

# CSC413: Homework 1

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## 1 Hard-Coding Networks

### 1.1 Verify Sort

*Soln.* The first layer performs pairwise comparison to construct indicators  $\mathbb{1}\{x_1 \leq x_2\}$ ,  $\mathbb{1}\{x_2 \leq x_3\}$ , and  $\mathbb{1}\{x_3 \leq x_4\}$ . The second layer performs an `all()` operation on indicators from the previous layer.

$$\mathbf{W}^{(1)} = \begin{pmatrix} -1 & 1 & 0 & 0 \\ 0 & -1 & 1 & 0 \\ 0 & 0 & -1 & 1 \end{pmatrix} \quad (1.1)$$

$$\mathbf{b}^{(1)} = \begin{pmatrix} 0 & 0 & 0 \end{pmatrix} \quad (1.2)$$

So that

$$\varphi(\mathbf{h}) = \varphi(\mathbf{W}^{(1)}\mathbf{x} + \mathbf{b}^{(1)}) = \varphi \begin{pmatrix} x_2 - x_1 \\ x_3 - x_2 \\ x_4 - x_3 \end{pmatrix} = \begin{pmatrix} \mathbb{1}\{x_2 \geq x_1\} \\ \mathbb{1}\{x_3 \geq x_2\} \\ \mathbb{1}\{x_4 \geq x_3\} \end{pmatrix} \quad (1.3)$$

$$\mathbf{w}^{(2)} = \begin{pmatrix} 1 & 1 & 1 \end{pmatrix} \quad (1.4)$$

$$b^{(2)} = -0.5 \quad (1.5)$$

Such that  $y = 1$  if and only if all components of  $\mathbf{h}$  are ones, i.e., the list is sorted. ■

### 1.2 Perform Sort

*Soln.* Algorithm:

1. Let  $\ell := ((x_{i1}, x_{i2}, x_{i3}, x_{i4}))_{i=1}^{4P4}$  denote the collection of all permutations of the input;
  2. Let  $\mathbf{y} := (\text{network}(x_{i1}, x_{i2}, x_{i3}, x_{i4}))_{i=1}^{4P4}$  denote variables indicating whether each permutation is sorted or not;
  3. Return  $\hat{f}(x_1, x_2, x_3, x_4)$  as the  $\ell[\mathbf{y}=\mathbf{1}]$ .
-

## 1.3 Universal Approximation Theorem

### 1.3.1

*Soln.* To avoid over-using of notations, let  $\varphi(y) := \mathbb{1}\{y > 0\}$  denote the activation function.

$$n = 2 \tag{1.6}$$

$$\mathbf{W}_0 = (1, -1) \tag{1.7}$$

$$\mathbf{b}_0 = (-a, b) \tag{1.8}$$

$$\mathbf{W}_1 = (1, 1) \tag{1.9}$$

$$\mathbf{b}_1 = -0.5 \tag{1.10}$$

Justification:

$$\varphi(\mathbf{h}) = \varphi((x - a, b - x)) \tag{1.11}$$

$$= (\mathbb{1}\{x - a > 0\}, \mathbb{1}\{b - x > 0\}) \tag{1.12}$$

$$= (\mathbb{1}\{x > a\}, \mathbb{1}\{x < b\}) \tag{1.13}$$

$$\varphi(\mathbf{W}_1\varphi(\mathbf{h}) + \mathbf{b}_1) = \mathbb{1}\{\mathbb{1}\{x > a\} + \mathbb{1}\{x < b\} - 0.5\} \tag{1.14}$$

$$= \mathbb{1}\{x > a\} \wedge \mathbb{1}\{x < b\} \tag{1.15}$$

$$= \mathbb{1}\{a < x < b\} \tag{1.16}$$

■

### 1.3.2

*Soln.*

$$\hat{f}_1(x) = \hat{f}_0(x) + g(h_1, a_1, b_1, x) \tag{1.17}$$

$$= 0 + g() \tag{1.18}$$

■

### 1.3.3

*Soln.*

■

### 1.3.4

*Soln.* Not required.

■

## 2 Backprop

### 2.1 Computational Graph

#### 2.1.1

*Soln.* **TODO:** Add graph

■

### 2.1.2

*Soln.*

$$\bar{\mathbf{x}} = \bar{\mathbf{z}} \frac{\partial \mathbf{z}}{\partial \mathbf{x}} \quad (2.1)$$

$$= \bar{\mathbf{z}} \mathbf{W}^{(1)} \quad (2.2)$$

$$= \bar{\mathbf{h}} \frac{\partial \mathbf{h}}{\partial \mathbf{z}} \mathbf{W}^{(1)} \quad (2.3)$$

$$= \bar{\mathbf{h}} \mathbb{1}_{\{\mathbf{z} \geq 0\}} \mathbf{W}^{(1)} \quad (2.4)$$

$$= \left( \bar{\mathcal{R}} \frac{\partial \mathcal{R}}{\partial \mathbf{h}} + \bar{\mathbf{y}} \frac{\partial \mathbf{y}}{\partial \mathbf{h}} \right) \mathbb{1}_{\{\mathbf{z} \geq 0\}} \mathbf{W}^{(1)} \quad (2.5)$$

$$= \left( \bar{\mathcal{R}} \mathbf{r}^T + \bar{\mathbf{y}} \mathbf{W}^{(2)} \right) \mathbb{1}_{\{\mathbf{z} \geq 0\}} \mathbf{W}^{(1)} \quad (2.6)$$

