CMPE 462 Assignment 1 Report

Part 1

I have implemented the decision tree, represented as a recursive tuple of following:

(feature_index, threshold, lte_node, gt_node) | int

- feature_index is the index of the feature we use to do the current split.
- threshold is threshold number we use to compare the feature against
- lte_node is the subtree to follow if feature is less than or equal to the threshold
- gt_node is the subtree to follow if feature is greater than threshold
- a tree/subtree can be either a tuple as above or an integer representing the decided class.

Since all inputs are float values, I implemented it in a way that it assumes so. Above structure can be extended by adding a feature_type parameter maybe and don't include threshold for booleans.

I choose the simplest way to decide threshold values: calculating the mean value for the current feature of the elements of the current subtree. Of course, a more sophisticated approach can also be implemented, but this method was sufficient for the current dataset.

When I ran it across the dataset, I was somewhat disappointed seeing it consisted of only one split and its accuracy is 1.0 It seems that it can do a perfect split by either petal-length, or petal-width feature. In order to make sure it can form a tree via recursive behavior, I've modified some of the inputs to break the above fashion. Doing so I was able to obtain longer trees and validate that it works.

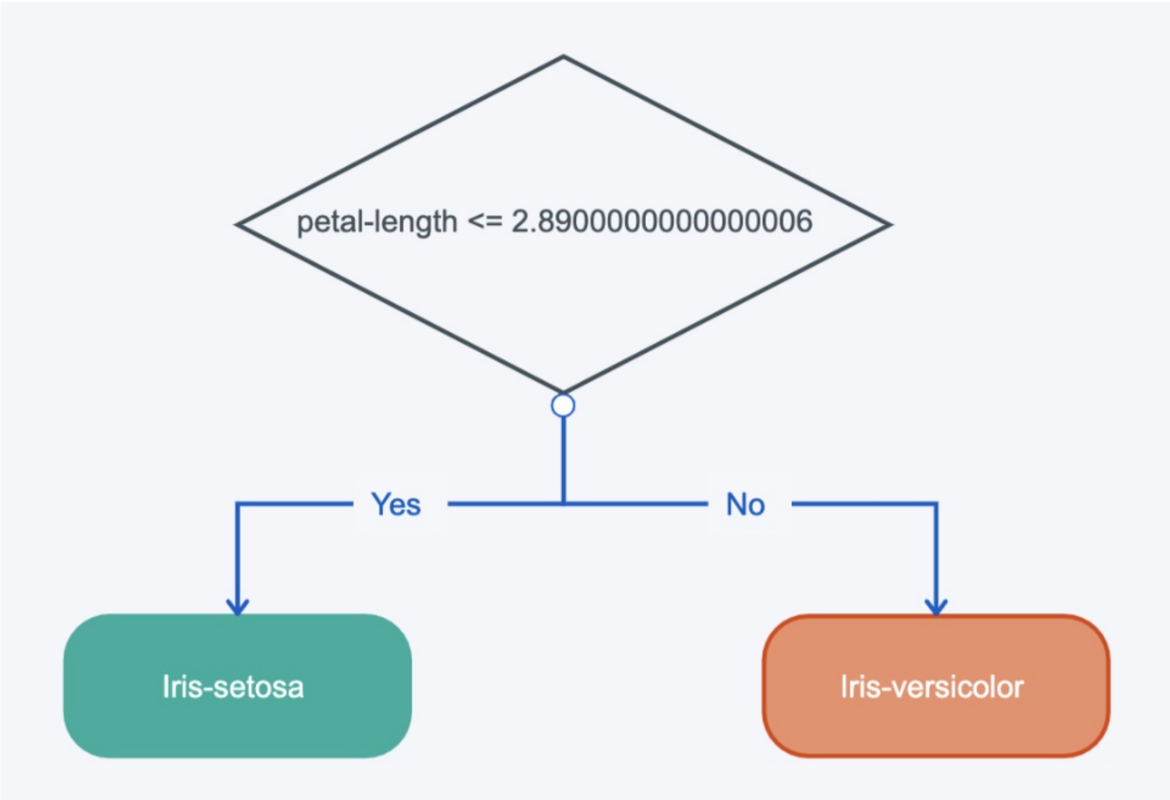
Part 1 Step 1

Below is the output:

DT petal-length 1.00

Below is the tree it forms:

(2, 2.8900000000000006, 0, 1)



Below is a sample tree from the modified input:

(2, 2.915, 0, (2, 4.295121951219513, (2, 3.8176470588235296, (3, 1.3714285714285714, 1, 0), 1), 1))

