SMAI Assignment Number 1

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Imports

In [117]:

```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

Problem 1 : Voted Perceptron

Vanila Perceptron Implementation

In [118]:

```
import numpy as np
class Perceptron:
    """
    An implementation of a percepton model
    """
    def __init__(self):
        self.X=None
        self.y=None
        self.w = None
        self.b = None
        self.learning_rate=1

    def fit(self, X, y, epochs):
        # Initialise weights and bias
        self.w = np.zeros(X.shape[1])
        self.b = 0
        for epoch in range(epochs):
            for i,x in enumerate(X):
                if y[i]*(np.dot(X[i], self.w)+self.b) <= 0:
                    self.w += self.learning_rate*y[i]*X[i]
                    self.b += self.learning_rate*y[i]
        return self

    def predict(self, X):
        y = np.dot(X, self.w) + self.b
        y[y>0]= 1
        y[y<=0]= -1
        return y
```

Voted Perceptron Implementation

In [119]:

```
import numpy as np
class VotedPerceptron:
    """
    An implementation of a voted iipercepton model
    """
    def __init__(self):
        self.X=None
        self.y=None
        self.learning_rate=1
        # Stores a tuple of weights, biases and votes (w,b,c)
        # for each of the weight changes
        self.outputs = None

    def fit(self, X, y, epochs):
        # Initialise weights and bias
        w,b,c = np.zeros(X.shape[1]), 0, 1
        self.outputs = [(w,b,c)]

        for epoch in range(epochs):
            for i in range(X.shape[0]):
                w,b,c = self.outputs[-1] #Last update
                if (np.dot(X[i], w) + b)*y[i] <= 0:
                    w += self.learning_rate*y[i]*X[i]
                    b += self.learning_rate*y[i]
                    c = 1
                    self.outputs.append((w,b,c))
                else:
                    c+=1
                    self.outputs[-1] = (w,b,c)
        return self

    def predict(self, X):
        y_voted = []
        for w,b,c in self.outputs:
            y_k = np.dot(X,w ) + b
            y_k[y_k>0]= 1
            y_k[y_k<=0]= -1
            y_scaled = c*y_k
            y_voted.append(y_scaled.tolist())
        y = np.asarray(y_voted)
        y = y.sum(axis=0)
        y[y>0]=1
        y[y<=0]=-1
        return y
```

Preparing the datasets for comparison

In [120]:

```
# Download the datasets
import pandas as pd
uris = [
    'https://archive.ics.uci.edu/ml/machine-learning-databases/breast-cancer-wis
consin/breast-cancer-wisconsin.data',
    'https://archive.ics.uci.edu/ml/machine-learning-databases/ionosphere/ionosp
here.data'
]

bcdataset, iodataset = [pd.read_csv(uri, header=None) for uri in uris]
```

In [121]:

```
#Ionoshpere Dataset Exploration
print('Ionoshpere Dataset Shape : {}'.format(iodataset.shape))
print(bcdataset.head(5))

# Remove rows with missing values
# No rows with missing values, skipping cleanup
print('Ionoshpere Dataset Shape After Cleanup : {}'.format(iodataset.shape))

X_io, y_io = iodataset.iloc[:,1:iodataset.shape[1]-1], iodataset.iloc[:,-1]
X_io, y_io = X_io.as_matrix() , y_io.as_matrix()

#Convert classification labels 'g', 'b' to +1, -1 for binary classification
labels = {'g':1, 'b': -1}
for key, val in labels.items():
    y_io[y_io==key] = val
print(X_io.shape)
```

```
Ionoshpere Dataset Shape : (351, 35)
        0   1   2   3   4   5   6   7   8   9   10
0  1000025   5   1   1   1   2   1   3   1   1   2
1  1002945   5   4   4   5   7  10   3   2   1   2
2  1015425   3   1   1   1   2   2   3   1   1   2
3  1016277   6   8   8   1   3   4   3   7   1   2
4  1017023   4   1   1   3   2   1   3   1   1   2
Ionoshpere Dataset Shape After Cleanup : (351, 35)
(351, 33)
```

In [122]:

