South China University of Technology

The Experiment Report of
Machine Learning

Using SGD in Logistic Regression and SVM

College Software College
Subject Software Engineering
Members 郭蕴喆
Student ID 201530611524
E-mail guoyunzhe.se@gmail.com
Tutor Mingkui Tan
Date submitted 2017.12.15

目录

A. Topic

Logistic Regression, Linear Classification and Stochastic Gradient Descent

B. Time

2017/12/15

C. Reporter

郭蕴喆

D. 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.

E. Data sets and data analysis

1. Logistic Regression

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

2. Linear classification

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

F. Experimental steps:

1. Logistic Regression and 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. Predict under validation set and get the different optimized method loss L_{NAG}, $L_{AdaDelta}$, L_{Adam} and $L_{RMSProp}$.

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

3. Linear Classification and 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. Predict under validation set and get the different optimized method loss L_{NAG}, $L_{AdaDelta}$, L_{Adam} and $L_{RMSProp}$. .
7. Repeate step 4 to 6 for several times, and drawing graph of L_{NAG}, $L_{AdaDelta}$, L_{Adam} and $L_{RMSProp}$. and with the number of iterations.

1. Logistic Regression and Gradient Descent

(1) Function: Draw

```python
def Draw(loops,train_loss,validation_loss):
    # the first 100loops
    print('Drawing...')
    plt.plot(np.arange(0,200,1), train_loss[0:200], label='Train Loss')
    plt.plot(np.arange(0,200,1), validation_loss[0:200], label='Validation Loss')
    plt.xlabel('loops')
    plt.ylabel('loss')
    plt.title('The First 200 loops')
    plt.legend()
    plt.show()

    # the last 10000 loops
    plt.plot(np.arange(201, loops-1, 1), train_loss[201:loops-1], label='Train Loss')
    plt.plot(np.arange(201, loops-1, 1), validation_loss[201:loops-1], label='Validation Loss')
    plt.xlabel('loops')
    plt.ylabel('loss')
    plt.title('The rest loops')
    plt.legend()
    plt.show()
    print('Draw Completed')
```

(2) main

```python
if __name__ == '__main__':
    # Read Data
    tic=time.time()
    Data_Path =
'/home/lucas/Codes/GitHub/ML_Assignment1/ML_Assignment1/DataSet/a9a.txt'

Test_Path='/home/lucas/Codes/GitHub/ML_Assignment1/ML_Assignment1/DataSet/a9a.t'
    Data_Parameter, Data_Value = load_svmlight_file(Data_Path)
    Test_Parameter,Test_Value=load_svmlight_file(Test_Path)
    Test_Parameter=Test_Parameter.toarray()

Test_Parameter=np.hstack([Test_Parameter,np.zeros(shape=(Test_Parameter.shape[0],1))])
    Test_Value=Test_Value.reshape(Test_Value.shape[0],1)
    Data_Parameter = Data_Parameter.toarray()
    train_X, val_X, train_Y, val_Y = train_test_split(Data_Parameter,
Data_Value, test_size=0.3, random_state=1)
    t_row = train_X.shape[0]  # Row Size
    col = train_X.shape[1]  # Column Size
    v_row = val_X.shape[0]
    train_Y = train_Y.reshape(t_row, 1)
    val_Y = val_Y.reshape(v_row, 1)
    W = np.random.random(size=(col, 1))
    Parameter={'Train_X':train_X,
```

```
            'Train_Y':train_Y,
            'Val_X':val_X,
            'Val_Y':val_Y,
            'Test_X':Test_Parameter,
            'Test_Y':Test_Value,
            'Weights':W,
            'Learning_Rate':0.01,
            'Max_Loops':5000,
            'Epsilon':0.00000001,
            'threshold':0.4,
            'decoy_rate':0.9,
            'eps':0.00000001,
            'Beta1':0.9,
            'Beta2':0.999
            }
   SGD_VL,SGD_test_accuracy=SGD(Parameter)

Momentum_VL,Momentum_test_accuracy=Momentum(Paramete
r)
   NAG_VL,NAG_test_accuracy=NAG(Parameter)
   Adagrad_VL,Adagrad_test_accuracy=Adagrad(Parameter)
   AdaDelta_VL,AdaDelta_test_accuracy=AdaDelta(Parameter)
   Adam_VL,Adam_test_accuracy=Adam(Parameter)
   print('All Time Used:{:0.2f}s'.format(time.time()-tic))

   plt.plot(np.arange(0,Parameter['Max_Loops']-1,1),
SGD_VL[0:Parameter['Max_Loops']-1], label='SGD')
   plt.plot(np.arange(0,Parameter['Max_Loops']-1,1),
Momentum_VL[0:Parameter['Max_Loops']-1], label='Momentum')
   plt.plot(np.arange(0, Parameter['Max_Loops'] - 1, 1),
NAG_VL[0:Parameter['Max_Loops'] - 1], label='NAG')
   plt.plot(np.arange(0, Parameter['Max_Loops'] - 1, 1),
Adagrad_VL[0:Parameter['Max_Loops'] - 1], label='Adagrad')
   plt.plot(np.arange(0, Parameter['Max_Loops'] - 1, 1),
AdaDelta_VL[0:Parameter['Max_Loops'] - 1], label='AdaDelta')
   plt.plot(np.arange(0, Parameter['Max_Loops'] - 1, 1),
Adam_VL[0:Parameter['Max_Loops'] - 1], label='Adam')
   plt.xlabel('loops')
   plt.ylabel('loss')
   plt.title('Validation Loss')
   plt.legend()
   plt.show()
```

```
    plt.plot(np.arange(0,Parameter['Max_Loops']-1,1),
SGD_test_accuracy[0:Parameter['Max_Loops']-1], label='SGD')
    plt.plot(np.arange(0,Parameter['Max_Loops']-1,1),
Momentum_test_accuracy[0:Parameter['Max_Loops']-1],
label='Momentum')
    plt.plot(np.arange(0, Parameter['Max_Loops'] - 1, 1),
NAG_test_accuracy[0:Parameter['Max_Loops'] - 1], label='NAG')
    plt.plot(np.arange(0, Parameter['Max_Loops'] - 1, 1),
Adagrad_test_accuracy[0:Parameter['Max_Loops'] - 1],
label='Adagrad')
    plt.plot(np.arange(0, Parameter['Max_Loops'] - 1, 1),
AdaDelta_test_accuracy[0:Parameter['Max_Loops'] - 1],
label='AdaDelta')
    plt.plot(np.arange(0, Parameter['Max_Loops'] - 1, 1),
Adam_test_accuracy[0:Parameter['Max_Loops'] - 1], label='Adam')
    plt.xlabel('loops')
    plt.ylabel('loss')
    plt.title('Test Accuracy')
    plt.legend()
    plt.show()
```

4. **Linear Classification and Gradient Descent**

(1) **Function: loss**

```
def Loss(X,Y,W,b,m_lambda):
    loss=0.5 * m_lambda * W.transpose().dot(W)
    for i in range(X.shape[0]):
        Tensor = Y[i][0] * (W.transpose().dot(X[i]) + b)
        if Tensor < 1:
            loss=loss+1-Tensor
        else:
            loss=loss+0
    return loss
```

(3) **Function: compare**

```
def compare(X,Y,W,b,i):
    if Y[i][0]*(W.transpose().dot(X[i])+b)<1:
        return 1
    else:
        return 0
```

(4) **Function: Grad**

```
def Grad(X,Y,W,b,m_lambda):
    grad=m_lambda*W
    for i in range(X.shape[0]):
        grad=grad-(compare(X,Y,W,b,i)*Y[i]*X[i]).reshape(X.shape[1],1)
    return grad
```

(5) **Function: corrate_rate**

```
def corrate_rate(X,Y,W,b,threshold):
    count=0
    temp=Y*(X.dot(W)+b)
    for j in temp:
        if j>=0.02:
            count+=1
        else:
            continue
    rate=count/temp.shape[0]
    return rate
```

(6) **Function: Draw**

```
def Draw(loops,train_loss,validation_loss,train_accuracy,val_accuracy):
    print('Drawing...')
    #the loss
    plt.plot(np.arange(0,loops-1,1), train_loss[0:loops-1], label='Train Loss')
    plt.plot(np.arange(0,loops-1,1), validation_loss[0:loops-1], label='Validation Loss')
    plt.xlabel('loops')
    plt.ylabel('loss')
    plt.title('Loss')
    plt.legend()
    plt.show()

    #the accuracy
    plt.plot(np.arange(0,loops-1,1), train_accuracy[0:loops-1], label='Train Accuracy')
    plt.plot(np.arange(0,loops-1,1), val_accuracy[0:loops-1], label='Validation Accuracy')
    plt.xlabel('loops')
    plt.ylabel('Accuracy')
    plt.title('Accuracy')
    plt.legend()
    plt.show()
    print('Draw Completed')
```

G. Selection of validation

1. Logistic Regression and Gradient Descent

I use Cross-Validation as the method to validate the result, during the whole experiment, the size of my validation set is

30%.

5. **Linear Classification and Gradient Descent**

I use Cross-Validation as the method to validate the result, during the whole experiment, the size of my validation set is 25%.

H. The initialization method of model parameters:

In two experiments, we all initialize the parameters in the same way:

W: Randomly initialize it in range of 0 and 1

the others: initialize according to experience

I. The selected loss function and its derivatives:

1. **Logistic Regression and Gradient Descent**

(1) **Loss Function**

$$J(\mathbf{w}) = -\frac{1}{n}\left[\sum_{i=1}^{n} y_i \log h_{\mathbf{w}}(\mathbf{x}_i) + (1-y_i)\log\left(1-h_{\mathbf{w}}(\mathbf{x}_i)\right)\right]$$

(2) **Gradient**

$$\frac{\partial J(\mathbf{w})}{\partial \mathbf{w}} = \frac{1}{n}\sum_{i=1}^{n}\left(h_{\mathbf{w}}(\mathbf{x}_i) - y\right)\mathbf{x}_i$$

6. **Linear Classification and Gradient Descent**

(1) **Loss Function**

$$F(X) = \frac{W^2}{2} + C\sum_{i=1}^{N} max(0, 1 - y_i(W^T * X_i + b))$$

(7) **Gradient**

$$Gradient = \begin{cases} Gradient - Y_i * X_i, \wedge Y_i * \left(W^T * X_i + b\right) < 1 \\ Gradient, \wedge Y_i * \left(W^T * X_i + b\right) \geq 1 \end{cases}$$

J. Experimental results and curve:

1. **Logistic Regression and Gradient Descent**

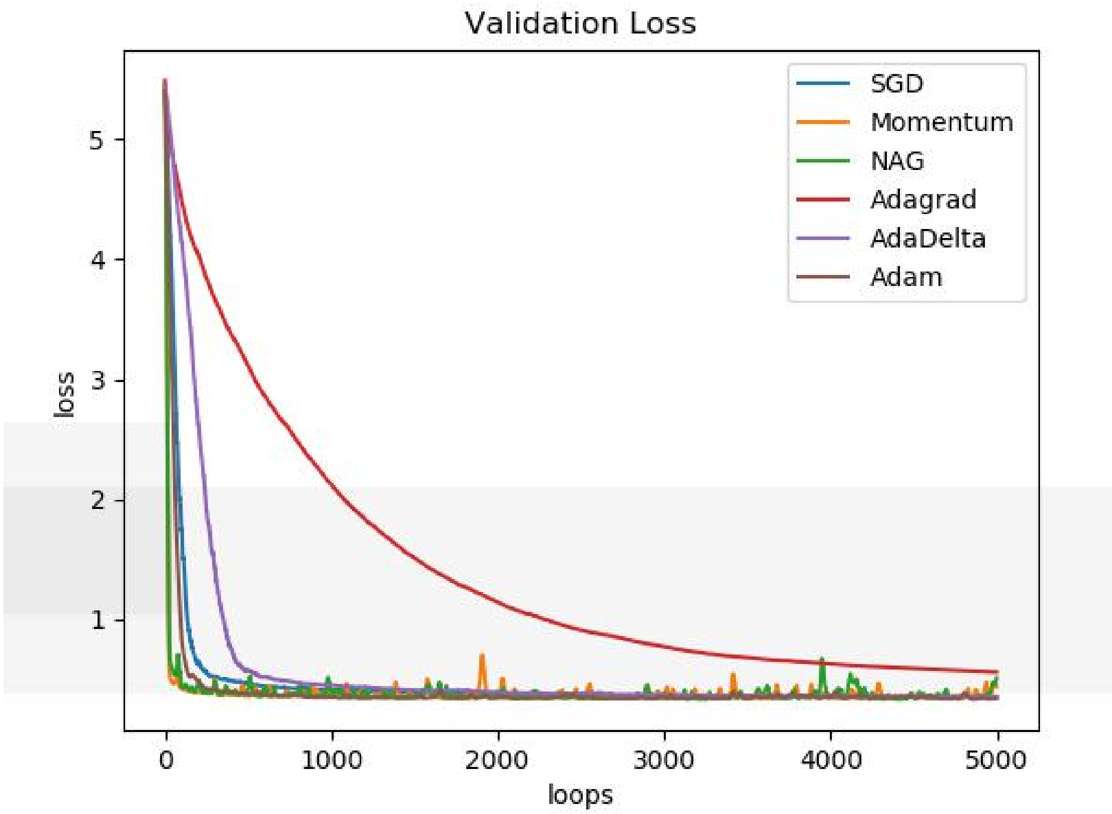
(1) **Hyper-parameter selection**

```
Parameter={'Train_X':train_X,
        'Train_Y':train_Y,
        'Val_X':val_X,
        'Val_Y':val_Y,
        'Test_X':Test_Parameter,
        'Test_Y':Test_Value,
        'Weights':W,
        'Learning_Rate':0.025,
        'Max_Loops':1500,
        'Epsilon':0.00000001,
        'threshold':0.4,
        'decoy_rate':0.9,
        'eps':0.00000001,
        'Beta1':0.9,
        'Beta2':0.999,
        'lambda': 0.01,  # regularize, C=1/lambda
        'b': 0.01
        }
```

(2) Assessment Results (based on selected validation)

