (image, label) in enumerate(zip(digits.data[0:5], digits.target[0:5])):

  plt.subplot(1, 5, index + 1)

  plt.imshow(np.reshape(image, (8,8)), cmap=plt.cm.gray)

  plt.title('Training: %i\n' % label, fontsize = 20)
```



Split the Data into Training and Test Sets

```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test =
train_test_split(digits.data, digits.target, test_size=0.25,
random_state=0)
```

Modeling

```
from sklearn.linear_model import LogisticRegression

logisticRegr = LogisticRegression()

logisticRegr.fit(x_train, y_train)
```

```
#predict for one image
logisticRegr.predict(x_test[0].reshape(1,-1))

#predict for multiple images
logisticRegr.predict(x_test[0:10])

#for the entire dataset
predictions = logisticRegr.predict(x_test)
```

```
[14] #predict for one image
     logisticRegr.predict(x_test[0].reshape(1,-1))
```

```
array([2])
```

```
[15] #predict for multiple images
     logisticRegr.predict(x_test[0:10])
```

```
array([2, 8, 2, 6, 6, 7, 1, 9, 8, 5])
```

```
[16] #for the entire dataset
     predictions = logisticRegr.predict(x_test)
```

```
[17] predictions
```

```
array([2, 8, 2, 6, 6, 7, 1, 9, 8, 5, 2, 8, 6, 6, 6, 6, 1, 0, 5, 8, 8, 7,
       8, 4, 7, 5, 4, 9, 2, 9, 4, 7, 6, 8, 9, 4, 3, 1, 0, 1, 8, 6, 7, 7,
       1, 0, 7, 6, 2, 1, 9, 6, 7, 9, 0, 0, 9, 1, 6, 3, 0, 2, 3, 4, 1, 9,
       2, 6, 9, 1, 8, 3, 5, 1, 2, 8, 2, 2, 9, 7, 2, 3, 6, 0, 5, 3, 7, 5,
       1, 2, 9, 9, 3, 1, 4, 7, 4, 8, 5, 8, 5, 5, 2, 5, 9, 0, 7, 1, 4, 7,
       3, 4, 8, 9, 7, 9, 8, 2, 1, 5, 2, 5, 8, 4, 1, 7, 0, 6, 1, 5, 5, 9,
       9, 5, 9, 9, 5, 7, 5, 6, 2, 8, 6, 9, 6, 1, 5, 1, 5, 9, 9, 1, 5, 3,
       6, 1, 8, 9, 8, 7, 6, 7, 6, 5, 6, 0, 8, 8, 9, 9, 6, 1, 0, 4, 1, 6,
       3, 8, 6, 7, 4, 9, 6, 3, 0, 3, 3, 3, 0, 7, 7, 5, 7, 8, 0, 7, 1, 9,
       6, 4, 5, 0, 1, 4, 6, 4, 3, 3, 0, 9, 5, 9, 2, 8, 4, 2, 1, 6, 8, 9,
       2, 4, 9, 3, 7, 6, 2, 3, 3, 1, 6, 9, 3, 6, 3, 3, 2, 0, 7, 6, 1, 1,
       9, 7, 2, 7, 8, 5, 5, 7, 5, 3, 3, 7, 2, 7, 5, 5, 7, 0, 9, 1, 6, 5,
       9, 7, 4, 3, 8, 0, 3, 6, 4, 6, 3, 2, 6, 8, 8, 8, 4, 6, 7, 5, 2, 4,
       5, 3, 2, 4, 6, 9, 4, 5, 4, 3, 4, 6, 2, 9, 0, 1, 7, 2, 0, 9, 6, 0,
       4, 2, 0, 7, 9, 8, 5, 7, 8, 2, 8, 4, 3, 7, 2, 6, 9, 9, 5, 1, 0, 8,
       2, 8, 9, 5, 6, 2, 2, 7, 2, 1, 5, 1, 6, 4, 5, 0, 9, 4, 1, 1, 7, 0,
       8, 9, 0, 5, 4, 3, 8, 8, 6, 5, 3, 4, 4, 4, 8, 8, 7, 0, 9, 6, 3, 5,
       2, 3, 0, 8, 8, 3, 1, 3, 3, 0, 0, 4, 6, 0, 7, 7, 6, 2, 0, 4, 4, 2,
       3, 7, 1, 9, 8, 6, 8, 5, 6, 2, 2, 3, 1, 7, 7, 8, 0, 3, 3, 1, 1, 5,
       5, 9, 1, 3, 7, 0, 0, 3, 0, 4, 5, 8, 9, 3, 4, 3, 1, 8, 9, 8, 3, 6,
       3, 1, 6, 2, 1, 7, 5, 5, 1, 9])
```

Evaluation

```
#Accuracy = correct predictions / total number of data points

#Use score method to get accuracy of model

score = logisticRegr.score(x_test, y_test)

print(score)
```

```
[18] #Use score method to get accuracy of model
     score = logisticRegr.score(x_test, y_test)
     print(score)

