Assignment 1

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In [ ]:
```python
# import all the necessary libraries here
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import plot_tree
import graphviz
from IPython.display import Image, display
```

In [ ]:
```python
df = pd.read_csv('../../dataset/decision-tree.csv')
X = df.iloc[:, :-1].values
y = df.iloc[:, -1].values

# normalising the data
st = StandardScaler()
X_norm = st.fit_transform(X)

# access the column names
columns = df.columns[:-1]

# convert columns to array of strings
columns = np.array(columns)
print(columns)

print(df)
```

```
['Pregnancies' 'Glucose' 'BloodPressure' 'SkinThickness' 'Insulin' 'BMI'
 'DiabetesPedigreeFunction' 'Age']
     Pregnancies  Glucose  BloodPressure  SkinThickness  Insulin   BMI  \
0              6      148             72             35        0  33.6
1              1       85             66             29        0  26.6
2              8      183             64              0        0  23.3
3              1       89             66             23       94  28.1
4              0      137             40             35      168  43.1
..           ...      ...            ...            ...      ...   ...
763           10      101             76             48      180  32.9
764            2      122             70             27        0  36.8
765            5      121             72             23      112  26.2
766            1      126             60              0        0  30.1
767            1       93             70             31        0  30.4

     DiabetesPedigreeFunction  Age  Outcome
0                       0.627   50        1
1                       0.351   31        0
2                       0.672   32        1
3                       0.167   21        0
4                       2.288   33        1
..                        ...  ...      ...
763                     0.171   63        0
764                     0.340   27        0
765                     0.245   30        0
766                     0.349   47        1
767                     0.315   23        0

[768 rows x 9 columns]
```

In [ ]:
```python
# splitting the  dataset into training , validation and testing wihtout normalising the data
X_train,X_test,y_train,y_test = train_test_split(X,y,random_state=104,train_size=0.8,shuffle=True)
X_train,X_val,y_train,y_val = train_test_split(X_train,y_train,random_state=104,train_size=5/8,shuffle=True)
```

Making the decision Tree

A class Node determines the nodes for the decision tree where each tree stores the entropy of the training data that it has received , the feature that is best to split upon for that node , the thresfold value to make the split and also what the majority outcome of the dataset is that node

In [ ]:
```python
# function to find the entropy
def entropy(y) :
    x=np.count_nonzero(y==1)/len(y)
    if x==1 or x==0 :
        return 0

    e= -x*np.log2(x) - (1-x)*np.log2(1-x)

    return e
```

In [ ]:
```python
# creating a node class for the tree
class NODE :
    def __init__(self,depth,ind):
        self.id = ind
        self.type="internal"
        self.entropy = None
        self.left = None
        self.right = None
        self.feature = None
        self.label = None
        self.pred = None
        self.depth=depth
```

In [ ]:
```python
# finding the feature_split value for a feature

def feature_split(X,y,feature) :
    m = X.shape[0]
    x=X[:,feature]

    y_copy = np.copy(y)

    ind = np.argsort(x)
    x=x[ind]
    y_copy = y_copy[ind]

    feature_split_list = []

    for i in range(1,m) :
        if y_copy[i]!=y_copy[i-1] :
            feature_split_list.append((x[i-1]+x[i])/2)

    entropy_list=[]



    for feature_split in feature_split_list :
        y_left=np.array([])
        y_right=np.array([])

        for i in range(m):
            if(x[i]<=feature_split) :
                y_left=np.append(y_left,y_copy[i])
            else :
                y_right=np.append(y_right,y_copy[i])

        if(len(y_left)==0 or len(y_right) == 0) :
                feature_split_list.remove(feature_split)
                continue
        # the weighted sum of entropies of daughter nodes
        entropy_sum = len(y_left)*entropy(y_left)/len(y_copy) + len(y_right)*entropy(y_right)/len(y_copy)
        entropy_list.append(entropy_sum)


    if len(entropy_list) == 0 :
        return None ,None
    min_entropy_sum = np.min(entropy_list)
    t=np.argmin(entropy_list)
    feature_split = feature_split_list[t]

    return min_entropy_sum , feature_split
```

