# 1. import nessasary libraries

# In [1]:

```
import pandas as pd
import warnings
warnings.filterwarnings("ignore")
```

# 2. import DataSets

### In [2]:

```
data=pd.read_csv("claimants.csv")
data.head()
```

### Out[2]:

	CASENUM	ATTORNEY	CLMSEX	CLMINSUR	SEATBELT	CLMAGE	LOSS
0	5	0	0.0	1.0	0.0	50.0	34.940
1	3	1	1.0	0.0	0.0	18.0	0.891
2	66	1	0.0	1.0	0.0	5.0	0.330
3	70	0	0.0	1.0	1.0	31.0	0.037
4	96	1	0.0	1.0	0.0	30.0	0.038

# 3.Data Undestanding

### In [3]:

```
data.isnull().sum()
```

### Out[3]:

CASENUM 0
ATTORNEY 0
CLMSEX 12
CLMINSUR 41
SEATBELT 48
CLMAGE 189
LOSS 0
dtype: int64

### In [4]:

```
data=data.dropna()
```

### In [5]:

```
data=data.drop(['CASENUM'],axis=1)
```

```
In [6]:
data.shape
Out[6]:
(1096, 6)
In [7]:
data.dtypes
Out[7]:
ATTORNEY
              int64
            float64
CLMSEX
            float64
CLMINSUR
            float64
SEATBELT
            float64
CLMAGE
            float64
LOSS
dtype: object
Model building
In [8]:
x=data.drop(['ATTORNEY'],axis=1)
y=data[['ATTORNEY']]
In [9]:
from sklearn.model selection import train test split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=12,stratify=
In [10]:
from sklearn.linear_model import LogisticRegression
linear model=LogisticRegression()
linear_model.fit(x_train,y_train)
Out[10]:
LogisticRegression()
In [29]:
linear_model.coef_
```

array([[ 0.54894944, 0.7041359 , -0.37355842, 0.00691333, -0.39317982]])

Out[29]:

#### In [31]:

```
from sklearn.tree import DecisionTreeClassifier
dt_model=DecisionTreeClassifier()
dt_model.fit(x_train,y_train)
```

### Out[31]:

DecisionTreeClassifier()

### In [44]:

```
y_train_pred=dt_model.predict(x_train)
```

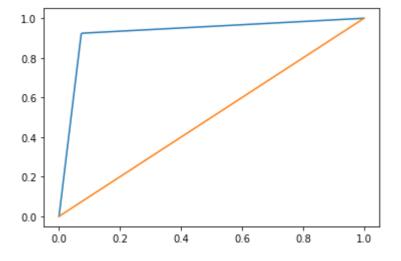
### In [40]:

```
from sklearn.metrics import roc_auc_score,roc_auc_score,roc_curve,roc_auc_score
import matplotlib.pyplot as plt
fpr,tpr,thresholds=roc_curve(y,dt_model.predict_proba(x)[:,1])
auc=roc_auc_score(y_train,y_train_pred)
print(auc)
plt.plot(fpr,tpr)
plt.plot([0,1],[0,1])
```

#### 0.9975845410628019

### Out[40]:

[<matplotlib.lines.Line2D at 0x23765b5e700>]

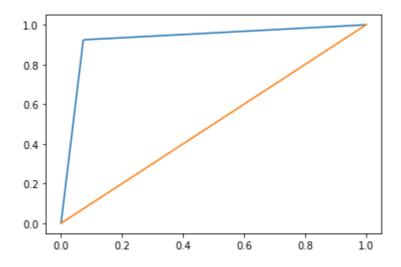


# In [59]:

```
from sklearn.metrics import roc_auc_score,roc_curve
fpr,tpr,threshold=roc_curve(y,dt_model.predict_proba(x)[:,1])
plt.plot(fpr,tpr)
plt.plot([0,1],[0,1])
```

# Out[59]:

[<matplotlib.lines.Line2D at 0x23766d221c0>]



# In [61]:

from sklearn import datasets

```
In [71]:
```

```
print(data.DESCR)
```

.. \_iris\_dataset:

Iris plants dataset

\_\_\_\_\_

\*\*Data Set Characteristics:\*\*

:Number of Instances: 150 (50 in each of three classes)

:Number of Attributes: 4 numeric, predictive attributes and the class

:Attribute Information:

- sepal length in cm
- sepal width in cm
- petal length in cm
- petal width in cm
- class:
  - Iris-Setosa
  - Iris-Versicolour
  - Iris-Virginica

#### :Summary Statistics:

==========	====	====	======	=====	=======	=======
	Min	Max	Mean	SD	Class Cor	relation
==========	====	====	======	=====	=======	=======
sepal length:	4.3	7.9	5.84	0.83	0.7826	
sepal width:	2.0	4.4	3.05	0.43	-0.4194	
petal length:	1.0	6.9	3.76	1.76	0.9490	(high!)
petal width:	0.1	2.5	1.20	0.76	0.9565	(high!)

