华南理工大学

South China University of Technology

《机器学习》课程实验报告

学　　院　软件学院

专　　业　软件工程

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提交日期 2017 年 12 月 15 日

1. 实验题目: 线性回归、线性分类与梯度下降

2. 实验时间：2017 年 12 月 2 日

3. 报告人: 吕睿

4. 实验目的:

(1)对比理解梯度下降和随机梯度下降的区别与联系。

(2)对比理解逻辑回归和线性分类的区别与联系。

(3)进一步理解 SVM 的原理并在较大数据上实践。

5. 数据集以及数据分析：

实验使用的是 LIBSVM Data 的中的 a9a 数据，包含 32561 / 16281(testing)个样本，每个样本有 123/123 (testing)个属性。请自行下载训练集和验证集。

6. 实验步骤:

逻辑回归与随机梯度下降

1. 读取实验训练集和验证集。
2. 逻辑回归模型参数初始化，可以考虑全零初始化，随机初始化或者正态分布初始化。
3. 选择 Loss 函数及对其求导，过程详见课件 ppt。
4. 求得**部分样本**对 Loss 函数的梯度 G。
5. **使用不同的优化方法更新模型参数（NAG，RMSProp，AdaDelta 和 Adam）**。
6. 选择合适的阈值，将验证集中计算结果**大于阈值的标记为正类，反之为负类**。在验证集上测试并得到不同优化方法的 Loss 函数值 LNAG，LRMSProp，LAdaDelta 和 LAdam。
7. 重复步骤 4-6 若干次，**画出 LNAG，LRMSProp，LAdaDelta 和 LAdam 随迭代次数的变化图**。

线性分类与随机梯度下降

1. 读取实验训练集和验证集。
2. 支持向量机模型参数初始化，可以考虑全零初始化，随机初始化或者正态分布初始化。
3. 选择 Loss 函数及对其求导，过程详见课件 ppt。
4. 求得**部分样本**对 Loss 函数的梯度 G。

5. **使用不同的优化方法更新模型参数（NAG，RMSProp，AdaDelta 和 Adam）。**

8. 选择合适的阈值，将验证集中计算结果**大于阈值的标记为正类，反之为负类**。在验证集上测试并得到不同优化方法的 Loss 函数值 LNAG，LRMSProp，LAdaDelta 和 LAdam。
9. 重复步骤 4-6 若干次，**画出 LNAG，LRMSProp，LAdaDelta 和 LAdam 随迭代次数的变化图。**

7. 代码内容:

逻辑回归和随机梯度下降

```
from sklearn.externals.joblib import Memory
from sklearn.datasets import load_svmlight_file

X_train, y_train = load_svmlight_file("a9a.txt")[0], load_svmlight_file("a9a.txt")[1]
X_test, y_test = load_svmlight_file("a9a.t.txt")[0], load_svmlight_file("a9a.t.txt")[1]

import numpy as np
X_train = X_train.dot(np.eye(X_train.shape[1]))
X_test = X_test.dot(np.eye(X_test.shape[1]))

X_train = np.hstack((X_train,np.ones((X_train.shape[0],1)))) #把所有 x 的属性加上一个 1，用于和 w14（b）相乘

X_test = np.hstack((X_test,np.ones((X_test.shape[0],1)))) #把所有 x 的属性加上一个 0，（补齐数据文件的全零特征）
X_test = np.hstack((X_test,np.ones((X_test.shape[0],1)))) #把所有 x 的
```

属性加上一个 1，用于和 w14（b）相乘

```
def changeLabel(y):#将 label 中的-1 值全部改为 0 以便设计 Loss 函数
    for i in range (y.shape[0]):
        if y[i] == -1:
            y[i] = 0

changeLabel(y_train)
changeLabel(y_test)

y_train = y_train.reshape((y_train.shape[0],1))
y_test = y_test.reshape((y_test.shape[0],1))
```

w_sgd = np.zeros((X_train.shape[1],1)) #将 SGD 模型参数 w 初始化为全零

w_nag = np.zeros((X_train.shape[1],1)) #将 NAG 模型参数 w 初始化为全零

w_rmsp = np.zeros((X_train.shape[1],1)) #将 RMSProp 模型参数 w 初始化为全零

w_adaD = np.zeros((X_train.shape[1],1)) #将 AdaDelta 模型参数 w 初始化为全零

w_adam = np.zeros((X_train.shape[1],1)) #将 Adam 模型参数 w 初始化为全零

n = 10000 #设置迭代次数

LSGD = np.zeros((n)) #初始化用于保存 LSGD 的值随迭代次数变化的数组

LNAG = np.zeros((n)) #初始化用于保存 LNAG 的值随迭代次数变化

```
的数组
    LRMSProp = np.zeros((n)) #初始化用于保存 LRMSProp 的值随迭代次数变化的数组
    LAdaDelta = np.zeros((n)) #初始化用于保存 LAdaDelta 的值随迭代次数变化的数组
    LAdam = np.zeros((n)) #初始化用于保存 LAdam 的值随迭代次数变化的数组

    def Sigmod(w,X):#定义 Sigmod 函数,输出对每个样本都进行计算后的列向量
        return 1/(1+np.exp(-((X.dot(w)))))

    def Lfun(w,X,y):#定义 Loss 函数
        m = y.shape[0]
        s = Sigmod(w,X)
        l = -(y*np.log(s)+(1-y)*np.log(1-s))
        return l.sum()

    def DER_SGD(w,X,y):#定义随机梯度下降的梯度函数
        m = 100 #从数据集中随机取样
        index = np.random.randint(0,X.shape[0],m)
        X_sample = np.zeros((m,X.shape[1]))
        y_sample = np.zeros((m,y.shape[1]))

        for i in range (m):
            X_sample[m-1] = X[index[m-1]]
            y_sample[m-1] = y[index[m-1]]

        return -((X_sample.T).dot(y_sample-Sigmod(w,X_sample)))
```

```
def cRate(w,X,y):#定义用于计算预测正确率的函数
    m = y.shape[0]
    j = (X.dot(w))
    c = 0
    for i in range (m):
        if (j[i]>0 and y[i]==1) or (j[i]<0 and y[i]==0):
            c = c + 1
    return c/m


def SGD(w,lnrt):
    lnrt = lnrt
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        w -= lnrt*g
        LSGD[i] = Lfun(w,X_test,y_test)


def NAG(w,lnrt,u):
    V = 0
    u = u
    lnrt = lnrt
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        V = u*V + lnrt*g
        w -= V
        LNAG[i] = Lfun(w,X_test,y_test)


def RMSProp(w,lnrt,u,e):
```

```
    G = 0
    u = u
    e = e
    lnrt = lnrt
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        G = u*G + (1-u)*g*g
        w -=    (lnrt/((G+e)**0.5))*g
        LRMSProp[i] = Lfun(w,X_test,y_test)

def AdaDelta(w,u,e):
    G = 0
    u = u
    delta = 0
    e = e
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        G = u*G + (1-u)*(g*g)
        wdelta = -(((delta+e)**0.5)/((G+e)**0.5)) * g
        w += wdelta
        delta = u*delta + (1-u)*(wdelta*wdelta)
        LAdaDelta[i] = Lfun(w,X_test,y_test)

def Adam(w,lnrt,u,e,B):
    G = 0
    u = u
    B = B
    m = 0
```

```
    e = e
    lnrt = lnrt
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        m = B*m + (1-B)*g
        G = u*G + (1-u)*(g*g)
        w-=(lnrt*((1-u**(i+1))**0.5)*m)/((1-B**(i+1))*((G+e)**0.5))
        LAdam[i] = Lfun(w,X_test,y_test)

SGD(w_sgd,0.01)
NAG(w_nag,0.001,0.9)
RMSProp(w_rmsp,0.0015,0.99,1e-7)
AdaDelta(w_adaD,0.95,1e-6)
Adam(w_adam,0.002,0.999,1e-8,0.9)

import matplotlib.pyplot as plt
#绘制总图
x = np.arange(0,n,1)
plt.rcParams['figure.figsize']=(40,20)
plt.plot(x, LSGD,    'black',label = 'LSGD')
plt.plot(x, LNAG,    'r',label = 'LNAG')
plt.plot(x, LRMSProp,    'b',label = 'LARMSProp')
plt.plot(x, LAdaDelta,    'y',label = 'LAdaDelta')
plt.plot(x, LAdam,    'g',label = 'LAdam')
plt.legend(loc='upper right')
plt.xlabel('Times of iteration')
plt.ylabel('Loss')
plt.show()
```

线性分类和随机梯度下降

```
from sklearn.externals.joblib import Memory
from sklearn.datasets import load_svmlight_file

X_train, y_train = load_svmlight_file("a9a.txt")[0], load_svmlight_file("a9a.txt")[1]
X_test, y_test = load_svmlight_file("a9a.t.txt")[0], load_svmlight_file("a9a.t.txt")[1]

import numpy as np
X_train = X_train.dot(np.eye(X_train.shape[1]))
X_test = X_test.dot(np.eye(X_test.shape[1]))

X_train = np.hstack((X_train,np.ones((X_train.shape[0],1)))) #把所有 x 的属性加上一个 1，用于和 w14（b）相乘

X_test = np.hstack((X_test,np.ones((X_test.shape[0],1)))) #把所有 x 的属性加上一个 0，（补齐数据文件的全零特征）
X_test = np.hstack((X_test,np.ones((X_test.shape[0],1)))) #把所有 x 的属性加上一个 1，用于和 w14（b）相乘

y_train = y_train.reshape((y_train.shape[0],1))
y_test = y_test.reshape((y_test.shape[0],1))

w_sgd = np.zeros((X_train.shape[1],1)) #将 SGD 模型参数 w 初始化为全零
w_nag = np.zeros((X_train.shape[1],1)) #将 NAG 模型参数 w 初始化为全零
w_rmsp = np.zeros((X_train.shape[1],1)) #将 RMSProp 模型参数 w 初始化为全零
```

```
    w_adaD = np.zeros((X_train.shape[1],1)) #将 AdaDelta 模型参数 w 初始化为全零

    w_adam = np.zeros((X_train.shape[1],1)) #将 Adam 模型参数 w 初始化为全零


    n = 10000 #设置迭代次数


    LSGD = np.zeros((n)) #初始化用于保存 LSGD 的值随迭代次数变化的数组

    LNAG = np.zeros((n)) #初始化用于保存 LNAG 的值随迭代次数变化的数组

    LRMSProp = np.zeros((n)) #初始化用于保存 LRMSProp 的值随迭代次数变化的数组

    LAdaDelta = np.zeros((n)) #初始化用于保存 LAdaDelta 的值随迭代次数变化的数组

    LAdam = np.zeros((n)) #初始化用于保存 LAdam 的值随迭代次数变化的数组


    def Lfun(w,X,y):#定义 Loss 函数
        m = y.shape[0]
        l = 1-(X.dot(w))*y
        for i in range (m):
            if l[i] < 0:
                l[i] = 0
        return l.sum()+0.5*np.sum(w*w)


    def DER_SGD(w,X,y):#定义随机梯度下降的梯度函数
        m = 100 #从数据集中随机取样
        index = np.random.randint(0,X.shape[0],m)
        X_sample = np.zeros((m,X.shape[1]))
        y_sample = np.zeros((m,y.shape[1]))


        for i in range (m):
```

```
            X_sample[m-1] = X[index[m-1]]
            y_sample[m-1] = y[index[m-1]]

        j = (X_sample.dot(w))*y_sample
        o = np.zeros((m,1))
        for i in range (m):
            if j[i] < 1:
                o[i] = y_sample[i]
        return -((X_sample.T).dot(o))

def cRate(w,X,y):
        m = y.shape[0]
        j = (X.dot(w))*y
        c = 0
        for i in range (m):
            if j[i] > 0:
                c = c + 1
        return c/m

def SGD(w,lnrt):
        lnrt = lnrt
        for i in range (n):#迭代若干次，更新模型参数 w
            g = (DER_SGD(w,X_train,y_train))
            w -= lnrt*g
            LSGD[i] = Lfun(w,X_test,y_test)

def NAG(w,lnrt,u):
        V = 0
```

```
    u = u
    lnrt = lnrt
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        V = u*V + lnrt*g
        w -= V
        LNAG[i] = Lfun(w,X_test,y_test)

def RMSProp(w,lnrt,u,e):
    G = 0
    u = u
    e = e
    lnrt = lnrt
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        G = u*G + (1-u)*g*g
        w -=    (lnrt/((G+e)**0.5))*g
        LRMSProp[i] = Lfun(w,X_test,y_test)

def AdaDelta(w,u,e):
    G = 0
    u = u
    delta = 0
    e = e
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        G = u*G + (1-u)*(g*g)
        wdelta = -(((delta+e)**0.5)/((G+e)**0.5)) * g
```

```
            w += wdelta
            delta = u*delta + (1-u)*(wdelta*wdelta)
            LAdaDelta[i] = Lfun(w,X_test,y_test)

def Adam(w,lnrt,u,e,B):
    G = 0
    u = u
    B = B
    m = 0
    e = e
    lnrt = lnrt
    for i in range (n):#迭代若干次，更新模型参数 w
        g = (DER_SGD(w,X_train,y_train))
        m = B*m + (1-B)*g
        G = u*G + (1-u)*(g*g)
        w -= (lnrt*((1-u**(i+1))**0.5)*m)/((1-B**(i+1))*((G+e)**0.5))
        LAdam[i] = Lfun(w,X_test,y_test)

SGD(w_sgd,0.001)
NAG(w_nag,0.0001,0.9)
RMSProp(w_rmsp,0.001,0.9,1e-8)
AdaDelta(w_adaD,0.8,1e-6)
Adam(w_adam,0.001,0.999,1e-8,0.9)

import matplotlib.pyplot as plt

x = np.arange(0,n,1)
plt.rcParams['figure.figsize']=(40,20)
```

```
plt.plot(x, LSGD,    'black',label = 'LSGD')
plt.plot(x, LNAG,    'r',label = 'LNAG')
plt.plot(x, LRMSProp,    'b',label = 'LARMSProp')
plt.plot(x, LAdaDelta,    'y',label = 'LAdaDelta')
plt.plot(x, LAdam,    'g',label = 'LAdam')
plt.legend(loc='upper right')
plt.xlabel('Times of iteration')
plt.ylabel('Loss')
plt.show()
```

逻辑回归和随机梯度下降 8-12：

8.模型参数的初始化方法:

全零初始化。

9.选择的 loss 函数及其导数:

Loss 函数： $L=\sum_{n}-[y_n \ln f(x_n)+(1-y_n)(1-\ln f(x_n))]$

其中 $f(x_n)=\sigma(z)=\frac{1}{1+e^{-z}}$， $z=\sum w_i x_i+b$

梯度： w_i 的梯度 $G=\sum_{n}-(y_i-f(x^{(n)}))x_i^{(n)}$

（对于 w14(b)而言 x=1）

则整个向量 $\mathbf{w}$ 的梯度向量 $\mathbf{G}=\mathbf{X}^T(\mathbf{Xw}-\mathbf{y})$

10.实验结果和曲线图:

超参数选择（η,epoch 等）：

SGD 的学习率 η 取 0.005

NAG 的学习率 η 取 0.001, γ 取 0.9

RMSProp 的学习率 η 取 0.001, γ 取 0.9, ε 取 1e-8

AdaDelta 的 γ 取 0.9, ε 取 1e-6

Adam 的学习率 η 取 0.002, γ 取 0.999, ε 取 1e-8, β 取 0.9

预测结果（最佳结果）：

Wsgd

```
[ -8.33881251e-01  -3.80854456e-01   1.38862512e-01   4.36959612e-01
   3.18640237e-01  -2.59416321e-03  -3.16249133e-01   1.78163547e-01
   2.38683655e-01   5.71512368e-03  -5.60261661e-02  -1.53187393e-02
  -2.74374610e-03  -1.80426102e-01   2.11619438e-02  -7.83913545e-02
  -3.00913622e-02  -5.25264708e-02   3.04510014e-02  -4.87357409e-02
  -2.12982950e-01  -2.21452686e-01   2.57797624e-01   2.14565595e-02
   1.14191371e-02  -1.17707387e-01  -2.09235986e-01  -5.92052234e-02
   2.71828708e-01  -4.37526521e-02  -1.37567269e-01   2.20541442e-01
  -6.72581172e-02  -1.58698057e-02  -8.63579390e-01  -2.21452686e-01
  -4.87357409e-02   3.28756967e-02   7.80618775e-01   9.56355942e-01
  -2.56707353e-01  -7.60723469e-01  -1.76979525e-01  -1.50256986e-02
  -7.34182191e-02   6.22497707e-03   1.79109047e-01  -4.62593275e-02
  -4.44430160e-01   3.00435133e-01   6.09183312e-01   4.83575768e-01
  -3.24058111e-01  -2.65157687e-01  -2.92775811e-02  -3.04784668e-01
```

-2.42720018e-01 -2.31888415e-02 1.41803325e-01 -1.85606647e-03

6.71009564e-01 -5.97791321e-01 2.93756958e-01 -2.42412384e-01

-1.28782387e-01 -3.16053777e-01 9.68254581e-02 -8.31373250e-02

-6.73145736e-02 -6.12111827e-02 -2.05435723e-01 -2.83615089e-01

-3.66582569e-02 -9.68351825e-01 6.48078479e-01 -5.92644743e-01

2.72371397e-01 -5.95679421e-01 -1.41554897e-01 -1.20580180e-01

8.35239766e-02 4.54017175e-01 1.20676626e-01 6.93923639e-03

3.40509509e-03 -3.42517319e-02 9.94886803e-03 -2.10421557e-02

-5.76639014e-03 1.72882070e-02 9.48279544e-03 -1.74087217e-02

-5.88502339e-02 -1.58798772e-02 1.03443336e-02 -1.37471754e-02

2.56820960e-03 2.60135489e-02 1.67846065e-02 -1.04131887e-02

-2.25372264e-02 -2.39012374e-02 -1.61172572e-01 -2.96195781e-02

1.96186781e-03 1.47667041e-02 -4.70822415e-03 -9.18772966e-03

1.44776437e-03 -9.86239536e-03 -2.10682096e-02 -1.78007638e-02

8.50652093e-03 5.72512724e-03 2.35912962e-03 -4.09122526e-03

-1.32967608e-02 -6.88759217e-03 -3.38042444e-02 -7.72571873e-03

-1.50689852e-02 4.35679099e-04 -9.47113700e-04 -3.20273346e-01]

Wnag

[-7.97307702e-01 -2.99765776e-01 5.91765986e-02 3.37019546e-01

3.74222541e-01 -5.20451506e-02 -1.97233419e-01 7.16956201e-02

2.52961933e-01 -9.60805074e-03 -2.27481562e-02 -8.31767983e-03

-1.82029514e-04 -1.06589188e-01 -3.02824225e-02 -1.74512434e-01

-2.27309253e-02 7.46017727e-03 1.09875406e-01 -4.75339950e-02

-1.99079865e-01 -2.48488372e-01 1.80150821e-01 6.24375351e-02

8.82808583e-02 -1.11392352e-01 -2.16959874e-01 -5.34526563e-02

2.36132229e-01 -6.31069898e-02 -1.52286748e-01 2.16672725e-01

-1.12521648e-01 -1.53818668e-02 -9.24182001e-01 -2.48488372e-01

-4.75339950e-02 1.50718393e-01 7.42831182e-01 8.71621295e-01

-2.58962467e-01 -7.26049865e-01 -1.79011122e-01 -6.17269269e-03

-6.26283977e-02 3.45484573e-02 1.49229863e-01 -5.13982522e-02

-3.58638248e-01 1.19616328e-01 6.77815922e-01 4.61150547e-01

-2.32742331e-01 -2.61668813e-01 -7.16860339e-02 -2.92868807e-01

-1.86177848e-01 -3.37109325e-02 1.18485634e-01 -2.70193285e-03

5.63822414e-01 -5.15940221e-01 3.60124740e-01 -1.81676909e-01

-1.68671483e-01 -3.84313333e-01 -1.47732434e-01 2.75732528e-03

-4.35551269e-02 -5.43349407e-02 -8.37896156e-02 -3.11634203e-01

-1.50205896e-02 -9.35288749e-01 6.08633956e-01 -6.61594071e-01

3.34939279e-01 -7.82975687e-01 -1.64685511e-01 2.31636608e-02

1.65090712e-01 4.32752033e-01 9.91831735e-02 -1.14258638e-03

2.71321264e-03 1.36260272e-03 5.02399814e-02 8.51491186e-03

-6.93520206e-03 -3.19393032e-02 1.09705152e-02 -9.68659845e-03

-6.20362866e-03 -2.26362354e-02 3.09532862e-03 1.03907625e-04

-4.45511241e-03 4.26331839e-02 9.71769356e-03 -1.31606600e-02

-2.33064013e-02 -1.62800386e-02 -1.91918792e-01 -7.26693057e-03

-1.97136687e-02 1.00754955e-02 -2.49836279e-02 -5.62630222e-03

-2.05043285e-02 1.56141822e-02 3.58109006e-03 -3.77937300e-02

7.11053080e-03 -1.65338267e-02 -1.80959838e-02 -8.13139654e-03

3.35599806e-03 2.16392738e-04 -2.76193958e-02 -1.24249543e-02

-1.58334510e-02 1.54492482e-03 0.00000000e+00 -3.26654792e-01]

Wrmsp

[-1.82290302 -0.39944496 0.08235624 0.29082787 0.12284566 0.03903618

-0.45982501 0.34327776 0.22070314 -0.16079908 -0.00490288 0.

-0.0149968 -0.35588743 0.01863553 -0.02636312 0.01006281 -0.12853012
-0.01691826 -0.11509634 -1.04054239 -0.36147345 0.69177251 -0.16025578
-0.28741606 -0.71770843 -0.88354666 -0.28554298 0.41123283 -0.41703898
-0.54595143 0.48071534 -0.68556458 -0.13618219 -1.11855275 -0.36147345
-0.11509634 -0.1438043   0.50064044 0.46557244 -0.7572294 -0.83374389
-0.80207282 -0.76562394 -0.80431253 -0.04481144 0.13148396 -0.30814729
-0.96978795 -0.00258113 0.5199767   0.39746306 -0.90493394 -0.39760826
-0.25189964 -0.97259283 -0.27938852 -0.36333028 -0.08964824 -0.0262306
 0.60522417 -1.52344785 0.1650713 -0.53089281 -0.80208892 -1.00877817
 0.0249936 -0.0088516 -0.30003439 -0.51337886 -0.45424556 -0.30866586
 0.02391507 -0.4068039   0.94737249 -0.22108305 0.6559244 -0.97229012
-0.43736071 -0.15624541 0.15248095 0.32432245 0.13088012 -0.05821475
-0.2493025 -0.2644763 -0.18685165 -0.12717106 -0.04985173 -0.00438221
 0.0308367 -0.04217135 -0.19172402 0.00394091 -0.09513826 -0.06762565
-0.04497839 -0.02686318 -0.05743514 -0.08012644 -0.17765226 -0.18884754
-0.79249134 -0.11143035 -0.10074021 -0.02419776 -0.23831788 -0.10342438
-0.16708397 -0.04304236 -0.18149769 -0.24347408 -0.07003352 -0.17858007
-0.10383786 0.04499836 -0.04165681 0.0046202 -0.28936746 -0.11486311
-0.08647986 0.00820767 0.   -0.02094322]

WadaD

[-1.93301878e+00 -8.22069160e-01 -1.50623377e-01   2.21964943e-01
   5.58224335e-02   1.43520181e-01 -4.22363663e-01   1.99380631e-01
  -2.57894059e-02 -2.48824398e-01 -2.53983134e-01 -4.42602301e-03
  -5.31686084e-03 -4.62733686e-01 -2.64850676e-01 -9.87675225e-02
  -1.56456098e-01 -2.50003887e-01 -4.44095985e-02 -3.18571748e-01
  -5.21504136e-01 -3.95935610e-01   4.05037027e-01 -3.10012916e-01

-2.83906868e-01 -3.47894252e-01 -5.40189804e-01 -2.81681461e-01

2.04421966e-01 -1.72011489e-01 -4.36850033e-01 2.31007528e-01

-3.21285011e-01 -1.14535831e-01 -1.40203776e+00 -3.95935610e-01

-3.18571748e-01 -3.47290249e-01 6.61504155e-01 6.20417966e-01

-1.07199939e+00 -1.36012398e+00 -7.45506057e-01 -7.27903280e-01

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-6.31859511e-01 -1.78591296e-01 -1.76555845e-01 -4.34405001e-03

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-2.14071126e-01 -1.95666110e-01 -4.54138991e-01 -4.04106611e-01

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3.32096966e-02 3.12882675e-01 3.81104155e-01 3.73389777e-04

-2.25347060e-02 -8.81532163e-02 -3.36571496e-02 -6.35512962e-02

-8.90250630e-03 -1.94607422e-02 4.89026149e-03 -2.41266214e-03

-5.70758625e-02 -3.34582680e-03 -3.59101963e-02 -1.75045366e-02

-1.77858969e-02 -3.38318735e-02 -8.66374196e-03 -6.71066905e-02

-5.86298769e-02 -5.07494328e-02 -5.18428236e-01 -2.79340937e-02

-2.65795487e-02 -1.30535484e-02 -3.19224802e-02 -2.22287244e-02

-2.38590328e-02 -2.11147899e-02 -1.89635669e-02 -6.55907212e-02

4.47586529e-03 -5.03438219e-02 -2.47549481e-02 -3.06521134e-02

-1.38838787e-02 -5.68087788e-03 -8.13534106e-02 -2.83939985e-02

-4.55989902e-02 -1.25665784e-02 -4.35707620e-03 3.86378866e-01]

Wadam

```
[ -1.20026577e+00  -4.34419192e-01   9.31710071e-02   1.60540845e-01
   2.62459460e-01   3.22875554e-02  -4.41439646e-01   4.00001489e-01
   1.60270304e-01  -1.81587643e-01  -7.12675760e-02  -1.81613357e-01
  -5.61797400e-02  -1.96394814e-01  -6.95565191e-02  -3.04551707e-02
  -7.26670247e-02  -3.38574231e-02   7.30497811e-02  -5.66624843e-02
  -6.30998106e-01  -3.14890421e-01   6.27236642e-01   5.52475453e-02
   4.30469746e-02  -6.04143513e-01  -6.19247909e-01  -2.71210834e-01
   2.88509779e-01  -4.82257774e-01  -5.35280778e-01   6.21063532e-01
  -6.01504347e-01  -3.03745534e-01  -1.15400909e+00  -3.14890421e-01
  -5.66624843e-02   9.13432799e-02   5.26945625e-01   5.60999311e-01
  -8.05015310e-01  -7.92518272e-01  -4.47851587e-01  -3.41726176e-01
  -2.36271968e-01  -2.37051222e-02   5.28264624e-01  -2.09248413e-01
  -7.70265393e-01  -8.54555047e-02   6.20435054e-01   5.13326139e-01
  -5.61362097e-01  -3.18653598e-01  -2.29076015e-01  -8.19403516e-01
  -2.76591045e-01  -4.16824059e-01   5.89768015e-02  -6.34287906e-02
   9.65894996e-01  -1.16886101e+00   2.66456072e-01  -4.14731570e-01
  -9.09446989e-01  -8.24324700e-01  -8.95547827e-02   9.17395677e-02
  -6.83618747e-01  -4.04476046e-01  -1.74506492e-01  -4.03205347e-01
   3.01065967e-02  -5.62699471e-01   1.06668136e+00  -3.24746570e-01
   6.61355038e-01  -8.92880390e-01  -2.28512025e-01  -3.41779065e-02
   7.23902956e-02   2.70438989e-01  -6.23312539e-02  -8.58844935e-02
   6.44518846e-02  -2.14056197e-01   1.71978846e-01  -2.42882785e-02
  -2.06728940e-01   1.84924738e-01   9.11472183e-02  -1.38456899e-01
  -2.28061562e-01  -6.61182369e-02   5.18882273e-02  -1.79641547e-01
  -1.51368597e-01   9.28019069e-02  -4.99751890e-02  -5.36254448e-02
  -1.34853200e-01  -3.26922197e-01  -2.52209145e-01  -2.41363463e-01
  -1.51189898e-01   1.03672090e-01  -4.61736839e-01  -5.51203144e-02
  -1.25472601e-01   1.76314993e-01  -1.86640179e-01  -3.54792597e-01
```

-1.24199249e-01 -2.74168565e-01 -4.35679661e-01 -1.09275927e-03

-1.65536902e-01 3.13813306e-02 -4.97760585e-01 -2.58871332e-01

-2.53485030e-01 2.77617978e-02 0.00000000e+00 -1.46129100e-01]

SGD 模型的最终正确率： 0.8474909403599288

NAG 模型的最终正确率： 0.8454640378355138

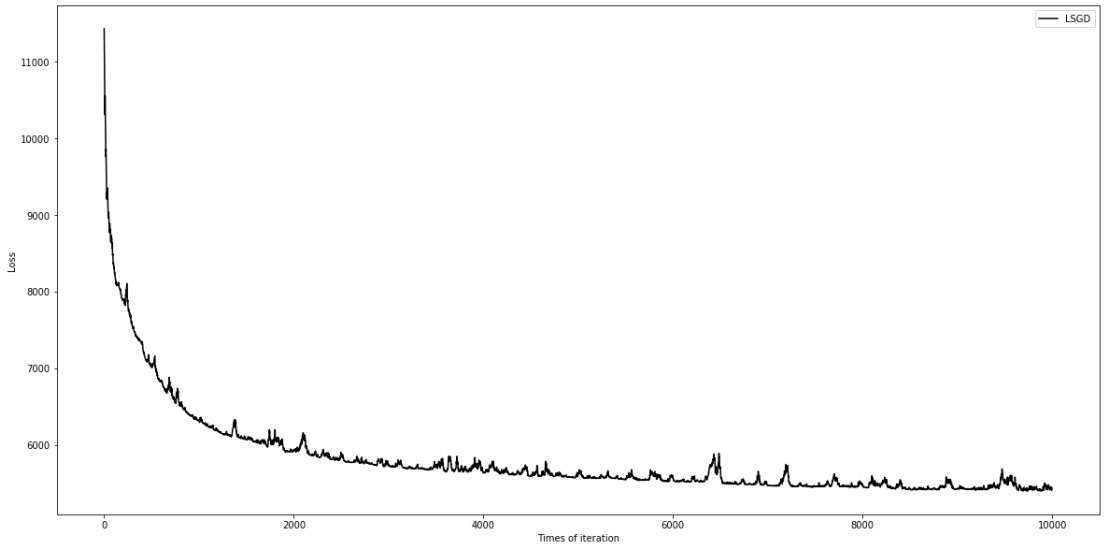
RMSProp 模型的最终正确率： 0.849640685461581

AdaDelta 模型的最终正确率：0.8434371353110989

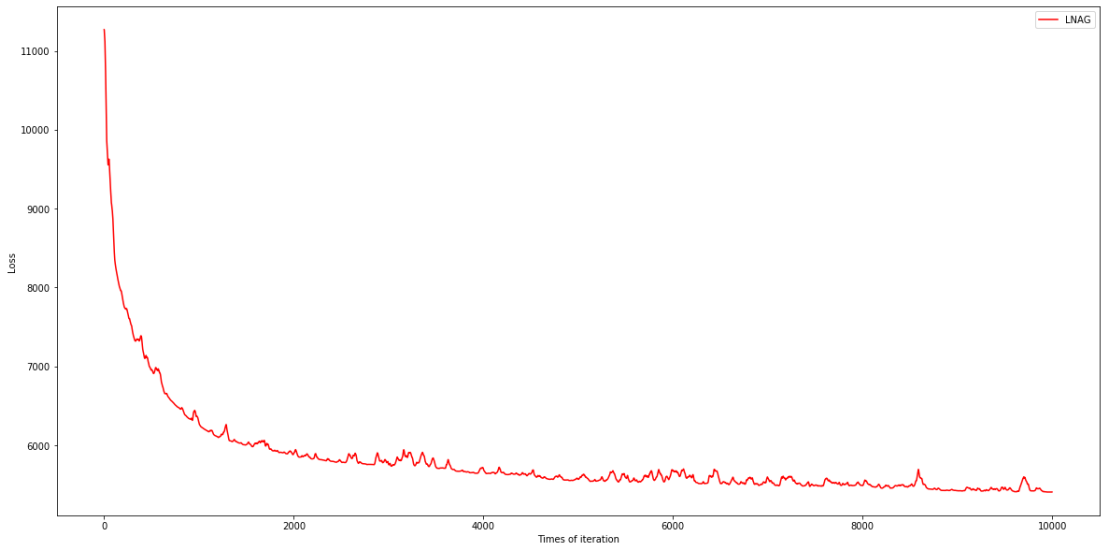
Adam 模型的最终正确率： 0.8486579448436828

loss 曲线图：

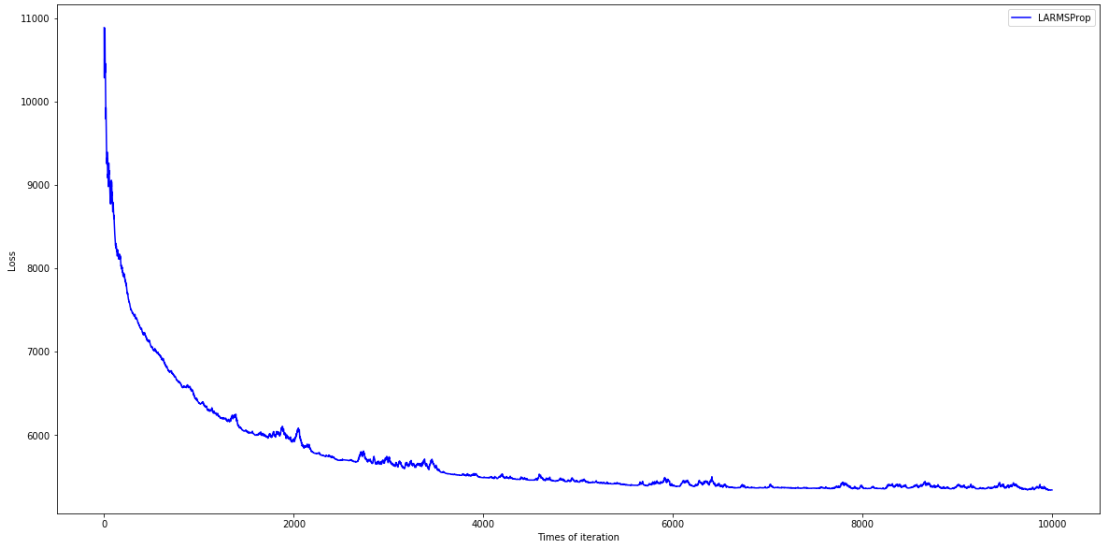
SGD



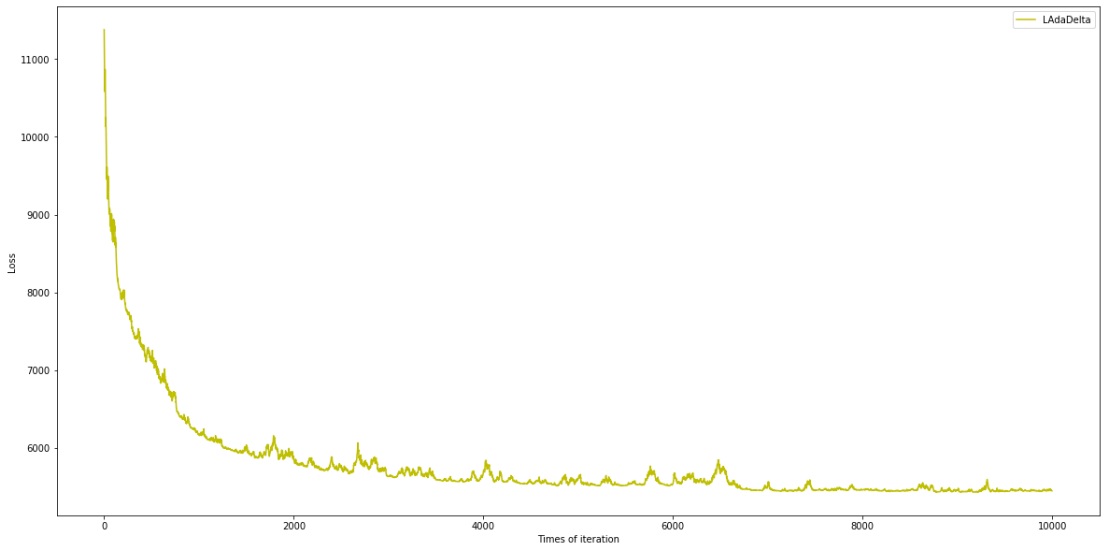
NAG



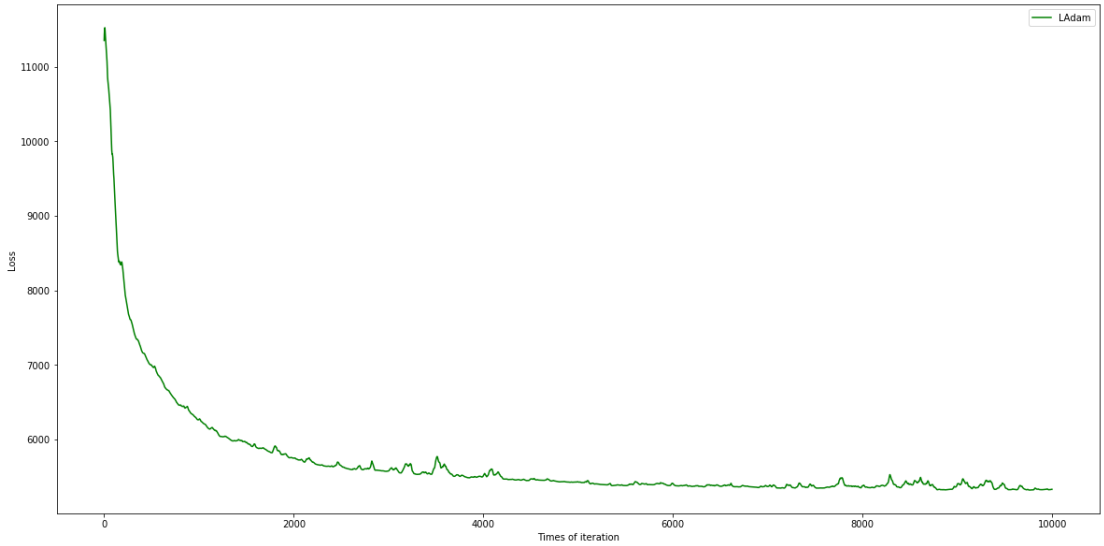
RMSProp



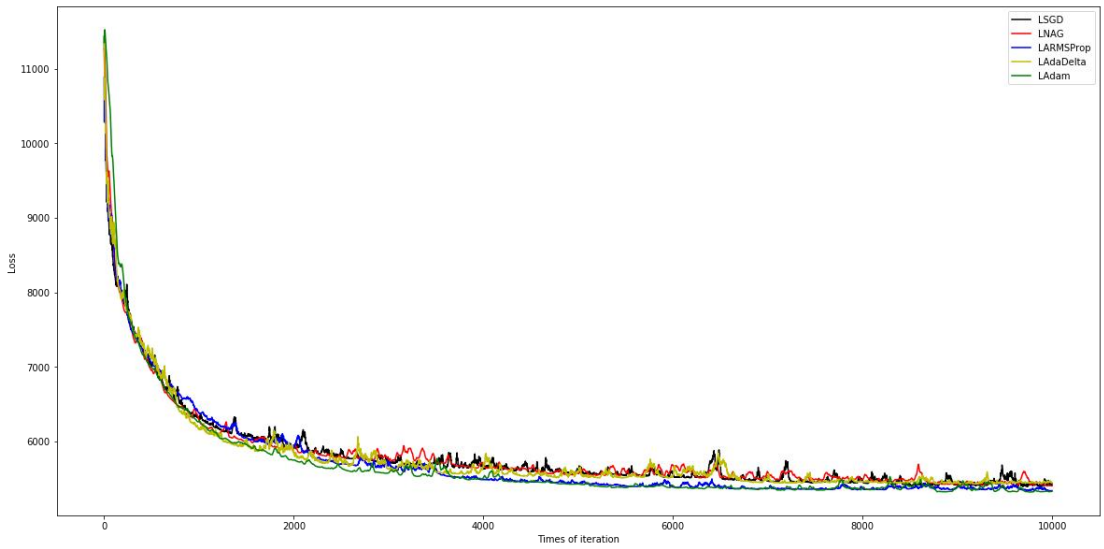
AdaDelta


LAdaDelta
11000
10000
9000
8000
7000
6000
Loss
0
2000
4000
6000
8000
10000
Times of iteration

Adam


LAdam
11000
10000
9000
8000
7000
6000
Loss
0
2000
4000
6000
8000
10000
Times of iteration

总图：



11.实验结果分析:

5 种优化模型均在前 200 次迭代内就能使测试集上的 Loss 值大幅下降，然后在 200-2000 次迭代内 Loss 值的降幅逐渐降低，在 2000 次迭代后 Loss 值达到 6000 以下，在 2000-10000 次迭代内 Loss 值缓慢降到 5500 左右，此时在测试集上对应的正确率均可达 84%以上。

5 种优化模型在经过多次调参以后曲线趋于一致。

以上 5 种优化模型的曲线在整个迭代中均有不同程度的上下波动,推测是因为 Loss 函数没有对样本取平均数的原因。

线性分类和随机梯度下降 8-11：

8.模型参数的初始化方法:

全零初始化。

9.选择的 loss 函数及其导数:

Loss 函数： $L=\sum_{m}(\max(0,1-y^{m}(wx^{m}+b))+\frac{1}{2}\|\mathbf{w}\|^{2}$

梯度：对 wi 的梯度 $G=\sum_{n}-\delta(y^{n}(w_{i}x^{n}+b)y^{n}x^{i}$

10.实验结果和曲线图:

超参数选择（η,epoch 等）：

SGD 的学习率 η 取 0.001

NAG 的学习率 η 取 0.0001, γ 取 0.9

RMSProp 的学习率 η 取 0.001, γ 取 0.9, ε 取 1e-8

AdaDelta 的 γ 取 0.8, ε 取 1e-6

Adam 的学习率 η 取 0.001, γ 取 0.999, ε 取 1e-8, β 取 0.9

预测结果（最佳结果）：

Wsgd

[-0.149 -0.127 -0.013 0.085 0.042 -0.01 -0.114 0.056 0.031 -0.034
 -0.003 0.   0.   -0.052 -0.017 -0.053 -0.011 -0.029 0.096 -0.058
 -0.043 -0.142 0.078 -0.029 -0.005 -0.04 -0.059 -0.02   0.096 -0.021
 -0.046 0.061 -0.025 -0.005 -0.259 -0.142 -0.058 -0.034 0.331 0.236
 -0.096 -0.218 -0.041 -0.016 -0.03   0.003 0.035 -0.099 -0.092 0.051
  0.198 0.139 -0.055 -0.047 -0.05 -0.094 -0.059 -0.007 0.006 0.
  0.089 -0.092 0.161 -0.157 -0.042 -0.121 -0.023 -0.045 -0.018 -0.016
 -0.06 -0.161 -0.001 -0.428 0.266 -0.236 0.074 -0.187 -0.048 -0.085
  0.052 0.106 0.007 -0.002 0.003 -0.005 0.002 -0.002 -0.001 -0.006
  0.001 0.   -0.011 -0.011 0.001 0.   -0.001 -0.005 -0.001 -0.005
 -0.004 -0.002 -0.052 -0.001 -0.001 0.002 -0.001 -0.002 -0.001 -0.005
 -0.007 0.002 -0.001 -0.006 -0.003 -0.002 -0.004 -0.003 -0.005 -0.001

-0.004 0.001 0. -0.162]

Wnag

[-1.38000000e-01 -1.26109933e-01 -8.21258713e-03 5.20340586e-02
  4.93587673e-02 -1.33309106e-02 -8.59990674e-02 1.00220123e-01
  2.09750370e-02 -3.79123226e-02 -3.80041305e-02 0.00000000e+00
  0.00000000e+00 -8.89961833e-02 -3.93767342e-03 7.16594019e-03
  -4.29376837e-02 -4.22240940e-02 7.70367965e-02 -7.48064084e-02
  -3.80000000e-02 -1.31133072e-01 9.49833891e-02 -1.90000019e-02
  -2.10182463e-02 -3.80000000e-02 -6.00000000e-02 -1.20000000e-02
  7.31621163e-02 -1.10000000e-02 -4.69999985e-02 6.88457308e-02
  -2.19999999e-02 -1.10000000e-02 -2.38999998e-01 -1.31133072e-01
  -7.48064084e-02 -4.00182482e-02 3.14028033e-01 2.15899610e-01
  -1.07809996e-01 -1.97018801e-01 -3.80005075e-02 -1.99999993e-02
  -2.80000000e-02 4.00000000e-03 1.90000000e-02 -7.64980999e-02
  -8.69903024e-02 1.49944732e-02 2.15418073e-01 1.17091233e-01
  -4.60001024e-02 -7.50550105e-02 -2.90220503e-02 -6.29912720e-02
  -3.99981926e-02 -5.00000000e-03 2.99998064e-03 -2.00000000e-03
  9.30000000e-02 -9.89997815e-02 1.26899610e-01 -1.48829527e-01
  -3.59999993e-02 -1.06999996e-01 -2.29189609e-02 -1.90000005e-02
  -2.99999314e-02 -1.70000000e-02 -8.20108013e-02 -1.71719901e-01
  7.90206365e-04 -4.26311927e-01 2.55382233e-01 -2.78901873e-01
  1.07972179e-01 -1.88150092e-01 -3.70107762e-02 -8.01509259e-02
  1.98547491e-02 1.14527351e-01 -2.59297499e-02 3.00000000e-03
  -1.00000000e-03 -1.30000000e-02 1.00000000e-03 -3.00000000e-03
  -1.00000000e-03 2.00000000e-03 -3.00000000e-03 -4.00000000e-03
  -3.00000000e-03 -5.00000000e-03 -6.25267648e-14 -3.00000000e-03

```
  0.00000000e+00  -9.99999261e-04   4.00000000e-03   1.30477769e-18
 -3.00000000e-03  -8.00000125e-03  -4.19999999e-02  -5.99995952e-03
 -2.00000000e-03   4.00000000e-03  -6.00000000e-03  -2.00000000e-03
 -2.00000000e-03   3.00000000e-03  -2.00000000e-03  -4.00000000e-03
  4.37415955e-19  -1.00000000e-03  -2.00000000e-03   1.00000000e-03
 -3.00000000e-03  -2.00000000e-03  -7.99998432e-03  -4.36967988e-19
 -1.00000000e-03   1.00000000e-03   0.00000000e+00  -1.70929694e-01]
```

Wrmsp

```
[ -2.99383930e-01  -2.84098404e-01  -6.89589379e-02   1.83946367e-01
   5.76690129e-02  -2.44741889e-02  -1.59013392e-01   7.11326135e-02
   1.10271269e-01  -9.13477551e-03   2.43600303e-02   0.00000000e+00
   0.00000000e+00  -6.63904709e-02  -5.72301254e-02  -4.28200040e-02
  -6.36947350e-02   1.22561057e-02   8.39385030e-02  -5.58275412e-02
  -7.84097978e-02  -2.22527978e-01   2.13421105e-01  -6.69627354e-02
  -4.38161938e-02  -8.53866906e-02  -1.23854520e-01  -3.31392054e-02
   1.96776137e-01  -2.84578095e-02  -7.52290038e-02   1.53755474e-01
  -6.29174909e-02  -1.58113234e-02  -4.59625468e-01  -2.22527978e-01
  -5.58275412e-02  -1.05582705e-01   4.63500584e-01   3.15430020e-01
  -2.47960653e-01  -3.92014359e-01  -9.27198929e-02  -6.91843737e-02
  -4.26492736e-02   1.26491100e-02   8.85211710e-02  -1.00082968e-01
  -1.79069029e-01   2.02805102e-02   3.53472866e-01   2.26066656e-01
  -1.02867880e-01  -1.12970510e-01  -5.37215076e-02  -1.86006645e-01
  -1.47512786e-01  -9.48683251e-03   3.05481549e-02   0.00000000e+00
   2.41649828e-01  -2.05811171e-01   2.18013027e-01  -3.23183128e-01
  -7.00198067e-02  -2.77257626e-01  -1.23178695e-02  -5.83522399e-02
  -5.72060447e-02  -5.63209547e-02  -7.04390611e-02  -2.15024812e-01
```

-1.08862824e-02 -4.05669144e-01 4.68337415e-01 -2.54653080e-01

2.41498860e-01 -3.22635433e-01 -7.66103678e-02 -1.12078339e-01

1.08345631e-01 1.25511919e-01 -1.15659566e-02 9.48683251e-03

-2.58405262e-04 -3.16227750e-03 -2.18508258e-03 1.26329061e-02

-6.32455500e-03 3.13915458e-03 6.32455498e-03 -6.32455500e-03

-1.29758005e-02 -1.59179446e-02 -1.86643329e-02 6.32455500e-03

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-6.42201555e-03 -1.58113627e-02 -1.18297457e-01 -1.26491100e-02

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-9.48683250e-03 6.32455500e-03 0.00000000e+00 -1.27159926e-01]

WadaD

[-2.44260589e-01 -1.83161152e-01 -2.25308127e-03 1.92061989e-01

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Wadam

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0. -0.14301079 0.02294739 0.0101441 -0.03154773 0.00080182

0.09950376 -0.10814786 -0.1963368 -0.28165565 0.48420591 -0.08924095

0.03228623 -0.22869068 -0.27957517 -0.13145875 0.23910102 -0.14645872

-0.17299829 0.44203518 -0.11318398 -0.1317031 -0.55541688 -0.28165565

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-0.16123007 -0.22674538 -0.12144972 0.06250157 0.12234226 -0.22910594
-0.40676797 0.10786053 0.44125944 0.32153005 -0.27476156 -0.24333881
 0.01625686 -0.32091362 -0.24008613 -0.05895082 0.00348435 0.
 0.38298192 -0.39954886 0.20220438 -0.41291548 -0.18617428 -0.30506948
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-0.15940354 -0.05006328 0.06478685 0.20380812 0.01542436 -0.1061737
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-0.05163124 -0.06754389 0.02058178 -0.1327663 -0.01246329 -0.00437086
-0.02100945 0.   -0.03045058 -0.0125085 -0.10652573 -0.03413585
-0.02067143 0.02424852 0.   -0.07121325]

SGD 模型的最终正确率： 0.8263005957864996

NAG 模型的最终正确率： 0.8110066949204594

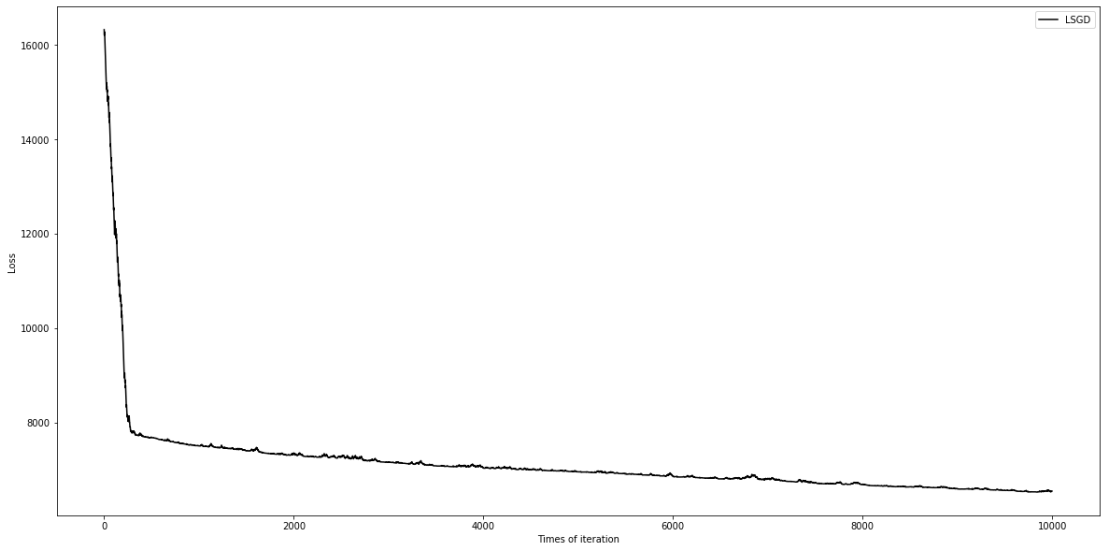
RMSProp 模型的最终正确率： 0.840366070880167

AdaDelta 模型的最终正确率： 0.8417173392297771

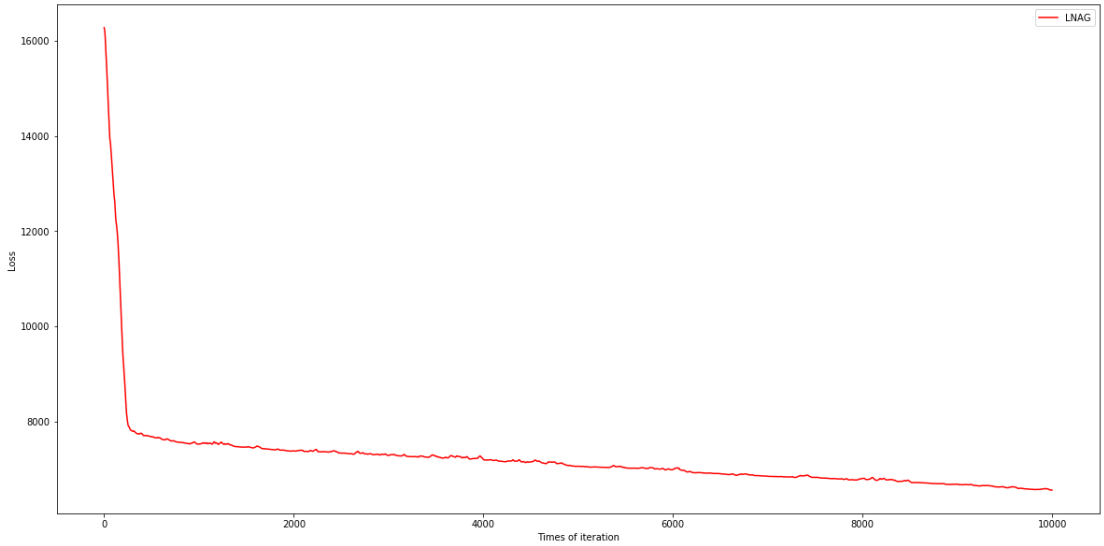
Adam 模型的最终正确率： 0.8458939868558443

loss 曲线图：

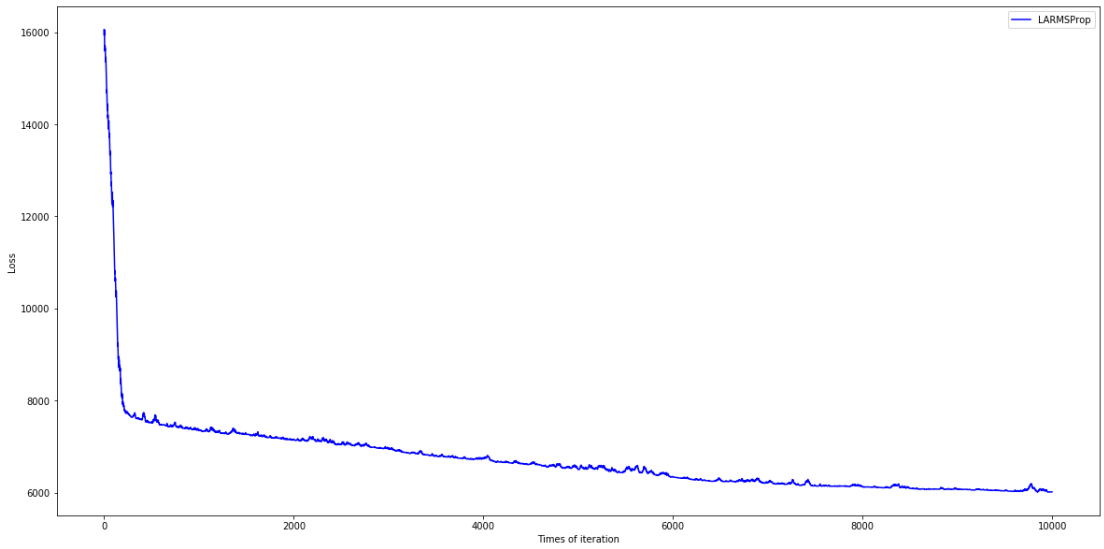
SGD


LSGD
16000
14000
12000
10000
8000
Loss
0
2000
4000
6000
8000
10000
Times of iteration

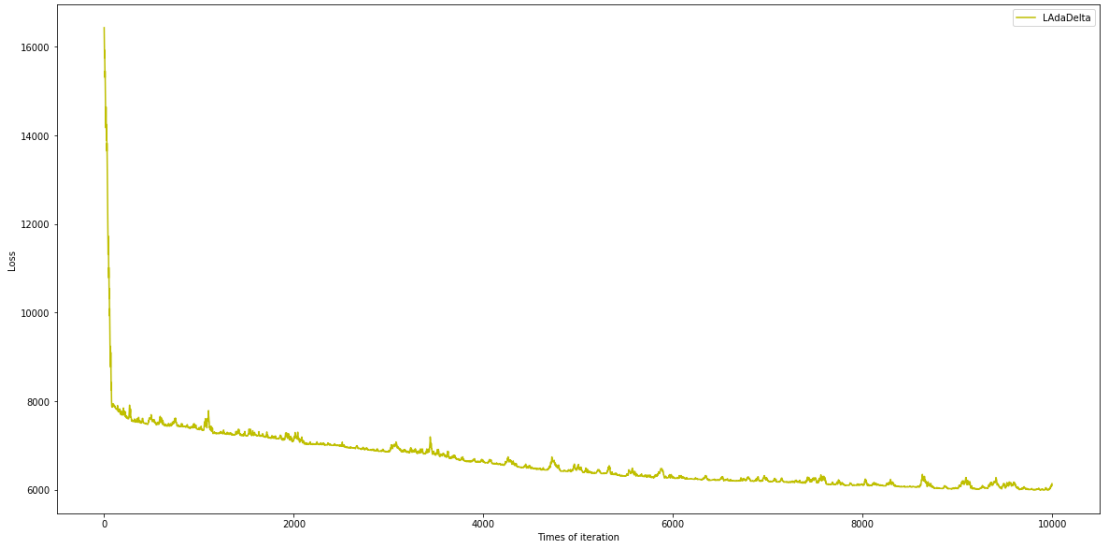
NAG


LNAG
16000
14000
12000
10000
8000
Loss
0
2000
4000
6000
8000
10000
Times of iteration

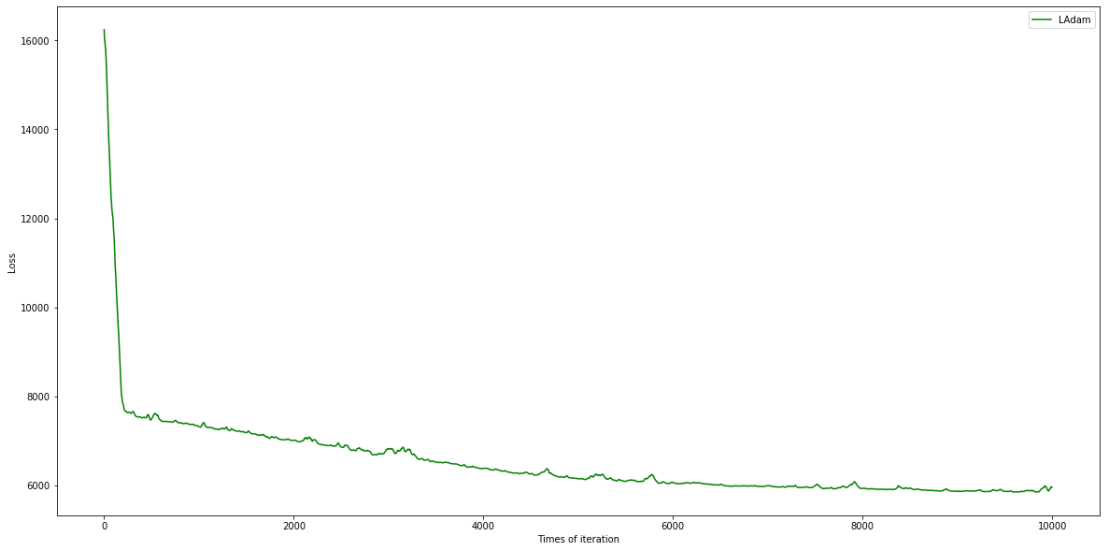
RMSProp



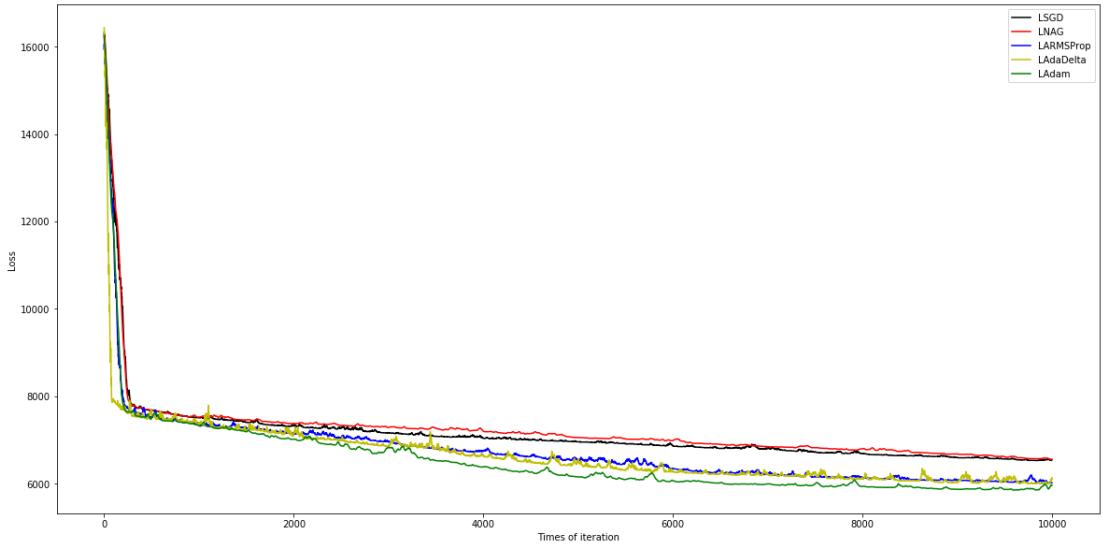
AdaDelta



Adam



总图：



11.实验结果分析:

5 种优化模型均在前 200 次迭代内就能使测试集上的 Loss 值大幅下降，然后在 200-10000 次迭代内 Loss 值缓慢地下降，最终达到 6000 左右，此时在测试集上对应的正确率均可达 80%以上。

普通 SGD 和 NAG 模型的 Loss 曲线非常相近，最后的准确率也很相近，而比另外三种模型低一些。

RMSProp，AdaDelta 和 Adam 模型的曲线在迭代后半段能够达到更低的 Loss 值，其中又以 Adam 的效果最优。

以上 5 种优化模型的曲线在整个迭代中均有不同程度的上下波动,推测是因为 Loss 函数没有对样本取平均数的原因。

12.对比逻辑回归和线性分类的异同点：

逻辑回归和线性分类最基本的共同点就是通过 $f(x)=(\sum_{i=1}^{m} w_i x_i)+b$ 的线性公式构造模型，不同的是逻辑回归再对 f(x)进行了 Sigmod 运算。

逻辑回归和线性分类的标签 y 取值都是有限的几个（本实验为 2 个）离散值，同一个值可以同时对应超空间中一定区域的 x 的取值。

从实验结果来看，逻辑回归和线性分类的 Loss 值大小都始终和数据集样本数成正比，对于不同大小的数据集，具有相同“训练程度”的模型产生不匹配的概率是一定的，所以数据集越大，Loss 值越大。

逻辑回归是通过预测函数来进行分类，y 的标签值是已知的（0，1），而线性分类是通过拟合函数来进行预测，y 的值是未知的。

13.实验总结：

本次实验让我更深地了解了通过数据样本训练特定机器学习模型的过程，不同的优化模型让我意识到了机器学习中模型的重要性，我认为充分运用代码的模块化有助于基本函数和较优化模型间的组合，也方便对超参数进行调整。并且让我更加熟悉了 python 中矩阵的基本运算的相关函数。