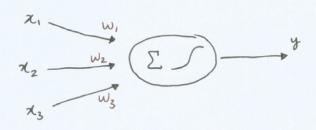
# NEURAL UNITS



1) Compute the neuron's activation

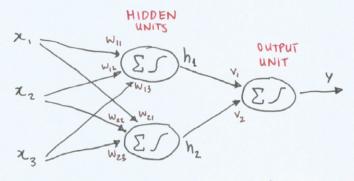
$$a = X^{T}W + W_{0}$$
$$= \sum_{d=1}^{D} X_{d}W_{d} + W_{0}$$

2) Set output as a fn of its activation y=g(a)

$$g(a) = \sigma(a) = \frac{1}{1 + e^{-a}}$$
 i.e. sigmoid

3) If y > 0.5, assign x to class 1. Otherwise 0.

# NEURAL NETWORK



tach unit also gets a bias weight!

To compute a class label in this network:

1) 
$$h_1 \leftarrow g(w_1^T \times + w_{10})$$

3) 
$$Y \leftarrow 9\left(V^{T}\binom{h_1}{h_2} + V_0\right)$$

4) If y > 0.5, assign class 1.

-> To do regression instead of classification, don't squash the output.

Replace step 3 w/ 
$$Y \leftarrow g_3 \left( V^T \binom{h_1}{h_2} + V_0 \right)$$
 where  $g_3 (a) = a$ 

$$\frac{1}{1 \cdot dentity \cdot fn}$$

### MULTICLASS PREDICTION

- → Define one output for each class. (i.e. 3 classes → 3 output units)
- + Step 3 is now:

$$\forall m \in 1, 2, ... M, \quad \forall_m \leftarrow V_m^T \binom{h_1}{h_2} + V_{m0}$$

Step 4 is now :

Prediction f(x) is the class w/ the highest probability

$$f(x) = \max_{m=1}^{M} p(y=m \mid x)$$

(Same trick w/ log Regr) 
$$P(y=m|x) = \frac{e^{y_m}}{\sum_{k=1}^{m} e^{y_k}}$$

# TRAINING ANNS

- We want to find best weights for each unit
- → Create an error fn tht. measures the agreement of target y; and the prediction f(x)

CLASSIFICATION

$$E = \sum_{i=1}^{n} Y_i \log f(X_i) + (1 - Y_i) \log (1 - f(X_i))$$

REGRESSION
$$E = \sum_{i=1}^{n} (y_i - f(x_i))^2$$

- → It can make sense to use regularization penalty (e.g. \log \log \log well with control overfitting \log called 'WEIGHT DECAY'
- Find w so that E is minimized.
- For Linear Regr. & Log. Regr., the optimization problem for w had a unique optimum.

  For ANNs, there are local minima
- $\rightarrow$  We need the gradient descent of E w.r.t. all the params.  $w\left[i.e.\ g(w) = \frac{\partial E}{\partial w}\right]$  (Look at Optimization notes)

#### HOW TO DEAL W/ LOCAL MINIMA?

· Train multiple nets frm. diff. starting places and then choose best