#### Flipped Classroom Questions on Recurrent Networks

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**Question 1:** Consider the equations for a simple recurrent model mapping an input  $x_1 \dots x_n$  to a label y:

**Inputs:** A sequence  $x_1 
ldots x_n$  where each  $x_j \in \mathbb{R}^d$ . A label  $y \in \{1 
ldots K\}$ . An integer m defining size of hidden dimension. Parameters  $W^{hh} \in \mathbb{R}^{m \times m}$ ,  $W^{hx} \in \mathbb{R}^{m \times d}$ ,  $b^h \in \mathbb{R}^m$ ,  $h^0 \in \mathbb{R}^m$ ,  $V \in \mathbb{R}^{K \times m}$ ,  $\gamma \in \mathbb{R}^K$ . Transfer function  $g : \mathbb{R}^m \to \mathbb{R}^m$ .

### **Computational Graph:**

• For  $t = 1 \dots n$ 

$$- h^{(t)} = g(W^{hx}x^{(t)} + W^{hh}h^{(t-1)} + b^h)$$

•  $l = Vh^{(n)} + \gamma$ , q = LS(l),  $o = -q_y$ 

**Question 1a:** Draw the computational graph for the above equations with n = 3.

There are three directed paths in the computational graph from  $W^{hx}$  to o. One of them is

$$W^{hx} \to h^{(3)} \to l \to q \to o$$

What are the other two directed paths?

**Question 1b:** For each pair of variables (a,b) with a directed arc from a to b in the computational graph, define  $D(a \to b)$  to be the Jacobian associated with the edge from a to b, as calculated in the backpropagation algorithm. For example,  $D(q \to o)$  is the Jacobian on the edge from q to o.

For convenience, define the matrix A to be

$$A = D(q \to o) \times D(l \to q) \times D(h^{(3)} \to l)$$

and in addition define matrices

$$B^2 = D(h^{(2)} \to h^{(3)})$$

$$B^1 = D(h^{(1)} \to h^{(2)})$$

Now write down the expression for

$$\frac{\partial o}{\partial W^{hx}}$$

using the fact that we can sum over all paths from  $W^{hx}$  to o, taking a product of Jacobians along each path.

**Question 1c:** For which edge or edges in the graph does the Jacobian vary as the value for  $x_1$  varies? That is, which Jacobian or Jacobians are sensitive to the input  $x_1$ ?

**Question 2:** Consider the following set of equations for a Bidirectional recurrent network:

**Inputs:** A sequence  $x_1 \dots x_n$  where each  $x_j \in \mathbb{R}^d$ . A label  $y \in \{1 \dots K\}$ for position i.

# **Computational Graph:**

- For  $t = 1 \dots n$ ,  $h^{(t)} = q(W^{hx}x^{(t)} + W^{hh}h^{(t-1)} + b^h)$
- For  $t = n \dots 1$ ,  $\eta^{(t)} = g(W^{bhx}x^{(t)} + W^{bhh}\eta^{(t+1)} + b^{bh})$
- $l = V \times \text{CONCAT}(h^{(i)}, \eta^{(i)}) + \gamma$ , q = LS(l),  $o = -q_u$

Question 2a: Complete the pseudo-code below to give a recurrent model with two levels of recurrent units, where the second level depends on the sequences  $h^{(1)} \dots h^{(n)}$  and  $\eta^{(1)} \dots \eta^{(n)}$ .

**Inputs:** A sequence  $x_1 \dots x_n$  where each  $x_i \in \mathbb{R}^d$ . A label  $y \in \{1 \dots K\}$ for position i.

# **Computational Graph:**

- For  $t = 1 \dots n$ ,  $h^{(t)} = q(W^{hx}x^{(t)} + W^{hh}h^{(t-1)} + b^h)$
- For  $t = n \dots 1$ ,  $\eta^{(t)} = g(W^{bhx}x^{(t)} + W^{bhh}\eta^{(t+1)} + b^{bh})$
- For  $t=1\dots n,$   $h^{(2,t)}=$  Complete code here

• For  $t = n \dots 1$ ,  $\eta^{(2,t)} =$  Complete code here

•  $l = V \times \text{CONCAT}(h^{(2,i)}, \eta^{(2,i)}) + \gamma$ , q = LS(l),  $o = -q_u$ 

**Question 2b:** Complete the pseudo-code below to give a recurrent model which takes as input a sequence  $x_1 \dots x_n$ , a position i, and in addition **a sequence of tags**  $y_1 \dots y_{i-1}$ , and computes the probability of a label  $y_i$ .

**Inputs:** A sequence  $x_1 \dots x_n$  where each  $x_j \in \mathbb{R}^d$ . A label  $y \in \{1 \dots K\}$  for position i. A sequence of tags  $y_1 \dots y_{i-1}$ .

#### **Computational Graph:**

- For  $t = 1 \dots n$ ,  $h^{(t)} = g(W^{hx}x^{(t)} + W^{hh}h^{(t-1)} + b^h)$
- For  $t = n \dots 1$ ,  $\eta^{(t)} = g(W^{bhx}x^{(t)} + W^{bhh}\eta^{(t+1)} + b^h)$
- For  $j=1\dots(i-1),$   $\beta^{(j)}=$  \_\_\_\_\_\_\_ Complete code here
- $\bullet \ \ l = V \times \text{CONCAT}(h^{(i)}, \eta^{(i)}, \beta^{(i-1)}) + \gamma, \ \ q = \text{LS}(l), o = -q_y$

**Question 3:** Consider the following equations that define a *gated recurrent unit*, which takes an input  $x^{(t)}$  together with the previous hidden state  $h^{(t-1)}$ , and returns a new hidden state  $h^{(t)}$ :

$$\begin{split} z^{(t)} &\in \mathbb{R}^m &= \sigma^m(W^z x^{(t)} + U^z h^{(t-1)} + b^z) \\ r^{(t)} &\in \mathbb{R}^m &= \sigma^m(W^r x^{(t)} + U^r h^{(t-1)} + b^r) \\ h^{(t)} &\in \mathbb{R}^m &= (1 - z^{(t)}) \odot h^{(t-1)} + z^{(t)} \odot g(W^h x^{(t)} + U^h(r^{(t)} \odot h^{(t-1)}) + b^h) \end{split}$$

Here we have followed the conventions in the slides.  $a \odot b$  is the element-wise product of vectors a and b: that is, if  $c = a \odot b$  then  $c_i = a_i \times b_i$  for all i.

 $\sigma^m: \mathbb{R}^m \to \mathbb{R}^m$  maps a vector v to a vector  $\sigma^m(v)$  with components

$$\sigma_i^m(v) = \frac{e^{v_i}}{1 + e^{v_i}}$$

**Question 3a:** Explain the role of the  $z^{(t)}$  and  $r^{(t)}$  vectors in these updates.