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# Back Propagation

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# Approach

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- | Given a set of training data
  - | Each sample a tuple  $\langle \mathbf{x}, \mathbf{y} \rangle$
  - | Where  $\mathbf{x}$  is the input and  $\mathbf{y}$  is the desired output
  - | Train network such that
$$\underline{NN(\mathbf{x}) \approx \mathbf{y}} \quad \underline{\forall \mathbf{x} \in X}$$
  - | Assumes labeled training data
  - | Typically labels are provided by human annotation

# Back Propagation Algorithm

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- | Algorithm for training the weights
- | Start with random weights
- | Adjust the weights to reduce error
- | How do we adjust the weights?
- | Random search?

loss ←  
 $E = \text{deviation}$

# Back Propagation (BP)

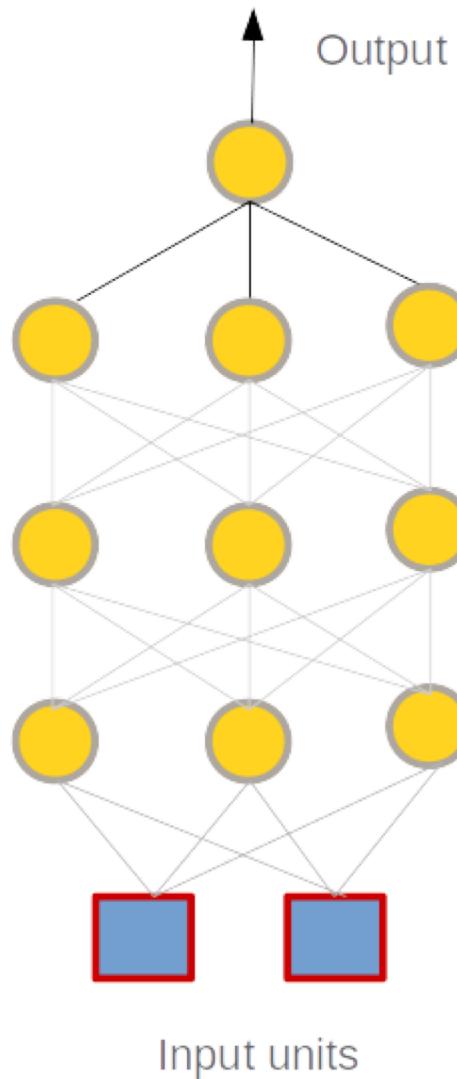
- | Given input and output, learn **weights**
- | Gradient descent minimizing quadratic error:

$$E = \frac{1}{2} \sum_{i=1}^N ||y_i - \hat{y}_i||^2$$

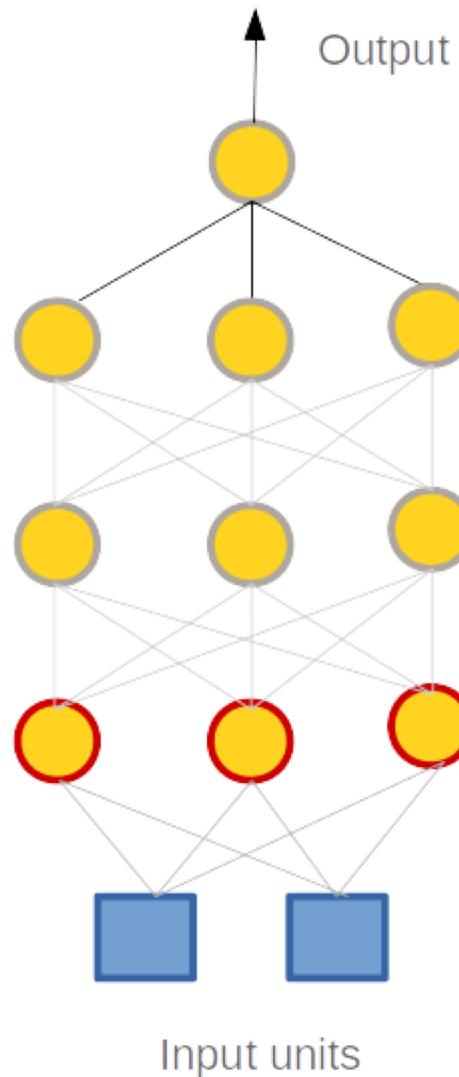
*y<sub>i</sub>*      *target*      *output of ANN*

- | In other words, minimize quadratic difference between target and output of the network

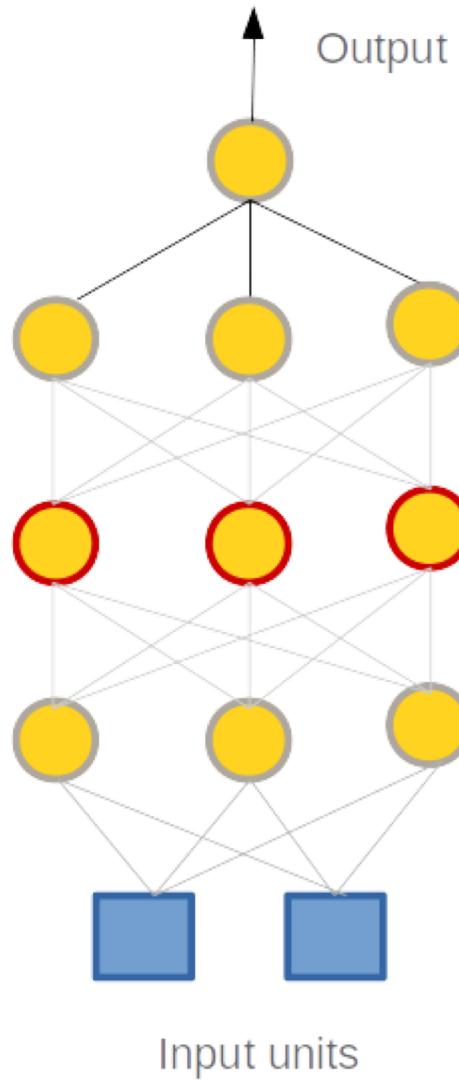
# Forward Propagation



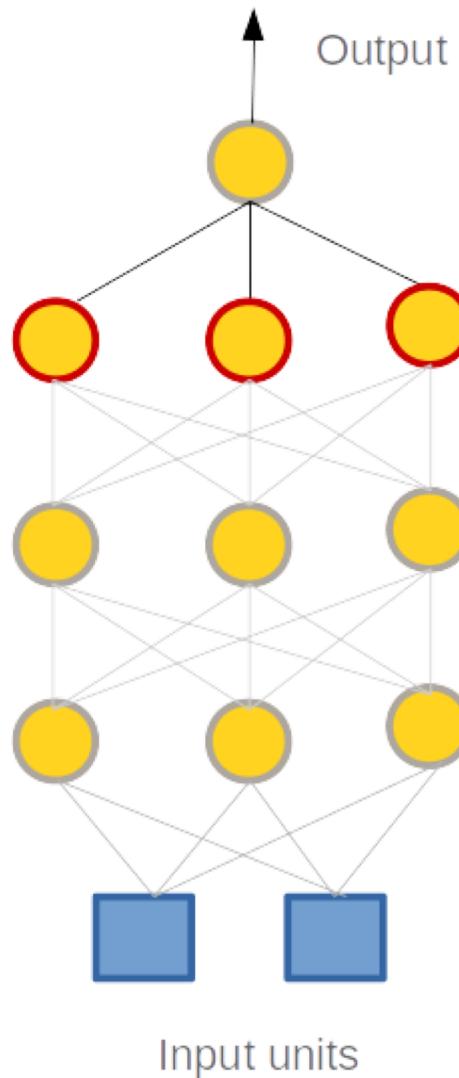
# Forward Propagation



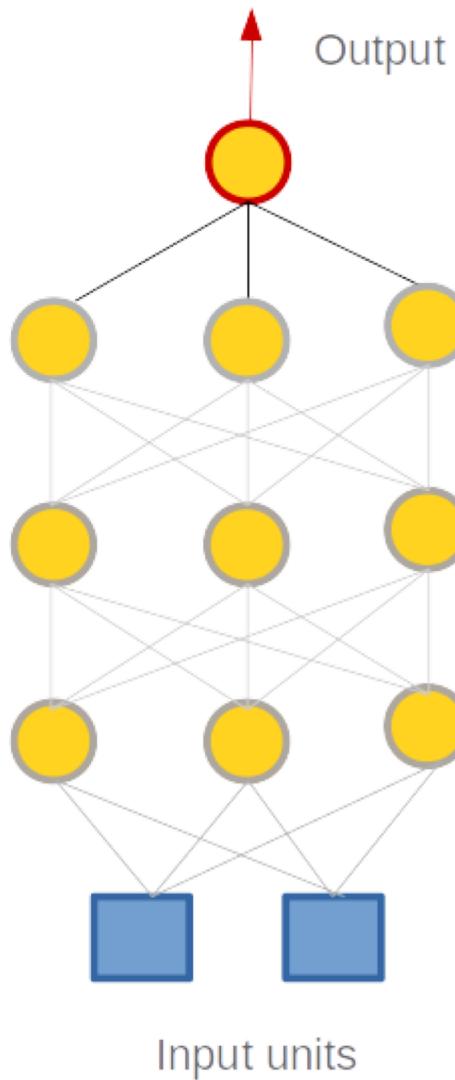
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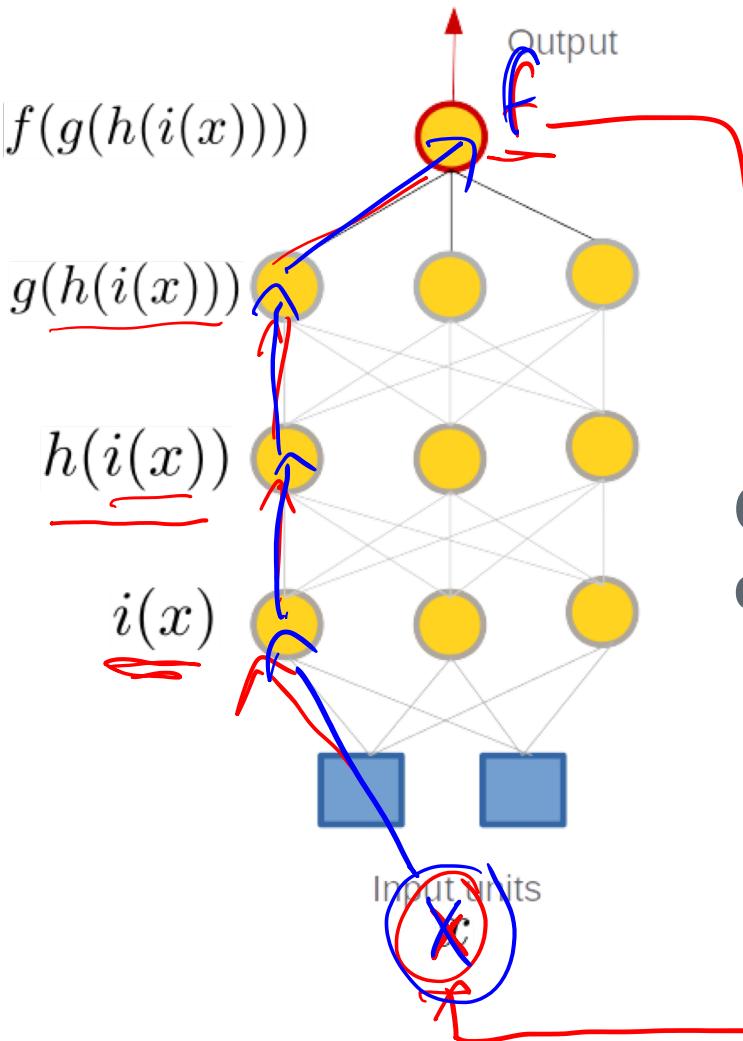
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# Neural Networks as Nested Functions



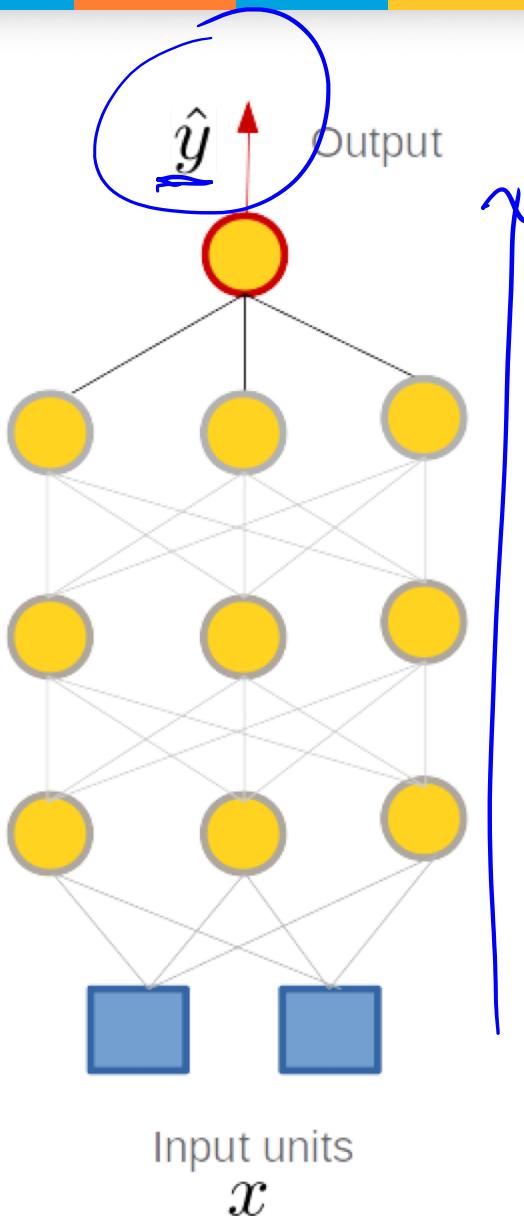
Neural Network as a Nested Function

$$f(g(h(i(x))))$$

Calculating the partial derivatives via chain rule

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial g} \frac{\partial g}{\partial h} \frac{\partial h}{\partial i} \frac{\partial i}{\partial x}$$

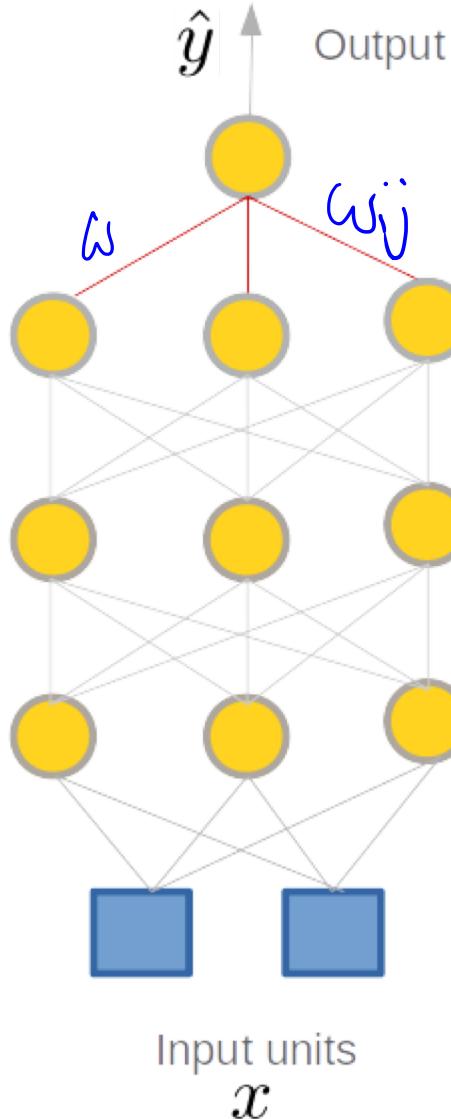
# Intuition of Back Propagation



1. Calculate Error at Final Layer

$$E = \frac{1}{2} (\underline{y} - \hat{y})^2$$

# Intuition of Back Propagation

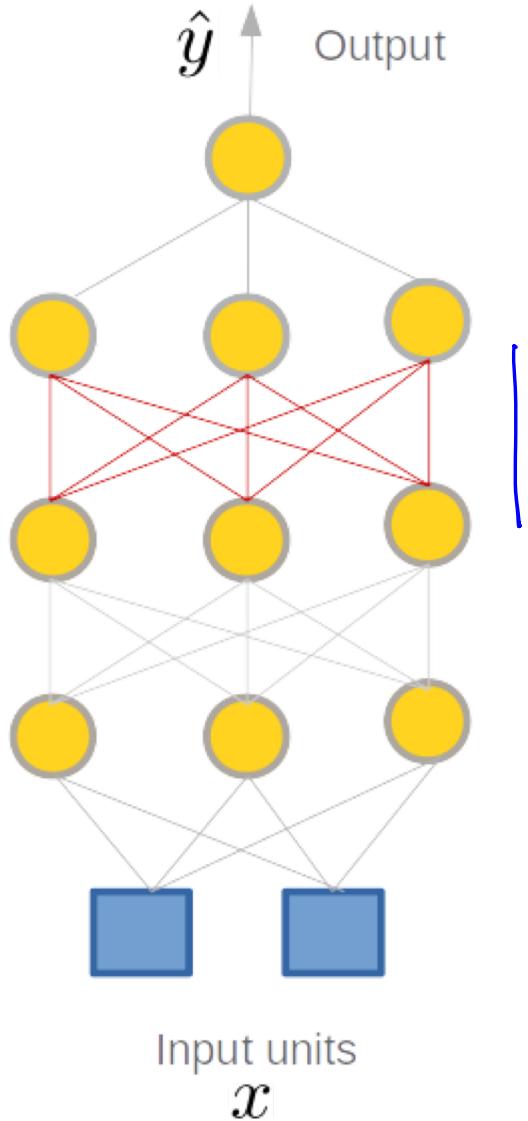


**1. Calculate Error at Final Layer**

$$E = \frac{1}{2}(y - \hat{y})^2$$

**2. Go back through layers and calculate changes to all weights**

# Intuition of Back Propagation

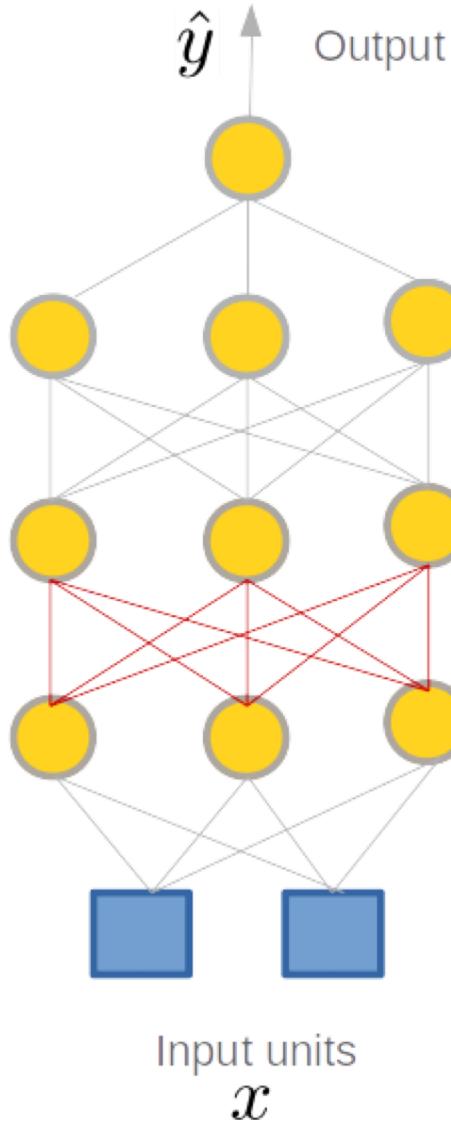


1. Calculate Error at Final Layer

$$E = \frac{1}{2}(y - \hat{y})^2$$

2. Go back through layers and calculate changes to all weights
3. Repeat step 2 for all previous layers

# Intuition of Back Propagation

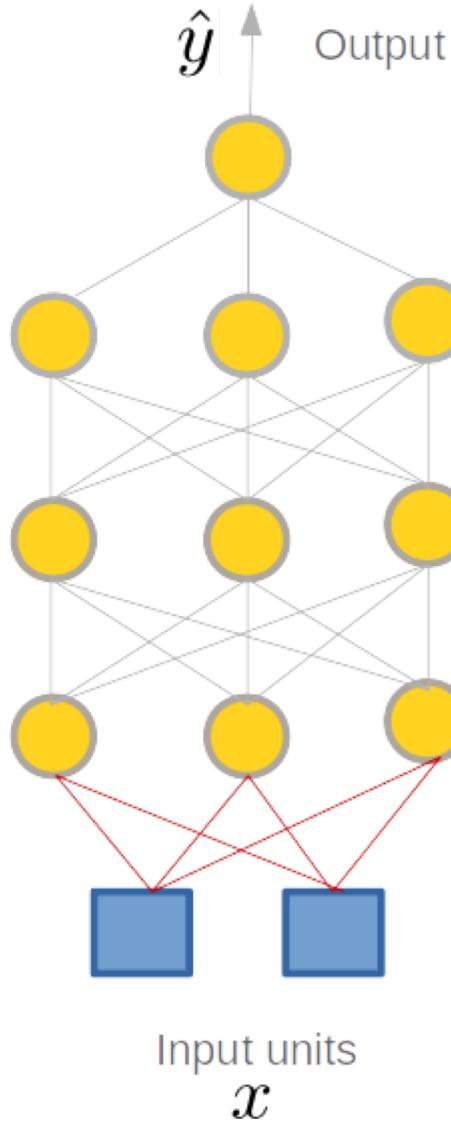


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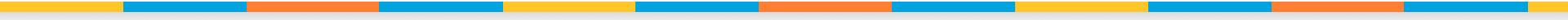


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# Summary



- | **Back propagation algorithm**
- | **Generates the weights of the network**
- | **Objective is to minimize the training error**
- | **Perform gradient descent**
- | **Calculate derivative of network**
- | **Derivatives are propagated backwards**