INNOMATICS HACKATHON-18/09/2021

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In [202…
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.metrics import mean_squared_error,r2_score
import seaborn as sns
from matplotlib import pyplot as plt
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC, LinearSVC
from sklearn.metrics import confusion_matrix, accuracy_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
```

Reading the Dataset

In [125…
```
path = r"C:\Users\JAYADEVA JAVALI\Downloads\data.csv"
df = pd.read_csv(path)
```

Basic Information of the dataset

In [126…
```
df.head()
```

Out[126…

	x1	x2	y
0	-119.37	115.00	1.0
1	-101.11	97.78	1.0
2	-130.28	106.77	1.0
3	-114.70	101.20	1.0
4	-119.37	115.00	1.0

In [127…
```
df.tail()
```

Out[127…

	x1	x2	y
2222	98.71	89.64	0.0
2223	96.63	91.00	0.0
2224	85.67	103.84	0.0
2225	78.96	78.61	0.0
2226	109.62	99999999.00	0.0

In [128…
```
df.shape
```

Out[128… (2227, 3)

In [129…
```
df.columns
```

Out[129… Index(['x1', 'x2', 'y'], dtype='object')

High Level Information

In [130…
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2227 entries, 0 to 2226
Data columns (total 3 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   x1      2222 non-null   float64
 1   x2      2224 non-null   float64
 2   y       2227 non-null   float64
dtypes: float64(3)
memory usage: 52.3 KB
```

In [131…
```
df.isnull().sum()
```

Out[131…
```
x1    5
x2    3
y     0
dtype: int64
```

In [132…
```
if df.isnull().sum().any() == False:
    print("There are no missing values")
else:
    print("There are missing values")
```

```
There are missing values
```

In [133…
```
df.describe()
```

Out[133…

	x1	x2	y
count	2222.000000	2.224000e+03	2227.000000
mean	-4.819694	8.947626e+04	0.442299
std	74.939978	2.983323e+06	0.496771
min	-134.370000	-1.348800e+02	0.000000
25%	-71.757500	-8.013000e+01	0.000000
50%	-9.835000	-1.045000e+00	0.000000
75%	59.810000	6.389250e+01	1.000000
max	134.510000	1.000000e+08	1.000000

Checking Correlations

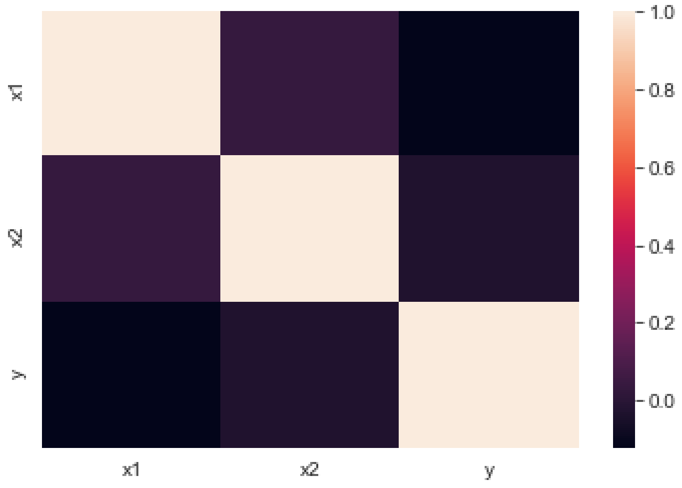
In [134…
```
df.corr()
```

Out[134…

	x1	x2	y
x1	1.000000	0.037287	-0.121299
x2	0.037287	1.000000	-0.026724

	x1	x2	y
y	-0.121299	-0.026724	1.000000

In [135…
```
sns.heatmap(df.corr())
```
Out[135… <AxesSubplot:>



In [136…
```
# Checking for duplicate rows
print("number of duplicate rows: ", df.duplicated().sum())
```
```
number of duplicate rows:  16
```

In [137…
```
format_dict = {"x1" : "{:.2f}", "x2" : "{:.1f}", "y" : "{:.1f}"}
```