     0.9511111111111111
```

Confusion Matrix

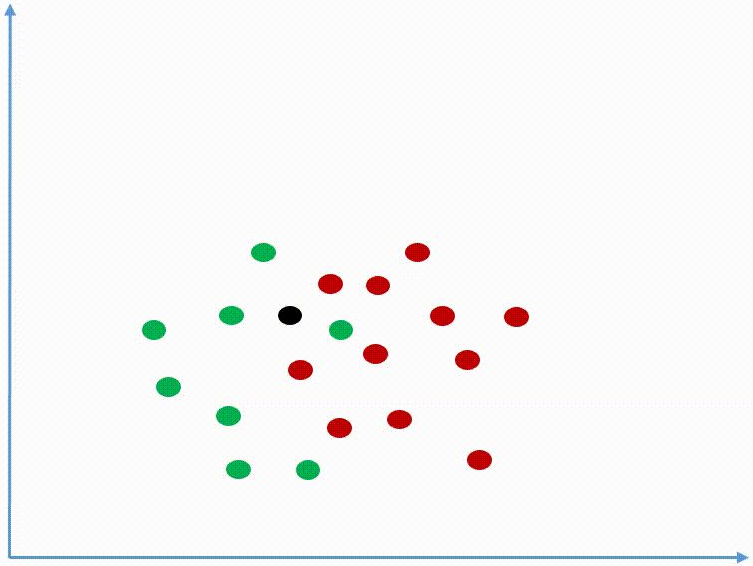
```
from sklearn import metrics


cm = metrics.confusion_matrix(y_test, predictions)

print(cm)
```

```
[19] from sklearn import metrics

     cm = metrics.confusion_matrix(y_test, predictions)
     print(cm)

