

# DS-GA 1008 - Deep Learning, Spring 2016

## Assignment 3

**This is an individual assignment.**

**Due: Tuesday, April 12th, 2016 at 7:00 pm**

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### 1. General Questions

- (a) Consider the case where no non-linear activation functions are applied between modules, explain the approach to simplify (distill) the whole network into one module?
- (b) What is the difference between the dictionary used in sparse coding and the counterpart in autoencoders?

### 2. Softmax regression gradient calculation

Consider a simple Softmax regression model,

$$\hat{\mathbf{y}} = \sigma(\mathbf{W}\mathbf{x} + \mathbf{b})$$

$$\mathbf{x} \in \mathbb{R}^d, \mathbf{W} \in \mathbb{R}^{k \times d}, \mathbf{b} \in \mathbb{R}^k$$

where  $d$  is the input dimension,  $k$  is the number of classes,  $\sigma$  is the softmax function:

$$\sigma(\mathbf{a})_i = \frac{\exp(a_i)}{\sum_j \exp(a_j)}$$

- (a) Given the cross-entropy loss

$$l(\mathbf{y}, \hat{\mathbf{y}}) = - \sum_i y_i \log \hat{y}_i$$

$\mathbf{y}$  is the one-hot vector representing true labels  $([0, 0, \dots, 1, 0, 0, \dots]^T$  with the 1 corresponding to the true label), **derive  $\frac{\partial l}{\partial W_{i,j}}$** . (You can use your results from Assignment 1)

- (b) What happens to the loss function and the gradients when  $y_{c_1} = 1, \hat{y}_{c_2} = 1, c_1 \neq c_2$ ? Why there is no need to worry about this situation?

### 3. Chain rule

We have the following function

$$f(x, y) = \frac{x^2 + \sigma(y)}{3x + y - \sigma(x)}$$

where  $\sigma$  is the sigmoid function.

- (a) Without explicitly deriving the formula for  $\frac{\partial f}{\partial x}$  and  $\frac{\partial f}{\partial y}$ , describe how you would calculate the gradients using chain rule.
- (b) Evaluate the gradients at  $x = 1, y = 0$  using your approach.

### 4. Variants of pooling

- (a) List three different kinds of pooling, and their corresponding module implemented in torch.
- (b) Write down the mathematical forms of these three pooling modules.
- (c) Pick one of the pooling listed and describe the reason for incorporating it into a deep learning system.

### 5. Convolution

Table 1 depicts two matrices. One of them (5x5 one) represents an image. The second (3x3 matrix) represents a convolution kernel. (Consider the bias term to be zero)

- (a) How many values will be generated if we forward propagate the image over the given convolution kernel?
- (b) Calculate these values.
- (c) Suppose the gradient backpropagated from the layers above this layer is a 3x3 matrix of all 1s. Write the value of the gradient (w.r.t. input) backpropagated out of this layer.

4	5	2	2	1
3	3	2	2	4
4	3	4	1	1
5	1	4	1	2
5	1	3	1	4

4	3	3
5	5	5
2	4	3

Table 1: Image Matrix (5x5) and a convolution filter (3x3)

### 6. Optimization

- (a) Write down the mathematical formula for the reconstruction loss of an autoencoder.
- (b) Write down the mathematical formula for the gradient of the loss with respect to the parameters.

- (c) Write down the gradient descent step for this reconstruction loss.
- (d) Write down this step with a momentum term.

## 7. Top-k error

ImageNet uses top-5 and top-1 errors to evaluate classification performances. Define top-k error. Why do you think ImageNet uses both top-5 and top-1 errors?

## 8. t-SNE

- (a) What is the crowding problem and how does t-SNE alleviate it? Give details.
- (b) The cost function of symmetric SNE is given by:

$$C = KL(P||Q) = \sum_i \sum_j p_{ij} \log \frac{p_{ij}}{q_{ij}}$$

where:

$$q_{ij} = \frac{\exp(-\|y_i - y_j\|^2)}{\sum_{k \neq l} \exp(-\|y_k - y_l\|^2)}$$

and:

$$p_{ij} = \frac{\exp(-\|x_i - x_j\|^2/2\sigma^2)}{\sum_{k \neq l} \exp(-\|x_k - x_l\|^2/2\sigma^2)}.$$

Derive  $\frac{\partial C}{\partial y_i}$ .

## 9. Proximal gradient descent

- (a) Proximal operator is defined as

$$\text{prox}_{h,t}(\mathbf{x}) = \underset{\mathbf{z}}{\text{argmin}} \frac{1}{2} \|\mathbf{z} - \mathbf{x}\|_2^2 + th(\mathbf{z})$$

Prove that when  $h(\mathbf{z}) = \|\mathbf{z}\|_1$ , the solution is the soft-thresholding function  $S_t(\mathbf{x}) = (|\mathbf{x}| - t\mathbf{1})_+ \odot \text{sign}(\mathbf{x})$ . (operations are all element-wise)

- (b) Recall the optimization problem we discussed with function  $f(x)$

$$f(x) = g(x) + h(x)$$

$$g(x) : \text{convex, differentiable}$$

$$h(x) : \text{convex, simple}$$

Proximal gradient descent uses the following update rule:

$$x_{k+1} = \text{prox}_{h,\alpha_k}(x_k - \alpha_k \nabla g(x_k))$$

Show that ISTA is one example of proximal gradient descent methods.

- (c) Given  $u = \text{prox}_{h,t}(x)$ , show

$$\frac{x - u}{t} \in \partial h(u)$$

where  $\partial h(u)$  is the subdifferential of function  $h$  evaluated at  $u$ .

(d) The update rule for proximal gradient descent method can be reformulated as

$$x_{k+1} = x_k - \alpha_k G_{\alpha_k}(x_k)$$

$$G_{\alpha_k}(x_k) = \frac{x_k - \text{prox}_{h, \alpha_k}(x_k - \alpha_k \nabla g(x_k))}{\alpha_k}$$

Show that

$$G_{\alpha_k}(x_k) - \nabla g(x_k) \in \partial h(x_{k+1})$$

## Submission

Send your submission to your corresponding TA by the deadline. Please use the following title for your email.

[DS-GA-1008 YOUR\_NAME] Submission A3