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The Experiment Report of *Machine Learning*

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Subject Software Engineering

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

2. Time: 2017.12.9

3. Reporter: 黄黎龙

4. Purposes:

a. Further understand of linear regression and gradient descent.

b. Conduct some experiments under small scale dataset.

c. Realize the process of optimization and adjusting parameters.

5. Data sets and data analysis:

Linear Regression uses Housing in LIBSVM Data, including 506 samples and each sample has 13 features. Then, it's divided into training set and validation set.

Linear classification uses australian in LIBSVM Data, including 690 samples and each sample has 14 features. Then, it's divided into training set and validation set.

6. Experimental steps:

The experimental code and drawing are completed on jupyter.

Linear Regression and Gradient Descent

a. Use load_svmlight_file function in sklearn library to load the experiment data.

b. Divide dataset into training set and validation set using train_test_split function.

c. Initialize linear model parameters. Set all parameter into one.

d. Choose loss function and derivation.

e. Calculate gradient G toward loss function from all samples.

f. Denote the opposite direction of gradient G as D.

g. Update model: .$W_t = W_{t-1} + \eta D$, η is learning rate, set as 0.1 .

h. Get the loss L_{train} under the training set and $L_{validation}$ by validating under validation set.

i. Repeat step e to h for several times, and drawing graph of L_{train} as well as $L_{validation}$ with the number of iterations.

Linear Classification and Gradient Descent

a. Use load_svmlight_file function in sklearn library to load the experiment data.

b. Divide dataset into training set and validation set using train_test_split function.

c. Initialize SVM model parameters. Set all parameter into one.

d. Choose loss function and derivation.

e. Calculate gradient G toward loss function from all samples.

f. Denote the opposite direction of gradient G as D.

g. Update model: $W_t = W_{t-1} + \eta D$, η is learning rate, set as 0.1 .

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

Get the loss L_{train} under the training set and $L_{validation}$ by validating under validation set.

i. Repeat step e to h for several times, and drawing graph of L_{train} as well as $L_{validation}$ with the number of iterations.

7. Code:

Linear Regression:

```
def LR(delta,updatenum,X_train,y_train,X_test,y_test):
    W = np.zeros((X.shape[1],1))
    print(W)
    b = 0
    trainCost = []
    validationCost = []
    for i in range(updatenum):
        trainCost.append(np.sum(np.square(X_train.dot(W) + b - y_train))/
(2*X_train.shape[0]))
        validationCost.append(np.sum(np.square(X_test.dot(W) + b - y_test))/
(2*X_test.shape[0]))
        GW = X_train.T.dot((X_train.dot(W) + b - y_train)) / X_train.shape[0]
        Gb = np.sum((X_train.dot(W) + b - y_train)) / X_train.shape[0]
        DW = -GW
        Db = -Gb
        W = W + delta*DW
        b = b + delta*Db
    return trainCost,validationCost
```

Linear Classification:

```
def SVM(delta,iternum,X_train,y_train,X_test,y_test,threshold):

    #Initialize linear model parameters. Set all parameter into one
    W = np.ones((X.shape[1],1))
    b = 1
    C = 10

    Ctrain = []
    Cvalidation = []
    Accuracy = []
    for i in range(iternum):
        trainCount = 0
```

```
validationCount = 0
GW = 0
Gb = 0
AccurateCount = 0
for j in range(X_train.shape[0]):
    if (1-y_train[j]*(X_train[j].dot(W)+b)) > 0 :
        trainCount += C*(1-y_train[j]*(X_train[j].dot(W)+b))
        Gb += C*-1*y_train[j]
        GW += C*-1*y_train[j]*X_train[j]

for j in range(X_test.shape[0]):
    if (X_test[j].dot(W)+b >= threshold) and y_test[j] == 1 :
        AccurateCount +=1
    if (X_test[j].dot(W)+b < threshold) and y_test[j] == -1 :
        AccurateCount +=1
    if (1-y_test[j]*(X_test[j].dot(W)+b)) > 0 :
        validationCount += C*(1-y_test[j]*(X_test[j].dot(W)+b))

Ctrain.append(np.sum(trainCount/X_train.shape[0] + 0.5*np.sum(W.T.dot(W))))
Cvalidation.append(np.sum(validationCount/X_test.shape[0] + 0.5*np.sum(W.T.dot(W))))
Accuracy.append(AccurateCount/X_test.shape[0])
GW = GW.T/X_train.shape[0] + W
Gb = Gb/X_train.shape[0]
DW = -GW
Db = -Gb
W = W + delta*DW
b = b + delta*Db
return Ctrain,Cvalidation,Accuracy
```

8. Selection of validation (hold-out, cross-validation, k-folds cross-validation, etc.):

Linear Regression: hold-out

Linear Classification: hold-out

9. The initialization method of model parameters:

Linear Regression: set both parameters as zero.

Linear Classification: set both parameters as zero.

10. The selected loss function and its derivatives:

Linear Regression:

$$LossFunction = \frac{1}{2m}\sum_{i=1}^{m}(X_i * A + b - y_i)^2$$

$$G_A = \frac{1}{m}\sum_{i=1}^{m}(X_i * A + b - y_i) * X_i$$

$$G_b = \frac{1}{m}\sum_{i=1}^{m}(X_i * A + b - y_i)$$

Linear Classification:

SVM

$$LossFunction = \frac{\|w\|^2}{2} + \frac{C}{m}\sum_{i=1}^{m} max(0, 1 - y_i(W^T x_i + b)$$

$$G_W = W + \frac{C}{m}\sum_{i=1}^{m} -y_i * x_i \text{ ,if } 1 - y_i(W^T x_i + b) > 0$$

$$G_b = \frac{C}{m}\sum_{i=1}^{m} -y_i \text{ ,if } 1 - y_i(W^T x_i + b) > 0$$

11. Experimental results and curve:

Hyper-parameter selection (η , epoch, etc.):

Linear Regression:

η = 0.1, epoch = 100

Linear Classification:

η = 0.01, epoch = 100

Assessment Results (based on selected validation):

Linear Regression: train loss may be smaller than validation loss.

Linear Classification: train loss may be smaller than validation loss.

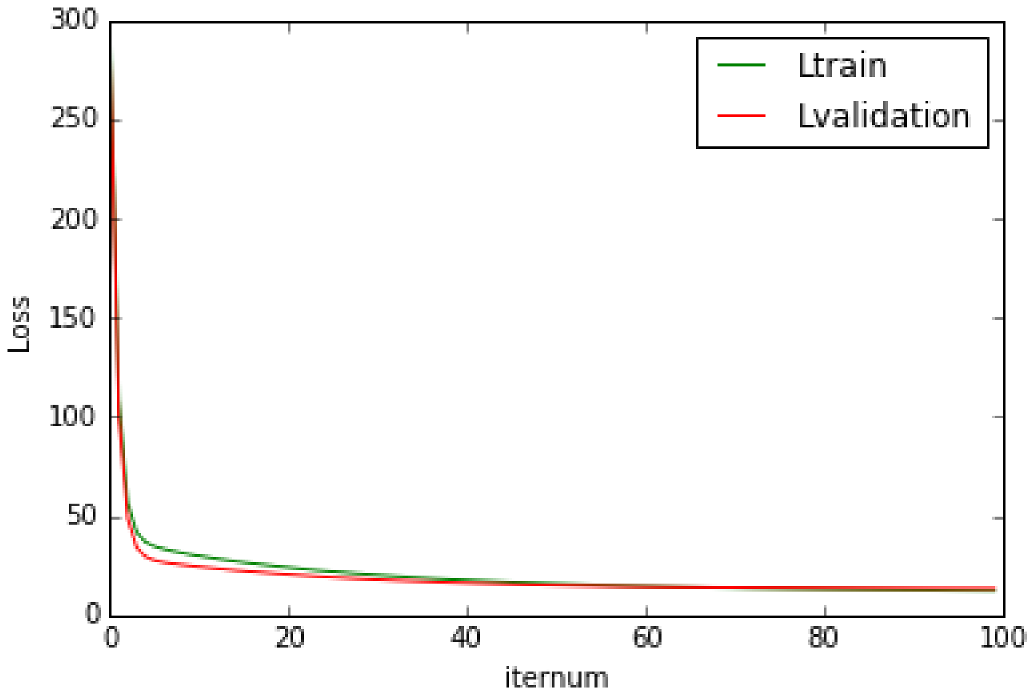
Predicted Results (Best Results):

Linear Regression: validation loss can be smaller than 20.

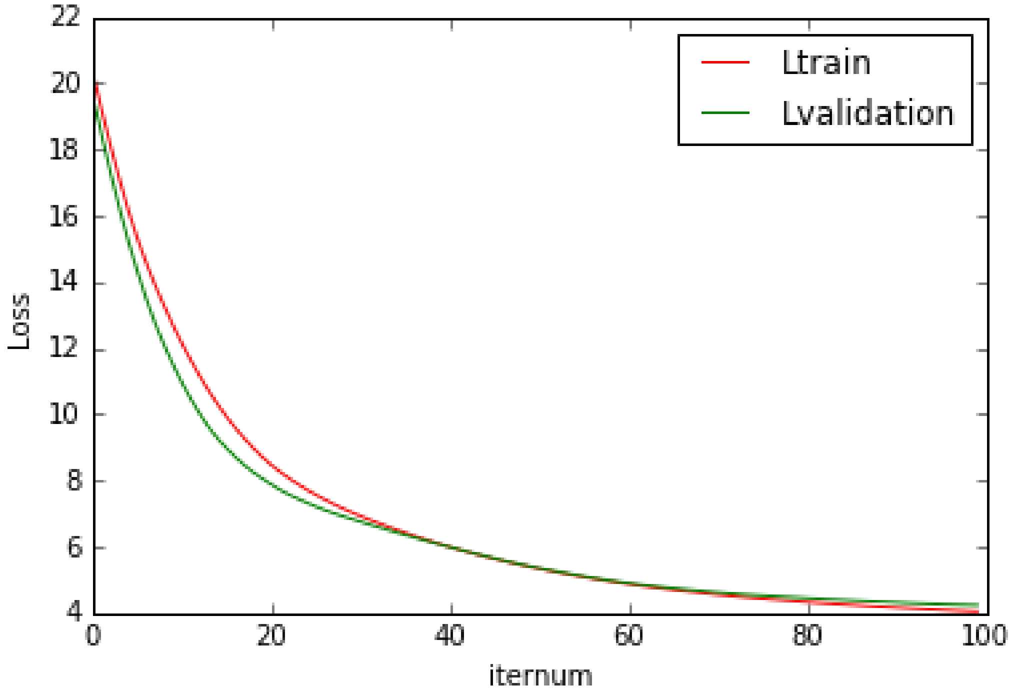
Linear Classification: validation loss can be smaller than 4.

Loss curve:

Linear Regression:



Linear Classification:



12. Results analysis:

both the train loss and the validation loss are becoming smaller and smaller,but none of them can reach zero because the data isn't mapped on a line or optimization is not enough. Most of the time the train loss would be smaller than the validation loss, because the training is based on the training data, and it will make sure the model suits the training data well.

13. Similarities and differences between linear regression and linear classification:

Similarities:At the heart of both linear regression and linear classification are linear regression algorithms.

Differences: The linear regression's mapping space is a real number field, and the linear classification is -1 and 1

14. Summary:

Through this experiment, I initially learned and mastered Linear Regression and Linear Classification. Know the role of machine learning in the classification problem optimization, in the future I will use it more to solve the problem.