In [139…
```
# Transforming them into NaN values
df.loc[df["x1"] == 0, "x1"] = np.nan
df.loc[df["x2"] == 0, "x2"] = np.nan
```

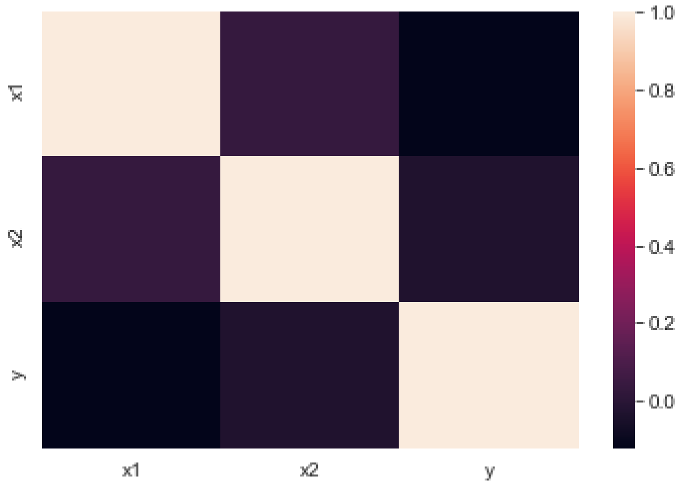
In [140…
```
# Seeing the number of the new missing values
df[["x1", "x2", "y"]].isnull().sum()
```
Out[140…
```
x1    5
x2    5
y     0
dtype: int64
```

Checking Correlations after Transforming

In [141…
```
df.corr()
```
Out[141…

	x1	x2	y
x1	1.000000	0.037291	-0.121299
x2	0.037291	1.000000	-0.026733
y	-0.121299	-0.026733	1.000000

In [142…
```
sns.heatmap(df.corr())
```
Out[142… <AxesSubplot:>



In [143…
```
def get_corr(col):
    return df.corr().unstack()[col].sort_values(ascending = False)
```

Correlation

In [144…
```
print("x1 correlations\n\n{0}\n\n{3}\n\nx2 correlations\n\n{1}\n\n{3}\n\ny correlati
```

```
x1 correlations

x1    1.000000
x2    0.037291
y    -0.121299
dtype: float64

-------------------------

x2 correlations

x2    1.000000
x1    0.037291
y    -0.026733
dtype: float64

-------------------------

y correlations

y     1.000000
x2   -0.026733
x1   -0.121299
dtype: float64
```

