

## Theory and Practice of Deep Learning

### Theory HW #03

Nigel Chan 1002027

#### Task 1: Some Einsum

a)  $C_{j,k} = \sum_i A_{ijk} b_i \rightarrow \text{einsum}('ijk, i \rightarrow jk', A, b)$

b)  $C_j = \sum_{i,k} A_{ijk} b_{ij} \rightarrow \text{einsum}('ijk, ik \rightarrow j', A, b)$

c)  $A_{ijk} = \sum_l A_{ijkl} \rightarrow \text{einsum}('ijkl \rightarrow ik', A)$

d)  $A_{ki} = \sum_{j,l} A_{ijkl} \rightarrow \text{einsum}('ijkl \rightarrow ki', A)$

e)  $C_i = \sum_{j,k} A_{ijk} A_{ijk} \rightarrow \text{einsum}('ijk, ijk \rightarrow i', A, A)$

f)  $C = x^T A x \rightarrow \text{einsum}('i, ij, j \rightarrow', x, A, x)$

g)  $C = A G^T B \rightarrow \text{einsum}('ik, lk, lj \rightarrow ij', A, G, B)$ , second order

h)  $C_{abef} = \sum_{cd} A_{abcd} B_{bcde} E_{cdef} \rightarrow \text{einsum}('abcd, bcde, cdef \rightarrow abef', A, B, E)$

## Task 2

a)

$$P(X^{(1)} < 0 | Y = -1) = 0.5$$

$$P(X^{(1)} < 0 | Y = +1) = 0.5$$

$$f_0(x) = 2I[x^{(1)} \geq 0] - 1 = \begin{cases} -1 & x^{(1)} < 0 \\ +1 & x^{(1)} \geq 0 \end{cases}$$

$$a) E_{(x,y) \sim p} [I[f_0(x) \neq y]] = P(f_0(x) = 1, y = -1) + P(f_0(x) = -1, y = 1)$$

using the formula,

$$P(X|Y) = \frac{P(X,Y)}{P(Y)}$$

$$\begin{aligned} E_{(x,y) \sim p} [I[f_0(x) \neq y]] &= P(f_0(x) = 1, y = -1) + P(f_0(x) = -1, y = 1) \\ &= P(f_0(x) = 1 | y = -1)P(y = -1) + P(f_0(x) = -1 | y = 1)P(y = 1) \\ &= P(X \geq 0 | y = -1)(1 - 0.5) + P(X < 0 | y = 1)(0.5) \\ &= (1 - 0.5)(0.5) + 0.5(0.5) \\ &= 1(0.5) \\ &= 0.5 \end{aligned}$$

b) For the points with class -1, the probability that the error on the training dataset being zero is  $P(f_0(x_i) = -1 | y_i = -1) = 0.5$ , based on the resulting probability we found in part (a). Likewise for class +1 points,  $P(f_0(x_i) = 1 | y_i = 1) = 0.5$

$$\begin{aligned} \text{Overall probability} &= P(\text{first } N/2 \text{ points of class } -1) \times P(\text{last } N/2 \text{ points of class } +1) \\ &= [P(f_0(x_i) = -1 | y_i = -1)]^{N/2} \times [P(f_0(x_i) = 1 | y_i = 1)]^{N/2} \\ &= (0.5)^{N/2} \times (0.5)^{N/2} \\ &= 0.5^N \end{aligned}$$

c) We use Binomial Distribution here, where  $n = D$ ,  $p = 0.5^N$ ,  $k = K$

$$\begin{aligned} d) \text{Probability to draw } N \text{ samples with at least one dimension } d \text{ out of } D \text{ dimensions} &= [P(X \geq 1)]^N \\ &= [1 - P(X < 1)]^N \\ &= [1 - P(X = 0)]^N \\ &= [1 - P_0(\frac{1}{2})^0 (\frac{1}{2})^{D-0}]^N \\ &= [1 - (\frac{1}{2})^D]^N \end{aligned}$$

e) As  $D \rightarrow \infty$ ,  $[1 - (\frac{1}{2})^D]^N \rightarrow 1$   $\therefore$  probability of zero error  $\rightarrow 1$

The complexity for convergence given  $N$  samples is an exponential of the form:  $O(\frac{1}{2})^D$