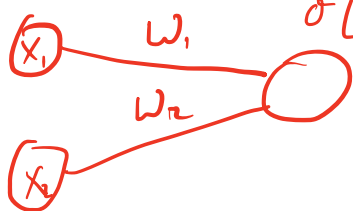
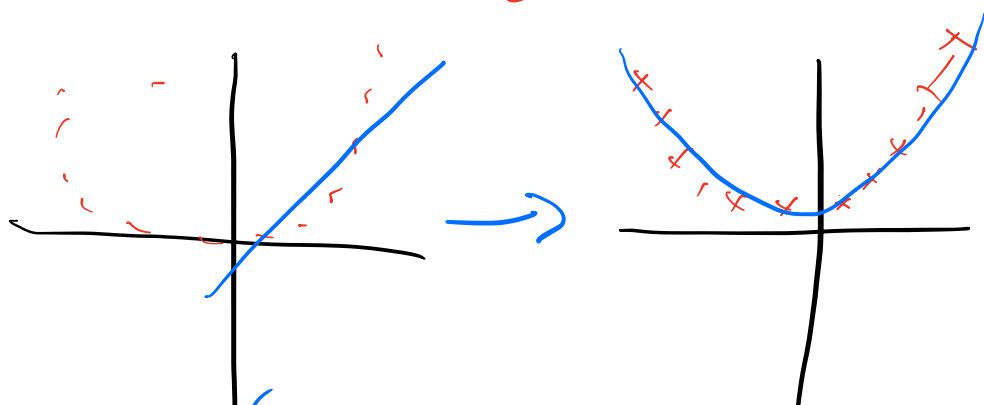


$$\sigma(x^T w) = \sigma(x_1 w_1 + x_2 w_2) = P(y=1 | x, w)$$

Logistic



$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$



$$\phi(x) = \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix} \rightarrow \text{Linear} \quad \phi(x)^T w = x_1 w_1 + x_2 w_2 + 1(b)$$

Logistic

$$P(y=1 | x, w) = \sigma(\phi^T w)$$

Neural network

$$\phi(x) = \begin{bmatrix} g_1(x) \\ g_2(x) \\ g_3(x) \end{bmatrix} \rightarrow \begin{bmatrix} \sigma(x^T w_1) \\ \sigma(x^T w_2) \\ \sigma(x^T w_3) \end{bmatrix}$$

neural network  
regression

$$y = \phi(x)^T w_0 \rightarrow \underbrace{\sigma(x^T w_1)}_{\phi_1(x)} w_{01} + \underbrace{\sigma(x^T w_2)}_{\phi_2(x)} w_{02} + \underbrace{\sigma(x^T w_3)}_{\phi_3(x)} w_{03}$$

$$= \sigma(x_1 w_{11} + x_2 w_{12} \dots)$$

Parameters

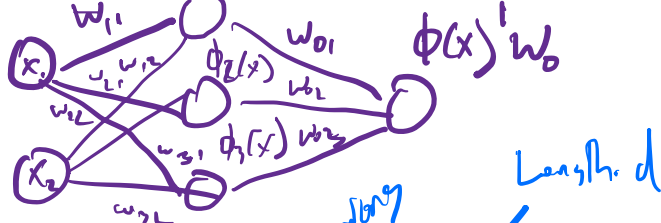
$$X = \begin{bmatrix} \text{obs.}(w) \\ \vdots \end{bmatrix} \quad \text{measurements}(\phi)$$

$$w_1 \dots = \begin{bmatrix} w_{11} \\ w_{12} \\ \vdots \\ w_{1d} \end{bmatrix}$$

$$w_0 = \begin{bmatrix} w_{01} \\ w_{02} \\ w_{03} \end{bmatrix}$$

$\phi_1(x)$

"Linear regression"



$$p(x=1|x_1, w) = \sigma(\phi(x)^T w)$$

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad \phi(x) = \begin{bmatrix} x^T w_1 \\ x^T w_2 \\ x^T w_3 \end{bmatrix} = \begin{bmatrix} x_1 w_{11} + x_2 w_{12} \\ x_1 w_{21} + x_2 w_{22} \\ x_1 w_{31} + x_2 w_{32} \end{bmatrix} \begin{bmatrix} w_{01} \\ w_{02} \\ w_{03} \end{bmatrix}$$

$$y = \phi(x)^T w_0 = w_{01}(x_1 w_{11} + x_2 w_{12}) + w_{02}(x_1 w_{21} + x_2 w_{22}) + w_{03}(x_1 w_{31} + x_2 w_{32})$$

$$= \underbrace{x_1 w_{11} w_{01} + x_1 w_{21} w_{02} + x_1 w_{31} w_{03} + \dots}_{x_1 (w_{11} w_{01} + w_{21} w_{02} + w_{31} w_{03})}$$

→ Linear in our Input

$$W = \begin{bmatrix} w_{11}^T \\ w_{21}^T \\ w_{31}^T \end{bmatrix} \rightarrow \begin{bmatrix} w_{11} & w_{12} & w_{13} & \dots \\ w_{21} & w_{22} & w_{23} & \dots \\ w_{31} & w_{32} & w_{33} & \dots \end{bmatrix}$$

$$\phi(x) = \begin{bmatrix} \sigma(x^T w_1) \\ \sigma(x^T w_2) \\ \sigma(x^T w_3) \end{bmatrix} = \sigma(x^T W^T) = \sigma(\underbrace{W}_{q \times d} \underbrace{x}_d)$$

$$x = \begin{bmatrix} \phantom{0} \end{bmatrix} \quad (1 \times d)(d \times q) = (1 \times q)$$

