华南理工大学

South China University of Technology

The Experiment Report of *Machine Learning*

College Software College

Subject Software Engineering

Members Mo Junwen

Student ID 201530612545

E-mail 545096186@qq.com

Tutor Tan Mingkui

Date submitted 2017. 12 .11

1. Topic:Logistic Regression, Linear Classification and Stochastic Gradient Descent

2. Time: 2017.12.11

3. Reporter:Mo Junwen

4. Purposes:

(1)Compare and understand the difference between gradient descent and stochastic gradient descent.

(2)Compare and understand the differences and relationships between Logistic regression and linear classification.

(3)Further understand the principles of SVM and practice on larger data.

5. Data sets and data analysis:

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

6. Experimental steps:

Logistic Regression and Stochastic Gradient Descent

(1)Load the training set and validation set.

(2)Initalize logistic regression model parameters, you can consider initalizing zeros, random numbers or normal distribution.

(3)Select the loss function and calculate its derivation, find more detail in PPT.

(4)Calculate gradient toward loss function from partial samples.

(5)Update model parameters using different optimized methods(NAG，RMSProp，AdaDelta and Adam).

(6)Select the appropriate threshold, mark the sample whose predict scores greater than the threshold as positive, on the contrary as negative.

(7)Predict under validation set and get the different optimized method loss L_{NAG}，$L_{RMSprop}$，$L_{AdaDelta}$ and L_{Adam} .

(8)Repeat step 4 to 6 for several times, and drawing graph of L_{NAG}，$L_{RMSprop}$，$L_{AdaDelta}$ and L_{Adam} and with the number of iterations.

Linear Classification and Stochastic Gradient Descent

(1)Load the training set and validation set.

(2)Initalize SVM model parameters, you can consider initalizing zeros, random numbers or normal distribution.

(3)Select the loss function and calculate its derivation, find more detail in PPT.

(4)Calculate gradient toward loss function from partial samples.

(5)Update model parameters using different optimized methods(NAG，RMSProp，AdaDelta and Adam).

(6)Select the appropriate threshold, mark the sample whose predict scores greater than the threshold as positive, on the contrary as negative.

(7)Predict under validation set and get the different optimized method loss L_{NAG}，$L_{RMSprop}$，$L_{AdaDelta}$ and L_{Adam} and .

(8)Repeate step 4 to 6 for several times, and drawing graph of L_{NAG}, $L_{RMSprop}$, $L_{AdaDelta}$ and L_{Adam} and with the number of iterations.

7. Code:

Logistic regression gradient:

```
def gradient(w,x,y,lamda=0):
    y_=x*w
    index=np.multiply(y,y_)
    mul=np.multiply(y,x)
    g=-np.mean(mul/(1+np.exp(index)),0).T+lamda*w
    return g
```

Logistic regression loss function:

```
def loss(w,x,y):
    y_=x*w
    index=-np.multiply(y_,y)
    #print(index)
    l=np.mean(np.log(1+np.exp(index)))
    return l
```

Linear Classification gradient:

```
def gradient(w,x,y,C=1):  #svm的梯度计算，包括正则项，C默认为1
    l=1-np.multiply(y,x*w)    #先做点乘
    l2=(l>=0)           #然后求出哪个元素大于等于0，化成布尔矩阵
    tmp=np.multiply(y,l2)  #通过点乘进行筛选，大于等于0的项保留，小于0的项清除变为0
    return w-C*np.sum(np.multiply(x,tmp),0).T   #计算最终梯度
```

Linear Classification loss function:

```
def loss(w,x,y):    #hinge loss
    l=1-np.multiply(y,x*w)
    l2=(l>=0)
    r=np.multiply(l,l2)
    return np.mean(r)
```

NAG main code:

```
for i in range(epoch):
    k=random.randint(0,m_train-1-m)
    x_t=x[k:k+m]
    y_t=y[k:k+m]
    g=gradient(w-gamma*delta_w,x_t,y_t,lamda)
    delta_w=gamma*delta_w+eta*g
    w=w-delta_w
```

RMSprop main code:

```
    for i in range(epoch):
        k=random.randint(0,m_train-m)
        x_t=x[k:k+m]
        y_t=y[k:k+m]
        g=gradient(w,x_t,y_t,lamda)
        G=gamma*G+(1-gamma)*np.square(g)
        delta_w=eta*np.multiply(1/np.sqrt(G+epison),g)
        w=w-delta_w
```