Handling Missing Values

Based on the data mean imputation suits the data better

In [145…
```
df['x1']=df['x1'].fillna(df['x1'].mean())
```

In [146…
```
df['x2']=df['x2'].fillna(df['x2'].mean())
```

In [147…
```
df.isnull().sum()
```

Out[147…
```
x1    0
x2    0
y     0
dtype: int64
```

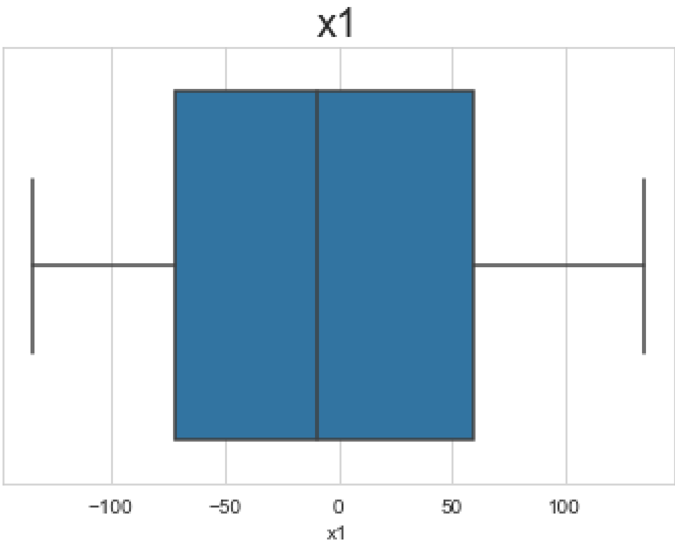
Checking for Outliers

Outliers Using BoxPlot

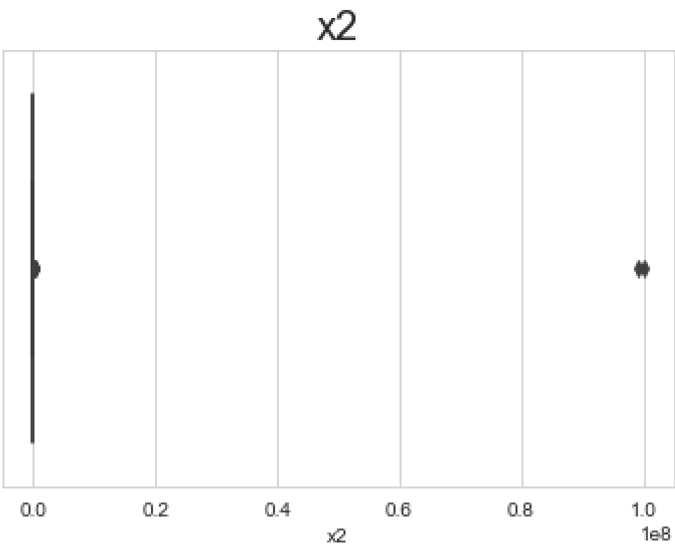
In [148…

```
for c in ['x1', 'x2', 'y']:
    #plt.figure(figsize=(3, 3))
    sns.boxplot(df[c])
    plt.title(c, fontsize=20)
    plt.show()
```

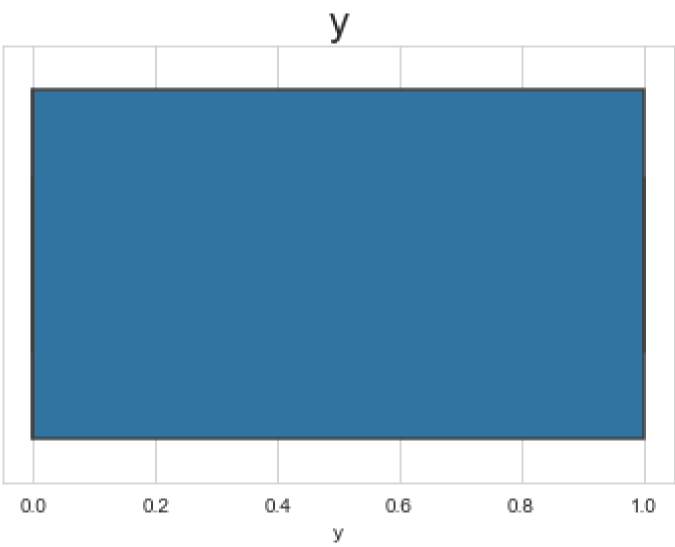
```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```




