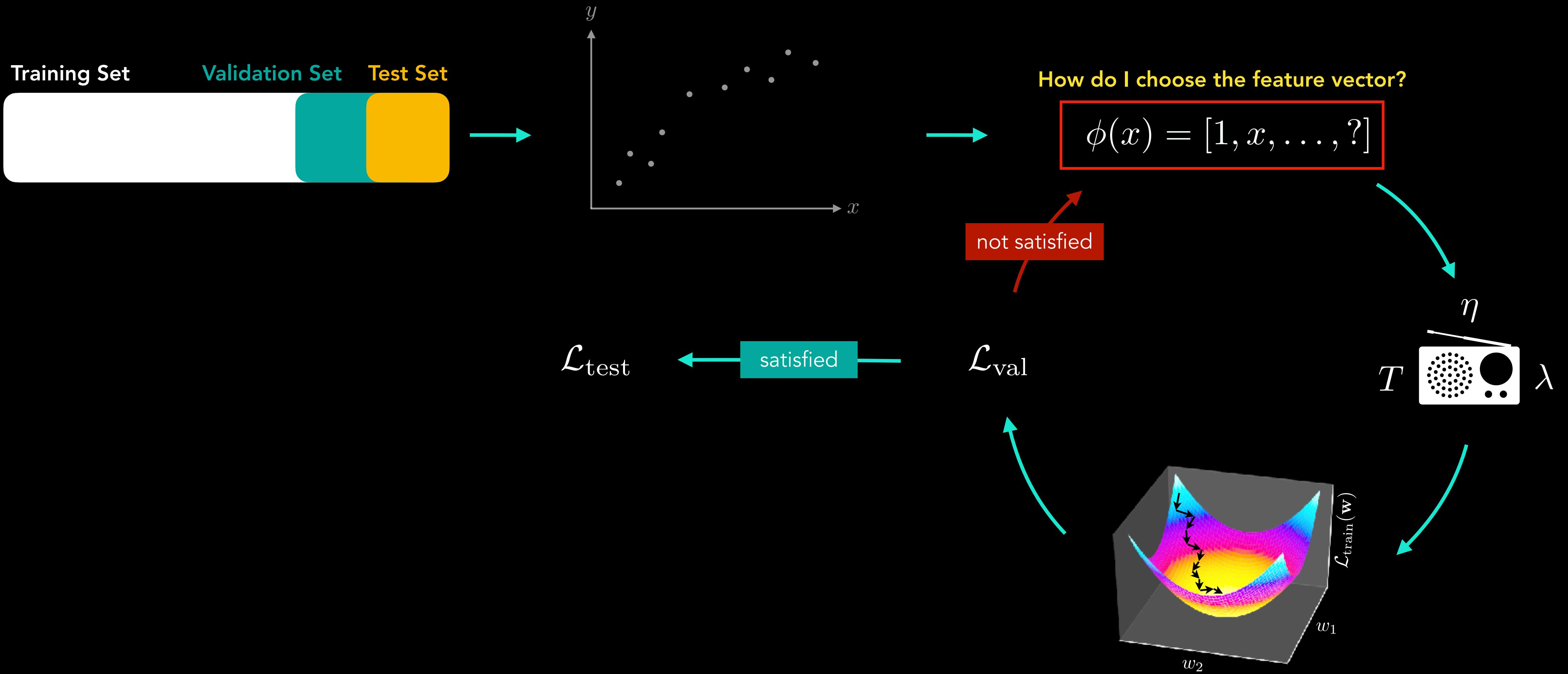


Deep Learning

The ML workflow



How do I choose the feature vector?

$$\phi(x) = [1, x, \dots, ?]$$

$$f_{\mathbf{w}}(x) = \mathbf{w} \cdot \phi(x)$$

X

The diagram illustrates the concept of choosing a feature vector $\phi(x)$. It shows the equation $f_{\mathbf{w}}(x) = \mathbf{w} \cdot \phi(x)$ where $\phi(x)$ is highlighted with a green box. Four arrows point from this highlighted term to four examples of what $\phi(x)$ could be:

- $\phi(x) = [1, x]$
- $\phi(x) = [1, x, x^2, x^3]$
- $\phi(x) = [1, x, \sin(3x)]$
- ???????????????

How do I choose the feature vector?