$$= \left( \mathbf{r}^T + \bar{\mathbf{y}}' \frac{\partial \mathbf{y}'}{\partial \mathbf{y}} \mathbf{W}^{(2)} \right) \mathbb{1}_{\{\mathbf{z} \geq 0\}} \mathbf{W}^{(1)} \quad (2.7)$$

$$= \left( \mathbf{r}^T + \bar{\mathbf{y}}' \text{softmax}'(\mathbf{y}) \mathbf{W}^{(2)} \right) \mathbb{1}_{\{\mathbf{z} \geq 0\}} \mathbf{W}^{(1)} \quad (2.8)$$

$$= \left( \mathbf{r}^T + \bar{\mathcal{S}} \frac{\partial \mathcal{S}}{\partial \mathbf{y}'} \text{softmax}'(\mathbf{y}) \mathbf{W}^{(2)} \right) \mathbb{1}_{\{\mathbf{z} \geq 0\}} \mathbf{W}^{(1)} \quad (2.9)$$

$$= \left( \mathbf{r}^T + \mathbf{e}_k \text{softmax}'(\mathbf{y}) \mathbf{W}^{(2)} \right) \mathbb{1}_{\{\mathbf{z} \geq 0\}} \mathbf{W}^{(1)} \quad (2.10)$$

where  $\mathbf{e}_k$  denotes the one-hot vector in  $\mathbb{R}^M$  in which the  $k^{th}$  element is one. ■

## 2.2 Vector-Jacobian Product (VJPs)

### 2.2.1

### 2.2.2

### 2.2.3

## 3 Linear Regression

### 3.1 Driving the Gradient

*Soln.*

$$\frac{d}{d\hat{\mathbf{w}}} \frac{1}{n} (X\hat{\mathbf{w}} - \mathbf{t})^2 = \frac{d}{d\hat{\mathbf{w}}} \frac{1}{n} \|X\hat{\mathbf{w}} - \mathbf{t}\|_2^2 \quad (3.1)$$

$$= \frac{2}{n} (X\hat{\mathbf{w}} - \mathbf{t})^T X \quad (3.2)$$

■

## 3.2 Under-parameterized Model

### 3.2.1

*Soln.* Assume  $d < n$  so that  $X^T X$  is invertible. The gradient descent algorithm converges when the gradient equals zero:

$$\frac{2}{n}(X\hat{\mathbf{w}} - \mathbf{t})^T X = 0 \quad (3.3)$$

$$\implies (X\hat{\mathbf{w}} - \mathbf{t})^T X = 0 \quad (3.4)$$

$$\implies X^T(X\hat{\mathbf{w}} - \mathbf{t}) = 0^T \quad (3.5)$$

$$\implies X^T X\hat{\mathbf{w}} - X^T \mathbf{t} = 0^T \quad (3.6)$$

$$\implies X^T X\hat{\mathbf{w}} = X^T \mathbf{t} \quad (3.7)$$

$$\implies \hat{\mathbf{w}} = (X^T X)^{-1} X^T \mathbf{t} \quad (3.8)$$

■

### 3.2.2

*Soln.* Let  $\mathbf{x} \in \mathbb{R}^d$ , note that  $(X^T X)^{-1}$  is symmetric. Assuming target  $\mathbf{t}$  is generated by a linear process, then  $\mathbf{t} = X\mathbf{w}^*$ . Immediately,  $\mathbf{t}^T = \mathbf{w}^{*T} X^T$ .

$$(\mathbf{w}^{*T} \mathbf{x} - \hat{\mathbf{w}}^T \mathbf{x})^2 = (\mathbf{w}^{*T} \mathbf{x} - [(X^T X)^{-1} X^T \mathbf{t}]^T \mathbf{x})^2 \quad (3.9)$$

$$= (\mathbf{w}^{*T} \mathbf{x} - \mathbf{t}^T X (X^T X)^{-1} \mathbf{x})^2 \quad (3.10)$$

$$= (\mathbf{w}^{*T} \mathbf{x} - \mathbf{w}^{*T} X^T X (X^T X)^{-1} \mathbf{x})^2 \quad (3.11)$$

$$= (\mathbf{w}^{*T} \mathbf{x} - \mathbf{w}^{*T} \mathbf{x})^2 \quad (3.12)$$

$$= 0 \quad (3.13)$$

■

## 3.3 Over-parameterized Model: 2D Example

### 3.3.1

*Soln.* To minimize the empirical risk minimizer,

$$\min_{w_1, w_2} (w_1 x_1 + w_2 x_2 - t_1)^2 \quad (3.14)$$

$$\text{equivalently, } \min_{w_1, w_2} (2w_1 + w_2 - 2)^2 \quad (3.15)$$

Any pair of  $(w_1, w_2)$  satisfying

$$2w_1 + w_2 - 2 = 0 \quad (\dagger) \quad (3.16)$$

attains the minimum level of empirical risk (zero). Equivalently, any  $\hat{\mathbf{w}}$  on the line

$$\hat{\mathbf{w}} = \begin{pmatrix} 0 \\ 2 \end{pmatrix} + t \begin{pmatrix} 1 \\ -2 \end{pmatrix} \text{ for } t \in \mathbb{R} \quad (3.17)$$

satisfies  $(\dagger)$ . Therefore, there are infinitely many empirical risk minimizers. ■

### 3.3.2

*Soln.* ■