```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```




```
E:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the fol
lowing variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



We see outliers in x2 only

Plotting Regression Fit with respect to target variable to visualize and find outliers

Outliers using Regression Fit

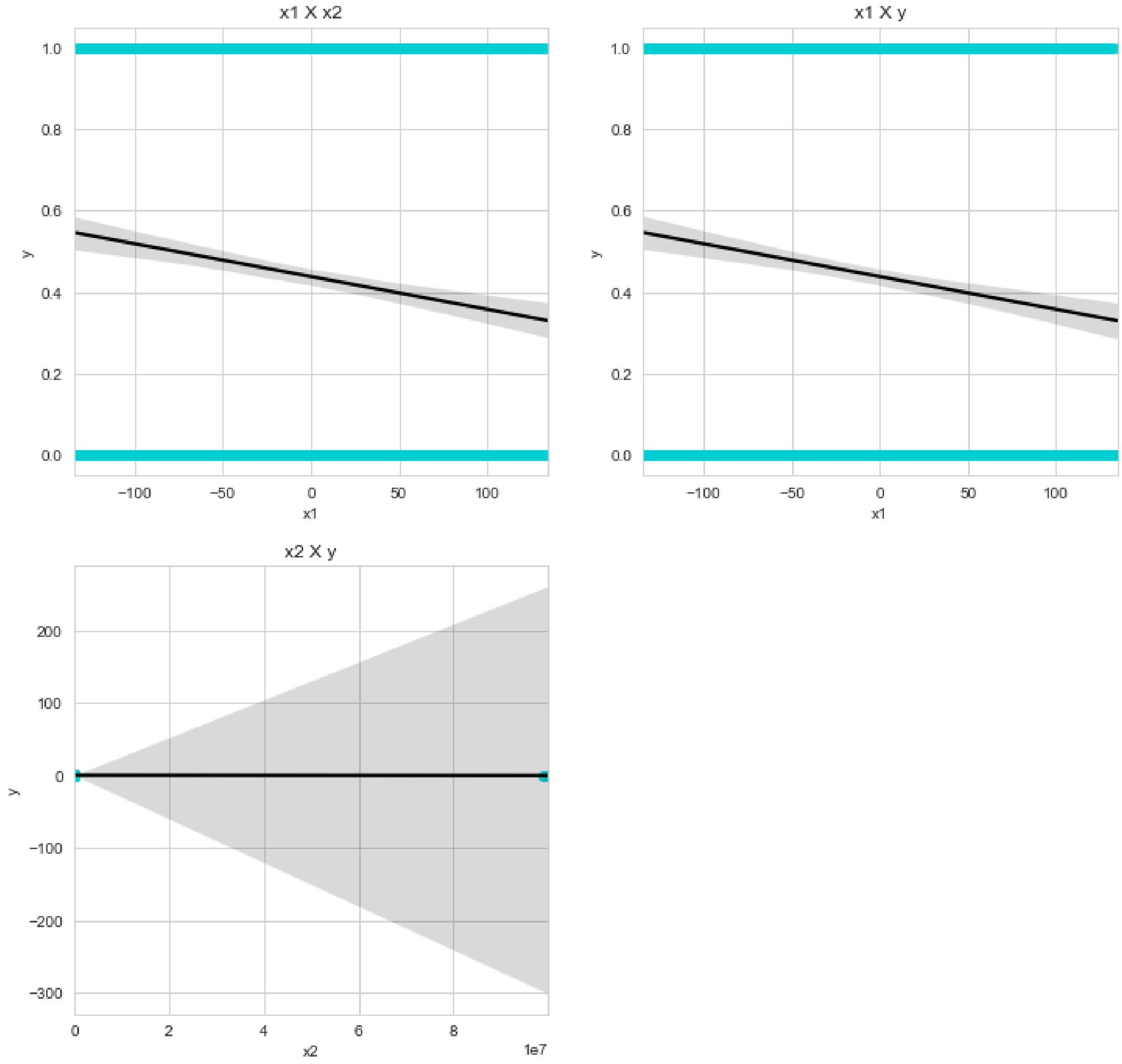
In [149…

```
sns.set_style("whitegrid")
c = "darkturquoise"
#c = "lightsalmon"
#c = "crimson"

plt.figure(figsize = (12, 18))
plt.subplot(3, 2, 1)
plt.title("x1 X x2")
sns.regplot(data = df, x = "x1", y = "y", color = c, line_kws = {"color" : "black"})
plt.subplot(3, 2, 2)
plt.title("x1 X y")
sns.regplot(data = df, x = "x1", y = "y", color = c, line_kws = {"color" : "black"})
plt.subplot(3, 2, 3)
plt.title("x2 X y")
sns.regplot(data = df, x = "x2", y = "y", color = c, line_kws = {"color" : "black"})
#plt.subplot(3, 2, 4)
```

Out[149…

```
<AxesSubplot:title={'center':'x2 X y'}, xlabel='x2', ylabel='y'>
```



we see outliers in x2 only

Outliers Using IQR

In [150…