In [ ]:
```python
# function to best feature

def best_feature(X,y) :
    m=X.shape[0]
    n=X.shape[1]

    # stores the smallest entropy possible for each feature
    entropy_list=[]
    label_list = []

    for i in range(n) :
        entropy , label = feature_split(X,y,i)
        if entropy != None and label != None :
            entropy_list.append(entropy)
            label_list.append(label)


    min_entropy = np.min(entropy_list)
    feature = np.argmin(entropy_list)
    label = label_list[feature]

    return feature,min_entropy,label
```

In [ ]:
```python
global node_id
node_id=0
```

In [ ]:
```python
# function to build the decision tree
def DecisionTree(X,y,depth=0) :

    m=X.shape[0]
    n=X.shape[1]
    global node_id

    root = NODE(depth,node_id)
    node_id = node_id+1

    # base case
    if m <10 or y.ptp() == 0 or n==0 :
        root.type = "leaf"
        values , counts = np.unique(y,return_counts=True)
        root.pred=values[counts.argmax()]
        return root

    root.entropy = entropy(y)


    feature,entropy_sum,label = best_feature(X,y)

    information_gain = root.entropy - entropy_sum
    root.feature = feature
    root.label = label
    values , counts = np.unique(y,return_counts=True)
    root.pred=values[counts.argmax()]

    # splitting X and y based on the feature
    X_left = np.empty((0,n))
    X_right = np.empty((0,n))
    y_left = np.array([])
    y_right = np.array([])

    for i in range(m) :
        if(X[i][root.feature] <= root.label) :
            X_left = np.r_[X_left,[X[i]]]
            y_left = np.append(y_left,y[i])
        else :
            X_right = np.r_[X_right,[X[i]]]
            y_right = np.append(y_right,y[i])



    root.left = DecisionTree(X_left,y_left,depth+1)
    root.right = DecisionTree(X_right,y_right,depth+1)

    return root
```

In [ ]:
```python
root=DecisionTree(X_train,y_train)
```

In [ ]:
```python
# code to finding number of nodes in the tree
def nodes(root) :
    if root.type == "leaf" :
        return 1
    return 1 + nodes(root.left) + nodes(root.right)
```

In [ ]:
```python
initial_nodes = nodes(root)
```

Testing the decision tree on a Validation set

The decision tree is then tested on the validation set and we calculate the accuracy precision and recall values for them We also try this for various values of max depth that the test can go to and based on this we decide whats the best size for our tree . We use this info to prune the tree

In [ ]:
```python
# making a new prediction function with max depth
def predicted(root,x,max_depth=100):
    if root.type == "leaf" or root.depth == max_depth :
        return root.pred
    if x[root.feature] <= root.label :
        pred = predicted(root.left,x,max_depth)
    else :
        pred = predicted(root.right,x,max_depth)
    return pred
```

In [ ]:
```python
# obtaining the predicted values over the test set for different max_depths
# The tree was found to have a depth of 13 so we are taking max_depths from 1 to 13
depth = [i for i in range(1,14)]
accuracy = np.array([])
precision = np.array([])
recall = np.array([])
for max_depth in depth:

    y_pred = np.array([])
    m = X_val.shape[0]
    for i in range(m) :
        test = predicted(root,X_val[i],max_depth)
        y_pred = np.append(y_pred,test)

    # making the confusion matrix
    c = np.zeros((2,2))

    for i in range(m) :
        c[y_val[i]][int(y_pred[i])] =c[y_val[i]][int(y_pred[i])] + 1


    # calculating accuracy
    acc = (c[0][0] + c[1][1])/(c[0][0] + c[0][1] + c[1][0] + c[1][1])
    accuracy=np.append(accuracy,acc)

    # calculating precision
    pre = c[1][1] / (c[1][1] + c[0][1])
    precision=np.append(precision,pre)

    #calculating recall
    rec = c[1][1] / (c[1][1] + c[1][0])
    recall=np.append(recall,rec)
```

In [ ]:
```python
# plotting the accuracy, precision and recall vs max_depth
plt.plot(depth,accuracy,label="accuracy")
plt.plot(depth,precision,label="precision")
plt.plot(depth,recall,label="recall")
plt.xlabel("max_depth")
plt.ylabel("accuracy/precision/recall")
plt.legend()
plt.show()
```