$$\phi(x) = [1, x, \dots, ?]$$



Decision Boundary

$$\phi(x) \cdot w = 0$$



Boat

Linear Predictor

$$f_{\mathbf{w}}(\mathbf{x}) = \mathbf{x} \cdot \mathbf{w}$$

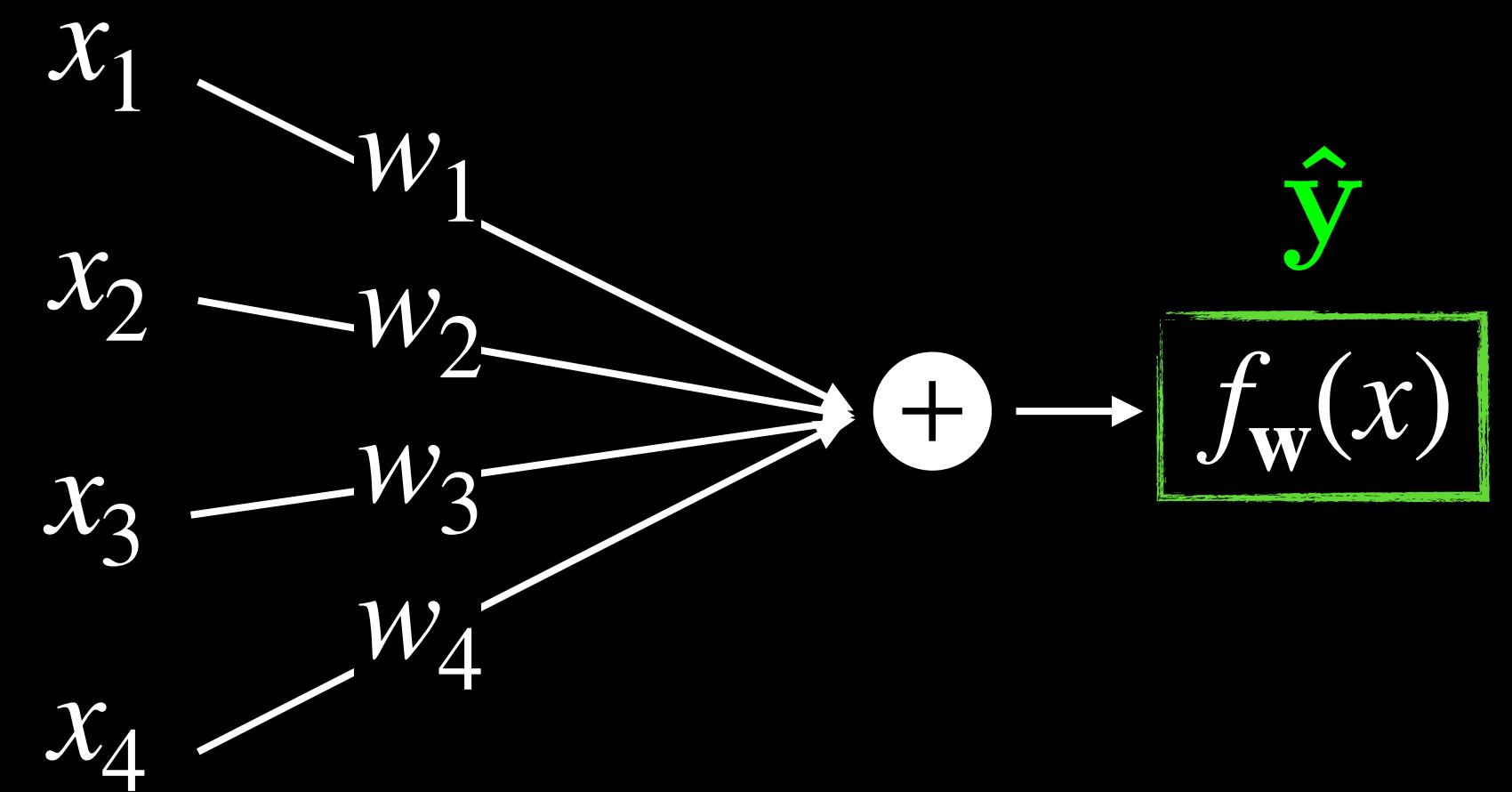
$$\mathbf{w} = [w_1, w_2, w_3, w_4]$$

$$\mathbf{x} = [x_1, x_2, x_3, x_4]$$

$$f_{\mathbf{w}}(\mathbf{x}) = w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4$$

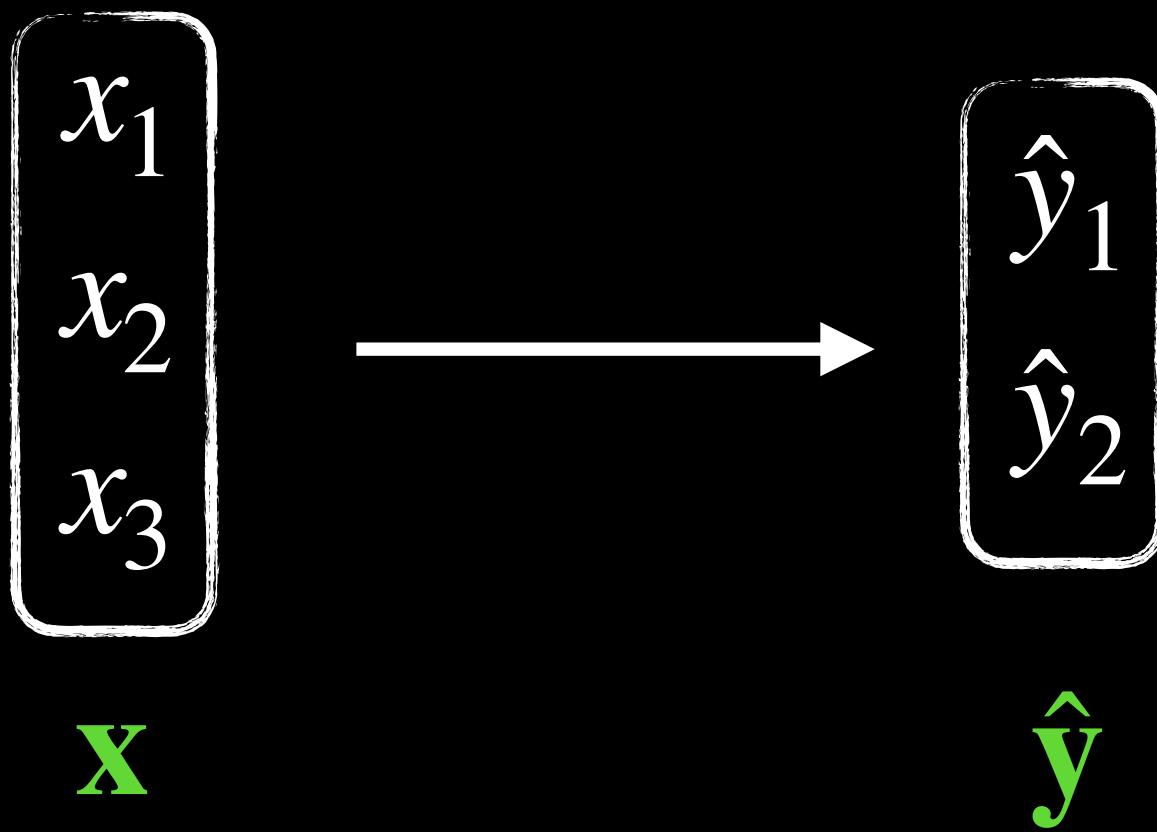


Network Representation



Linear Predictor

2 outputs?