```
def highlight_outliers(outliers, col):
    outliers_index = outliers.index
    i = pd.IndexSlice[outliers_index, col]
    return outliers.style.applymap(lambda x: "background-color: red", subset = i).fo
```

In [151…

```
def detect_outlier(col):
    quartile1 = col.quantile(0.25)
    quartile3 = col.quantile(0.75)
    IQR = quartile3 - quartile1
    lower = quartile1 - (1.5 * IQR)
    upper = quartile3 +  (1.5 * IQR)
    return lower, upper

col1=df['x1']
print("Outliers of X1")
detect_outlier(col1)
```

```
Outliers of X1
```

Out[151…

```
(-268.4075, 256.4525)
```

In [152…

```
lower,upper = detect_outlier(df['x1'])
df['x1'] = np.where(df['x1']<lower,lower,df['x1'])
```

```
df['x1'] = np.where(df['x1']>upper,upper,df['x1'])
```

In [153…

```
df_outliers = df.loc[df["x1"] < -268].copy()
highlight_outliers(df_outliers, "x1")
#No values exist outside the outlier range
```

Out[153…

x1	x2	y

In [154…

```
df_outliers = df.loc[df["x1"] >256].copy()
highlight_outliers(df_outliers, "x1")
#No values exist outside the outlier range
```

Out[154…

x1	x2	y

In [155…

```
col1=df['x2']
print("Outliers of X2")
detect_outlier(col1)
```

```
Outliers of X2
```

Out[155…

```
(-296.28999999999996, 280.54999999999995)
```

In [156…

```
lower,upper = detect_outlier(df['x2'])
df['x2'] = np.where(df['x2']<lower,lower,df['x2'])
df['x2'] = np.where(df['x2']>upper,upper,df['x2'])
```

In [157…

```
df_outliers = df.loc[df["x2"] > 279].copy()
highlight_outliers(df_outliers, "x2")
```

Out[157…

	x1	x2	y
44	-99.63	280.5	1.0
841	-64.37	280.5	1.0
1092	55.16	280.5	0.0
1430	-74.13	280.5	0.0
1541	66.63	280.5	0.0
1573	32.63	280.5	0.0
2226	109.62	280.5	0.0

In [158…

```
# Transforming them into NaN values
df.loc[df["x2"] > 279, "x2"] = np.nan
```

Imputing Outliers

In [159…

```
df['x2']=df['x2'].fillna(df['x2'].mean())
```

In [160…

```
df_outliers = df.loc[df["x2"] > 279].copy()
highlight_outliers(df_outliers, "x2")
```

Out[160…

x1	x2	y

In [161…

```
df['y']=df['y'].fillna(df['y']==1)
```

In [162…

```
df.isna().sum()
```

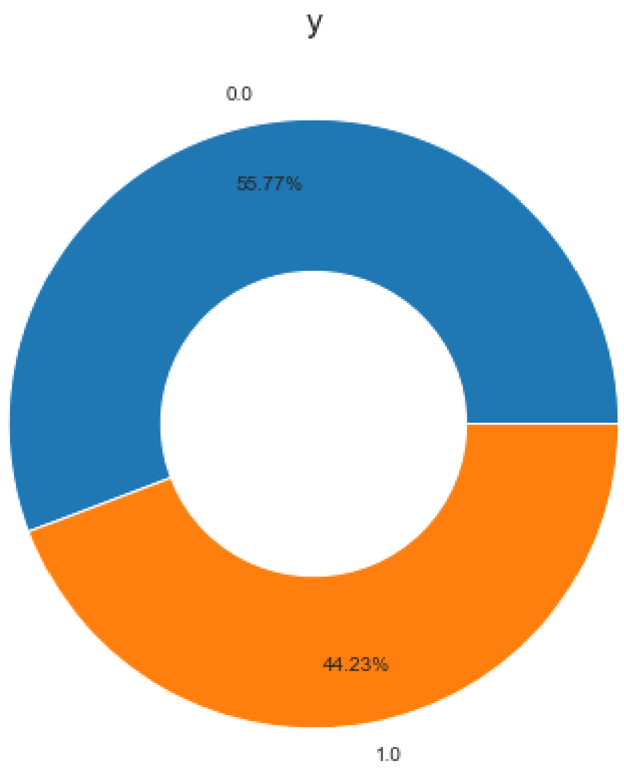
```
Out[162...  x1    0
            x2    0
            y     0
            dtype: int64
```

we dont see outliers now

Pie Chart for Y Column

