You can find my results on my github: https://github.com/Barrel-Titor/homework-MLDL

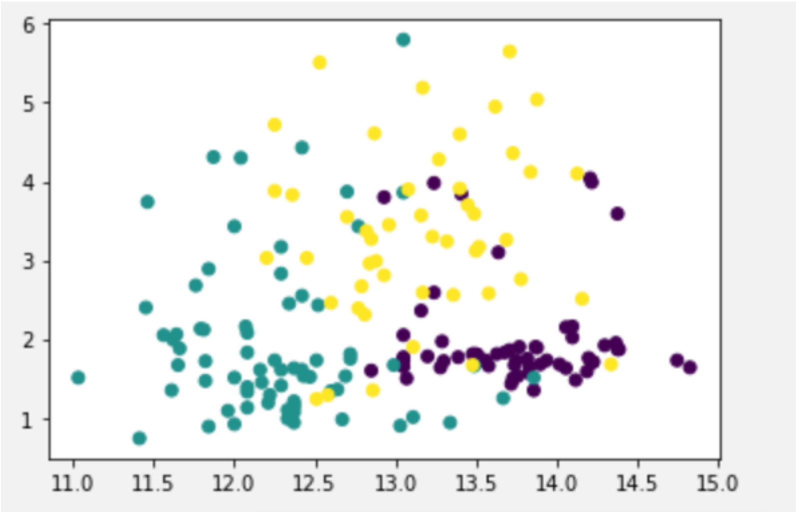
KNN

1. Load Wine dataset

```python
from sklearn.datasets import load_wine
data, target = load_wine(True)
```

2. Select two attributes

```python
data = data[:, :2]
data.shape  # (178, 2)
```



3. Split data into train, validation and test

Use train_test_split twice to randomly cut data into three sets, with proportion 5: 2: 3

```
from sklearn.model_selection import train_test_split

# Train V.S. Val + Test
X_train, X_test, y_train, y_test = train_test_split(
    data, target, test_size=0.5, random_state=0
)

# Train V.S. Val V.S. Test
X_val, X_test, y_val, y_test = train_test_split(
    X_test, y_test, test_size=0.6, random_state=0
)

len(y_train), len(y_val), len(y_test)   # (89, 35, 54)
```

4. Try K = [1, 3, 5, 7]

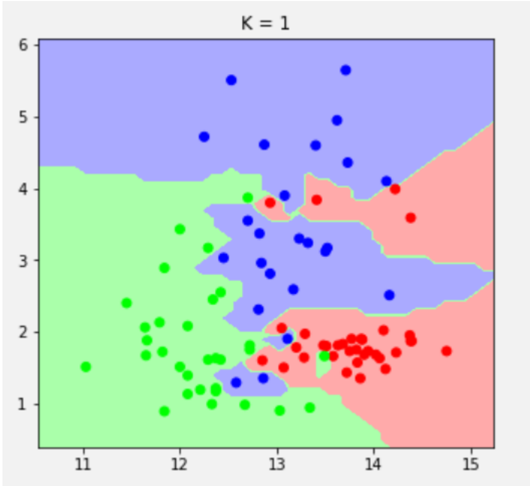
Define function `plot_boundary`, using `plt.contourf()` to help visualize the decision boundaries of KNN

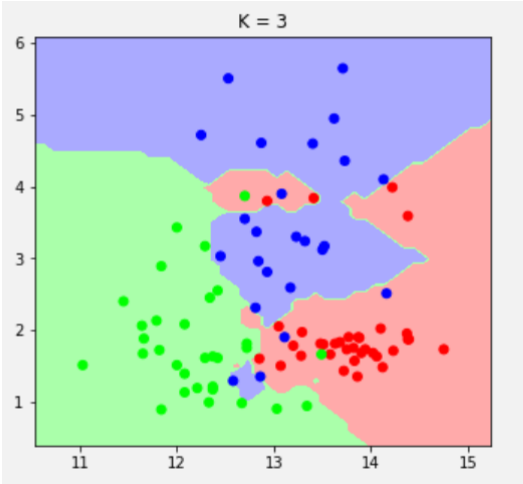
```
lc1 = ListedColormap(['#FFAAAA','#AAFFAA','#AAAAFF'])
lc2 = ListedColormap(['#FF0000','#00FF00','#0000FF'])

def plot_boundary(func, points, labels):
    x_min = X_train[:, 0].min() - .5
    x_max = X_train[:, 0].max() + .5
    y_min = X_train[:, 1].min() - .5
    y_max = X_train[:, 1].max() + .5
    h = 0.1

    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    Z = func.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    plt.contourf(xx, yy, Z, cmap=lc1)
    plt.scatter(points[:, 0], points[:, 1], c=labels, cmap=lc2)
```

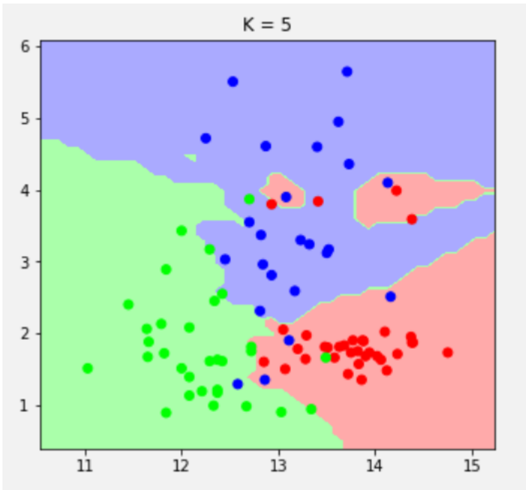
Define function `K_KNN` to fit data and validate