     [[37  0  0  0  0  0  0  0  0  0]
      [ 0 40  0  0  0  0  0  0  2  1]
      [ 0  1 40  3  0  0  0  0  0  0]
      [ 0  0  0 43  0  0  0  0  1  1]
      [ 0  0  0  0 37  0  0  1  0  0]
      [ 0  0  0  0  0 46  0  0  0  2]
      [ 0  1  0  0  0  0 51  0  0  0]
      [ 0  0  0  1  1  0  0 46  0  0]
      [ 0  3  1  0  0  0  0  0 43  1]
      [ 0  0  0  0  0  1  0  0  1 45]]
```

KNN

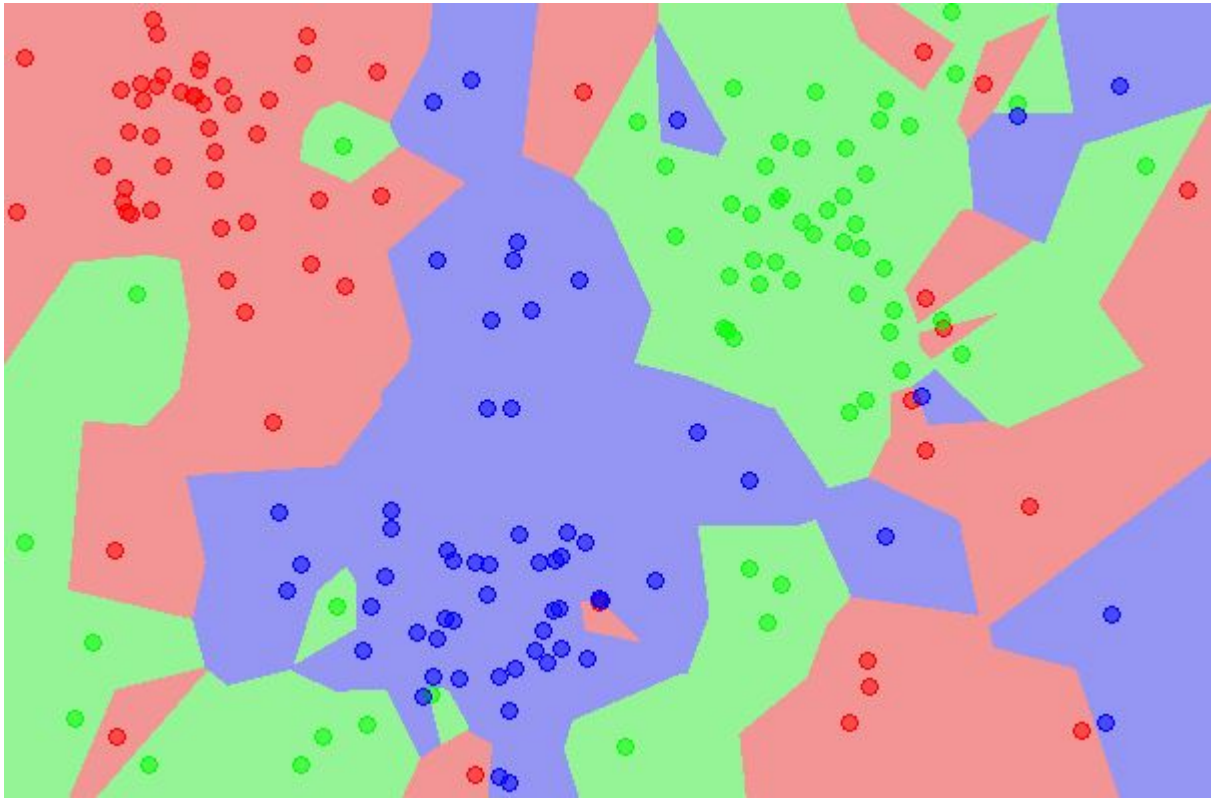
KNN

Choice of value of K



machinelearningknowledge.ai

How Does KNN Work?

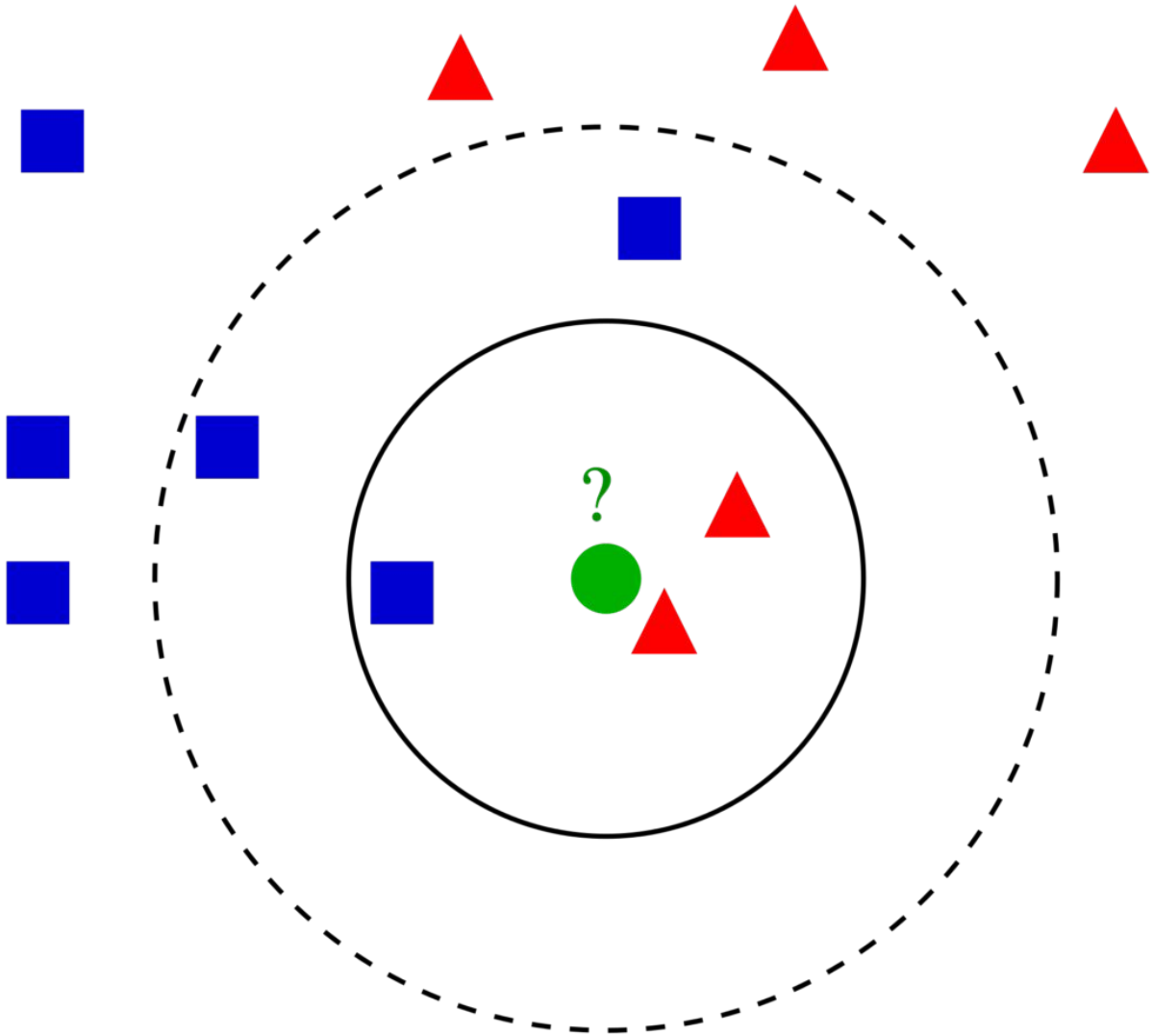


Distance in KNN

$$d(\mathbf{p}, \mathbf{q}) = d(\mathbf{q}, \mathbf{p}) = \sqrt{(q_1 - p_1)^2 + (q_2 - p_2)^2 + \cdots + (q_n - p_n)^2}$$

$$= \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}.$$

Nearest?



Steps to Solve a KNN Problem

1. Load and store the data.
2. Calculate the distance from x (new data point) to all other data points.
3. Sort all the distances from your data in ascending order.
4. Initialize the K value for the nearest data points.
5. Make a prediction based on the majority of data points with the same label within the K value.
6. Evaluate your machine learning model.

The Use Case...

we want to create a machine model that will allow botanists to classify different species of iris flowers.

Let's Build The Model

Imports

```
import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

%matplotlib
```

Data Preparation

```
from sklearn.datasets import load_iris

iris_dataset = load_iris()

print("Keys of iris_dataset:\n", iris_dataset.keys())
```

OUTPUT

```
Keys of iris_dataset:

 dict_keys(['data', 'target', 'target_names', 'DESCR',
'feature_names', 'filename'])
```

Data Type

```
print("Data Type:", type(iris_dataset['data']))
```

OUTPUT:

```
Data Type: <class 'numpy.ndarray'>
```

Shape

```
print("Shape of Data:", iris_dataset['data'].shape)
```

Features

```
print("First 10 Samples and Their Features:\n",
iris_dataset['data'][:10])
```

Target

```
print("Type of Target:", type(iris_dataset['target']))
print("Shape of Target:", iris_dataset['target'].shape)
print(iris_dataset['target'])
```

Target Names

```
print("Target names:", iris_dataset['target_names'])
```

Description

```
print(iris_dataset['DESCR'])
```

OR

```
print(iris_dataset['DESCR'][:500] + "\n...")
```

Feature Names

```
print("Feature Names:", iris_dataset['feature_names'])
```

Training and Testing Data

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(

    iris_dataset['data'], iris_dataset['target'],
random_state=0)
```

