In [1]:
```
#练习8： 异常检测与推荐系统
```

In [2]:
```
##异常检测 （非监督学习）
```

In [3]:
```
import matplotlib.pyplot as plt
%matplotlib inline

import numpy as np
import pandas as pd

import seaborn as sns

import scipy.io as sio
from scipy import stats

import sys
sys.path.append('..')

from ml import anomaly

from sklearn.cross_validation import train_test_split
```

In [4]:
```
mat = sio.loadmat('./data/ex8data1.mat')
mat.keys()
```

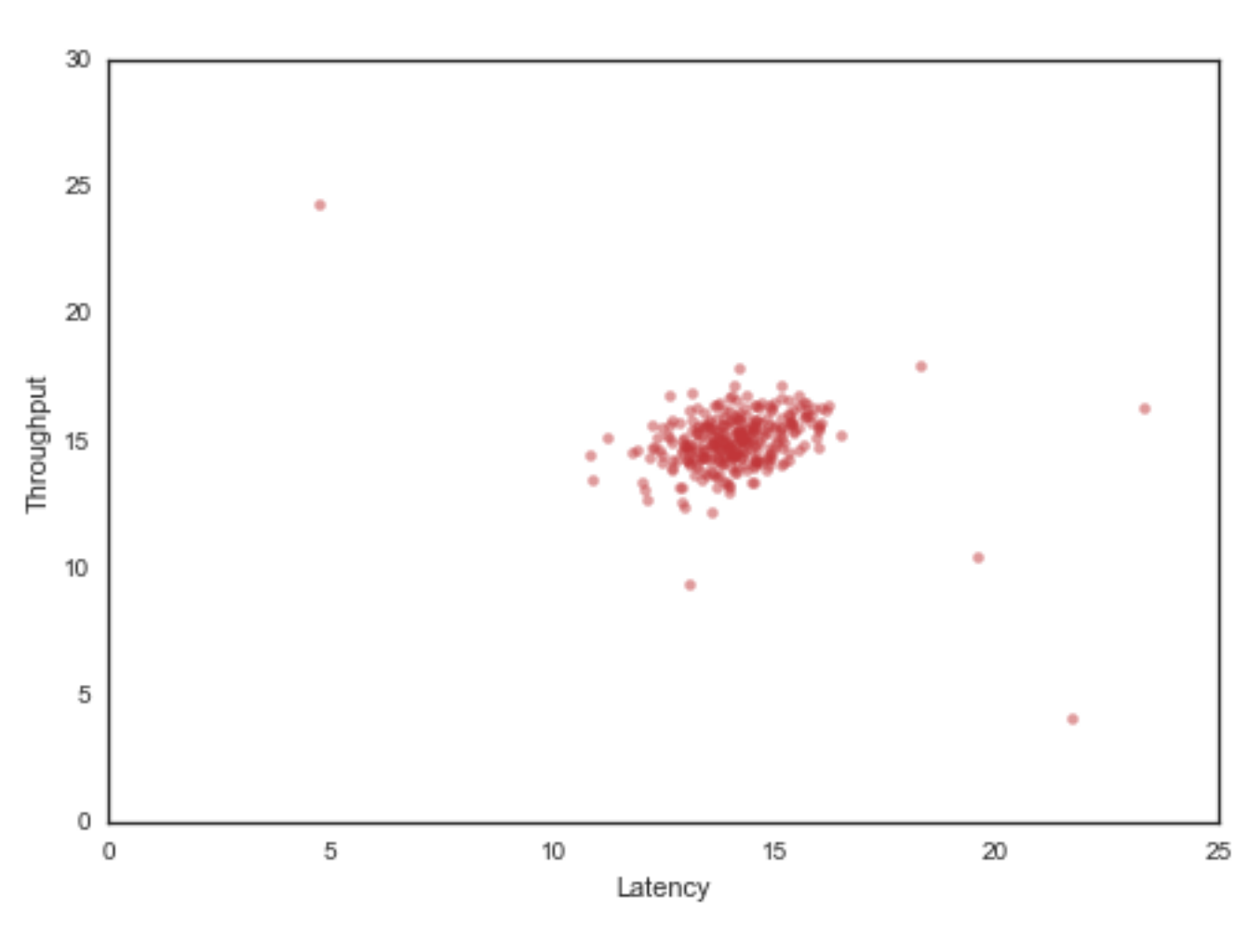
Out[4]:
```
dict_keys(['__globals__', 'Xval', 'X', '__header__', '__versi
on__', 'yval'])
```

In [5]:
```
X_data = mat.get('X')
```

In [6]:
```
#分为训练和测试数据
X_train,X_test, y_train, y_test = train_test_split(mat.get('Xv
al'),mat.get('yval').ravel(), test_size=0.7)
```

In [7]:
```
#可视化

sns.set(context="notebook", style="white", palette=sns.color_p
alette("RdBu"))
sns.regplot('Latency', 'Throughput',
           data=pd.DataFrame(X_data, columns=['Latency', 'Thro
ughput']),
           fit_reg=False,
           scatter_kws={"s":20,
                        "alpha":0.5})
```

Out[7]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x119e7bf28>
```



In [8]:
```
#平均值
X_mean = X_data.mean(axis=0)
print(X_mean)

#估算协方差
cov = np.cov(X_data.T)
print(cov)
```

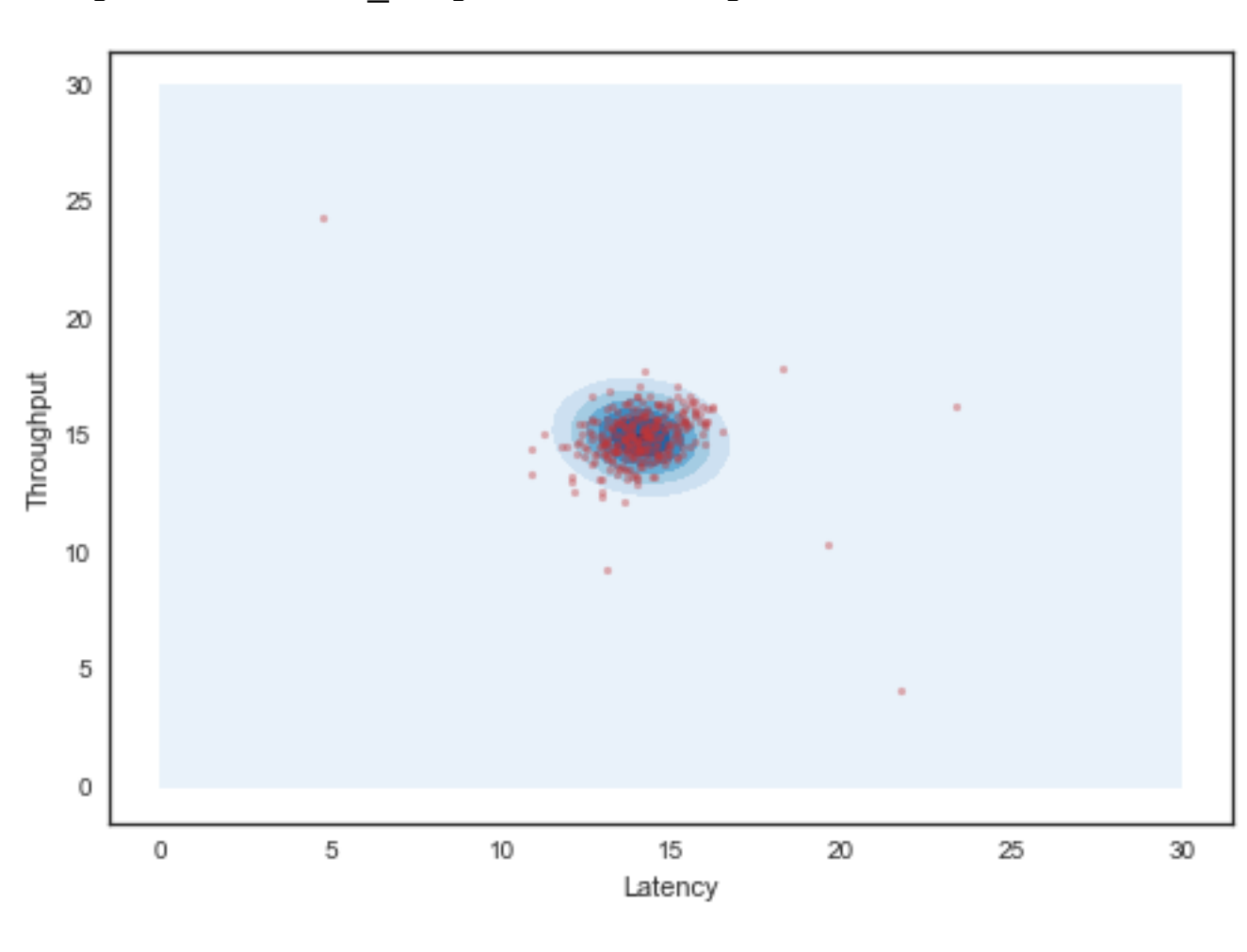
```
[ 14.11222578  14.99771051]
[[ 1.83862041 -0.22786456]
 [-0.22786456  1.71533273]]
```

In [9]:
```
np.dstack(np.mgrid[0:3,0:3])
```

Out[9]:
```
array([[[0, 0],
        [0, 1],
        [0, 2]],

       [[1, 0],
        [1, 1],
        [1, 2]],

       [[2, 0],
        [2, 1],
        [2, 2]]])
```

In [10]:
```
#多元高斯分布模型

multi_normal = stats.multivariate_normal(X_mean, cov)


x, y = np.mgrid[0:30:0.01, 0:30:0.01]
pos = np.dstack((x, y))

fig, ax = plt.subplots()


ax.contourf(x, y, multi_normal.pdf(pos), cmap='Blues')


sns.regplot('Latency', 'Throughput',
           data=pd.DataFrame(X_data, columns=['Latency', 'Thro
ughput']),
           fit_reg=False,
           ax=ax,
           scatter_kws={"s":10,
                        "alpha":0.4})
```

Out[10]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11c89d6a0>
```



F1的算法

The F_1 score is computed using precision ($prec$) and recall (rec):

$$F_1 = \frac{2 \cdot prec \cdot rec}{prec + rec},$$

You compute precision and recall by:

$$prec = \frac{tp}{tp + fp}$$
$$rec = \frac{tp}{tp + fn},$$

In [11]:
```
e, fs = anomaly.select_threshold(X_data, X_train,y_train)
print('Best epsilon: {}\nBest F-score on validation data: {}'.
format(e, fs))
```

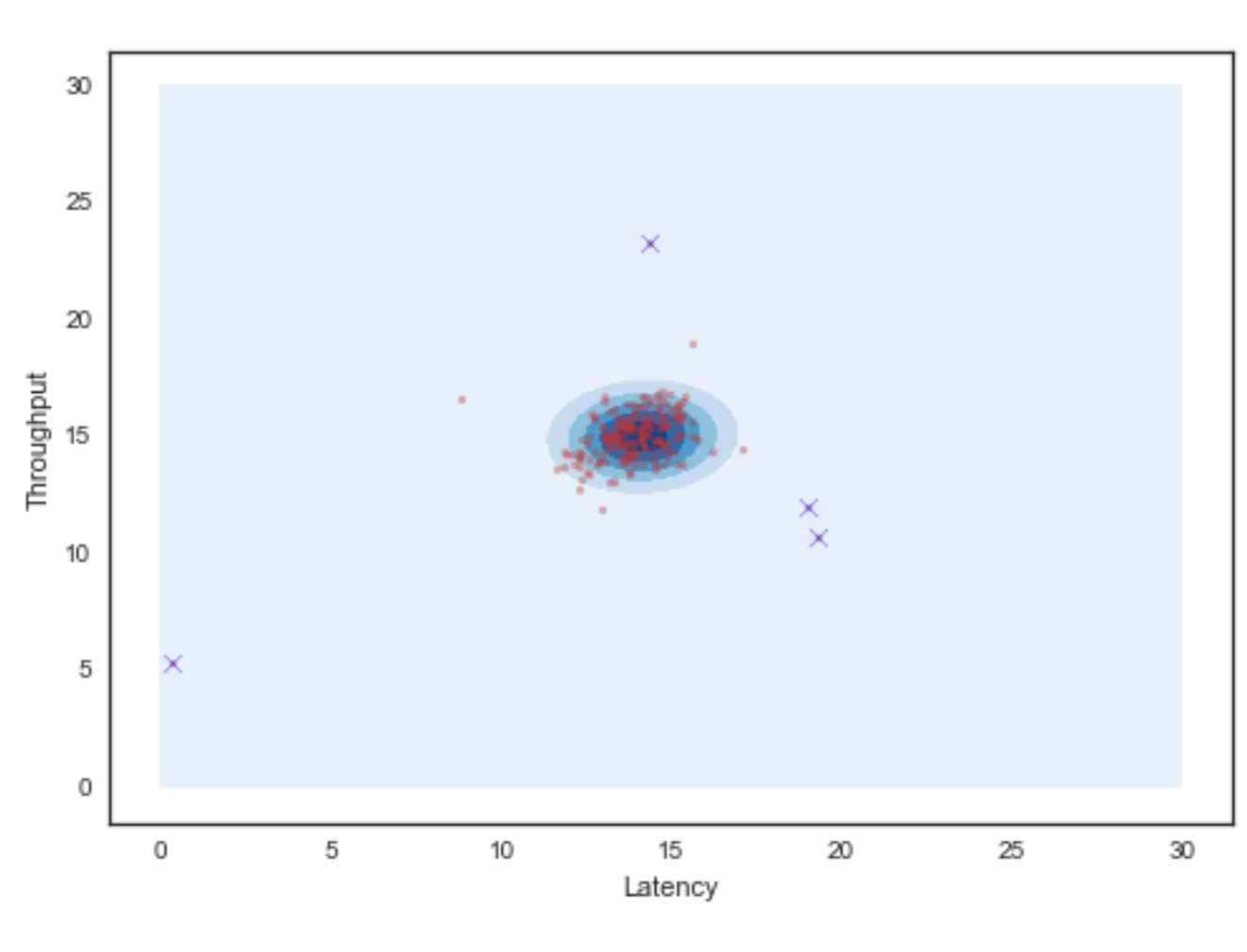
```
Best epsilon: 2.7023073618235194e-05
Best F-score on validation data: 0.8
```

In [12]:
```
multi_normal, y_pred = anomaly.predict(X_data, X_train, e, X_t
est, y_test)
```

```
             precision    recall  f1-score   support

          0       0.99      1.00      1.00       209
          1       1.00      0.67      0.80         6

avg / total       0.99      0.99      0.99       215
```

In [13]:
```
# construct test DataFrame
data = pd.DataFrame(X_test, columns=['Latency', 'Throughput'])
data['y_pred'] = y_pred

# create a grid for graphing
x, y = np.mgrid[0:30:0.01, 0:30:0.01]
pos = np.dstack((x, y))

fig, ax = plt.subplots()

# plot probability density
ax.contourf(x, y, multi_normal.pdf(pos), cmap='Blues')

# plot original Xval points
sns.regplot('Latency', 'Throughput',
            data=data,
            fit_reg=False,
            ax=ax,
            scatter_kws={"s":10,
                         "alpha":0.4})

# mark the predicted anamoly of CV data. We should have a test
set for this...
anamoly_data = data[data['y_pred']==1]
ax.scatter(anamoly_data['Latency'], anamoly_data['Throughput']
, marker='x', s=50)
```

Out[13]:
```
<matplotlib.collections.PathCollection at 0x137838fd0>
```



In [14]:
```
mat = sio.loadmat('./data/ex8data2.mat')
```

In [15]:
```
X = mat.get('X')
Xval, Xtest, yval, ytest = train_test_split(mat.get('Xval'),
                                            mat.get('yval').ra
vel(),
                                            test_size=0.5)
```

In [16]:
```
e, fs = anomaly.select_threshold(X, Xval, yval)
print('Best epsilon: {}\nBest F-score on validation data: {}'.
format(e, fs))
```

```
Best epsilon: 1.74667432759803e-19
Best F-score on validation data: 0.7499999999999999
```

In [17]:
```
multi_normal, y_pred = anomaly.predict(X, Xval, e, Xtest, ytes
t)
```

```
             precision    recall  f1-score   support

          0       0.93      1.00      0.97        43
          1       1.00      0.57      0.73         7

avg / total       0.94      0.94      0.93        50
```

In [18]:
```
print('find {} anamolies'.format(y_pred.sum()))
```

```
find 4 anamolies
```

In [19]:
```
##推荐系统  基于用户的电影推荐

from ml import  recommender as rcmd
```

In [20]:
```
#加载数据

movies_mat = sio.loadmat('./data/ex8_movies.mat')

print(movies_mat.keys())

# Y 电影 和 用户 R 是 用户在某个电影中是否评分
Y, R = movies_mat.get('Y'), movies_mat.get('R')

Y.shape, R.shape


#  Y is a 1682x943 matrix, containing ratings (1-5) of 1682 mo
vies on
#  943 users
#
#  R is a 1682x943 matrix, where R(i,j) = 1 if and only if use
r j gave a
#  rating to movie i
```

```
dict_keys(['__header__', '__globals__', '__version__', 'R', '
Y'])
```

Out[20]:
```
((1682, 943), (1682, 943))
```

In [21]:
```
n_movie, n_user = Y.shape

n_feature = 10
```

In [22]:
```
param_mat = sio.loadmat('./data/ex8_movieParams.mat')
print(param_mat.keys())

#theta
theta, X = param_mat.get('Theta'), param_mat.get('X')

theta.shape, X.shape
```

```
dict_keys(['__globals__', 'X', 'Theta', '__header__', 'num_fe
atures', '__version__', 'num_users', 'num_movies'])
```

Out[22]:
```
((943, 10), (1682, 10))
```

代价函数

$$J(x^{(1)}, ..., x^{(n_m)}, \theta^{(1)}, ..., \theta^{(n_u)}) = \frac{1}{2} \sum_{(i,j):r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)})^2.$$

In [23]:
```
#小数据量测试

users = 4
movies = 5
features = 3

X_sub = X[:movies, :features]
theta_sub = theta[:users, :features]
Y_sub = Y[:movies, :users]
R_sub = R[:movies, :users]

param_sub = rcmd.serialize(X_sub, theta_sub)

rcmd.cost(param_sub, Y_sub, R_sub, features)
```

Out[23]:
```
22.224603725685675
```

In [24]:
```
# 计算代价
param = rcmd.serialize(X, theta)

rcmd.cost(rcmd.serialize(X, theta), Y, R, 10)
```

Out[24]:
```
27918.64012454421
```

gradient

$$\frac{\partial J}{\partial x_k^{(i)}} = \sum_{j:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) \theta_k^{(j)}$$
$$\frac{\partial J}{\partial \theta_k^{(j)}} = \sum_{i:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) x_k^{(i)}.$$

In [25]:
```
X_grad, theta_grad = rcmd.deserialize(rcmd.gradient(param, Y,
R, 10),
                                      n_movie, n_user, 10)
```

$$X_{grad}(i,:) = (X(i,:) * Theta_{temp}^T - Y_{temp}) * Theta_{temp}.$$

In [26]:
```
assert X_grad.shape == X.shape
assert theta_grad.shape == theta.shape
```

In [27]:
```
# regularized cost

rcmd.regularized_cost(param, Y, R, 10, l=1)  # total regulariz
ed cost
```

Out[27]:
```
32520.682450229557
```

regularized gradient

$$\frac{\partial J}{\partial x_k^{(i)}} = \sum_{j:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) \theta_k^{(j)} + \lambda x_k^{(i)}$$
$$\frac{\partial J}{\partial \theta_k^{(j)}} = \sum_{i:r(i,j)=1} ((\theta^{(j)})^T x^{(i)} - y^{(i,j)}) x_k^{(i)} + \lambda \theta_k^{(j)}.$$

In [28]:
```
n_movie, n_user = Y.shape

X_grad, theta_grad = rcmd.deserialize(rcmd.regularized_gradien
t(param, Y, R, 10),

n_movie, n_user, 10)

assert X_grad.shape == X.shape
assert theta_grad.shape == theta.shape
```

In [29]:
```
#解析movie_id.txt

movie_list = []

with open('./data/movie_ids.txt', encoding='latin-1') as f:
    for line in f:
        tokens = line.strip().split(' ')
        movie_list.append(' '.join(tokens[1:]))

movie_list = np.array(movie_list)
```

In [30]:
```
ratings = np.zeros(1682)

ratings[0] = 4
ratings[6] = 3
ratings[11] = 5
ratings[53] = 4
ratings[63] = 5
ratings[65] = 3
ratings[68] = 5
ratings[97] = 2
ratings[182] = 4
ratings[225] = 5
ratings[354] = 5
```

In [31]:
```
##准备数据

Y, R = movies_mat.get('Y'), movies_mat.get('R')

Y = np.insert(Y, 0, ratings, axis=1)
Y.shape
```

Out[31]:
```
(1682, 944)
```

In [32]:
```
R = np.insert(R, 0, ratings != 0, axis=1)
R.shape
```

Out[32]:
```
(1682, 944)
```

In [33]:
```
n_features = 50
n_movie, n_user = Y.shape
l = 10
```

In [34]:
```
X = np.random.standard_normal((n_movie, n_features))
theta = np.random.standard_normal((n_user, n_features))

X.shape, theta.shape
```

Out[34]:
```
((1682, 50), (944, 50))
```

In [35]:
```
param = rcmd.serialize(X, theta)
```

In [36]:
```
Y_norm = Y - Y.mean()
Y_norm.mean()
```

Out[36]:
```
4.6862111343939375e-17
```

In [37]:
```
##训练
import scipy.optimize as opt
```

In [38]:
```
res = opt.minimize(fun=rcmd.regularized_cost,
                   x0=param,
                   args=(Y_norm, R, n_features, l),
                   method='TNC',
                   jac=rcmd.regularized_gradient)
```

In [39]:
```
res
```

Out[39]:
```
     fun: 64721.497815075141
     jac: array([  1.00880791e-05,  -7.81101492e-07,  -1.7367
9901e-06, ...,
         6.62309420e-07,  -8.64922452e-07,  -5.74048722e-07])
 message: 'Converged (|f_n-f_(n-1)| ~= 0)'
    nfev: 2442
     nit: 78
  status: 1
 success: True
       x: array([-0.03862355, -0.24487032,  0.38665165, ...,
0.13673055,
       -0.54222834, -0.69394197])
```

In [40]:
```
X_trained, theta_trained = rcmd.deserialize(res.x, n_movie, n_
user, n_features)
X_trained.shape, theta_trained.shape
```

Out[40]:
```
((1682, 50), (944, 50))
```

In [41]:
```
#预测
prediction = X_trained @ theta_trained.T
```

In [42]:
```
my_preds = prediction[:, 0] + Y.mean()
```

In [43]:
```
idx = np.argsort(my_preds)[::-1]
idx.shape
```

Out[43]:
```
(1682,)
```

In [44]:
```
my_preds[idx][:10]
```

Out[44]:
```
array([ 4.12535104,  4.04413692,  3.99324354,  3.91902979,  3
.81690931,
        3.81556246,  3.76602464,  3.76322789,  3.75904956,  3
.75077295])
```

In [45]:
```
#打印top10

for m in movie_list[idx][:10]:
    print(m)
```

```
Titanic (1997)
Star Wars (1977)
Shawshank Redemption, The (1994)
Forrest Gump (1994)
Raiders of the Lost Ark (1981)
Braveheart (1995)
Return of the Jedi (1983)
Usual Suspects, The (1995)
Godfather, The (1972)
Schindler's List (1993)
```

In [ ]:
```
#练习8 完
```