3 * 2 fitting parameters

$$\begin{aligned}\hat{y}_1 &= \mathbf{w}_1 \cdot \mathbf{x} = w_{11}x_1 + w_{12}x_2 + w_{13}x_3 \\ \hat{y}_2 &= \mathbf{w}_2 \cdot \mathbf{x} = w_{21}x_1 + w_{22}x_2 + w_{23}x_3\end{aligned}$$

Matrix form

$$\begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$$\hat{\mathbf{y}} = \mathbf{W} \mathbf{x}$$

From Matrix to Network

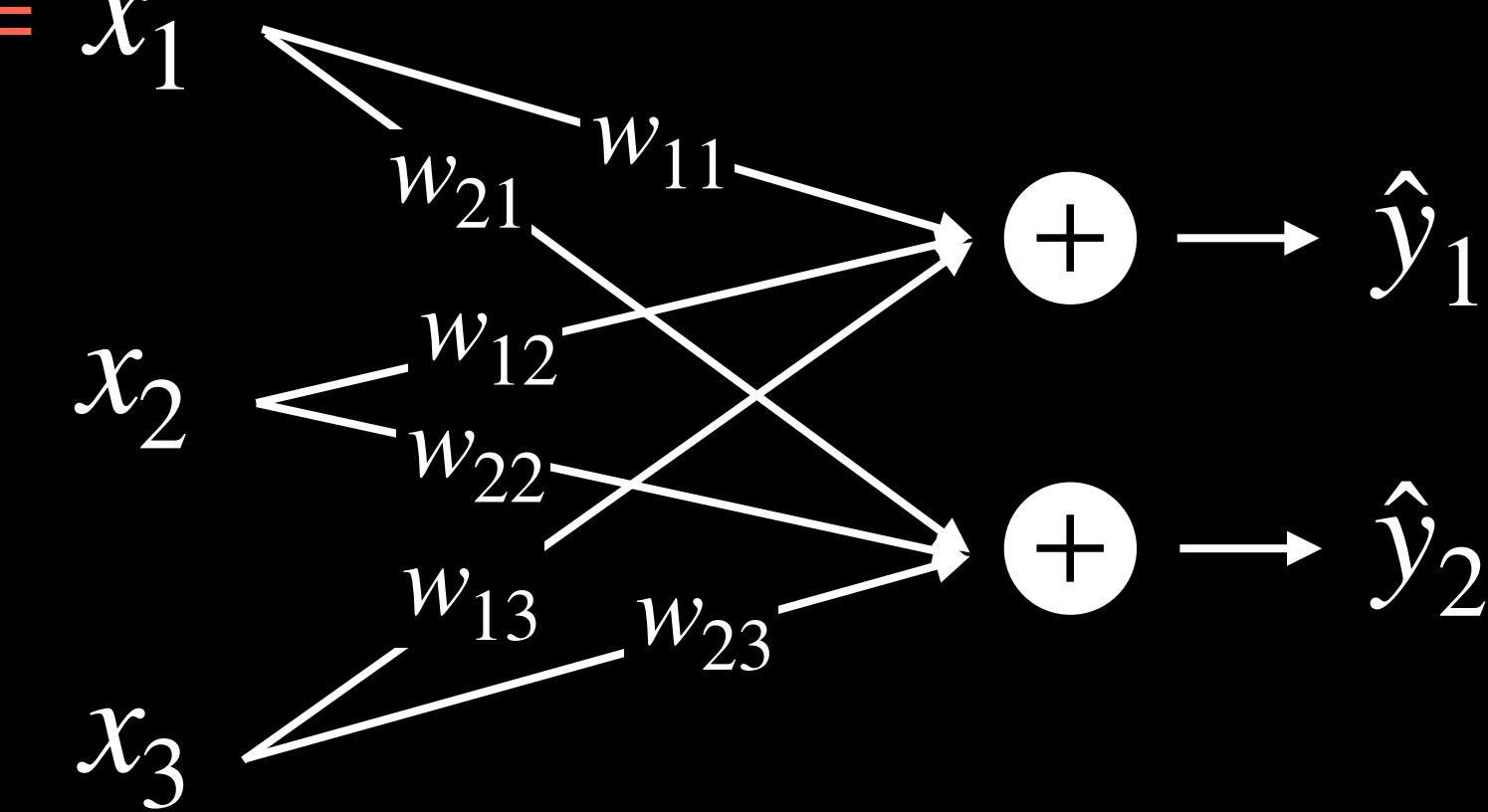
Matrix Representation

$$\begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

$\hat{\mathbf{y}} = \mathbf{W} \mathbf{x}$



Account for Bias: $1 = x_1$



Index notation

$$\hat{y}_i = \sum_{j=1}^n w_{ij} x_j$$

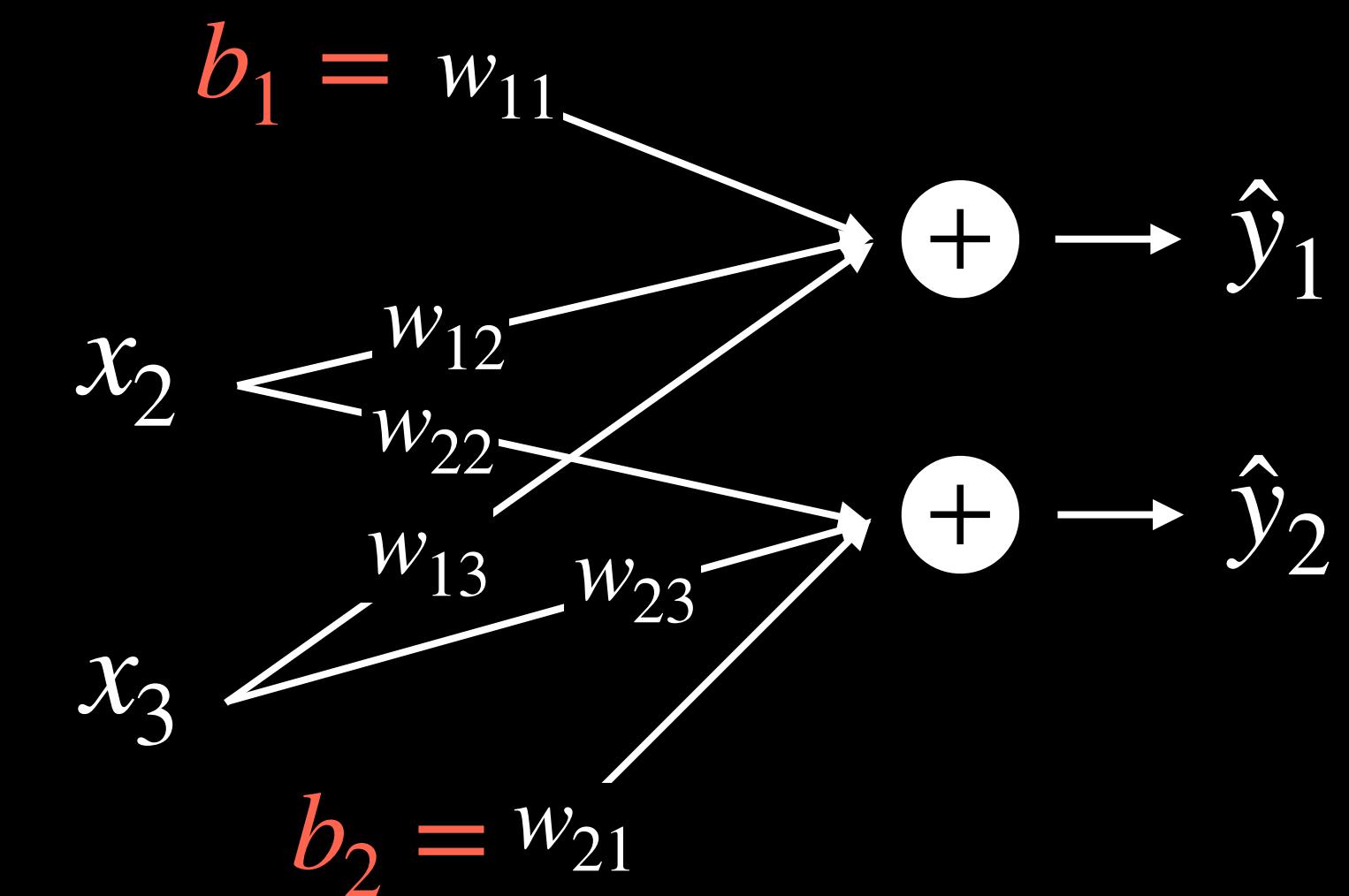
Linear Predictor - Explicit Bias

Matrix Representation

$$\begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \end{bmatrix} = \begin{bmatrix} w_{12} & w_{13} \\ w_{22} & w_{23} \end{bmatrix} \begin{bmatrix} x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} w_{11} \\ w_{21} \end{bmatrix}$$

$$\hat{\mathbf{y}} = \mathbf{W} \mathbf{x} \mathbf{b}$$

Network Representation



Linear Predictor

$$\hat{\mathbf{y}} = \mathbf{W} \mathbf{x} + \mathbf{b}$$

Dimensions:

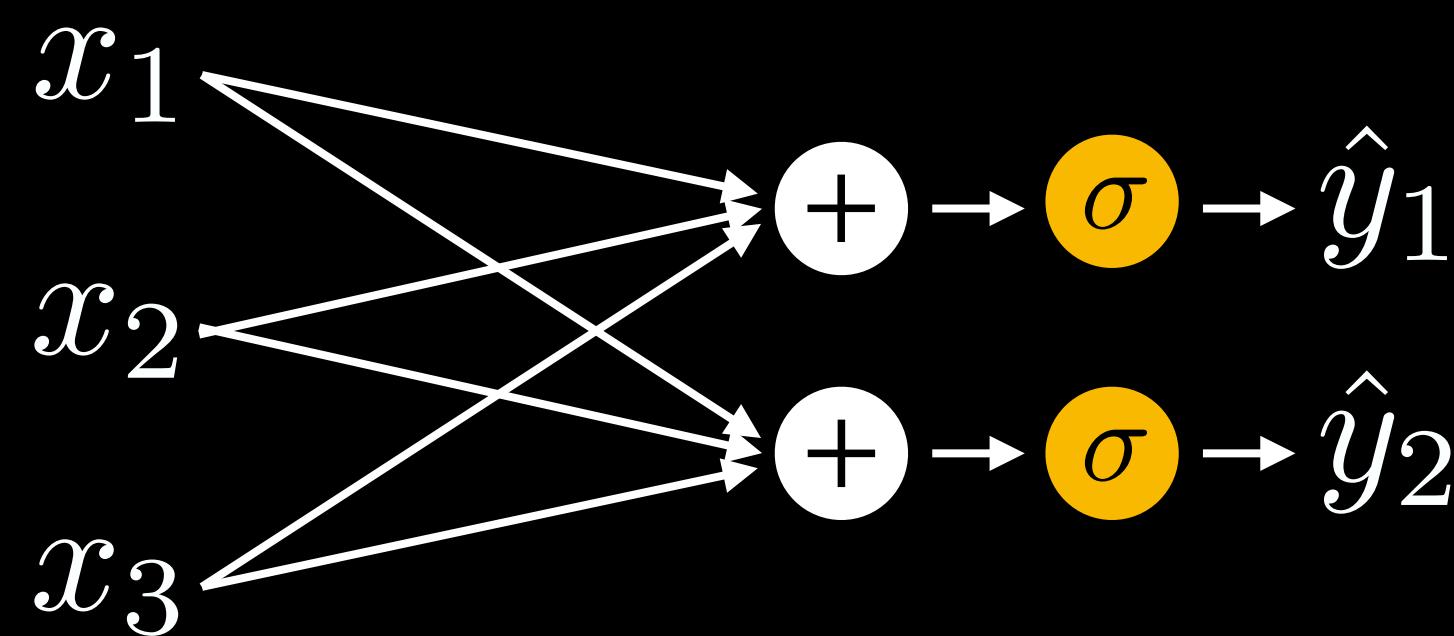
- $\hat{\mathbf{y}}$: $m \times 1$
Number of outputs
- \mathbf{W} : $m \times n$
Number of inputs
- \mathbf{x} : $n \times 1$
- \mathbf{b} : $m \times 1$

Some formulations explicitly account for \mathbf{b} , while others include the bias as part of \mathbf{x}

