ML_HW2_tree

March 24, 2019

```
In [33]: #Question 1(b.i)
         #Load the csv file into a dataframe
         import pandas as pd
         input_df = pd.read_csv("hw2_question1.csv")

         #Number of samples belonging to benign and number belonging to malignant case
         num_samples_benign = input_df.loc[input_df['Class'] == 2].shape
         print("Number of benign samples: ",num_samples_benign)

         num_samples_malignant = input_df.loc[input_df['Class'] == 4].shape
         print("Number of malignant samples: ",num_samples_malignant)

         #The two classes percentage distribution
         #Benign: 65%
         #Malignant: 35%
```

```
Number of benign samples:  (444, 10)
Number of malignant samples:  (239, 10)
```

```
In [28]: #Randomly shuffle the data and divide into train and test sets
         #2/3rd training data
         #1/3rd testing data
         from sklearn.utils import shuffle
         benign_samples = input_df.loc[input_df['Class'] == 2]
         benign_samples = shuffle(benign_samples)

         benign_train = benign_samples.iloc[0:296,:]
         benign_test = benign_samples.iloc[296:,:]

         malign_samples = input_df.loc[input_df['Class'] == 4]
         malign_samples = shuffle(malign_samples)

         malign_train = malign_samples.iloc[0:159,:]
         malign_test = malign_samples.iloc[159:,:]

         train_set = pd.concat([benign_train, malign_train])
         X_train = train_set.iloc[:,0:9]
```

```
Y_train = train_set.iloc[:,-1]
print("X_train:",X_train.shape)
print("Y_train:",Y_train.shape)

test_set = pd.concat([benign_test , malign_test])
X_test = test_set.iloc[:,0:9]
Y_test = test_set.iloc[:,-1]
print("X_test:",X_test.shape)
print("Y_test:",Y_test.shape)
```

```
X_train: (455, 9)
Y_train: (455,)
X_test: (228, 9)
Y_test: (228,)
```

In [3]:
```
import math
import sys
#Function computes entropy given a feature
#input is an array containing different feature values
def computeBranchEntropy(feature_values):
    total = feature_values.shape[0]
    num_benign = len(feature_values.index[feature_values == 2].tolist())
    if(num_benign == 0 or num_benign == total):
        return 0.0
    num_malign = len(feature_values.index[feature_values == 4].tolist())
    entropy = (num_benign)/(total) * math.log2(num_benign/total) + \
                ((num_malign)/(total))* math.log2(num_malign/total)
    entropy = entropy*(-1)
    return entropy
```

In [4]:
```
#Input is a dataframe which corresponds to values of a feature.
#Considers 9 possible splits of input features
#and returns the split which gives minimum entropy
def computeConditionalEntropy(feature_df):
    min_entropy = sys.maxsize
    min_split_index = -1
    for i in range(1,10):
        branch_1 = feature_df.index[feature_df <= i]
        branch_2 = feature_df.index[feature_df > i]
        branch_1_values = Y_train.loc[branch_1]
        branch_2_values = Y_train.loc[branch_2]
        branch_1_num = branch_1_values.shape[0]
        branch_2_num = branch_2_values.shape[0]
        if(branch_1_num !=0 or branch_2_num != 0):
            branch_1_entropy = computeBranchEntropy(branch_1_values)
            branch_2_entropy = computeBranchEntropy(branch_2_values)
            total = branch_1_num + branch_2_num
```

```
                entropy_split = (branch_1_num/total)*(branch_1_entropy) \
                                + (branch_2_num/total)*(branch_2_entropy)
                if(entropy_split < min_entropy):
                    min_entropy = entropy_split
                    min_split_index = i
        return (min_entropy, min_split_index)
```

In [5]:
```
#Function which gives the attribute for which
#the entropy is minimum
#Also gives the range at which that particular attribute
#has to be split
def SplitAttribute(train_set):
    min_entropy = sys.maxsize
    min_attribute = -1
    min_attribute_split = -1
    for i in train_set:
        if (i != 'Class' and train_set.loc[:,i].shape[0] != 0):
            (cond_entropy, index) = computeConditionalEntropy(train_set.loc[:,i])
            if(cond_entropy < min_entropy):
                min_entropy = cond_entropy
                min_attribute = i
                min_attribute_split = index
    return (min_attribute, min_attribute_split, min_entropy)
```

In [6]:
```
class Tree:
    def _init_(self):
        self.left = None
        self.right = None
        self.split_index = None
        self.split_attribute = None
        self.type = None

root = Tree()
root.data = "root"
root.left = Tree()
root.left.data = "left"
root.right = Tree()
root.right.data = "right"
```

In [7]:
```
#Generates leaf node based on majority voting
def generateLeaf(train_values):
    num_benign = len(train_values.index[train_values.iloc[:,-1] == 2].tolist())
    num_malign = len(train_values.index[train_values.iloc[:,-1] ==4].tolist())
    root = Tree()
    if(num_benign > num_malign):
        root.type = 2
    else:
        root.type = 4
    return root
```

In [8]:
```
#Question 1(b.ii)
#Decision tree with entropy as splitting criteria
#Stop gorwing the tree by conditioning on maximum depth
def GenerateTree(train_set,max_depth,curr_depth):
    if(curr_depth >= max_depth):
        return generateLeaf(train_set)
    else:
        best_attribute, best_index, best_entropy = SplitAttribute(train_set)

        left_data = train_set[train_set.loc[:,best_attribute] <= best_index]
        right_data = train_set[train_set.loc[:,best_attribute] > best_index]

        #left_data = left_data.drop(best_attribute,axis=1)
        #right_data = right_data.drop(best_attribute,axis=1)

        if(left_data.shape[0] == 0 or left_data.shape[0] == train_set.shape[0]):
            return generateLeaf(train_set)
        root = Tree()
        root.split_index = best_index
        root.split_attribute = best_attribute
        root.left = GenerateTree(left_data,max_depth,curr_depth+1)
        root.right = GenerateTree(right_data,max_depth,curr_depth+1)
        return root
```

In [9]:
```
#Predicts the class of a sample
def predictSample(root, sample_row):
    if hasattr(root,'split_attribute'):
        #this is a non-leaf node
        if(sample_row[root.split_attribute] <= root.split_index):
            return predictSample(root.left, sample_row)
        else:
            return predictSample(root.right,sample_row)
    else:
        return root.type

def predict(root,train_set):
    train_len = train_set.shape[0]
    correct_labels = 0
    for i in range(train_len):
        train_row = train_set.iloc[i,:]
        predicted_label = predictSample(root,train_row)
        actual_label = train_set.iloc[i,-1]
        if(predicted_label == actual_label):
            correct_labels = correct_labels + 1
    return (correct_labels/train_len)
```

In [29]:
```
#Iterate over the training and testing set
#and report accuracy as the number of nodes increase
```

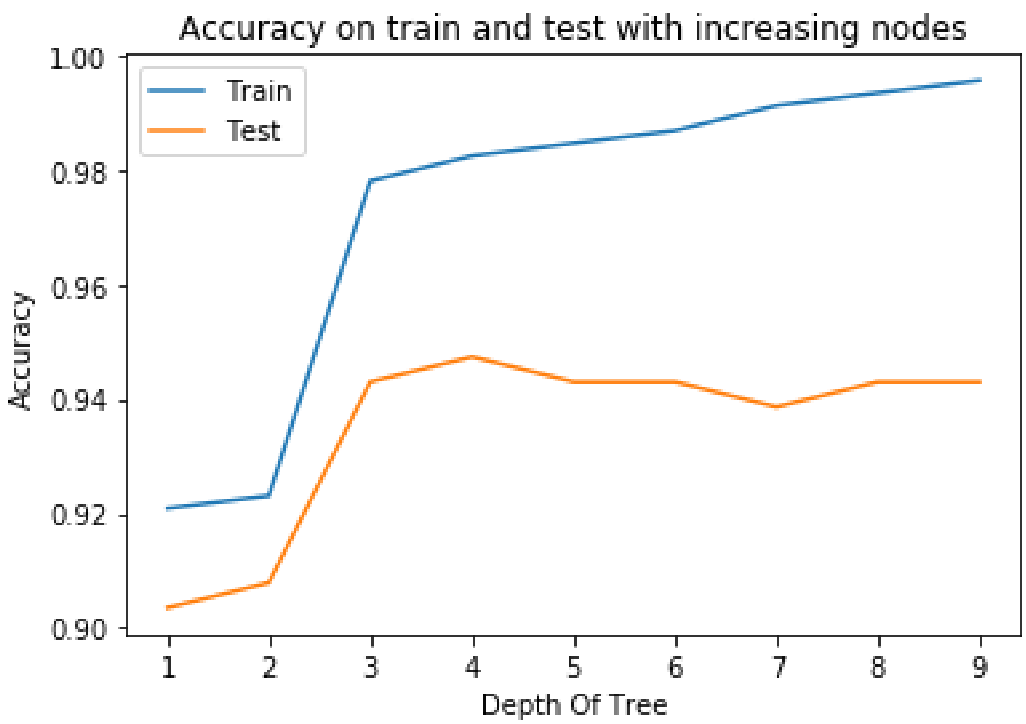
```
accuracylist_train = []
accuracylist_test = []
depth_tree = []
for i in range(1,10):
    depth_tree.append(i)
    root = GenerateTree(train_set,i,0)
    accuracy_train = predict(root,train_set)
    accuracy_test = predict(root,test_set)
    print("Number of levels in tree: ",i)
    print("Accuracy on training set: ",accuracy_train)
    print("Accuracy on testing set: ",accuracy_test)
    accuracylist_train.append(accuracy_train)
    accuracylist_test.append(accuracy_test)
```

```
Number of levels in tree:  1
Accuracy on training set:  0.9208791208791208
Accuracy on testing set:  0.9035087719298246
Number of levels in tree:  2
Accuracy on training set:  0.9230769230769231
Accuracy on testing set:  0.9078947368421053
Number of levels in tree:  3
Accuracy on training set:  0.978021978021978
Accuracy on testing set:  0.9429824561403509
Number of levels in tree:  4
Accuracy on training set:  0.9824175824175824
Accuracy on testing set:  0.9473684210526315
Number of levels in tree:  5
Accuracy on training set:  0.9846153846153847
Accuracy on testing set:  0.9429824561403509
Number of levels in tree:  6
Accuracy on training set:  0.9868131868131869
Accuracy on testing set:  0.9429824561403509
Number of levels in tree:  7
Accuracy on training set:  0.9912087912087912
Accuracy on testing set:  0.9385964912280702
Number of levels in tree:  8
Accuracy on training set:  0.9934065934065934
Accuracy on testing set:  0.9429824561403509
Number of levels in tree:  9
Accuracy on training set:  0.9956043956043956
Accuracy on testing set:  0.9429824561403509
```

In [30]:
```
#plot accuracy for training and testing data
import matplotlib.pyplot as plt
import numpy as np

plt.plot(depth_tree, accuracylist_train, label='Train')
```

```
plt.plot(depth_tree, accuracylist_test, label ='Test')
plt.title('Accuracy on train and test with increasing nodes')
plt.xlabel('Depth Of Tree')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```




```
In [13]: #Question 1(b.ii)
         #Gini Index as splitting criterion
         #Function to compute Gini index
         def computeGiniIndex(feature_values):
             total = feature_values.shape[0]
             num_benign = len(feature_values.index[feature_values == 2].tolist())
             if(num_benign == 0 or num_benign == total):
                 return 0.0
             num_malign = len(feature_values.index[feature_values == 4].tolist())
             p1 = (num_benign)/(total)
             giniIndex = 2*p1*(1-p1)
             return giniIndex
```

```
In [14]: #Find the best split using gini Index
         def best_split_giniIndex(feature_df):
             min_gini = sys.maxsize
```

```
        min_split_index = 0
        for i in range(1,10):
            branch_1 = feature_df.index[feature_df <= i]
            branch_2 = feature_df.index[feature_df > i]
            branch_1_values = Y_train.loc[branch_1]
            branch_2_values = Y_train.loc[branch_2]
            branch_1_num = branch_1_values.shape[0]
            branch_2_num = branch_2_values.shape[0]
            if(branch_1_num !=0 or branch_2_num != 0):
                branch_1_giniIndex = computeGiniIndex(branch_1_values)
                branch_2_giniIndex = computeGiniIndex(branch_2_values)
                total = branch_1_num + branch_2_num
                gini_split = (branch_1_num/total)*(branch_1_giniIndex) + \
                                (branch_2_num/total)*(branch_2_giniIndex)
                if(gini_split < min_gini):
                    min_gini = gini_split
                    min_split_index = i
        return (min_gini, min_split_index)
```

```
In [15]: def best_split_attribute_gini(train_set):
             min_gini = sys.maxsize
             min_attribute = -1
             min_attribute_split = -1
             for i in train_set:
                 if (i != 'Class' and train_set.loc[:,i].shape[0] != 0):
                     (gini, index) = best_split_giniIndex(train_set.loc[:,i])
                     if(gini < min_gini):
                         min_gini = gini
                         min_attribute = i
                         min_attribute_split = index
             return (min_attribute, min_attribute_split, min_gini)
```

```
In [16]: #Decision tree with gini index as splitting criterion
         def GenerateTree_gini(train_set,max_depth,curr_depth):
             if(curr_depth >= max_depth):
                 return generateLeaf(train_set)
             else:
                 best_attribute, best_index, best_gini = best_split_attribute_gini(train_set)
                 left_data = train_set[train_set.loc[:,best_attribute] <= best_index]
                 right_data = train_set[train_set.loc[:,best_attribute] > best_index]

                 #left_data = left_data.drop(best_attribute,axis=1)
                 #right_data = right_data.drop(best_attribute,axis=1)

                 if(left_data.shape[0] == 0 or left_data.shape[0] == train_set.shape[0]):
                     return generateLeaf(train_set)

                 root = Tree()
```

```
            root.split_index = best_index
            root.split_attribute = best_attribute
            root.left = GenerateTree_gini(left_data,max_depth,curr_depth+1)
            root.right = GenerateTree_gini(right_data,max_depth,curr_depth+1)
            return root
```

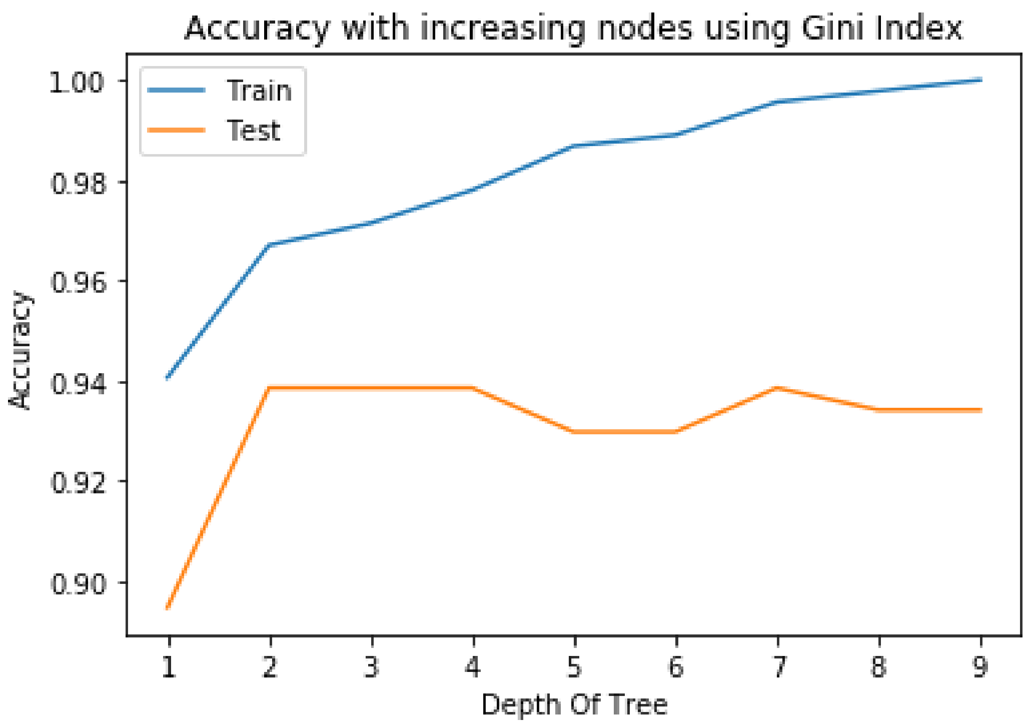
In [31]:
```
#Accuracy on train and test sets with increasing
#number of nodes and gini index as splitting criterion
accuracylist_train = []
accuracylist_test = []
depth_tree = []
for i in range(1,10):
    depth_tree.append(i)
    root = GenerateTree_gini(train_set,i,0)
    accuracy_train = predict(root,train_set)
    accuracy_test = predict(root,test_set)
    print("Number of levels in the tree :",i)
    print("Accuracy on the training set: ",accuracy_train)
    print("Accuracy on the testing set: ",accuracy_test)
    accuracylist_train.append(accuracy_train)
    accuracylist_test.append(accuracy_test)
```

```
Number of levels in the tree : 1
Accuracy on the training set:  0.9406593406593406
Accuracy on the testing set:  0.8947368421052632
Number of levels in the tree : 2
Accuracy on the training set:  0.967032967032967
Accuracy on the testing set:  0.9385964912280702
Number of levels in the tree : 3
Accuracy on the training set:  0.9714285714285714
Accuracy on the testing set:  0.9385964912280702
Number of levels in the tree : 4
Accuracy on the training set:  0.978021978021978
Accuracy on the testing set:  0.9385964912280702
Number of levels in the tree : 5
Accuracy on the training set:  0.9868131868131869
Accuracy on the testing set:  0.9298245614035088
Number of levels in the tree : 6
Accuracy on the training set:  0.989010989010989
Accuracy on the testing set:  0.9298245614035088
Number of levels in the tree : 7
Accuracy on the training set:  0.9956043956043956
Accuracy on the testing set:  0.9385964912280702
Number of levels in the tree : 8
Accuracy on the training set:  0.9978021978021978
Accuracy on the testing set:  0.9342105263157895
Number of levels in the tree : 9
Accuracy on the training set:  1.0
```

```
Accuracy on the testing set:  0.9342105263157895
```

```
In [32]: #plot accuracy for training data
         import matplotlib.pyplot as plt
         import numpy as np

         plt.plot(depth_tree, accuracylist_train, label='Train')
         plt.plot(depth_tree, accuracylist_test, label ='Test')
         plt.xlabel('Depth Of Tree')
         plt.ylabel('Accuracy')
         plt.title('Accuracy with increasing nodes using Gini Index')
         plt.legend()
         plt.show()
```




```
In [19]: #Question 1(b.iii)
         #Bonus part: Implement Prepruning by keeping a threshold on
         #the number of training samples
         def GenerateTree_threshold_samples(train_set,max_depth,curr_depth,min_samples):
             if(curr_depth >= max_depth or train_set.shape[0] < min_samples):
                 return generateLeaf(train_set)
             else:
                 best_attribute, best_index, best_entropy = SplitAttribute(train_set)
```

```
                left_data = train_set[train_set.loc[:,best_attribute] <= best_index]
                right_data = train_set[train_set.loc[:,best_attribute] > best_index]

                #left_data = left_data.drop(best_attribute,axis=1)
                #right_data = right_data.drop(best_attribute,axis=1)

                if(left_data.shape[0] == 0 or left_data.shape[0] == train_set.shape[0]):
                    return generateLeaf(train_set)
                root = Tree()
                root.split_index = best_index
                root.split_attribute = best_attribute
                root.left = GenerateTree_threshold_samples(left_data,max_depth,curr_depth+1 \
                                                            ,min_samples)
                root.right = GenerateTree_threshold_samples(right_data,max_depth,curr_depth+1,
                                                             min_samples)
                return root
```

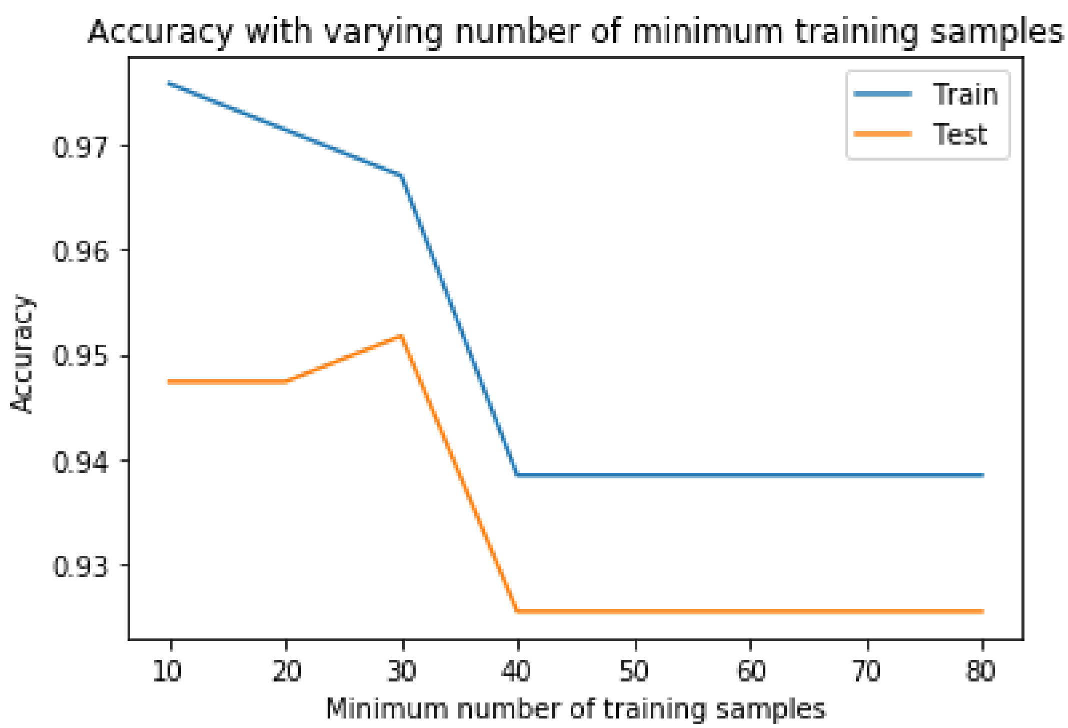
```
In [20]: #Depth of tree considered = 9
         #minimum number of training samples has been considered as stopping criterion
         accuracylist_train = []
         accuracylist_test = []
         thresholds = [10, 20, 30, 40, 50, 60, 70, 80]
         for i in thresholds:
             root = GenerateTree_threshold_samples(train_set,9,0,i)
             accuracy_train = predict(root,train_set)
             accuracy_test = predict(root,test_set)
             print("Minimum number of training samples: ",i)
             print("Accuracy on the training set: ",accuracy_train)
             print("Accuracy on the test set: ",accuracy_test)
             accuracylist_train.append(accuracy_train)
             accuracylist_test.append(accuracy_test)
```

```
Minimum number of training samples:  10
Accuracy on the training set:  0.9758241758241758
Accuracy on the test set:  0.9473684210526315
Minimum number of training samples:  20
Accuracy on the training set:  0.9714285714285714
Accuracy on the test set:  0.9473684210526315
Minimum number of training samples:  30
Accuracy on the training set:  0.967032967032967
Accuracy on the test set:  0.9517543859649122
Minimum number of training samples:  40
Accuracy on the training set:  0.9384615384615385
Accuracy on the test set:  0.9254385964912281
Minimum number of training samples:  50
Accuracy on the training set:  0.9384615384615385
Accuracy on the test set:  0.9254385964912281
Minimum number of training samples:  60
```

```
Accuracy on the training set:  0.9384615384615385
Accuracy on the test set:  0.9254385964912281
Minimum number of training samples:  70
Accuracy on the training set:  0.9384615384615385
Accuracy on the test set:  0.9254385964912281
Minimum number of training samples:  80
Accuracy on the training set:  0.9384615384615385
Accuracy on the test set:  0.9254385964912281
```

In [21]:
```
#plot accuracy for training data
import matplotlib.pyplot as plt
import numpy as np

plt.plot(thresholds, accuracylist_train, label='Train')
plt.plot(thresholds, accuracylist_test, label ='Test')
plt.xlabel('Minimum number of training samples')
plt.ylabel('Accuracy')
plt.title('Accuracy with varying number of minimum training samples')
plt.legend()
plt.show()
```



In [22]:
```
#Pre pruning based on a minimum value of entropy
#Minimum entropy is set as stopping criterion for growing the tree
```

```
def GenerateTree_threshold_entropy(train_set,max_depth,curr_depth,min_entropy):
    if(curr_depth >= max_depth):
        return generateLeaf(train_set)
    else:
        best_attribute, best_index, best_entropy = SplitAttribute(train_set)
        if(best_entropy < min_entropy):
            return generateLeaf(train_set)

        left_data = train_set[train_set.loc[:,best_attribute] <= best_index]
        right_data = train_set[train_set.loc[:,best_attribute] > best_index]

        #left_data = left_data.drop(best_attribute,axis=1)
        #right_data = right_data.drop(best_attribute,axis=1)

        #check for no split
        if(left_data.shape[0] == 0 or right_data.shape[0] == 0):
            return generateLeaf(train_set)

        root = Tree()
        root.split_index = best_index
        root.split_attribute = best_attribute

        root.left = GenerateTree_threshold_entropy(left_data,max_depth,curr_depth+1, \
                                                    min_entropy)
        root.right = GenerateTree_threshold_entropy(right_data,max_depth,curr_depth+1,\
                                                     min_entropy)
        return root
```

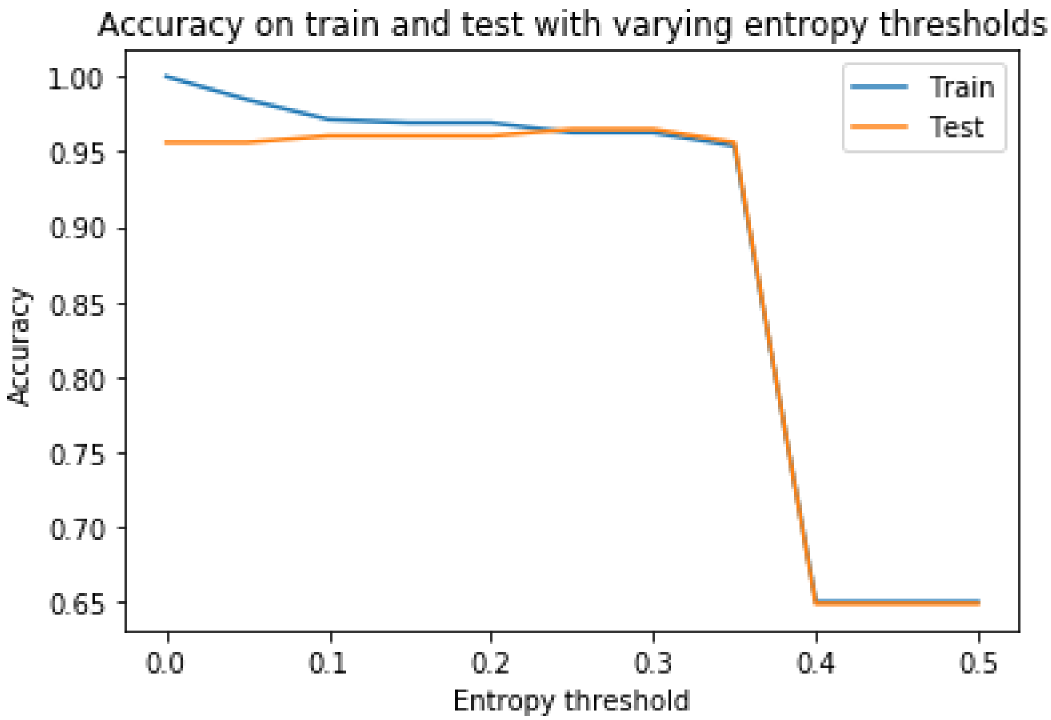
In [23]:
```
#Various entropy values are considered as thresholds
accuracylist_train = []
accuracylist_test = []
entropy_thresholds = [0.0, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5]
for i in entropy_thresholds:
    root = GenerateTree_threshold_entropy(train_set,9,0,i)
    accuracy_train = predict(root,train_set)
    accuracy_test = predict(root,test_set)
    print("Minimum entropy threshold: ",i)
    print("Accuracy on the training set: ",accuracy_train)
    print("Accuracy on the testing set: ",accuracy_test)
    accuracylist_train.append(accuracy_train)
    accuracylist_test.append(accuracy_test)
```

```
Minimum entropy threshold:  0.0
Accuracy on the training set:  1.0
Accuracy on the testing set:  0.956140350877193
Minimum entropy threshold:  0.05
Accuracy on the training set:  0.9846153846153847
```

```
Accuracy on the testing set:  0.956140350877193
Minimum entropy threshold:  0.1
Accuracy on the training set:  0.9714285714285714
Accuracy on the testing set:  0.9605263157894737
Minimum entropy threshold:  0.15
Accuracy on the training set:  0.9692307692307692
Accuracy on the testing set:  0.9605263157894737
Minimum entropy threshold:  0.2
Accuracy on the training set:  0.9692307692307692
Accuracy on the testing set:  0.9605263157894737
Minimum entropy threshold:  0.25
Accuracy on the training set:  0.9626373626373627
Accuracy on the testing set:  0.9649122807017544
Minimum entropy threshold:  0.3
Accuracy on the training set:  0.9626373626373627
Accuracy on the testing set:  0.9649122807017544
Minimum entropy threshold:  0.35
Accuracy on the training set:  0.9538461538461539
Accuracy on the testing set:  0.956140350877193
Minimum entropy threshold:  0.4
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
Minimum entropy threshold:  0.45
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
Minimum entropy threshold:  0.5
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
```

In [24]:
```
#plot accuracy for training data
import matplotlib.pyplot as plt
import numpy as np

plt.plot(entropy_thresholds, accuracylist_train, label='Train')
plt.plot(entropy_thresholds, accuracylist_test, label ='Test')
plt.xlabel('Entropy threshold')
plt.title('Accuracy on train and test with varying entropy thresholds')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```




```
In [34]: #Pre pruning based on a minimum value of giniIndex
         #Minimum gini index is set as stopping criterion for growing the tree
         def GenerateTree_threshold_gini(train_set,max_depth,curr_depth,min_gini):
             if(curr_depth >= max_depth):
                 return generateLeaf(train_set)
             else:
                 best_attribute, best_index, best_gini = best_split_attribute_gini(train_set)
                 if(best_gini < min_gini):
                     return generateLeaf(train_set)

                 left_data = train_set[train_set.loc[:,best_attribute] <= best_index]
                 right_data = train_set[train_set.loc[:,best_attribute] > best_index]

                 #left_data = left_data.drop(best_attribute,axis=1)
                 #right_data = right_data.drop(best_attribute,axis=1)

                 #check for no split
                 if(left_data.shape[0] == 0 or right_data.shape[0] == 0):
                     return generateLeaf(train_set)

                 root = Tree()
                 root.split_index = best_index
                 root.split_attribute = best_attribute
```

```
            root.left = GenerateTree_threshold_gini(left_data,max_depth,curr_depth+1, \
                                                    min_gini)
            root.right = GenerateTree_threshold_gini(right_data,max_depth,curr_depth+1,\
                                                     min_gini)
            return root
```

In [35]:
```
#Various gini index values are considered as thresholds
accuracylist_train = []
accuracylist_test = []
gini_thresholds = [0.0, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5]
for i in gini_thresholds:
    root = GenerateTree_threshold_gini(train_set,9,0,i)
    accuracy_train = predict(root,train_set)
    accuracy_test = predict(root,test_set)
    print("Minimum gini threshold: ",i)
    print("Accuracy on the training set: ",accuracy_train)
    print("Accuracy on the testing set: ",accuracy_test)
    accuracylist_train.append(accuracy_train)
    accuracylist_test.append(accuracy_test)
```

```
Minimum gini threshold:  0.0
Accuracy on the training set:  1.0
Accuracy on the testing set:  0.9342105263157895
Minimum gini threshold:  0.05
Accuracy on the training set:  0.9648351648351648
Accuracy on the testing set:  0.8991228070175439
Minimum gini threshold:  0.1
Accuracy on the training set:  0.9472527472527472
Accuracy on the testing set:  0.8991228070175439
Minimum gini threshold:  0.15
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
Minimum gini threshold:  0.2
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
Minimum gini threshold:  0.25
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
Minimum gini threshold:  0.3
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
Minimum gini threshold:  0.35
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
Minimum gini threshold:  0.4
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
```

```
Minimum gini threshold:  0.45
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
Minimum gini threshold:  0.5
Accuracy on the training set:  0.6505494505494506
Accuracy on the testing set:  0.6491228070175439
```

In [36]:
```
#plot accuracy for training and testing data
import matplotlib.pyplot as plt
import numpy as np

plt.plot(gini_thresholds, accuracylist_train, label='Train')
plt.plot(gini_thresholds, accuracylist_test, label ='Test')
plt.xlabel('Gini Index threshold')
plt.title('Accuracy on train and test with varying gini thresholds')
plt.ylabel('Accuracy')
plt.legend()
plt.show()
```

In [ ]: