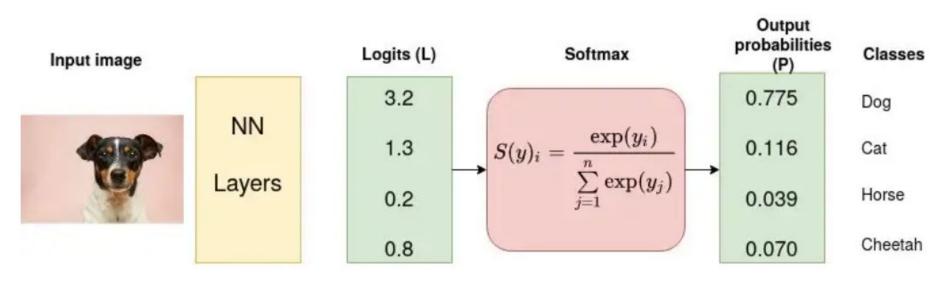
Multiclass Classification Softmax Sparse categorical cross-entropy

Softmax: From Logits to Probabilities



Input image source: Photo by Victor Grabarczyk on Unsplash. Diagram by author.

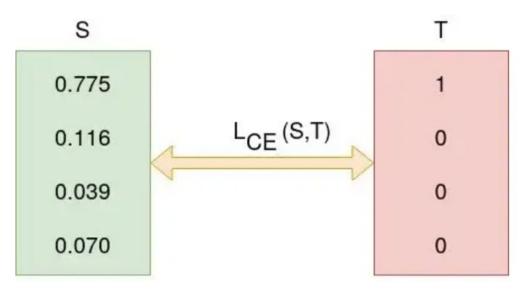
Softmax

$$\sigma(\mathbf{z})_i = rac{e^{z_i}}{\sum_{j=1}^K e^{z_j}}$$

- The softmax function takes as input a vector of K real numbers and normalizes it into a probability distribution consisting of K probabilities proportional to the exponentials of the input numbers. That is:
 - Prior to applying softmax, some vector components could be negative, or greater than one; and might not sum to 1; but after applying softmax, each component will be in the interval (0,1)
 - The components will add up to 1, so that they can be interpreted as probabilities
 - The larger input components will correspond to larger probabilities.

Categorical cross-entropy

- Computes the cross-entropy loss between the labels and predictions.
- Cross-entropy is a quantity from the field of information theory that measures the distance between probability distributions or, in this case, between the ground-truth distribution and the model's predictions.



Categorical cross-entropy

$$L_{\text{CE}} = -\sum_{i=1}^{n} t_i \log(p_i)$$
, for n classes,

where t_i is the truth label and p_i is the Softmax probability for the i^{th} class.

Categorical cross-entropy

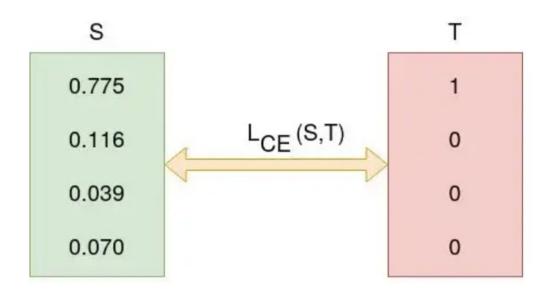
$$L_{\text{CE}} = -\sum_{i=1}^{n} t_i \log(p_i)$$
, for n classes,

$$L_{CE} = -\sum_{i=1}^{\infty} T_i \log(S_i)$$

$$= -\left[1 \log_2(0.775) + 0 \log_2(0.126) + 0 \log_2(0.039) + 0 \log_2(0.070)\right]$$

$$= -\log_2(0.775)$$

$$= 0.3677$$



Sparse Categorical cross-entropy

- Categorical cross-entropy is used when true labels are one-hot encoded, for example, we have the following true values for 3-class classification problem [1,0,0], [0,1,0] and [0,0,1].
- In **sparse categorical cross-entropy**, truth labels are integer encoded, for example, [1], [2] and [3] for 3-class problem.