Here we omit \mathbf{b} for simplicity of representation

Nonlinear Predictor

$$\hat{\mathbf{y}} = \sigma(\mathbf{W}\mathbf{x})$$

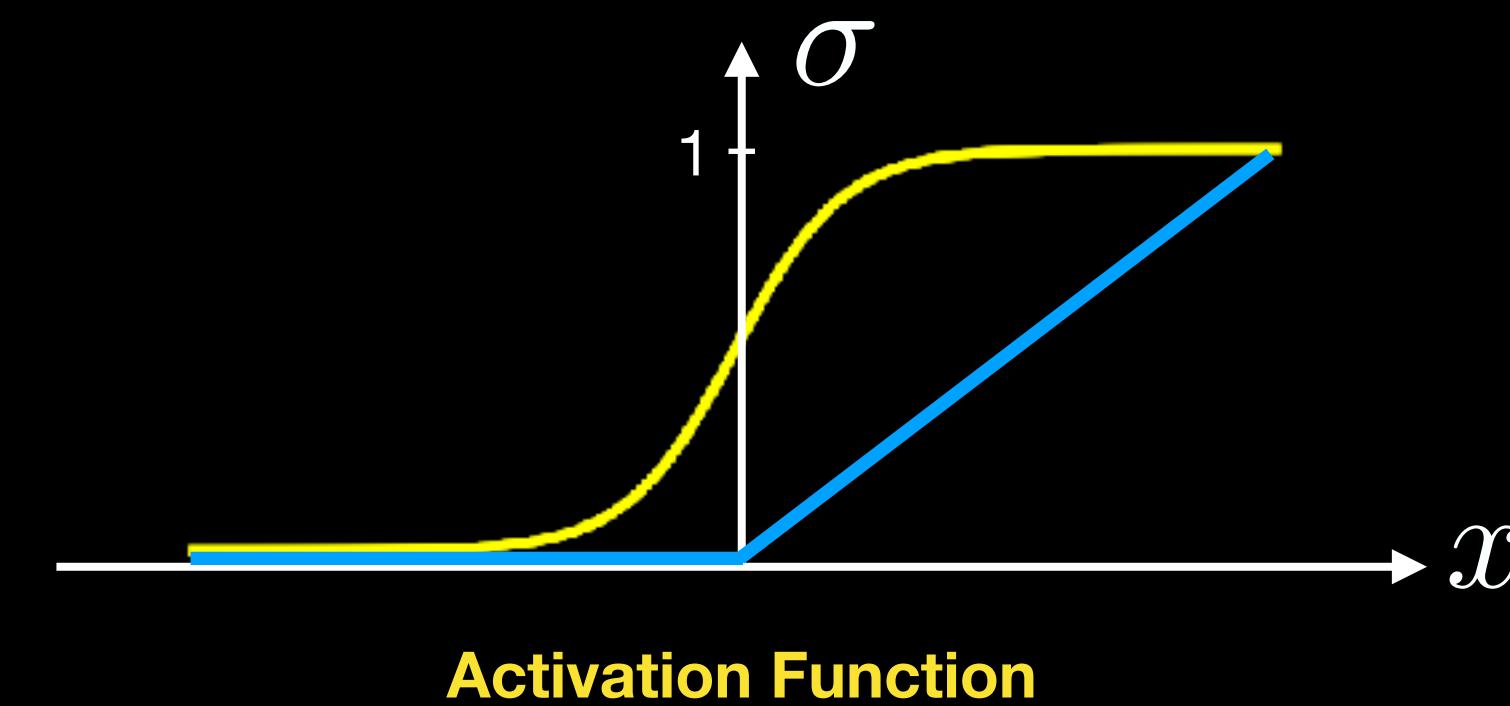
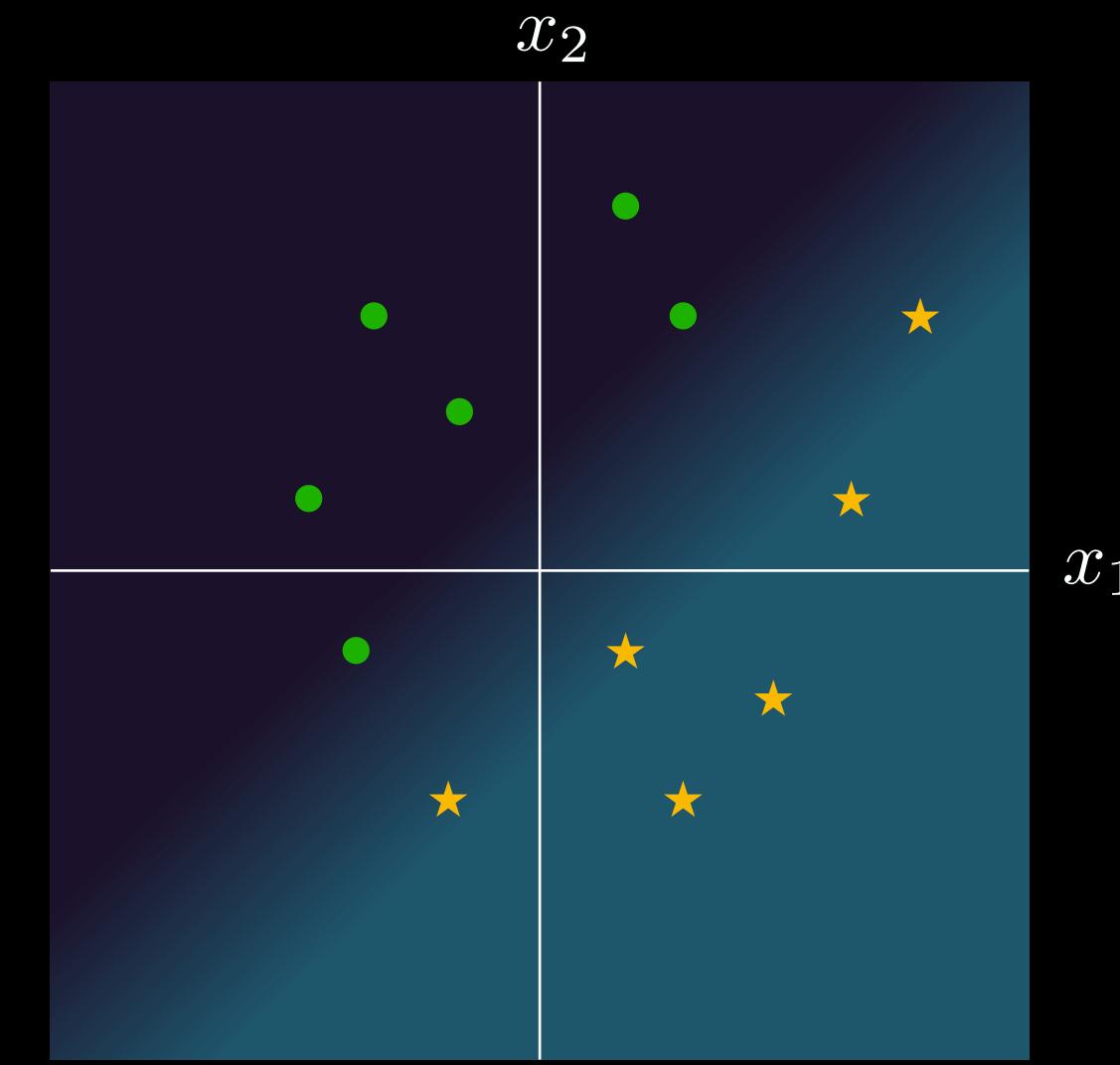


Logistic function:

$$\sigma(x) = \frac{1}{1 + e^{-x}}$$

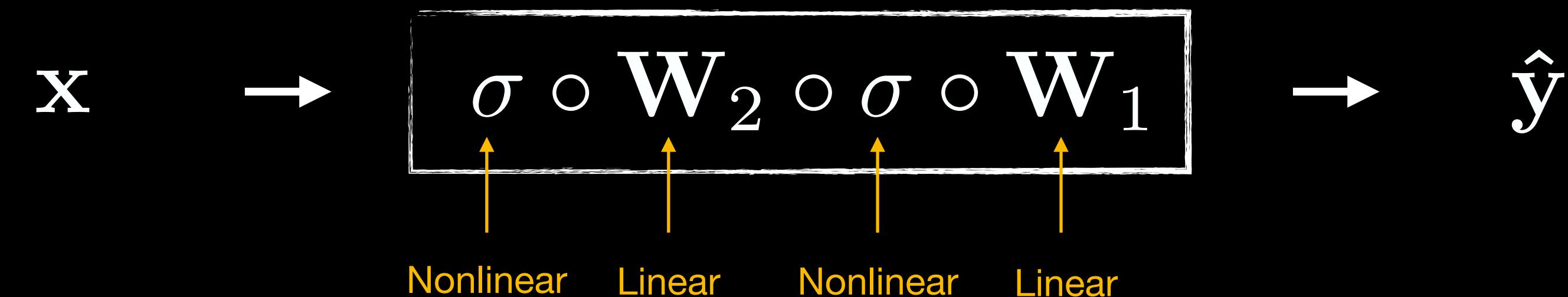
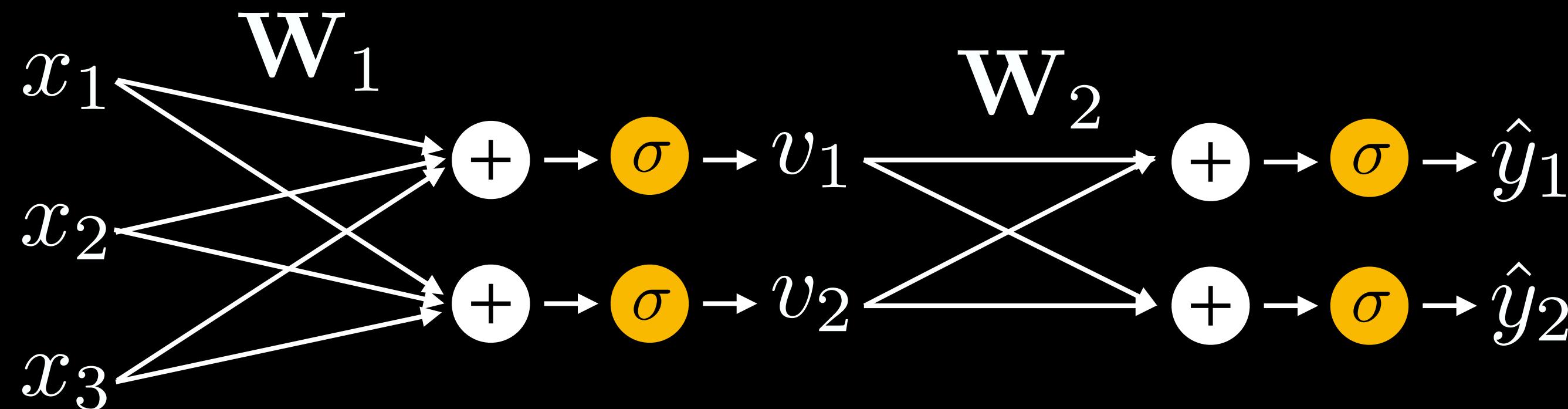
ReLU:

$$\sigma(x) = xH(x)$$



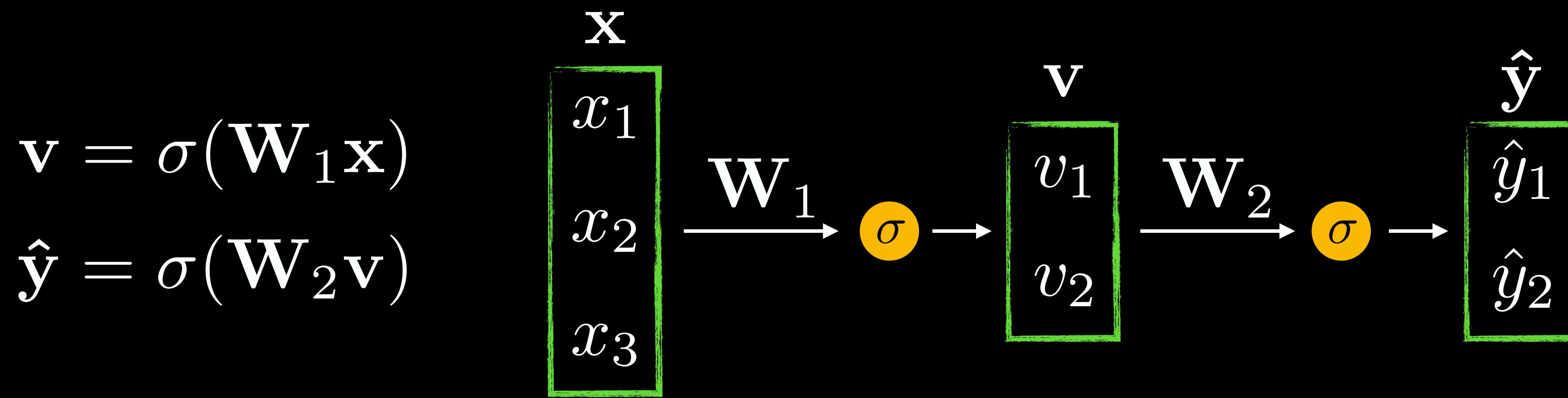
Neural network

$$\hat{\mathbf{y}} = \sigma(\mathbf{W}_2 \sigma(\mathbf{W}_1 \mathbf{x}))$$



Neural network

$$\hat{\mathbf{y}} = \sigma(\mathbf{W}_2 \sigma(\mathbf{W}_1 \mathbf{x}))$$

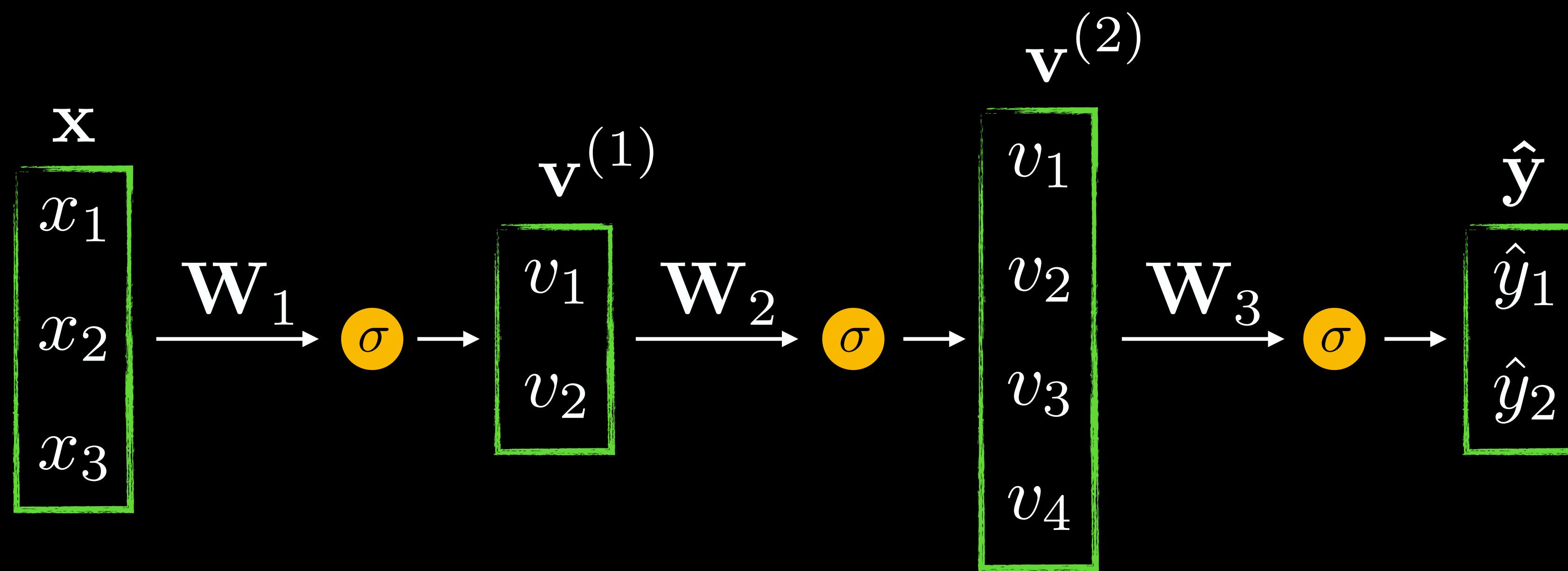


Hidden layer

Can be interpreted
as a learned $\phi(\mathbf{x})$

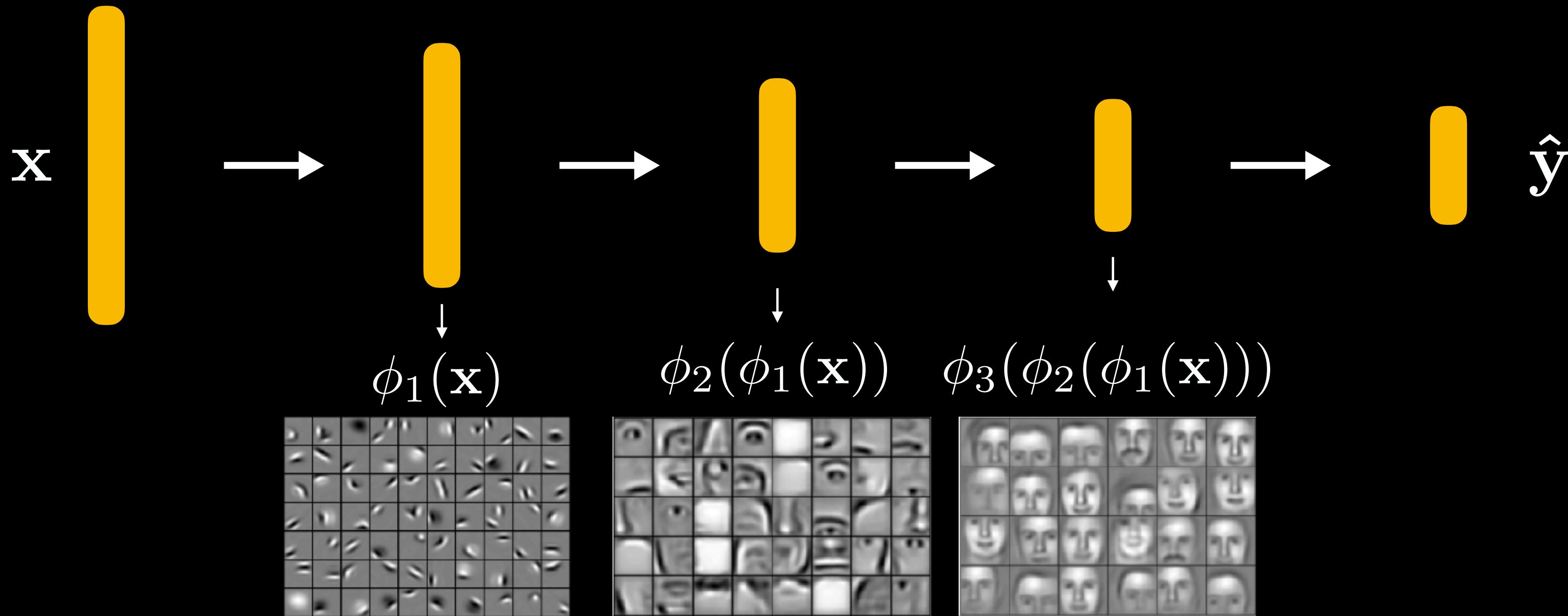
Deep network

$$\hat{\mathbf{y}} = \sigma(\mathbf{W}_3 \sigma(\mathbf{W}_2 \sigma(\mathbf{W}_1 \mathbf{x})))$$



$$\mathbf{v}^{(1)} = \sigma(\mathbf{W}_1 \mathbf{x}) \quad \mathbf{v}^{(2)} = \sigma(\mathbf{W}_2 \mathbf{v}^{(1)}) \quad \hat{\mathbf{y}} = \sigma(\mathbf{W}_3 \mathbf{v}^{(2)})$$

Why deep learning?



Feature learning