```
In [163...  df_y = df["y"].value_counts()

            plt.figure(figsize = (7,7))
            plt.pie(data = df_y, x = df_y.values, labels = df_y.index, autopct = "%.2f%%", pctdi
            circle = plt.Circle(xy = (0, 0), radius = 0.5, facecolor = 'white')
            plt.gca().add_artist(circle)
            plt.title("y", size = 16)
            plt.show()
```



Machine Learning Models

```
In [251...  X = df.drop(["y"], axis = 1).copy()
            y = df["y"].copy()
```

```
In [252...  X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.1, random_state=
```

1.Logistic Regression

```
In [253...  classifier = LogisticRegression(solver = 'lbfgs', random_state = 0)
```

```
In [254...  classifier.fit(X_train, y_train)
```

```
Out[254...  LogisticRegression(random_state=0)
```

```
In [255...  LogisticRegression(C = 1.0,class_weight = None, dual = False,
```

```
    fit_intercept = True,
    intercept_scaling = 1, max_iter = 100, multi_class = 'warn',
    n_jobs = None, penalty = '12', random_state = 0, solver = 'lbfgs', tol = 0.0001, ve
```

Out[255…

```
LogisticRegression(multi_class='warn', penalty='12', random_state=0)
```

In [256…

```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
Logistic_Regression=accuracy_score(y_test, y_pred)
print("Accuracy of testing data is:",metrics.accuracy_score(y_test, y_pred))
```

```
[[133   3]
 [ 48  39]]
Accuracy of testing data is: 0.7713004484304933
```

In [257…

```
prediction = classifier.predict(X_test)
rmse_Lreg = np.sqrt(mean_squared_error(y_test, prediction))
print('RMSE value is = {}'.format(rmse_Lreg))
r2_Lreg = r2_score(y_test, prediction)
print('R-squared value is {}'.format(r2_Lreg))
```

```
RMSE value is = 0.47822541920051337
R-squared value is 0.03879310344827591
```

2.SVM WITH LINEAR KERNAL

In [258…

```
C = 5
alpha = 1 / (C * len(X))


lin_clf = LinearSVC(loss = "hinge", random_state=42) #LinearSVC classifier
```

In [259…

```
scaler = StandardScaler()
x_scaled = scaler.fit_transform(X)
```

In [260…

```
lin_clf.fit(x_scaled, y)
```

```
E:\anaconda\lib\site-packages\sklearn\svm\_base.py:976: ConvergenceWarning: Liblinea
r failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
```

Out[260…

```
LinearSVC(loss='hinge', random_state=42)
```

In [261…

```
print("LinearSVC:                    ", lin_clf.intercept_, lin_clf.coef_)
```

```
LinearSVC:                    [-0.78592281] [[-0.66703049  0.61522214]]
```

Another method

In [262…

```
from sklearn.svm import SVC
model = SVC()
```

In [263…

```
model.fit(X_train, y_train)
```

Out[263…

```
SVC()
```

In [264…

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

Out[264…

```
array([0., 0., 1., 1., 0., 0., 0., 0., 1., 0., 1., 0., 1., 0., 1., 1., 1.,
       0., 1., 0., 0., 1., 0., 0., 0., 1., 0., 0., 1., 0., 0., 1., 0., 0.,
       0., 0., 1., 0., 1., 0., 1., 0., 0., 1., 0., 1., 0., 1., 1., 0., 1.,
```

