山东大学 计算机科学与技术 学院

机器学习(双语) 课程实验报告

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实验题目: Logistic 回归

实验目的:

一、掌握 Logistic 回归

二、掌握牛顿迭代法

三、能够区分牛顿迭代法和梯度下降法的优劣

硬件环境:

Intel Core i5-8300H @ 2.3GHz

软件环境:

Windows10 Pro 1903

Python 3.7

Visual Studio Code 1.38.1

Sublime Text 3

MinGW-w64

实验步骤与内容:

- 一、读取数据画出散点图
- 二、利用梯度下降法求 theta 以及迭代过程中的损失函数值

$$\nabla_{\theta} L = \frac{1}{m} \sum_{i=1}^{m} (h_{\theta}(x^{(i)}) - y^{(i)}) x^{(i)}$$

并且绘制决策边界,对[20,80]做预测。

- 三、利用牛顿下降法求 theta
 - 1. 牛顿法原理

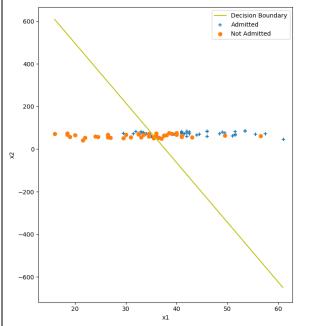
$$\theta^{(t+1)} = \theta^{(t)} - H^{-1} \nabla_{\theta} L$$

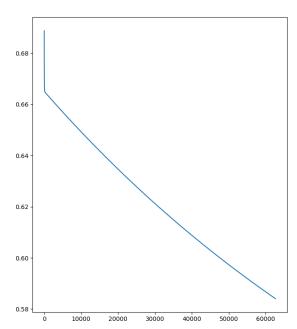
2. 求海森矩阵

$$H = \frac{1}{m} \sum_{i=1}^{m} \left[h_{\theta}(x^{(i)}) \left(1 - h_{\theta}(x^{(i)}) \right) x^{(i)} \left(x^{(i)} \right)^{T} \right]$$

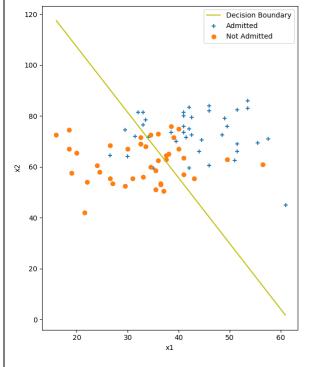
3. 绘制决策边界并且对[20, 80]做预测

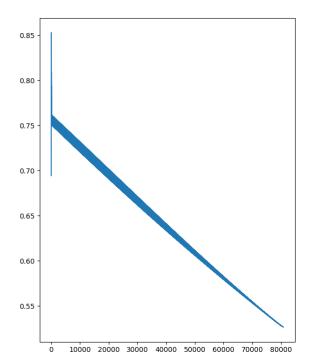
结论分析与体会: 对于梯度下降, 当学习率为 0.0009 时



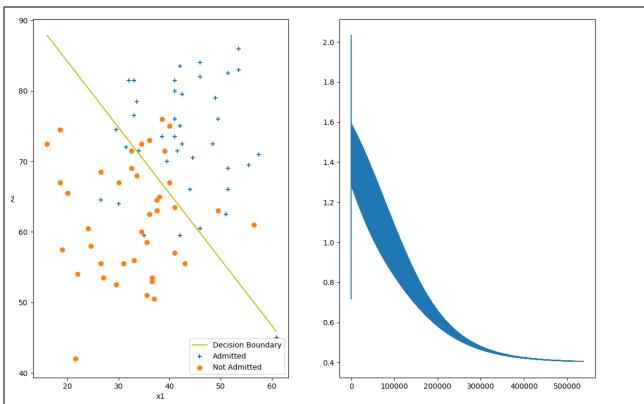


发现最终的损失函数只收敛到了 0.58 左右,而迭代了 60000 多次。把学习率调整至 0.0015 后





损失函数收敛至 0.5, 迭代 80000 多次 将学习率调整至 0.0025 后



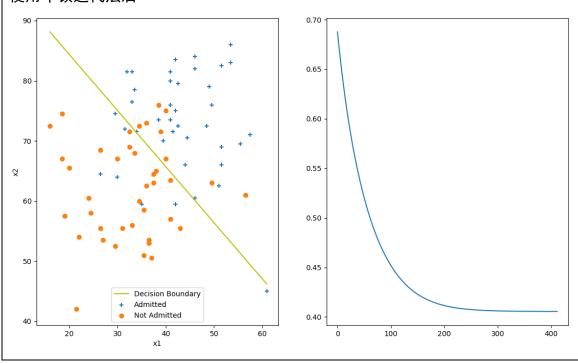
发现学习过程中损失函数不断震荡,最终收敛至 0.4 左右,但是迭代了 500000 次,相比于之前的效果更佳但是消耗的时间更多。

得到的 theta 值为 [[-16.1544 0.146911 0.157049]]

预测的概率为 [[0.65751957]]

在学习的过程中,由于需要迭代的次数过多,python 不能在短时间内计算出答案,于是使用 C++进行计算,计算时间在 5s 左右,最终把得到的结果在 python 中可视化。

使用牛顿迭代法后



发现只迭代了 400 多次就收敛到了 0.4, 迭代次数相比于梯度下降法大大减小, 节省了不少的时间, 得到的效果也很好。

得到的 theta 值为 [[-16.09688578 0.14575837 0.15620814]]

预测的概率为 [[0.66486864]]

```
附录:程序源代码
Python
import numpy as np
def sig(x): return 1 / (1 + np. exp(-x))
def J(feature, label, weights):
    ret = 0
    m = np. shape (feature) [0]
    for i in range(m):
        h = sig(feature[i] * weights)
        if h <= 0:
            h = 0.0000001
        elif h \ge 1:
            h = 0.9999999
        ret += -label[i, 0] * np. log(h) - (1 - label[i, 0]) * np. log(1 - h)
    return ret / m
def load data():
    feature = []
    label = []
    with open('exp2/data/ex2x.dat') as f:
        for each line in f. readlines():
            feature_temp = []
            feature_temp.append(1)
            for data in each_line.strip().split():
                feature temp. append(float(data))
            feature. append (feature_temp)
    with open('exp2/data/ex2y.dat') as f:
        for each line in f. readlines():
            label_temp = []
            for data in each_line.strip().split():
                label_temp. append(float(data))
            label.append(label temp)
    return np. mat(feature), np. mat(label)
```

```
def load_result(filename):
    w = np. mat(np. zeros((3, 1)))
    cost = []
    with open(filename) as f:
        alpha, w[0, 0], w[1, 0], w[2, 0], = f.readline().split()
        for each_line in f. readlines():
            cost. append (each_line. strip())
    return alpha, w, np. mat(cost). T
# 梯度下降 太慢
def fit(feature, label, alpha, epsilon=1e-7):
    m, n = np. shape (feature)
    \# w = np. mat([-4.96253179, 0.07103084, 0.03521583]). T
    w = np. mat(np. zeros((n, 1)))
    val = 0
    iteration = 0
    cost = []
    while True:
        iteration += 1
        h = sig(feature * w)
        err = label - h
        w = w + alpha * feature. T * err / m
        last = val
        val = J(feature, label, w)
        cost. append (val)
        if abs(val - last) < epsilon:
            break
    return w, np.mat(cost). T, iteration
def plot_fit(feature, label, **kwrags):
    x_pos = []
    y pos = []
    x_neg = []
    y neg = []
    for (x, y) in zip(feature, label):
        if y[0] == 1:
            x_pos. append(x[0, 1])
            y pos. append (x[0, 2])
        else:
            x_{neg.} append (x[0, 1])
            y neg. append (x[0, 2])
    file = kwrags.get('filename', None)
```

```
weights = kwrags.get('weights', [])
    cost = kwrags.get('cost', [])
    alpha = kwrags.get('alpha', -1)
    if file:
        alpha, weights, cost = load_result(file)
    print (weights. T)
    print(1 - predict(np. mat([1, 20, 80]), weights)) # probability of [20, 80]
will not be admitted
    import matplotlib.pyplot as plt
    plt.figure(str(alpha) if alpha != -1 else "Newton")
    plt. subplot (1, 2, 1)
    plt. scatter(x_pos, y_pos, marker='+', label='Admitted')
    plt. scatter(x_neg, y_neg, marker='o', label='Not Admitted')
    x = np. arange(min(feature[:, 1]), max(feature[:, 1]), 0.1)
    y = (-weights[0, 0] - weights[1, 0] * x) / weights[2, 0]
    plt.plot(x, y, 'y-', label='Decision Boundary')
    plt. xlabel('x1')
    plt.ylabel('x2')
    plt.legend()
    plt. subplot(1, 2, 2)
    plt.plot(np.linspace(0, len(cost), len(cost)), cost)
    plt.show()
def predict(data, w):
    h = sig(data * w)
    \# m = np. shape (h) [0]
    # for i in range(m):
    \# h[i, 0] = 0.0 \text{ if } h[i, 0] < 0.5 \text{ else } 1.0
    return h
def newton (feature, label, epsilon=1e-6):
    m, n = np. shape (feature)
    w = np. mat(np. zeros((n, 1)))
    val = 0
    iteration = 0
    cost = []
    while True:
        iteration += 1
        H = np. mat(np. zeros((n, n)))
        for i in range(m):
            h = sig(feature[i] * w)
            H += (h * (1 - h))[0, 0] * feature[i].T * feature[i]
        err = label - sig(feature * w)
```

```
w = w + H.I * feature.T * err / m
        last = val
        val = J(feature, label, w)
        cost.append(val[0, 0])
        if abs(val - last) < epsilon:
           break
    return w, cost, iteration
if __name__ == '__main__':
    feature, label = load_data()
    exe1 梯度下降法 C++计算结果, Python 可视化
    # # w, theta, iteration = fit(feature, label, 0.0012)
        result file = ["0.000900.txt", "0.001200.txt",
                                                                 "0. 001500. txt",
"0.001800.txt", "0.001900.txt", "0.002000.txt", "0.002500.txt"]
    # for file in result file:
         plot_fit(feature, label, filename="exp2/data/"+file)
    exe2 牛顿迭代
    w, cost, iteration = newton(feature, label)
    plot_fit(feature, label, weights=w, cost=cost)
C++
#include <algorithm>
#include <cassert>
#include <cmath>
#include <cstdio>
#include <cstring>
#include <iostream>
#include <map>
#include <set>
#include <string>
#include <vector>
#include <queue>
#include <fstream>
#define inf 0x3f3f3f3f
\#define cases(t) for (int cas = 1; cas \leq int(t); ++cas)
typedef long long II;
typedef double db;
using namespace std;
```

```
#ifdef NO_ONLINE_JUDGE
#define LOG(args...) do { cout << #args << " -> "; err(args); } while (0)
void err() { cout << endl; }</pre>
template<typename T, typename... Args> void err(T a, Args... args) { cout << a <<
' '; err(args...); }
#else
#define LOG(...)
#endif
const db eps = 1e-6;
db x[80][3];
db y[80];
db w[3], ww[3];
db sig(db x) {
    return 1.0 / (1.0 + \exp(-x));
}
db cal() {
    db ret = 0:
    for (int i = 0; i < 80; ++i) {
        db h = 0;
        for (int k = 0; k < 3; ++k) h += w[k] * x[i][k];
        h = sig(h);
        ret += -y[i] * log(h) - (1 - y[i]) * log(1 - h);
    }
    return ret / 80:
}
vector<db> fit(db alpha) {
    for (int i = 0; i < 3; ++i) w[i] = ww[i] = 0;
    db val = 0, last;
    vector <db> cost:
    while (1) {
        for (int j = 0; j < 3; ++ j) {
            db J = 0;
            for (int i = 0; i < 80; ++i) {
                db h = 0;
                for (int k = 0; k < 3; ++k) h += ww[k] * x[i][k];
                J += (sig(h) - y[i]) * x[i][j];
            w[j] = alpha * J / 80;
        }
```

```
for (int i = 0; i < 3; ++i) ww[i] = w[i];
        last = val;
        val = cal():
        cost.push_back(val);
        // LOG(iteration, val - last);
        if (fabs(val - last) <= eps)
    }
    return cost;
}
int main() {
    ifstream fin("data/ex2x.dat");
    for (int i = 0; i < 80; ++i) {
        x[i][0] = 1;
        fin >> x[i][1] >> x[i][2];
    fin. close();
    fin. open ("data/ex2y. dat");
    for (int i = 0; i < 80; ++i) {
        fin \gg y[i];
    }
    fin. close():
    // for (int i = 0; i < 80; ++i) {
           cout << x[i][0] << ' ' << x[i][1] << ' ' << x[i][2] << ' ' << y[i] <<
endl;
    // }
    db \ alpha = 0.002;
    vector<db> ret = fit(alpha);
    // LOG(alpha, w[0], w[1], w[2]);
    string name = "data/" + to_string(alpha) + ".txt";
    ofstream fout(name.c_str());
    fout << alpha << " " << w[0] << " " << w[1] << " " << w[2] << " " << cal() <<
endl:
    for(auto v:ret) fout << v << endl;
    return 0:
}
alpha, w[0], w[1], w[2], fit(alpha) \rightarrow 0.0004 -0.00924545 0.0459596 -0.0229827
535
alpha, w[0], w[1], w[2], fit(alpha) \rightarrow 0.0005 -0.0110848 0.0466746 -0.0233549 514
alpha, w[0], w[1], w[2], fit(alpha) \rightarrow 0.0006 -0.43249 0.0491012 -0.0185842 17245
alpha, w[0], w[1], w[2], fit(alpha) \rightarrow 0.0007 -1.10884 0.0519389 -0.0103293 39377
alpha, w[0], w[1], w[2], fit(alpha) -> 0.0008 -1.66343 0.0543808 -0.00361771 53419
alpha, w[0], w[1], w[2], fit(alpha) -> 0.0009 -2.1325 0.0565278 0.00201761 62666
alpha, w[0], w[1], w[2], fit(alpha) -> 0.001 -2.53826 0.0584452 0.00686168 68898
```

alpha, w[0], w[1], w[2], fit(alpha) \rightarrow 0.0012 \rightarrow 3.21363 0.0617594 0.0148612 76044 alpha, w[0], w[1], w[2], fit(alpha) \rightarrow 0.0015 \rightarrow 4.10757 0.066715 0.0258728 80821 alpha, w[0], w[1], w[2], fit(alpha) \rightarrow 0.0018 \rightarrow 8.70063 0.0939862 0.0776859 183547 */