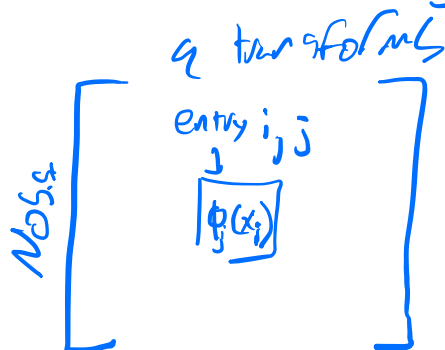
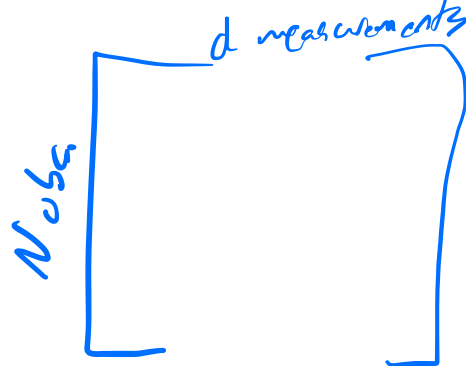
For a dataset  $X = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_n^T \end{bmatrix}$

$X = N \times d$  matrix

$W = q \times d$  matrix

$$\phi(X) = \sigma(XW^T) \rightarrow N \times q$$

$(N \times d) (d \times q) \rightarrow N \times q$   
 $N \times d$  matrix  
 $d \times q$  matrix  
 $N \times q$  vector



$$y = \phi(x)w_0 = \sigma(x^T W_1^T)w_0$$

Regression

Logistic Res.

$$P(y=1 | x, W_1, w_0) = \sigma(\sigma(x^T W_1^T)w_0)$$

Bias / offset

$$y = x^T w + b$$

$$X \rightarrow \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \rightarrow \begin{bmatrix} x_1 \\ x_2 \\ 1 \end{bmatrix}$$

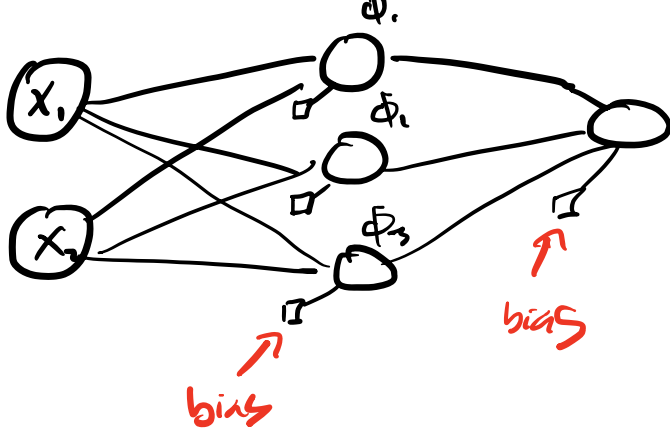
$$W \rightarrow \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \rightarrow \begin{bmatrix} w_1 \\ w_2 \\ b \end{bmatrix}$$

explicit offset

$$\sigma(x^T W_1^T + b_1)w_0 + b_0$$

$\uparrow$  Vector  $(q \times 1)$   
 $\uparrow$  Scalar

$$\phi(x) = \begin{bmatrix} \sigma(x^T w_1) + b_{11} \\ \sigma(x^T w_2) + b_{12} \\ \vdots \end{bmatrix}$$



Learn parameters  $\underline{W}_1, w_0$  [ $b_1$  and  $b_0$ ]  
 $\rightarrow$  Gradient descent

$$\text{Loss}(\underline{X}, y, \underline{W}_1, w_0)$$

$$\text{update } \underline{W}_1^{(i+1)} \leftarrow \underline{W}_1^{(i)} - \alpha \nabla_{\underline{W}_1} \text{Loss}(\underline{X}, y, \underline{W}_1^{(i)}, w_0^{(i)})$$

$$w_0^{(i+1)} \leftarrow w_0^{(i)} - \alpha \nabla_{w_0} \text{Loss}(\underline{X}, y, \underline{W}_1^{(i)}, w_0^{(i)})$$

Shape of  $\nabla_{\underline{W}_1} \text{Loss}(\ )$ ?  $\rightarrow q \times d$

$\underline{W}_1$ :  $q \times d$  matrix

$$\nabla_{\underline{W}_1} \text{Loss} \approx \begin{bmatrix} \frac{\partial L}{\partial W_{11}} & \frac{\partial L}{\partial W_{12}} \\ \frac{\partial L}{\partial W_{21}} & \frac{\partial L}{\partial W_{22}} \end{bmatrix}$$

Update  $(\underline{W}_1, w_0)$

$$(\underline{W}_1, w_0)^{(i+1)} \leftarrow (\underline{W}_1, w_0)^{(i)} - \alpha \nabla \text{Loss}$$

$$(\omega_1, \omega_2) \sim (\omega_1, \omega_2) \sim y_{\sigma, \omega_0} L^{\sigma_2} -$$