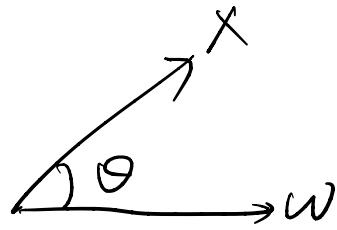


25. 09.22.

Geometric Interpretation of LR.

$X, w \in \mathbb{R}^D$

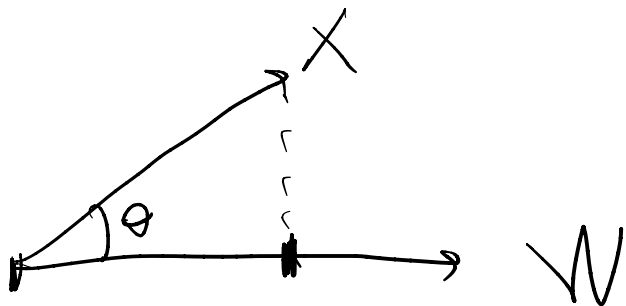
$$w^T X = \|w\| \|X\| \cos \theta$$



$$w^T X = w_1 x_1 + w_2 x_2 + \dots + w_D x_D = \|w\| \|X\| \cos \theta$$

$$\begin{aligned} \|X - w\|^2 &= (X - w)^T (X - w) = X^T X + w^T w - 2w^T X \\ &= \|X\|^2 + \|w\|^2 - 2w^T X \end{aligned}$$

$$\|X - w\|^2 = \|X\|^2 + \|w\|^2 - 2\|X\| \|w\| \cos \theta$$



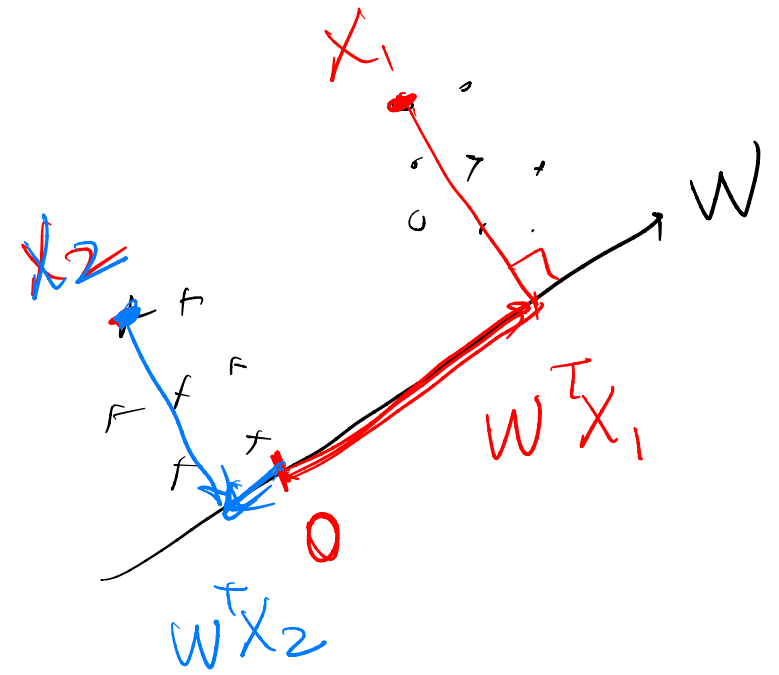
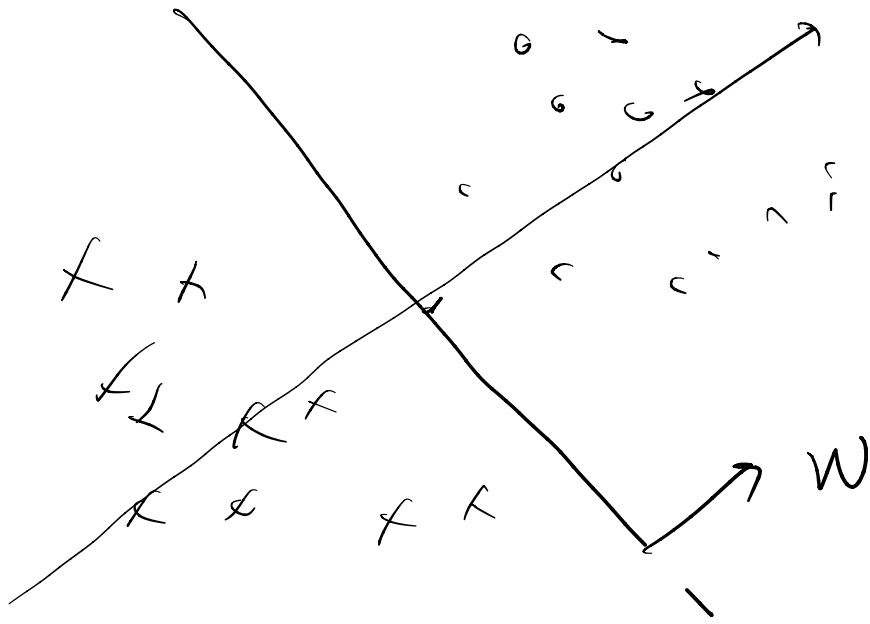
$$\|x\| \cos \theta = \cancel{\|x\|} \cdot \frac{w^T x}{\|w\| \cancel{\|x\|}}$$

