ML-MOOC-NPTEL (/github/Santara/ML-MOOC-NPTEL/tree/master)
/ lecture4 (/github/Santara/ML-MOOC-NPTEL/tree/master/lecture4)

In [1]:

```
from __future__ import division, print_function
import numpy as np
from sklearn import datasets, svm
from sklearn.cross_validation import train_test_split
import matplotlib.pyplot as plt
%matplotlib inline
```

```
/Users/Anirban/anaconda/lib/python2.7/site-packages/matplotlib/font_manager.p
  warnings.warn('Matplotlib is building the font cache using fc-list. This ma
```

1. Support Vector Classification

1.1 Load the Iris dataset

In [2]:

```
iris = datasets.load_iris()
X = iris.data[:,:2]
y = iris.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rar
```

1.2 Use Support Vector Machine with different kinds of kernels and evaluate performance

In [3]:

```
def evaluate_on_test_data(model=None):
    predictions = model.predict(X_test)
    correct_classifications = 0
    for i in range(len(y_test)):
        if predictions[i] == y_test[i]:
            correct_classifications += 1
    accuracy = 100*correct_classifications/len(y_test) #Accuracy as a percent
    return accuracy
```

In [4]:

```
kernels = ('linear','poly','rbf')
accuracies = []
for index, kernel in enumerate(kernels):
    model = svm.SVC(kernel=kernel)
    model.fit(X_train, y_train)
    acc = evaluate_on_test_data(model)
    accuracies.append(acc)
    print("{} % accuracy obtained with kernel = {}".format(acc, kernel))
```

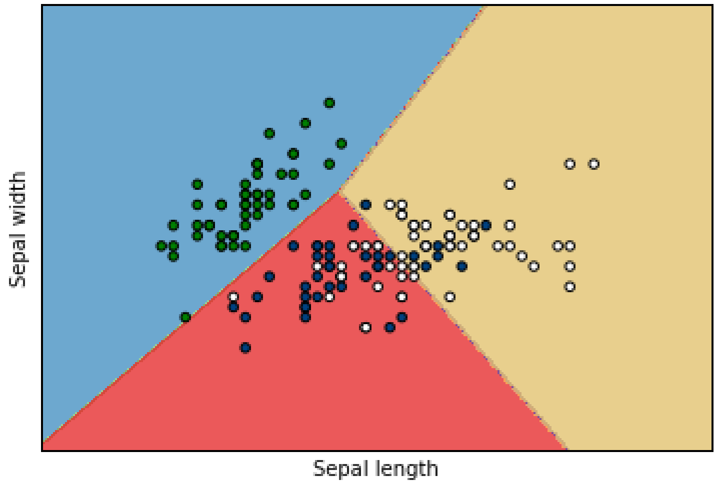
```
84.2105263158 % accuracy obtained with kernel = linear
81.5789473684 % accuracy obtained with kernel = poly
84.2105263158 % accuracy obtained with kernel = rbf
```

1.3 Visualize the decision boundaries

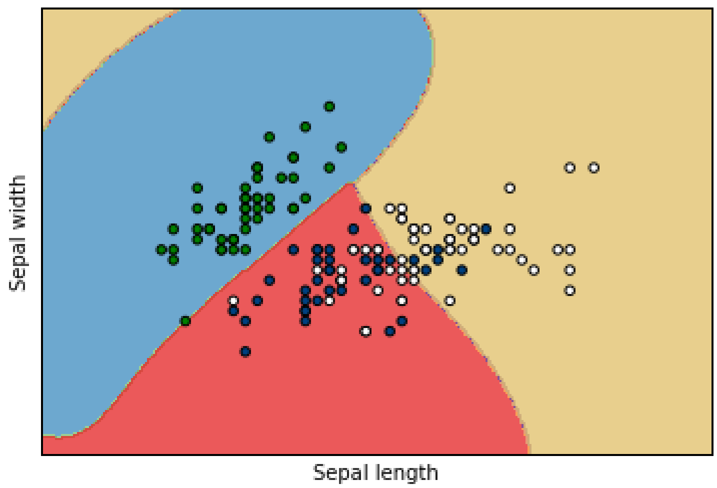
In [5]:

```
#Train SVMs with different kernels
svc = svm.SVC(kernel='linear').fit(X_train, y_train)
rbf_svc = svm.SVC(kernel='rbf', gamma=0.7).fit(X_train, y_train)
poly_svc = svm.SVC(kernel='poly', degree=3).fit(X_train, y_train)

#Create a mesh to plot in
h = .02  # step size in the mesh
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))

#Define title for the plots
titles = ['SVC with linear kernel',
          'SVC with RBF kernel',
          'SVC with polynomial (degree 3) kernel']


for i, clf in enumerate((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.figure(i)

    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.ocean)
    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()
```

