



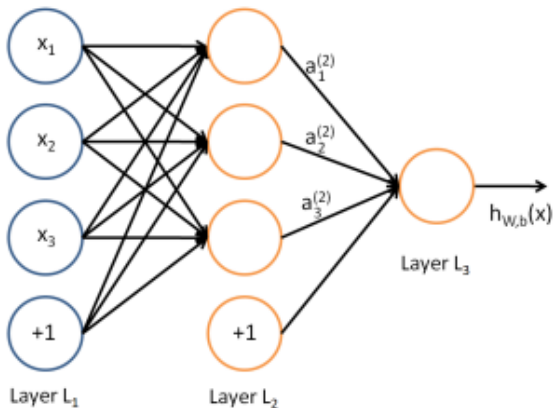
Multilayer Networks

Machine Learning: Jordan Boyd-Graber

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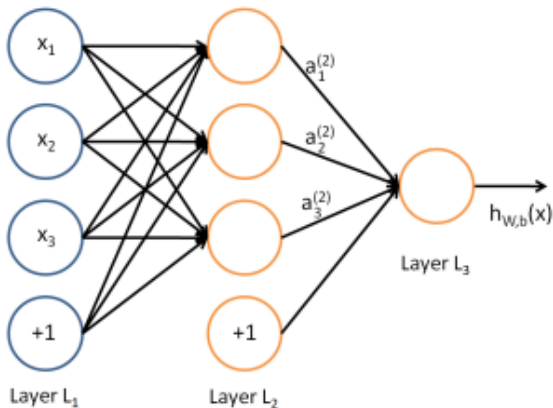
MATHEMATICAL DESCRIPTION

Learn the features and the function



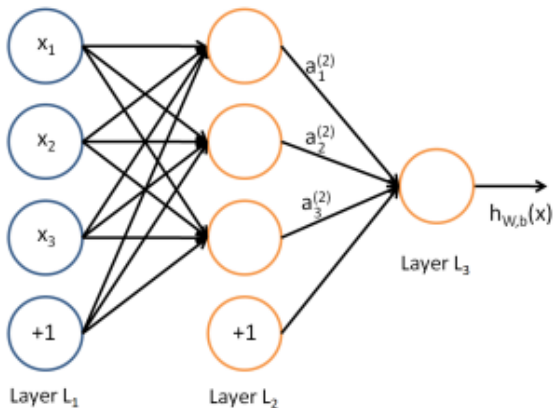
$$a_1^{(2)} = f\left(W_{11}^{(1)} x_1 + W_{12}^{(1)} x_2 + W_{13}^{(1)} x_3 + b_1^{(1)}\right)$$

Learn the features and the function



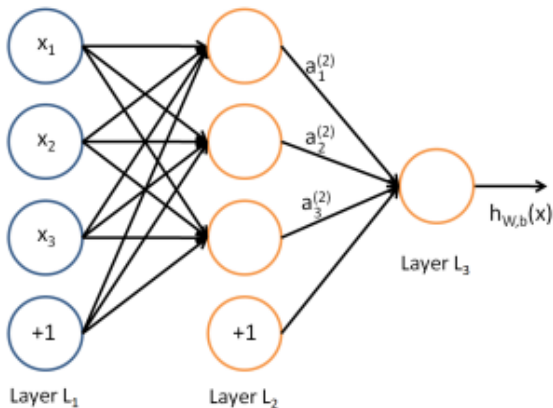
$$a_2^{(2)} = f\left(W_{21}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{23}^{(1)}x_3 + b_2^{(1)}\right)$$

Learn the features and the function



$$a_3^{(2)} = f\left(w_{31}^{(1)}x_1 + w_{32}^{(1)}x_2 + w_{33}^{(1)}x_3 + b_3^{(1)}\right)$$

Learn the features and the function



$$h_{W,b}(x) = a_1^{(3)} = f\left(W_{11}^{(2)} a_1^{(2)} + W_{12}^{(2)} a_2^{(2)} + W_{13}^{(2)} a_3^{(2)} + b_1^{(2)}\right)$$

Objective Function

- For every example x, y of our supervised training set, we want the label y to match the prediction $h_{W,b}(x)$.

$$J(W, b; x, y) \equiv \frac{1}{2} \|h_{W,b}(x) - y\|^2 \quad (1)$$

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Objective Function

Putting it all together:

$$J(W, b) = \left[\frac{1}{m} \sum_{i=1}^m \frac{1}{2} \|h_{W,b}(x^{(i)}) - y^{(i)}\|^2 \right] + \frac{\lambda}{2} \sum_l^{n_l-1} \sum_{i=1}^{s_l} \sum_{j=1}^{s_{l+1}} (w_{ji}^l)^2 \quad (3)$$

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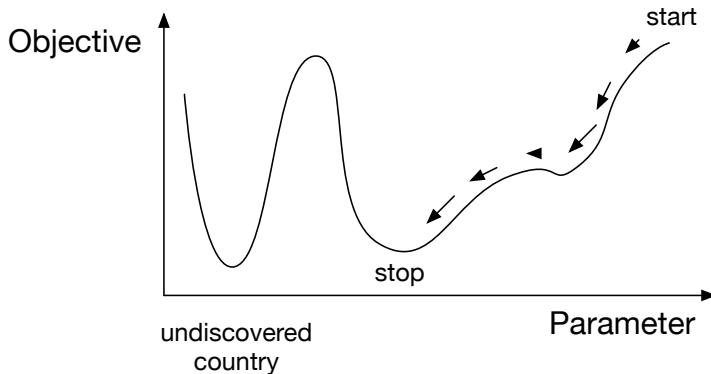
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- Initialize W and b to small random value near zero
- Adjust parameters to optimize J

Gradient Descent

Goal

Optimize J with respect to variables W and b



Backpropigation

- For convenience, write the input to sigmoid

$$z_i^{(l)} = \sum_{j=1}^n w_{ij}^{(l-1)} x_j + b_i^{(l-1)} \quad (4)$$

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- For output nodes, the error is obvious:

$$\delta_i^{(n_l)} = \frac{\partial}{\partial z_i^{(n_l)}} \|y - h_{w,b}(x)\|^2 = -(y_i - a_i^{(n_l)}) \cdot f'(z_i^{(n_l)}) \frac{1}{2} \quad (5)$$

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(chain rule)

Partial Derivatives

- For weights, the partial derivatives are

$$\frac{\partial}{\partial W_{ij}^{(l)}} J(W, b; x, y) = a_j^{(l)} \delta_i^{(l+1)} \quad (7)$$

- For the bias terms, the partial derivatives are

$$\frac{\partial}{\partial b_i^{(l)}} J(W, b; x, y) = \delta_i^{(l+1)} \quad (8)$$

- But this is just for a single example ...

Full Gradient Descent Algorithm

1. Initialize $U^{(l)}$ and $V^{(l)}$ as zero
2. For each example $i = 1 \dots m$
 - 2.1 Use backpropagation to compute $\nabla_W J$ and $\nabla_b J$
 - 2.2 Update weight shifts $U^{(l)} = U^{(l)} + \nabla_{W^{(l)}} J(W, b; x, y)$
 - 2.3 Update bias shifts $V^{(l)} = V^{(l)} + \nabla_{b^{(l)}} J(W, b; x, y)$
3. Update the parameters

$$W^{(l)} = W^{(l)} - \alpha \left[\left(\frac{1}{m} U^{(l)} \right) \right] \quad (9)$$

$$b^{(l)} = b^{(l)} - \alpha \left[\frac{1}{m} V^{(l)} \right] \quad (10)$$

4. Repeat until weights stop changing