16C-Classification-III-SVM-Demo

November 3, 2016

1 SVM in Python

1.1 Support Vector Machines (SVM)

Working with the wine dataset available here:
https://archive.ics.uci.edu/ml/datasets/Wine

```
In [63]: wine = pd.read_table("data/wine.data", sep=',')

         attributes = ['region',
         'Alcohol',
                      'Malic acid',
                      'Ash',
                      'Alcalinity of ash',
                      'Magnesium',
                      'Total phenols',
                      'Flavanoids',
                      'Nonflavanoid phenols',
                      'Proanthocyanins',
                      'Color intensity',
                      'Hue',
                      'OD280/OD315 of diluted wines',
                      'Proline']



         wine.columns = attributes
         # take 2 attributes and use a two dimensional training dataset
         X = wine[['Alcohol', 'Malic acid',]].values
         #             'Ash',
         #             'Alcalinity of ash',
         #             'Magnesium',
         #             'Total phenols',
         #             'Flavanoids', 'Nonflavanoid phenols','Proanthocyanins','Colo
```

```
grape = wine.pop('region')
y = grape.values

wine.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 177 entries, 0 to 176
Data columns (total 13 columns):
Alcohol                         177 non-null float64
Malic acid                      177 non-null float64
Ash                             177 non-null float64
Alcalinity of ash               177 non-null float64
Magnesium                       177 non-null int64
Total phenols                   177 non-null float64
Flavanoids                      177 non-null float64
Nonflavanoid phenols            177 non-null float64
Proanthocyanins                 177 non-null float64
Color intensity                 177 non-null float64
Hue                             177 non-null float64
OD280/OD315 of diluted wines    177 non-null float64
Proline                         177 non-null int64
dtypes: float64(11), int64(2)
memory usage: 18.1 KB
```

```
In [64]: wine.head()
         print(X.shape)

         X, y = utils.shuffle(X, y, random_state=1)
         print(X.shape)
         print(y.shape)
         print(y)

         train_set_size = 100
         X_train = X[:train_set_size]  # selects first 100 rows (examples) for trai
         y_train = y[:train_set_size]
         X_test = X[train_set_size:]   # selects from row 100 until the last one fo
         y_test = y[train_set_size:]
         print(X_train.shape, y_train.shape)
         print(X_test.shape, y_test.shape)
```

```
(177, 2)
(177, 2)
(177,)
[2 2 1 2 1 3 2 1 2 2 1 1 2 1 2 2 3 1 2 1 1 2 3 2 1 2 1 1 1 2 3 3 3 1 2 2 2
 3 2 1 1 2 2 1 1 1 2 1 1 2 2 2 3 1 2 2 1 2 3 2 2 1 3 3 2 1 2 1 2 1 3 3 3 3
 2 1 3 1 2 3 1 2 1 3 2 2 1 2 2 3 1 2 2 2 3 2 2 2 3 1 1 1 3 1 2 3 3 1 2 1 2
 2 1 3 2 3 3 3 2 2 2 3 3 2 1 2 1 3 2 2 1 1 2 1 1 1 3 1 3 3 1 2 2 3 1 2 2 1
```

```
 1 1 2 2 1 3 3 2 2 2 1 3 3 3 3 3 2 1 1 3 2 3 3 2 3 3 2 3 1]
(100, 2) (100,)
(77, 2) (77,)
```

Using the SVM library of scikit-learn: http://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.h

