



Machine Learning: Chenhao Tan University of Colorado Boulder LECTURE 10

Slides adapted from Jordan Boyd-Graber, Chris Ketelsen

# Logistics

• HW2 available on Github, due in 7 days

# Learning objectives

Understand stochastic gradient descent

**Outline** 

Stochastic Gradient Descent

### **Outline**

Stochastic Gradient Descent

### Review of Wednesday's lecture

# Objective function:

$$\mathcal{L} = -\sum_{i} \log P(y^{(i)} \mid \boldsymbol{x}^{(i)}, \beta)) + \frac{1}{2} \lambda \sum_{j} \beta_{j}^{2}$$

$$= \sum_{i} -y^{(i)} \left( \beta_{0} + \sum_{j} \beta_{i} \boldsymbol{x}_{j}^{(i)} \right) + \log \left[ 1 + \exp \left( \beta_{0} + \sum_{j} \beta_{i} \boldsymbol{x}_{j}^{(i)} \right) \right] + \frac{1}{2} \lambda \sum_{j} \beta_{j}^{2}$$

Gradient descent:

$$\beta_j^{l+1} = \beta_j^l - \eta \frac{\partial \mathcal{L}}{\partial \beta_j}$$

Gradient:

$$\frac{\partial \mathcal{L}}{\partial \beta_j} = \sum_{i} [-(y_i - \pi_i)x_j] + \lambda \beta_j$$

# **Approximating the Gradient**

- Our datasets are big (to fit into memory)
- ...or data are changing / streaming

### **Approximating the Gradient**

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- ...or data are changing / streaming
- Hard to compute true gradient

$$\mathscr{L}(\beta) \equiv \mathbb{E}_{\mathbf{x}} \left[ \nabla \mathscr{L}(\beta, \mathbf{x}) \right] \tag{1}$$

Average over all observations

### **Approximating the Gradient**

- Our datasets are big (to fit into memory)
- ...or data are changing / streaming
- Hard to compute true gradient

$$\mathscr{L}(\beta) \equiv \mathbb{E}_{\mathbf{x}} \left[ \nabla \mathscr{L}(\beta, \mathbf{x}) \right] \tag{1}$$

- Average over all observations
- What if we compute an update just from one observation?

# **Getting to Union Station**

Pretend it's a pre-smartphone world and you want to get to Union Station





# **Stochastic Gradient for Regularized Regression**

$$\mathcal{L} = -\log p(y \mid \mathbf{x}; \beta) + \frac{1}{2} \lambda \sum_{i} \beta_{i}^{2}$$
 (2)

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# Stochastic Gradient for Regularized Regression

$$\mathscr{L} = -\log p(y \mid \mathbf{x}; \beta) + \frac{1}{2} \lambda \sum_{j} \beta_{j}^{2}$$
 (2)

Taking the derivative (with respect to example  $x_i$ )

$$\frac{\partial \mathcal{L}}{\partial \beta_j} = -(y_i - \pi_i)x_{ij} + \lambda \beta_j \tag{3}$$

### **Stochastic Gradient for Logistic Regression**

Given a **single observation**  $x_i$  chosen at random from the dataset,

$$\beta_j \leftarrow \beta_j' - \eta \left( \lambda \beta_j' - x_{ij} \left[ y_i - \pi_i \right] \right) \tag{4}$$

$$\beta_j = \beta_j + \eta(y_i - \pi_i)x_{ij}$$
  
$$\vec{\beta} = \langle \beta_{bias} = 0, \beta_A = 0, \beta_B = 0, \beta_C = 0, \beta_D = 0 \rangle$$

$$y_1 = 1$$

AAAABBBC

(Assume step size  $\eta = 1.0$ .)

$$y_2 = 0$$

BCCCDDDD

You first see the positive example. First, compute  $\pi_1$ 

$$\beta_j = \beta_j + \eta(y_i - \pi_i)x_{ij}$$
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$$\pi_1 = \Pr(y_1 = 1 \mid x_1) = \frac{\exp \beta^T x_i}{1 + \exp \beta^T x_i} =$$

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A A A A B B B C

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$$\beta_j = \beta_j + \eta(y_i - \pi_i)x_{ij}$$
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 $\pi_1 = 0.5$  What's the update for  $\beta_{bias}$ ?

$$\beta_j = \beta_j + \eta(y_i - \pi_i)x_{ij}$$
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What's the update for  $\beta_{bias}$ ?

$$\beta_{bias} = \beta'_{bias} + \eta \cdot (y_1 - \pi_1) \cdot x_{1,bias} = 0.0 + 1.0 \cdot (1.0 - 0.5) \cdot 1.0$$

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$$\beta_j = \beta_j + \eta(y_i - \pi_i)x_{ij}$$
  
 $\vec{\beta} = \langle .5, 2, 1.5, 0.5, 0 \rangle$ 

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Now you see the negative example. What's  $\pi_2$ ?

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$$\pi_2 = \Pr(y_2 = 1 \mid \vec{x_2}) = \frac{\exp \beta^T x_i}{1 + \exp \beta^T x_i} = \frac{\exp \{.5 + 1.5 + 1.5 + 0\}}{\exp \{.5 + 1.5 + 1.5 + 0\} + 1} =$$

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$$\beta_C = \beta_C' + \eta \cdot (y_2 - \pi_2) \cdot x_{2,C} = 0.5 + 1.0 \cdot (0.0 - 0.97) \cdot 3.0 = -2.41$$

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 =-3.8

#### **Algorithm**

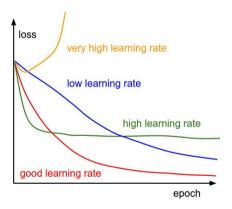
- 1. Initialize a vector  $\beta$  to be all zeros
- 2. For t = 1, ..., T
  - For each example  $x_i, y_i$  and feature j:
    - Compute  $\pi_i \equiv \Pr(y_i = 1 \mid \mathbf{x}_i)$
    - Set  $\beta_j = \beta'_j \eta(\lambda \beta'_j (y_i \pi_i)x_i)$
- 3. Output the parameters  $\beta_1, \ldots, \beta_d$ .

#### **Algorithm**

- 1. Initialize a vector  $\beta$  to be all zeros
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- 3. Output the parameters  $\beta_1, \ldots, \beta_d$ .

How to decide  $\eta$ ?

# **Choosing learning rate**



http://cs231n.github.io/neural-networks-3/

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#### Learning rate decay

- Decay after each epoch (e.g.,  $\frac{\eta_0}{t^2}$ ,  $\eta_0 e^{-kt}$ )
- Decay after each example (e.g.,  $\frac{\eta_0}{1+kn}$ )

Decay schedule can be seen as a hyperparameter too.

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Decay schedule can be seen as a hyperparameter too.

# Advanced stochastic gradient descent:

http://ruder.io/optimizing-gradient-descent/

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