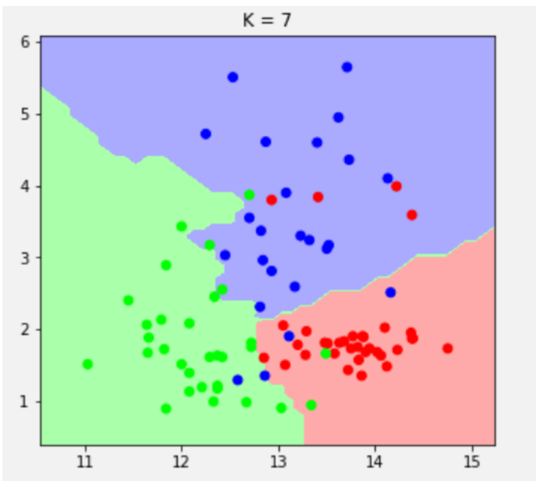
```
def K_KNN(K):
    clf = KNeighborsClassifier(K)
    clf.fit(X_train, y_train)
    clf_list.append(clf)
    plot_boundary(clf, X_train, y_train)
    y_val_predicted = clf.predict(X_val)
    accuracy = np.mean(y_val_predicted == y_val) * 100
    accuracies.append(accuracy)
```

The results look as follows:

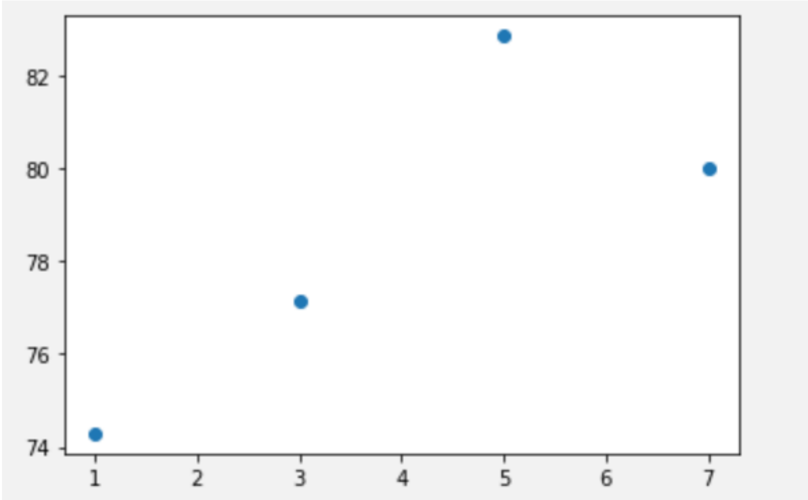

K = 1
6
5
4
3
2
1
11
12
13
14
15


K = 3
6
5
4
3
2
1
11
12
13
14
15


K = 5
6
5
4
3
2
1
11
12
13
14
15


K = 7
6
5
4
3
2
1
11
12
13
14
15

5. Show accuracy on validation set



It shows it's better when K = 5

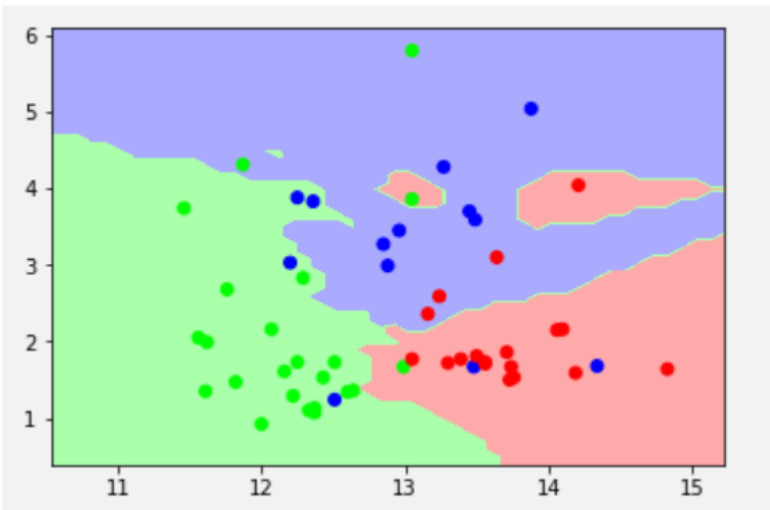
6. How the boundaries change?

When K is too small, neighborhood of each point is very small, which can lead to overfitting. Therefore, the boundary can be easily disturbed by noise and outliers.

As K increases, the boundary becomes simpler has more powerful generalization capabilities. However, if K is too large, points of different labels become its neighbors and the accuracy will become lower.

