In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import glob
import os
import scipy.io as sio
from sklearn.svm import SVC
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import PolynomialFeatures
from scipy.optimize import minimize
# %matplotlib widget
```

In [2]:
```python
plt.rcParams["font.sans-serif"] = 'SimHei'
plt.rcParams["axes.unicode_minus"] = False
```

逻辑回归(二分类)

读取数据

In [3]:
```python
paths = glob.glob("../Coursera-ML-AndrewNg-master/*")
path = glob.glob(os.path.join(paths[1], "*.txt"))
df = pd.read_csv(path[1], header=None)
```

损失函数

> $J_\theta = \frac{1}{m}\sum_{i=0}^{m}[y\log(h_\theta) + (1-y)\log(1-h_\theta)],\ h_\theta = \frac{1}{1+e^{-\theta x}}$

In [4]:
```python
def lossFunction(theta, x, y, lamda):
    cost = y * np.log(func(x, theta)) + (1 - y) * np.log(1 - func(x, theta))
    regula = np.power(theta, 2)
    return -np.sum(cost) / len(x) + np.sum(regula) * lamda / (2 * len(x))
```

梯度下降

In [5]:
```python
def gradientDescent(theta, x, y, alpha, lamda, iters):
    loss = list()
    for _ in range(iters):
        loss.append(lossFunction(theta, x, y, lamda))
        theta = theta * (1 - alpha * lamda / len(x)) - x.T @ (func(x, theta) - y) * alpha / len(x)
    return loss, theta
```

初始化参数

In [6]:
```python
poly = PolynomialFeatures() # 特征映射
x = poly.fit_transform(df[[0, 1]]) # 特征值
y = df[2] # 标签值
theta = np.zeros(x.shape[1]) # 权值
alpha = 0.1 # 学习率
lamda = 0.001 # 正则化系数
iters = 30000 # 迭代次数
func = lambda x, theta : 1 / (np.exp(-x @ theta) + 1) # sigmoid函数
lossFunction(theta, x, y, lamda)
```

Out[6]:
```
0.6931471805599454
```

训练过程

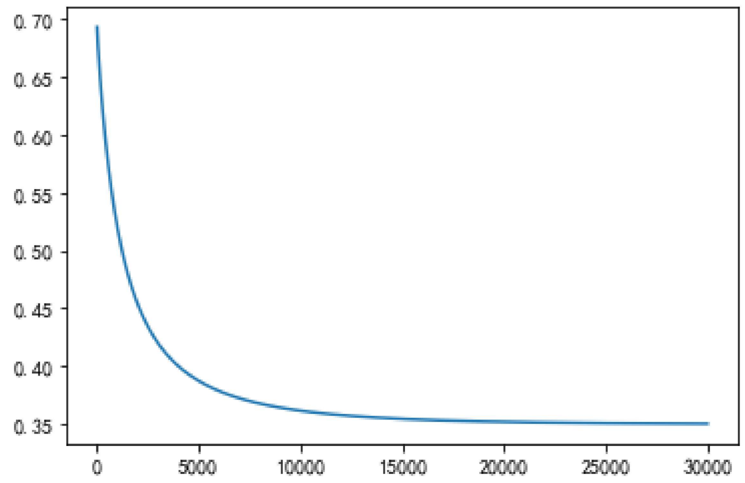
计算结果

In [7]:
```python
loss, theta_final = gradientDescent(theta, x, y, alpha, lamda, iters)
```

迭代过程

In [8]:
```python
plt.figure()
plt.plot(range(len(loss)), loss)
```

Out[8]:
```
[<matplotlib.lines.Line2D at 0x1adcc5da3d0>]
```



准确率

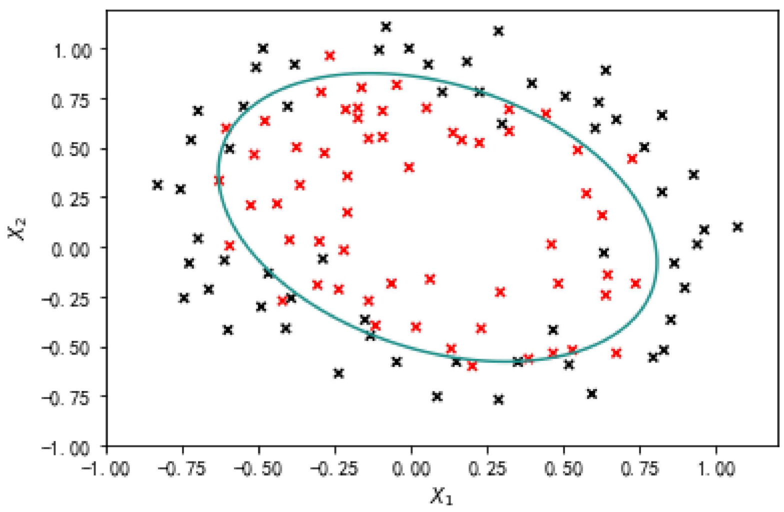
In [9]:
```
y_predict = np.where(func(x, theta_final) > 0.5, 1, 0)
np.mean(y_predict == y)
```

Out[9]:
```
0.8559322033898306
```

决策边界

In [10]:
```
x1 = np.linspace(-1, 1.2, 200)
xx1, xx2 = np.meshgrid(x1, x1)
z = poly.fit_transform(np.c_[xx1.ravel(), xx2.ravel()]) @ theta_final
zz = z.reshape((200, 200))
df.plot.scatter(0, 1, c=2, cmap=plt.cm.flag_r, colorbar=False, marker="x", xlabel="$X_1$", ylabel="$X_2$")
plt.contour(xx1, xx2, zz, 0)
```

Out[10]:
```
<matplotlib.contour.QuadContourSet at 0x1adcc5dafd0>
```



逻辑回归(多分类)

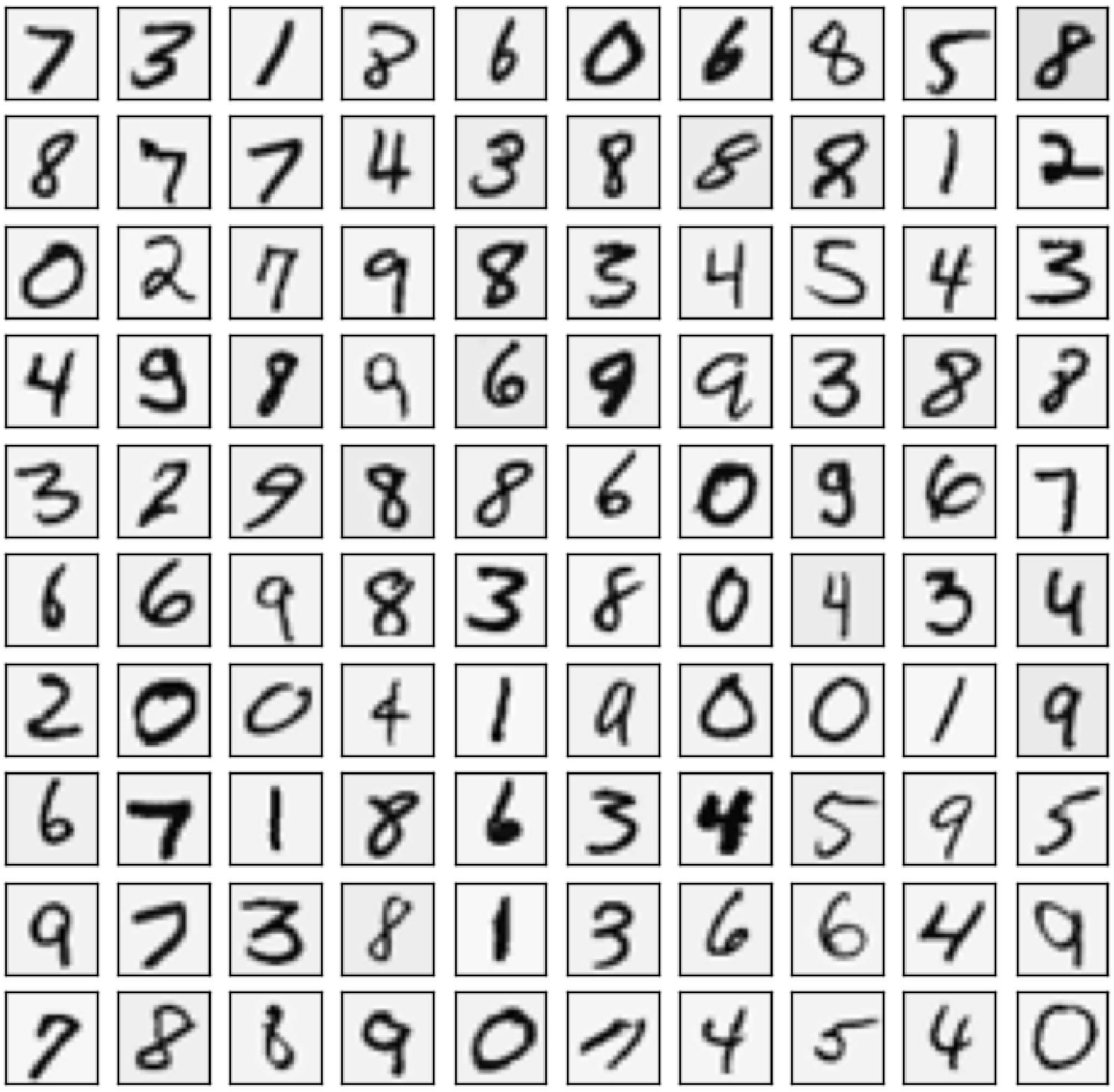
读取数据

In [11]:
```
paths = glob.glob("../Coursera-ML-AndrewNg-master/*")
path = glob.glob(os.path.join(paths[2], "*.mat"))
data = sio.loadmat(path[0])
datax = np.insert(data["X"], 0, 1, axis=1)
datay = data["y"].ravel()
train_x, test_x, train_y, test_y = train_test_split(datax, datay, random_state=4)
```

预览数据

In [12]:
```
fig, ax = plt.subplots(10, 10, sharex=True, sharey=True, figsize=(7, 7), dpi=120)
fig.suptitle("手写数字集")
plt.xticks([])
plt.yticks([])
i = np.random.choice(train_x.shape[0], 100, replace=False)
temp = train_x[i, 1:]
for r in range(10):
    for c in range(10):
        ax[r, c].imshow(temp[r * 10 + c].reshape((20, 20)).T, cmap="gray_r")
```

手写数字集



梯度向量

In [13]:

```
def gradientVector(theta, x, y, lamda):
    return (x.T @ (func(x, theta) - y) + lamda * theta) / len(x)
```

训练过程

In [14]:

```
lamda = 1
theta_all = np.zeros((10, datax.shape[1]))
for i in range(1, 11):
    theta_i = np.zeros(datax.shape[1])
    result = minimize(fun=lossFunction, x0=theta_i, args=(train_x, train_y == i, lamda), method="TNC", jac=gradientVector)
    theta_all[i-1, :] = result.x
```

训练结果

In [15]:

```
probability = func(test_x, theta_all.T)
predict = np.argmax(probability, axis=1) + 1
np.mean(predict == test_y)
```

Out[15]:

```
0.9136
```

数字识别

In [16]:

```
i = np.random.randint(len(test_x))
plt.close(4)
plt.figure(figsize=(1.8, 1.8))
plt.title(f"数字{predict[i] % 10}")
plt.imshow(test_x[i, 1:].reshape(20, 20).T, cmap="gray_r")
plt.axis("off")
```

Out[16]:

```
(-0.5, 19.5, 19.5, -0.5)
```

数字6