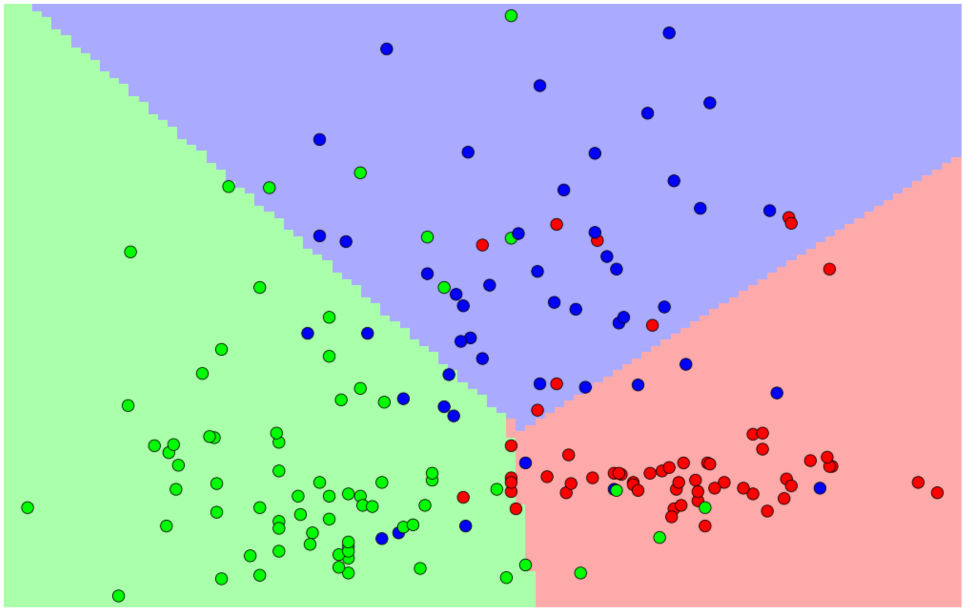
```
In [65]: svc = svm.SVC(kernel='linear')
         svc.fit(X_train, y_train)
         y_pred_test = svc.predict(X_test)
         print("Accuracy of SVM test set:", svc.score(X_test, y_test))
```

```
Accuracy of SVM test set: 0.714285714286
```

Evaluating the fit of the classifier graphically

```
In [66]: from matplotlib.colors import ListedColormap
         # Create color maps for 3-class classification problem, as with iris
         cmap_light = ListedColormap(['#FFAAAA', '#AAFFAA', '#AAAAFF'])
         cmap_bold = ListedColormap(['#FF0000', '#00FF00', '#0000FF'])

         def plot_estimator(estimator, X, y):

             try:
                 X, y = X.values, y.values
             except AttributeError:
                 pass

             estimator.fit(X, y)
             x_min, x_max = X[:, 0].min() - .1, X[:, 0].max() + .1
             y_min, y_max = X[:, 1].min() - .1, X[:, 1].max() + .1
             xx, yy = np.meshgrid(np.linspace(x_min, x_max, 100),
                                  np.linspace(y_min, y_max, 100))
             Z = estimator.predict(np.c_[xx.ravel(), yy.ravel()])

             # Put the result into a color plot
             Z = Z.reshape(xx.shape)
             plt.figure()
             plt.pcolormesh(xx, yy, Z, cmap=cmap_light)

             # Plot also the training points
             plt.scatter(X[:, 0], X[:, 1], c=y, cmap=cmap_bold)
             plt.axis('tight')
             plt.axis('off')
             plt.tight_layout()
```

```
In [67]: plot_estimator(svc, X, y)
```



The SVM gets its name from the samples in the dataset from each class that lie closest to the other class. These training samples are called "support vectors" because changing their position in p-dimensional space would change the location of the decision boundary.

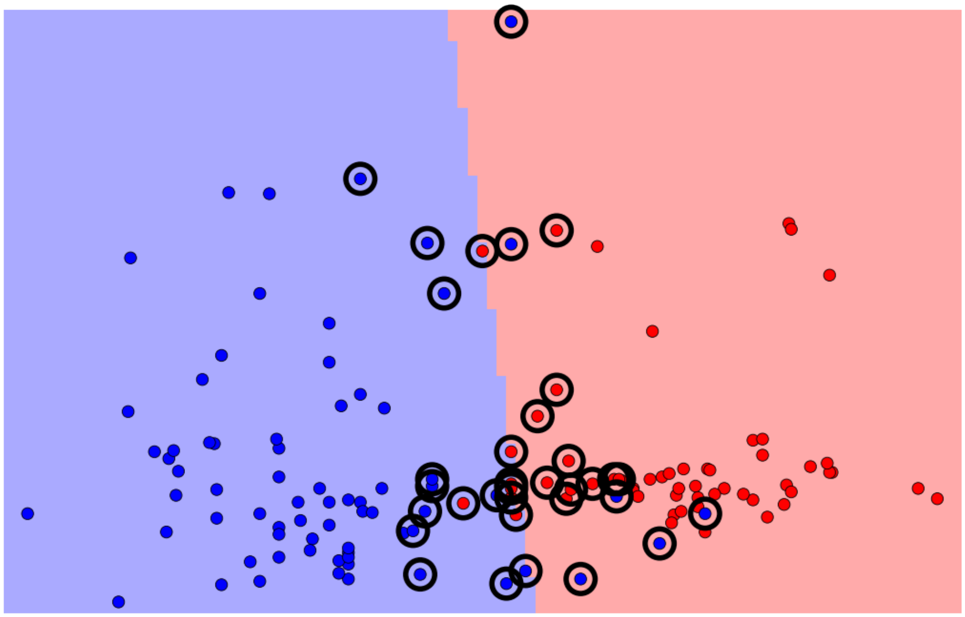
In `scikit-learn`, the indices of the support vectors for each class can be found in the `support_vectors_` attribute of the SVC object.

