word2vec

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April 26, 2017

1 A simple neural network

Consider a feed forward neural network with one hidden layer, as shown in figure 1. The input layer consists of a row[1] vector x of dimension D_x, i.e. $x \in \mathbb{R}^{1 \times D_x}$. The hidden layer has h neurons with a sigmoid activation function:

$$h = \sigma(xW^{(1)} + b^{(1)}) = \sigma(z^{(1)}), \quad z^{(1)} = xW^{(1)} + b^{(1)} \tag{1.1}$$

So $h \in \mathbb{R}^{1 \times H}, W^{(1)} \in \mathbb{R}^{D_x \times H}, b^{(1)} \in \mathbb{R}^{1 \times H}$. The output layer has D_y softmax neurons:

$$\hat{y} = s(hW^{(2)} + b^{(2)}) = s(z^{(2)}), \quad z^{(2)} = hW^{(2)} + b^{(2)} \tag{1.2}$$

Similarly $\hat{y} \in \mathbb{R}^{1 \times D_y}, W^{(2)} \in \mathbb{R}^{H \times D_y}, b^{(2)} \in \mathbb{R}^{1 \times D_y}$.

[1]Note that this is different from the column vector convention usually used.

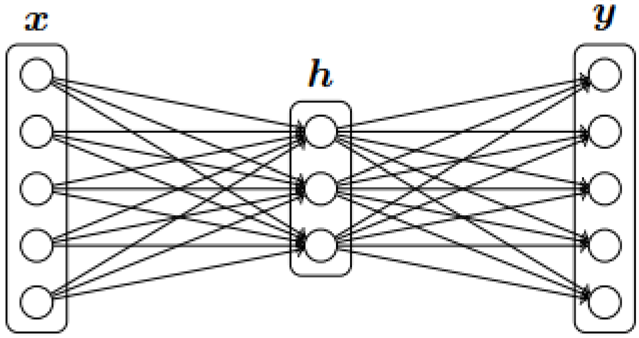

Figure 1: The neural network.

1.1 Error function

Assuming a labelled dataset x with the correct label c encoded as a one-hot vector $t \in \mathbb{R}^{1\times D_y}$, so $t_i = \delta_{ic}$. We will use the cross-entropy error function:

$$J(x) = -\sum_{i=1} t_i \log \hat{y}_i \tag{1.3}$$

Since t is one-hot encoded, only the correct label c will contribute to the sum, so:

$$J(x) = -\log \hat{y}_c \tag{1.4}$$

This does not mean that the other components of $\hat{y}$ will not matter, since the softmax indirectly depends on all components.

1.1.1 Derivative with respect to input

We now wish to compute the derivative of $J(x)$ with respect to x. In shorthand, the chain rule gives us:

$$\frac{\partial J}{\partial x} = \frac{\partial J}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial z^{(2)}} \frac{\partial z^{(2)}}{\partial h} \frac{\partial h}{\partial z^{(1)}} \frac{\partial z^{(1)}}{\partial x} \tag{1.5}$$

Writing out indices explicitly:

$$\frac{\partial J}{\partial x_m} = \sum_{i=1}^{D_y} \sum_{j=1}^{D_y} \sum_{k=1}^{H} \sum_{l=1}^{H} \frac{\partial J}{\partial \hat{y}_i} \frac{\partial \hat{y}_i}{\partial z_j^{(2)}} \frac{\partial z_j^{(2)}}{\partial h_k} \frac{\partial h_k}{\partial z_l^{(1)}} \frac{\partial z_l^{(1)}}{\partial x_m} \tag{1.6}$$

Let's compute these partial derivatives one by one:

$$\frac{\partial J}{\partial \hat{y}_i} = -\frac{\partial}{\partial \hat{y}_i} \log \hat{y}_c = -\frac{\delta_{ic}}{\hat{y}_c} \tag{1.7}$$

The second is a standard result for the softmax function:

$$\frac{\partial \hat{y}_i}{\partial z_j^{(2)}} = s_i(z^{(2)})(\delta_{ij} - s_j(z^{(2)}) = \hat{y}_i(\delta_{ij} - \hat{y}_j) \tag{1.8}$$

And:

$$\frac{\partial z_j^{(2)}}{\partial h_k} = W_{kj}^{(2)} \tag{1.9}$$

The fourth uses a standard result for the sigmoid:

$$\frac{\partial h_k}{\partial z_l^{(1)}} = \delta_{kl}\sigma(z_l^{(1)})(1 - \sigma(z_l^{(1)})) = \delta_{kl} h_l (1 - h_l) \tag{1.10}$$

And finally:

$$\frac{\partial z_l^{(1)}}{\partial x_m} = W_{ml}^{(1)} \tag{1.11}$$

Inserting, letting the delta functions cancel, and renaming indices, this becomes:

$$\frac{\partial J}{\partial x_i} = -\sum_{j=1}^{H} \sum_{k=1}^{D_y} W_{ij}^{(1)} h_j (1 - h_j) W_{jk}^{(2)} (\delta_{kc} - \hat{y}_k) \tag{1.12}$$