South China University of Technology

The Experiment Report of Machine Learning

SCHOOL: SCHOOL OF SOFTWARE ENGINEERING

SUBJECT: SOFTWARE ENGINEERING

Author:
Juncong Huang

Supervisor:
Mingkui Tan

Student ID：201530611746

Grade:
Undergraduate

December 14, 2017

1

Linear Regression, Linear Classification and Stochastic Gradient Descent

I. INTRODUCTION

The motivations of the second experiment are as follows. Firstly,Compare and understand the difference between gradient descent and stochastic gradient descent. Secondly,Compare and understand the differences and relationships between Logistic regression and linear classification. Thirdly, Further understand the principles of SVM and practice on larger data.

II. METHODS AND THEORY

SGD: a gradient descent algorithm may be difficult to use when the training data set is large. The computational cost of each iteration linearly increases with the number of samples. Therefore, we take the SGD:

$$\nabla f_B(x)=\frac{1}{|B|}\sum_{i\in B}\nabla f_i(x)$$

The computational cost of each iteration is O(|B|).So when the batch size is small ,the cost will decrease.

NAG:normal gradient descent parameters will move more violently in the vertical direction than in the horizontal direction. Therefore,we take the NAG:

$$v:=yv+n\nabla f_B(X)$$

$$x:=x-v$$

Adagrad:the main idea of Adagrad is that if the partial loss of a model loss function with respect to a parameter element is always large, then its learning rate will drop a little faster; on the contrary, if the partial derivative of a model loss function with respect to a parameter element is always small , then its learning rate will drop a little slow down.

$$s:=s+G*G$$

$$g':=\frac{n}{\sqrt{s+e}}G$$

$$x:=x-g'$$

RMSProp: Adagrad may find it harder to find a useful solution later in the iteration when the learning rate drops faster early in the iteration and the current solution is still not ideal. So RMSProp improves it.

$$s:=ys+(1-y)G*G$$

$$g':=\frac{n}{\sqrt{s+e}}G$$

$$x:=x-g'$$

It ensures the learning rate will decrease and increase possibly during the iteration

Adadelta:it dont't need the learning rate,though it is the same idea of RMSProp.

$$s:=ps+(1-p)G*G$$

$$g'=\frac{\sqrt{\Delta X+e}}{\sqrt{s+e}}G$$

$$\Delta X:=p\Delta X+(1-p)g'*g'$$

$$x:=x-g'$$

Adam:we take a momentum variable v and a exponentially wighted moving average variable s in RMSprop. In each iteration ,we compute the momentum variable v and wighted moving average variable s. Additionally, we use the deviation correction to avoid the effect of initializing the variables to 0.

$$t:=t+1$$

$$v:=\beta_1 v+(1-\beta_1)g$$

$$s:=\beta_2 s+(1-\beta_2)g*g$$

$$v'=\frac{v}{1-\beta_1^t}$$

$$s'=\frac{s}{1-\beta_2^t}$$

$$g':=\frac{nv'}{\sqrt{s'+e}}$$

$$x:=x-g'$$

III. EXPERIMENT

A. Dataset

Experiment uses a9a of LIBSVM Data, including 32561/16281(testing) samples and each sample has 123/123 (testing) features.

B. Implementation

Regression:

Fig. 1. NAG initializing parameter

Weight parameter	w=zeros
Momentum parameter	u=0.8
Momentum variable	v=0
Learning rate	rate=0.01

Fig. 2. RMSEprop initializing parameter

Weight parameter	w=zeros
Exponentially weighted moving average variable	r=0
Weighted parameter	u=0.8

1

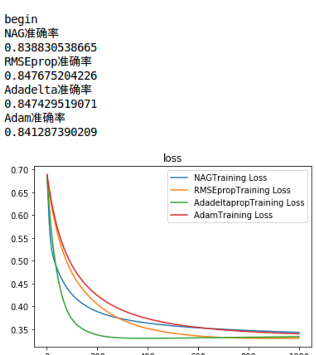
Stable constant	theta=0.000001
Learning rate	rate=0.001

Fig. 3. Adadelta initializing parameter

Weight parameter	w=zeros
Exponentially weighted moving average variable	s=0
Momentum parameter	u=0.8
Stable constant	theta=0.000001
Learning rate	rate=0.001
Another exponentially weighted moving average variable	delta=0

Fig. 4. Adam initializing parameter

Weight parameter	w=zeros
Momentum variable	v=0
Parameter one	p1==0.9
Parameter two	p2=0.999
Learning rate	rate=0.001
Stable constant	theta=0.000001
Exponentially weighted moving average variable	s=0
Times	t=0



Classification

Fig. 5. NAG initializing parameter

Weight parameter	w=zeros
Momentum parameter	u=0.8
Momentum variable	v=0
Learning rate	rate=0.0001
Punished parameter	reg=1

Fig. 6. RMSEprop initializing parameter

Weight parameter	w=zeros
Exponentially weighted moving average variable	r=0
Weighted parameter	u=0.8
Stable constant	theta=0.000001
Learning rate	rate=0.001
Punished parameter	reg=1

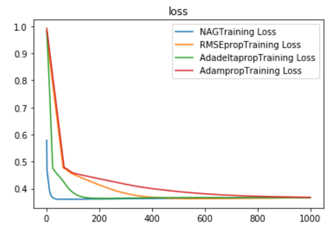
Fig. 7. Adadelta initializing parameter

Weight parameter	w=zeros
Exponentially weighted moving average variable	s=0
Momentum parameter	u=0.8
Stable constant	theta=0.000001
Learning rate	rate=0.0001
Another exponentially weighted moving average variable	delta=0
Weight parameter	w=zeros
Exponentially weighted moving average variable	s=0
Punished parameter	reg=1

Fig. 8. Adam initializing parameter

Weight parameter	w=zeros
Momentum variable	v=0
Parameter one	p1==0.9
Parameter two	p2=0.999
Learning rate	rate=0.001
Stable constant	theta=0.000001
Exponentially weighted moving average variable	s=0
Times	t=0
Punished parameter	reg=1

```
begin
NAG准确率
0.844297033352
RMSEprop准确率
0.844112769486
Adadelta准确率
0.844419875929
Adam准确率
0.840550334746
```



IV. Conclusion

From this experiment,I feel the efficiency of SGD and learn four different methods to find the optimized resolution. I think I could compared the four different methods on various datasets and summarize their strengths and weakness.