

CROSS ENTROPY

Give two discrete distributions  $p$  and  $q$ ,

$$p = \{p_1, \dots, p_n\} \quad 0 \leq p_i \leq 1 \quad \sum_{i=1}^n p_i = 1$$

$$q = \{q_1, \dots, q_n\} \quad 0 \leq q_i \leq 1 \quad \sum_{i=1}^n q_i = 1$$

the cross-entropy between  $p$  and  $q$  is

$$H(p, q) \triangleq \sum_{i=1}^n p_i \log \frac{1}{q_i}$$

Note that is not symmetric:  $H(p, q) \neq H(q, p)$

The cross-entropy is derived from the KL-DIVERGENCE (Kullback-Leibler) between  $p$  and  $q$

$$KL(p \parallel q) \triangleq \sum_{i=1}^n p_i \log \frac{p_i}{q_i}$$

KL is well-known in information theory and it is positive  $KL(p \parallel q) \geq 0 \quad \forall p, q$  and non symmetric  $KL(p \parallel q) \neq KL(q \parallel p)$  (see any introductory text on information theory). Rewriting

$$KL(p \parallel q) = \sum_{i=1}^n p_i \log \frac{1}{q_i} - \sum_{i=1}^n p_i \log \frac{1}{p_i}$$

we recognize the entropy of  $p$ , therefore

$$KL(p \parallel q) = H(p, q) - H(p),$$

and

$$H(p, q) = KL(p \parallel q) + H(p) \geq 0$$

because both terms are positive (the entropy is always  $\geq 0$ ).

The cross-entropy is used as a measure of "distance" between  $p$  and  $q$  even if when  $p=q$ ,  $KL(p||q)=0$  and  $H(p,q)=H(p)$ . This is acceptable because usually the cross-entropy is used to find  $q$ , with  $p$  fixed:

$$\min_q H(p,q) = \min_q (KL(p||q) + H(p)) = \min_q KL(p||q)$$

Therefore minimization of  $H(p,q)$  with respect to  $q$  is equivalent to KL minimization with respect to  $q$ .

More about cross-entropy and KL divergence can be found in our text of information theory. We limit ourselves here to what is directly relevant to machine learning.

#### GRADIENT OF CROSS-ENTROPY

In learning algorithms it is useful to consider the gradient of  $H(p,q)$  with respect to  $\{q_1, q_2, \dots, q_n\}$

$$\nabla_q H(p,q) = \begin{bmatrix} \frac{\partial H(p,q)}{\partial q_1} \\ \vdots \\ \frac{\partial H(p,q)}{\partial q_n} \end{bmatrix}$$

$$\frac{\partial}{\partial q_e} H(p,q) = \frac{\partial}{\partial q_e} \sum_{i=1}^n p_i \log \frac{1}{q_i} = - \frac{\partial}{\partial q_e} \sum_{i=1}^n p_i \log q_i = - \frac{p_e}{q_e}$$

$$\nabla_q H(p,q) = - \begin{bmatrix} \frac{p_1}{q_1} \\ \frac{p_2}{q_2} \\ \vdots \\ \frac{p_n}{q_n} \end{bmatrix}$$

## BINARY CROSS ENTROPY

CE.3

The binary case, as usual, deserves special attention  
Here  $p$  and  $q$  are binary distributions

$$p = \{\alpha, 1-\alpha\} \quad q = \{\beta, 1-\beta\}$$

The cross entropy is

$$H(p, q) = \alpha \log \frac{1}{\beta} + (1-\alpha) \log \frac{1}{1-\beta}$$

Now, if  $p$  is fixed and we look for the gradient  
with respect to  $q$ , we only need the derivative  
of  $H(p, q)$  with respect to  $\beta$  which is

$$\frac{\partial H(p, q)}{\partial \beta} = -\frac{\partial}{\partial \beta} [\alpha \log \beta + (1-\alpha) \log(1-\beta)]$$

$$= -\frac{\alpha}{\beta} + \frac{(1-\alpha)}{1-\beta} = \frac{-\alpha(1-\beta) + \beta(1-\alpha)}{\beta(1-\beta)} = \frac{-\alpha + \alpha\beta + \beta - \alpha\beta}{\beta(1-\beta)}$$

$$= \frac{\beta - \alpha}{\beta(1-\beta)}$$