Now we need to prune this tree so that we dont overfit the model A reduced error pruning is done to achieve this

In [ ]:
```python
# pruning the tree using reduced error pruning
def prune(root) :
    if root.type == "leaf" :
        return
    prune(root.left)
    prune(root.right)

    if root.left.type == "leaf" and root.right.type == "leaf" :
        left = root.left
        right = root.right

        # calculating the accuracy before pruning
        y_pred = np.array([])
        m = X_val.shape[0]
        for i in range(m) :
            test = predicted(root,X_val[i])
            y_pred = np.append(y_pred,test)

        # making the confusion matrix
        c = np.zeros((2,2))

        for i in range(m) :
            c[y_val[i]][int(y_pred[i])] =c[y_val[i]][int(y_pred[i])] + 1

        # calculating accuracy
        acc_bfr = (c[0][0] + c[1][1])/(c[0][0] + c[0][1] + c[1][0] + c[1][1])

        # now make root as the leaf node
        root.type = "leaf"
        root.left = None
        root.right = None


        # calculating the accuracy after pruning
        y_pred = np.array([])
        m = X_val.shape[0]
        for i in range(m) :
            test = predicted(root,X_val[i])
            y_pred = np.append(y_pred,test)

        # making the confusion matrix
        c = np.zeros((2,2))

        for i in range(m) :
            c[y_val[i]][int(y_pred[i])] =c[y_val[i]][int(y_pred[i])] + 1

        # calculating accuracy
        acc_aft = (c[0][0] + c[1][1])/(c[0][0] + c[0][1] + c[1][0] + c[1][1])

        if acc_bfr > acc_aft :
            root.type = "internal"
            root.left = left
            root.right = right

        return
```

In [ ]:
```python
prune(root)
final_nodes = nodes(root)

# the number of nodes before pruning and after pruning
print("Number of nodes before pruning : ",initial_nodes)
print("Number of nodes after pruning : ",final_nodes)
```

```
Number of nodes before pruning :  83
Number of nodes after pruning :  63
```

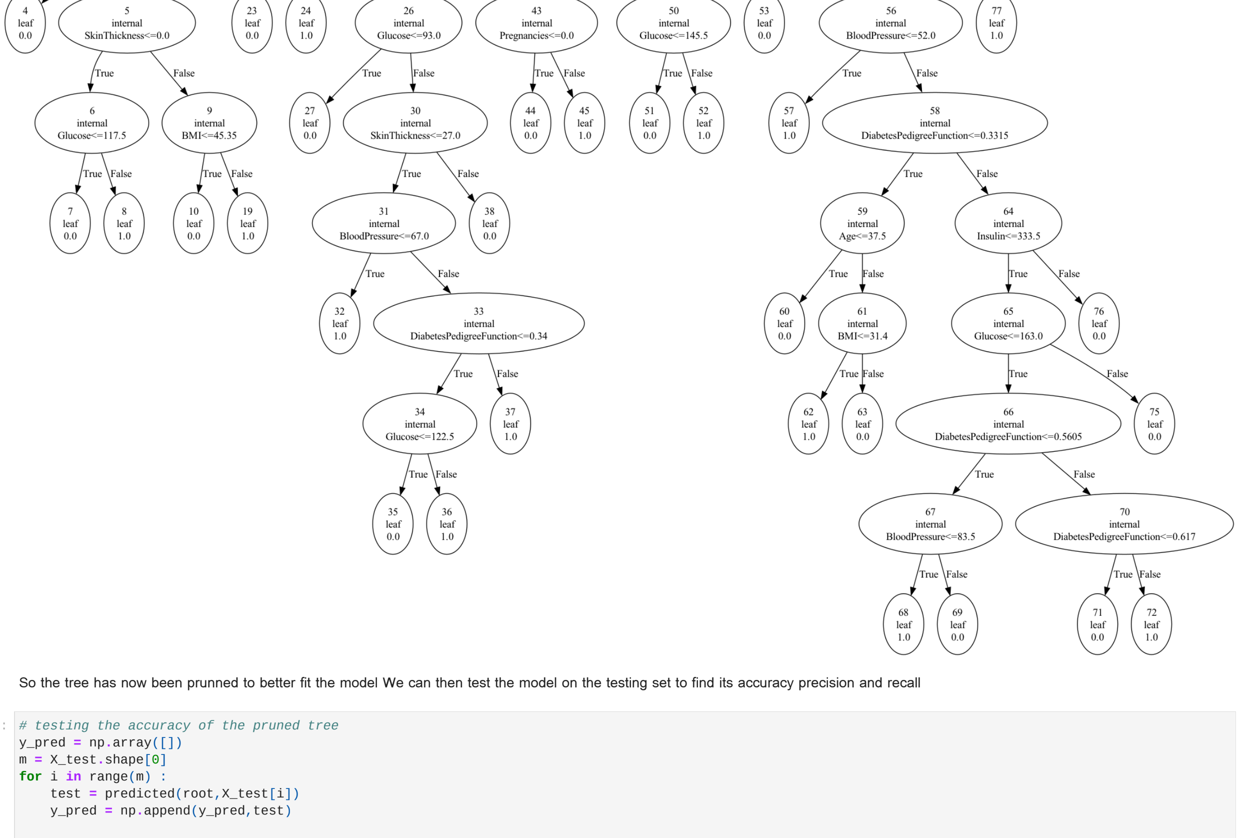
In [ ]:
```python
# plotting the tree
def plot(root):
    dot = graphviz.Digraph()

    dot.node( str(root.id) + "\n" + str(root.type) + "\n" + str(columns[root.feature]) + "<=" + str(root.label))

    def add_node_edges(node) :
        if node.left :
            if node.left.type == "leaf" :
                dot.node(str(node.left.id) + "\n" + str(node.left.type) + "\n" + str(node.left.pred))
                dot.edge(str(node.id) + "\n" + str(node.type) + "\n" + str(columns[node.feature]) + "<=" + str(node.label),str(node.left.id) + "\n" + str(no
            else :
                dot.node(str(node.left.id) + "\n" + str(node.left.type) + "\n" + str(columns[node.left.feature]) + "<=" + str(node.left.label))
                dot.edge(str(node.id) + "\n" + str(node.type) + "\n" + str(columns[node.feature]) + "<=" + str(node.label),str(node.left.id) + "\n" + str(no
                add_node_edges(node.left)
        if node.right :
            if node.right.type == "leaf" :
                dot.node(str(node.right.id) + "\n" + str(node.right.type) + "\n" + str(node.right.pred))
                dot.edge(str(node.id) + "\n" + str(node.type) + "\n" + str(columns[node.feature]) + "<=" + str(node.label),str(node.right.id) + "\n" + str(n
            else :
                dot.node(str(node.right.id) + "\n" + str(node.right.type) + "\n" + str(columns[node.right.feature]) + "<=" + str(node.right.label))
                dot.edge(str(node.id) + "\n" + str(node.type) + "\n" + str(columns[node.feature]) + "<=" + str(node.label),str(node.right.id) + "\n" + str(n
                add_node_edges(node.right)


    add_node_edges(root)
    display(Image(dot.pipe(format='png')))
    # dot.render('tree', view=True,format="png")

plot(root)
```



So the tree has now been prunned to better fit the model We can then test the model on the testing set to find its accuracy precision and recall

In [ ]:
```python
# testing the accuracy of the pruned tree
y_pred = np.array([])
m = X_test.shape[0]
for i in range(m) :
    test = predicted(root,X_test[i])
    y_pred = np.append(y_pred,test)

# making the confusion matrix
c = np.zeros((2,2))

for i in range(m) :
    c[y_test[i]][int(y_pred[i])] =c[y_test[i]][int(y_pred[i])] + 1

# calculating accuracy
acc = (c[0][0] + c[1][1])/(c[0][0] + c[0][1] + c[1][0] + c[1][1])
print("Accuracy of the pruned tree : ",acc)

# calculating precision
pre = c[1][1] / (c[1][1] + c[0][1])
print("Precision of the pruned tree : ",pre)

#calculating recall
rec = c[1][1] / (c[1][1] + c[1][0])
print("Recall of the pruned tree : ",rec)

print("\n\n\n")
```

```
Accuracy of the pruned tree :  0.7987012987012987
Precision of the pruned tree :  0.6666666666666666
Recall of the pruned tree :  0.7083333333333334
```