

## Series 4, Apr 10th, 2018 (ANNs)

**Solutions will be published on Friday, April 20th 2018.**

### Problem 1 (Recurrent Neural Networks):

In the lecture so far, we saw feedforward artificial neural networks, which do not contain any cycles and for which the nodes do not maintain a persistent state over several runs. This exercise considers artificial neural networks with nodes that maintain a persistent state that can be updated. This kind of neural network is called a recurrent neural networks (RNN). As an example, consider the following RNN with

$$y_t = Wx_t + Vs_t$$
$$s_{t+1} = y_t$$

from some initial state  $s_0$ , where  $t$  denotes the  $t$ th call of the RNN, i.e.,  $x_t$  is the  $t$ th input.

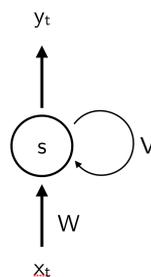


Figure 1

- What is the recurrent state in the RNN from Figure 1? Name one example that can be more naturally modeled with RNNs than with feedforward neural networks?
- As the state of an RNN changes over different runs of the RNN, the loss functions that we use for feedforward neural networks do not yield consistent results. For a dataset  $X := (x_t, y_t)_1^k$ , please propose a loss function (based on the mean square loss function) for RNNs and justify why you chose this loss function. (Hint: order is important).
- For a dataset  $X := (x_t, y_t)_1^k$  (for some  $k \in \mathbb{N}$ ), show how information is propagated by drawing a feedforward neural network that corresponds to the RNN from Figure 1 for  $k = 3$ . Recall that a feedforward neural network does not contain nodes with a persistent state. (Hint: unfold the RNN.)

### Problem 2 (Expressiveness of Neural Networks):

In this question we will consider neural networks with sigmoid activation functions of the form

$$\varphi(z) = \frac{1}{1 + \exp(-z)}.$$

If we denote by  $v_j^l$  the value of neuron  $j$  at layer  $l$  its value is computed as

$$v_j^l = \varphi \left( w_0 + \sum_{i \in \text{Layer}_{l-1}} w_{j,i} v_i^{l-1} \right).$$

In the following questions you will have to design neural networks that compute functions of two Boolean inputs  $X_1$  and  $X_2$ . Given that the outputs of the sigmoid units are real numbers  $Y \in (0, 1)$ , we will treat the final output as Boolean by considering it as 1 if greater than 0.5 and 0 otherwise.

- Give 3 weights  $w_0, w_1, w_2$  for a single unit with two inputs  $X_1$  and  $X_2$  that implements the logical OR function  $Y = X_1 \vee X_2$ .
- Can you implement the logical AND function  $Y = X_1 \wedge X_2$  using a single unit? If so, give weights that achieve this. If not, explain the problem.
- It is impossible to implement the XOR function  $Y = X_1 \oplus X_2$  using a single unit. However, you can do it using a multi-layer neural network. Use the smallest number of units you can to implement XOR function. Draw your network and show all the weights.
- Create a neural network with only one hidden layer (of any number of units) that implements

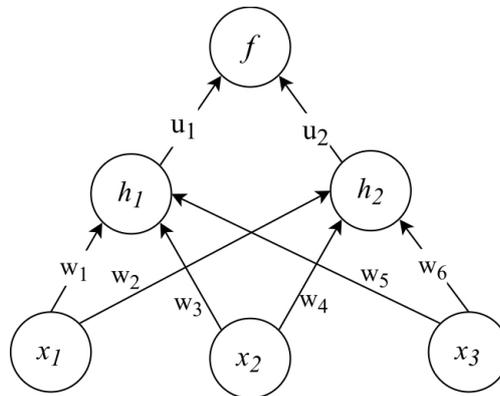
$$(A \vee \neg B) \oplus (\neg C \vee \neg D).$$

Draw your network and show all the weights.

**Problem 3 (Exam question: Artificial Neural Networks):**

Consider the following neural network with two logistic hidden units  $h_1, h_2$ , and three inputs  $x_1, x_2, x_3$ . The output neuron  $f$  is a linear unit, and we are using the squared error cost function  $E = (y - f)^2$ . The logistic function is defined as  $\rho(x) = 1 / (1 + e^{-x})$ .

[Note: You can solve part (c) without using the solution for part (b).]



- Consider a single training example  $\mathbf{x} = [x_1, x_2, x_3]$  with target output (label)  $y$ . Write down the sequence of calculations required to compute the squared error cost (called forward propagation).
- A way to reduce the number of parameters to avoid overfitting is to tie certain weights together, so that they share a parameter. Suppose we decide to tie the weights  $w_1$  and  $w_4$ , so that  $w_1 = w_4 = w_{\text{tied}}$ . What is the derivative of the error  $E$  with respect to  $w_{\text{tied}}$ , i.e.  $\nabla_{w_{\text{tied}}} E$ ?

- (c) For a data set  $D = \{(\mathbf{x}^{(1)}, y^{(1)}), \dots, (\mathbf{x}^{(n)}, y^{(n)})\}$  consisting of  $n$  labeled examples, write the pseudocode of the stochastic gradient descent algorithm with learning rate  $\eta_t$  for optimizing the weight  $w_{\text{tied}}$  (assume all the other parameters are fixed).