Network with 1 Hidden Layer

Input layer: X1, ..., Xd; Xd+1 = 1

Hidden units: hi, ..., hm; hm+1=1

Output layer: Z1,..., Zk [We might have more than one output so we can build multiple classifiers that share hidden units.]

Layer 1 weights: m x (d+1) matrix V

V; is row i

Layer 2 weights: Kx(m+1) matrix W

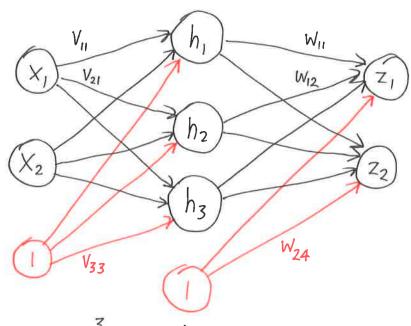
Wi is row i

Recall $s(\gamma) = \frac{1}{1+e^{-\gamma}}$

For vector V, $s(V) = \begin{bmatrix} s(v_1) \\ s(v_2) \end{bmatrix}$

other nonlinear fins can be used

[We apply s to a vector component by component]

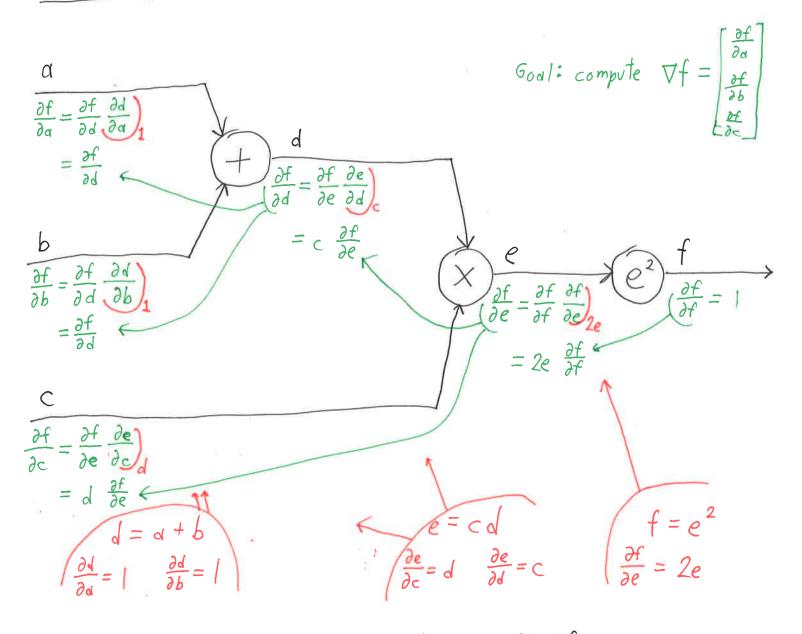


$$h_i = s\left(\sum_{j=1}^{3} V_{ij} x_j\right) \quad \text{In short, } h = s(V_X)$$

$$z = s(W_h) = s(W_S(V_X))$$

add a 1 to end of vector

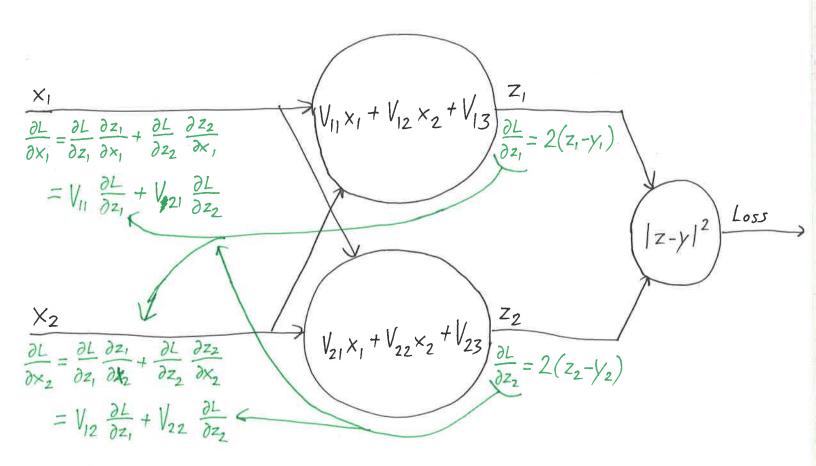
Computing Gradients for Arithmetic Expressions



Each value z gives partial derivative of the form

where z is input to n. $\frac{\partial f}{\partial z} = \left(\frac{\partial f}{\partial n} \frac{\partial n}{\partial z}\right)_{\text{computed during forward pass}}$ after forward pass "backpropagation"

[what if a unit's output goes to more than one unit?]



The Backpropagation Alg

Recall
$$s'(r) = s(r)(1-s(r))$$

$$h_i = s(V_i \cdot x), so \quad \nabla_{V_i} h_i = s'(V_i \cdot x) \times = h_i (1-h_i) \times$$

$$\nabla_{W_j} z_j = s'(W_j \cdot h) h$$

$$= z_j (1-z_j) h$$

$$\frac{V}{V_{W_{j}}L = \frac{\partial L}{\partial z_{j}}} V_{W_{j}} Z_{j}$$

$$= \frac{\partial L}{\partial z_{j}} Z_{j} (1-z_{j}) h$$

$$\frac{V}{V_{V_{i}}L = \frac{\partial L}{\partial h_{i}}} V_{V_{i}} h_{i}$$

$$\frac{\partial L}{\partial h_{i}} = \sum_{j=1}^{k} \frac{\partial L}{\partial z_{j}} \frac{\partial z_{j}}{\partial h_{i}}$$

$$= \sum_{j} W_{j}; Z_{j} (1-z_{j}) \frac{\partial L}{\partial z_{j}}$$

Compute V, L, Vw L one row at a time.