Validate the Shape of the Data and Test the Dataset

```
print("X_train Shape:", X_train.shape)
print("y_train Shape:", y_train.shape)

print("X_test Shape:", X_test.shape)
print("y_test Shape:", y_test.shape)
```

Visualize Your Data

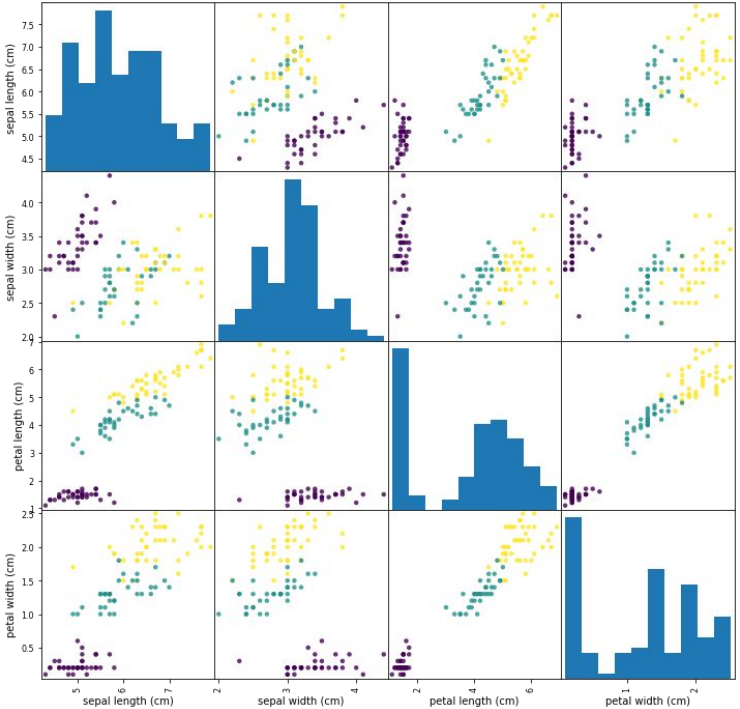
Create the DF for Visualizing

```
df = pd.DataFrame(X_train,
columns=iris_dataset.feature_names)

df.head()
```

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)
0	5.9	3.0	4.2	1.5
1	5.8	2.6	4.0	1.2
2	6.8	3.0	5.5	2.1
3	4.7	3.2	1.3	0.2
4	6.9	3.1	5.1	2.3

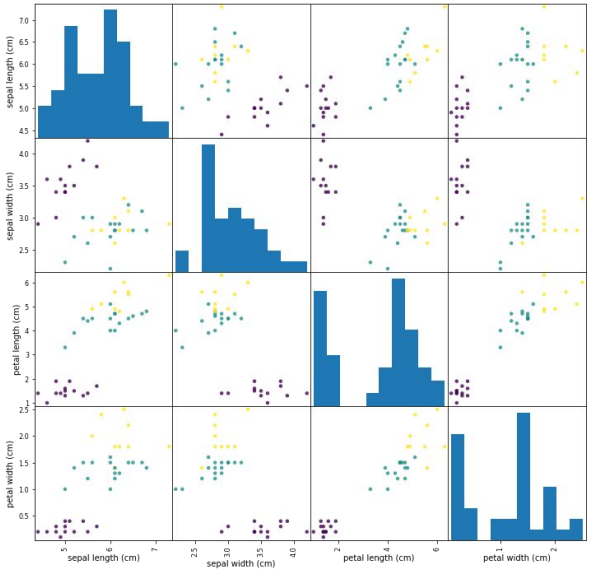
Show the Visualization

```
pd.plotting.scatter_matrix(df,c=y_train,figsize=(12,12),
marker='o',s=20,alpha=.8)

plt.show()
```



Do the same with X

```
df = pd.DataFrame(X_test,
columns=iris_dataset.feature_names)

pd.plotting.scatter_matrix(df,c=y_test,figsize=(12,12),
marker='o',s=20,alpha=.8)

plt.show()
```



Create the Model

```
from sklearn.neighbors import KNeighborsClassifier
knnObject = KNeighborsClassifier(n_neighbors=1)
knnObject.fit(X_train, y_train)
```

Making Predictions

Predictions on New Data

Imagine you are a machine learning engineer for a company. A client of yours reached out to you to verify an iris species they found in the wild. They only gave us the following information:

- Sepal length: 40 cm
- Sepal width: 10 cm
- Petal length: 5 cm
- Petal width: 2 cm

```
newIris = np.array([[40, 10, 5, 2]])

print("newIris Shape:", newIris.shape)
```

Predict

```
prediction = knnObject.predict(newIris)
print("Prediction Value:", prediction)
print("Predicted Target Name:",
       iris_dataset['target_names'][prediction])
```

Model Evaluation

See Your Test Predictions

```
testSetPredictions = knnObject.predict(X_test)

print("Test Set Predictions:", testSetPredictions)
```

Check for Accuracy

```
accuaracy = round(knnObject.score(X_test, y_test),2)

print("The Test Set Accuracy is:",accuracy)
```

Breast Cancer Use Case - KNN

Initialize the Libraries

```
import pandas as pd
 import numpy as np
 import seaborn as sns
 import matplotlib.pyplot as plt
```

