Margins and kernels

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1 Setup

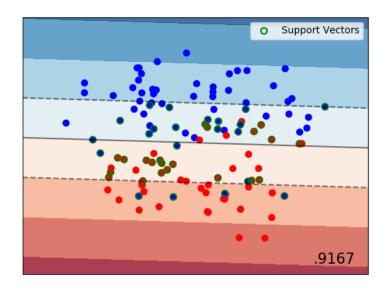
First of all, all three kernel methods are implemented in different .py files. Dataset is generated with 120 samples with 2 classes. For C and gamma ,values, $C=0.1,\ 1,\ 5$ and gamma = 0.001, 0.01 and 0.9 values are used. Moreover, dataset is divided for test and train.

2 Results

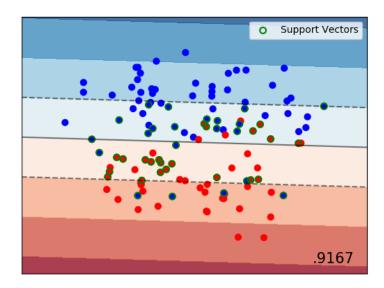
Some generated sub figures are not included in this report since I could not merge all of them and there are 9 sub figures for each kernel method. According to the results, we can interpret that C and gamma values affect the results. For each kernel method, when C is low, margin is so high that both decision boundaries cannot be seen on figures. Also, especially for the RBF kernel. when gamma is high, region closed by decision boundaries are smaller than bigger gamma values. Results for the several C and gamma values can be seen below.

2.1 Linear Kernel

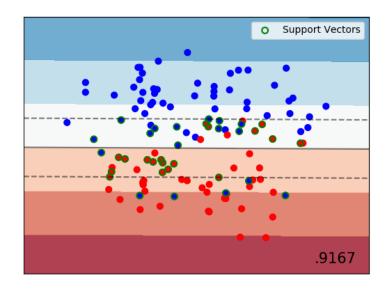
C=0.1, gamma=0.01



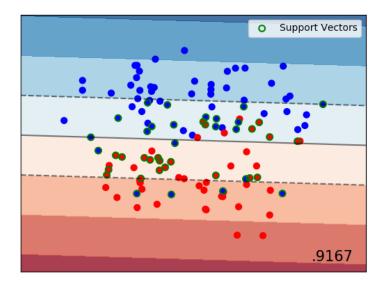
C=0.1, gamma=0.9



C=1, gamma=0.01

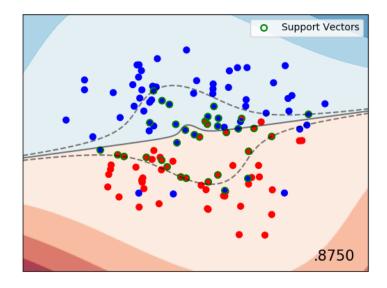


C=0.1, gamma=0.9

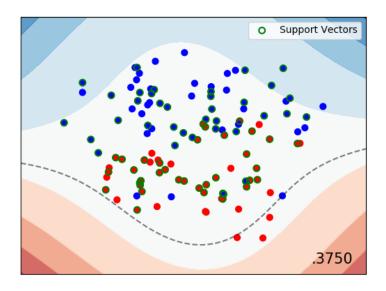


2.2 3-degree Polynomial Kernel

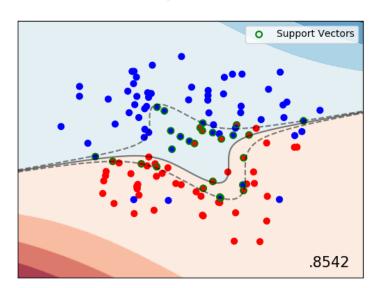
C=0.1, gamma=0.9



C=1, gamma=0.01

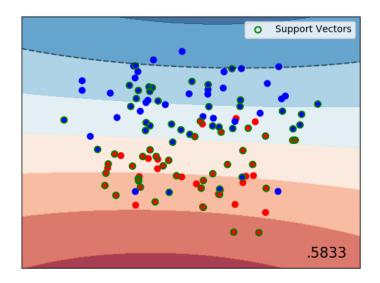


C=1, gamma=0.9

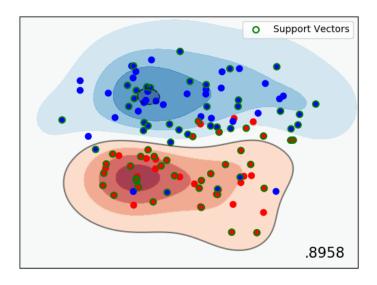


2.3 RBF Kernel

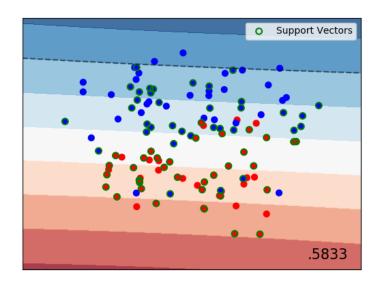
C=0.1, gamma=0.01



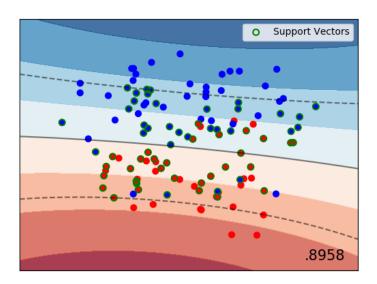
C=0.1, gamma=0.9



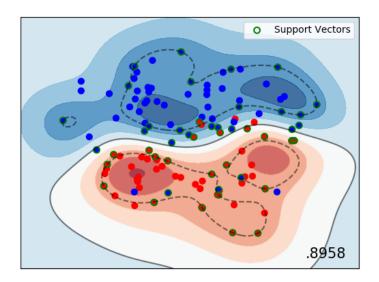
C=1, gamma=0.001



C=1, gamma=0.01



C=1, gamma=0.9



We can say that Linear Kernel is the best method since our dataset can be divided with a single line. Also, RBF kernel with low gamma value has also good accuracy score.