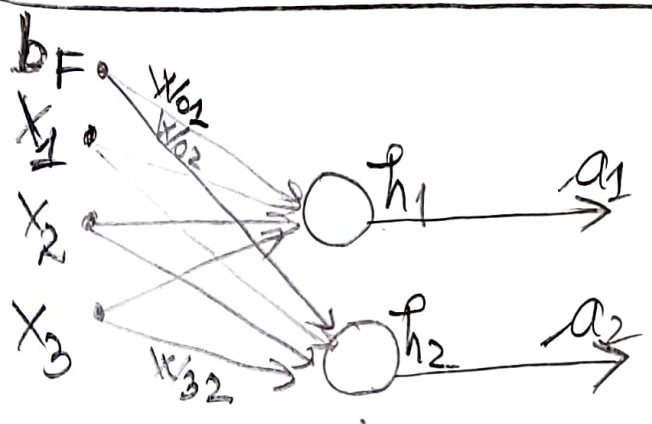


$\Gamma \Rightarrow$  no conn. between hidden nodes

# Restricted Boltzmann Machines (= symm., bipartite, bidirectional graph)



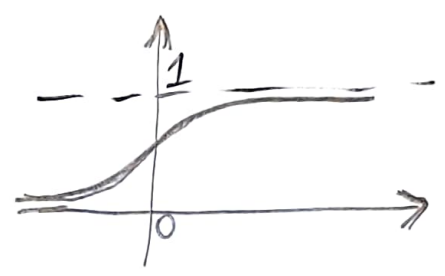
|       |          |     |
|-------|----------|-----|
|       | Elephant | Dog |
| $a_1$ | 1        | 0   |
| $a_2$ | 0        | 1   |

Input  
(ex. pixels of images)  
↑  
visible layer

↑  
hidden layer

output after activation fct.

$$a_1 = \sigma(\vec{w} \cdot \vec{x}) = \frac{1}{1 + e^{-\vec{w} \cdot \vec{x}}}$$



## Step 1 Forward pass (like in FFNN)

↳ captures  $P(a|x)$

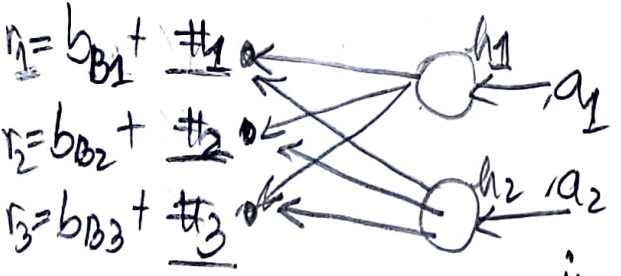
↳ **Q** Given the input pixels, should my weights send a signal to Eleph. or Dog node?

## Step 2 Backward pass = reconstruct input $x_i$ from output $a_i$

↳ captures  $P(x|a)$

↳ **Q** Given an Eleph., which distrib. of pixels should I expect?

new biases ↓



ep. ← (reconstructions of inputs)

Reconstr. error =  $\vec{r} - \vec{x} \Rightarrow$  update  $\vec{w}$  to min. it (uses the "contrastive divergence")

↳ all  $\vec{w}$ , including those for  $b_F$  (bias forward) &  $b_B$  (bias backward)

RBM can be used for  $\left\{ \begin{array}{l} \text{supervised} \\ \text{unsupervised} \end{array} \right\}$  learning

can be used for  $\left\{ \begin{array}{l} \text{feature learning} \\ \text{dimens. reduction} \\ \text{collaborative filtering} \\ \text{classif.} \\ \text{regression} \end{array} \right.$

(Obs.) We need the extra bias  $b_j$  (bias at Backward pass) to model  $a_i$  into  $x_i$ .