Import the Data Set

It is in the data folder and named dataR2.csv

```
data=pd.read_csv("./data/dataR2.csv")
```

Understand Your Data

```
data.shape
```

	Age	BMI	Glucose	Insulin	HOMA	Leptin	Adiponectin	Resistin	MCP.1	Classification
0	48	23.500000	70	2.707	0.467409	8.8071	9.702400	7.99585	417.114	1
1	83	20.690495	92	3.115	0.706897	8.8438	5.429285	4.06405	468.786	1
2	82	23.124670	91	4.498	1.009651	17.9393	22.432040	9.27715	554.697	1
3	68	21.367521	77	3.226	0.612725	9.8827	7.169560	12.76600	928.220	1
4	86	21.111111	92	3.549	0.805386	6.6994	4.819240	10.57635	773.920	1
...	...	...	...	...	...	...	...	...	...	...
111	45	26.850000	92	3.330	0.755688	54.6800	12.100000	10.96000	268.230	2
112	62	26.840000	100	4.530	1.117400	12.4500	21.420000	7.32000	330.160	2
113	65	32.050000	97	5.730	1.370998	61.4800	22.540000	10.33000	314.050	2
114	72	25.590000	82	2.820	0.570392	24.9600	33.750000	3.27000	392.460	2
115	86	27.180000	138	19.910	6.777364	90.2800	14.110000	4.35000	90.090	2

116 rows × 10 columns

Find Missing Values

```
data.isna().sum()
```

```
Age                 0
BMI                 0
Glucose             0
Insulin             0
HOMA                0
Leptin              0
Adiponectin         0
Resistin            0
MCP.1               0
Classification      0
dtype: int64
```

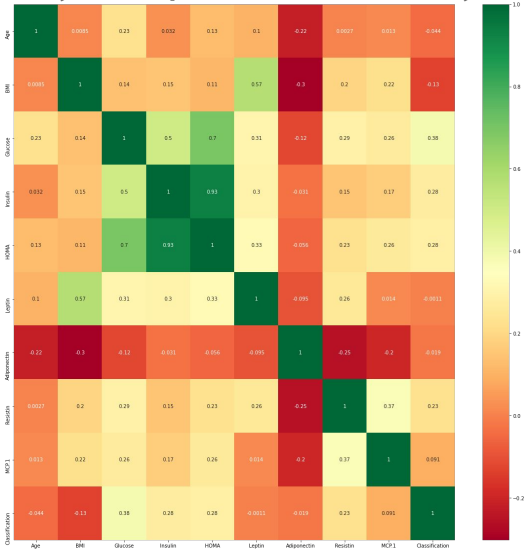
Exploratory Data Analysis

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 116 entries, 0 to 115
Data columns (total 10 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   Age             116 non-null    int64
 1   BMI             116 non-null    float64
 2   Glucose         116 non-null    int64
 3   Insulin         116 non-null    float64
 4   HOMA            116 non-null    float64
 5   Leptin          116 non-null    float64
 6   Adiponectin     116 non-null    float64
 7   Resistin        116 non-null    float64
 8   MCP.1           116 non-null    float64
 9   Classification  116 non-null    int64
dtypes: float64(7), int64(3)
memory usage: 9.2 KB
```

Heatmaps and Correlation

```
#Heatmap to find correlation

plt.subplots(figsize=(20,20))

sns.heatmap(data.corr(),cmap='RdYlGn',annot=True)
```



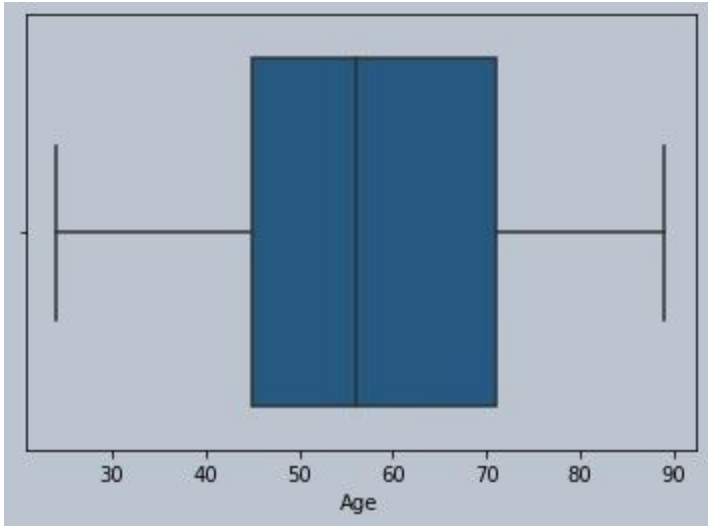
Columns

```
data.columns
```

KNN is Sensitive to Outliers

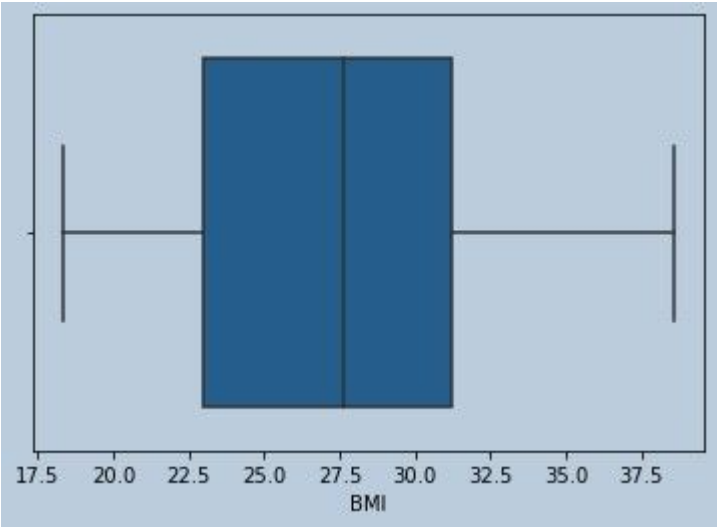
Outliers for Age?

