In [47]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remou
nt=True).
```

Generate the datasets A and B in R2 with each of them consisting 2000 data points from normal distribution. The dataset A and B has been drawn from the N (μ1, Σ1) and N(μ2, Σ2) . Let us fix the μ1 = [-1,1] and μ2 = [2,1] and Σ1 = Σ2 = 0.7 0 0 0.3. Separate the 250 data points from each classes as testing set. Plot the optimal Bayesian decision boundary.

Q1) Write a function implementing the standard SVM with linear kernel using the gradient descent method. Obtain the best accuracy on the test set by tuning the value of the parameter λ . Plot the decision boundary obtained by the standard SVM mode with linear kernel. Compare it with the Bayesian decision boundary.

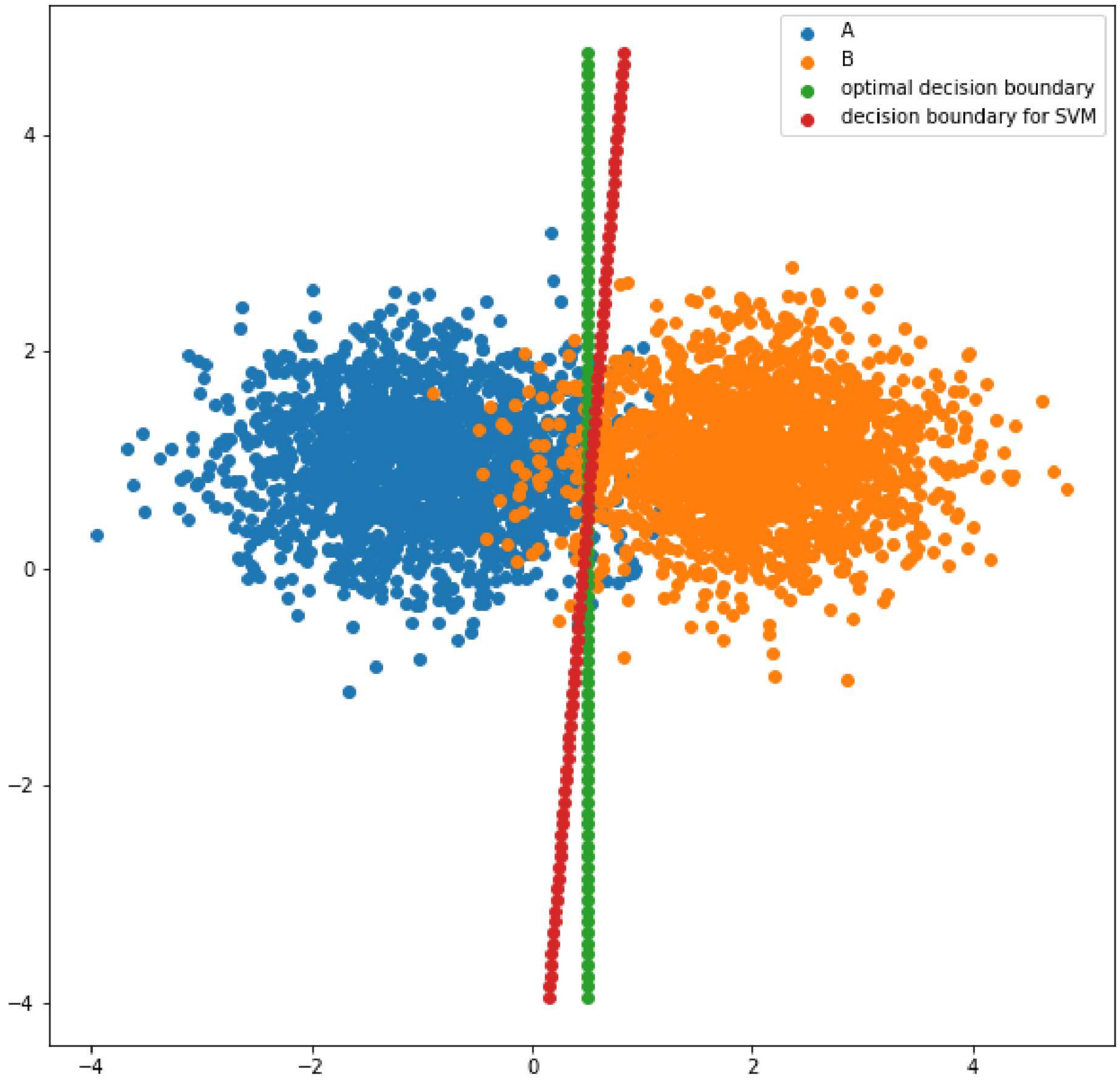
In [48]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import sklearn.metrics
import scipy.io
```