$$= \frac{w^T x}{\|w\|}$$

$\therefore$ Length of projected vector.

• Projected vector.

$$\frac{w^T x}{\|w\|} \cdot \frac{w}{\|w\|}$$

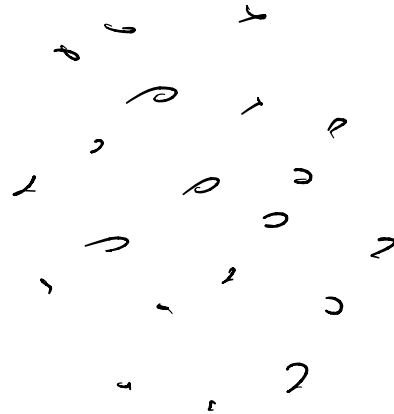


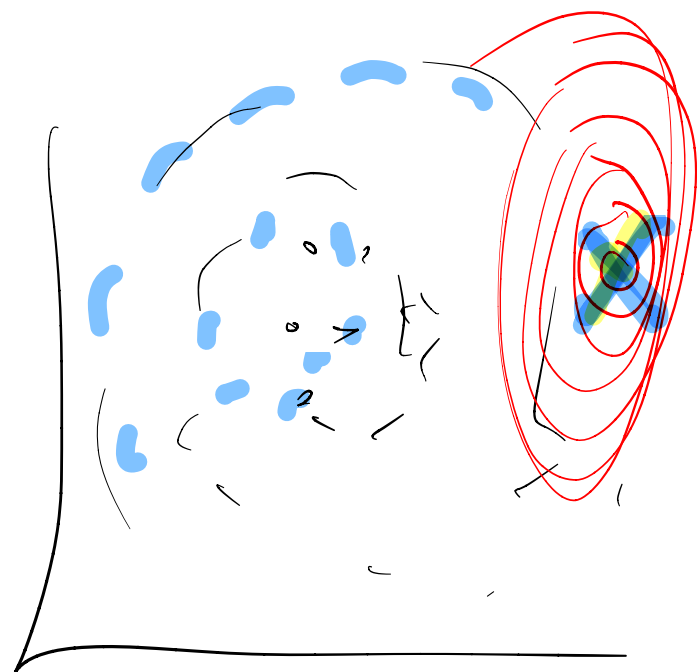
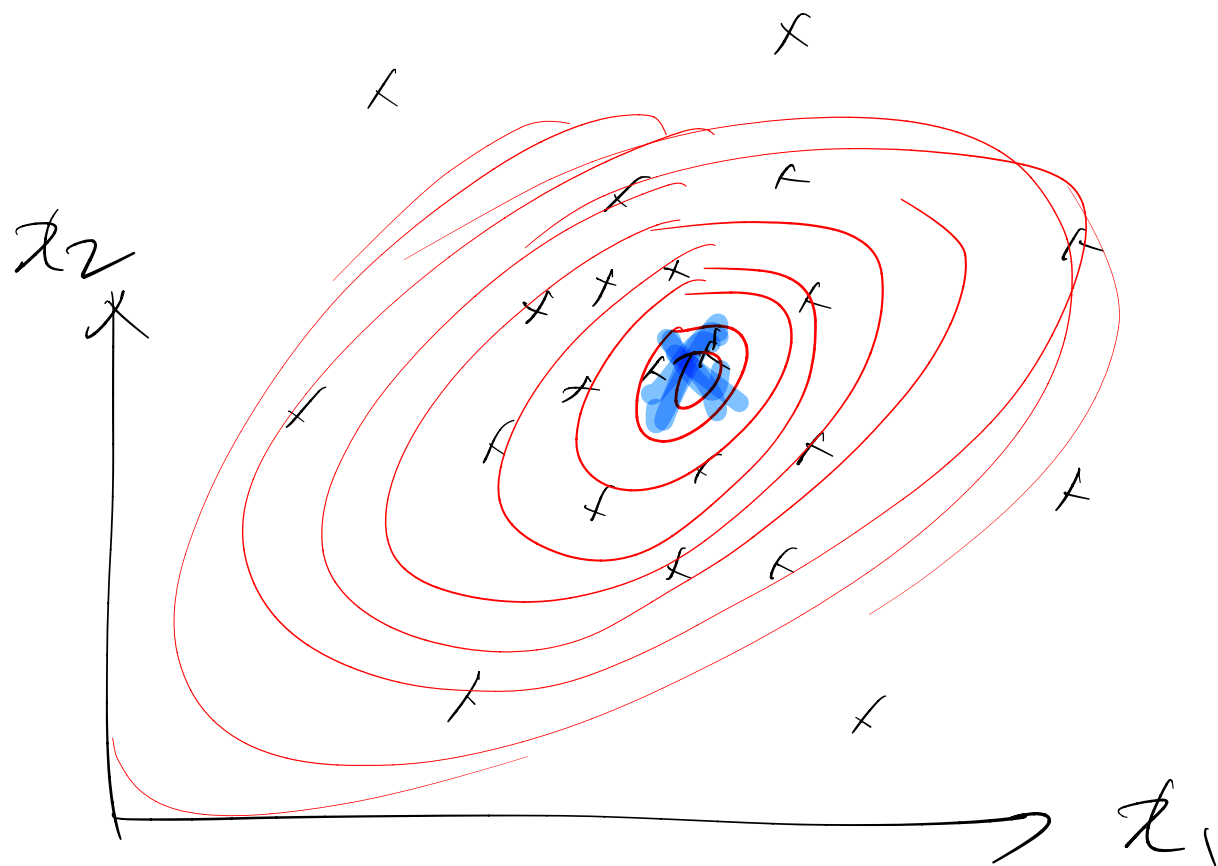
$$\|w\| = 1$$

