Programming assignment 7: SVM

In [21]:

import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

from sklearn.datasets import make_blobs

Your task

In this sheet we will implement a simple binary SVM classifier.

We will use **CVXOPT** http://cvxopt.org/ (http://cvxopt.org/ (http://cvxopt.org/) - a Python library for convex optimization. If you use Anaconda, you can install it using

conda install cvxopt

from cvxopt import matrix, solvers

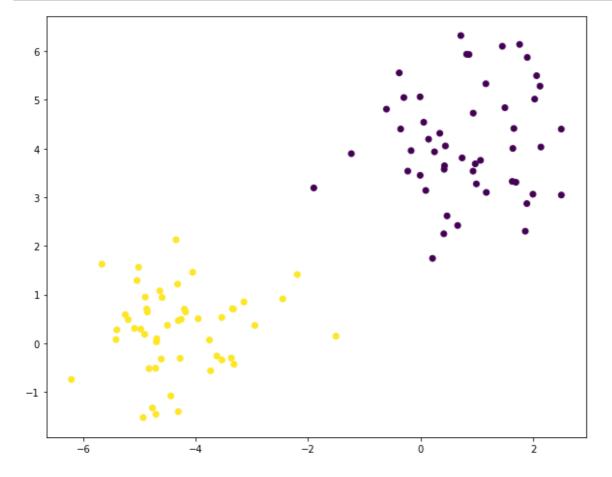
As usual, your task is to fill out the missing code, run the notebook, convert it to PDF and attach it you your HW solution.

Generate and visualize the data

In [22]:

```
N = 100 # number of samples
D = 2 # number of dimensions
C = 2 # number of classes
seed = 3 # for reproducible experiments

X, y = make_blobs(n_samples=N, n_features=D, centers=2, random_state=seed)
y[y == 0] = -1 # it is more convenient to have {-1, 1} as class labels (instead of {0, 1})
y = y.astype(np.float)
plt.figure(figsize=[10, 8])
plt.scatter(X[:, 0], X[:, 1], c=y)
plt.show()
```



Task 1: Solving the SVM dual problem

Remember, that the SVM dual problem can be formulated as a Quadratic programming (QP) problem. We will solve it using a QP solver from the CVX0PT library.

The general form of a QP is

$$\min_{\mathbf{x}} \frac{1}{2} \mathbf{x}^T \mathbf{P} \mathbf{x} - \mathbf{q}^T \mathbf{x}$$
 \mathbf{g}
 \mathbf{g}
 \mathbf{g}
 \mathbf{g}
 \mathbf{g}
 \mathbf{g}
 \mathbf{g}
 \mathbf{h}
 \mathbf{g}
 \mathbf{h}
 \mathbf{g}
 \mathbf{h}

where \leq denotes "elementwise less than or equal to".

Your task is to formulate the SVM dual problems as a QP and solve it using CVXOPT, i.e. specify the matrices P, G, A and vectors q, h, b.

In [23]:

```
def solve_dual_svm(X, y):
    """Solve the dual formulation of the SVM problem.
    Parameters
    X : array, shape [N, D]
        Input features.
    y : array, shape [N]
        Binary class labels (in {-1, 1} format).
    Returns
    alphas : array, shape [N]
        Solution of the dual problem.
    # TODO
    # These variables have to be of type cvxopt.matrix
    N = X.shape[0]
    DIM = X.shape[1]
    K = y[:, None] * X
    K = np.dot(K, K.T)
    P = matrix(K)
    q = matrix(-np.ones((N, 1)))
    G = matrix(-np.eye(N))
    h = matrix(np.zeros(N))
    A = matrix(y.reshape(1, -1))
    b = matrix(np.zeros(1))
    solvers.options['show_progress'] = False
    solution = solvers.qp(P, q, G, h, A, b)
    alphas = np.array(solution['x'])
    return alphas
```

Task 2: Recovering the weights and the bias

In [24]:

```
def compute_weights_and_bias(alpha, X, y):
    """Recover the weights w and the bias b using the dual solution alpha.
    Parameters
    alpha : array, shape [N]
       Solution of the dual problem.
   X : array, shape [N, D]
       Input features.
   y : array, shape [N]
       Binary class labels (in {-1, 1} format).
   Returns
    -----
    w : array, shape [D]
       Weight vector.
    b : float
    Bias term.
   # get weights
   w = np.sum(alpha * y[:, None] * X, axis = 0)
   # get bias
    cond = (alpha > 1e-4).reshape(-1)
    b = y[cond] - np.dot(X[cond], w)
    return w, b[0]
```

Visualize the result (nothing to do here)

In [25]:

```
def plot data with hyperplane and support vectors(X, y, alpha, w, b):
    """Plot the data as a scatter plot together with the separating hyperplane.
    Parameters
    -----
   X : array, shape [N, D]
        Input features.
    y : array, shape [N]
        Binary class labels (in {-1, 1} format).
    alpha: array, shape [N]
        Solution of the dual problem.
   w : array, shape [D]
        Weight vector.
    b: float
        Bias term.
    plt.figure(figsize=[10, 8])
    # Plot the hyperplane
    slope = -w[0] / w[1]
    intercept = -b / w[1]
    x = np.linspace(X[:, 0].min(), X[:, 0].max())
    plt.plot(x, x * slope + intercept, 'k-', label='decision boundary')
    # Plot all the datapoints
    plt.scatter(X[:, 0], X[:, 1], c=y)
    # Mark the support vectors
    support_vecs = (alpha > 1e-4).reshape(-1)
    plt.scatter(X[support_vecs, 0], X[support_vecs, 1], c=y[support_vecs], s=250, marke
r='*', label='support vectors')
    plt.xlabel('$x 1$')
    plt.ylabel('$x_2$')
    plt.legend(loc='upper left')
```

The reference solution is

Indices of the support vectors are

```
[38, 47, 92]
```

In [26]:

```
alpha = solve_dual_svm(X, y)
w, b = compute_weights_and_bias(alpha, X, y)
plot_data_with_hyperplane_and_support_vectors(X, y, alpha, w, b)
plt.show()
```

