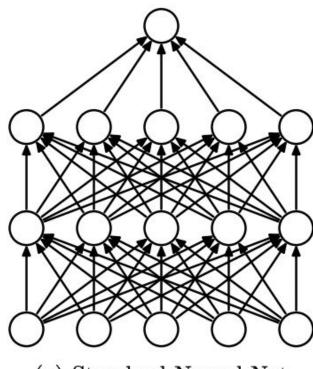
# Advanced Machine Learning

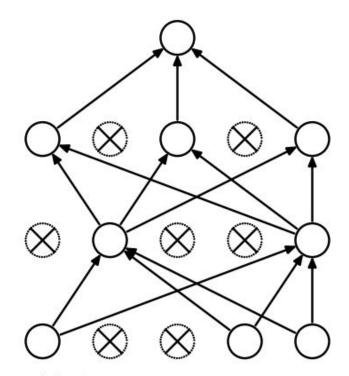
Likhit Nayak

Madimic Ecaning

### Dropout



(a) Standard Neural Net



(b) After applying dropout.

#### Why should we use dropout?

To make an ensemble of neural networks, they should either have

- 1. Different architectures
  - Finding optimal hyperparameters for each architecture is a daunting task
  - Training each large network requires a lot of computation
- 2. Be trained on different data
  - There may not be enough data available to train different networks on different subsets of the data

#### Dropout is a technique that addresses both these issues

# Implementing Dropout

In a neural network with *L* hidden layers and no dropout, the feed-forward operation can be described as:

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

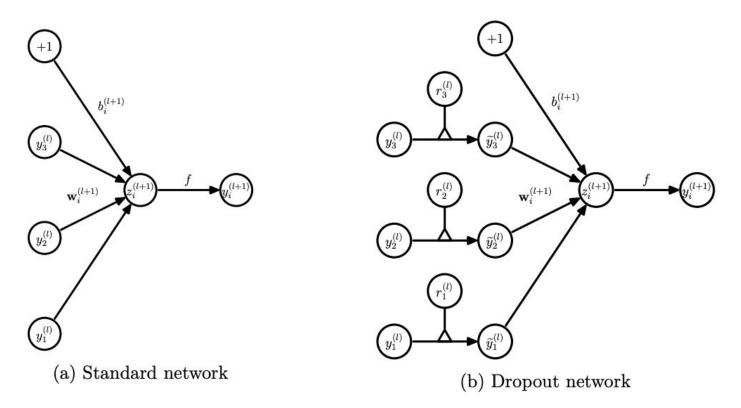
where z is the input into a layer, y is the output from a layer, w and b are the weights and biases of a layer, and f() is the activation function

# Implementing Dropout

With dropout, the feed-forward operation becomes:

$$r_j^{(l)} \sim \operatorname{Bernoulli}(p),$$
 $\widetilde{\mathbf{y}}^{(l)} = \mathbf{r}^{(l)} * \mathbf{y}^{(l)},$ 
 $z_i^{(l+1)} = \mathbf{w}_i^{(l+1)} \widetilde{\mathbf{y}}^l + b_i^{(l+1)},$ 
 $y_i^{(l+1)} = f(z_i^{(l+1)}).$ 

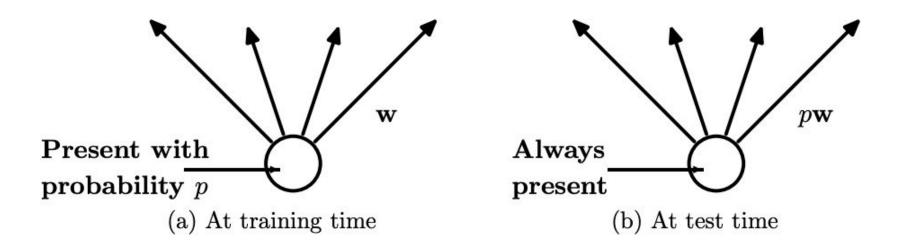
# Implementing Dropout



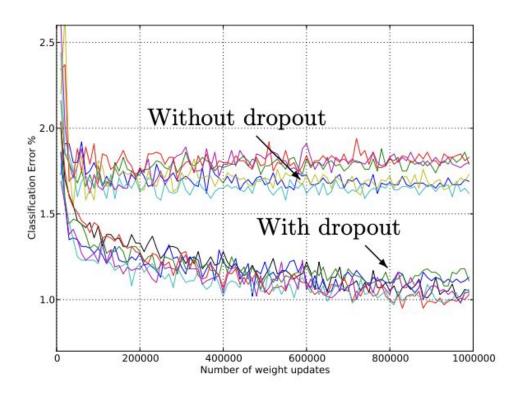
Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." *The journal of machine learning research* 15.1 (2014): 1929-1958.

# Implementing Dropout - Inference time

At inference time, it is not feasible to explicitly average the predictions all the different models like we do with bagging. So, we use scaling:



# Implementing Dropout - Results



# Implementing Dropout - Results

Method	Test Classification error $\%$
L2	1.62
L2 + L1 applied towards the end of training	1.60
L2 + KL-sparsity	1.55
Max-norm	1.35
Dropout + L2	1.25
Dropout + Max-norm	1.05

# Advantages of Dropout

- 1. Computationally cheap
- During training, dropout requires only O(n) computations per example per update, to generate n random numbers and multiply them
- During testing, the cost of dividing the weights (scaling) is a single operation per example

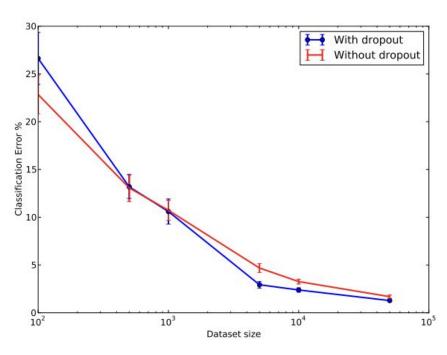
# **Advantages of Dropout**

2. It works well with nearly any model

Method	Phone Error Rate%
NN (6 layers) (Mohamed et al., 2010)	23.4
Dropout NN (6 layers)	21.8
DBN-pretrained NN (4 layers)	22.7
DBN-pretrained NN (6 layers) (Mohamed et al., 2010)	22.4
DBN-pretrained NN (8 layers) (Mohamed et al., 2010)	20.7
mcRBM-DBN-pretrained NN (5 layers) (Dahl et al., 2010)	20.5
DBN-pretrained NN (4 layers) + dropout	19.7
DBN-pretrained NN (8 layers) + dropout	19.7

## Limitations of Dropout

1. Works better with larger training datasets



Srivastava, Nitish, et al. "Dropout: a simple way to prevent neural networks from overfitting." *The journal of machine learning research* 15.1 (2014): 1929-1958.

# Limitations of Dropout

2. The cost function (or loss function) isn't well-defined

