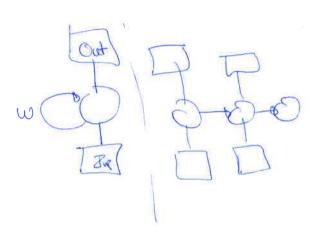
CS-E4890 DEEP LEARNING exam 24.10.2018

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Allowed equipment: pens, pencils, erasers, a non-programmable calculator

Question 1 [max. 9 points]: Explain the following concepts briefly but informatively (each with 30–50 words, with a mathematical definition and/or with an illustration):

- (i) activation function
- (ii) bias-variance tradeoff
- (iii) hyperparameters
- (iv) learning rate
- (v) recurrent neural networks
- (vi) stochastic gradient descent
- (vii) stochastic hidden unit
- (viii) universal approximation theory
- (ix) variational autoencoder



Question 2 [max. 3 points]:

Explain briefly why the selection of initial parameter values of a deep neural network is important. What are the common strategies for the parameter initialization?

Question 3 [max. 6 points]:

Explain verbally the principle and the motivation of the following three regularization methods. Also, enhance your explanation with mathematical expressions and/or graphical illustrations.

- (i) weight decay
- (ii) dropout
- (iii) early stopping

Question 4 [max. 6 points]:

Assume a multilayer perceptron with two input layer units x_1 and x_2 , one hidden layer with two units h_1 and h_2 , and an output layer with one unit \hat{y} , with the activation (and the parameters) of each unit being scalar-valued.

Furthermore, let $w_{i,j}^{(1)}$ denote the connection weight between the units x_i and h_j , $w_j^{(2)}$ the connection weight between the units h_j and \hat{y} , $b_j^{(1)}$ the bias of the unit h_j , and $b^{(2)}$ the bias of the unit \hat{y} . The activation function in the hidden units is the logistic sigmoid

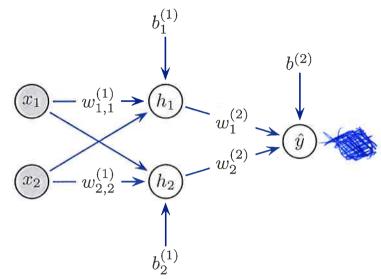
$$\sigma(z) = \frac{1}{1 + e^{-z}} \; ,$$

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and the activation function in the output unit is the linear function.



A graphical illustration of the very simple feedforward neural network:



Finally, the training cost function applied to the network output \hat{y} assuming target y is

$$J\left(x_1, x_2, y; \{w_{i,j}^{(1)}\}_{i,j=1}^2, \{b_j^{(1)}\}_{j=1}^2, \{w_j^{(2)}\}_{j=1}^2, b^{(2)}\right) = \frac{1}{2}(\hat{y} - y)^2.$$

Derive the analytical expressions of the following:

- (i) activations of the units h_1 , h_2 , and \hat{y} (in forward propagation)
- (ii) partial derivatives of the cost function with respect to the parameters $w_2^{(2)}$ and $w_{2,2}^{(1)}$, i.e., $\frac{\partial J}{\partial w_2^{(2)}}$ and $\frac{\partial J}{\partial w_{2,2}^{(1)}}$, using back-propagation
- (iii) parameter update equations for the parameters $w_2^{(2)}$ and $w_{2,2}^{(1)}$, assuming a gradient descent update

Question 5 [max. 4 points]:

Name the typical building blocks of convolutional neural networks. Describe their functionality and motivation.

Question 6 [max. 5 points]:

Assume a binary (Bernoulli-Bernoulli) restricted Boltzmann machine having the following energy function:

$$\mathrm{E}(\mathbf{v},\mathbf{h};\Theta) = -\sum_{i} a_i v_i - \sum_{j} b_j h_j - \sum_{j} \sum_{i} W_{j,i} h_j v_i \; ,$$

where $\mathbf{v} = \{v_i\}_{i=1}^{I}$ denotes the set of visible (observed) variable units, $\mathbf{h} = \{h_j\}_{j=1}^{J}$ the set of latent (hidden) variable units, and $\mathbf{\Theta} = \{\mathbf{a}, \mathbf{b}, \mathbf{W}\}$ the set of the model's parameters. The free-energy function of the model is

$$F(\mathbf{v}; \boldsymbol{\Theta}) = -\sum_{i} a_{i} v_{i} - \sum_{j} \log \left\{ 1 + \exp \left\{ b_{j} + \sum_{i} W_{j,i} v_{i} \right\} \right\}.$$

Derive the analytical form of the probability distribution of $v_i|\mathbf{h}$, where $i \in \{1, \dots, I\}$.