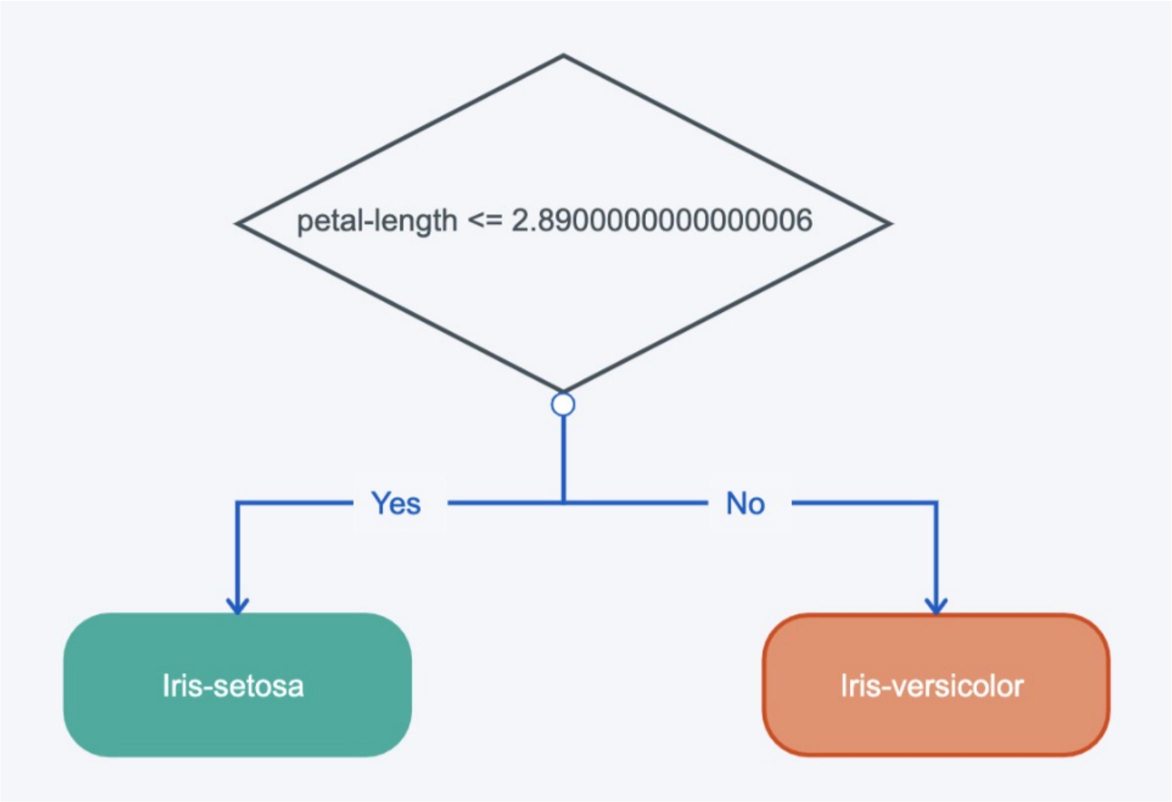
Part 1 Step 2

Below is the output:

DT petal-length 1.00

Below is the tree it forms:

(2, 2.8900000000000006, 0, 1)



Below is a sample tree from the modified input:

(2, 2.915, 0, (2, 4.295121951219513, (2, 3.8176470588235296, (3, 1.3714285714285714, 1, 0), 1), 1))

Part 1 Overview

I was able to validate that gain_ratio is applied on step 2 and not on step 1 while checking the calculations on debugger, but other than that it didn't seem to have an effect on the outputs, and a more complicated dataset is needed to do so. Thus, both step 1 and step 2 outcomes are the same. It achieves perfect accuracy very easily.

Might try applying it on a totally randomly generated dataset in the future to check out the difference from information gain.

Part 2

Overall, the implementation is pretty straightforward. Something interesting was that I first received `WARNING: reaching max number of iterations` on some C values. I checked out the related C++ source code and it works in a while loop with `while(iter<max_iter)`. So, the warning is important and the algorithm is stopped even if it didn't converge yet. I found out that if I apply normalization to the input features, it might make it converge faster and avoid the warning. Thus, I applied normalization and it worked successfully. (Did not affected accuracy much, but improved it by ~1%)

I've chosen alternative c values as 0.01, 0.1, 1.0, 10.0, 100.0 and ran across 4 kernel types linear, polynomial, radial basis function, sigmoid denoted by numbers as 0-3 respectively. I've ran it for 5x4 times as all combination of c values and kernel types to get an overview, first. (See below table) Then, I've chosen c=10.0 and kernel=0 as default values for step 1 and step 2

Kernel	C	Accuracy	#Vectors
0	0.01	0.7692	346
1	0.01	0.7692	346
2	0.01	0.7692	346
3	0.01	0.7692	346
0	0.1	0.7751	346
1	0.1	0.7692	346
2	0.1	0.7692	346
3	0.1	0.7692	346
0	1.0	0.9645	267
1	1.0	0.7692	346
2	1.0	0.7692	346
3	1.0	0.7692	346
0	10.0	0.9763	127
1	10.0	0.7692	346
2	10.0	0.9527	295
3	10.0	0.8876	335
0	100.0	0.9882	65
1	100.0	0.7692	346
2	100.0	0.9763	145
3	100.0	0.9704	180

Part 2 Step 1

Below is the output:

SVM kernel=0 C=0.01 acc=0.7692307692307694 n=346
SVM kernel=0 C=0.1 acc=0.7751479289940828 n=346
SVM kernel=0 C=1.0 acc=0.9644970414201184 n=267
SVM kernel=0 C=10.0 acc=0.9763313609467456 n=127
SVM kernel=0 C=100.0 acc=0.9881656804733728 n=65

- We can see that number of support vectors decreases as C value increases.
- We can see that accuracy also increases by preventing possible overfit.

Part 2 Step 2

Below is the output:

SVM kernel=0 C=10.0 acc=0.9763313609467456 n=127
SVM kernel=1 C=10.0 acc=0.7692307692307694 n=346
SVM kernel=2 C=10.0 acc=0.9526627218934911 n=295
SVM kernel=3 C=10.0 acc=0.8875739644970415 n=335

- We can see that number of support vectors is minimum for linear kernel but high and somewhat close in others.
- We can see that linear kernel performed best, radial basis function very close, sigmoid somewhat worse, and polynomial the worst.