In [49]:
```
u1 = np.array([-1, 1])
u2 = np.array([2, 1])
cov_mat = [[0.7, 0], [0, 0.3]]
A1, A2 = np.random.multivariate_normal(u1, cov_mat, 2000).T
B1, B2 = np.random.multivariate_normal(u2, cov_mat, 2000).T
df1 = pd.DataFrame([A1,A2, -np.ones(len(A1))])
df1 = df1.T
df1.columns = ['x1', 'x2', 'y']
df2 = pd.DataFrame([B1,B2, np.ones(len(A1))])
df2 = df2.T
df2.columns = ['x1', 'x2', 'y']
df = pd.concat([df1, df2])
train_x, test_x, train_y, test_y = train_test_split(df[['x1', 'x2']], df['y'],test_size=0.125, random_state=5)
a_x, ax_t, a_y, ay_t = train_test_split(A1, A2, test_size=0.125,random_state=5)
b_x, bx_t, b_y, by_t = train_test_split(B1, B2, test_size=0.125,random_state=5)
train_x = np.array(train_x)
train_y = np.array(train_y)
alpha = 0.01
lmda = 2**-8
theta = np.array([0,0])
```

```
b = 0
for k in range(1000):
  temp1, temp2 = 0,0
  for i in range(len(train_x)):
    if (np.dot(theta, train_x[i]) + b) * train_y[i] <= 1:
      temp1 += -train_y[i] * train_x[i]
      temp2 += -train_y[i]

  grad = lmda * theta + temp1
  theta = theta - alpha * grad
  b -= alpha * temp2


w = np.dot(np.linalg.inv(cov_mat), u1 - u2)
c = np.dot(w , (1/2) * (u1 + u2))
x2 = np.arange(np.append(a_x, b_x).min(), np.append(a_x, b_x).max(), 0.1)
x1 = (c - w[1] * x2) / w[0]

x2_svm = np.arange(np.append(a_x, b_x).min(), np.append(a_x, b_x).max(), 0.1)
x1_svm = (-x2_svm * theta[1] - b) / theta[0]
```

In [50]:

```
plt.figure(figsize = (10,10))
plt.scatter(A1, A2, label = 'A')
plt.scatter(B1, B2, label = 'B')
plt.scatter(x1,x2, label = 'optimal decision boundary')
plt.scatter(x1_svm,x2_svm, label = 'decision boundary for SVM')
plt.legend()
plt.show()
```



In [51]:
```
y_hat = np.dot(np.array(test_x), theta) + b
for i, y in enumerate(y_hat):
  if y > 0:
    y_hat[i] = 1
  else:
    y_hat[i] = -1
print('Accuracy :',sklearn.metrics.accuracy_score(test_y,y_hat))
```

```
Accuracy : 0.964
```

Q2) Consider the two moon dataset. Divide the training and testing point in the ratio of 4:1. Train the standard SVM model with RBF kernel and plot the optimal separating surface obtained by the SVM model by tuning the parameter λ and kernel parameter σ. Report Precision, Recall, F-measure and accuracy on testing set.

In [52]:
```
data = scipy.io.loadmat('/content/drive/MyDrive/2moons.mat')
alpha = 0.001
lmda = 2**-8
sigma = 2**-8
def kernel(x1,x2, sigma):
  return np.exp(((-1) / (2 * sigma)) * np.linalg.norm(x1-x2)**2)
train_x = data['x']
train_y = data['y']

train_x = np.array(train_x)

h_mat = []
for i in range(len(train_x)):
  temp = []
  for j in range(len(train_x)):
    temp.append(kernel(train_x[i], train_x[j], sigma))
  h_mat.append(temp)
h_mat = np.array(h_mat).T

theta = np.array([0 for _ in range(len(train_x))])
temp1, temp2 = 0,0
b = 0

for _ in range(700):
  for i in range(len(train_x)):
    if (np.dot(theta, h_mat[i]) + b) * train_y[i] <= 1:
      temp1 += -train_y[i] * h_mat[i]
      temp2 += -train_y[i]
  grad = lmda * theta + temp1
  theta = theta - alpha * grad
  b -= alpha * temp2

theta = np.append(theta, b)
test_x = data['xt']
test_y = data['yt']
test_x = np.array(test_x)
h_mat_t = []
for i in range(len(data['xt'])):
  temp = []
```

```
  for j in range(len(data['x'])):
    temp.append(kernel(train_x[j], test_x[i], sigma))
  h_mat_t.append(temp)


h_mat_t = np.array(h_mat_t)
h_mat_t = np.column_stack((h_mat_t, np.ones(len(data['xt']))))
h_mat_t = h_mat_t.T
y_hat = np.dot(h_mat_t.T,theta)

for i, y in enumerate(y_hat):
  if y > 0:
    y_hat[i] = 1
  else:
    y_hat[i] = -1

p = data['yt']

print('Accuracy: ',{sklearn.metrics.accuracy_score(p, y_hat)})
print('Recall: ',{sklearn.metrics.recall_score(p, y_hat)})
print('Precision: ',{sklearn.metrics.precision_score(p,y_hat)})
```

```
Accuracy:  {0.91}
Recall:  {1.0}
Precision:  {0.856}
```

Q3) Consider the Iris dataset. The dataset contains three types of flower described by the four features. Consider only the data points with label 1 and 2. Divide the dataset into training, testing and validation in the ration 8:1:1. Use the training set to train the SVM model with linear kernel. Use the validation set to tune the parameter

In [53]:

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
data = load_iris()
train_x = []
train_y = []

for i in range(len(data['data'])):
  if data['target'][i] == 1:
    train_y = np.append(train_y, np.array([-1]))
    train_x.append(data['data'][i])
  elif data['target'][i] == 2:
    train_y = np.append(train_y, np.array([1]))
    train_x.append(data['data'][i])
```

```
train_x = np.array(train_x)
train_x, test_x, train_y, test_y = train_test_split(train_x, train_y,random_state=1, test_size = 0.2, shuffle = True)
test_x, val_x, test_y, val_y = train_test_split(test_x, test_y,random_state=1, test_size = 0.5, shuffle = True)

alpha = 0.001
lmda = 2**-10
theta = np.array([0,0,0,0])
b = 0
for k in range(10000):
  temp1, temp2 = 0,0
  for i in range(len(train_x)):
    if (np.dot(theta, train_x[i]) + b) * train_y[i] <= 1:
      temp1 += -train_y[i] * train_x[i]
      temp2 += -train_y[i]
  grad = lmda * theta + temp1
  theta = theta - alpha * grad
  b -= alpha * temp2

theta = np.append(theta, np.array([b]))

val_x_app = np.column_stack((val_x, np.ones(len(val_x))))
y_hat = np.dot(val_x_app,theta)
for i, y in enumerate(y_hat):
  if y > 0:
    y_hat[i] = 1
  else:
    y_hat[i] = -1

print('Accuracy: ',{sklearn.metrics.accuracy_score(val_y,y_hat)})
print('Recall: ',{sklearn.metrics.recall_score(val_y,y_hat)})
print('Precision: ',{sklearn.metrics.precision_score(val_y, y_hat)})
```

```
Accuracy:  {0.9}
Recall:  {1.0}
Precision:  {0.8571428571428571}
```

In [54]:

```
test_x_app = np.column_stack((test_x, np.ones(len(test_x))))
y_hat = np.dot(test_x_app,theta)
for i, y in enumerate(y_hat):
  if y > 0:
    y_hat[i] = 1
  else:
    y_hat[i] = -1
```

```
print('Accuracy: ', {sklearn.metrics.accuracy_score(test_y,y_hat)})
print('Recall: ' ,{sklearn.metrics.recall_score(test_y, y_hat)})
print('Precision: ',{sklearn.metrics.precision_score(test_y,y_hat)})
```

```
Accuracy:  {1.0}
Recall:  {1.0}
Precision:  {1.0}
```