```
#No outliers for age
 sns.boxplot(data['Age'])
```



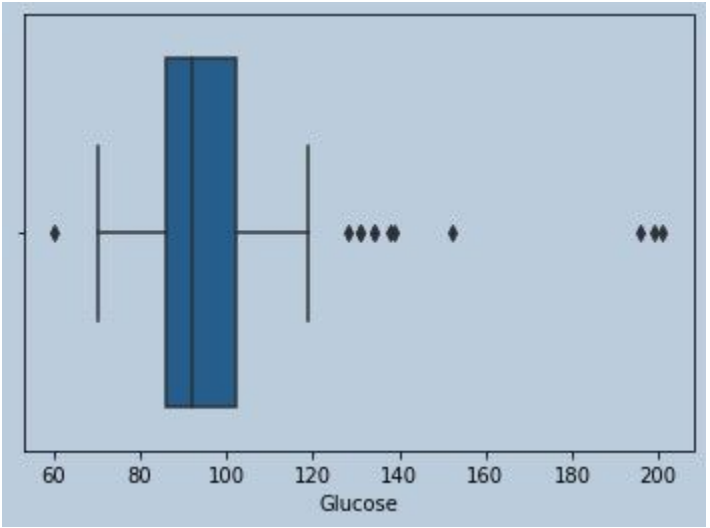
Outliers for BMI?

```
#NO outliers for BMI

sns.boxplot(data['BMI'])
```



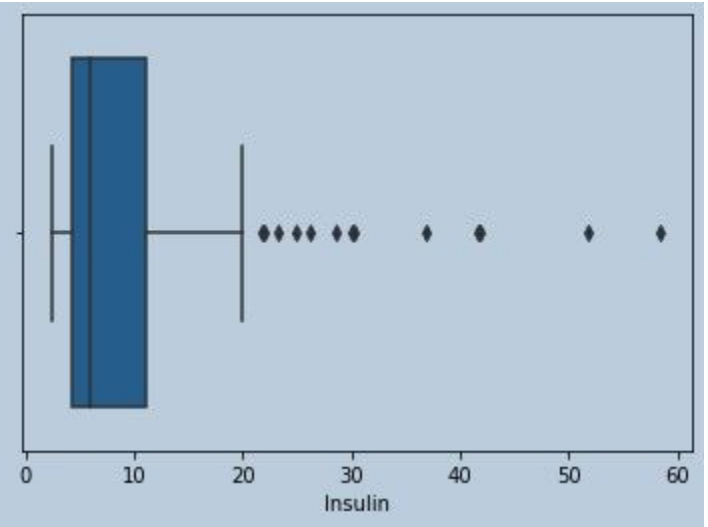
Outliers for Glucose

```
#Some outliers are there for Glucose and  data is Skewed
sns.boxplot(data['Glucose'])
```



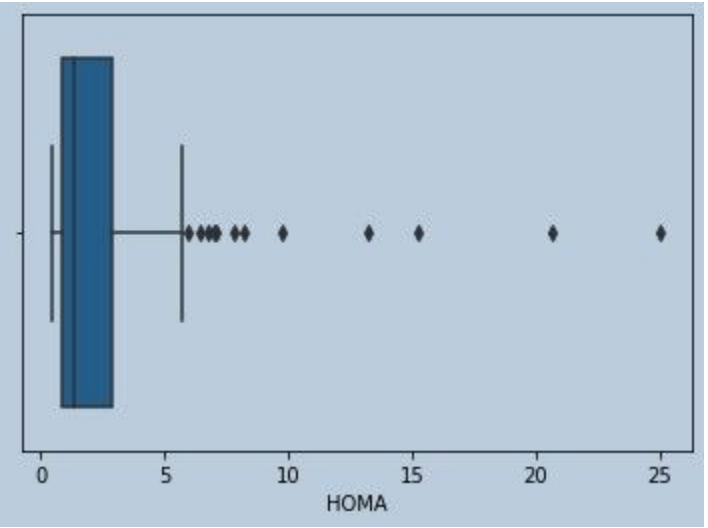
Outliers for Insulin?

```
#Outliers are present in Insulin

sns.boxplot(data['Insulin'])
```



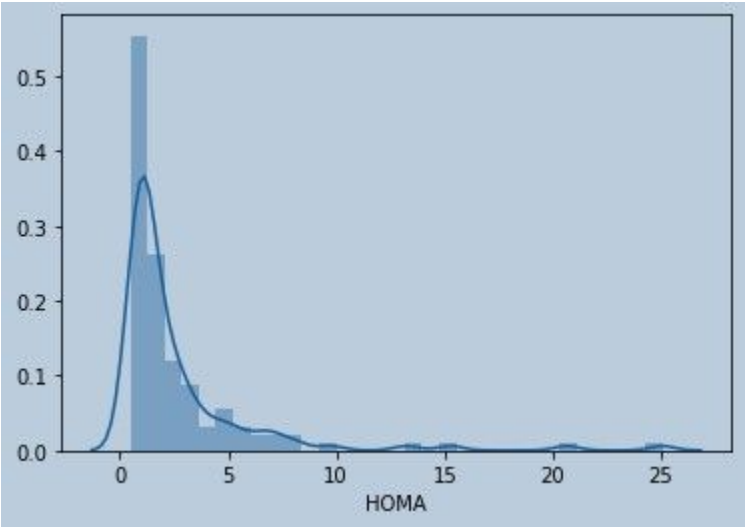
Outliers for Homa