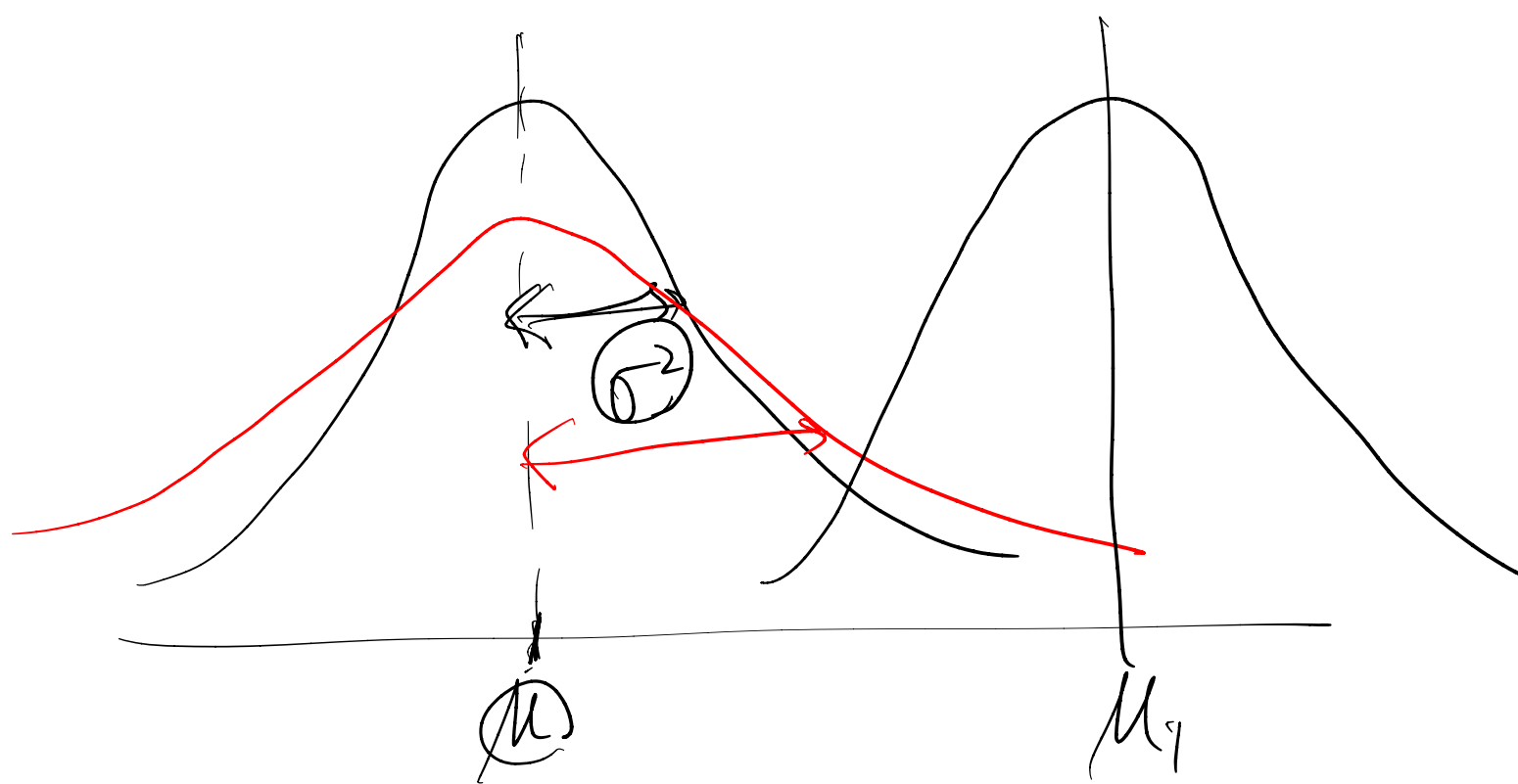
$$\begin{cases} w^T x_i \geq b & \rightarrow y_i = 1 \\ w^T x_i < b & \rightarrow y_i = 2 \end{cases}$$