```
#Breast Cancer Dataset Exploration
print('Breast Cancer Dataset Shape : {}'.format(bcdataset.shape))
print(bcdataset.head(5))

# Remove rows with missing values
bcdataset.iloc[:,6] = pd.to_numeric(bcdataset.iloc[:,6], errors='coerce')
bcdataset = bcdataset.dropna()
print('Breast Cancer Dataset Shape After Cleanup : {}'.format(bcdataset.shape))

X_bc, y_bc = bcdataset.iloc[:,1:10], bcdataset.iloc[:,10]
X_bc, y_bc = X_bc.as_matrix() , y_bc.as_matrix()

#Convert classification labels 2, 4 to +1, -1 for binary classification
labels = {2:1, 4: -1}
for key, val in labels.items():
    y_bc[y_bc==key] = val
```

```
Breast Cancer Dataset Shape : (699, 11)
         0   1   2   3   4   5   6   7   8   9   10
0  1000025   5   1   1   1   2   1   3   1   1   2
1  1002945   5   4   4   5   7  10   3   2   1   2
2  1015425   3   1   1   1   2   2   3   1   1   2
3  1016277   6   8   8   1   3   4   3   7   1   2
4  1017023   4   1   1   3   2   1   3   1   1   2
Breast Cancer Dataset Shape After Cleanup : (683, 11)
```

In [123]:

```
def generate_k_folds(dataset, k):
    """
    Returns a list of folds, where each fold is a tuple like (training_set, test
_set), where each set is a tuple like (examples, classes)
    """
    folds=[]
    n=dataset[0].shape[0]
    fold_size = n//k


    # Divide the data into k equal subsections, keep k-1 section for training an
d 1 for testing, repeat k times to generate folds
    for i in range(k):
        indices = [j for j in range(n)]
        if i == k-1:
            fold_size = n - i*fold_size
        test_idx, training_idx = indices[i*fold_size:i*fold_size+fold_size], ind
ices[0:i*fold_size] + indices[i*fold_size+fold_size:]

        examples=dataset[0]
        classes=dataset[1]

        training_set_examples=examples[training_idx,:]
        training_set_classes=np.array(classes)[training_idx]
        training_set=(training_set_examples,training_set_classes)

        test_set_examples=examples[test_idx,:]
        test_set_classes=np.array(classes)[test_idx]
        test_set=(test_set_examples,test_set_classes)
        fold =(training_set,test_set)
        folds.append(fold)
    return folds
```

In [124]:

```
def accuracy(predicted, actual):
    """
    Returns a score denoting percentage of correct predictions
    """
    return np.mean(predicted == actual)
def get_model_accuracy(model, X_train, y_train, X_test, y_test, epochs):
    """
    Trains a model on train set and returns the model's accuracy score on test s
et
    """
    model.fit(X_train, y_train, epochs=epochs)
    prediction = model.predict(X_test)
    return accuracy(prediction, y_test)

def k_fold_cross_validation_accuracy(model_name, folds, epochs):
    """
    Trains the model and returns its k-fold cross validation accuracy
    """
    scores = []
    for i, fold in enumerate(folds):
        train, valid = fold
        X_valid, y_valid = valid
        X_train, y_train = train
        model = get_model_by_name(model_name)
        scores.append(get_model_accuracy(model, X_train, y_train, X_valid, y_val
id, epochs))
    k_fold_cross_validation_accuracy = 0
    if len(scores) > 0:
        k_fold_cross_validation_accuracy = sum(scores)/len(scores)
    return k_fold_cross_validation_accuracy

def get_model_by_name(model_name):
    """
    Returns an intance of the given model name
    """
    if model_name == 'Perceptron':
        return Perceptron()
    elif model_name == 'VotedPerceptron':
        return VotedPerceptron()
    return None

def generate_comparision_result(X, y, num_of_folds, epochs_list, model_names):
    """
    Returns an array of accuracy scores. Each element in the array corresponds t
o
    the accuracy scores of various models for an epoch in given epoch list.
    """
    scores_per_epoch = []
    voted_perceptron_score_per_epoch = []
    folds = generate_k_folds([X,y],num_of_folds)
    for epochs in epochs_list:
        scores_per_model = []
        for model_name in model_names:
            scores_per_model.append(k_fold_cross_validation_accuracy(model_name,
 folds, epochs))
        scores_per_epoch.append(scores_per_model)
    return scores_per_epoch
```

In [125]:

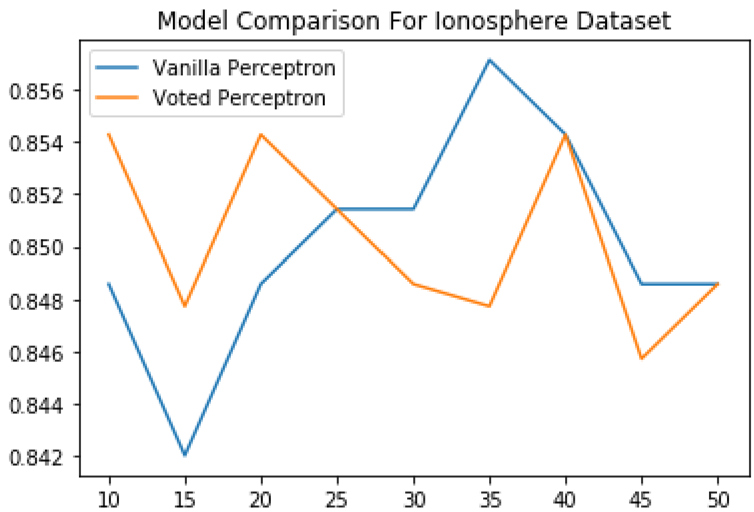
```
def plot_comparison_results(dataset_name, comparison_results, epoch_list):
    """
    Utility method to plot the model comparision results
    """
    perceptron_result = comparison_results[:,0].reshape([-1])
    print(perceptron_result)
    voted_perceptron_result = comparison_results[:,1].reshape([-1])
    print(voted_perceptron_result)
    fig, ax = plt.subplots()
    ax.set_title('Model Comparison For {}'.format(dataset_name))
    ax.plot(epoch_list, perceptron_result, label="Vanilla Perceptron")
    ax.plot(epoch_list, voted_perceptron_result, label="Voted Perceptron")
    leg = ax.legend();
    plt.show()
```

Model Comparison

In [126]:

```
model_names = ['Perceptron','VotedPerceptron']
epoch_list = [10,15, 20, 25, 30, 35, 40, 45, 50]


iodataset_results =  generate_comparision_result(X_io, y_io, 10, epoch_list, mod
el_names)
plot_comparison_results('Ionosphere Dataset', np.asarray(iodataset_results) , ep
och_list)
```

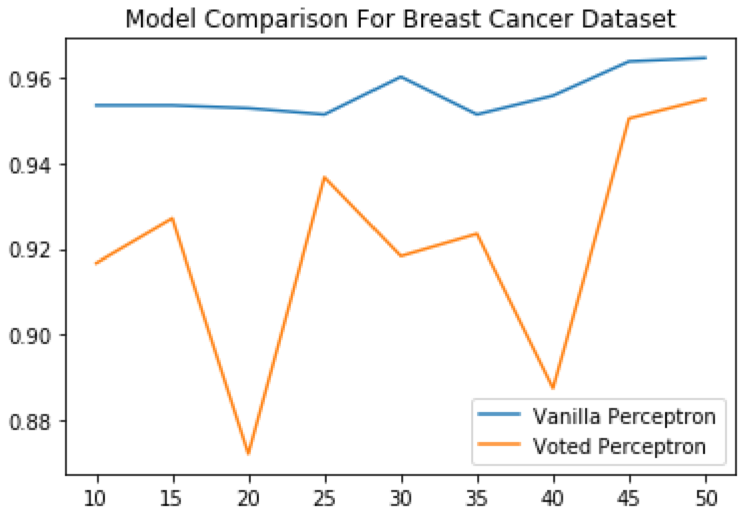
```
[ 0.84857143  0.84201058  0.84857143  0.85142857  0.85142857  0.8571
4286
  0.85428571  0.84857143  0.84857143]
[ 0.85428571  0.84772487  0.85428571  0.85142857  0.84857143  0.8477
2487
  0.85428571  0.84571429  0.84857143]
```



In [127]:

```
bcdataset_results = generate_comparision_result(X_bc, y_bc, 10, epoch_list, mode
l_names)
plot_comparison_results('Breast Cancer Dataset', np.asarray(bcdataset_results) ,
 epoch_list)
```

```
[ 0.95360963  0.95360963  0.95294118  0.95147059  0.96029412  0.9514
7059
  0.95588235  0.96390374  0.96470588]
[ 0.91671123  0.92713904  0.87205882  0.93676471  0.91831551  0.9235
2941
  0.88743316  0.95053476  0.95508021]
```



Problem 1 Comments

As we can observe from the above computations, we do incur additional computational expense due to maintenance and storgae of weight updates and votes. However, the number of mistakes is upper bounded by a function of the gap between the positive and negative examples. Also, good prediction vectors tend to survive for a longer time and thus have larger weight in the majority vote, minimising the overhead.

Problem 2: Least Square Approach

Data Preparation

In [128]:

```
# Representing dataset D1 with 8 samples (Each class with 4 samples) and 2 featu
res as 8x2 matrix XD1
# and corresponding binary class labels for 8 samples as 1-d (8x1 matrix) vector
 yD1
# Value at any given index i in yD1 corresponds to class label for sample i in X
D1
# Value 1 in yD1  represents class label 1 and 0 represents (class label 2)
     #x1   x2
XD1=np.asarray([[ 3,   3],
     [ 3,   0],
     [ 2,   1],
     [ 0,   2],
     [-1,   1],
     [ 0,   0],
     [-1,  -1],
     [ 1,   0]])

yD1=np.asarray([1,1,1,1,0,0,0,0])

# Representing dataset D2 with 8 samples (Each class with 4 samples) and 2 featu
res as 8x2 matrix XD2
# and corresponding binary class labels for 8 samples as 1-d (8x1 matrix) vector
 yD2
# Value at any given index i in yD1 corresponds to class label for sample i in X
D2
# Value 1 in yD2  represents class label 1 and 0 represents (class label 2)
     #x1   x2
XD2=np.asarray([[ 3,   3],
     [ 3,   0],
     [ 2,   1],
     [ 0, 1.5],
     [-1,   1],
     [ 0,   0],
     [-1,  -1],
     [ 1,   0]])

yD2=np.asarray([1,1,1,1,0,0,0,0])
```

Least Square Linear Classifier Implementation

In [129]:

```
import numpy
class LMS:
    def __init__(self):
        self.X=None
        self.y=None
        self.W = None
        self.b = None
        self.learning_rate=1
        self.error_threshold = 0.0001


    def fit(self, X, y):
        # Initialise weights and bias
        self.w = np.zeros(len(X[0]))
        for i,x in enumerate(X):
            error = (y[i] - np.dot(X[i], self.w))
            self.w += self.learning_rate*error*X[i]
        return self

    def predict(self, X):
        y = np.dot(X, self.w)
        for i in range(y.shape[0]):
            if y[i] > self.error_threshold:
                y[i] = 1
            else:
                y[i] = 0
        return y
```

In [130]:

```
import numpy
class LDA:
    def __init__(self):
        self.X=None
        self.y=None
        self.class_labels= None
        self.mean_vectors = None
        self.overall_mean = None
        self.S_W = None
        self.S_B = None
        self.W = None
        self.projection_centroids = {}
        self.classifier_threshold = 0

    def compute_classwise_mean_vectors(self):
        mean_vectors = {}
        class_labels = self.get_class_labels()
        for class_label in class_labels:
            mean_vectors[class_label] = (np.mean(self.X[self.y==class_label], ax
is=0))
        return mean_vectors

    def compute_overall_mean(self):
        return np.mean(self.X, axis=0)

    def get_class_labels(self):
        if self.class_labels is not None:
            return self.class_labels
```

