Spring 2021
CMPE 462: Machine Learning
Assignment 3 Report
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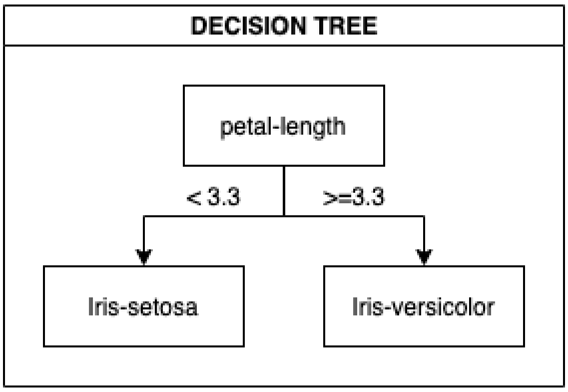
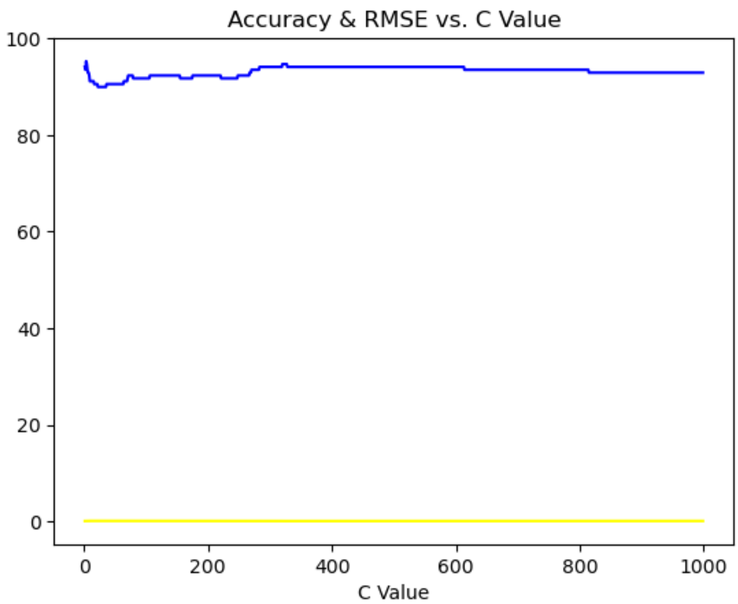
Part 1:



My decision tree model is the **same** for both **step 1 and step 2**.

Train accuracy: 100%
Test accuracy: 95%

Part 2:



● → Root Mean Square,
● → Test Accuracy

a) **Step 1:**

To visualize the difference between C values, I first plot a graph of rmse and accuracy of C values starting from 1 to 1000. Then choose 5 different C values that cause different accuracies. I chose **3, 22, 80, 300, 1000.** The reason that I chose 3 and 22 is the accuracy is maximized in 3 with 95.27% and in 22 with 89.94%. I also wanted to keep the C value range large to see the differences in a bigger perspective.

Kernel: Linear

C Values	3	22	80	300	1000
Accuracy	95.27	89.94	91.72	94.08	92.9
#of Support Vectors	53	37	33	31	29

We can infer from the results that
→ the number of support vectors is decreased, while the C value is increased
→ the accuracy range is relatively close to each other, even the C range is large

b) Step 2:

```
-t kernel_type : set type of kernel function (default 2)
    0 -- linear: u'*v
    1 -- polynomial: (gamma*u'*v + coef0)^degree
    2 -- radial basis function: exp(-gamma*|u-v|^2)
    3 -- sigmoid: tanh(gamma*u'*v + coef0)
```

I used the kernels in the picture above.
C Value: 3

Kernel	Linear	Polynomial	Radial Basis Function	Sigmoid
Accuracy	95.27	91.12	97.04	98.22
#of Support Vectors	53	322	118	147

We can infer from the results that
→ the polynomial kernel costs the maximum number of support vectors, however it has also the minimum accuracy. (bad approach)
→ Radial basis function and sigmoid kernels gained more accuracy than the linear kernel. One reason is the data might not be linearly separable in an efficient way. However, the accuracy of the linear kernel is also good which is 95.27%.