# THE MATHEMATICS OF DEEP LEARNING\*

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# ABSTRACT

Deep Learning is a branch of Machine Learning in which 'deep' neural networks are used for various purposes.

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#### 1. PRELIMINARIES

### 2. NOTATION

Tensors are associated with layers. The  $p \times q$  tensor  $\mathbf{A}$  when associated with layer l is denoted  $\mathbf{A}_{p \times q}^{[l]}$ . The transpose of this tensor is denoted by  $(\mathbf{A}_{p \times q}^{[l]})^{\top}$ . If the tensor is an input tensor to a layer, it may additionally have a minibatch number, m, and instance within the minibatch, i, associated with it. Thus  $(\mathbf{A}_{p \times q}^{[l]\{m\}(i)})^{\top}$  is the transpose of the i-th training example from the m-th minibatch in the l-th layer from the input tensor  $\mathbf{A}$  which is p rows high by q columns long. Furthermore, layers associated with convolutional neural networks may have *channels* associated with them. Channels add extra dimensions to tensors and so  $(\mathbf{A}_{p \times q \times k_1 \times k_2}^{[l]\{m\}(i)})^{\top}$  is the transpose of the i-th training example from the m-th minibatch in the l-th layer from the input tensor  $\mathbf{A}$  which is p rows high by q columns long and has two sets of channels of depth  $k_1$  and  $k_2$  respectively.

The n<sup>[l]</sup> operator returns the number of nodes, i.e. the width, of the l-th layer. Traditionally, the depth of the neural network is denoted by L, and hence we must have  $0 \le l \le L$ .

We transform the l-1-th layer of activations  $\mathbf{A}_{p\times q}^{[l-1]\{m\}(i)}$ , using neural network operations such as convolution etc... in the l-th layer to produce the l-th layer of activations i.e.  $\mathbf{A}_{p\times q}^{[l]\{m\}(i)}$ .

### 3. ACTIVATION FUNCTIONS

#### 3.1. Sigmoid Activation Function

The sigmoid activation function takes the form

$$g(z) = \sigma(z) = \frac{1}{1 + e^{-z}}.$$
 (1)

The derivative of the sigmoid activation function is

$$\frac{\mathrm{d}\sigma}{\mathrm{d}z} = \sigma(1-\sigma). \tag{2}$$

3.1.1. Derivation

By definition

$$\sigma(z) = \frac{1}{1 + e^{-z}} = (1 + e^{-z})^{-1},$$

and so

$$\frac{d\sigma(z)}{dz} = -(1 + e^{-z})^{-2} \frac{d(1 + e^{-z})}{dz}.$$

But this is just

$$-(1 + e^{-z})^{-2}(-e^{-z}) = \sigma^2 e^{-z}.$$

Now  $e^{-z} = \frac{1}{\sigma} - 1 = \frac{1-\sigma}{\sigma}$  and so

$$\frac{d\sigma(z)}{dz} = \sigma^2 e^{-z} = \sigma^2 \frac{1-\sigma}{\sigma} = \sigma(1-\sigma),$$

Q.E.D.

- 4. OUTPUT LAYERS
- 5. FEED-FORWARD LAYERS
- 6. CONVOLUTIONAL LAYERS
  - 6.1.  $1 \times 1$  Convolution
  - 7. POOLING LAYERS

APPENDIX

REFERENCES