:Missing Attribute Values: None

:Class Distribution: 33.3% for each of 3 classes.

:Creator: R.A. Fisher

:Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)

:Date: July, 1988

The famous Iris database, first used by Sir R.A. Fisher. The dataset is take n

from Fisher's paper. Note that it's the same as in R, but not as in the UCI Machine Learning Repository, which has two wrong data points.

This is perhaps the best known database to be found in the pattern recognition literature. Fisher's paper is a classic in the field an d

is referenced frequently to this day. (See Duda & Hart, for example.) The data set contains 3 classes of 50 instances each, where each class refers to

type of iris plant. One class is linearly separable from the other 2; the latter are NOT linearly separable from each other.

#### .. topic:: References

- Fisher, R.A. "The use of multiple measurements in taxonomic problems" Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to Mathematical Statistics" (John Wiley, NY, 1950).
- Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analys

is.

- (Q327.D83) John Wiley & Sons. ISBN 0-471-22361-1. See page 218.
- Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System Structure and Classification Rule for Recognition in Partially Exposed Environments". IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. PAMI-2, No. 1, 67-71.
- Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule". IEEE Transactions
  - on Information Theory, May 1972, 431-433.
  - See also: 1988 MLC Proceedings, 54-64. Cheeseman et al"s AUTOCLASS II conceptual clustering system finds 3 classes in the data.
  - Many, many more ...

### In [80]:

```
data=datasets.load_iris()
data_df=pd.DataFrame(data.data,columns=data.feature_names)
data_df['target']=data.target
data_df
```

### Out[80]:

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0
145	6.7	3.0	5.2	2.3	2
146	6.3	2.5	5.0	1.9	2
147	6.5	3.0	5.2	2.0	2
148	6.2	3.4	5.4	2.3	2
149	5.9	3.0	5.1	1.8	2

150 rows × 5 columns

# 3.Data Undestanding

# In [84]:

```
data_df.shape
```

# Out[84]:

(150, 5)

```
In [87]:
```

```
data_df.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
     Column
                        Non-Null Count Dtype
0
     sepal length (cm)
                        150 non-null
                                         float64
 1
     sepal width (cm)
                        150 non-null
                                         float64
 2
     petal length (cm)
                        150 non-null
                                         float64
     petal width (cm)
                        150 non-null
                                         float64
                        150 non-null
                                         int32
     target
dtypes: float64(4), int32(1)
memory usage: 5.4 KB
```

# 4. Model Building

```
In [91]:
```

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_state=12,shuffle=y
x_train.shape,y_train.shape
```

```
Out[91]:
```

```
((876, 5), (876, 1))
```

#### In [11]:

```
from sklearn.linear_model import LogisticRegression
l_model=LogisticRegression()
l_model.fit(x_train,y_train)
```

#### Out[11]:

LogisticRegression()

#### In [94]:

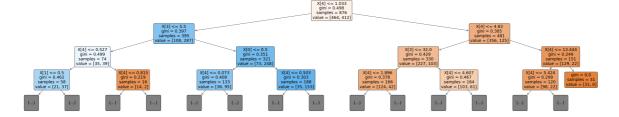
```
from sklearn.tree import DecisionTreeClassifier
dt_model=DecisionTreeClassifier()
dt_model.fit(x_train,y_train)
```

### Out[94]:

DecisionTreeClassifier()

#### In [103]:

```
from sklearn.tree import plot_tree
plt.figure(figsize=(50,10))
plot_tree(dt_model,max_depth=3,filled=True,rounded=True)
plt.show()
```



### In [106]:

```
y_train_pred=dt_model.predict(x_train)
y_test_pred=dt_model.predict(x_test)
```

#### Out[106]:

### 3. Model Evalution

#### In [119]:

from sklearn.metrics import accuracy\_score,mean\_absolute\_error,mean\_squared\_error,confusion

### In [121]:

```
confusion_matrix(y_test,y_test_pred)
```

#### Out[121]:

```
array([[64, 50],
[42, 64]], dtype=int64)
```

#### In [116]:

```
y_pred_train=l_model.predict(x_train)
y_pred_test=l_model.predict(x_test)
```

### In [117]:

```
print(mean_absolute_error(y_train,y_pred_train))
print(mean_squared_error(y_train,y_pred_train))
```

- 0.2888127853881279
- 0.2888127853881279

# In [118]:

```
print(mean_absolute_error(y_test,y_pred_test))
print(mean_squared_error(y_test,y_pred_test))
```

- 0.31363636363636366
- 0.31363636363636366