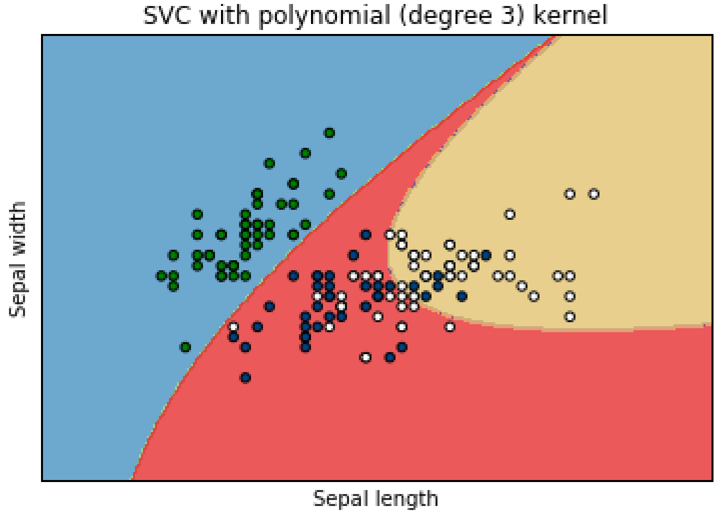
SVC with linear kernel



SVC with RBF kernel



SVC with polynomial (degree 3) kernel



1.4 Check the support vectors

In [6]:

```
#Checking the support vectors of the polynomial kernel (for example)
print("The support vectors are:\n", poly_svc.support_vectors_)
```

```
The support vectors are:
 [[ 4.5  2.3]
 [ 5.4  3.4]
 [ 6.   3.4]
 [ 6.7  3.1]
 [ 6.6  3. ]
 [ 5.7  2.9]
 [ 5.6  3. ]
 [ 5.8  2.7]
 [ 5.7  3. ]
 [ 6.2  2.9]
 [ 6.7  3. ]
 [ 5.9  3.2]
 [ 6.   2.7]
 [ 6.3  2.5]
 [ 6.1  2.9]
 [ 6.5  2.8]
 [ 7.   3.2]
 [ 5.9  3. ]
 [ 5.7  2.6]
 [ 6.1  3. ]
 [ 6.6  2.9]
 [ 5.6  3. ]
 [ 4.9  2.4]
 [ 6.9  3.1]
 [ 5.7  2.8]
 [ 6.3  2.3]
 [ 6.4  2.9]
 [ 6.1  2.8]
 [ 5.8  2.6]
 [ 5.8  2.7]
 [ 6.3  2.8]
 [ 6.4  3.1]
 [ 6.3  2.7]
 [ 5.7  2.5]
 [ 6.   3. ]
 [ 5.8  2.7]
 [ 6.2  3.4]
 [ 6.4  2.7]
 [ 5.8  2.8]
 [ 6.1  2.6]
 [ 6.   2.2]
 [ 6.3  3.4]
 [ 6.8  3. ]
 [ 6.3  3.3]
 [ 6.2  2.8]
 [ 6.4  3.2]
 [ 6.5  3. ]
 [ 6.7  3.3]
 [ 6.7  3.3]
 [ 6.7  3.1]
 [ 6.3  2.9]
 [ 6.5  3. ]
 [ 5.6  2.8]
```

```
[ 5.9  3. ]
[ 4.9  2.5]]
```

2. Support Vector Regression

2.1 Load data from the Boston dataset

In [7]:

```
boston = datasets.load_boston()
X = boston.data
y = boston.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25, rar
```

2.2 Use Support Vector Machine with different kinds of kernels and evaluate performance

In [8]:

```
def evaluate_on_test_data(model=None):
    predictions = model.predict(X_test)
    sum_of_squared_error = 0
    for i in range(len(y_test)):
        err = (predictions[i]-y_test[i]) **2
        sum_of_squared_error += err
    mean_squared_error = sum_of_squared_error/len(y_test)
    RMSE = np.sqrt(mean_squared_error)
    return RMSE
```

In [9]:

```
kernels = ('linear','rbf')
RMSE_vec = []
for index, kernel in enumerate(kernels):
    model = svm.SVR(kernel=kernel)
    model.fit(X_train, y_train)
    RMSE = evaluate_on_test_data(model)
    RMSE_vec.append(RMSE)
    print("RMSE={} obtained with kernel = {}".format(RMSE, kernel))
```

```
RMSE=5.30510081135 obtained with kernel = linear
RMSE=8.28026482035 obtained with kernel = rbf
```