Here is a 2 class problem using only classes 1 and 2 in the wine dataset.

The support vectors are circled.

```
In [68]: # Extract classes 1 and 2
         X, y = X[np.in1d(y, [1, 2])], y[np.in1d(y, [1, 2])]

         plot_estimator(svc, X, y)
         plt.scatter(svc.support_vectors_[:, 0],
                     svc.support_vectors_[:, 1],
                     s=120,
                     facecolors='none',
                     linewidths=2,
                     zorder=10)
```

```
Out[68]: <matplotlib.collections.PathCollection at 0x11f0075f8>
```



1.2 Regularization

These two classes do not appear to be linearly separable.

For non-linearly separable classes we turn to **regularization.**

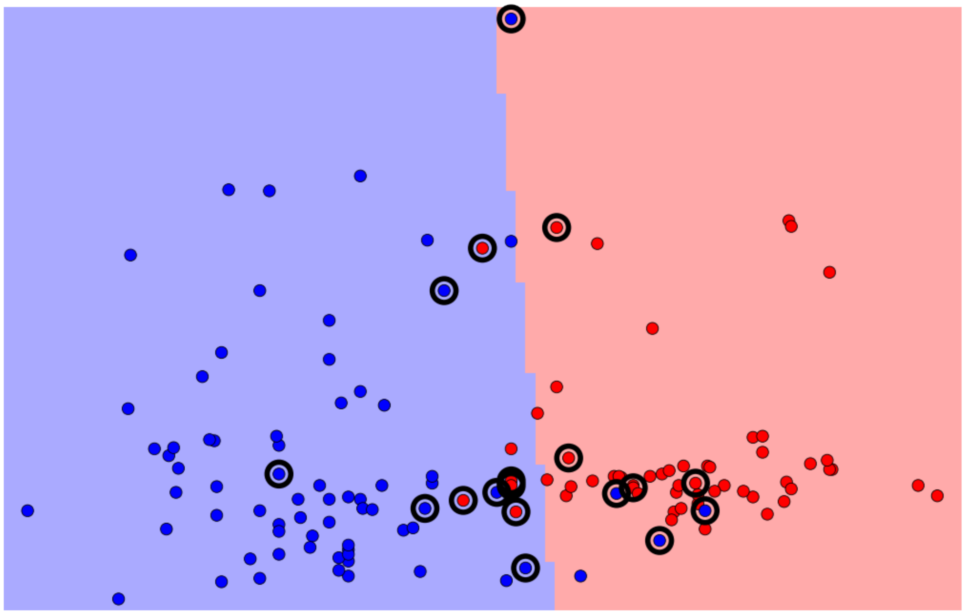
Regularization is tuned via the C parameter.

In practice, a large C value means that the number of support vectors is small (less regularization), while a small C implies many support vectors (more regularization).

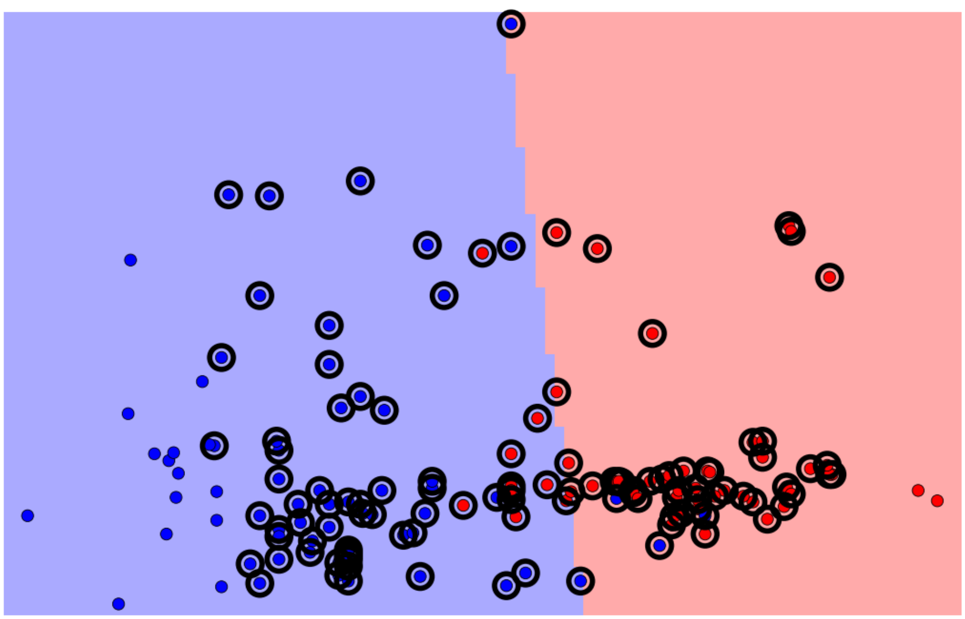
`scikit-learn` sets a default value of C=1.

```
In [69]: svc = svm.SVC(kernel='linear', C=1e6)
         plot_estimator(svc, X, y)
         plt.scatter(svc.support_vectors_[:, 0], svc.support_vectors_[:, 1], s=80,
                     facecolors='none', linewidths=2, zorder=10)
         plt.title('High C values: small number of support vectors')

         svc = svm.SVC(kernel='linear', C=1e-2)
         plot_estimator(svc, X, y)
         plt.scatter(svc.support_vectors_[:, 0], svc.support_vectors_[:, 1], s=80,
                     facecolors='none', linewidths=2, zorder=10)
         plt.title('Low C values: high number of support vectors')

Out[69]: <matplotlib.text.Text at 0x11d853be0>
```

High C values: small number of support vectors



Low C values: high number of support vectors



1.3 Kernels

We can also choose from a suite of available kernels:

- linear,
- poly,
- rbf,
- sigmoid, or
- precomputed.

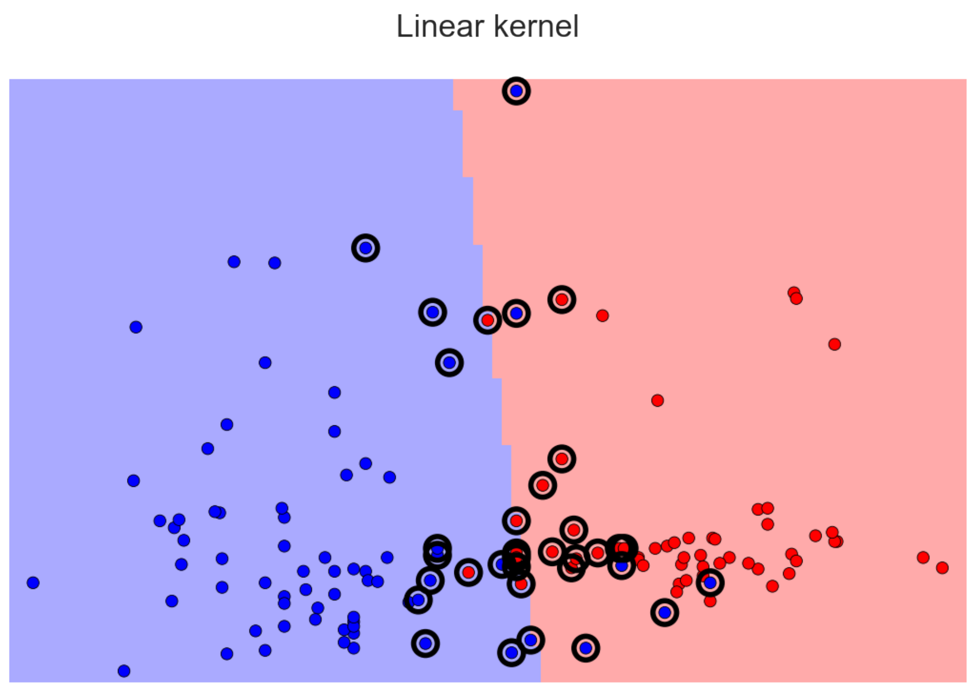
Or, a custom kernel can be passed as a function.

Note that the radial basis function (rbf) kernel is just a Gaussian kernel, but with parameter $\gamma = \frac{1}{\sigma^2}$.

