

# South China University of Technology

# The Experiment Report of Machine Learning

# SCHOOL: SCHOOL OF SOFTWARE ENGINEERING

## **SUBJECT: SOFTWARE ENGINEERING**

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December 9, 2017

# Linear Regression, Linear Classification and Gradient Descent

#### I. INTRODUCTION

Motivation of Experiment

- 1. Compare and understand the difference between gradient descent and stochastic gradient descent.
- 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.

### II. METHODS AND THEORY

Logistic Regression Loss functon:

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

Gradient:

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

Linear Classification Loss function:

$$\frac{\|\mathbf{w}\|^2}{2} + \frac{C}{n} \sum_{i=1}^{n} \max(0, 1 - y_i(\mathbf{w}^{\top} \mathbf{x}_i + b))$$

Gradient:

$$\nabla f(\beta) = \begin{cases} \mathbf{w}^{\top} - C\mathbf{y}^{\top}\mathbf{X} & 1 - y_i(\mathbf{w}^{\top}x_i + b) >= 0\\ \mathbf{w}^{\top} & 1 - y_i(\mathbf{w}^{\top}x_i + b) < 0 \end{cases}$$

optimized methods

NAG:

$$\mathbf{g}_t \leftarrow \nabla J(\boldsymbol{\theta}_{t-1} - \gamma \mathbf{v}_{t-1})$$

$$\mathbf{v}_t \leftarrow \gamma \mathbf{v}_{t-1} + \eta \mathbf{g}_t$$

$$\theta_t \leftarrow \theta_{t-1} - \mathbf{v}_t$$

RMSProp:

$$\mathbf{g}_t \leftarrow \nabla J(\boldsymbol{\theta}_{t-1})$$

$$G_t \leftarrow \gamma G_t + (1 - \gamma) \mathbf{g}_t \odot \mathbf{g}_t$$

$$\boldsymbol{\theta}_t \leftarrow \boldsymbol{\theta}_{t-1} - \frac{\eta}{\sqrt{G_t + \epsilon}} \odot \mathbf{g}_t$$

AdaDelta:

$$\mathbf{g}_t \leftarrow \nabla J(\boldsymbol{\theta}_{t-1})$$

$$G_t \leftarrow \gamma G_t + (1 - \gamma) \mathbf{g}_t \odot \mathbf{g}_t$$

$$\Delta \boldsymbol{\theta}_t \leftarrow -\frac{\sqrt{\Delta_{t-1} + \epsilon}}{\sqrt{G_t + \epsilon}} \odot \mathbf{g}_t$$

$$\theta_t \leftarrow \theta_{t-1} + \Delta \theta_t$$

$$\Delta_t \leftarrow \gamma \Delta_{t-1} + (1 - \gamma) \Delta \theta_t \odot \Delta \theta_t$$

Adam:

$$\mathbf{g}_t \leftarrow \nabla J(\boldsymbol{\theta}_{t-1})$$

$$\mathbf{m}_t \leftarrow \beta_1 \mathbf{m}_{t-1} + (1 - \beta_1) \mathbf{g}_t$$

$$G_t \leftarrow \gamma G_t + (1 - \gamma) \mathbf{g}_t \odot \mathbf{g}_t$$

$$\alpha \leftarrow \eta \frac{\sqrt{1 - \gamma^t}}{1 - \beta^t}$$

$$\boldsymbol{\theta}_t \leftarrow \boldsymbol{\theta}_{t-1} - \alpha \frac{\mathbf{m}_t}{\sqrt{G_t + \epsilon}}$$

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#### 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

#### Parameter selection

NGA:w=0, V=0, learning\_rate=0.01, y=0.9

RMSProp: w=0, G=0, learning\_rate=0.001, y=0.9

AdaDelta: w=0, G=0, delta\_t=0, y=0.95

Adam: w=0, b=0.9, m=0, G=0, learning\_rate=0.001, y=0.999

#### C.Step

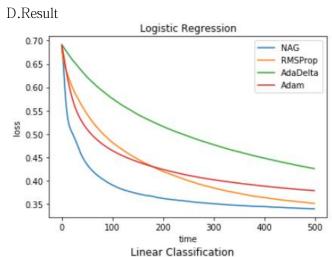
#### Logistic Regression and Stochastic Gradient Descent

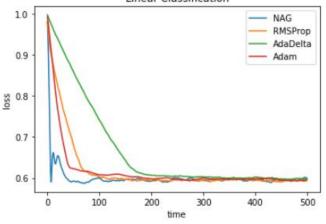
- 1. Load the training set and validation set.
- 2. Initalize logistic regression model parameters, you can consider initalizing zeros, random numbers or normal distribution.
- 3. Select the loss function and calculate its derivation, find more detail in PPT.
- 4. Calculate gradient G toward loss function 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<sub>NAG</sub>, L<sub>RMSProp</sub>, L<sub>AdaDelta</sub> and L<sub>Adam</sub>.
- 7. Repeate 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.

#### Linear Classification and Stochastic Gradient Descent

- 1. Load the training set and validation set.
- 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 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<sub>NAG</sub>, L<sub>RMSProp</sub>, L<sub>AdaDelta</sub> and L<sub>Adam</sub>.
- 7. Repeate 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.





#### IV. CONCLUSION

Through the experiment I deeply understanding the difference between logistic regression and linear classification, and how do they work. What's more, I learn the advantage and disadvantage about NAG, RMSProp, Adadelta and Adam. I think I will practice more and study.