7. Use the best value of K on the test set

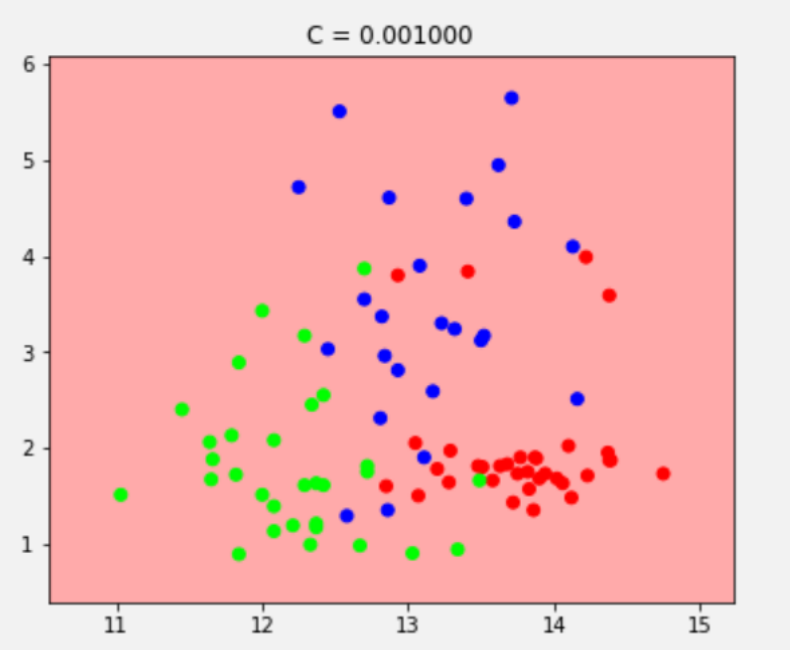
```
![6](6.png)y_test_predicted = clf_list[2].predict(X_test)
accuracy = np.mean(y_test_predicted == y_test) * 100
accuracy    # 75.92592592592592
```