Train loss is about 0.1 bigger than validation loss

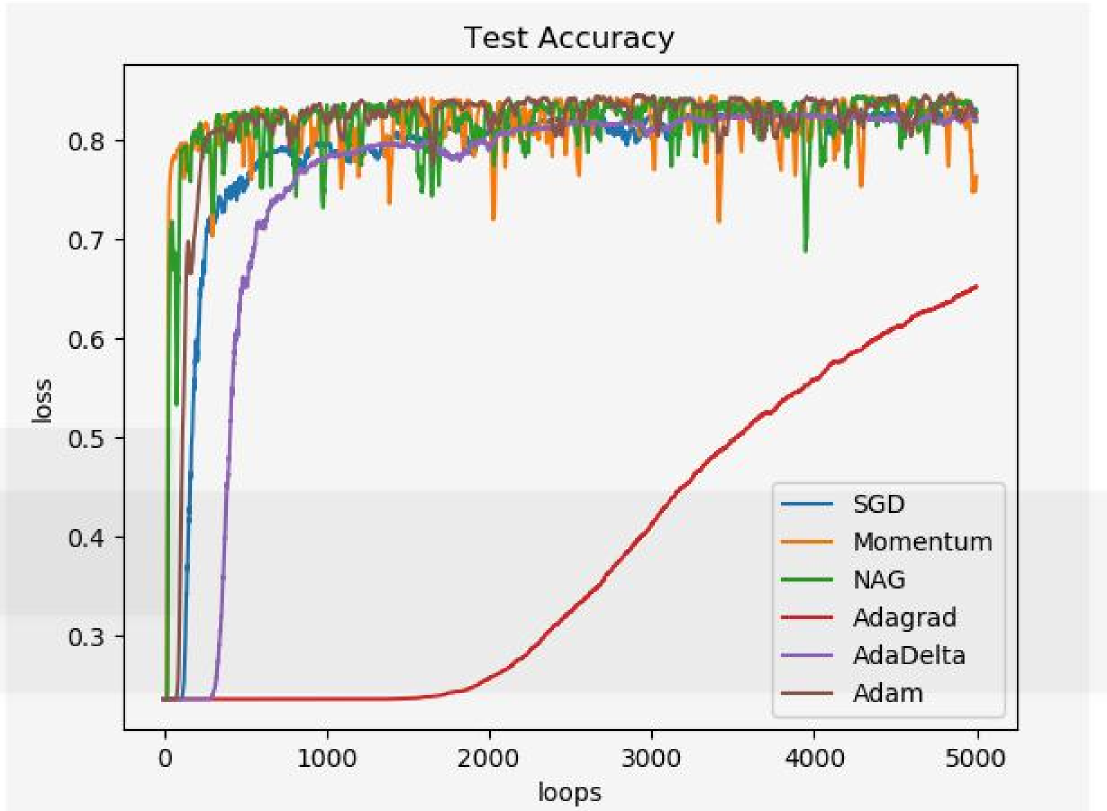
(3) Loss curve



7. Linear Classification and Stochastic Gradient Descent

(1) Hyper-parameter selection

```
Parameter={'Train_X':train_X,
    'Train_Y':train_Y,
    'Val_X':val_X,
    'Val_Y':val_Y,
    'Test_X':Test_Parameter,
    'Test_Y':Test_Value,
    'Weights':W,
    'Learning_Rate':0.025,
    'Max_Loops':1500,
    'Epsilon':0.00000001,
    'threshold':0.4,
    'decoy_rate':0.9,
    'eps':0.00000001,
    'Beta1':0.9,
    'Beta2':0.999,
    'lambda': 0.01,  # regularize, C=1/lambda
    'b': 0.01
    }
```



(2) Assessment Results (based on selected validation)

Train loss is about 0.15 bigger than validation loss, the accuracy in validation set will better than that in train set.

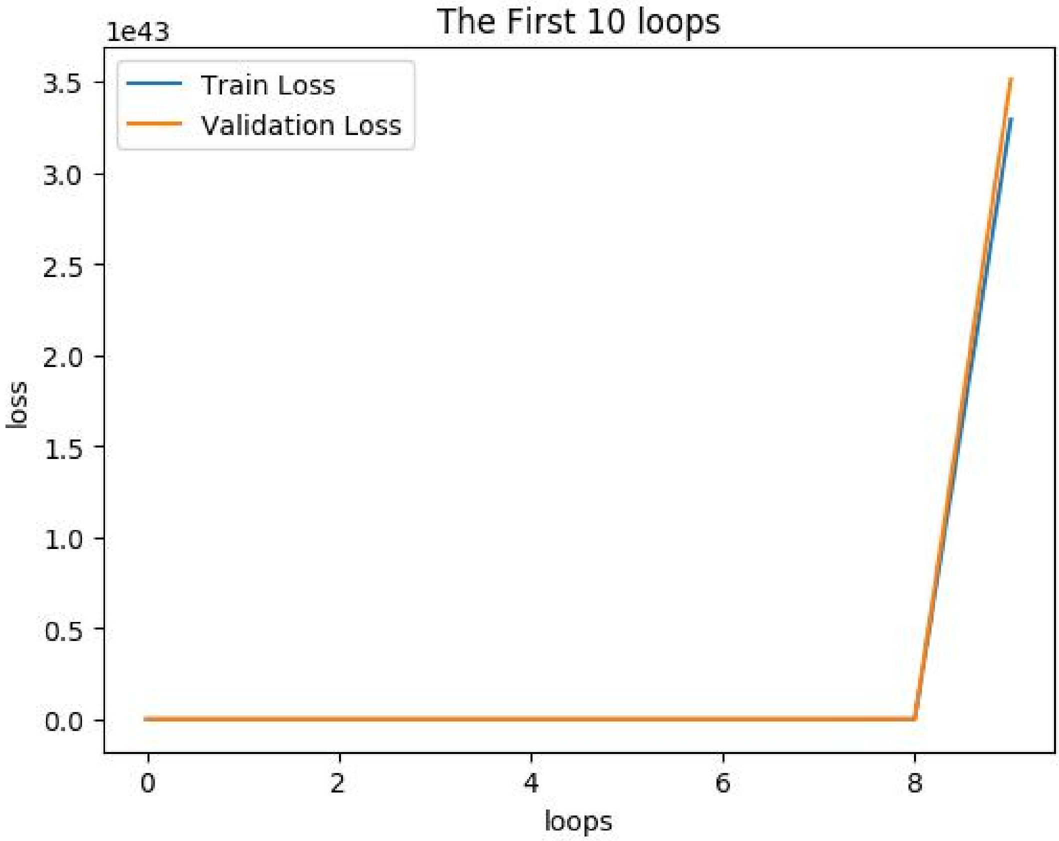
(3) **Predicted Results (Best Results)**

Loss_Train: [0.34371135] **Loss_Validation:** [0.2769692]
Accuracy: Train: 0.8588007736943907, **Validation:** 0.8728323699421965

K. Results analysis

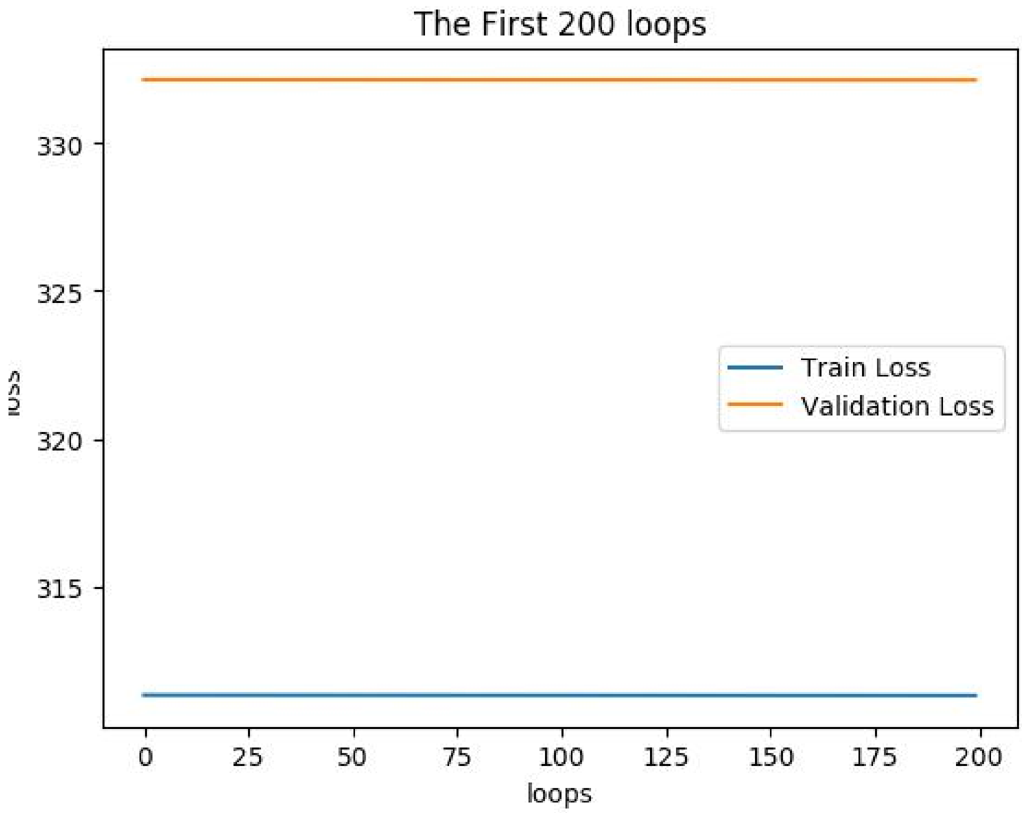
1. Logistic Regression and Gradient Descent