$$\sum_{i=1}^N \frac{1}{2} \| \underbrace{f(x_i; w) - y_i}_{\text{MSE loss}} \|^2 \quad D = (x_i, \underbrace{y_i}_{\text{loss}})$$

Likelihood







Logistic

Regression

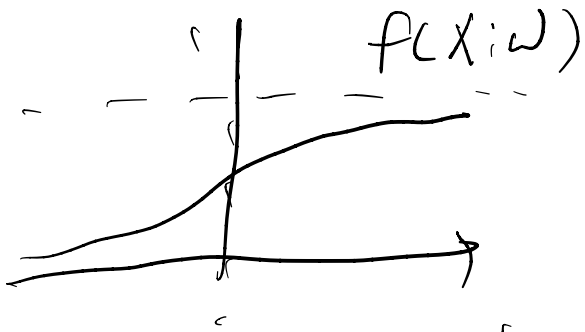
Revisited.

$$y_i \in \{0, 1\}$$

$$x_i \in \mathbb{R}^D$$

$$f(x; w) = \frac{1}{1 + \exp(-w^T x)}$$

$$i = 1, \dots, N \quad \max L(w) = \prod_{i=1}^N f(x_i)^{y_i} (1 - f(x_i))^{(1-y_i)}$$



$f(x_i)$: Prob. of choosing $y_i = 1$

$1 - f(x_i)$: Prob. of choosing $y_i = 0$

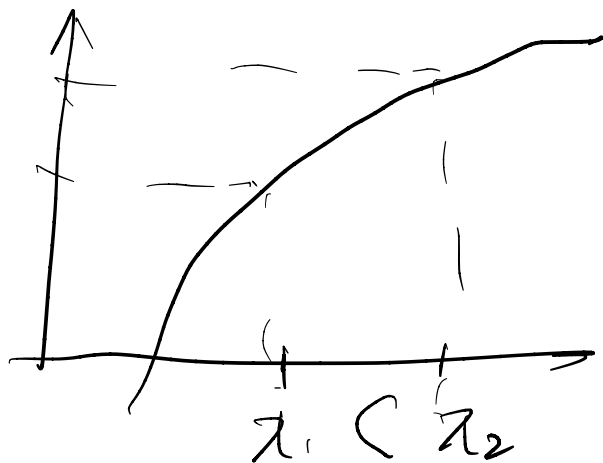
$L(w)$: Prob. that $f(x)$ classifies all data correctly.

$$\max_w L(w) = \prod_{i=1}^N f(x_i)^{y_i} \{1 - f(x_i)\}^{1-y_i}$$

$$\max_w \ln L(w) = \sum_{i=1}^N y_i \ln f(x_i) + (1-y_i) \ln (1-f(x_i))$$

$$w^* = \operatorname{argmax}_w L(w) = \operatorname{argmax}_w \ln L(w)$$

$\therefore \ln$ is a monotonically increasing function.



$$y \ln f + (1-y) \ln (1-f) \rightarrow \textcircled{1}$$

$$\frac{d\textcircled{1}}{dw} = y \cdot \frac{1}{f} \cdot \frac{df}{dw} + (1-y) \cdot \frac{1}{1-f} \cdot \frac{d(1-f)}{dw}$$

$$\boxed{\frac{df}{dw} = f(1-f)x}$$

$$= y \cdot \frac{1}{f} \cdot f(1-f)x + (1-y) \cdot \frac{1}{1-f} \cdot (-f(1-f)x)$$

$$= y(1-f)x - (1-y)f(x) = (y-f)x$$

$$\frac{d}{dw} \ln L(w) = \sum_{i=1}^N (y_i - f(x_i)) x_i.$$

Update rule:

$$w_{t+1} = w_t + \eta \sum_{i=1}^N (y_i - f(x_i)) x_i$$