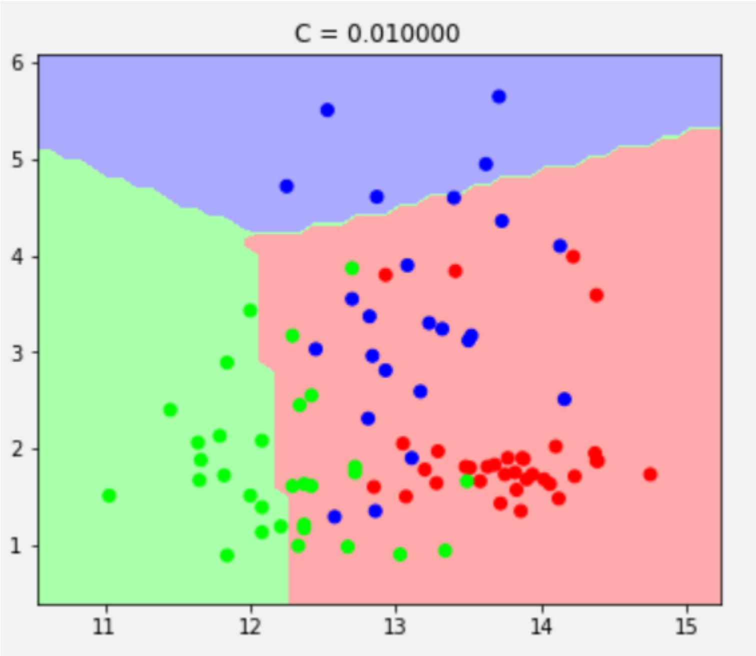


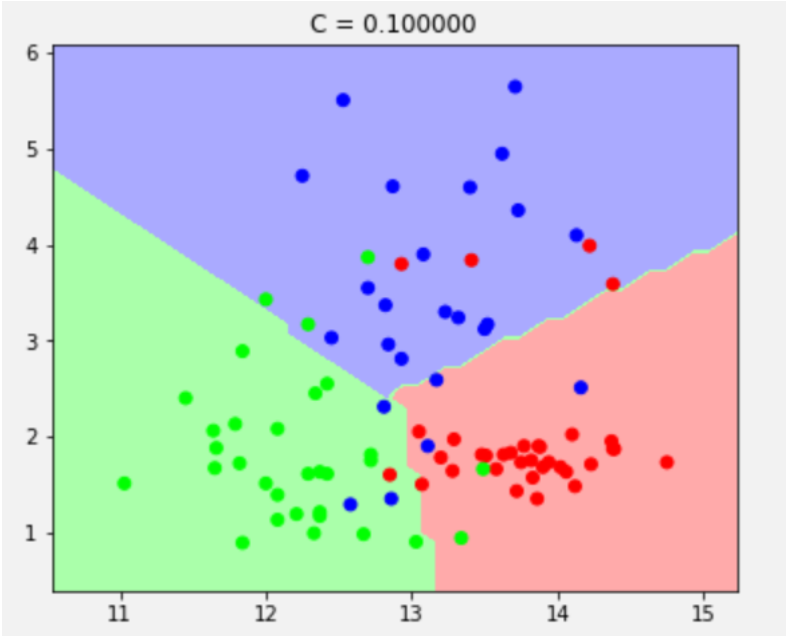
Linear SVM

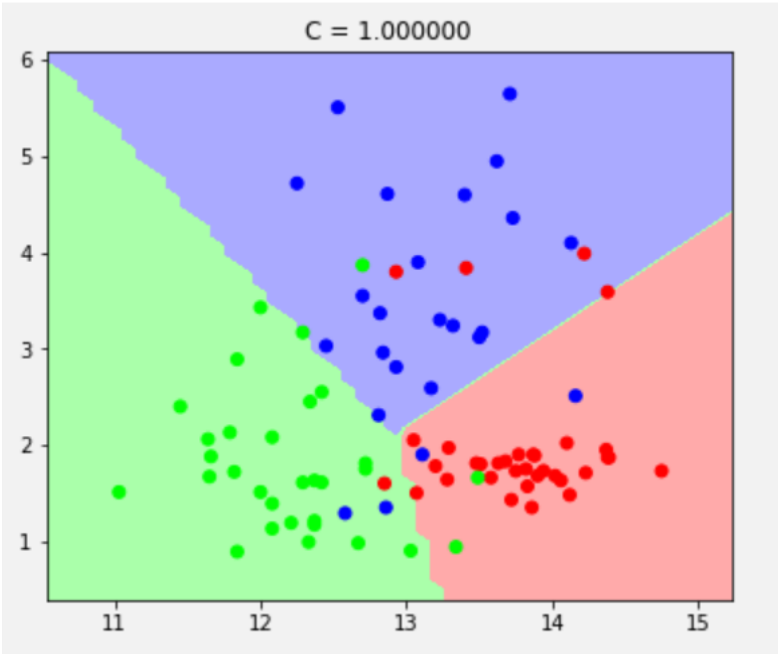
8. Try C = [0.001, 0.01, 0.1, 1, 10, 100,1000]

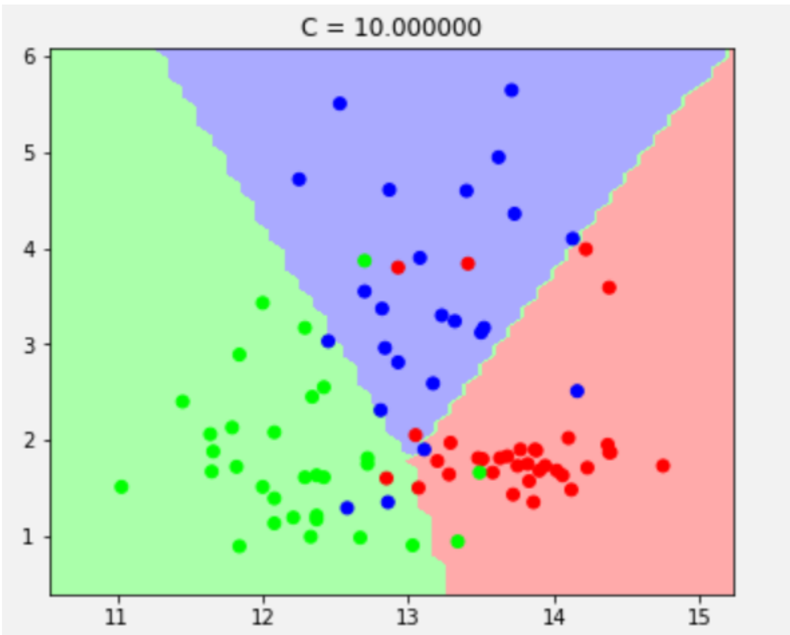
Use `plot_boundary` above to plot decision boundary of SVM

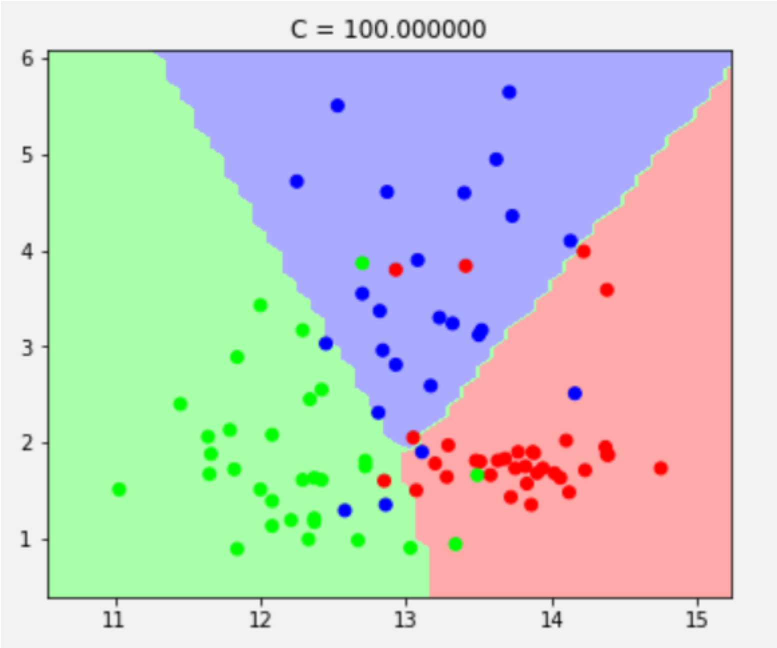


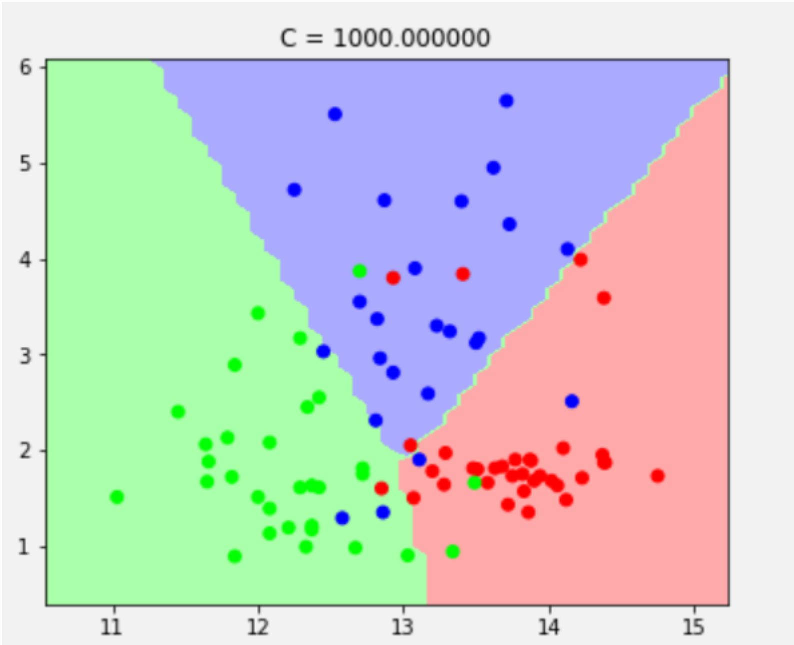



C = 0.100000
6
5
4
3
2
1
11
12
13
14
15

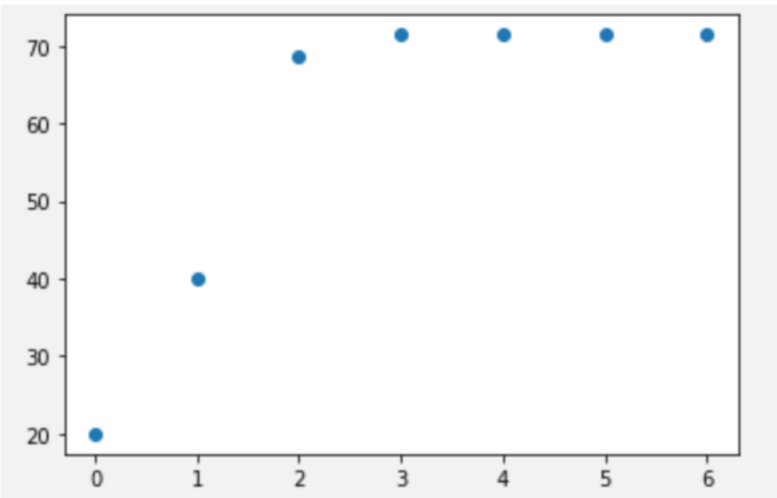

C = 1.000000
6
5
4
3
2
1
11
12
13
14
15


C = 10.000000
6
5
4
3
2
1
11
12
13
14
15





9. Show accuracy on validation set



It seems when C >= 1, the accuracy doesn't vary much.

10. How the boundaries change?

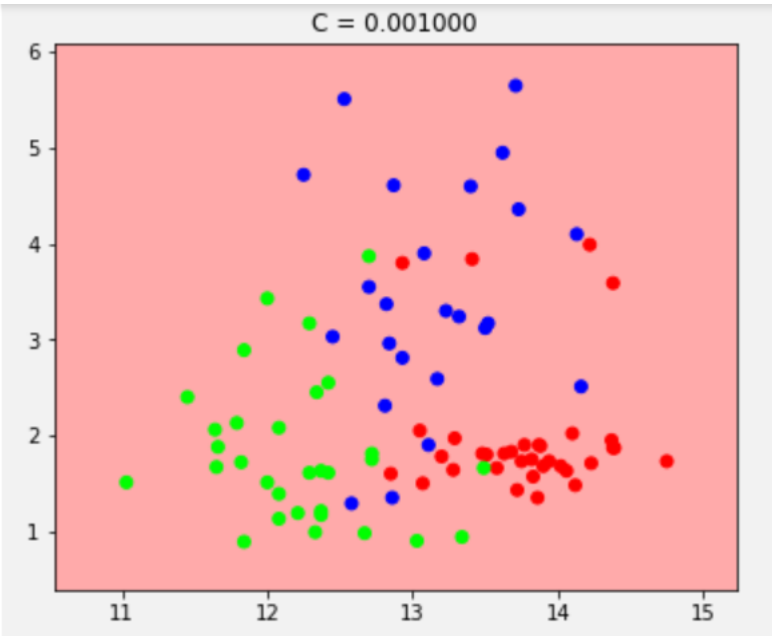
The larger the value of C, the greater the penalty for outliers, and the less willing the classifier is to allow outliers.