Linear Kernel

```
In [70]: svc_lin = svm.SVC(kernel='linear')
         plot_estimator(svc_lin, X, y)
         plt.scatter(svc_lin.support_vectors_[:, 0], svc_lin.support_vectors_[:, 1]
                     s=80, facecolors='none', linewidths=2, zorder=10)
         plt.title('Linear kernel')
         y_pred_test = svc_lin.predict(X_test)
         print("Accuracy of SVM test set:", svc.score(X_test, y_pred_test))
```

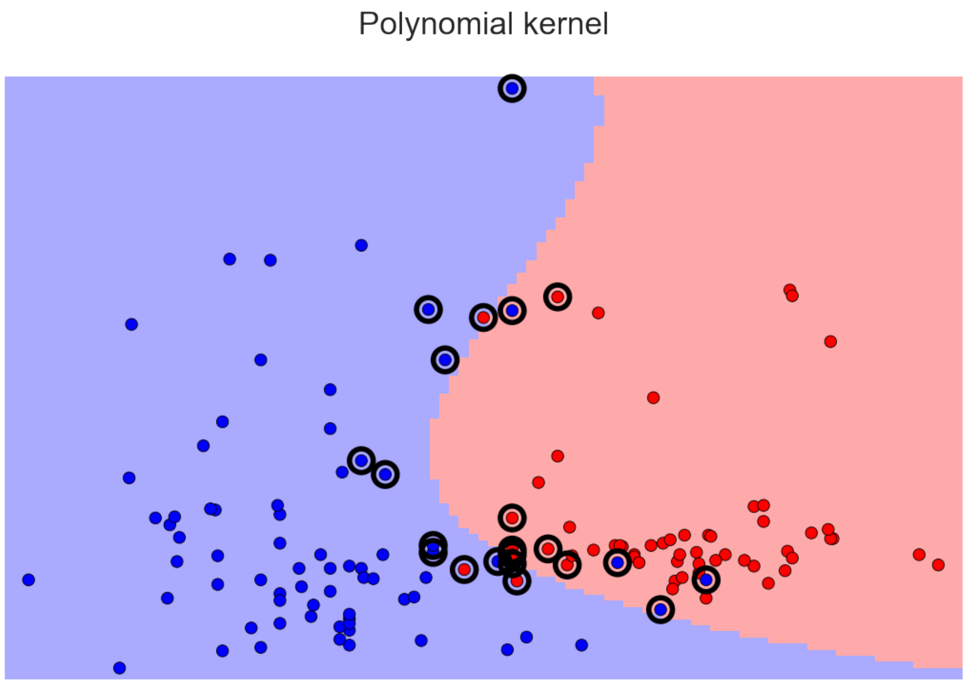
```
Accuracy of SVM test set: 0.922077922078
```



Polynomial Kernel

```
In [71]: svc_poly = svm.SVC(kernel='poly', degree=3)
         plot_estimator(svc_poly, X, y)
         plt.scatter(svc_poly.support_vectors_[:, 0], svc_poly.support_vectors_[:,
                     s=80, facecolors='none', linewidths=2, zorder=10)
         plt.title('Polynomial kernel')
         y_pred_test = svc_poly.predict(X_test)
         print("Accuracy of SVM test set:", svc.score(X_test, y_pred_test))
```

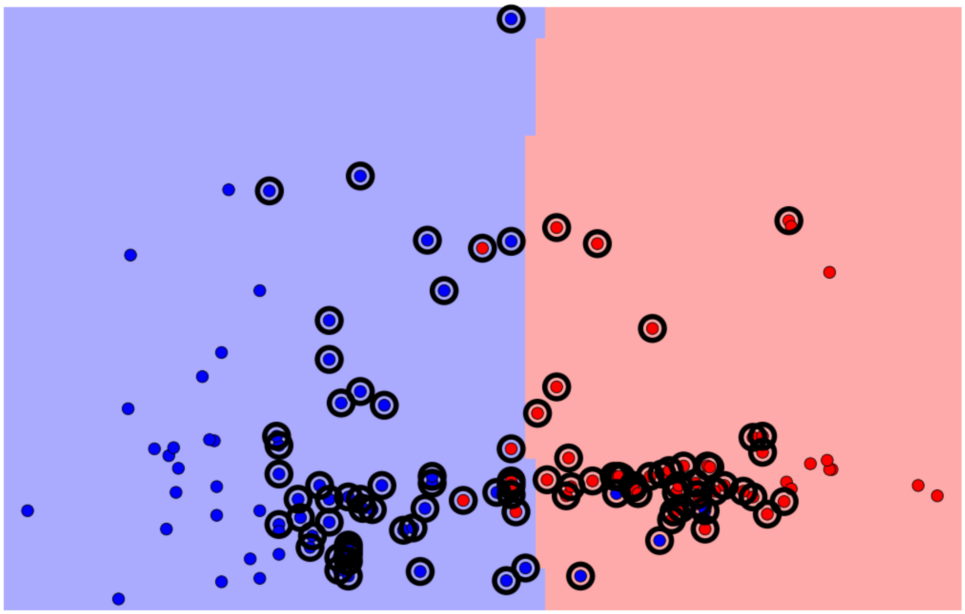
```
Accuracy of SVM test set: 0.831168831169
```



RBF kernel

```
In [72]: svc_rbf = svm.SVC(kernel='rbf', gamma=1e-2)
         plot_estimator(svc_rbf, X, y)
         plt.scatter(svc_rbf.support_vectors_[:, 0], svc_rbf.support_vectors_[:, 1]
                     s=80, facecolors='none', linewidths=2, zorder=10)
         plt.title('RBF kernel')
         y_pred_test = svc_rbf.predict(X_test)
         print("Accuracy of SVM test set:", svc.score(X_test, y_pred_test))
```

```
Accuracy of SVM test set: 0.987012987013
```



1.4 Cross-Validation

So far we've been evaluating our classifiers by 'holding out' test data.

There is a problem with this, however: if we use the test data over and over, while varying model parameters, there is a new danger of overfitting.

The best way around this is to not use a fixed set of test data, but to sample the test data multiple times and look at the average behavior of the classifier.

```
In [73]: X_train, X_test, y_train, y_test = cross_validation.train_test_split(
                  wine.values, grape.values, test_size=0.4, random_state=0)
```

```
In [74]: f = svm.SVC(kernel='linear', C=1)
         f.fit(X_train, y_train)
         f.score(X_test, y_test)
```

```
Out[74]: 0.9577464788732 3938
```

So far, this is fine – but what if we want to vary C? Now, we are in danger of overfitting if we use the same test data to find the 'best' value of C.

```
In [75]: #mean accuracy
         scores = cross_validation.cross_val_score(f, wine.values, grape.values, cv
         print(scores)
         print("Accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.std() * 2))
```

```
[ 0.86486486  0.97222222  0.94444444  1.          1.        ]
Accuracy: 0.96 (+/- 0.10)
```

1.5 Analyzing the iris dataset

```
In [76]: iris = datasets.load_iris()
         X = iris.data[:, :2]  # we only take the first two features. We could
                               # avoid this ugly slicing by using a two-dim dataset
         y = iris.target

         h = .02  # step size in the mesh

         # we create an instance of SVM and fit out data. We do not scale our
         # data since we want to plot the support vectors
         C = 1.0  # SVM regularization parameter
         svc = svm.SVC(kernel='linear', C=C).fit(X, y)
         rbf_svc = svm.SVC(kernel='rbf', gamma=0.7, C=C).fit(X, y)
         poly_svc = svm.SVC(kernel='poly', degree=3, C=C).fit(X, y)
         lin_svc = svm.LinearSVC(C=C).fit(X, y)

         # create a mesh to plot in
         x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
         y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
         xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                              np.arange(y_min, y_max, h))

         # title for the plots
         titles = ['SVC with linear kernel',
                   'LinearSVC (linear kernel)',
                   'SVC with RBF kernel', 'SVC with poly kernel']

         fig = plt.figure(figsize=(10,10))

         for i, clf in enumerate((svc, lin_svc, rbf_svc, poly_svc)):
             # Plot the decision boundary. For that, we will assign a color to each
             # point in the mesh [x_min, m_max]x[y_min, y_max].
             plt.subplot(2, 2, i + 1)
             plt.subplots_adjust(wspace=0.4, hspace=0.4)

             Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])

             # Put the result into a color plot
```

```
    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, cmap=plt.cm.Paired, alpha=0.8)

    # Plot also the training points
    plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Paired)
    plt.xlabel('Sepal length')
    plt.ylabel('Sepal width')
    plt.xlim(xx.min(), xx.max())
    plt.ylim(yy.min(), yy.max())
    plt.xticks(())
    plt.yticks(())
    plt.title(titles[i])

plt.show()
```