(1) 'Weights': 0.085, others the same



The curve won't converge, because the learning rate is too big, it will always miss the local/global minimum and go away from it.

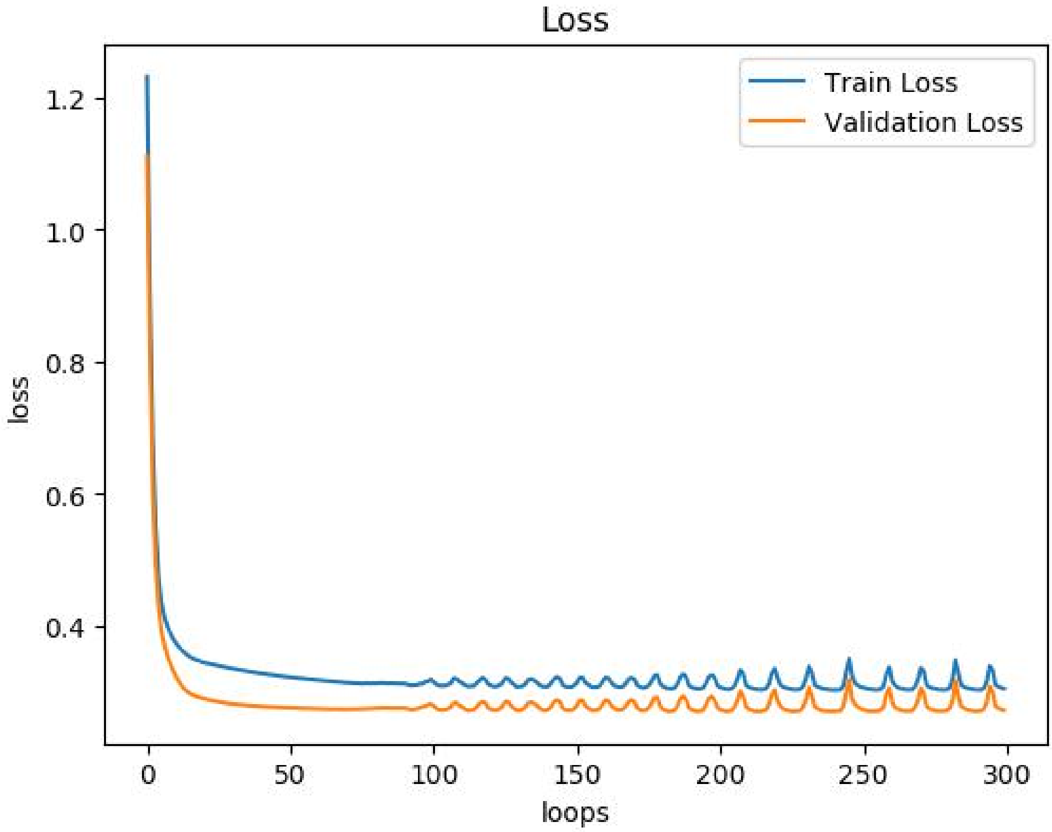
(8) 'Weights': 0.000000000085, others the same



The curve won't converge either, because W is too small that it will take a very long time period.

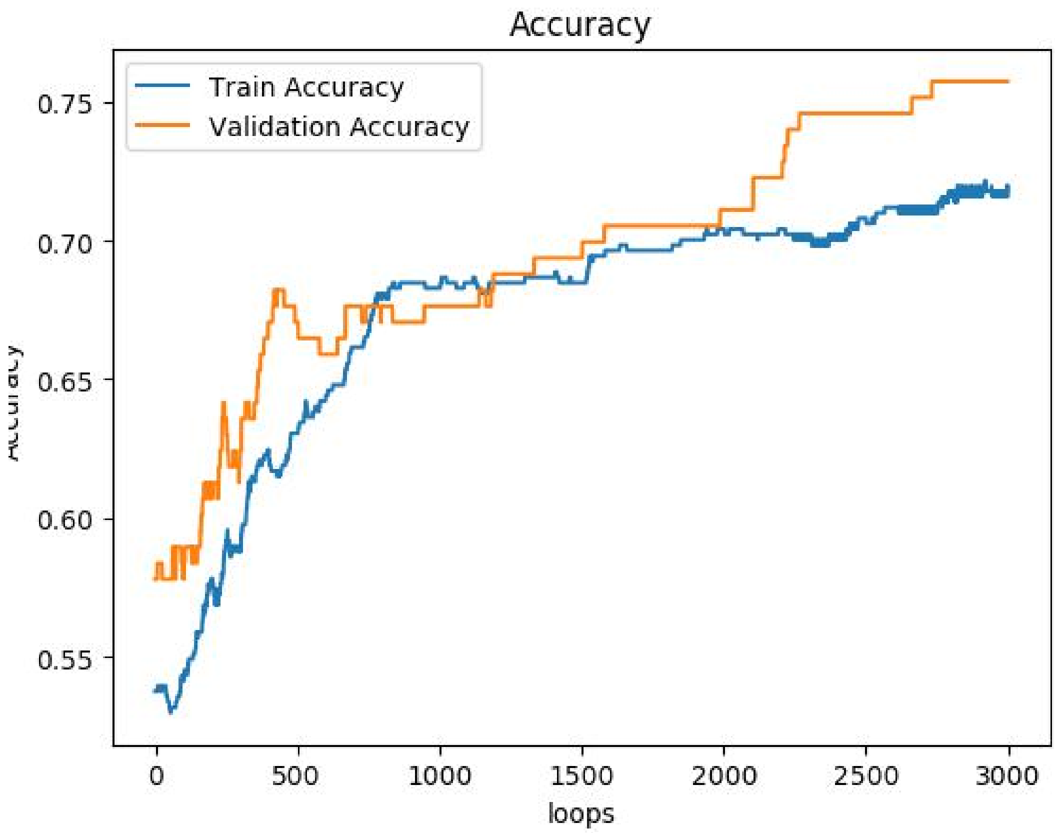
8. Linear Classification and Stochastic Gradient Descent

(1) 'learning_rate': 0.00085, others the same



We can see clearly that at the last, our curve welter, I think the reason is the learning rate is a little big so it will go from a point close to the minimum to the symmetry point and then go back, it's rather interesting.

(9) 'threshold':1, others the same



We can find the accuracy is much less than the curve of 'threshold':0, I think this is due to there are little outliers in the dataset.

L. Similarities and differences

I think both problem are trying to find a loss function and using some method to make it smaller and smaller. In this way, we can use gradient decent in the two problem. However, linear regression focus on finding a function to solve the problem with successive values while classification focus on problem with discrete value and make classification. The loss they used are also different.

M. Summary

I do believe we can overcome all the difficulties on our way learning machine learning, we should learn more from teachers, papers, books, and even from the web. We should also practice more, we can join kaggle or other competitions in the AI field. I think with the help of computer science, we will have a brighter future and I hope I can be one of the scientists and make something for the world.