```
#lots of Outliers in Homa

sns.boxplot(data['HOMA'])
```



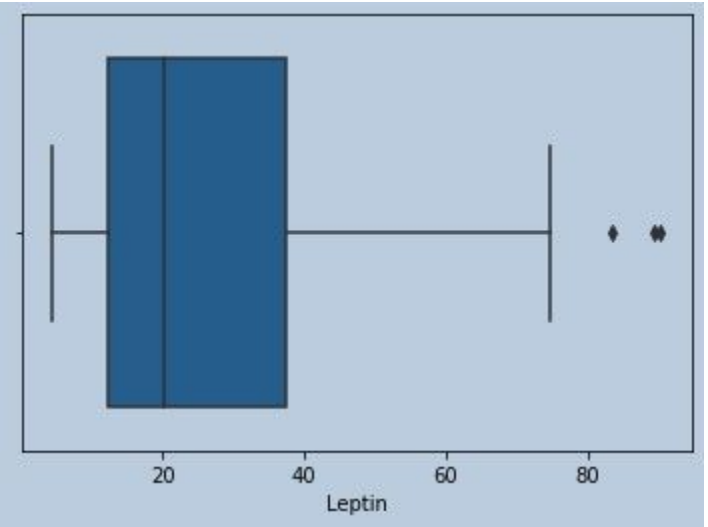
Distribution of HOMA

```
#Distribution plot of HOMA

sns.distplot(data['HOMA'])
```

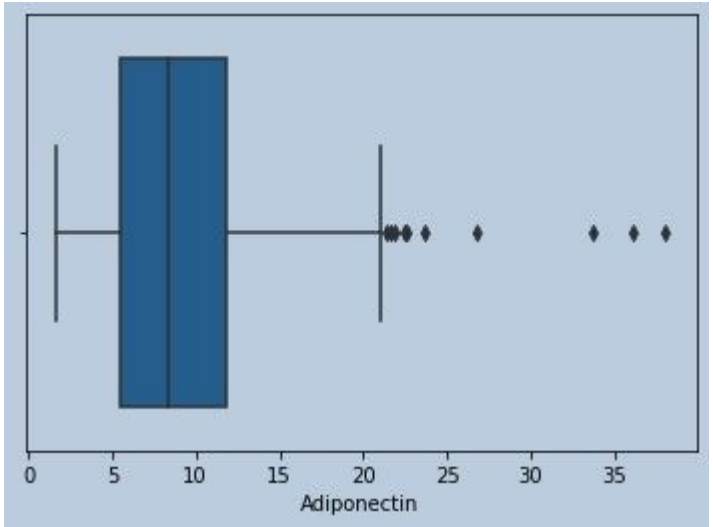


Outliers for Leptin

```
#Outliers present for Leptin

sns.boxplot(data['Leptin'])
```

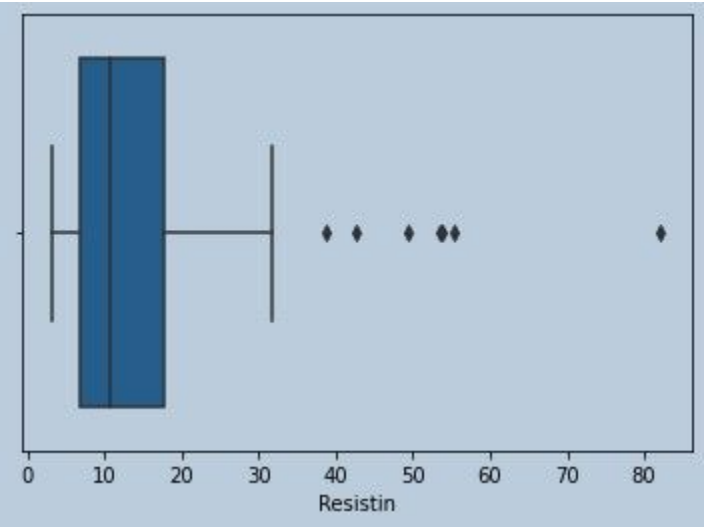


```
#Outliers present for Adiponectin

sns.boxplot(data['Adiponectin'])
```



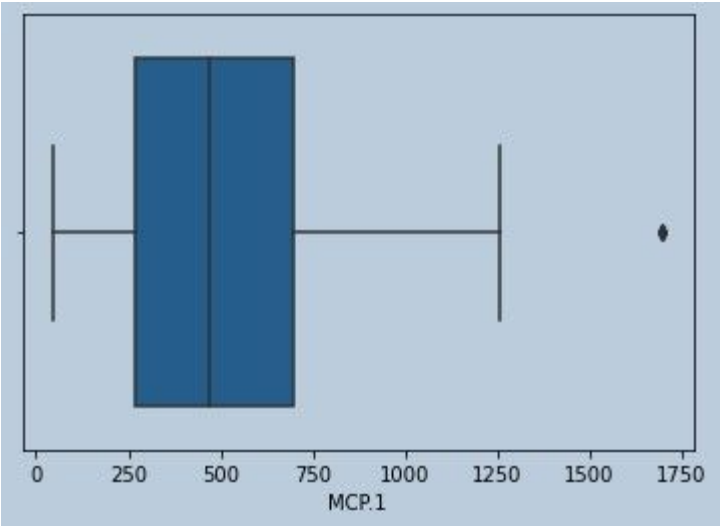
Outliers for Resistin

```
#Ouliers present for Resistin

sns.boxplot(data['Resistin'])
```



Outliers for MCP.1?

```
#Outliers present for MCP.1

sns.boxplot(data['MCP.1'])
```



Remove Outliers

```
#Removing Outliers Since they may affect prediction for KNN (quantile method)

    cancer=data.copy()

    insulinQ1=cancer['Insulin'].quantile(0.25)

    insulinQ3=cancer['Insulin'].quantile(0.75)

    insulinIQR=insulinQ3-insulinQ1

    lowerliminsulin=insulinQ1-1.5*insulinIQR

    upperliminsulin=insulinQ3+1.5*insulinIQR

    insulrem=cancer[(cancer['Insulin']>lowerliminsulin)&(upperliminsulin >
cancer['Insulin'])]
```

```
sns.boxplot(insulrem['Glucose'])

glucoseQ1=insulrem['Glucose'].quantile(0.25)

glucoseQ3=insulrem['Glucose'].quantile(0.75)

glucoseIQR=glucoseQ3-glucoseQ1

upperlimglucose=glucoseQ3+1.5*glucoseIQR

lowerlimglucose=glucoseQ1-1.5*glucoseIQR

glucoserem=insulrem[(insulrem['Glucose'] >
lowerlimglucose)&(upperlimglucose > insulrem['Glucose'])]
```

```
sns.boxplot(glucoserem['HOMA'])

homaQ1=glucoserem['HOMA'].quantile(0.25)

homaQ3=glucoserem['HOMA'].quantile(0.75)

homaIQR=homaQ3-homaQ1

upperlimhoma=homaQ3+1.5*homaIQR

lowerlimhoma=homaQ1-1.5*homaIQR

homarem=glucoserem[(glucoserem['HOMA'] >
lowerlimhoma)&(upperlimhoma > glucoserem['HOMA'])
```

```
sns.boxplot(homarem['Adiponectin'])

AdiponectinQ1=homarem['Adiponectin'].quantile(0.25)

AdiponectinQ3=homarem['Adiponectin'].quantile(0.75)

AdiponectinIQR=AdiponectinQ3-AdiponectinQ1

upperlimAdiponectin=AdiponectinQ3+1.5*AdiponectinIQR

lowerlimAdiponectin=AdiponectinQ1-1.5*AdiponectinIQR

adirem=homarem[(homarem['Adiponectin'] >
lowerlimAdiponectin)&(upperlimAdiponectin >
homarem['Adiponectin'])]
```

```
sns.boxplot(adirem['Resistin'])
```

```
sns.boxplot(adirem['Leptin'])
```

```
sns.boxplot(adirem['MCP.1'])
```

```
# create the features from data
X=mcprem.iloc[:,0:9]

# create the target variable from data
Y=mcprem.iloc[:,9]
```

Standardize

Standardize to Bring All to the Same Scale

```
from sklearn.preprocessing import StandardScaler

ss=StandardScaler()

X=ss.fit_transform(X)

X=pd.DataFrame(X)
```

Split Data

```
from sklearn.model_selection import train_test_split

xtrain,xtest,ytrain,ytest=train_test_split(X,Y,test_size=0.3)
```

Build the Classifier

Build the Model

```
#Finding accuracies  on TrainData and Test data with euclidean distance(by default
p=2)

from sklearn.neighbors import KNeighborsClassifier

from sklearn.metrics import accuracy_score

for x in range(5,10,2):

        knn=KNeighborsClassifier(n_neighbors=x,metric='minkowski',weights='distance')

        knn.fit(xtrain,ytrain)

        train_ypred=knn.predict(xtrain)

        acc_train_score=accuracy_score(train_ypred,ytrain)

        test_ypred=knn.predict(xtest)

        acc_test_score=accuracy_score(test_ypred,ytest)

        print(f'Accuracy score for  train data and test data is {acc_train_score} and
{acc_test_score} respectively for {x} neighbours')
```

Build the Model with Euclidean Distance

```
knn=KNeighborsClassifier(n_neighbors=7,metric='minkowski',we
ights='distance')

knn.fit(xtrain,ytrain)

trainypred=knn.predict(xtrain)
```

Run a Metric Report

```
from sklearn.metrics import classification_report

print(classification_report(trainypred,ytrain))

accuracy_score(trainypred,ytrain)

testypredicted=knn.predict(xtest)

from sklearn.metrics import accuracy_score

accuracy_score(testypredicted,ytest)
```

	precision	recall	f1-score	support
1	0.92	0.71	0.80	31
2	0.64	0.89	0.74	18
accuracy			0.78	49
macro avg	0.78	0.80	0.77	49
weighted avg	0.82	0.78	0.78	49

Pickles

```
import pickle

#Save our model as a pickle to a file

pickle.dump(knn, open("my_knn_model.pickle.dat", "wb"))

# delete the existing knn model from the environment

del knn

#Load the pickled object from the file

load_knn=pickle.load(open("my_knn_model.pickle.dat", "rb"))

# Use the loaded model to make predictions

load_knn.predict(xtest)
```

Summary