

Honor statement:

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**Solution:** Complete



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**Homework 3 (Calculus) Problem 4**

Let  $\mathbf{x}$  be the  $K \times 1$  vector output of the last layer of a xNN and  $e = \text{crossEntropy}(\mathbf{p}^*, \text{softmax}(\mathbf{x}))$  be the error where  $\mathbf{p}^*$  is a  $K \times 1$  vector with a 1 in position  $k^*$  representing the correct class and 0s elsewhere. Derive  $\partial e / \partial \mathbf{x}$

**Solution:**

$$\frac{\partial e}{\partial \mathbf{x}} = ? \quad (1)$$

■

**Proof:** First, note that error function  $e$  is given by the cross entropy of a softmax, the typical error function chosen for **classification** networks. This establishes a  $f(g(x))$  relationship wherein we must use the chain rule to differentiate  $e$ . Specifically, we will need to compute the following to apply the chain rule

$$\frac{d}{d\mathbf{x}} \text{softmax}(\mathbf{x}) \quad \frac{\partial}{\partial \mathbf{p}} \text{crossEntropy}(\mathbf{p}^*, \mathbf{p}) \quad (2)$$

We will start with cross entropy. Recall that cross entropy is given by

$$\text{crossEntropy}(\mathbf{p}^*, \mathbf{p}) = - \sum_{x_i \in \mathbf{x}} p^*(x_i) \log p(x_i) \quad (3)$$

Differentiating cross entropy for each of  $x_i \in \mathbf{x}$  produces a gradient vector. Recognizing that differentiating the summation in cross entropy with respect to a single  $x_i$  will produce a single nonzero term, we can say

$$\nabla_{\mathbf{x}} \left( - \sum_{x_i \in \mathbf{x}} p^*(x_i) \log p(x_i) \right) = \begin{pmatrix} -\frac{\partial}{\partial x_1} p^*(x_1) \log p(x_1) \\ -\frac{\partial}{\partial x_2} p^*(x_2) \log p(x_2) \\ \vdots \\ -\frac{\partial}{\partial x_k} p^*(x_k) \log p(x_k) \\ \vdots \\ -\frac{\partial}{\partial x_N} p^*(x_N) \log p(x_N) \end{pmatrix} \quad (4)$$

$$= \begin{pmatrix} 0 \\ 0 \\ \vdots \\ -\frac{1}{p(x_k)} \\ \vdots \\ 0 \end{pmatrix} \leftarrow k \quad (5)$$

So our cross entropy gradient for a one hot vector  $\mathbf{p}^*$  with nonzero position  $k$  is 0 everywhere except at position  $k$ .

Now we compute our next required derivative: softmax The softmax function is given by

$$\text{softmax}(\mathbf{x}) = \frac{1}{\sum_{k=1}^K e^{x_k}} \begin{pmatrix} e^{x_0} \\ e^{x_1} \\ \vdots \\ e^{x_K} \end{pmatrix} \quad (6)$$

We need to derive the Jacobian of this function in denominator notation. □

**Homework 2 (Linear Algebra) Problem 2**

- (a) What is the arithmetic intensity for matrix matrix multiplication with sizes  $M, N, K$ .