```
        else:
            return np.unique(self.y)

    def compute_within_class_scatter(self):
        # Compute within class scatter matrix
        num_of_features=self.X.shape[1]
        if self.mean_vectors is None:
            self.mean_vectors = self.compute_classwise_mean_vectors()
        self.S_W = np.zeros((num_of_features, num_of_features))
        for class_label, mean_vector in self.mean_vectors.items():
            class_scatter_matrix = np.zeros((num_of_features, num_of_features))
            #Compute scatter within each class
            for sample in self.X[self.y == class_label]:
                class_scatter_matrix += np.outer((sample - mean_vector), (sample
 - mean_vector))
            self.S_W +=class_scatter_matrix

    def compute_between_class_scatter(self):
        num_of_features=self.X.shape[1]
        if self.mean_vectors is None:
            self.mean_vectors = self.compute_classwise_mean_vectors()

        if self.overall_mean is None:
            self.overall_mean = self.compute_overall_mean()

        self.S_B = np.zeros((num_of_features, num_of_features))
        for class_label, mean_vector in self.mean_vectors.items():
            num_of_samples_per_class = self.X[self.y==class_label].shape[0]
            self.S_B += np.multiply(num_of_samples_per_class,
                                    np.outer((mean_vector - self.overall_mean),
                                             (mean_vector - self.overall_mean)))

    def compute_linear_discriminants(self, num_of_dimensions):

        if self.S_W is None:
            self.compute_within_class_scatter()
        if self.S_B is None:
            self.compute_between_class_scatter()
        eig_vals, eig_vecs = np.linalg.eig(np.linalg.inv(self.S_W).dot(self.S_B
))

        #Sort the (eig_value, eig_vec) pair in decreasing order
        eigen_pairs = [(eig_vals[i], eig_vecs[:, i]) for i in range(len(eig_vals
))]
        sorted_eigen_pairs = sorted(eigen_pairs, key = lambda x : x[0], reverse
= True)

        num_of_features = self.X.shape[1]
        self.W = np.hstack([eigen_pairs[i][1].reshape(num_of_features, 1) for i
in range(0, num_of_dimensions)])
        return self

    def fit(self, X,y):
        if (X is None or y is None) or X.shape[0] != y.shape[0]:
            raise ValueError('Invalid data!')
        else:
            self.X = X
            self.y = y
        number_of_dimensions = self.get_class_labels().shape[0] - 1 #We can have
 C-1 discriminants
        self.compute_linear_discriminants(number_of_dimensions)
```

```
        print(self.W)
        # Since LDA maps the data linearly in the direction of W, and we have on
ly two classes
        # It would be reasonable to assume the classifier threshold to be the ce
ntroid of the mean vectors
        for class_label, mean_vector in self.mean_vectors.items():
            self.projection_centroids[class_label] = np.dot(mean_vector, self.W)
[0]
        self.classifier_threshold = sum(self.projection_centroids.values())/len(
self.projection_centroids.values()) #Centroid of the centroids of the projected
 classes
        return self

    def transform(self,X):
        if self.W is None:
            raise ValueError('Trying to transform feature space without computin
g linear discriminants! Make sure you have called fit() before applying transfor
m()')
        return np.dot(X, self.W)

