# CMSC 510 – L19 Regularization Methods for Machine Learning

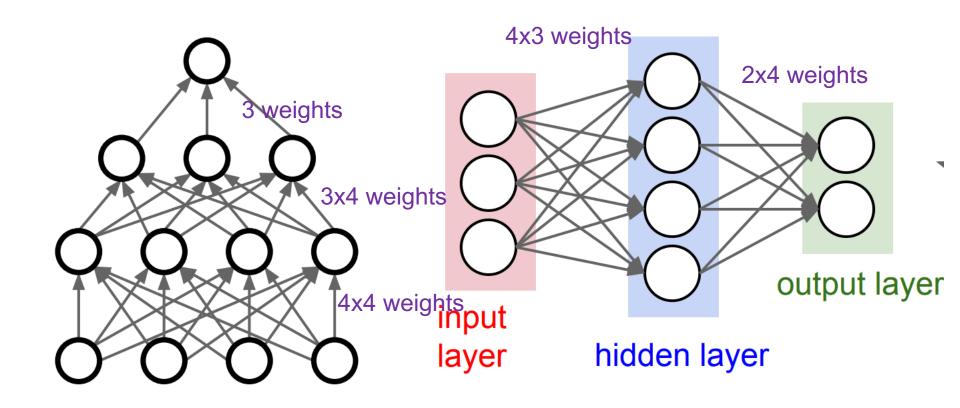


#### Part 19a: Dropout

**Instructor:** 

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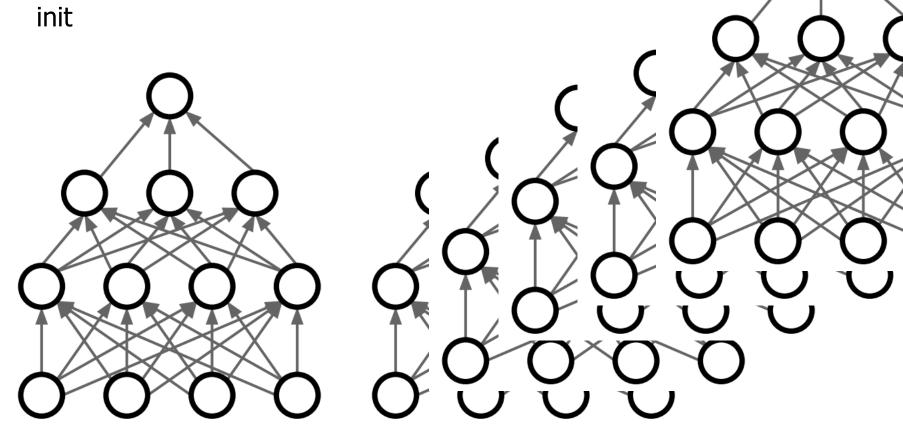
A feedforward network has many many weights



 Each different initialization from random weights will lead to a different network

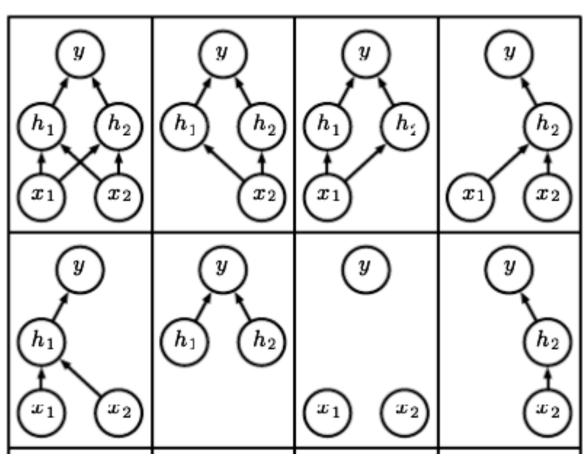


E.g. 10 networks, each from different init



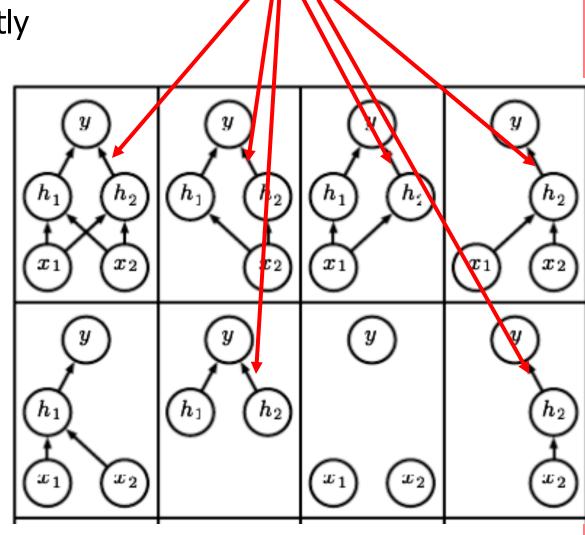
 We can also train an ensemble of networks with slightly different architectures

- A large ensemble:
- => a lot of weights!



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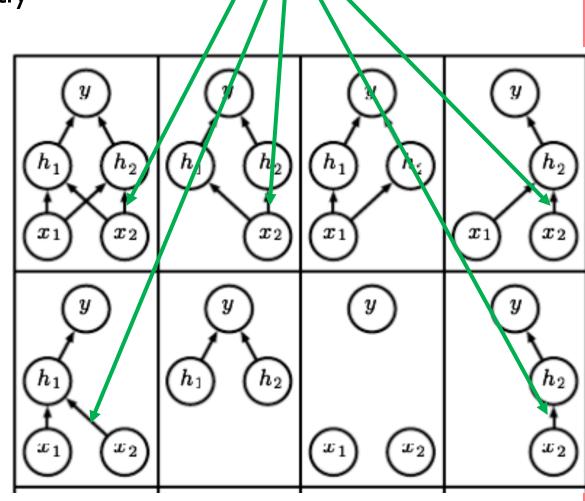
- A large ensemble:
- => a lot of weights!
- How to reduce number of weights?
  - Weight sharing



Şame "shared" weight

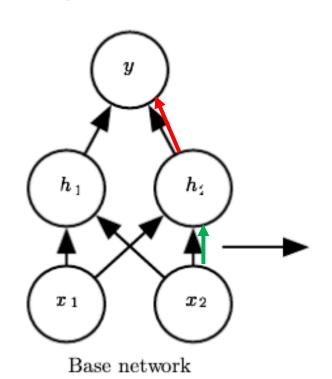
 We can also train an ensemble of networks with slightly different architectures

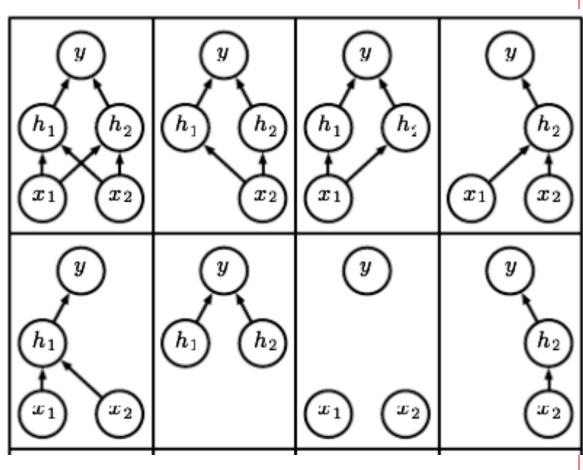
- A large ensemble:
- => a lot of weights!
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Same "shared" weight

- How to reduce number of weights?
  - Weight sharing
- We only have 6 weights to train

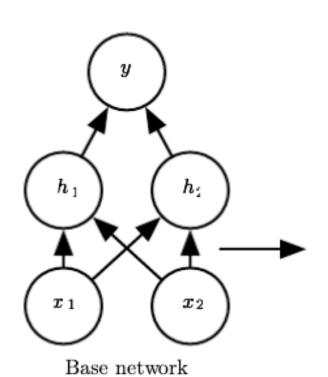


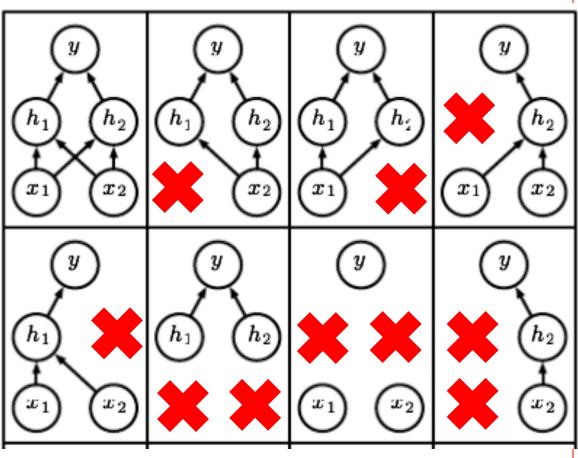


Dropout: how to train all these ensembles?

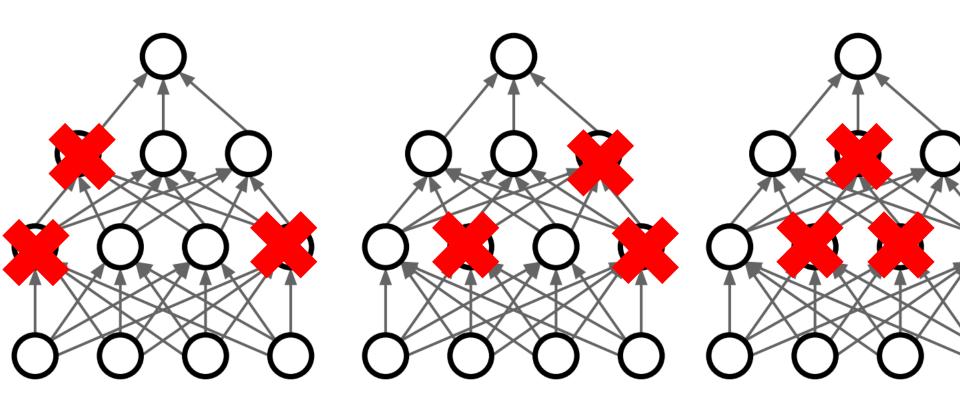
Keep the base network with its weights, just randomly "drop" neurons

Multiply their output by 0

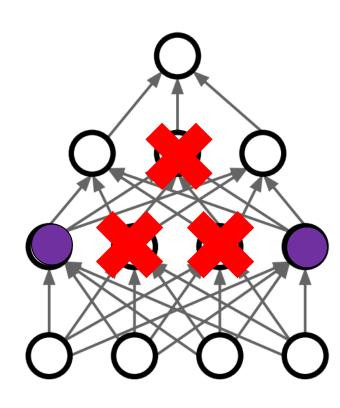




- Weight sharing in an ensemble
  - Dropout train multiple networks, each with some neurons missing
  - The edges/weights are kept the same across networks



- Dropout during testing:
  - Using the whole network "as is" is not optimal
  - During training we e.g. in layer 3 have input from e.g. two neurons
  - If during testing we use all four neurons, we'll have a higher input to layer 3 neurons
- Solution:
  - Reduce the weights after training
  - E.g. if you drop out 50% of neurons
    - Then reduce weights by 2

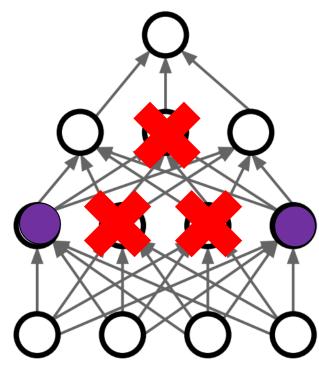


- E.g. if you drop out 50% of neurons
  - Then reduce weights by 2
- It's an approximation:
  - True solution is to multiply outputs p(y|x) by p(mu), probability of the drop pattern

$$\sum_{\boldsymbol{\mu}} p(\boldsymbol{\mu}) p(y \mid \boldsymbol{x}, \boldsymbol{\mu})$$

- Difficult, needs to actually run all networks
- Alternative: use geometric mean

$$ilde{p}_{ ext{ensemble}}(y \mid oldsymbol{x}) = \sqrt[2^d]{\prod_{oldsymbol{\mu}} p(y \mid oldsymbol{x}, oldsymbol{\mu})}$$

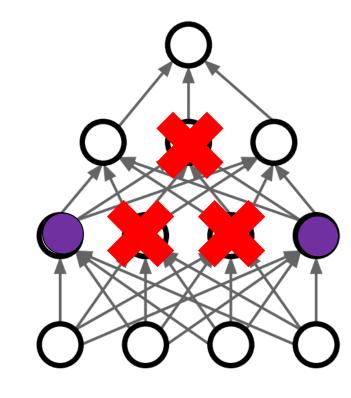


- Alternative: use geometric mean
  - Weights v, binary drop vector d

$$\tilde{P}_{\text{ensemble}}(y = y \mid \mathbf{v}) = \sqrt[2^n]{\prod_{\mathbf{d} \in \{0,1\}^n} P(y = y \mid \mathbf{v}; \mathbf{d})}$$

For softmax + just linear layer: 
$$P(y = y \mid \mathbf{v}; \mathbf{d}) = \operatorname{softmax} \left( \mathbf{W}^{\top} (\mathbf{d} \odot \mathbf{v}) + \mathbf{b} \right)_y$$

$$\begin{split} \tilde{P}_{\text{ensemble}}(\mathbf{y} &= y \mid \mathbf{v}) = \sqrt[2^n]{\prod_{\boldsymbol{d} \in \{0,1\}^n} P(\mathbf{y} = y \mid \mathbf{v}; \boldsymbol{d})} \\ &= \sqrt[2^n]{\prod_{\boldsymbol{d} \in \{0,1\}^n} \operatorname{softmax} \left( \boldsymbol{W}^\top \left( \boldsymbol{d} \odot \mathbf{v} \right) + \boldsymbol{b} \right)_{\!\!\! y}} \\ &= \sqrt[2^n]{\prod_{\boldsymbol{d} \in \{0,1\}^n} \frac{\exp \left( \boldsymbol{W}_{y,:}^\top (\boldsymbol{d} \odot \mathbf{v}) + b_y \right)}{\sum_{y'} \exp \left( \boldsymbol{W}_{y',:}^\top (\boldsymbol{d} \odot \mathbf{v}) + b_{y'} \right)}} \\ &= \frac{\sqrt[2^n]{\prod_{\boldsymbol{d} \in \{0,1\}^n} \exp \left( \boldsymbol{W}_{y,:}^\top (\boldsymbol{d} \odot \mathbf{v}) + b_y \right)}}{\sqrt[2^n]{\prod_{\boldsymbol{d} \in \{0,1\}^n} \sum_{y'} \exp \left( \boldsymbol{W}_{y',:}^\top (\boldsymbol{d} \odot \mathbf{v}) + b_{y'} \right)}} \end{split}$$



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$$\tilde{P}_{\text{ensemble}}(\mathbf{y} = y \mid \mathbf{v}) \propto \sqrt[2^n]{\prod_{\boldsymbol{d} \in \{0,1\}^n} \exp\left(\boldsymbol{W}_{y,:}^\top (\boldsymbol{d} \odot \mathbf{v}) + b_y\right)}$$

$$= \exp\left(\frac{1}{2^n} \sum_{\boldsymbol{d} \in \{0,1\}^n} \boldsymbol{W}_{y,:}^{\top} (\boldsymbol{d} \odot \mathbf{v}) + b_y\right)$$
$$= \exp\left(\frac{1}{2} \boldsymbol{W}_{y,:}^{\top} \mathbf{v} + b_y\right).$$

 For general net, cutting weights by half is just an approximation

## Dropout technique summary

- Dropout during training:
  - Define a single network
  - In each iteration (mini-batch), select random 50% of neurons and multiply their output by 0
- Dropout during testing:
  - Use the single trained network
  - Just divide all weights by 2