```
        1., 0., 1., 0., 1., 1., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 1.,
        0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 0., 1., 1.,
        0., 1., 0., 1., 1., 1., 1., 0., 1., 1., 1., 1., 1., 0., 0., 1., 0.,
        1., 1., 1., 1., 0., 1., 0., 0., 0., 0., 0., 1., 1., 1., 1., 0., 1.,
        0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 1., 1., 1., 1., 0., 0., 0.,
        0., 1., 1., 0., 0., 0., 0., 1., 0., 0., 1., 1., 1., 1., 1., 0., 1.,
        0., 0., 0., 0., 0., 0., 1., 1., 1., 1., 1., 1., 0., 1., 0., 1., 0.,
        0., 0., 1., 0., 1., 0., 1., 0., 0., 0., 0., 1., 0., 1., 0., 1., 0.,
        1., 1., 0., 1., 0., 0., 1., 1., 0., 0., 1., 0., 0., 0., 1., 0., 1.,
        1., 0., 0., 1., 0., 1., 0., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0.,
        0., 0.])
```

In [265…

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

Out[265…

```
0.9192825112107623
```

In [266…

```
from sklearn import metrics
print("Accuracy of testing data is:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy of testing data is: 0.9192825112107623
```

In [267…

```
model_K = SVC(kernel='linear')
model_K.fit(X_train, y_train)
model_K.score(X_test, y_test)
```

Out[267…

```
0.7668161434977578
```

In [268…

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

Out[268…

```
array([0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 1., 0., 0., 1., 0., 0.,
       1., 0., 1., 0., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 1.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 1., 1.,
       0., 1., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 1., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 1., 0., 1., 0., 0.,
       0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 0., 0., 0., 0., 1., 0.,
       0., 0., 1., 0., 0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0.,
       0., 0., 0., 0., 0., 0., 1., 1., 0., 0., 0., 0., 0., 0., 1., 0., 1.,
       0., 0., 0., 1., 0., 0., 0., 0., 1., 0., 0., 0., 0., 0., 0., 0., 0.,
       0., 0.])
```

In [269…

```
Linear=metrics.accuracy_score(y_test, y_pred)
print("Accuracy of linear kernel is:",Linear)
```

```
Accuracy of linear kernel is: 0.7668161434977578
```

3. SVM WITH RBF KERNEL

In [270…

```
model_K = SVC(kernel='rbf')
model_K.fit(X_train, y_train)
model_K.score(X_test, y_test)
```

Out[270…

```
0.9192825112107623
```

In [271…

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

Out[271…

```
array([0., 0., 1., 1., 0., 0., 0., 0., 1., 0., 1., 0., 1., 0., 1., 1., 1.,
       0., 1., 0., 0., 1., 0., 0., 0., 1., 0., 0., 1., 0., 0., 1., 0., 0.,
       0., 0., 1., 0., 1., 0., 1., 0., 0., 1., 0., 1., 0., 1., 1., 0., 1.,
       1., 0., 1., 0., 1., 1., 0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 1.,
```

```
       0., 0., 0., 0., 0., 0., 0., 0., 0., 1., 0., 0., 1., 1., 0., 1., 1.,
       0., 1., 0., 1., 1., 1., 1., 0., 1., 1., 1., 1., 1., 0., 0., 1., 0.,
       1., 1., 1., 1., 0., 1., 0., 0., 0., 0., 0., 1., 1., 1., 1., 0., 1.,
       0., 1., 0., 1., 0., 0., 0., 0., 0., 0., 1., 1., 1., 1., 0., 0., 0.,
       0., 1., 1., 0., 0., 0., 0., 1., 0., 0., 1., 1., 1., 1., 1., 0., 1.,
       0., 0., 0., 0., 0., 0., 1., 1., 1., 1., 1., 1., 0., 1., 0., 1., 0.,
       0., 0., 1., 0., 1., 0., 1., 0., 0., 0., 0., 1., 0., 1., 0., 1., 0.,
       1., 1., 0., 1., 0., 0., 1., 1., 0., 0., 1., 0., 0., 0., 1., 0., 1.,
       1., 0., 0., 1., 0., 1., 0., 1., 1., 0., 0., 1., 0., 0., 0., 0., 0.,
       0., 0.])
```

In [272…
```
Rbf=metrics.accuracy_score(y_test, y_pred)
print("Accuracy of rbf kernel is:",Rbf)
```

```
Accuracy of rbf kernel is: 0.9192825112107623
```

Parameter Tuning

In [289…
```
model_g = SVC(gamma=1)
model_g.fit(X_train, y_train)
model_g.score(X_test, y_test)
```

Out[289…
```
0.9192825112107623
```

In [310…
```
model_g = SVC(gamma=67)
model_g.fit(X_train, y_train)
model_g.score(X_test, y_test)
```

Out[310…
```
0.9192825112107623
```

In [318…
```
model_C = SVC(C=10)
model_C.fit(X_train, y_train)
model_C.score(X_test, y_test)
```

Out[318…
```
0.9147982062780269
```

In [319…
```
model_C = SVC(C=100)
model_C.fit(X_train, y_train)
model_C.score(X_test, y_test)
```

Out[319…
```
0.9192825112107623
```

We observe very slight difference in model score when tuned the parameters

4.DECISION TREE

In [273…
```
regressor1 = DecisionTreeRegressor(random_state = 0)
regressor1.fit(X_train, y_train)
prediction4 = regressor1.predict(X_test)
dt_reg = np.sqrt(mean_squared_error(y_test, prediction4))
print('RMSE value is = {}'.format(dt_reg))
r2_dt_reg = r2_score(y_test, prediction4)
print('R-squared value is {}'.format(r2_dt_reg))
Decision_Tree=metrics.accuracy_score(y_test, y_pred)
print("Accuracy of testing data is:",Decision_Tree)
```

```
RMSE value is = 0.26785981207297
R-squared value is 0.6984448951994591
Accuracy of testing data is: 0.9192825112107623
```

In [274…
```
classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
classifier.fit(X_train, y_train)
```

Out[274… DecisionTreeClassifier(criterion='entropy', random_state=0)

In [275…
```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
Decision_Tree=accuracy_score(y_test, y_pred)
print(Decision_Tree)
```

```
[[125  11]
 [  4  83]]
0.9327354260089686
```

5.KNN

In [276…
```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [277…
```
classifier = KNeighborsClassifier(n_neighbors = 5, metric = 'minkowski', p = 2)
classifier.fit(X_train, y_train)
```

Out[277… KNeighborsClassifier()

In [278…
```
y_pred = classifier.predict(X_test)
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[126  10]
 [  3  84]]
```

Out[278… 0.9417040358744395

In [279…
```
Knn=metrics.accuracy_score(y_test, y_pred)
print("Accuracy of testing data is:",knn)
```

```
Accuracy of testing data is: 0.9417040358744395
```

Comparision of Models

In [280…
```
print("Accuracy of testing data for Logistic Regression Model is:",Logistic_Regressi
print("Accuracy of testing data for SVM with Linear Kernel is:",Linear)
print("Accuracy of testing data for SVM with Rbf Kernel is:",Rbf)
print("Accuracy of testing data for Decision Tree Model is:",Decision_Tree)
print("Accuracy of testing data for KNN Model is:",Knn)
```

```
Accuracy of testing data for Logistic Regression Model is: 0.7713004484304933
Accuracy of testing data for SVM with Linear Kernel is: 0.7668161434977578
Accuracy of testing data for SVM with Rbf Kernel is: 0.9192825112107623
Accuracy of testing data for Decision Tree Model is: 0.9327354260089686
Accuracy of testing data for KNN Model is: 0.9417040358744395
```

Conclusion

With KNN being the highest accuracy ,it is the best fit for the data While SVM with RBF kernel and Decision Tree is not negligible,there is very slight difference in accuracy,which can still be effective for the data

In [ ]: