

COMP 307 Assignment 1

Yongbo Yu ID: 300390526

Part 1 (KNN) :

Q1:

With using $k=1$ the predicted label is shown below:

setosa	Correct	setosa	Correct	setosa	Correct	setosa	Correct
setosa	Correct	setosa	Correct	setosa	Correct		
setosa	Correct	setosa	Correct	setosa	Correct		
setosa	Correct	setosa	Correct	setosa	Correct		
setosa	Correct	setosa	Correct	setosa	Correct		
setosa	Correct	setosa	Correct	setosa	Correct		
versicolor	Correct	versicolor	Correct	virginica	InCorrect		
versicolor	Correct	versicolor	Correct	versicolor	Correct		
virginica	InCorrect	versicolor	Correct	versicolor	Correct		
versicolor	Correct	versicolor	Correct	versicolor	Correct		
versicolor	Correct	versicolor	Correct	versicolor	Correct		
versicolor	Correct	versicolor	Correct	versicolor	Correct		
versicolor	Correct	virginica	Correct	virginica	Correct		
virginica	Correct	virginica	Correct	virginica	Correct		
virginica	Correct	versicolor	InCorrect	versicolor	InCorrect		
virginica	Correct	virginica	Correct	versicolor	InCorrect		
virginica	Correct	virginica	Correct	virginica	Correct		
virginica	Correct	virginica	Correct	virginica	Correct		
virginica	Correct	versicolor	InCorrect				

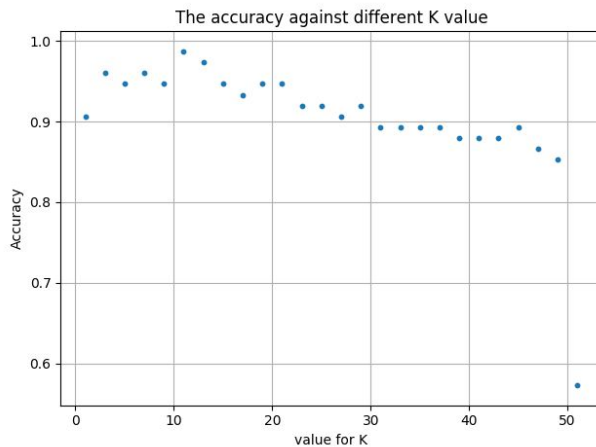
The accuracy for test set is: 0.9066666666666666

Question 2:

For $K=3$, the test accuracy increased to 96% which is higher than the accuracy for $k=1$ (0.9067). Which means by select $K=3$ can improve the performance of KNN on this certain dataset. Therefore for this certain dataset we can say, KNN can perform better than just Nearest Neighbour.

The reason of the performance of $k=3$ is better is it not only compare with the one nearest neighbour but comparing to the top 3 nearest neighbour, and choose the most frequency class among this three neighbours. By choosing the most frequency, the probability of wrong classification is much lower than just pick one nearest neighbour and assign the label of the neighbour to the instance.

The figure is shown below is the accuracy against different value of K :



Question 3:

Pros:

1. KNN is one simple algorithm, it is easy to implement, and it can easily to apply to lots different cases. More specifically, KNN can have a great performance on a low dimensional data.
2. KNN is a lazy learning technique, it has no learning process, which can leads to a low computation cost.
3. Robust to noisy training data (especially using a weighted distance)

Cons:

1. Need to determine value of parameter K.
2. It can not distinguish the importance of each feature. It only use all the features to compute the euclidean distances.
3. It may requires a high computing cost when dealing with a large dataset which contains high dimensionality. Because compute the euclidean distance need to sum up the distance for each feature between each instance.

Question 4:

Step 1: Separate all the instances(150 instances) in the dataset into 5 subsets.(30 instances each)

Step 2: Use one of the subsets as test set and treat the rest as training sets. And apply the test data to training data with KNN method. And it will provide the accuracy of this classifier.

Step 3: For each subset, we treat it as test set once, and using the rest subsets as training and repeat step2 4 times. After all the subsets have been used as test set, we can finally have five accuracy, and take the mean value of this accuracy as the accuracy for KNN on this dataset.

Question 5:

I would use K-means cluster method where $K = 3$. (3-means cluster)

Step 1:

Set $K = 3$, and initialise three clusters randomly.

Step 2:

Calculate the distance between the instance to each cluster, and associate the nearest mean to the instance. Repeat the this procedure for each instance in the dataset.

Step 3:

Replace the old means with the centroid of each of the 3 clusters as the new means

Step 4: Repeat the Step2 and Step3 until no change in each cluster center.

Question 6:

3-means clusters implemented.

Part 2:

Question 1:

The trained tree is :

ASCITES = True

SPIDERS = True

VARICES = True

FIRMLIVER = True

Class live, prob = 1, instance_left = 12

FIRMLIVER = False

BIGLIVER = True

STEROID = True

Class live, prob = 1, instance_left = 2

STEROID = False

SGOT = True

Class live, prob = 1, instance_left = 1

SGOT = False

HISTOLOGY = True

Class die, prob = 1, instance_left = 1

HISTOLOGY = False

MALAISE = True

Class live, prob = 1, instance_left = 1

MALAISE = False

Class die, prob = 1, instance_left = 1

BIGLIVER = False

Class live, prob = 1, instance_left = 3

VARICES = False

Class die, prob = 1, instance_left = 1

SPIDERS = False

FIRMLIVER = True

SGOT = True

Class live, prob = 1, instance_left = 1

SGOT = False

FEMALE = True

Class live, prob = 1, instance_left = 1

FEMALE = False

HISTOLOGY = True

Class die, prob = 1, instance_left = 3

HISTOLOGY = False

Class die, prob = 1, instance_left = 1

FIRMLIVER = False

SGOT = True

BIGLIVER = True

SPLEENPALPABLE = True

Class live, prob = 1, instance_left = 2

SPLEENPALPABLE = False

Class die, prob = 1, instance_left = 2

BIGLIVER = False

Class die, prob = 1, instance_left = 1

SGOT = False

Class live, prob = 1, instance_left = 6

ASCITES = False

BIGLIVER = True

STEROID = True

Class die, prob = 1, instance_left = 6

STEROID = False

Class die, prob = 1, instance_left = 2

BIGLIVER = False

Class live, prob = 1, instance_left = 1

The tree construct by the Decision Tree is shown above

The accuracy of the baseline is 85.185%. In this dataset, the baseline model always predict live for the test instances. Because in the training set the live class is the dominate class.

The accuracy of the Decision Tree is 81.48%

The accuracy of the baseline is slightly higher than Decision Tree. This is because the training set is highly imbalanced and the test set is also a highly imbalanced set, and they have the same bias (Live), therefore baseline model have a slightly better performance on this dataset. But if we change the test set to a balanced dataset or a most instances are 'die'

class, the performance of the baseline model will be very poor. The baseline model is way too overfitting to this certain dataset.

Question 2:

The index of the dataset pair we are using is : 1

Read: 37 instances

Baseline class is: live

Accuracy: 64.86%

The index of the dataset pair we are using is : 2

Read: 37 instances

Baseline class is: live

Accuracy: 86.49%

The index of the dataset pair we are using is : 3

Read: 37 instances

Baseline class is: live

Accuracy: 86.49%

The index of the dataset pair we are using is : 4

Read: 37 instances

Baseline class is: live

Accuracy: 72.97%

The index of the dataset pair we are using is : 5

Read: 37 instances

Baseline class is: live

Accuracy: 78.38%

The index of the dataset pair we are using is : 6

Read: 37 instances

Baseline class is: live

Accuracy: 67.57%

The index of the dataset pair we are using is : 7

Read: 37 instances

Baseline class is: live

Accuracy: 81.08%

The index of the dataset pair we are using is : 8

Read: 37 instances

Baseline class is: live

Accuracy: 70.27%

The index of the dataset pair we are using is : 9

Read: 37 instances

Baseline class is: live

Accuracy: 75.68%

The index of the dataset pair we are using is : 10

Read: 37 instances

Baseline class is: live

Accuracy: 81.08%

The average of these 10 training-test pairs is : 76.48648648648648

Question 3:

(a):

Pruning is the inverse of splitting.

There are two common kind of pruning techniques, one is top down and the other one is bottom up. The top down pruning will traverse nodes and trim subtrees starting at the root. The bottom up will start at the leaf nodes.

In order to reduce the complexity of the decision tree or reduce the computation cost, we can prune any pair whose elimination yields a satisfactory or only a small increase in impurity is eliminated. And also the change the common parent node to a leaf node.

b:

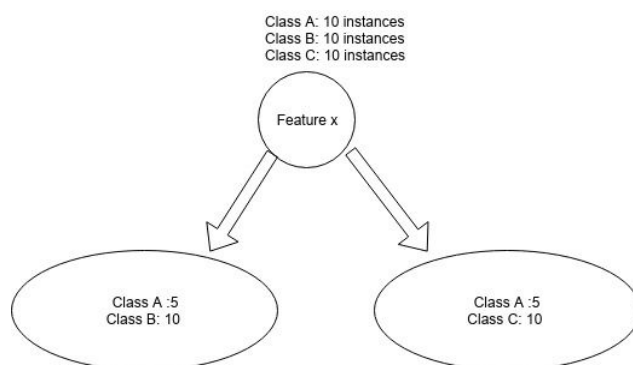
By doing pruning we reduce the complexity of the Decision tree. It could also reduce the fitness of the DT for the training data. Without pruning, DT can be very complex but it can dig out all the details to classify the training data. Therefore without pruning the training accuracy will be higher than apply pruning.

c :

Without pruning can have a higher training rate, but it may be overfitting, which leads to a poor performance on the test data. Pruning is a useful technique to reduce overfitting hence it can increase the accuracy on the test set.

Question 4 :

As we discussed in the lecture, the formula for calculating the impurity is not very suitable for multi-classes(more than 2 classes.)



Using the formula to calculate the impurity :

$$\text{Impurity} = 0.5(\text{weight}) * ((5/15) (\text{probability for class A in the left node}) * (10/15) (\text{probability for class B in the right node}) * 0/15(\text{probability for class C in left node})) + 0.5 * ((5/15) + (0/15))$$

From the calculation we can see the impurity is zero now, but from the graph we can clearly see that it not 100% pure. Therefore the formula may not suitable for a dataset which has more than 2 classes.

As our lecture mentioned, I also did some research, for a dataset which contains more than 2 classes we can based on gini-impurity instead of based on the impurity calculated by the formula we are taught in the class.

Part 3:

1. In this algorithm I set $m = 250$, the accuracy I got is 100% Therefore it do find the correct set of weight. The number of cycle it converge is 222 (seed(307))

Final-weight-matrix:

```
[-25.679369005297755, -12.581381580241818, -32.59630828133717,  
-32.11770922384291, -4.207725928853199, 9.023057775167054,  
-4.511733898353011, 17.426147683607635, 34.906077970345656,  
-29.34547687805869, 17.251492027990533, -1.0021385897737467,  
-4.251247191715965, -5.645924539815258, 18.07217083808407,  
1.9643561312950801, 1.5862549437249989, 11.312423569903354,  
2.9291007520243926, 4.534380422619169, 10.638408887313716,  
1.854175342114447, -0.6213398092081981, 37.56376775992486,  
7.490564649533134, 21.408695455274778, -1.8989336837463355,  
12.698889957999823, -16.550444058956927, 10.697886409831884,  
-19.017110165117558, 17.428150507744242, -15.327617414185305,  
-0.27988082767180167, 20.355899169281336, 10.901798932558108,  
-3.475459467681569, -0.3237816106597915, 27.753827753085115,  
-1.2702240155130222, -2.6540628215365807, -8.378778846104918,  
-14.063300194451664, 1.7960763488011615, 14.329622651870977,  
-2.6941363749060994, -27.83187115750613, -1.5871715988300297,  
-4.0109318670068355, -22.293557390454204, -1.4574000977863284]
```

2:

Because having a high training accuracy does not mean the model is perfect, the high training accuracy may caused by overfitting. Therefore we should use some test, or we can use the technique K-cross-validation as I mentioned above to reduce overfitting, or we can use a validation set which is discussed in the lecture. Therefore we should not only care about the training accuracy but both the validation accuracy(test accuracy) and the training accuracy are important. I do tried some data I created, with feeding a typical "X" image, the model can classify it correctly, but once feed the model with some "X" which is not very obvious, it will give an accuracy around 50%. Hence, I think this model is overfitting.