

South China University of Technology

The Experiment Report of Machine Learning

College

<u></u>	2010HW10 COHOGO
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Software College

1. Topic: NAG, RMSProp, AdaDelta and Adam's Comparison

2. Time: 2017/12/15

3. Reporter: wende zhu

4. Purposes: compare the ways of SGD, such as NAG, RMSProp,

AdaDelta and Adam

5. Data sets and data analysis: a9a.txt: 32561 items, 123 features

a9a.t: 16281 items, 122(123) features

6. Experimental steps:

1. Load the training set and validation set.

2. Initialize logistic regression model parameters, you can consider initializing zeros, random numbers or normal distribution.

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

- 4. Calculate gradient G 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. Predict under validation set and get the different optimized method loss L_{NAG} , $L_{RMSProp}$, $L_{AdaDelta}$ and L_{Adam} .
- 7. Repeat step 4 to 6 for several times, and drawing graph of L_{NAG} , $L_{RMSProp}$, $L_{AdaDelta}$ and L_{Adam} with the number of iterations.

7. Code:

```
def compute_gradient_NAG(v,m_current,x,y,rp,size=200):
   m_gradient = 0
   gama = 0.9
   v.shape=(124,1)
   n=len(y)
   N = float(n)
   y.shape=(n,1)
   m_current.shape=(124,1)
   temp = random.randint(0, n - 200)
   for i in range(size):
       tt=x[temp+i].dot(m_current)
       m_gradient+=(sigmod(tt)-y[temp+i])*x[temp+i]
   m_gradient=m_gradient/N
   v = gama*v+rp*m_gradient.T
   new_m = m_current-v
   return new_m, v
def compute_gradient_RMSProp(v,m_current,x,y,rp,size=200):
   m_gradient = 0
   gama = 0.9
   v.shape=(124,1)
   n=len(y)
   N = float(n)
   y.shape=(n,1)
   m_current.shape=(124,1)
   temp = random.randint(0, n - 200)
   for i in range(size):
       tt=x[temp+i].dot(m_current)
       m_gradient+=(sigmod(tt)-y[temp+i])*x[temp+i]
   m_gradient=(m_gradient/N)
   v = gama*v+(1-gama)*(m_gradient*m_gradient.T)
   temp = rp/np.sqrt(v+np.exp(-8))
   new_m = m_current-np.multiply(temp,m_gradient.T)
   return new_m, v
```

```
def compute_gradient_AdaDelta(delta,v,m_current,x,y,rp,size=200):
   m_gradient = 0
   gama = 0.95
   v.shape=(124,1)
   n=len(y)
   N = float(n)
   y.shape=(n,1)
   m_current.shape=(124,1)
   temp = random.randint(0, n - 200)
   for i in range(size):
       tt=x[temp+i].dot(m_current)
       m_gradient+=(sigmod(tt)-y[temp+i])*x[temp+i]
   m_gradient=m_gradient/N
   v = gama*v+(1-gama)*np.multiply(m_gradient.T,m_gradient.T)
   temp = np.sqrt(delta+np.exp(-8))/np.sqrt(v+np.exp(-8))
   temp2 = -np.multiply(temp,m_gradient.T)
   new_m = m_current+temp2
   delta=gama*delta+(1-gama)*np.multiply(temp2,temp2)
   return new_m,v,delta
def compute_gradient_Adam(g,v,m_current,x,y,rp,size=200):
   m gradient = 0
   gama = 0.999
   beta = 0.9
   v.shape=(124,1)
   n=len(y)
   N = float(n)
   y.shape=(n,1)
   m_current.shape=(124,1)
   temp = random.randint(0, n - 200)
   for i in range(size):
       tt=x[temp+i].dot(m_current)
       m gradient+=(sigmod(tt)-y[temp+i])*x[temp+i]
   m_gradient=m_gradient/N
   v = beta*v+(1-beta)*m_gradient.T
   g = gama*g+(1-gama)*np.multiply(g,g)
   alpha = rp*math.sqrt(1-gama)/(1-beta)
   new_m = m_current-alpha*v/np.sqrt(g+np.exp(-8))
   return new_m, v, g
```

- 8. The initialization method of model parameters: all zeros.
- 9. The selected loss function and its derivatives:

Loss function =
$$\frac{1}{n} \sum_{i=1}^{n} \log(1 + e^{-y_i \cdot w^T x})$$

$$\frac{\partial L}{\partial w} = \frac{1}{n} \sum_{i=1}^{n} (h_w(x_i) - y_i) x_i$$

10. Experimental results and curve:

Hyper-parameter selection: NAG: $\lambda = 0.5$

RMSProp: $\gamma = 0.9 \lambda = 0.5$

AdaDelta: $\gamma = 0.95 \ \lambda = 0.5$ Adam: $\gamma = 0.999 \ \beta = 0.9 \ \lambda = 0.5$

Predicted Results (Best Results): m of NAG=[[-5.75492401e-01]\n",

```
"[-3.83374102e-01]\n",
"[-2.82010464e-01]\n",
"[-1.82141673e-01]\n",
"[-2.48246259e-01]\n",
"[-1.24376509e+00]\n",
"[-1.17882084e-01]\n",
"[ 5.59648564e-03]\n",
"[-2.65202741e-02]\n",
"[-8.94329045e-02]\n",
"[-6.61472502e-02]\n",
"[-5.18299588e-04]\n",
"[-8.97189656e-04]\n",
"[-3.34563713e-01]\n",
"[-3.17093445e-01]\n",
"[-3.29517050e-01]\n",
"[-3.42683159e-01]\n",
"[-3.47407532e-01]\n",
"[-1.17636272e-01]\n",
"[-4.29753284e-01]\n",
"[-1.03722895e-01]\n",
"[-6.89417604e-01]\n",
"[ 1.54595131e-02]\n",
"[-5.51211981e-02]\n",
"[-6.48132507e-02]\n",
```

```
"[-4.26564091e-02]\n",
```

" [
$$-2.47529544e-01$$
]\n",

" [
$$-3.05970907e-02$$
]\n",

```
"[-4.91373175e-02]\n",
```

" [
$$-2.83478757e-02$$
]\n",

" [
$$-2.18574145e-02$$
]\n",

```
"[-1.66079182e+00]\n",
```

" [
$$-7.06348245e-04$$
]\n",

" [
$$-6.26744146e-04$$
]\n",

```
"[-6.42486270e-03]\n",
```

" [-2.86588729e-03]
$$\n$$
",

" [
$$-1.80867458e-03$$
]\n",

```
" m of RMSProp = [[ -2.89011682e+00]\n",
" [ -1.85826608e+00]\n",
"[-1.27727425e+00]\n",
"[-7.10645132e-01]\n",
"[-1.09423688e+00]\n",
"[-6.02771400e+00]\n",
"[-5.17963510e-01]\n",
"[ 8.39997083e-02]\n",
"[-9.36918071e-02]\n",
"[-3.14041048e-01]\n",
"[-2.46869772e-01]\n",
"[-1.15732903e-02]\n",
" [ -7.58102242e-03]\n",
"[-1.61999769e+00]\n",
" [ -1.52089186e+00]\n",
"[-1.43592054e+00]\n",
"[-1.64956513e+00]\n",
"[-1.60416393e+00]\n",
"[-4.10517014e-01]\n",
"[-2.09946339e+00]\n",
"[-4.46960258e-01]\n",
" [ -3.33057318e+00]\n",
"[ 1.29092557e-01]\n",
" [ -2.69521732e-01]\n",
```

"[-2.68483392e-01]\n",

```
"[-2.35715760e-01]\n",
```

```
"[-3.78500293e-02]\n",
```

" [-1.00948538e-01]
$$\n"$$
,

" [
$$-8.11316075e+00$$
]\n",

```
"[-7.86546771e+00]\n",
```

" [
$$-3.80019718e-03$$
]\n",

```
"[-3.15940068e-02]\n",
```

" [
$$-5.26740069e-03$$
]\n",

" [
$$-5.30060833e-03$$
]\n",

```
" /m of AdaDelta = [[ -1.36649609e-01]\n",
" [ -9.57774921e-02]\n",
"[-7.84592514e-02]\n",
"[-5.13519863e-02]\n",
"[-7.09256527e-02]\n",
"[-3.19564333e-01]\n",
"[-2.97658776e-02]\n",
"[-2.24867524e-03]\n",
"[-8.47325103e-03]\n",
"[-2.21392740e-02]\n",
"[-1.60248369e-02]\n",
"[-4.07153762e-04]\n",
" [ -1.76993713e-04]\n",
"[-8.95013500e-02]\n",
" [ -8.18095215e-02]\n",
"[-8.61690057e-02]\n",
"[-8.89772839e-02]\n",
"[-8.67078612e-02]\n",
"[-3.92089647e-02]\n",
" [ -1.08753566e-01]\n",
"[-2.30662314e-02]\n",
"[-1.71518112e-01]\n",
"[ 2.06105345e-03]\n",
" [ -1.34882505e-02]\n",
```

"[-1.78743027e-02]\n",

```
"[-1.01021287e-02]\n",
```

" [
$$-6.89402134e-02$$
]\n",

```
"[-1.75191285e-02]\n",
```

" [-2.19417215e-02]
$$\n"$$
,

" [
$$-5.75265317e-03$$
]\n",

" [-1.55824283e-01]
$$\n$$
",

" [
$$-4.68776875e-03$$
]\n",

" [-4.34528060e-01]
$$\n$$
",

```
"[-4.28421079e-01]\n",
```

" [
$$-2.22568147e-04$$
]\n",

```
"[-1.50541306e-03]\n",
```

```
" m of Adam = [[ -9.97315173e-01]\n",
" [ -6.34649505e-01]\n",
"[-4.55626680e-01]\n",
"[-2.79188368e-01]\n",
"[-3.76680287e-01]\n",
" [ -2.07389601e+00]\n",
"[-1.80585979e-01]\n",
"[ 4.35227976e-03]\n",
"[-2.74958508e-02]\n",
" [ -1.42962619e-01]\n",
"[-9.45288376e-02]\n",
"[-3.45397916e-03]\n",
" [ 0.00000000e+00]\n",
"[-5.58345901e-01]\n",
" [ -5.22713374e-01]\n",
"[-5.17406489e-01]\n",
"[-5.87564893e-01]\n",
"[-5.57429356e-01]\n",
"[-1.63578740e-01]\n",
" [ -7.56964972e-01]\n",
"[-1.53350883e-01]\n",
" [ -1.11741774e+00]\n",
"[ 3.39046346e-02]\n",
" [ -8.83997716e-02]\n",
```

"[-1.12846699e-01]\n",

```
"[-8.12036135e-02]\n",
```

" [-7.83333102e-02]
$$\n"$$
,

" [-9.78020677e-03]
$$\n"$$
,

" [
$$-5.77557842e-02$$
]\n",

```
"[-5.23497514e-02]\n",
```

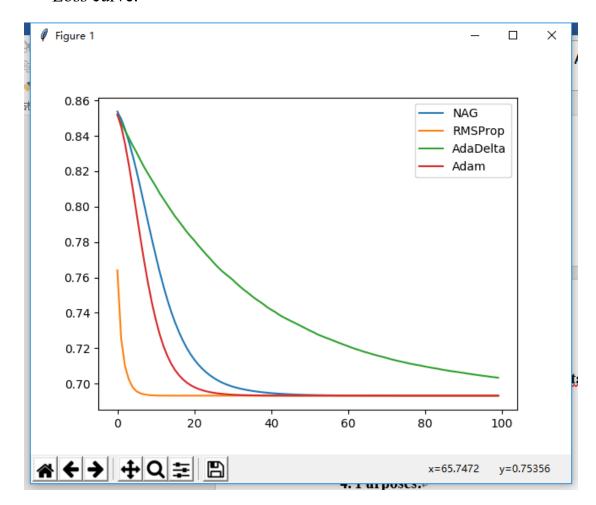
```
"[-2.72374084e+00]\n",
```

" [-2.42507738e-01]
$$\n"$$
,

```
"[-9.24283650e-03]\n",
```

" [
$$-2.68384474e-04$$
]\n",

Loss curve:



11. Results analysis:

In graph, we can see that RMSProp has the fast speed to gradient, but Adam has batter in other three methods. AdaDelta's speed is lowest, I think it maybe modify the AdaDelta's λ .

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

Logistic regression is prediction of probability, and linear classification is split types of data.

13. Summary:

In logistic regression, I find the loss function' value is between

 $0.410037596 \ \frac{\log 2 + \log (1 + e^{-2})}{2} \ \ and \ \ 1.00320443 \frac{\log 2 + \log (1 + e)}{2}.$