1 支持向量

使用高斯核函数的支持向量机（SVM）来构建垃圾邮件分类器。

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from scipy.io import loadmat
```

In [2]:

```
raw_data = loadmat('data/ex6data1.mat')
data = pd.DataFrame(raw_data.get('X'), columns=['X1', 'X2'])
data['y'] = raw_data.get('y')

data.head()
```

Out[2]:

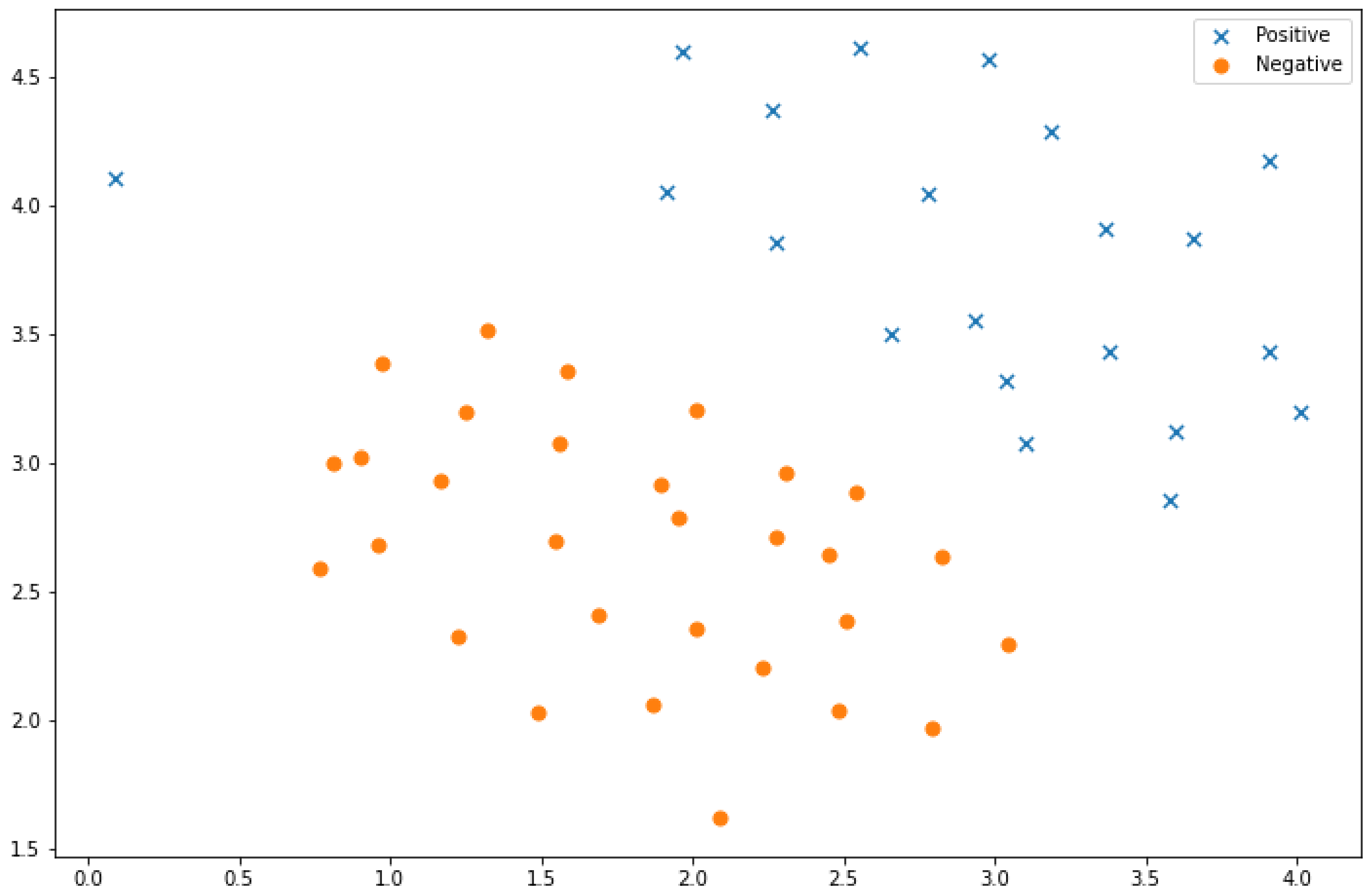
	X1	X2	y
0	1.9643	4.5957	1
1	2.2753	3.8589	1
2	2.9781	4.5651	1
3	2.9320	3.5519	1
4	3.5772	2.8560	1

In [3]:

```
def plot_init_data(data, fig, ax):
    positive = data[data['y'].isin([1])]
    negative = data[data['y'].isin([0])] #清洗数据，删选过滤掉DataFrame中一些行

    ax.scatter(positive['X1'], positive['X2'], s=50, marker='x', label='Positive')
    ax.scatter(negative['X1'], negative['X2'], s=50, marker='o', label='Negative')
```

In [4]:

```
fig, ax = plt.subplots(figsize=(12,8))
plot_init_data(data, fig, ax)
ax.legend()
plt.show()
```



In [5]:

```
from sklearn import svm
svc = svm.LinearSVC(C=1, loss='hinge', max_iter=10000)
"""
C : float, optional (default=1.0)错误项的惩罚参数
loss : string, 'hinge' or 'squared_hinge' (default='squared_hinge') 指定损失函数。
"hinge"是标准的SVM损失（例如由SVC类使用），而"squared_hinge"是hinge损失的平方。
max_iter : int, (default=1000) 要运行的最大迭代次数。
"""
svc
```

Out[5]: LinearSVC(C=1, loss='hinge', max_iter=10000)

In [6]:

```
svc.fit(data[['X1', 'X2']], data['y']) #输入参数训练模型
svc.score(data[['X1', 'X2']], data['y']) #得到分数
```

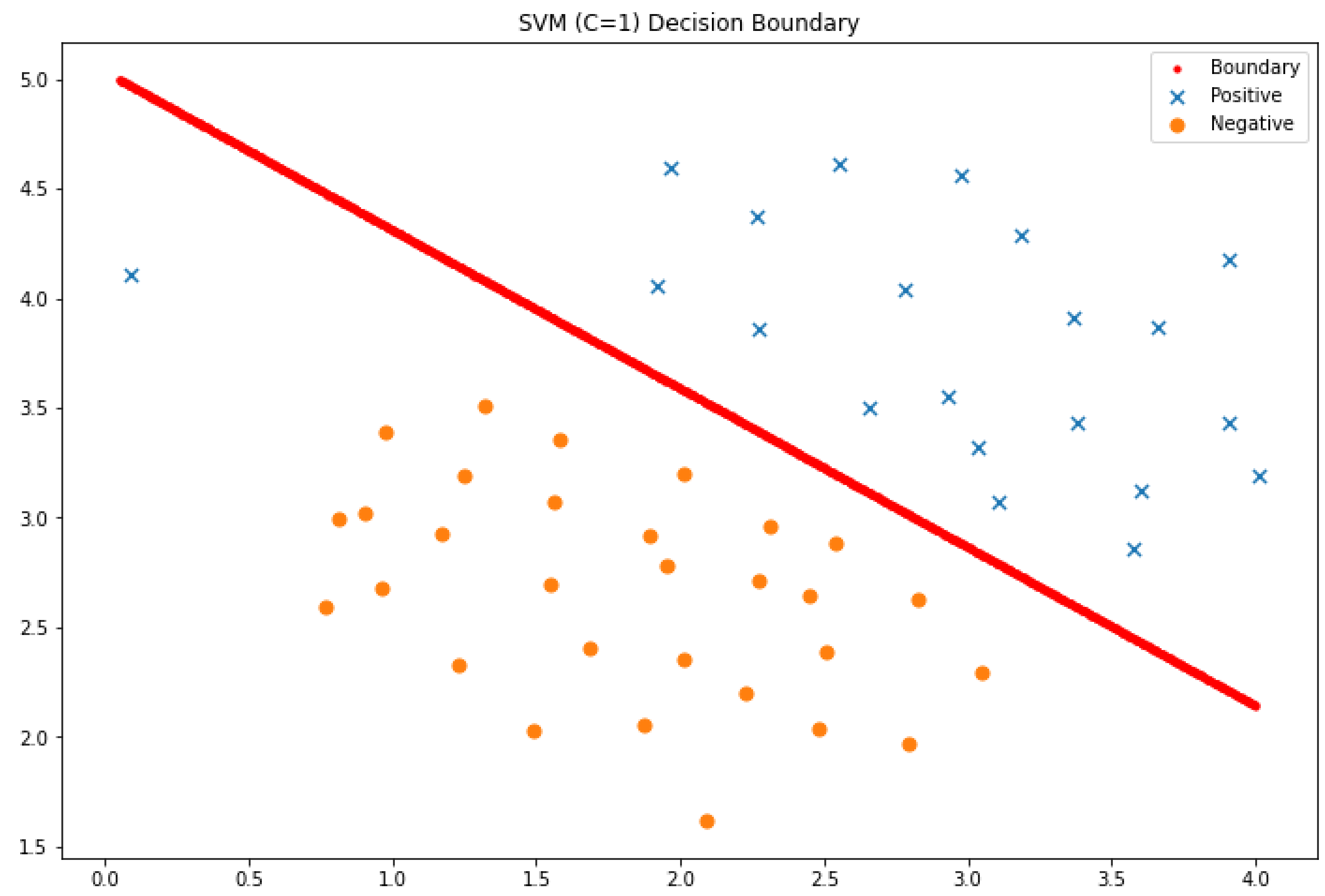
Out[6]: 0.9803921568627451

In [7]:

```
def find_decision_boundary(svc, x1min, x1max, x2min, x2max, diff):
    x1 = np.linspace(x1min, x1max, 1000)
    x2 = np.linspace(x2min, x2max, 1000) #创建等差数列

    cordinates = [(x, y) for x in x1 for y in x2]
    x_cord, y_cord = zip(*cordinates) #zip(*) 解压
    c_val = pd.DataFrame({'x1':x_cord, 'x2':y_cord})
    c_val['cval'] = svc.decision_function(c_val[['x1', 'x2']])

    decision = c_val[np.abs(c_val['cval']) < diff]

    return decision.x1, decision.x2
```

In [8]:

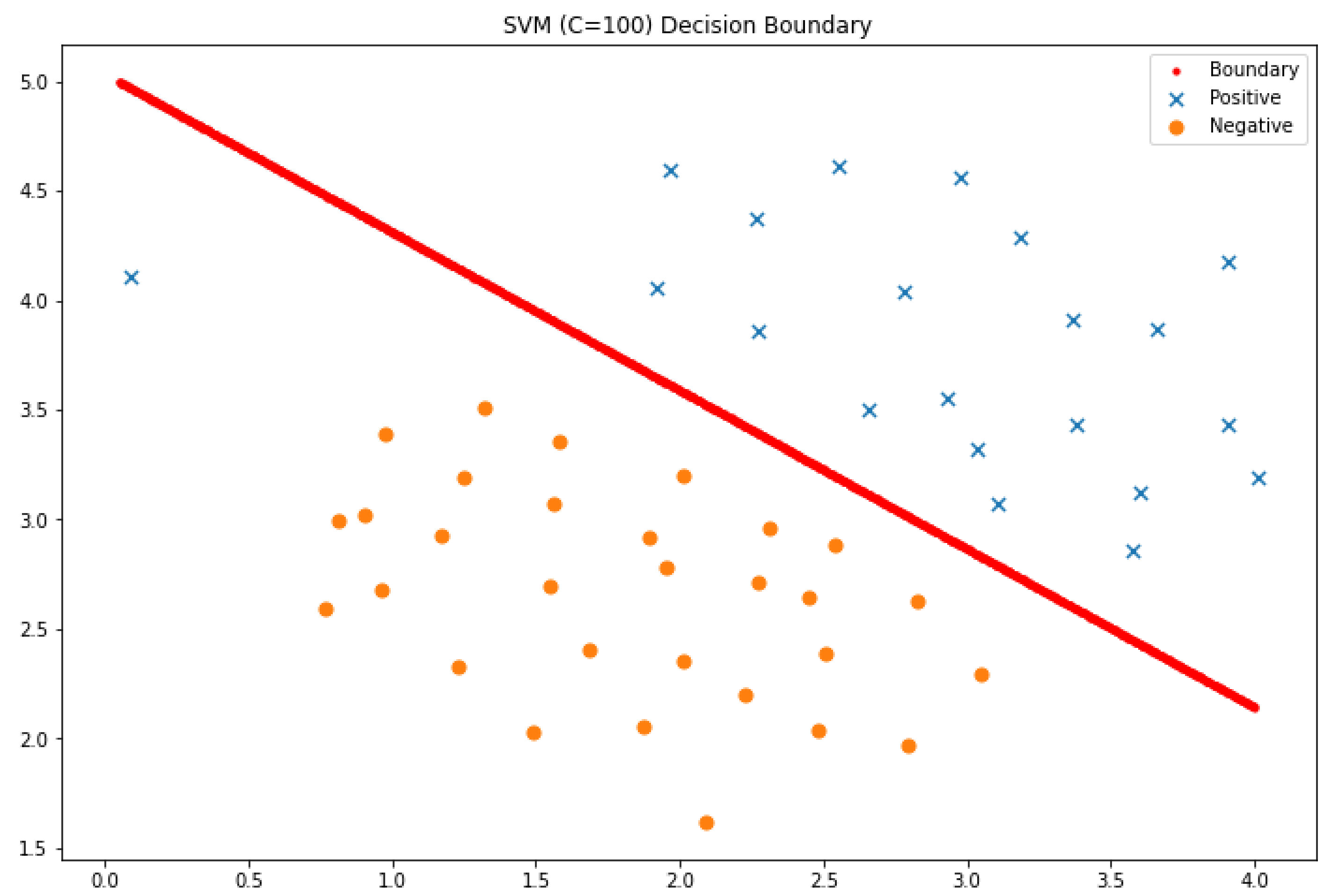
```
x1, x2 = find_decision_boundary(svc, 0, 4, 1.5, 5, 2 * 10**-3)
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(x1, x2, s=10, c='r',label='Boundary')
plot_init_data(data, fig, ax)
ax.set_title('SVM (C=1) Decision Boundary')
ax.legend()
plt.show()
```



In [9]:
```
svc2 = svm.LinearSVC(C=100, loss='hinge', max_iter=20000)
svc2.fit(data[['X1', 'X2']], data['y'])
svc2.score(data[['X1', 'X2']], data['y'])
```

Out[9]: 0.9803921568627451

In [10]:
```
x1, x2 = find_decision_boundary(svc, 0, 4, 1.5, 5, 2 * 10**-3)
fig, ax = plt.subplots(figsize=(12,8))
ax.scatter(x1, x2, s=10, c='r',label='Boundary')
plot_init_data(data, fig, ax)
ax.set_title('SVM (C=100) Decision Boundary')
ax.legend()
plt.show()
```



1.2 高斯内核的SVM

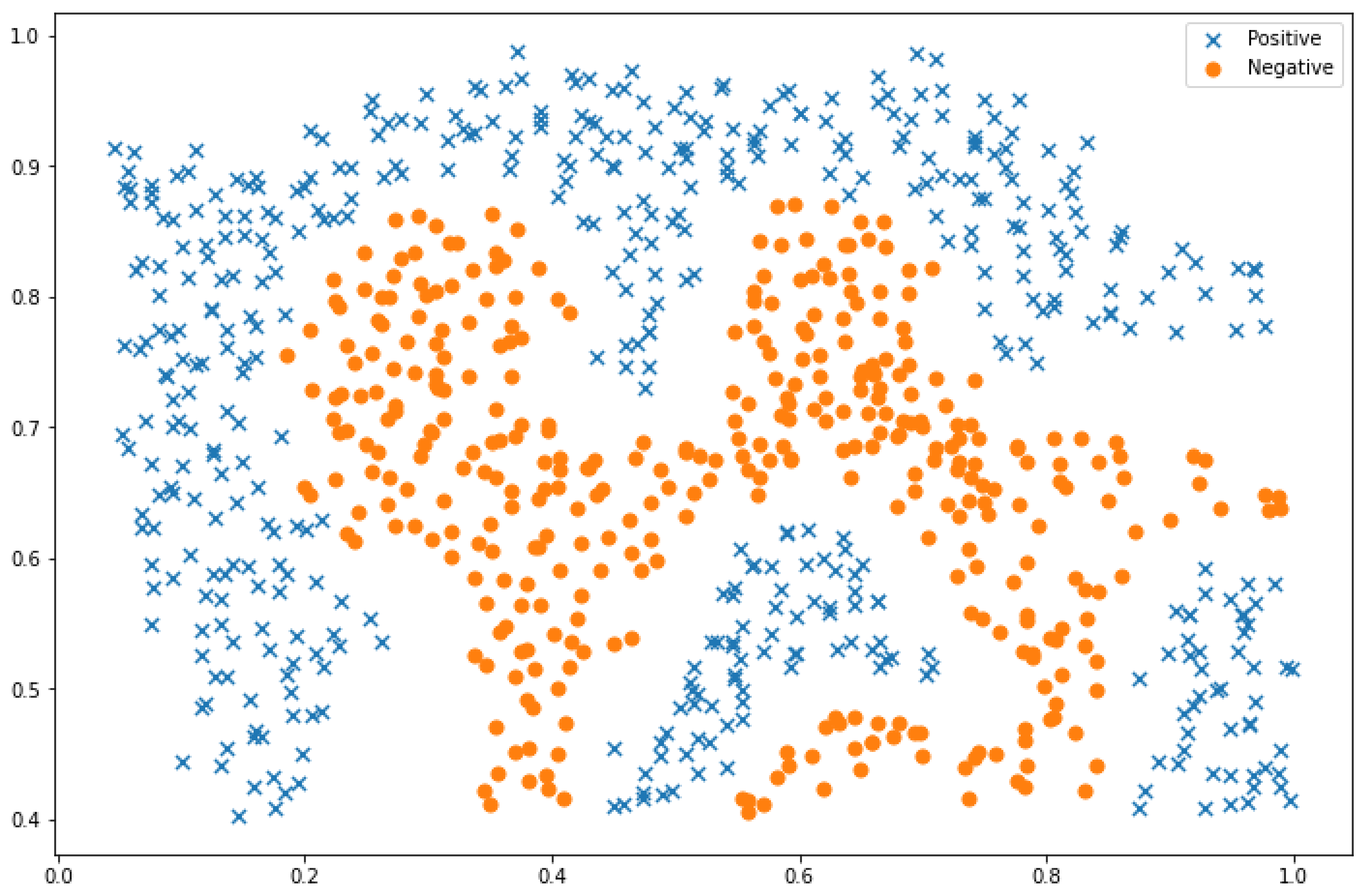
将从线性SVM转移到能够使用内核进行非线性分类的SVM。 虽然scikit-learn具有内置的高斯内核，但为实现更清楚，将从头开始实现。

In [11]:
```
def gaussian_kernel(x1, x2, sigma):
    return np.exp(-(np.sum((x1 - x2) ** 2) / (2 * (sigma ** 2))))
```

In [12]:
```
x1 = np.array([1.0, 2.0, 1.0])
x2 = np.array([0.0, 4.0, -1.0])
sigma = 2

gaussian_kernel(x1, x2, sigma)
```

Out[12]: 0.32465246735834974

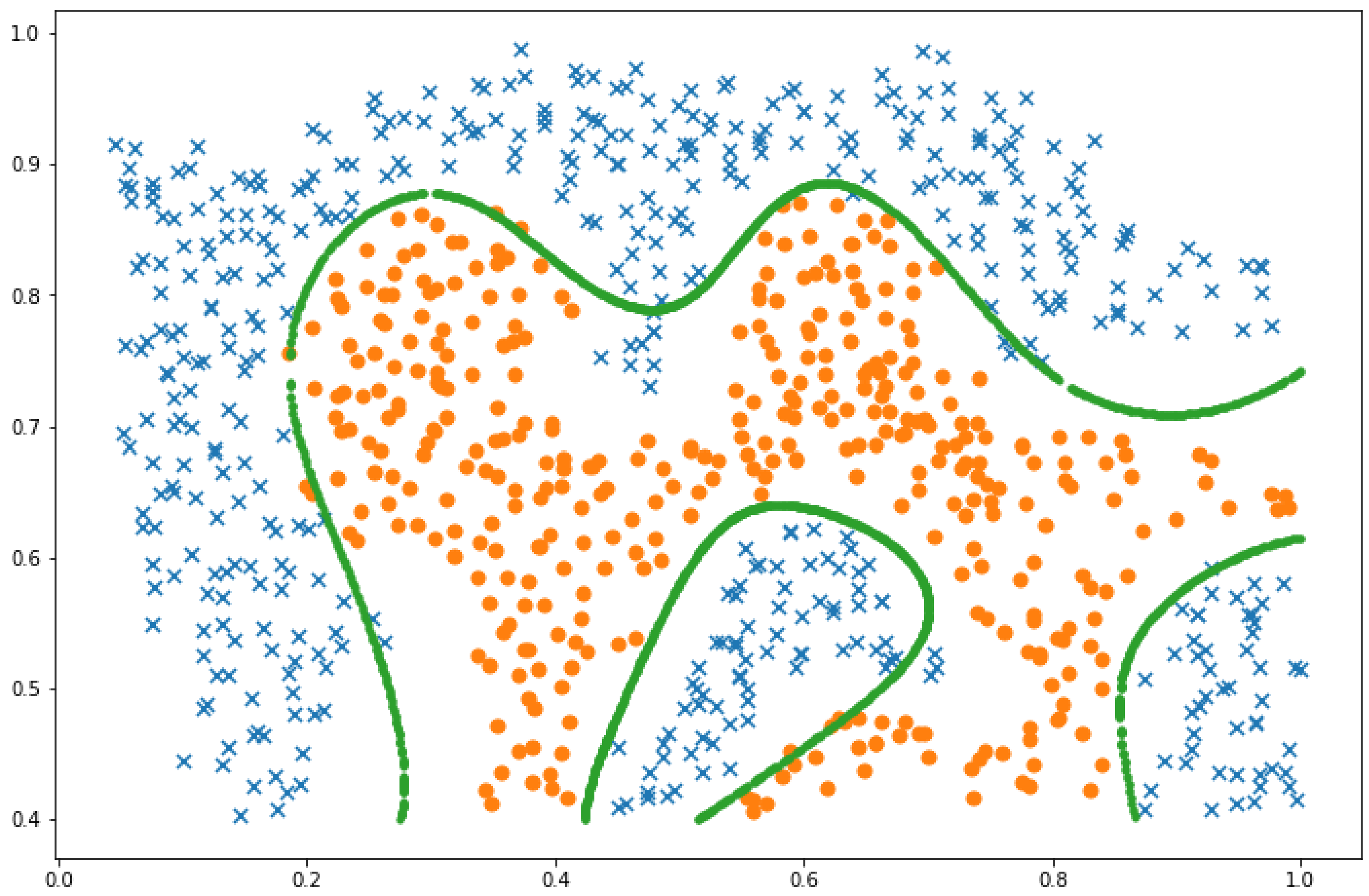
In [13]:
```
raw_data = loadmat('data/ex6data2.mat')

data = pd.DataFrame(raw_data['X'], columns=['X1', 'X2'])
data['y'] = raw_data['y']

fig, ax = plt.subplots(figsize=(12,8))
plot_init_data(data, fig, ax)
ax.legend()
plt.show()
```



In [14]:
```
svc = svm.SVC(C=100, gamma=10, probability=True)
"""
gamma :  ‘rbf’, ‘poly’ 和 ‘sigmoid’ 的核函数参数。默认是’auto’，则会选择1/n_features
kernel : 核函数，默认是rbf，可以是 ‘linear’, ‘poly’, ‘rbf’, ‘sigmoid’, ‘precomputed’
RBF函数：exp(-gamma|u-v|^2)

"""
svc.fit(data[['X1', 'X2']], data['y'])
svc.score(data[['X1', 'X2']], data['y'])
```

Out[14]: 0.9698725376593279

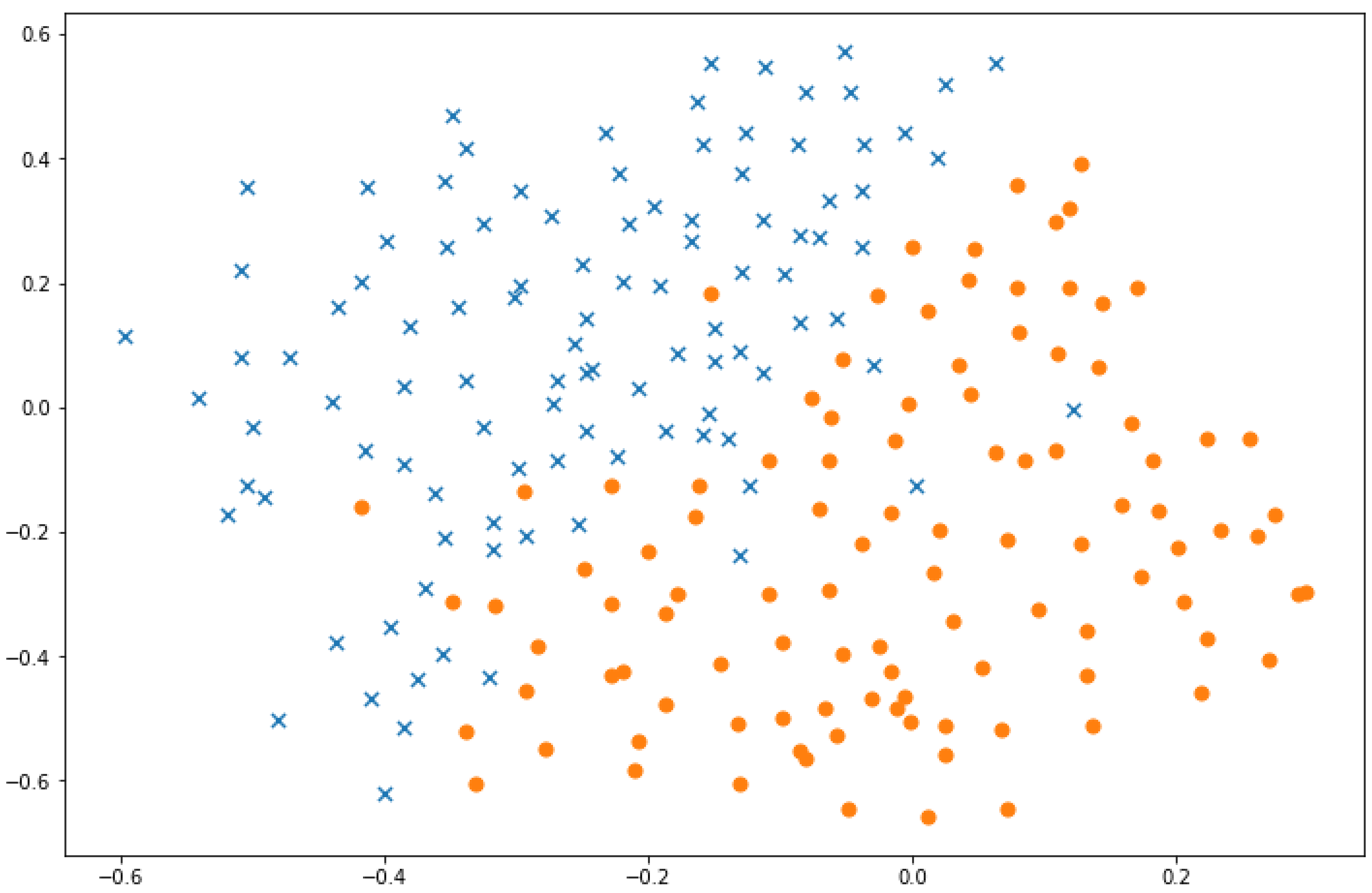
In [15]:
```
x1, x2 = find_decision_boundary(svc, 0, 1, 0.4, 1, 0.01)
fig, ax = plt.subplots(figsize=(12,8))
plot_init_data(data, fig, ax)
ax.scatter(x1, x2, s=10)
plt.show()
```



1.2.3 数据集3

对于第三个数据集，我们给出了训练和验证集，并且基于验证集性能为SVM模型找到最优超参数。超参数是在开始学习过程之前设置值的参数 我们现在需要寻找最优和，候选数值为[0.01, 0.03, 0.1, 0.3, 1, 3, 10, 30, 100]

In [16]:
```
raw_data = loadmat('data/ex6data3.mat')

X = raw_data['X']
Xval = raw_data['Xval']
y = raw_data['y'].ravel()
yval = raw_data['yval'].ravel()

fig, ax = plt.subplots(figsize=(12,8))
data = pd.DataFrame(raw_data.get('X'), columns=['X1', 'X2'])
data['y'] = raw_data.get('y')
plot_init_data(data, fig, ax)
plt.show()
```



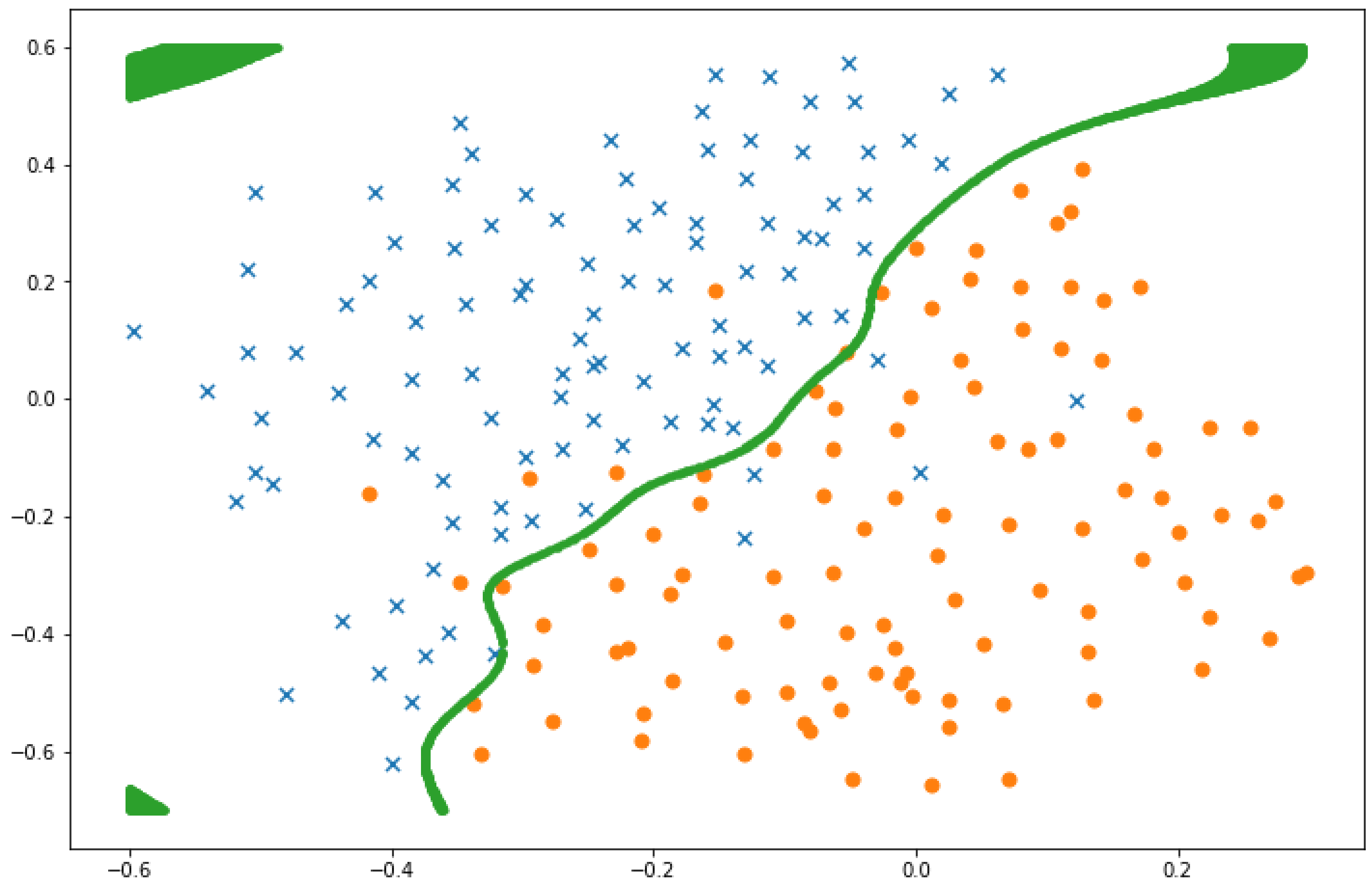
In [17]:
```
C_values = [0.01, 0.03, 0.1, 0.3, 1, 3, 10, 30, 100]
gamma_values = [0.01, 0.03, 0.1, 0.3, 1, 3, 10, 30, 100]

best_score = 0
best_params = {'C': None, 'gamma': None}
```

```
for C in C_values:
    for gamma in gamma_values:
        svc = svm.SVC(C=C, gamma=gamma)
        svc.fit(X, y)
        score = svc.score(Xval, yval)

        if score > best_score:
            best_score = score
            best_params['C'] = C
            best_params['gamma'] = gamma

best_score, best_params
```

Out[17]: (0.965, {'C': 0.3, 'gamma': 100})

In [18]:

```
svc = svm.SVC(C=best_params['C'], gamma=best_params['gamma'])
svc.fit(X, y)

x1, x2 = find_decision_boundary(svc, -0.6, 0.3, -0.7, 0.6, 0.005)
fig, ax = plt.subplots(figsize=(12,8))
plot_init_data(data, fig, ax)
ax.scatter(x1, x2, s=10)
plt.show()
```



2 垃圾邮件分类

使用SVM来构建垃圾邮件过滤器。 预处理步骤（如HTML删除，词干，标准化等）已经完成，只需将字词映射到为练习提供的字典中的ID

In [19]:

```
spam_train = loadmat('data/machine-learning-ex6/ex6/spamTrain.mat')
spam_test = loadmat('data/machine-learning-ex6/ex6/spamTest.mat')

spam_train
```

Out[19]:

```
{'__header__': b'MATLAB 5.0 MAT-file, Platform: GLNXA64, Created on: Sun Nov 13 14:27:25 2011',
 '__version__': '1.0',
 '__globals__': [],
 'X': array([[0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0],
        ...,
        [0, 0, 0, ..., 0, 0, 0],
        [0, 0, 1, ..., 0, 0, 0],
        [0, 0, 0, ..., 0, 0, 0]], dtype=uint8),
 'y': array([[1],
        [1],
        [0],
        ...,
        [1],
        [0],
        [0]], dtype=uint8)}
```

In [20]:

```
#每个文档转换为一个向量，其中1,899个维对应于词汇表中的1,899个单词。 它们的值为二进制，表示文档中是否存在单词
X = spam_train['X']
Xtest = spam_test['Xtest']
y = spam_train['y'].ravel()
ytest = spam_test['ytest'].ravel()

X.shape, y.shape, Xtest.shape, ytest.shape
```

Out[20]: ((4000, 1899), (4000,), (1000, 1899), (1000,))

In [21]:

```
svc = svm.SVC()
svc.fit(X, y)
```

Out[21]: SVC()

In [22]:

```
print('Training accuracy = {0}%'.format(np.round(svc.score(X, y) * 100, 2))) #np.round: 取整
print('Test accuracy = {0}%'.format(np.round(svc.score(Xtest, ytest) * 100, 2)))
#.format(), 字符串格式化, 例: '数字{1}{2}和{0}'.format("123",456,'789')>>>'数字456789和123'
```

```
Training accuracy = 99.32%
Test accuracy = 98.7%
```

In [23]:

```
kw = np.eye(1899) #生成对角阵
kw[:3,:]
```

Out[23]:

```
array([[1., 0., 0., ..., 0., 0., 0.],
       [0., 1., 0., ..., 0., 0., 0.],
       [0., 0., 1., ..., 0., 0., 0.]])
```

In [24]:

```
spam_val = pd.DataFrame({'idx':range(1899)})
spam_val['isspam'] = svc.decision_function(kw)
spam_val['isspam'].describe() #打印数据的统计信息
```

Out[24]:

```
count    1899.000000
mean       -0.110039
std         0.049094
min        -0.428396
25%        -0.131213
50%        -0.111985
75%        -0.091973
max         0.396286
Name: isspam, dtype: float64
```

In [25]:
```
decision = spam_val[spam_val['isspam'] > -0.55]
decision
```

Out[25]:

	idx	isspam
0	0	-0.093653
1	1	-0.083078
2	2	-0.109401
3	3	-0.119685
4	4	-0.165824
...	...	...
1894	1894	0.101613
1895	1895	-0.016065
1896	1896	-0.151573
1897	1897	-0.109022
1898	1898	-0.091970

1899 rows × 2 columns

In [26]:
```
path =  'data/machine-learning-ex6/ex6/vocab.txt'
voc = pd.read_csv(path, header=None, names=['idx', 'voc'], sep = '\t')
voc.head()
```

Out[26]:

	idx	voc
0	1	aa
1	2	ab
2	3	abil
3	4	abl
4	5	about

In [27]:
```
spamvoc = voc.loc[list(decision['idx'])]
spamvoc
```

Out[27]:

	idx	voc
0	1	aa
1	2	ab
2	3	abil
3	4	abl
4	5	about
...	...	...
1894	1895	your
1895	1896	yourself
1896	1897	zdnet
1897	1898	zero
1898	1899	zip

1899 rows × 2 columns