華南理工大學

South China University of Technology

The Experiment Report of Machine Learning

SCHOOL: SCHOOL OF SOFTWARE ENGINEERING

SUBJECT: SOFTWARE ENGINEERING

Author:
Shoukai Xu and Yaofu Chen

Supervisor:
Mingkui Tan or Qingyao Wu

Student ID：
201530611111 and 201530600000

Grade:
Undergraduate or Graduate

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Linear Regression, Linear Classification and Gradient Descent

Abstract—

I. INTRODUCTION

逻辑回归、线性分类与随机梯度下降

1. 对比理解梯度下降和随机梯度下降的区别和联系

2. 对比理解逻辑回归和线性分类的区别和联系

3. 进一步理解 svm 的原理并在较大数据上实践

II. METHODS AND THEORY

逻辑回归：全零初始化，随机梯度下降

Loss 函数：

$$L(w,b)=f_{w,b}(x^1)f_{w,b}(x^2)\left(1-f_{w,b}(x^3)\right)\cdots f_{w,b}(x^N)$$

线性分类：全零初始化，随机梯度下降

Loss 函数：

$$L(f)=\sum_{n}\delta(f(x^n)\neq\hat{y}^n)$$

III. EXPERIMENT

6. 实验步骤:

逻辑回归和随机梯度下降

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 ppt

4. 求得部份样品对 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的优化方法的 Loss

7. 重复步骤 4-6 若干次，画出 Loss 随迭代次数变化图

代码内容：

```python
def NAG(train_x,  train_y, text_x, text_y, gamma =0.9, threshold =0.5, rate =0.1, size=64, epoch=500):
    gradients = np.zeros((train_x.shape[1],1))
    weights = np.random.rand(train_x.shape[1],1)
    momentum = np.zeros((train_x.shape[1],1))

    epoch_set = []
    l_nag = []
    a_nag = []


    for k in range(epoch+1):
        batch_step = random.randint(0,train_x.shape[0]-size-1)
        for i in range(batch_step,batch_step+size):
            gradients = gradients+((sigmoid(np.dot(train_x[i],(weights-gamma*momentum)))-train_y[i])*train_x[i]).reshape((train_x.shape[1],1))
        gradients = gradients/size
        momentum = gamma*momentum+rate*gradients
        weights = weights - momentum
        if(k>0)or(k%100==0):
            epoch_set.append(k)
            loss = 0
            res = 0
            for j in range(test_x.shape[0]):
                h = sigmoid(np.dot(test_x[j],(weights-gamma*momentum)))
                loss = loss+(test_y[j]*np.log(h)+(1-test_y[j])*np.log(1-h))
                if sign(h,threshold) == test_y[j]:
                    res = res+1
            accuracy = res/test_x.shape[0]
            loss = -loss/test_x.shape[0]
```

```python
            a_nag.append(accuracy)
            l_nag.append(loss)
    return a_nag,l_nag,epoch_set
```

```python
def RMSProp(train_x,train_y,test_x,test_y,gamma =0.9,epsilon=1e-10,threshold=0.5,rate=0.1,size=64,epoch=500):
    gradients = np.zeros((train_x.shape[1],1))
    weights = np.random.rand(train_x.shape[1],1)
    g = np.zeros((train_x.shape[1],1))
    epoch_set =[]
    l_rmsp = []
    a_rmsp =[]
    for k in range(epoch+1):
        batch_step = random.randint(0,train_x.shape[0]-size-1)
        for i in range(batch_step,batch_step+size):
            gradients = gradients+((sigmoid(np.dot(train_x[i],weights))-train_y[i])*train_x[i]).reshape((train_x.shape[1],1))
        gradients = gradients/size
        g = gamma*g+np.multiply((1-gamma)*gradients,gradients)
        weights = weights - np.multiply(rate/(np.sqrt(g+epsilon)),gradients)
        if(k>0)or(k%100==0):
            epoch_set.append(k)
            loss = 0
            res = 0
            for j in range(test_x.shape[0]):
                h = sigmoid(np.dot(test_x[j],weights))
                loss = loss+(test_y[j]*np.log(h)+(1-test_y[j])*np.log(1-h))
                if sign(h,threshold) == test_y[j]:
                    res = res+1
            accuracy = res/test_x.shape[0]
            loss = -loss/test_x.shape[0]
            a_rmsp.append(accuracy)
            l_rmsp.append(loss)
    return a_rmsp,l_rmsp
```

```python
def AdaDelta(train_x,train_y,test_x,test_y,gamma=0.9,epsilon=1e-10,threshold=0.5,dx=0.001,size=64,epoch=500):
    gradients = np.zeros((train_x.shape[1],1))
    weights = np.random.rand(train_x.shape[1],1)
    g = np.zeros((train_x.shape[1],1))
    epoch_set =[]
    l_adad = []
    a_adad =[]
    for k in range(epoch+1):
        batch_step = random.randint(0,train_x.shape[0]-size-1)
        for i in range(batch_step,batch_step+size):
            gradients = gradients+((sigmoid(np.dot(train_x[i],weights))-train_y[i])*train_x[i]).reshape((train_x.shape[1],1))
        gradients = gradients/size
        g = gamma*g+np.multiply((1-gamma)*gradients,gradients)
        dw = -np.multiply((np.sqrt(dx+epsilon))/(np.sqrt(g+epsilon)),gradients)
        weights = weights +dw
        dx = gamma*dx+np.multiply((1-gamma)*dw,dw)
        if(k>0)or(k%100==0):
            epoch_set.append(k)
            loss = 0
            res = 0
            for j in range(test_x.shape[0]):
                h = sigmoid(np.dot(test_x[j],weights))
                loss = loss+(test_y[j]*np.log(h)+(1-test_y[j])*np.log(1-h))
                if sign(h,threshold) == test_y[j]:
                    res = res+1
            accuracy = res/test_x.shape[0]
            loss = -loss/test_x.shape[0]
            a_adad.append(accuracy)
```

```python
            l_adad.append(loss)
    return a_adad,l_adad
```

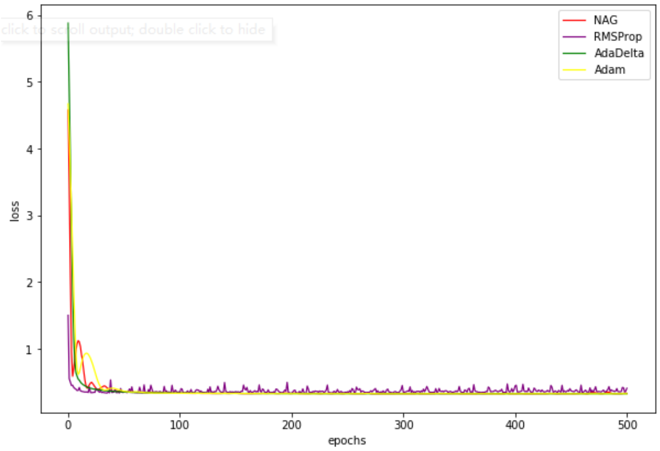
```python
def Adam(train_x,train_y,test_x,test_y,beta=0.9,gamma=0.999,epsilon=1e-8,threshold=0.5,rate=0.01,size=64,epoch=500):
    gradients = np.zeros((train_x.shape[1],1))
    weights = np.random.rand(train_x.shape[1],1)
    g = np.zeros((train_x.shape[1],1))
    moments = np.zeros((train_x.shape[1],1))
    epoch_set =[]
    l_adam = []
    a_adam =[]
    for k in range(epoch+1):
        batch_step = random.randint(0,train_x.shape[0]-size-1)
        for i in range(batch_step,batch_step+size):
            gradients = gradients+((sigmoid(np.dot(train_x[i],weights))-train_y[i])*train_x[i]).reshape((train_x.shape[1],1))
        gradients = gradients/size
        moments = beta*moments+(1-beta)*gradients
        g = gamma*g+np.multiply((1-gamma)*gradients,gradients)
        alpha = rate
        dw = -alpha*moments/(np.sqrt(g+epsilon))
        weights = weights +dw
        if(k>0)or(k%100==0):
            epoch_set.append(k)
            loss = 0
            res = 0
            for j in range(test_x.shape[0]):
                h = sigmoid(np.dot(test_x[j],weights))
                loss = loss+(test_y[j]*np.log(h)+(1-test_y[j])*np.log(1-h))
                if sign(h,threshold) == test_y[j]:
                    res = res+1
            accuracy = res/test_x.shape[0]
```

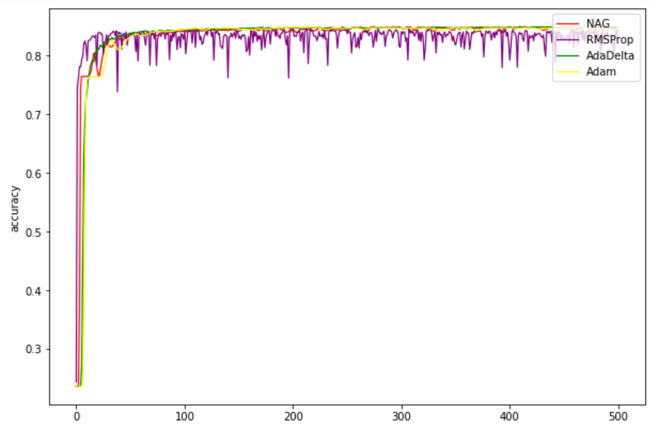
```
            loss = -loss/test_x.shape[0]
            a_adam.append(accuracy)
            l_adam.append(loss)
    return a_adam,l_adam
```

*此处为部分代码，详情见附录 ipynb 文件

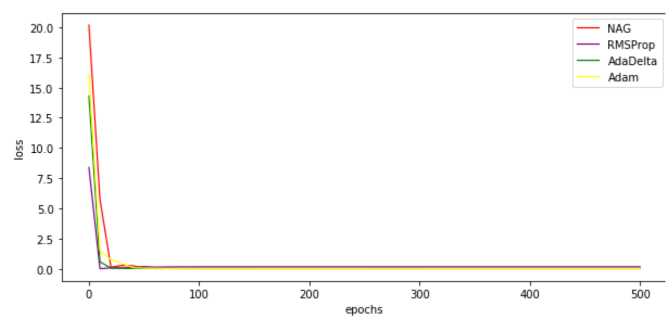
结果：

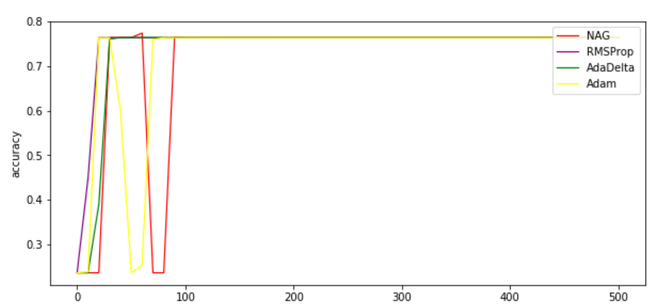
逻辑回归：





线性分类：





IV. CONCLUSION

这次的实验运用了比上一次更大的数据集做训练，使用多种梯度下降方法，从结果可以看出，其各有优劣，同时随着迭代次数的增加，最终得出的结果趋于一致。比起线性分类，逻辑回归的走向前期更为稳妥，但是后期有锯齿产生

对比逻辑回归和线性分类的异同点：

相同点：LR 和 SVM 都是分类算法，都可以处理离散的 label 的数据集

如果不考虑核函数，二者都是线性分类算法

二者都是监督学习算法

都是判别模型

不同点：LR 和 SVM 的 Loss 函数不同，后者只考虑局部边界线附近的点，而前者考虑全局