report-homework-1

November 17, 2019

1 Project Structure

This homework contains four files and all these files **must remain in the same folder**:

- **main.py libs.py**: these files represent the code section of the homework, main.py contains the analysis workflow while libs.py contains all the functions used to do the exercise (both plot and score calculations)
- **report-homework-1.lpynb**: these file contains the jupyter notebook version of the report, this can be useful because I didn't show the code to plot report graphs
- **report-homework-1.pdf**: the pdf file version of the report

2 Dataset

The following machine learning exercises are applied on sklearn wine dataset that is taken from UCI wine dataset. Before to go deep into the analysis it's useful for the reader to understand how wine dataset is composed, that is it might be helpful to give a look at its features, features distribution, cardinalities, kind of labels that are in the dataset and so on, since it's a crucial task in a data analysis. We can get a brief description of the dataset in the following table.

Features	Min	Max	Mean	SD
Alcohol	11.0	14.8	13.0	0.8
Malic Acid	0.74	5.80	2.34	1.12
Ash	1.36	3.23	2.36	0.27
Alcalinity of Ash	10.6	30.0	19.5	3.3
Magnesium	70.0	162.0	99.7	14.3
Total Phenols	0.98	3.88	2.29	0.63
Flavanoids:	0.34	5.08	2.03	1.00
Nonflavanoid Phenols	0.13	0.66	0.36	0.12
Proanthocyanins	0.41	3.58	1.59	0.57
Colour Intensity	1.3	13.0	5.1	2.3
Hue	0.48	1.71	0.96	0.23
OD280/OD315 of diluted wines	1.27	4.00	2.61	0.71
Proline	278	1680	746	315

- Missing Attribute Values: None
- Class Distribution: class_0 (59), class_1 (71), class_2 (48)

From this brief description we can see that the dataset is composed by 13 continuos features and there are 3 class lables that represent 3 different wine categories. For the following exercises we will use a 2D representation of the dataset, in particular we will use only the first two features (i.e Alchol and Malic Acid). It could be interesting to see the distribution of these features, among all classes and one per class.

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<Figure size 2500x2500 with 4 Axes>
```

From these graphs we can see an interesting distribution of *alcohol* among each class, it seems that each wine category have different percentages of alcohol inside, like a low-mid-high distribution. The other feature, *malic_acid*, give us an interesting information too, indeed it seems that the first wine category has a specific value range for these feature, even the third category seems to have a quite well separated range of value for this feature. We have to keep in mind that all these values are not scaled, scaling them could lead to more precise informations on how these wine categories are separated in terms of these features.

3 Sets preparation

Before to proceed with the requested analysis I have split the data into a train, validate and test subsets as suggested. The proportion used is 5:3:2, so the 50% of the data are used as training set, 30% are used for the validation set and the remaining are used to test classifiers. To do so I have used the `train_test_split` function of the `sklearn` package.