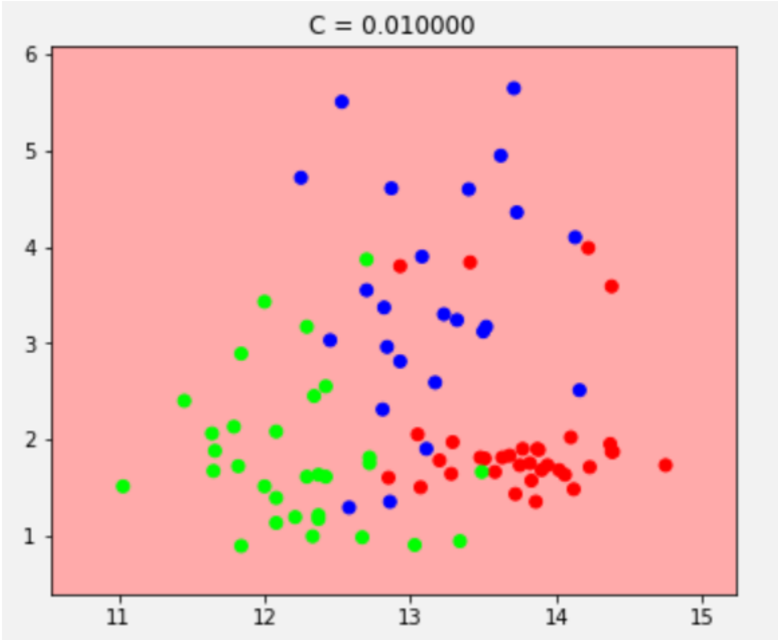
11.Use the best value of C on the test set

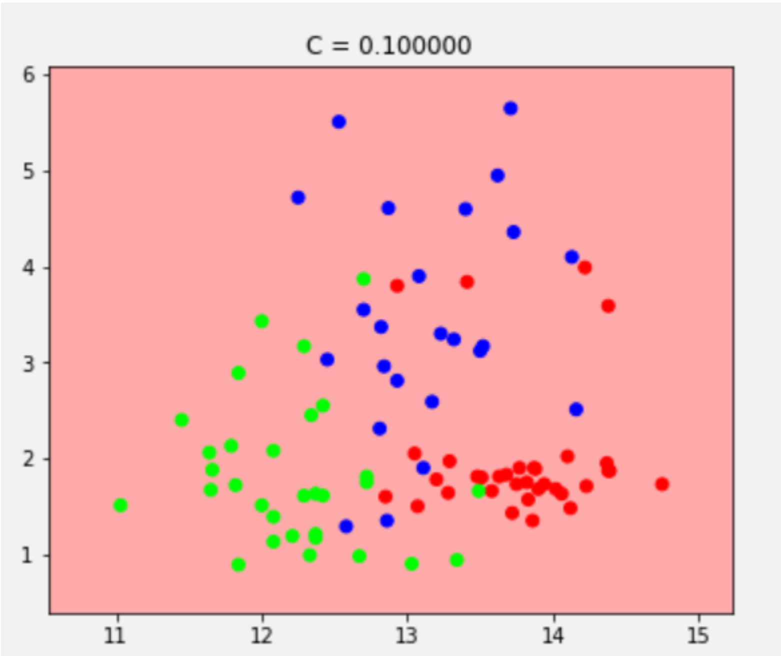
```
accuracy = np.mean(y_test_predicted == y_test) * 100
accuracy    # 79.62962962962963 when C = 1
accuracy    # 83.33333333333334 when C = 10
accuracy    # 83.33333333333334 when C = 100
accuracy    # 83.33333333333334 when C = 1000
```

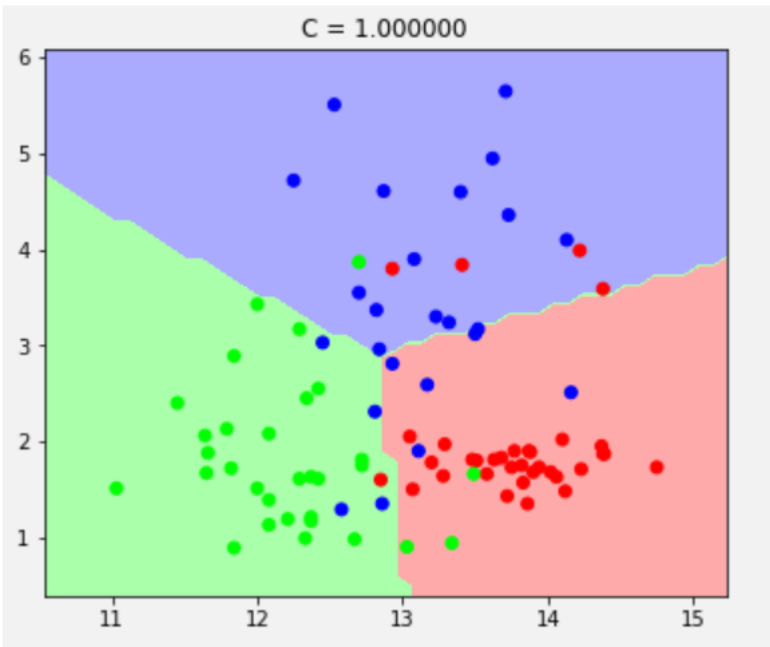
SVM with RBF Kernel

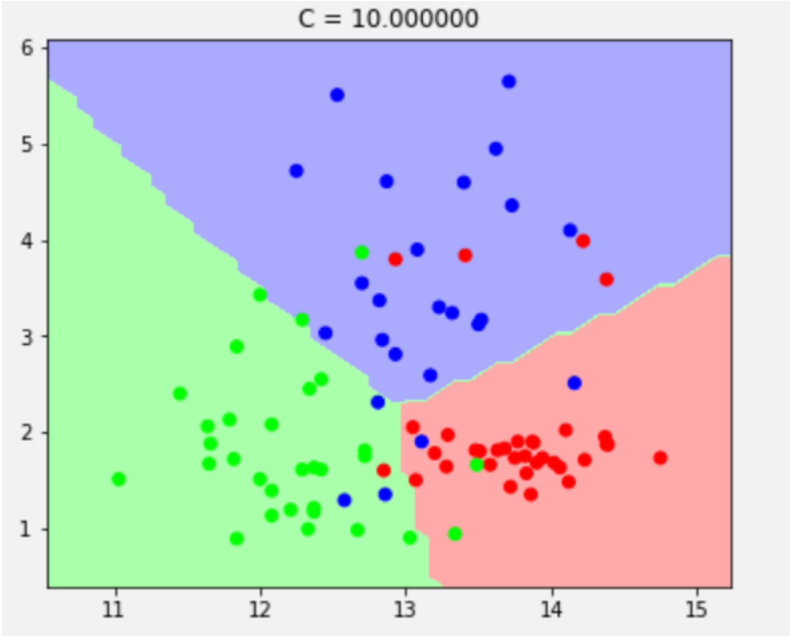
12. Repeat point 8. (train, plot) but using RBF kernel

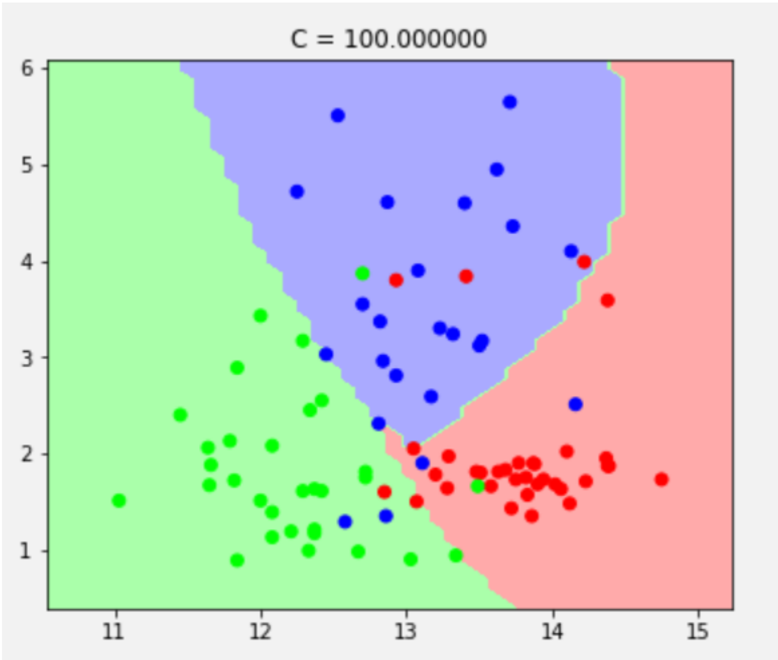


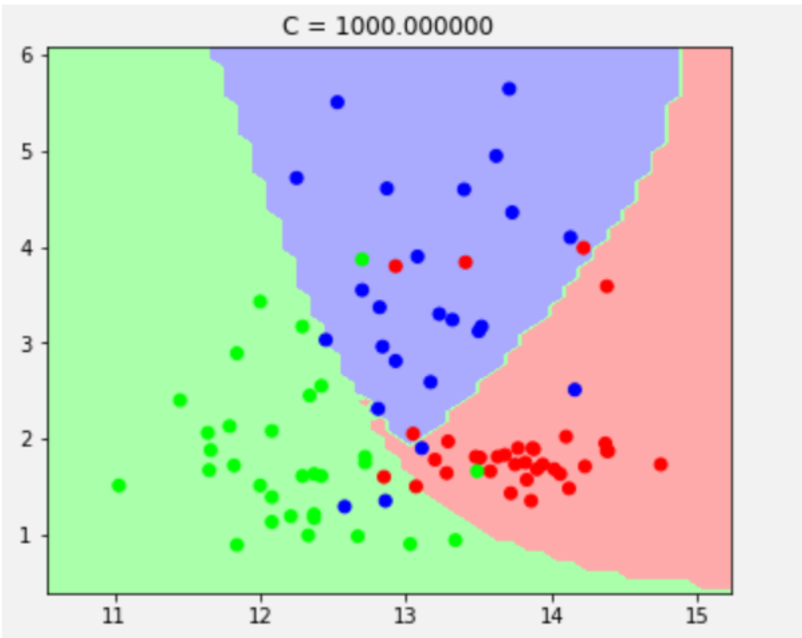

C = 0.010000
6
5
4
3
2
1
11
12
13
14
15


C = 0.100000
6
5
4
3
2
1
11
12
13
14
15


C = 1.000000
6
5
4
3
2
1
11
12
13
14
15







13. Evaluate the best C on the test set

```
accuracies  # [20.0, 20.0, 20.0, 60.0, 71.42857142857143, 68.57142857142857, 77.14285714285715]
y_test_predicted = clf_list[6].predict(X_test)
accuracy = np.mean(y_test_predicted == y_test) * 100
accuracy    # 81.48148148148148
```

14. Differences compared to the linear kernel

The boundaries become non-linear because of the kernel.

15. Perform grid search for both gamma and C at the same time

By checking the source code of `svm.SVC()`, I calculate two default values of gamma

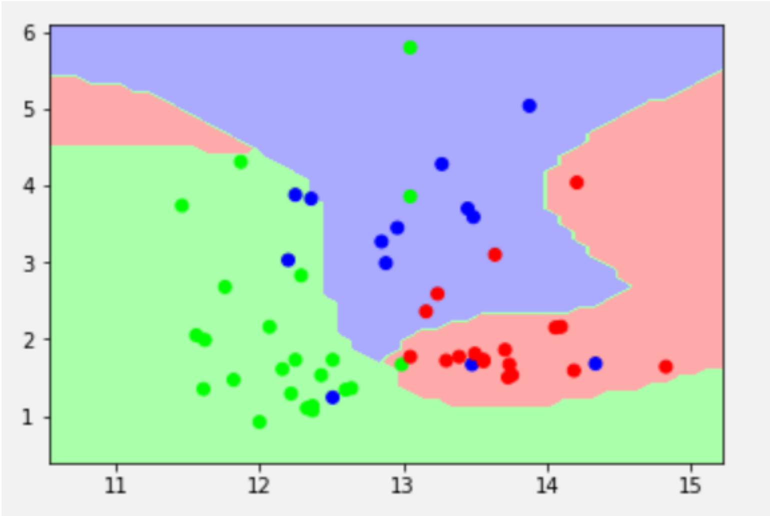
```
# value of gamma='scale' in SVC
1 / (X_train.shape[0] * X_train.var())  # 0.000377073287583712

# value of gamma='auto' in SVC
1 / (X_train.shape[0])  # 0.011235955056179775
```

Therefore I try gamma from 1e-5 to 1, and C from 0.1 to 1000

```
best_score = 0
for gamma in [1e-5, 1e-4, 1e-3, 1e-2, 0.1, 1]:
    for C in [0.1, 1, 10, 100, 1000]:
        clf = svm.SVC(gamma=gamma,C=C)
        clf.fit(X_train,y_train)
        score = clf.score(X_val, y_val)
        if score > best_score:
            best_score = score
            best_parameters = {'gamma':gamma,'C':C}
            best_clf = deepcopy(clf)
```

Best parameters are as follow:

```
best_score, best_parameters # (0.8571428571428571, {'C': 1000, 'gamma': 0.1})
best_clf.score(X_test, y_test)  # 0.7777777777777778
```



K-Fold

16. Merge training and validation split

```
X_train.shape, X_val.shape  # ((89, 2), (35, 2))

X_train = np.concatenate((X_train, X_val), axis=0)
y_train = np.concatenate((y_train, y_val), axis=0)
X_train.shape, y_train.shape    # ((124, 2), (124,))
```

17. Grid search with 5-fold cross validation for gamma and C

`sklearn.model_selection` provides `GridSearchCV` for grid search with cross validation

```
params = {
    "gamma": [1e-5, 1e-4, 1e-3, 1e-2, 0.1, 1],
    "C": [0.1, 1, 10, 100, 1000]
}
grid = GridSearchCV(svm.SVC(), params, cv=5)
grid.fit(X_train, y_train)
```

18. Evaluate on test set

```
grid.best_score_, grid.best_params_ # (0.8226666666666667, {'C': 1000, 'gamma': 0.1})
grid.score(X_test, y_test)  # 0.7777777777777778
```

Extra

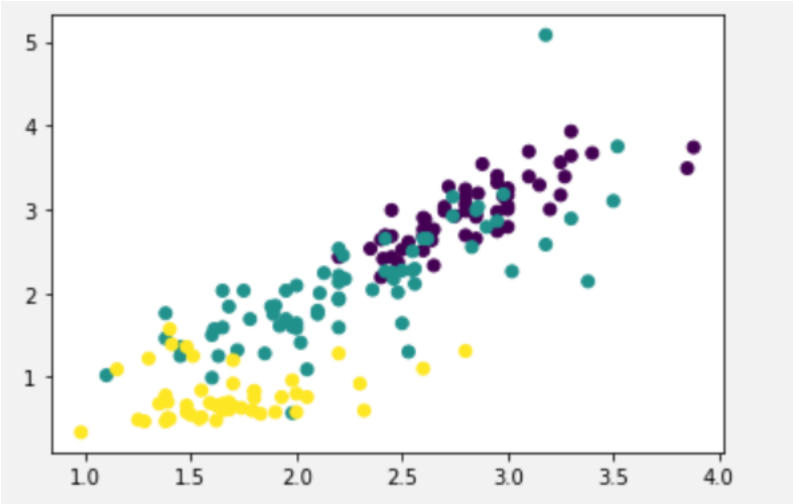
19. Discuss the difference between KNN and SVM

1. SVM is less affected by outliers than KNN
2. Once SVM is trained, we can quickly predict labels, while we don't have a training phase on KNN and we have to calculate distances with neighbors every time new data comes in

20. Try also with different pairs of attributes

Methodology is the same with above. Using `GridSearchCV` is convenient and the result is reliable

I choose the 5th and 6th dimensions to perform SVM with RBF kernel




```
grid.best_score_, grid.best_params_ # (0.7993333333333333, {'C': 1000,
'gamma': 1})
grid.score(X_test, y_test)  # 0.7592592592592593
```

Decision boundary: