Algorithm that performs update for each example
$$\theta \Rightarrow \theta = \{W_0, W_1, W_2, \dots, W_L\}$$

initialize
$$\theta \Rightarrow \theta = \{W_0, W_1, W_2, ..., W_L\}$$
For N epochs, for each training example Xi.

Pre-activation layer
$$o(r)^{i+1} = \sum_{i=1}^{n} (w_i * r_i) \Rightarrow W^i \times X^i$$

 $L^{i+1} = sigmoid(g(x)^{i+1})$

$$g(x)^{i+1} = \sum_{i}^{n} (w_i * x_i) \implies W^i \times X^i$$



Error =
$$\frac{1}{2} \sum_{i}^{n} (y - \hat{y})^{2}$$

 $\frac{\partial E}{\partial w} = \frac{\partial}{\partial w} \frac{1}{2} \sum_{i}^{n} (y - \hat{y})^{2}$

Back propagation

 $\nabla_{n-1} = \nabla_n * W_{n-1}^T$

gradients, top to bottom
$$or = \frac{1}{2} \sum_{i}^{n} (y - \hat{y})^{2}$$

 $\frac{\partial E}{\partial w} = \sum_{i}^{n} (y - \hat{y})(-\frac{\partial E}{\partial w}\hat{y}) \qquad \Rightarrow (-\frac{\partial E}{\partial w}\hat{y}) = \hat{y}(1 - \hat{y})$

Use the chain rule to efficiently compute gradients, top to bottom
$$\widehat{\mathbf{v}} = Sigmoid(\mathbf{x})$$

$$\hat{y} = Sigmoid(x_i \times w_i)$$