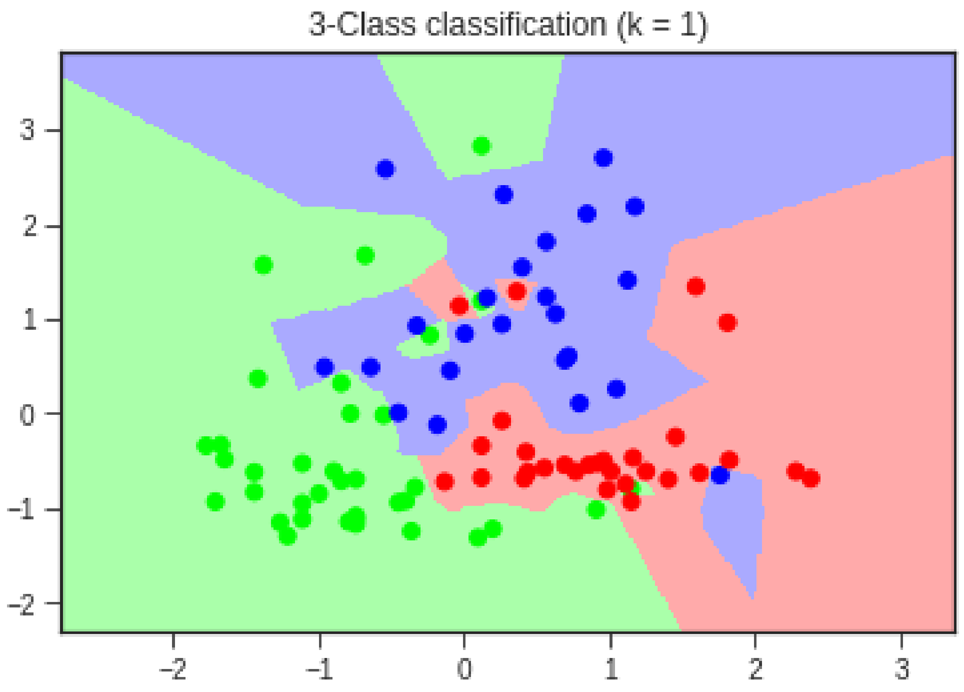
I've split the process into two steps, in the first step I've split data into train and test set and then I've split the train set again to get the final training set and a validation set. Using the number of samples instead of the percentage in the `test_size` option of the function I've preserved the proportion between each subsets. The seed used for random split is given by `random_state` variable that in the following analysis will be 1, so please use this value to get the same result of the report. Finally data was scaled using the scaler class. To do so scaler was fitted with train data and than all sets (train, validate and test) was transformed by the scaler using the `transform` function.

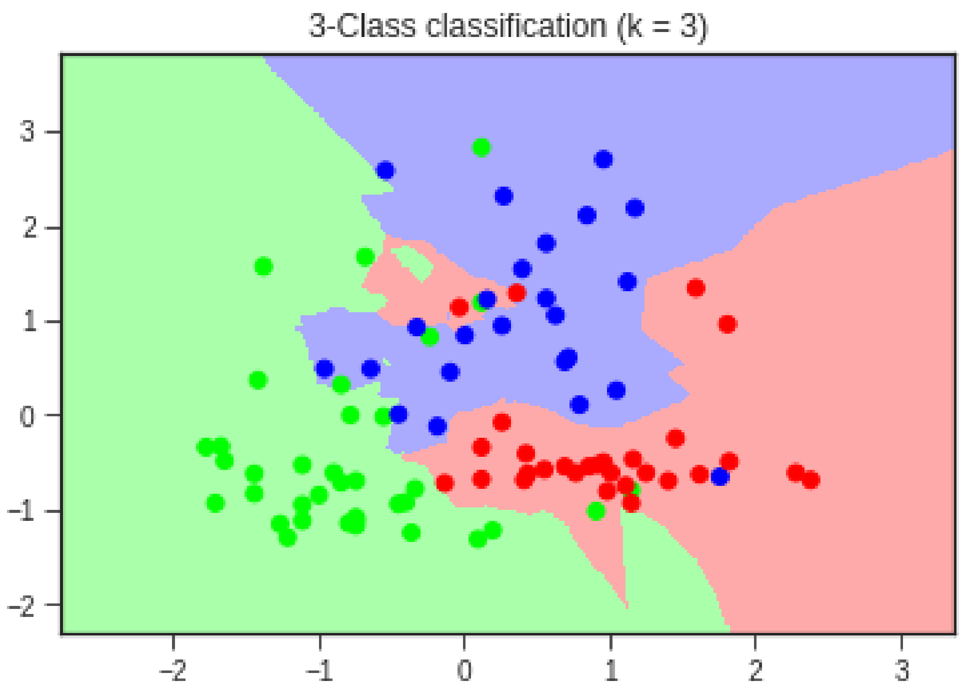
4 K-Nearest Neighbors

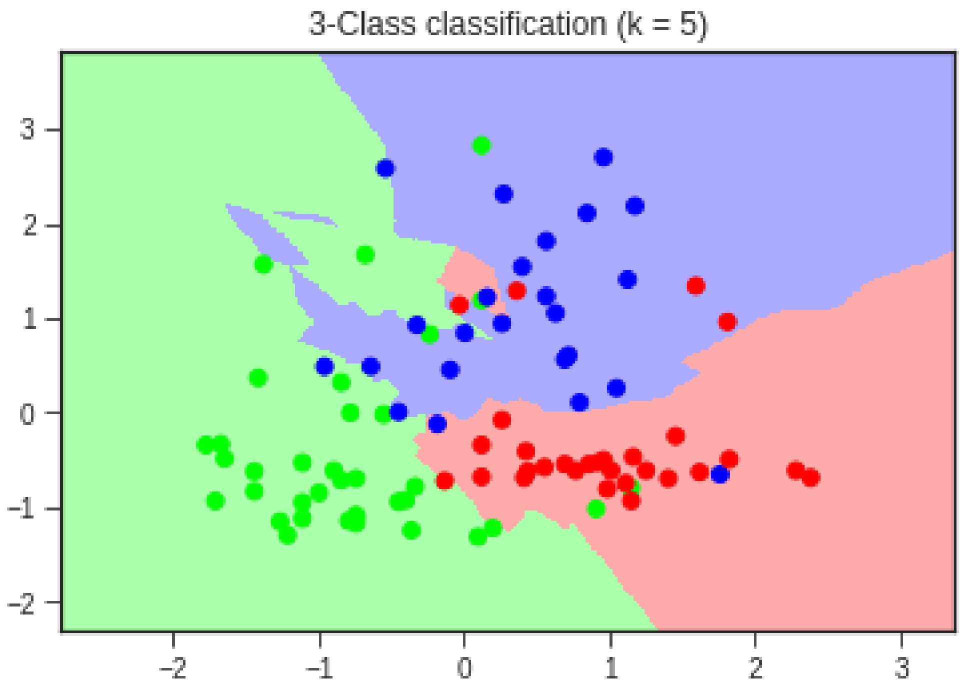
To do the KNN classification I've just created an array `kn_values=[1,3,5,7]` then I used a foreach loop to iterate through this array and at each step:

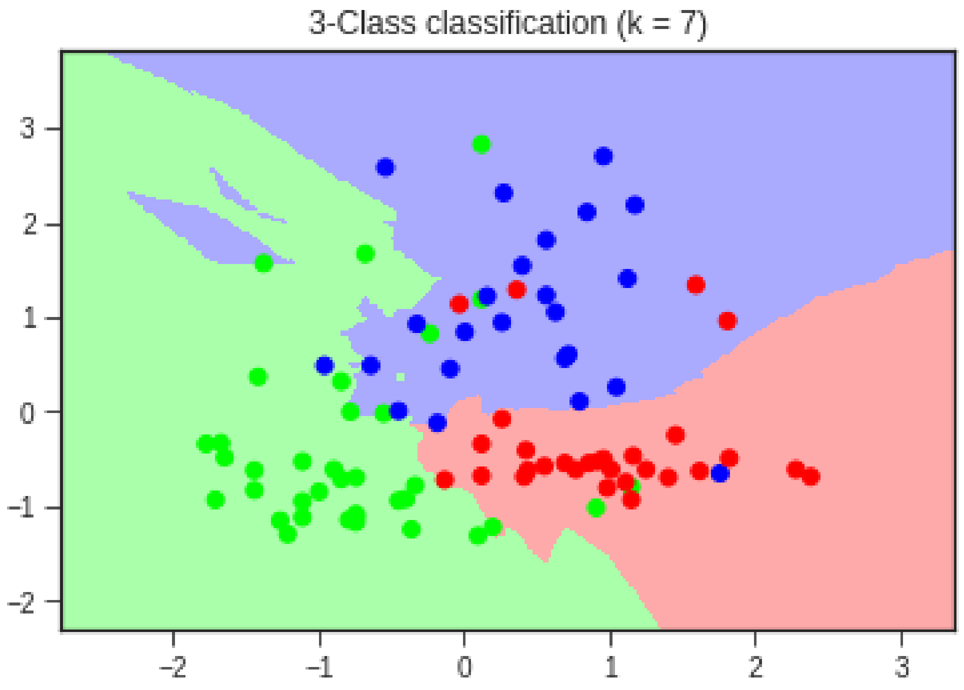
- I've saved in a variable called `kn` the current value of `k`.
- I've created and fitted a knn model using KneighborsCLassifier function
- I've plotted the model with Matplot library. By default this classifier uses the same weight for each attribute and a `minkowski` distance metric.
- I've took the prediction score evaluated with the validation test, and if it was the current best I've store it in a variable. Here the definition of score, this function returns the mean prediction accuracy of the model over a test set.
- At the end of the loop I was able to see how the best knn classifier stored in `best_clf` can perform over the test data.

In the following figures you can see knn classifiers, in every figure there are training samples represented with a colored dot, classifiers boundaries and prediction areas. The color of the dot represents the true label of that sample while the colored area represents how a dot that resides in that area will be classified. So if we have for example a blue dot inside a green area it means that a sample that is blue was classified as green.

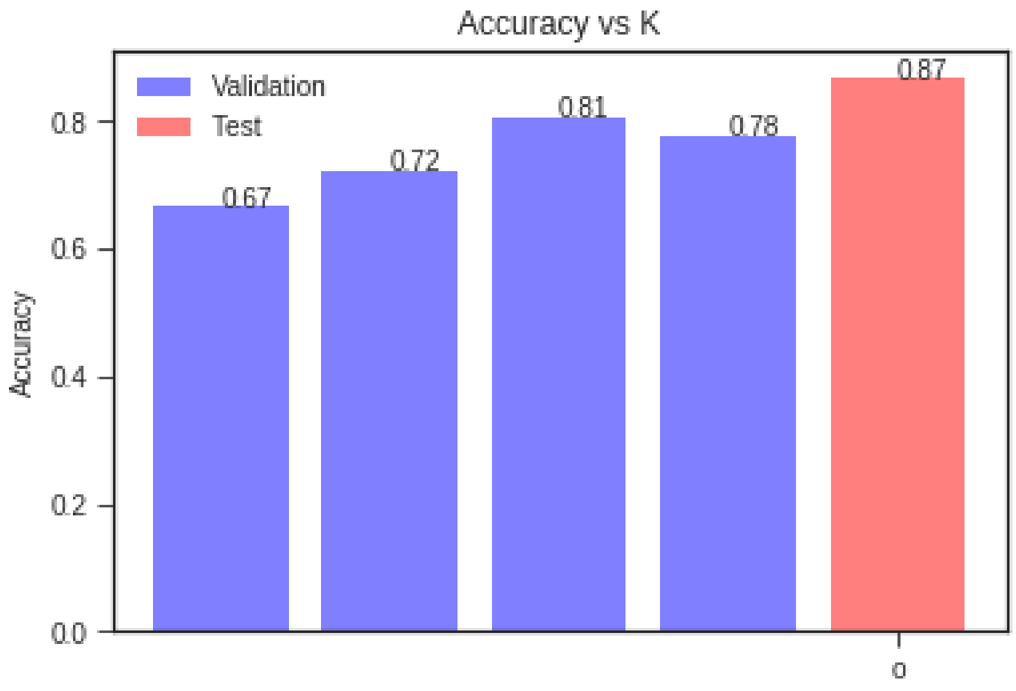





3-Class classification (k = 5)
3
2
1
0
-1
-2
-2
-1
0
1
2
3


3-Class classification (k = 7)
3
2
1
0
-1
-2
-2
-1
0
1
2
3

When K is equal to one we cannot see misclassification, for other values o K instead we can see few points misclassified, so it seems that these models perform well on training data. The most important thing that we can state from these graphs is that boundaries are not linear so a non linear model will tend to overperform against a linear one. Following the accuracy results of these models on validation and test sets.



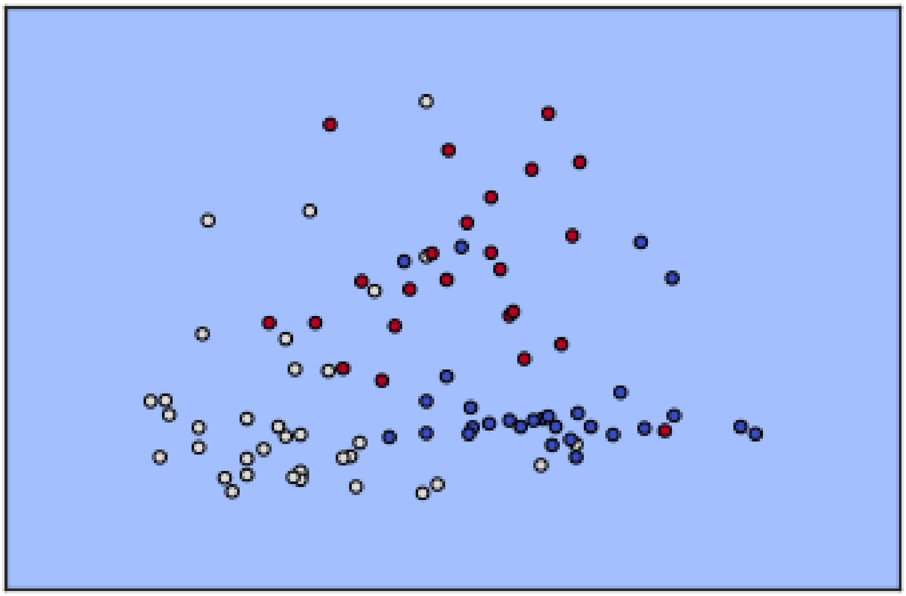
5 SVM Linear

In orderd to perform SVM with a linear kernel I've used a similar approach to the KNN problem, so I've

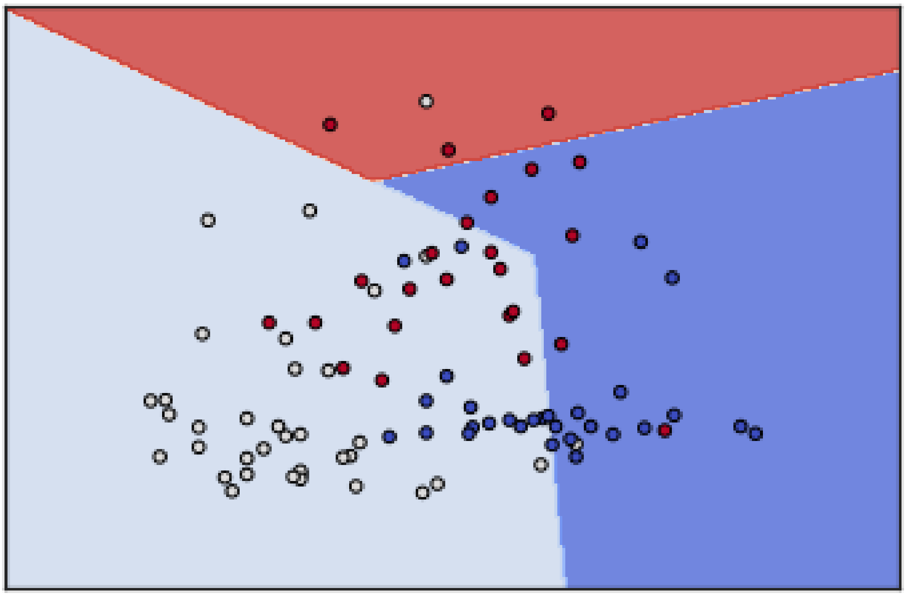
- picked the proposed values of C and filled an array with these values
- iterate through C and at each step I've trained a SVM linear model in order to check its performance against validation set
- at the end I've used the best classifier to check performance its performance against the test set

the function that I used to get SVM classifier is svm.SVC, in this case the value of gamma is setted to `auto` since we have not gamma.

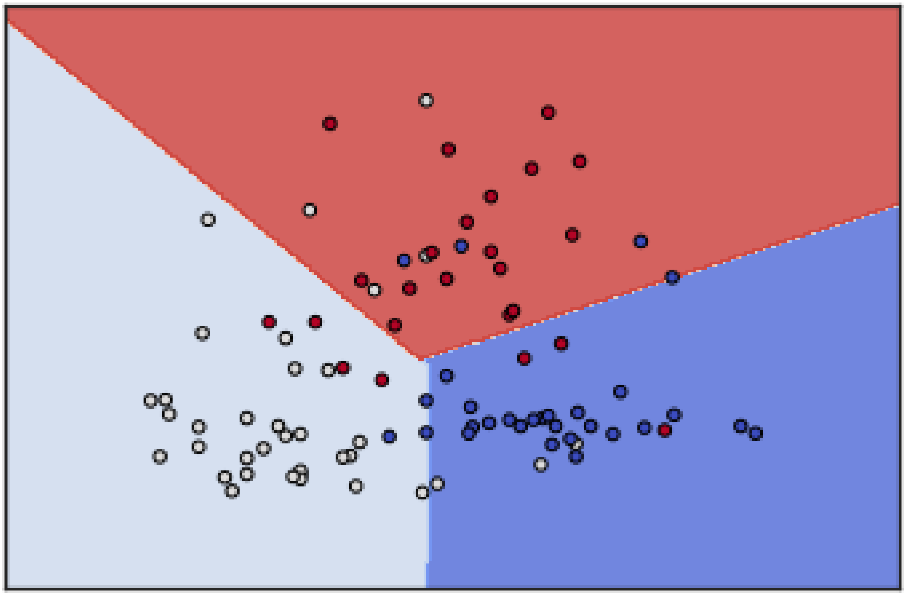
SVC data and boundaries for C= 0.001000



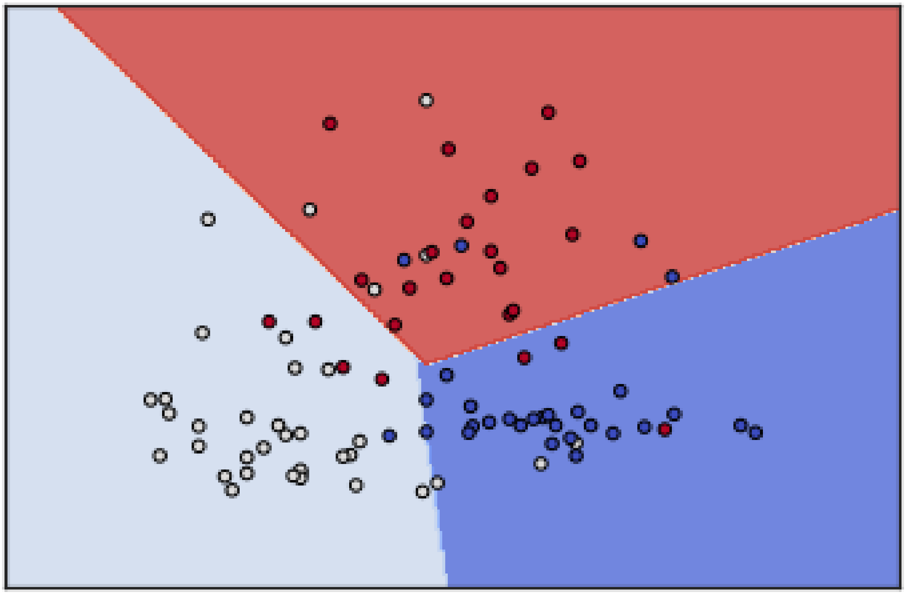
SVC data and boundaries for C= 0.010000



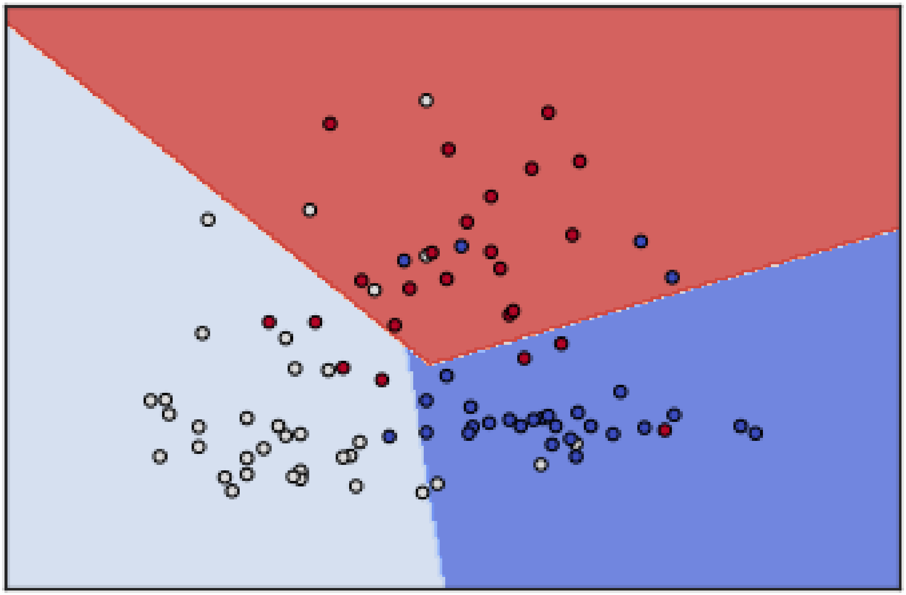
SVC data and boundaries for C= 0.100000



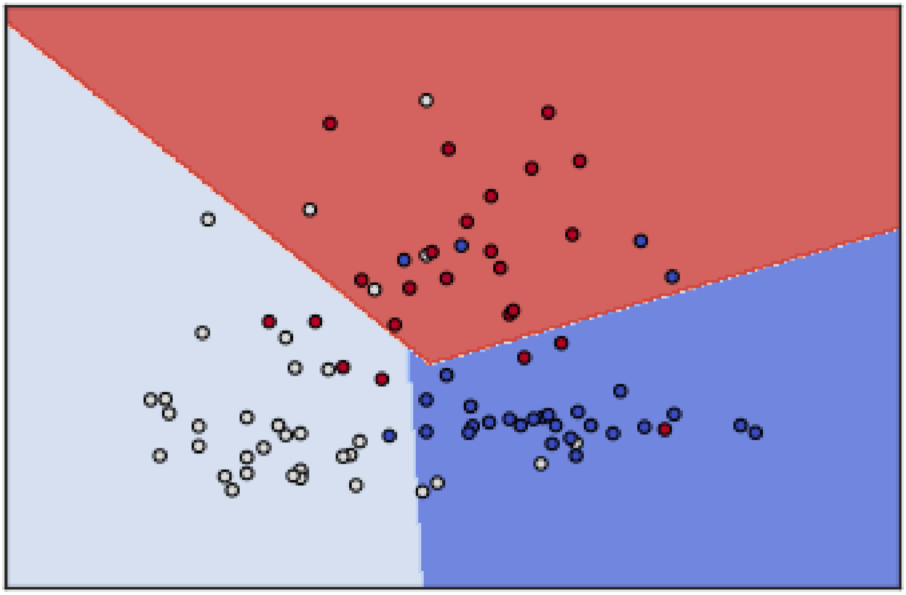
SVC data and boundaries for C= 1.000000

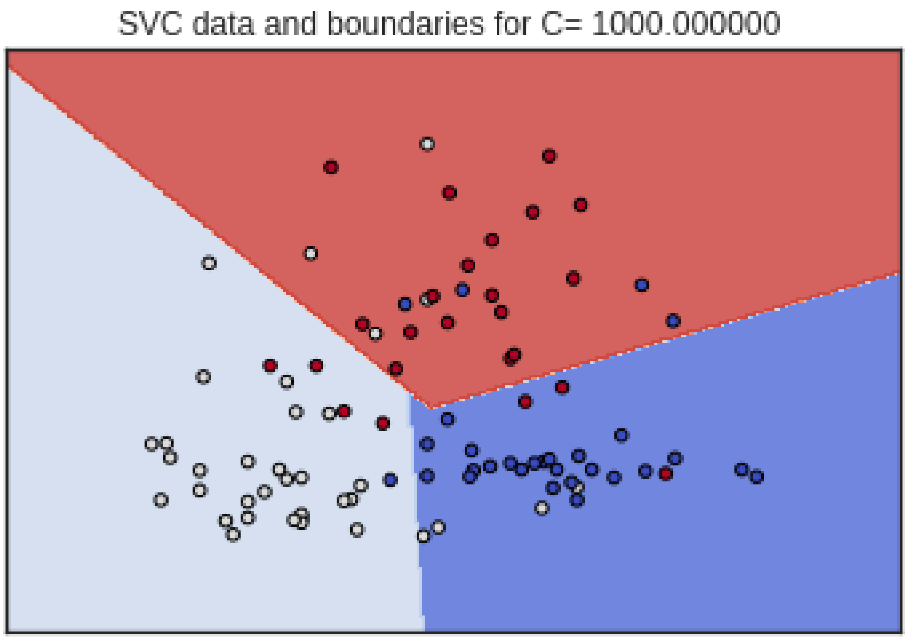


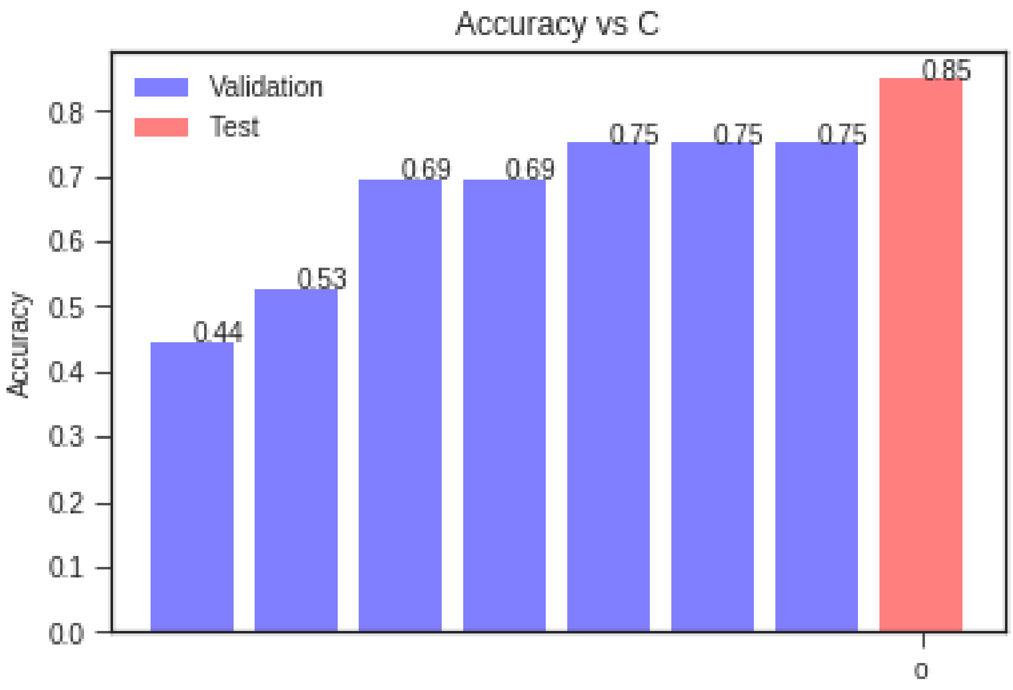
SVC data and boundaries for C= 10.000000



SVC data and boundaries for C= 100.000000




SVC data and boundaries for C= 1000.000000


Accuracy vs C
Validation
Test
Accuracy
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.44
0.53
0.69
0.69
0.75
0.75
0.75
0.85
0