AdaDelta main code:

```
  for i in range(epoch):
      k=random.randint(0,m_train-m)
      x_t=x[k:k+m]
      y_t=y[k:k+m]
      g=gradient(w,x_t,y_t,lamda)
      G=gamma*G+(1-gamma)*np.square(g)
      delta_w=-np.multiply(np.sqrt(delta+epison)/np.sqrt(G+epison),g)
      w=w+delta_w
      delta=gamma*delta+(1-gamma)*np.square(delta_w)
```

Adam main code:

```
     for i in range(epoch):
         k=random.randint(0,m_train-batch_size)
         x_t=x[k:k+batch_size]
         y_t=y[k:k+batch_size]
         g=gradient(w,x_t,y_t,lamda)
         m=beta*m+(1-beta)*g
         G=gamma*G+(1-gamma)*np.square(g)
         alpha=eta*np.sqrt(1-gamma)/(1-beta)
         w=w-alpha*m/np.sqrt(G+epison)
```

8. The initialization method of model parameters:

Logistic Regression:random numbers or normal distribution.

Linear Classification:random numbers or normal distribution.

9. **The selected loss function and its derivatives:**

Logistic Regression:

Loss function:

$$J(\mathbf{w}) = \frac{1}{n}\sum_{i=1}^{n}\log(1+e^{-y_i\cdot\mathbf{w}^\top\mathbf{x}_i}) + \frac{\lambda}{2}||\mathbf{w}||_2^2$$

Derivatives:

$$\frac{\partial \mathrm{J}}{\partial w} = \frac{1}{n}\sum_{i=1}^{n}\frac{-y_i x_i}{1+e^{-y_i w^T x_i}} + \lambda w$$

Linear Classification:

Loss function:

$$\text{Hinge loss} = \xi_i = \max(0, 1 - y_i(\mathbf{w}^\top\mathbf{x}_i + b))$$

Derivatives:

$$\frac{1}{2}\cdot\frac{\partial(\|\mathbf{w}\|^2)}{\partial\mathbf{w}} = \mathbf{w}$$

if $1 - y_i(\mathbf{w}^\top\mathbf{x}_i + b) >= 0$:

$$\begin{aligned} g_{\mathbf{w}}(\mathbf{x}_i) &= \frac{\partial(-y_i(\mathbf{w}^\top\mathbf{x}_i + b))}{\partial\mathbf{w}} \\ &= -\frac{\partial(y_i\mathbf{w}^\top\mathbf{x}_i)}{\partial\mathbf{w}} \\ &= -y_i\mathbf{x}_i \end{aligned}$$

if $1 - y_i(\mathbf{w}^\top\mathbf{x}_i + b) < 0$:

$$g_{\mathbf{w}}(\mathbf{x}_i) = 0$$

$$g_{\mathbf{w}}(\mathbf{x}_i) = \begin{cases} -y_i \mathbf{x}_i & 1 - y_i(\mathbf{w}^\top \mathbf{x}_i + b) >= 0 \\ 0 & 1 - y_i(\mathbf{w}^\top \mathbf{x}_i + b) < 0 \end{cases}$$

$$\frac{\partial f(\mathbf{w}, b)}{\mathbf{w}} = \mathbf{w} + C \sum_{i=1}^{N} g_{\mathbf{w}}(\mathbf{x}_i)$$

10. Experimental results and curve:

Logistic Regression:

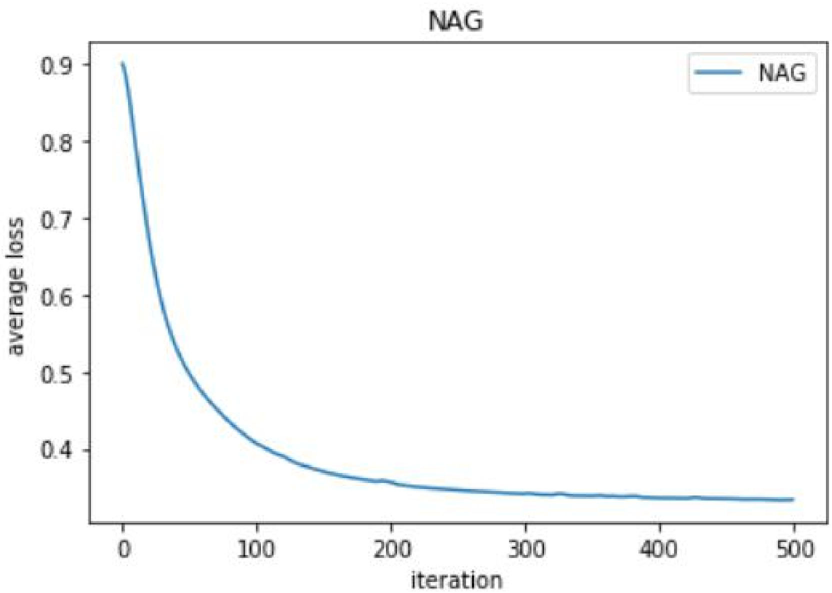
(1)NAG

Hyper-parameter selection:

η =0.05 λ =0.001 γ =0.9 batch_size=256 epoch=500

Predicted Results (Best Results):84.61%

Loss curve:



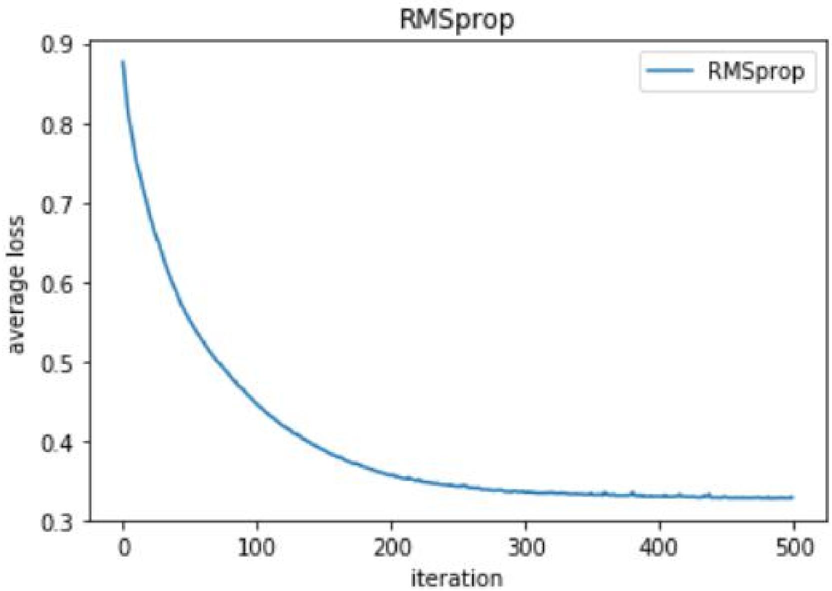
(2) RMSprop

Hyper-parameter selection:

η =0.01 λ =0.001 γ =0.9 batch_size=256 epoch=500

Predicted Results (Best Results):84.97%

Loss curve:



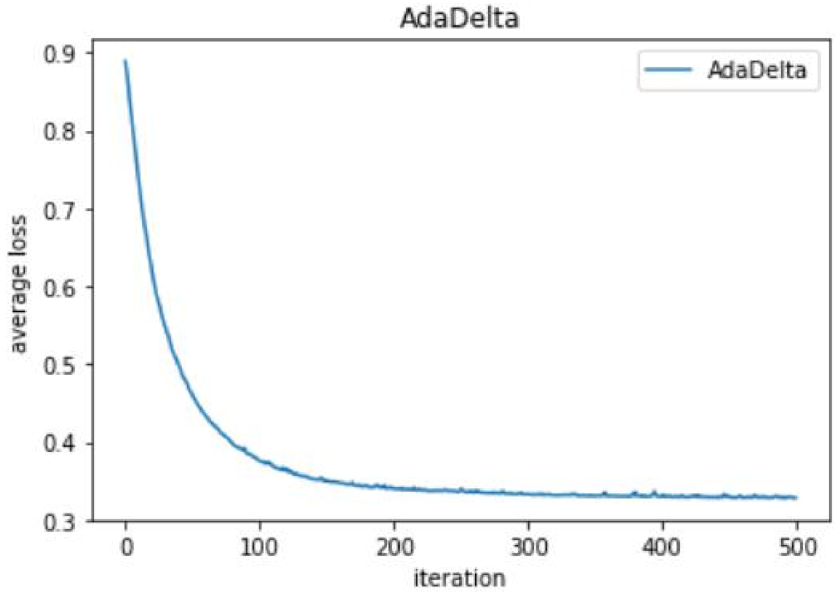
(3) AdaDelta

Hyper-parameter selection:

λ =0.001 γ =0.4 batch_size=256 epoch=500

Predicted Results (Best Results):85.03%

Loss curve:



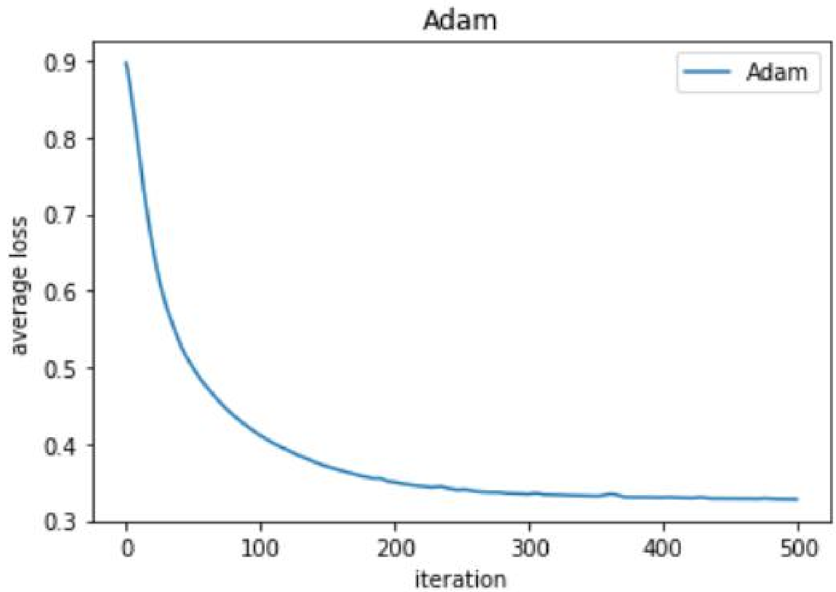
(4) Adam

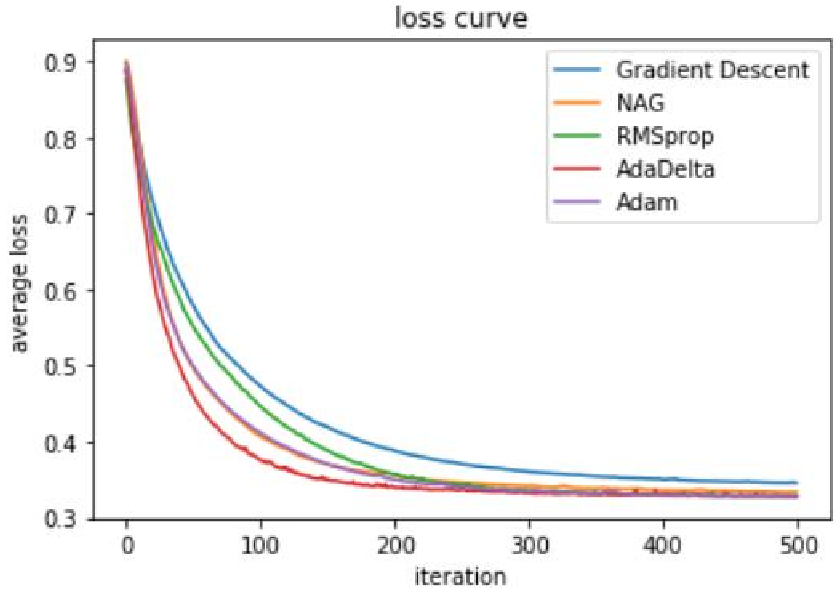
Hyper-parameter selection:

η =0.005 λ =0.001 γ =0.99 β =0.9 batch_size=256 epoch=500

Predicted Results (Best Results):84.96%

Loss curve:





Linear Classification:

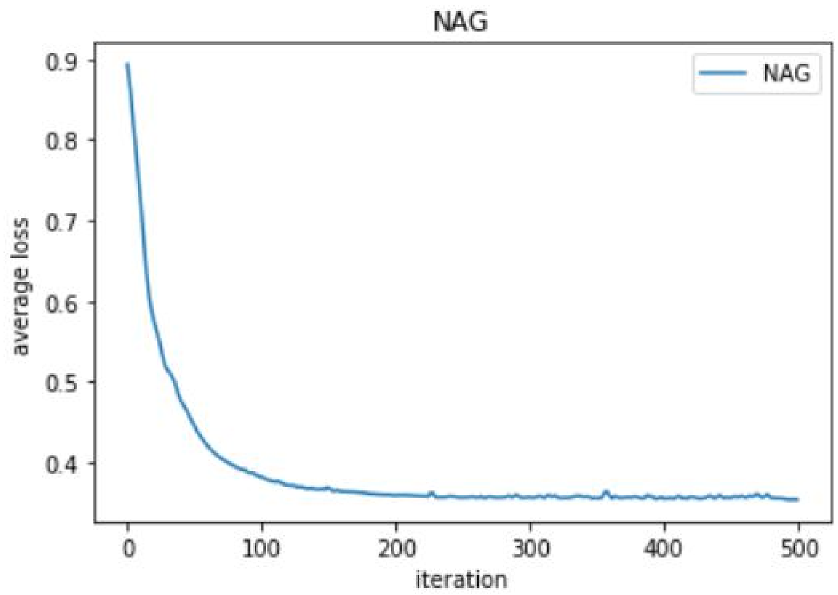
(1)NAG

Hyper-parameter selection:

η =0.0003 C=1 γ =0.9 batch_size=256 epoch=500

Predicted Results (Best Results):84.61%

Loss curve:



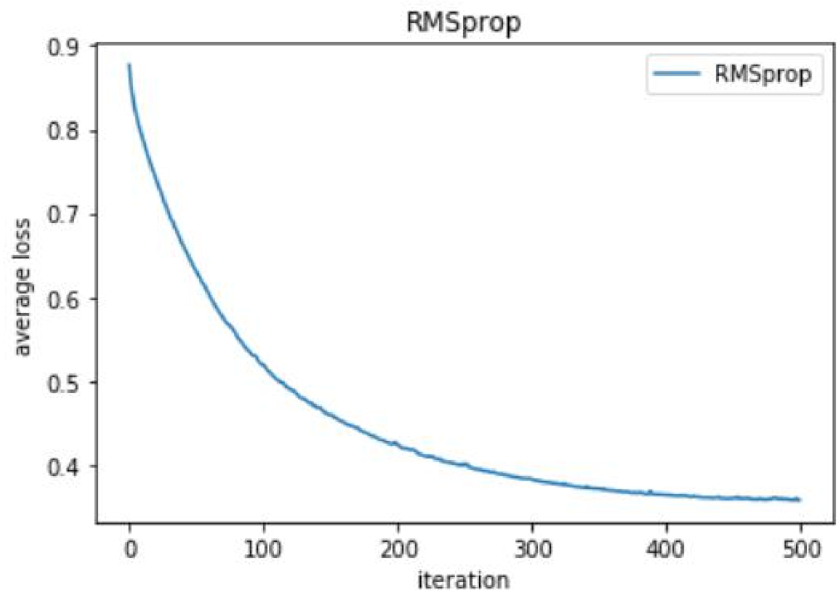
(2)RMSprop

Hyper-parameter selection:

η =0.005 C=1 γ =0.9 batch_size=256 epoch=500

Predicted Results (Best Results):84.78%

Loss curve:



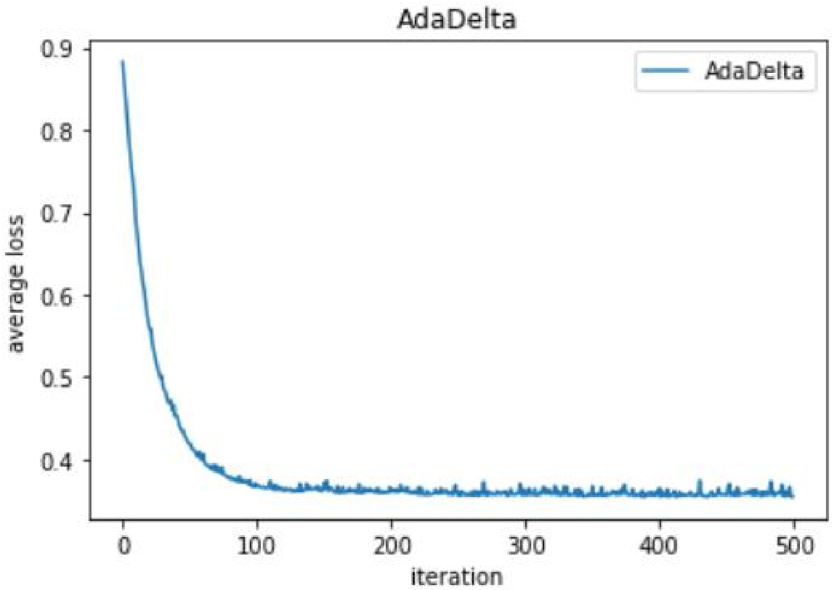
(3)AdaDelta

Hyper-parameter selection:

C=0.9 γ =0.3 batch_size=256 epoch=500

Predicted Results (Best Results):84.95%

Loss curve:



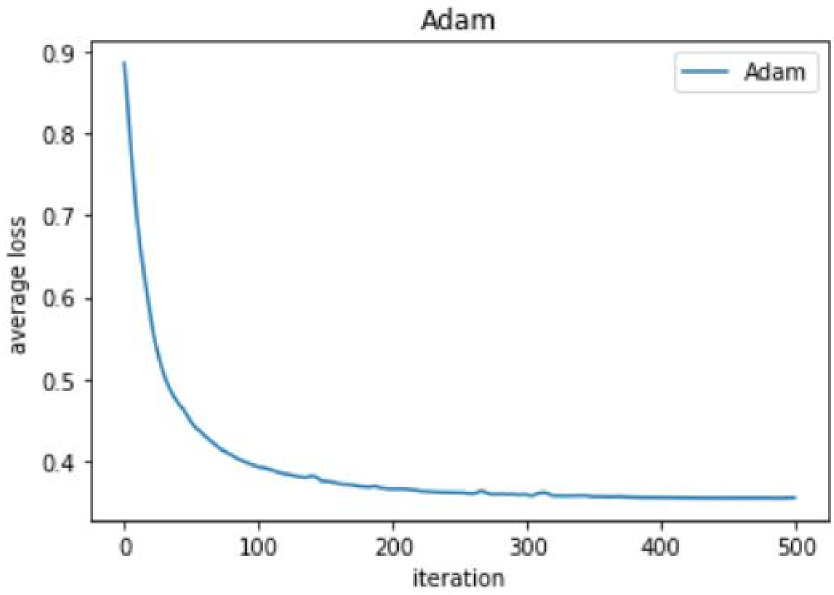
(4)Adam

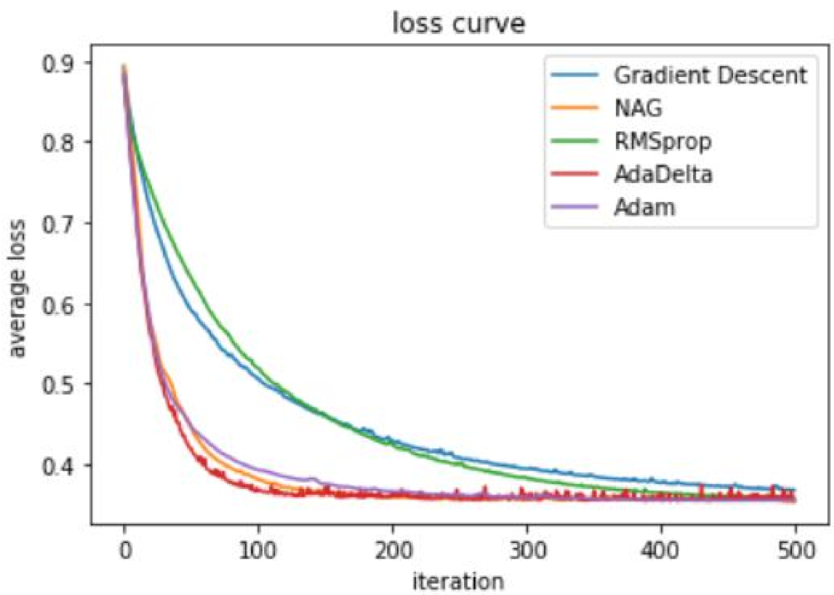
Hyper-parameter selection:

η =0.01 C=1 γ =0.999 β =0.9 batch_size=256 epoch=500

Predicted Results (Best Results):84.78%

Loss curve:





11. Results analysis:

In this experiment, we compare logistic regression and linear classification. We can find in the loss curve that the loss of the logistic regression is more stable. And their accuracy is similar. We also compare different stochastic gradient descent in this experiment. We can find that AdaDelta converge fastest. Adam and the NAG are similar in the convergence speed.

12. Similarities and differences between logistic regression and linear classification：

13. Summary: