project1:naive bayes and logistic regression

Navie bayes

在sklearn中实现了三类朴素贝叶斯：**GaussianNB(高斯朴素贝叶斯)、MultinomialNB(多项式朴素贝叶斯)、BernoulliNB(伯努利朴素贝叶斯)，他们的区别是似然函数不同**

Bernoulli Naive Bayes

$$P\left(x_i \mid y\right)=P(i \mid y) x_i+(1-P(i \mid y))\left(1-x_i\right)$$

适合服从根据多元伯努利分布分布的数据

Gaussian Naive Bayes

$$P\left(x_i \mid y\right)=\frac{1}{\sqrt{2 \pi \sigma_y^2}} \exp \left(-\frac{\left(x_i-\mu_y\right)^2}{2 \sigma_y^2}\right)$$

适合处理连续变量

Multinomial Naive Bayes

$$\hat{\theta}_{y i}=\frac{N_{y i}+\alpha}{N_y+\alpha n}$$

适合处理离散变量

本次尝试用这三种分类器来进行分类从而对比

import

```
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
import csv
import time
```

load data

```
X_train_file = csv.reader(open('../data/X_train.csv'))
Y_train_file = csv.reader(open('../data/Y_train.csv'))
X_test_file = csv.reader(open('../data/X_test.csv'))
Y_test_file = csv.reader(open('../data/Y_test.csv'))
X_train = []
Y_train = []
X_test = []
Y_test = []
```

```
def loadData():
    i = 0
    for content in X_train_file:
        i += 1
        if (i == 1):
            continue
        content = list(map(int, content))
        if len(content) != 0:
            X_train.append(content)
    i = 0;
    for content in Y_train_file:
        i += 1
        if (i == 1):
            continue
        content = list(map(int, content))
        if len(content) != 0:
            Y_train.append(content)
    i = 0;
    for content in X_test_file:
        i += 1
        if (i == 1):
            continue
        content = list(map(int, content))
        if len(content) != 0:
            X_test.append(content)

    i = 0;
    for content in Y_test_file:
        i += 1
        if (i == 1):
            continue
        content = list(map(int, content))
        if len(content) != 0:
            Y_test.append(content)
```

主函数

```
startTime = time.time()
loadData()
endLoadTime = time.time()
bernNB()/ MultiNB()/GausNB()
endTime =time.time()
print("load file time: %.2f\ncalculating time: %.2f\ntotal time: %.2f"% (endLoadTime-
startTime, endTime-endLoadTime, endTime-startTime))
```

BernoulliNB

```python
def bernNB():
    BernNB = BernoulliNB(binarize=True)
    BernNB.fit(X_train, Y_train)
    print(BernNB)
    y_expect = Y_test
    y_pred = BernNB.predict(X_test)
    print(accuracy_score(y_expect, y_pred))
```

主函数输出

```
BernoulliNB(binarize=True)
0.7825072170014127
load file time: 1.23
calculating time: 0.56
total time: 1.79
```

MultinomialNB

```python
def MultiNB():
    MultiNB = MultinomialNB()
    MultiNB.fit(X_train, Y_train)
    print(MultiNB)
    y_expect = Y_test
    y_pred = MultiNB.predict(X_test)
    print(accuracy_score(y_expect, y_pred))
```

主函数输出

```
MultinomialNB()
0.785148332412014
load file time: 1.25
calculating time: 0.51
total time: 1.76
```

GaussianNB

```python
def GausNB():
    GausNB = GaussianNB()
    GausNB.fit(X_train, Y_train)
    print(GausNB)
    y_expect = Y_test
    y_pred = GausNB.predict(X_test)
    print(accuracy_score(y_expect, y_pred))
```

```
GaussianNB()
0.7952828450340889
load file time: 1.23
calculating time: 0.53
total time: 1.77
```

因为加载数据的代码一致，应该比较calculating time, 得出性能应该是 MultinomialNB > GaussianNB>BernoulliNB

因为输入的数据是离散值并且没有符合伯努利分布，所以使用MultinomialNB最好，实际结果和理论分析一致

logistic regression

数学推导

假设函数 $h_w(X)=\frac{1}{1+e^{-W^TX}}$

参数 w

$$
\begin{aligned}
&h_w(X)=g\left(W^TX\right)\\
&g(z)=\frac{1}{1+e^{-z}}\\
&z=W^TX
\end{aligned}
$$

SGD for logistic regression 损失函数

$$
J(w)=-y^{(i)}\log\left(g\left(W^Tx\right)\right)-\left(1-y^{(i)}\right)\log\left(1-g\left(W^Tx\right)\right)
$$

$$
\begin{aligned}
g(z)' &= \frac{e^{-z}}{\left(1+e^{-z}\right)^2}\\
&= \frac{1}{1+e^{-z}}\frac{e^{-z}}{1+e^{-z}}\\
&= \frac{1}{1+e^{-z}}\frac{1+e^{-z}-1}{1+e^{-z}}\\
&= g(z)(1-g(z))
\end{aligned}
$$

所以

$$
\begin{aligned}
\frac{\partial}{\partial w}J(w) &= -\left[y^{(i)}\frac{1}{g\left(W^Tx^{(i)}\right)}+\left(1-y^{(i)}\right)\frac{1}{1-g\left(W^Tx^{(i)}\right)}\right]\frac{\partial}{\partial w}g\left(W^Tx^{(i)}\right)\\
&= -\times\frac{y^{(i)}\left(1-g\left(W^Tx^{(i)}\right)\right)+\left(1-y^{(i)}\right)g\left(W^Tx^{(i)}\right)}{g\left(W^Tx^{(i)}\right)\left(1-g\left(W^Tx^{(i)}\right)\right)}\\
&\times g\left(W^Tx^{(i)}\right)\left(1-g\left(W^Tx^{(i)}\right)\right)\frac{\partial}{\partial w}\left(W^Tx^{(i)}\right)\\
&= -\left(y^{(i)}-g\left(W^Tx^{(i)}\right)\right)x^{(i)}\\
&= \left(h_w\left(x^{(i)}\right)-y^{(i)}\right)x^{(i)}
\end{aligned}
$$

更新函数为

$$w_j := w_j - \eta\left(h_w\left(x^{(i)}\right) - y^{(i)}\right)x_j^{(i)}$$

（与线性回归参数更新公式的形式相同，但 $h\left(x^{(i)}\right)$ 不同。）

$$h_w(X) = g\left(W^T X\right)$$

辅助构造函数

1. 激活函数/sigmoid函数：

```
def sigmoid(z):
    a = 1/(1+np.exp(-z))
    return a
```

就这么easy，sigmoid的公式就是1/(1+e-x)，这里用 **np.exp()**就可以轻松构建。

2. 参数初始化函数（给参数都初始化为0）：

```
def initialize_with_zeros(dim):
    w = np.zeros((dim,1))
    b = 0
    return w,b
```

W是一个列向量，传入维度dim，返回shape为（dim,1）的W，b就是一个数。这里用到的方法是 **np.zeros(shape)**.

3.propagate函数：这里再次解释一下这个propagate，它包含了forward-propagate和backward-propagate，即正向传播和反向传播。正向传播求的是cost，反向传播是从cost的表达式倒推W和b的偏导数.

```
w -- 权重, shape： (num_px * num_px * 3, 1)
b -- 偏置项, 一个标量
X -- 数据集, shape： (num_px * num_px * 3, m),m为样本数
Y -- 真实标签, shape： (1,m)
```

```
def propagate(w, b, X, Y):

    # Sample number m:
    m = X.shape[1]

    # Forward propagation:
    A = sigmoid(np.dot(w.T, X) + b)  # use sigmoid func
    cost = -(np.sum(Y * np.log(A) + (1 - Y) * np.log(1 - A))) / m

    # Back propagation:
    dZ = A - Y
    dw = (np.dot(X, dZ.T)) / m
    db = (np.sum(dZ)) / m
```

```
    # return value
    grads = {"dw": dw,
             "db": db}

    return grads, cost
```

numpy中矩阵的点乘, 也就是内积运算, 是用 np.dot(A,B), 它要求前 一个矩阵的列数等于后一个矩阵的行数。但矩阵也可以进行 元素相乘 (element product) , 就是 两个相同形状的矩阵对于元素相乘得到一个新的相同形状的矩阵, 可以直接用 A^*B 或者用 np.multiply (A, B) 。矩阵求log用 np.log (), 对矩阵元素求和用 np.sum().

1. **optimize函数：**

```
def optimize(w, b, X, Y, num_iterations, learning_rate, costs, startStep,
print_cost=False):
    for i in range(num_iterations):
        # use propagate func to calculate the cost and gradient every iteration
        grads, cost = propagate(w, b, X, Y)
        dw = grads["dw"]
        db = grads["db"]

        # update parameters
        w = w - learning_rate * dw
        b = b - learning_rate * db

        # every num_iterations iterations, save the cost
        if i % num_iterations == 0:
            costs.append(cost)

        # print cost every num_iterations to keep track of the progress of the model
        if print_cost and i % (num_iterations / 10) == 0:
            print("Cost after iteration %i: %f" % (i+startStep, cost))
    # After iterating, place the final parameters in the dictionary and return:
    params = {"w": w,
              "b": b}
    grads = {"dw": dw,
             "db": db}
    return params, grads, costs
```

5.predict函数：

按照预测的结果和0.5比来决定结果是1还是0.因此，我们可以设立规则：0.5~1的A对于预测值1,小于0.5的对应预测值0。

```python
def predict(w, b, X):
    m = X.shape[1]
    Y_prediction = np.zeros((1, m))

    A = sigmoid(np.dot(w.T, X) + b)
    for i in range(m):
        if A[0, i] > 0.5:
            Y_prediction[0, i] = 1
        else:
            Y_prediction[0, i] = 0

    return Y_prediction
```

1. **logistic_model 函数**

不断调用optimize函数训练模型并实时输出模型训练情况（accuracy, costs)

```python
def logistic_model(x_train, y_train, x_test, y_test, learning_rate=0.1,
num_iterations=2000, print_cost=False):
    # To obtain characteristic dimensions, initialization parameters:
    dim = X_train.shape[0]
    W, b = initialize_with_zeros(dim)
    step = 100
    # Define a Costs array to store the cost after each several iterations, so that we
can draw a graph to see the change trend of cost:
    costs = []
    # Define the accuracy array to store accuracy after several iterations, so that a
graph can be drawn to see the variation trend of accuracy:
    accuracys_train = []
    accuracys_test = []
    for i in range(int(num_iterations / step)):
        # Gradient descent, model parameters can be calculated iteratively:
        params, grads, costs = optimize(W, b, x_train, y_train, step, learning_rate,
costs,i*step, print_cost)
        W = params['w']
        b = params['b']

        # Use the parameters learned to make predictions:
        prediction_train = predict(W, b, x_train)

        # Calculation accuracy, respectively in training set and test set:
        accuracy_train = 1 - np.mean(np.abs(prediction_train - y_train))
        print("Accuracy on train set:", accuracy_train)
        accuracys_train.append(accuracy_train)
    # To facilitate analysis and inspection, we store all the parameters and
hyperparameters obtained into a dictionary and return them:
    d = {"costs": costs,
         "Y_prediction_train": prediction_train,
         "w": W,
```

```
            "b": b,
            "learning_rate": learning_rate,
            "num_iterations": num_iterations,
            "train_acy": accuracy_train,
            "accuracys_train": accuracys_train
            }
    # Use the parameters learned to make predictions:
    prediction_test = predict(W, b, x_test)

    # Calculation accuracy, respectively in training set and test set:
    accuracy_test = 1 - np.mean(np.abs(prediction_test - y_test))
    print("Accuracy on test set:", accuracy_test)

    return d
```

1. **导入数据,归一化**

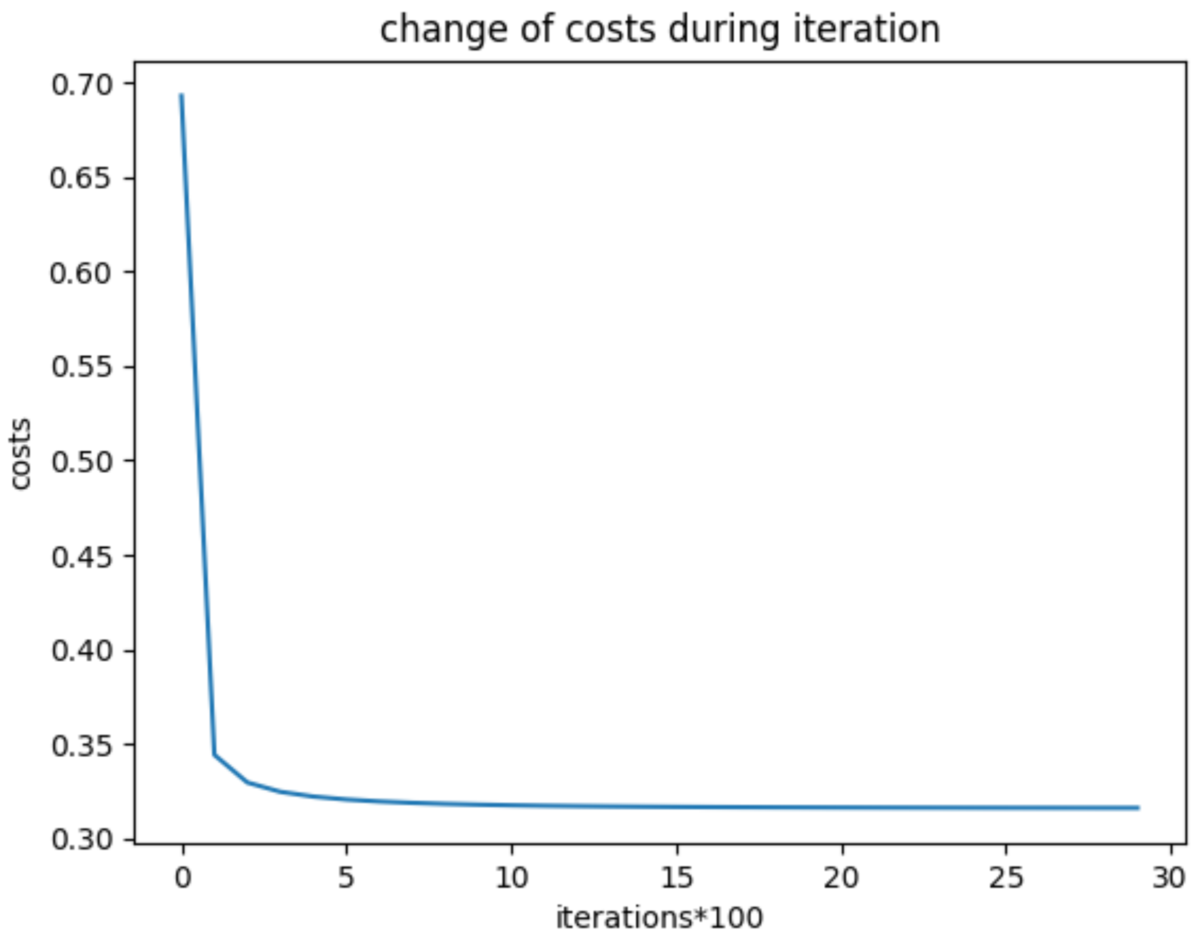
使用panda导入，并使用reshape将数据归一化

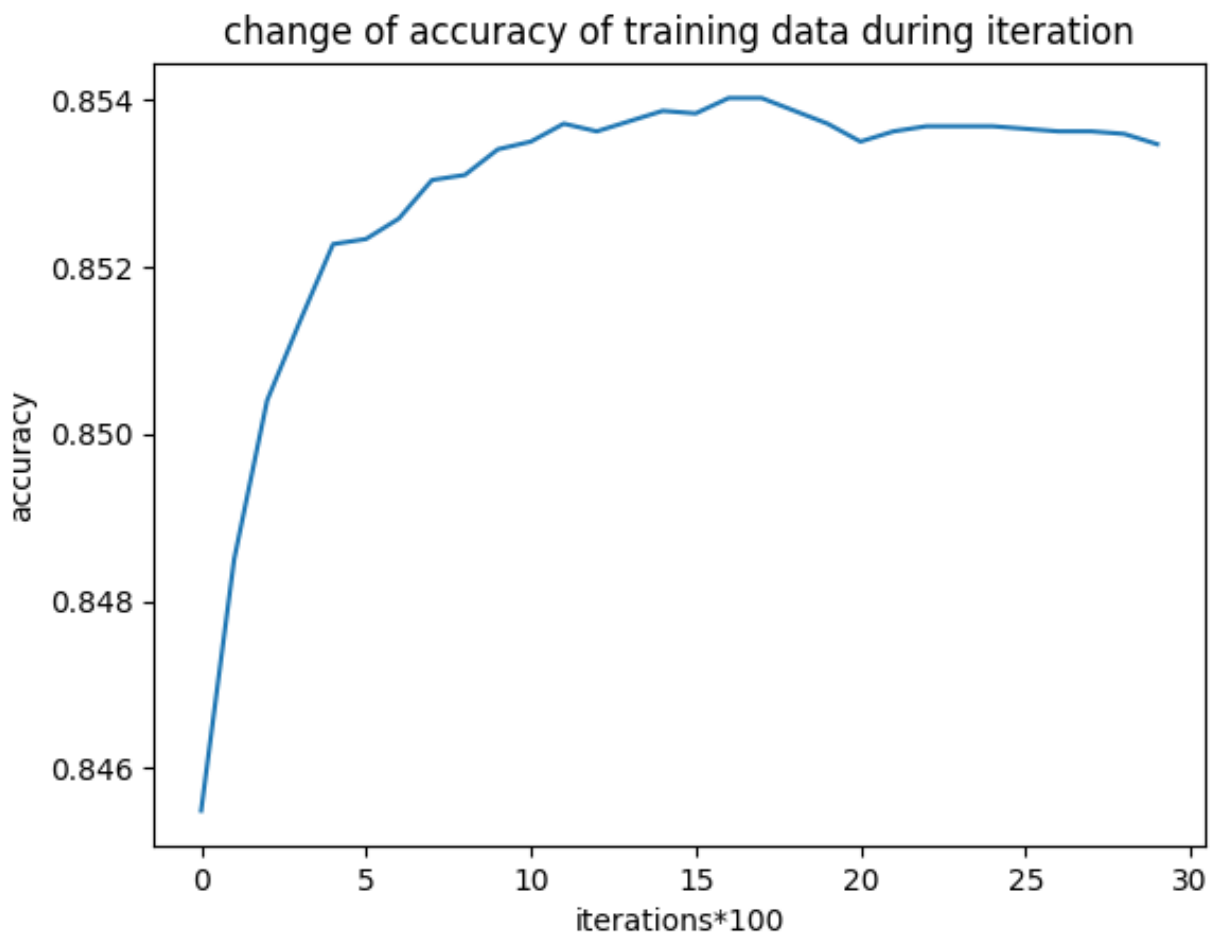
```
def load_data():
    __filepath__ = ['../data/X_train.csv', '../data/Y_train.csv', '../data/X_test.csv',
'../data/Y_test.csv']
    __X_train__ = pd.read_csv(__filepath__[0]).values
    __X_train__ = preprocessing.scale(__X_train__)
    __Y_train__ = pd.read_csv(__filepath__[1])['label']
    __Y_train__ = __Y_train__.values
    __X_test__ = pd.read_csv(__filepath__[2]).values
    __X_test__ = preprocessing.scale(__X_test__)
    __Y_test__ = pd.read_csv(__filepath__[3])['label'].values
    __X_train__ = __X_train__.reshape(__X_train__.shape[0], -1).T
    __Y_train__ = __Y_train__.reshape(__Y_train__.shape[0], -1).T
    __X_test__ = __X_test__.reshape(__X_test__.shape[0], -1).T
    __Y_test__ = __Y_test__.reshape(__Y_test__.shape[0], -1).T
    return __X_train__, __Y_train__, __X_test__, __Y_test__
```

1. **主函数运行**

设置学习率为0.15， 迭代次数为3000次，并画出每次迭代的损失函数的变化情况

```
startTime = time.time()
X_train, Y_train, X_test, Y_test = load_data()
endLoadTime = time.time()
d = logistic_model(X_train, Y_train, X_test, Y_test, num_iterations=3000,
                   learning_rate=0.15, print_cost=True)
endTime=time.time()
print("load file time: %.2f\ncalculating time: %.2f \ntotal time: %.2f" % (endLoadTime-
startTime, endTime-endLoadTime, endTime-startTime))
plt.ylabel('costs')
plt.xlabel('iterations*100')
plt.plot(d['costs'])
plt.show()
```





可以看见超过了85%的正确率

```
/Users/kangyixiao/EchoFile/coding/SE125_ML/lab1/venv/bin/python
/Users/kangyixiao/EchoFile/coding/SE125_ML/lab1/src/logi/logi.py
Cost after iteration 0: 0.693147
Cost after iteration 10: 0.496506
Cost after iteration 20: 0.436814
Cost after iteration 30: 0.405058
Cost after iteration 40: 0.385495
Cost after iteration 50: 0.372463
Cost after iteration 60: 0.363283
Cost after iteration 70: 0.356528
Cost after iteration 80: 0.351380
Cost after iteration 90: 0.347343
Accuracy on train set: 0.8454900033782746
Cost after iteration 100: 0.344100
Cost after iteration 110: 0.341442
Cost after iteration 120: 0.339225
Cost after iteration 130: 0.337349
Cost after iteration 140: 0.335742
Cost after iteration 150: 0.334349
Cost after iteration 160: 0.333130
Cost after iteration 170: 0.332054
```

```
Cost after iteration 180: 0.331097
Cost after iteration 190: 0.330240
Accuracy on train set: 0.8484997389515064
Cost after iteration 200: 0.329468
Cost after iteration 210: 0.328769
Cost after iteration 220: 0.328132
Cost after iteration 230: 0.327550
Cost after iteration 240: 0.327015
Cost after iteration 250: 0.326522
Cost after iteration 260: 0.326065
Cost after iteration 270: 0.325642
Cost after iteration 280: 0.325248
Cost after iteration 290: 0.324880
Accuracy on train set: 0.8504038573753877
Cost after iteration 300: 0.324536
Cost after iteration 310: 0.324213
Cost after iteration 320: 0.323909
Cost after iteration 330: 0.323624
Cost after iteration 340: 0.323354
Cost after iteration 350: 0.323099
Cost after iteration 360: 0.322858
Cost after iteration 370: 0.322629
Cost after iteration 380: 0.322412
Cost after iteration 390: 0.322206
Accuracy on train set: 0.8513559165873283
Cost after iteration 400: 0.322009
Cost after iteration 410: 0.321822
Cost after iteration 420: 0.321643
Cost after iteration 430: 0.321472
Cost after iteration 440: 0.321309
Cost after iteration 450: 0.321153
Cost after iteration 460: 0.321003
Cost after iteration 470: 0.320860
Cost after iteration 480: 0.320722
Cost after iteration 490: 0.320590
Accuracy on train set: 0.8522772642117871
Cost after iteration 500: 0.320463
Cost after iteration 510: 0.320341
Cost after iteration 520: 0.320223
Cost after iteration 530: 0.320110
Cost after iteration 540: 0.320001
Cost after iteration 550: 0.319896
Cost after iteration 560: 0.319795
Cost after iteration 570: 0.319697
Cost after iteration 580: 0.319603
Cost after iteration 590: 0.319511
Accuracy on train set: 0.852338687386751
Cost after iteration 600: 0.319423
Cost after iteration 610: 0.319338
```

```
Cost after iteration 620: 0.319256
Cost after iteration 630: 0.319176
Cost after iteration 640: 0.319099
Cost after iteration 650: 0.319024
Cost after iteration 660: 0.318952
Cost after iteration 670: 0.318882
Cost after iteration 680: 0.318814
Cost after iteration 690: 0.318748
Accuracy on train set: 0.8525843800866066
Cost after iteration 700: 0.318684
Cost after iteration 710: 0.318622
Cost after iteration 720: 0.318562
Cost after iteration 730: 0.318503
Cost after iteration 740: 0.318446
Cost after iteration 750: 0.318391
Cost after iteration 760: 0.318338
Cost after iteration 770: 0.318285
Cost after iteration 780: 0.318235
Cost after iteration 790: 0.318186
Accuracy on train set: 0.853045053898836
Cost after iteration 800: 0.318138
Cost after iteration 810: 0.318091
Cost after iteration 820: 0.318046
Cost after iteration 830: 0.318002
Cost after iteration 840: 0.317959
Cost after iteration 850: 0.317917
Cost after iteration 860: 0.317876
Cost after iteration 870: 0.317837
Cost after iteration 880: 0.317798
Cost after iteration 890: 0.317760
Accuracy on train set: 0.8531064770737999
Cost after iteration 900: 0.317723
Cost after iteration 910: 0.317688
Cost after iteration 920: 0.317653
Cost after iteration 930: 0.317619
Cost after iteration 940: 0.317586
Cost after iteration 950: 0.317553
Cost after iteration 960: 0.317522
Cost after iteration 970: 0.317491
Cost after iteration 980: 0.317461
Cost after iteration 990: 0.317431
Accuracy on train set: 0.8534135929486195
Cost after iteration 1000: 0.317403
Cost after iteration 1010: 0.317375
Cost after iteration 1020: 0.317347
Cost after iteration 1030: 0.317321
Cost after iteration 1040: 0.317295
Cost after iteration 1050: 0.317269
Cost after iteration 1060: 0.317244
```

```
Cost after iteration 1070: 0.317220
Cost after iteration 1080: 0.317196
Cost after iteration 1090: 0.317173
Accuracy on train set: 0.8535057277110654
Cost after iteration 1100: 0.317150
Cost after iteration 1110: 0.317128
Cost after iteration 1120: 0.317106
Cost after iteration 1130: 0.317085
Cost after iteration 1140: 0.317064
Cost after iteration 1150: 0.317044
Cost after iteration 1160: 0.317024
Cost after iteration 1170: 0.317004
Cost after iteration 1180: 0.316985
Cost after iteration 1190: 0.316967
Accuracy on train set: 0.8537207088234391
Cost after iteration 1200: 0.316948
Cost after iteration 1210: 0.316930
Cost after iteration 1220: 0.316913
Cost after iteration 1230: 0.316896
Cost after iteration 1240: 0.316879
Cost after iteration 1250: 0.316863
Cost after iteration 1260: 0.316846
Cost after iteration 1270: 0.316831
Cost after iteration 1280: 0.316815
Cost after iteration 1290: 0.316800
Accuracy on train set: 0.8536285740609932
Cost after iteration 1300: 0.316785
Cost after iteration 1310: 0.316771
Cost after iteration 1320: 0.316756
Cost after iteration 1330: 0.316742
Cost after iteration 1340: 0.316729
Cost after iteration 1350: 0.316715
Cost after iteration 1360: 0.316702
Cost after iteration 1370: 0.316689
Cost after iteration 1380: 0.316677
Cost after iteration 1390: 0.316664
Accuracy on train set: 0.853751420410921
Cost after iteration 1400: 0.316652
Cost after iteration 1410: 0.316640
Cost after iteration 1420: 0.316628
Cost after iteration 1430: 0.316617
Cost after iteration 1440: 0.316606
Cost after iteration 1450: 0.316595
Cost after iteration 1460: 0.316584
Cost after iteration 1470: 0.316573
Cost after iteration 1480: 0.316563
Cost after iteration 1490: 0.316552
Accuracy on train set: 0.8538742667608489
Cost after iteration 1500: 0.316542
```

```
Cost after iteration 1510: 0.316532
Cost after iteration 1520: 0.316523
Cost after iteration 1530: 0.316513
Cost after iteration 1540: 0.316504
Cost after iteration 1550: 0.316494
Cost after iteration 1560: 0.316485
Cost after iteration 1570: 0.316476
Cost after iteration 1580: 0.316468
Cost after iteration 1590: 0.316459
Accuracy on train set: 0.853843555173367
Cost after iteration 1600: 0.316451
Cost after iteration 1610: 0.316442
Cost after iteration 1620: 0.316434
Cost after iteration 1630: 0.316426
Cost after iteration 1640: 0.316418
Cost after iteration 1650: 0.316411
Cost after iteration 1660: 0.316403
Cost after iteration 1670: 0.316396
Cost after iteration 1680: 0.316388
Cost after iteration 1690: 0.316381
Accuracy on train set: 0.8540278246982587
Cost after iteration 1700: 0.316374
Cost after iteration 1710: 0.316367
Cost after iteration 1720: 0.316360
Cost after iteration 1730: 0.316353
Cost after iteration 1740: 0.316347
Cost after iteration 1750: 0.316340
Cost after iteration 1760: 0.316334
Cost after iteration 1770: 0.316328
Cost after iteration 1780: 0.316321
Cost after iteration 1790: 0.316315
Accuracy on train set: 0.8540278246982587
Cost after iteration 1800: 0.316309
Cost after iteration 1810: 0.316303
Cost after iteration 1820: 0.316297
Cost after iteration 1830: 0.316292
Cost after iteration 1840: 0.316286
Cost after iteration 1850: 0.316281
Cost after iteration 1860: 0.316275
Cost after iteration 1870: 0.316270
Cost after iteration 1880: 0.316264
Cost after iteration 1890: 0.316259
Accuracy on train set: 0.8538742667608489
Cost after iteration 1900: 0.316254
Cost after iteration 1910: 0.316249
Cost after iteration 1920: 0.316244
Cost after iteration 1930: 0.316239
Cost after iteration 1940: 0.316234
Cost after iteration 1950: 0.316230
```

```
Cost after iteration 1960: 0.316225
Cost after iteration 1970: 0.316220
Cost after iteration 1980: 0.316216
Cost after iteration 1990: 0.316211
Accuracy on train set: 0.8537207088234391
Cost after iteration 2000: 0.316207
Cost after iteration 2010: 0.316202
Cost after iteration 2020: 0.316198
Cost after iteration 2030: 0.316194
Cost after iteration 2040: 0.316190
Cost after iteration 2050: 0.316186
Cost after iteration 2060: 0.316182
Cost after iteration 2070: 0.316178
Cost after iteration 2080: 0.316174
Cost after iteration 2090: 0.316170
Accuracy on train set: 0.8535057277110654
Cost after iteration 2100: 0.316166
Cost after iteration 2110: 0.316162
Cost after iteration 2120: 0.316159
Cost after iteration 2130: 0.316155
Cost after iteration 2140: 0.316151
Cost after iteration 2150: 0.316148
Cost after iteration 2160: 0.316144
Cost after iteration 2170: 0.316141
Cost after iteration 2180: 0.316138
Cost after iteration 2190: 0.316134
Accuracy on train set: 0.8536285740609932
Cost after iteration 2200: 0.316131
Cost after iteration 2210: 0.316128
Cost after iteration 2220: 0.316124
Cost after iteration 2230: 0.316121
Cost after iteration 2240: 0.316118
Cost after iteration 2250: 0.316115
Cost after iteration 2260: 0.316112
Cost after iteration 2270: 0.316109
Cost after iteration 2280: 0.316106
Cost after iteration 2290: 0.316103
Accuracy on train set: 0.8536899972359571
Cost after iteration 2300: 0.316100
Cost after iteration 2310: 0.316097
Cost after iteration 2320: 0.316094
Cost after iteration 2330: 0.316092
Cost after iteration 2340: 0.316089
Cost after iteration 2350: 0.316086
Cost after iteration 2360: 0.316084
Cost after iteration 2370: 0.316081
Cost after iteration 2380: 0.316078
Cost after iteration 2390: 0.316076
Accuracy on train set: 0.8536899972359571
```

```
Cost after iteration 2400: 0.316073
Cost after iteration 2410: 0.316071
Cost after iteration 2420: 0.316068
Cost after iteration 2430: 0.316066
Cost after iteration 2440: 0.316063
Cost after iteration 2450: 0.316061
Cost after iteration 2460: 0.316059
Cost after iteration 2470: 0.316056
Cost after iteration 2480: 0.316054
Cost after iteration 2490: 0.316052
Accuracy on train set: 0.8536899972359571
Cost after iteration 2500: 0.316050
Cost after iteration 2510: 0.316047
Cost after iteration 2520: 0.316045
Cost after iteration 2530: 0.316043
Cost after iteration 2540: 0.316041
Cost after iteration 2550: 0.316039
Cost after iteration 2560: 0.316037
Cost after iteration 2570: 0.316035
Cost after iteration 2580: 0.316033
Cost after iteration 2590: 0.316031
Accuracy on train set: 0.8536592856484752
Cost after iteration 2600: 0.316029
Cost after iteration 2610: 0.316027
Cost after iteration 2620: 0.316025
Cost after iteration 2630: 0.316023
Cost after iteration 2640: 0.316021
Cost after iteration 2650: 0.316019
Cost after iteration 2660: 0.316017
Cost after iteration 2670: 0.316016
Cost after iteration 2680: 0.316014
Cost after iteration 2690: 0.316012
Accuracy on train set: 0.8536285740609932
Cost after iteration 2700: 0.316010
Cost after iteration 2710: 0.316009
Cost after iteration 2720: 0.316007
Cost after iteration 2730: 0.316005
Cost after iteration 2740: 0.316003
Cost after iteration 2750: 0.316002
Cost after iteration 2760: 0.316000
Cost after iteration 2770: 0.315999
Cost after iteration 2780: 0.315997
Cost after iteration 2790: 0.315995
Accuracy on train set: 0.8536285740609932
Cost after iteration 2800: 0.315994
Cost after iteration 2810: 0.315992
Cost after iteration 2820: 0.315991
Cost after iteration 2830: 0.315989
Cost after iteration 2840: 0.315988
```

```
Cost after iteration 2850: 0.315986
Cost after iteration 2860: 0.315985
Cost after iteration 2870: 0.315983
Cost after iteration 2880: 0.315982
Cost after iteration 2890: 0.315980
Accuracy on train set: 0.8535978624735112
Cost after iteration 2900: 0.315979
Cost after iteration 2910: 0.315978
Cost after iteration 2920: 0.315976
Cost after iteration 2930: 0.315975
Cost after iteration 2940: 0.315974
Cost after iteration 2950: 0.315972
Cost after iteration 2960: 0.315971
Cost after iteration 2970: 0.315970
Cost after iteration 2980: 0.315968
Cost after iteration 2990: 0.315967
Accuracy on train set: 0.8534750161235835
Accuracy on test set: 0.8524046434494196
load file time: 0.49
calculating time: 8.72
total time: 9.21
```

在上一个sklearn中使用logistics regression来进行对比

```
def logisticRegrression():
    log_reg = LogisticRegression()
    log_reg.fit(X_train, Y_train)
    y_expect = Y_test
    y_pred = log_reg.predict(X_test)
    print(accuracy_score(y_expect, y_pred))
```

```
0.7978011178674529
load file time: 1.15
calculating time: 0.57
total time: 1.72

Process finished with exit code 0
```

发现正确率由自己实现的高，但是我的实现时间比较长，因为在我的实现中有大量的I/O 操作。

比较和分析

1. 逻辑回归属于判别式模型，而朴素贝叶斯属于生成式模型。具体来说，两者的目标虽然都是最大化后验概率，但是逻辑回归是直接对后验概率P(Y|X)进行建模，而朴素贝叶斯是对联合概率P(X,Y)进行建模，所以说两者的出发点是不同的。
2. 朴素贝叶斯分类器要求“属性条件独立假设”即，对于已知类别的样本x，假设x的所有属性是相互独立的。
3. 更**直观**的来看，逻辑回归是通过学习超平面来实现分类，而朴素贝叶斯通过考虑特征的概率来实现分类。
4. 逻辑回归在有相关性feature上面学习得到的模型在测试数据的performance更好。也就是说，逻辑回归在训

练时，不管特征之间有没有相关性，它都能找到最优的参数。而在朴素贝叶斯中，由于我们给定特征直接相互独立的严格设定，在有相关性的feature上面学习到的权重同时变大或变小，它们之间的权重不会相互影响。

5. 在本次实现中，朴素贝叶斯的时间比较短，而logistics regression的时间由迭代次数决定，如果需要较高的精度，就需要较长的时间，因为在后来会收敛所以可以观察大致多少步可以结束。同时自己实现的方式和sklearn的logistic 的性能差异较大，可能是数据优化和IO输出导致的。
6. 本次实现中，逻辑回归的精度比较大，可能是由于不断调整参数（迭代次数、学习率...)的结果。