    def predict(self,X):
        y = np.dot(X,self.W)
        class_label_0 = self.get_class_labels()[0]
        class_label_1 = self.get_class_labels()[1]
        for i in range(y.shape[0]):
            if y[i] >= self.classifier_threshold and self.projection_centroids[c
lass_label_0] < self.classifier_threshold :
                y[i] = class_label_1
            else:
                y[i] = class_label_0
        return y
```

Plotting Utils

In [131]:

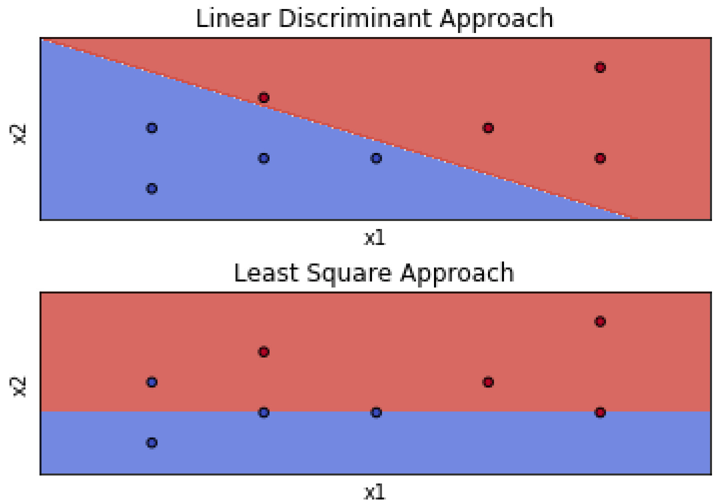
```
# Note: Below plotting idea have been taken from
# http://scikit-learn.org/stable/auto_examples/svm/plot_iris.html
def make_meshgrid(x, y, h=.02):
    """Create a mesh of points to plot in

    Parameters
    ----------
    x: data to base x-axis meshgrid on
    y: data to base y-axis meshgrid on
    h: stepsize for meshgrid, optional

    Returns
    -------
    xx, yy : ndarray
    """
    x_min, x_max = x.min() - 1, x.max() + 1
    y_min, y_max = y.min() - 1, y.max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
                         np.arange(y_min, y_max, h))
    return xx, yy


def plot_contours(ax, clf, xx, yy, **params):
    """Plot the decision boundaries for a classifier.

    Parameters
    ----------
    ax: matplotlib axes object
    clf: a classifier
    xx: meshgrid ndarray
    yy: meshgrid ndarray
    params: dictionary of params to pass to contourf, optional
    """
    Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)
    out = ax.contourf(xx, yy, Z, **params)
    return out
```

Dataset 1 Exploration

In [132]:

```
X = XD1
y = yD1

#Create instances of LMS and LDA models
models = (LDA(), LMS())
models = (clf.fit(X, y) for clf in models)

# title for the plots
titles = ('Linear Discriminant Approach',
          'Least Square Approach',)

# Set-up 2x2 grid for plotting.
fig, sub = plt.subplots(2, 1)
plt.subplots_adjust(wspace=0.4, hspace=0.4)

X0, X1 = X[:, 0], X[:, 1]
xx, yy = make_meshgrid(X0, X1)

for clf, title, ax in zip(models, titles, sub.flatten()):
    plot_contours(ax, clf, xx, yy,
                  cmap=plt.cm.coolwarm, alpha=0.8)
    ax.scatter(X0, X1, c=y, cmap=plt.cm.coolwarm, s=20, edgecolors='k')
    ax.set_xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    ax.set_xlabel('x1')
    ax.set_ylabel('x2')
    ax.set_xticks(())
    ax.set_yticks(())
    ax.set_title(title)

plt.show()
```

```
[[ 0.74651327]
 [ 0.66537052]]
```

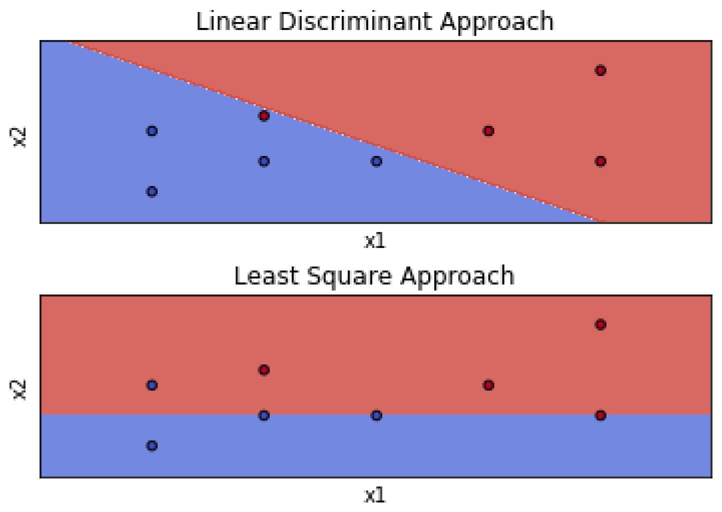


Dataset 2 Exploration

In [133]:

