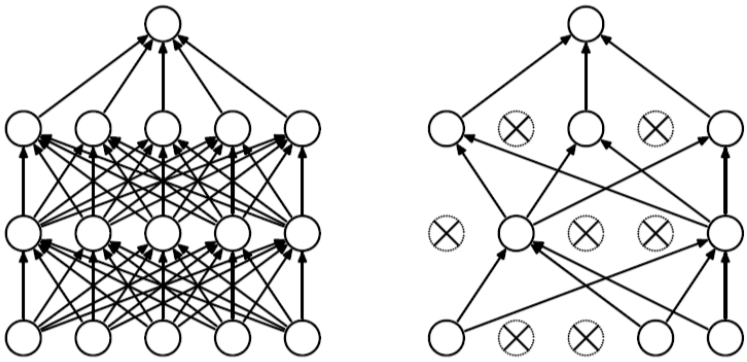
DROPOUTS

Deep neural nets with many parameters are powerful but prone to overfitting and can be slow. Dropout addresses this by randomly dropping units and their connections during training, preventing units from co-adapting. This creates many "thinned" networks, and at test time, a single unthinned network with smaller weights approximates the effect of averaging these networks. Dropout significantly reduces overfitting and improves performance on tasks like vision, speech recognition, document classification, and computational biology, achieving state-of-the-art results on many benchmarks



(a) Standard Neural Net (b) After applying dropout.

Figure 1: Dropout Neural Net Model. **Left**: A standard neural net with 2 hidden layers. **Right**: An example of a thinned net produced by applying dropout to the network on the left. Crossed units have been dropped.

Model Description

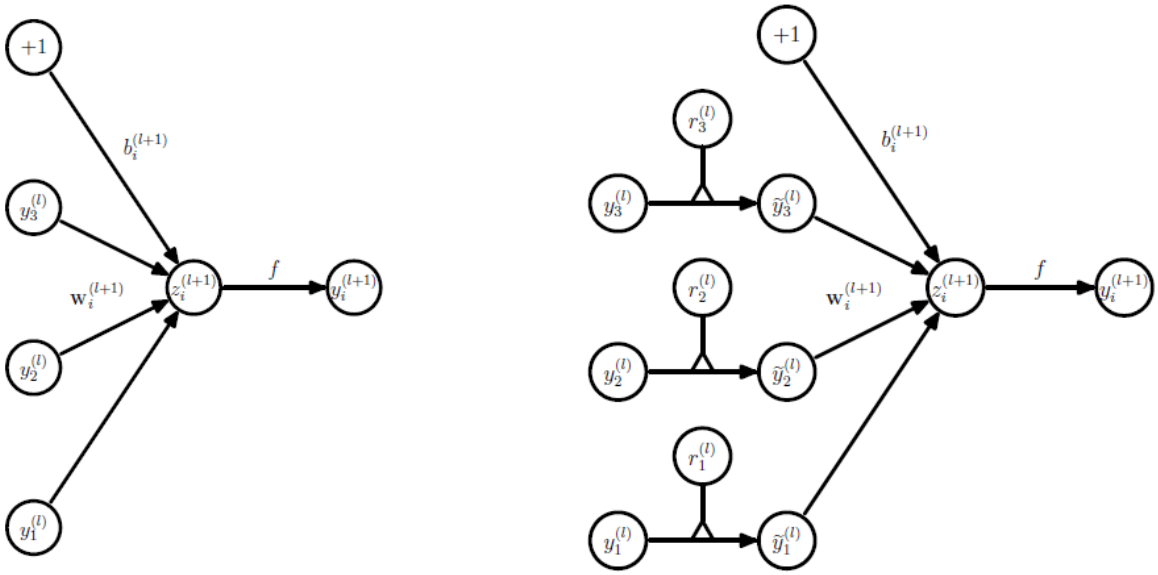
This section describes the dropout neural network model. Consider a neural network with L hidden layers. Let $l \in \{1, \ldots, L\}$ index the hidden layers of the network. Let $\mathbf{z}^{(l)}$ denote the vector of inputs into layer l, $\mathbf{y}^{(l)}$ denote the vector of outputs from layer l ($\mathbf{y}^{(0)} = \mathbf{x}$ is the input). $W^{(l)}$ and $\mathbf{b}^{(l)}$ are the weights and biases at layer l. The feed-forward operation of a standard neural network (Figure 3a) can be described as (for $l \in \{0, \ldots, L-1\}$ and any hidden unit i)

$$\begin{aligned} z_i^{(l+1)} &= \mathbf{w}_i^{(l+1)} \mathbf{y}^l + b_i^{(l+1)}, \\ y_i^{(l+1)} &= f(z_i^{(l+1)}), \end{aligned}$$

where f is any activation function, for example, $f(x) = 1/\left(1 + \exp(-x)\right)$.

With dropout, the feed-forward operation becomes (Figure 3b)

$$\begin{aligned} r_j^{(l)} &\sim \text{Bernoulli}(p), \\ \tilde{\mathbf{y}}^{(l)} &= \mathbf{r}^{(l)} * \mathbf{y}^{(l)}, \\ z_i^{(l+1)} &= \mathbf{w}_i^{(l+1)} \tilde{\mathbf{y}}^l + b_i^{(l+1)}, \\ y_i^{(l+1)} &= f(z_i^{(l+1)}). \end{aligned}$$



(a) Standard network

(b) Dropout network

Figure 3: Comparison of the basic operations of a standard and dropout network.

Here $*$ denotes an element-wise product. For any layer l, $\mathbf{r}^{(l)}$ is a vector of independent Bernoulli random variables each of which has probability p of being 1. This vector is sampled and multiplied element-wise with the outputs of that layer, $\mathbf{y}^{(l)}$, to create the thinned outputs $\tilde{\mathbf{y}}^{(l)}$. The thinned outputs are then used as input to the next layer. This process is applied at each layer. This amounts to sampling a sub-network from a larger network. For learning, the derivatives of the loss function are backpropagated through the sub-network. At test time, the weights are scaled as $W_{test}^{(l)} = pW^{(l)}$ as shown in Figure 2. The resulting neural network is used without dropout.