

1. Linear neural networks

- (a) Suppose we have a three layer linear neural network with one input layer \mathbf{x} , one hidden layer \mathbf{h} , and one output layer \mathbf{y} . Each layer can be expressed as a vector of the values of the nodes in that layer. For example, $\mathbf{y} = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{pmatrix}$. Assume that each neural node has its own set of weights \mathbf{w}_i where i is the node index. We can express the value of the a particular output in terms of the hidden layer:

$$y_k = c_k \cdot \mathbf{w}_k \cdot \mathbf{h}$$

Similarly, we can express the value of each node in the hidden layer in terms of the inputs.

$$h_j = c_j \cdot \mathbf{w}_j \cdot \mathbf{x}$$

Now, we can see that the output layer nodes can simply be written in terms of the inputs without the hidden layer. For a particular output node:

$$\begin{aligned} y_k &= c_k \cdot \mathbf{w}_k \cdot \mathbf{h} \\ &= c_k \cdot \mathbf{w}_k \cdot \begin{pmatrix} c_{j_1} \cdot \mathbf{w}_{j_1} \cdot \mathbf{x} \\ c_{j_2} \cdot \mathbf{w}_{j_2} \cdot \mathbf{x} \\ \dots \\ c_{j_n} \cdot \mathbf{w}_{j_n} \cdot \mathbf{x} \end{pmatrix} \\ &= c_k \cdot \begin{pmatrix} w_{k_1} & w_{k_2} & \dots & w_{k_n} \end{pmatrix} \begin{pmatrix} c_{j_1} \cdot \mathbf{w}_{j_1} \cdot \mathbf{x} \\ c_{j_2} \cdot \mathbf{w}_{j_2} \cdot \mathbf{x} \\ \dots \\ c_{j_n} \cdot \mathbf{w}_{j_n} \cdot \mathbf{x} \end{pmatrix} \\ &= c_k \sum_{i=1}^n w_{k_i} \cdot c_{j_i} \cdot \mathbf{w}_{j_i} \cdot \mathbf{x} \\ &= c_k \left(\sum_{i=1}^n w_{k_i} \cdot c_{j_i} \cdot \mathbf{w}_{j_i} \right) \mathbf{x} \end{aligned}$$

- (b) For an arbitrary number of hidden nodes, the same computation can be done. We demonstrate

below with two hidden layers: $\mathbf{h}_m, \mathbf{h}_n$

$$\begin{aligned}
y_k &= c_k \cdot \mathbf{w}_k \cdot \mathbf{h}_m \\
&= c_k \cdot \mathbf{w}_k \cdot \begin{pmatrix} c_{j_1} \cdot \mathbf{w}_{j_1} \cdot \mathbf{h}_m \\ c_{j_2} \cdot \mathbf{w}_{j_2} \cdot \mathbf{h}_m \\ \dots \\ c_{j_n} \cdot \mathbf{w}_{j_n} \cdot \mathbf{h}_m \end{pmatrix} \\
&= c_k \cdot \begin{pmatrix} w_{k_1} & w_{k_2} & \dots & w_{k_n} \end{pmatrix} \begin{pmatrix} c_{j_1} \cdot \mathbf{w}_{j_1} \cdot \mathbf{h}_m \\ c_{j_2} \cdot \mathbf{w}_{j_2} \cdot \mathbf{h}_m \\ \dots \\ c_{j_n} \cdot \mathbf{w}_{j_n} \cdot \mathbf{h}_m \end{pmatrix} \\
&= c_k \sum_{i=1}^n w_{k_i} \cdot c_{j_i} \cdot \mathbf{w}_{j_i} \cdot \mathbf{h}_m \\
&= c_k \sum_{i=1}^n w_{k_i} \cdot c_{j_i} \cdot \begin{pmatrix} w_{j_1} & w_{j_2} & \dots & w_{j_n} \end{pmatrix} \begin{pmatrix} c_{m_1} \cdot \mathbf{w}_{m_1} \cdot \mathbf{h}_n \\ c_{m_2} \cdot \mathbf{w}_{m_2} \cdot \mathbf{h}_n \\ \dots \\ c_{m_n} \cdot \mathbf{w}_{m_n} \cdot \mathbf{h}_n \end{pmatrix} \\
&= c_k \sum_{i=1}^n w_{k_i} \cdot c_{j_i} \cdot \left(\sum_{a=1}^{n \text{FIXTHIS!!!}} w_{j_a} \cdot c_{m_a} \cdot \mathbf{w}_{m_a} \cdot \mathbf{h}_n \right)
\end{aligned}$$

This thus generalizes to any number of hidden layers: TODO

- (c) For the case when $h \ll n$, a neural net with the hidden layer will do $O(hn)$ computations to find the linear combination of the weighted sum of inputs where as without the hidden layer, as shown in (a), the output is only dependent on $O(n)$, so we save those $h - 1$ other computations over the inputs.

2. ML estimation of exponential model
3. ML estimation of noisy-OR model