```
X = XD2
y = yD2

#Create instances of LMS and LDA models
models = (LDA(), LMS())
models = (clf.fit(X, y) for clf in models)

# title for the plots
titles = ('Linear Discriminant Approach',
          'Least Square Approach',)

# Set-up 2x2 grid for plotting.
fig, sub = plt.subplots(2, 1)
plt.subplots_adjust(wspace=0.4, hspace=0.4)

X0, X1 = X[:, 0], X[:, 1]
xx, yy = make_meshgrid(X0, X1)

for clf, title, ax in zip(models, titles, sub.flatten()):
    plot_contours(ax, clf, xx, yy,
                  cmap=plt.cm.coolwarm, alpha=0.8)
    ax.scatter(X0, X1, c=y, cmap=plt.cm.coolwarm, s=20, edgecolors='k')
    ax.set_xlim(xx.min(), xx.max())
    ax.set_ylim(yy.min(), yy.max())
    ax.set_xlabel('x1')
    ax.set_ylabel('x2')
    ax.set_xticks(())
    ax.set_yticks(())
    ax.set_title(title)

plt.show()
```

```
[[ 0.78102704]
 [ 0.62449721]]
```



Problem 2 Comment:

In both the datasets, Linear Discriminant Approch gives better results. As we can observe clearly, Least Squares approach is trying to estimate w such that the model predictions are as close as possible to a set of target values making it more susceptible to any aberration to unseen data. On the other hand, LDA is trying to find the direction of the line that best separates the data by identifying the projection W that maximises between-class variance while minimising in class variance.

Problem 3: Latent Semantic Analysis

In [134]:

```
import os
from collections import Counter
print(os.getcwd())
class DataLoader:
    def __init__(self):
        self.train = []
        self.valid = []
        self.test = []

    def read_from_directory(self, data_dir, train='train', test ='test', val_spl
it=.2):
        """
        Reads train and test set from the given input directory.
        Assumes the data is divided into train and test folder.
        Each of the test and train are futher divided into sub folder by class l
abels
        Example:
        /directory
        |--/test
        |----/label1
        |----/labeln
        |
        |--/train
        |----/label1
        |----/labeln
        """
        X = []
        y = []
        path_extension = 'txt'

        if train is not None and len(train)>0:
            for root, dirs, files in os.walk(os.path.join(data_dir,train)):
                for file in files:
                    if file.endswith(path_extension):
                        paths = root.split('/')
                        document_label = paths[-1]
                        document_id = "{}{}".format(document_label, file.split(
'.')[0])
                        with open(os.path.join(root,file), 'rb') as f:
                            wordcounter = Counter(f.read().strip().split())
                            doc_word_frequency = [document_id,wordcounter ,docum
ent_id]
                            self.train.append(doc_word_frequency)

        if test is not None and len(test)>0:
            for root, dirs, files in os.walk(os.path.join(data_dir,train)):
                for file in files:
                    if file.endswith(path_extension):
                        paths = root.split('/')
                        document_label = paths[-1]
                        document_id = "{}{}".format(document_label, file.split(
'.')[0])
                        with open(os.path.join(root,file),'rb') as f:
                            wordcounter = Counter(f.read().strip().split())
                            doc_word_frequency = [document_id,wordcounter ,docum
ent_id]
                            self.test.append(doc_word_frequency)
```

```
/Users/naveenpandey/Projects/learn/smai
```

In [135]:

```
!pwd
```

```
/Users/naveenpandey/Projects/learn/smai
```

In [136]:

```
data_dir = '/Users/naveenpandey/Projects/learn/smai/dataset' #Full path
dataloader = DataLoader()
dataloader.read_from_directory(data_dir, train='train', test=None)
```

In [ ]:

```

```

In [ ]:

```

```