$$\Theta = \left(\left(\frac{\sigma_\Theta}{\sigma_Z}\right)^2 XX^T + I\right)^{-1} \cdot \left(\left(\frac{\sigma_\Theta}{\sigma_Z}\right)^2 XY^T + \mu I\right) = \mu$$

$$\Theta = (XR^{-1}X^T + H^{-1})^{-1}(XR^{-1}Y^T + H^{-1}\mu)$$

$$R = \begin{bmatrix} \sigma_Z^2 & \cdots & 0 \\ \vdots & \sigma_Z^2 & \vdots \\ 0 & \cdots & \sigma_Z^2 \end{bmatrix} = \sigma_Z^2 I \qquad H = \begin{bmatrix} \sigma_\Theta^2 & \cdots & 0 \\ \vdots & \sigma_\Theta^2 & \vdots \\ 0 & \cdots & \sigma_\Theta^2 \end{bmatrix} = \sigma_\Theta^2 I$$

niezależne obserwacje

niezależne cechy

ustandaryzowane

$$\frac{x - \mu}{\rho(\ldots)}$$

1° $\sigma_Z << \sigma_\Theta$ $\quad \frac{\sigma_Z}{\sigma_\Theta} \to 0$

2° $\sigma_Z >> \sigma_\Theta$ $\quad \frac{\sigma_\Theta}{\sigma_Z} \to 0$

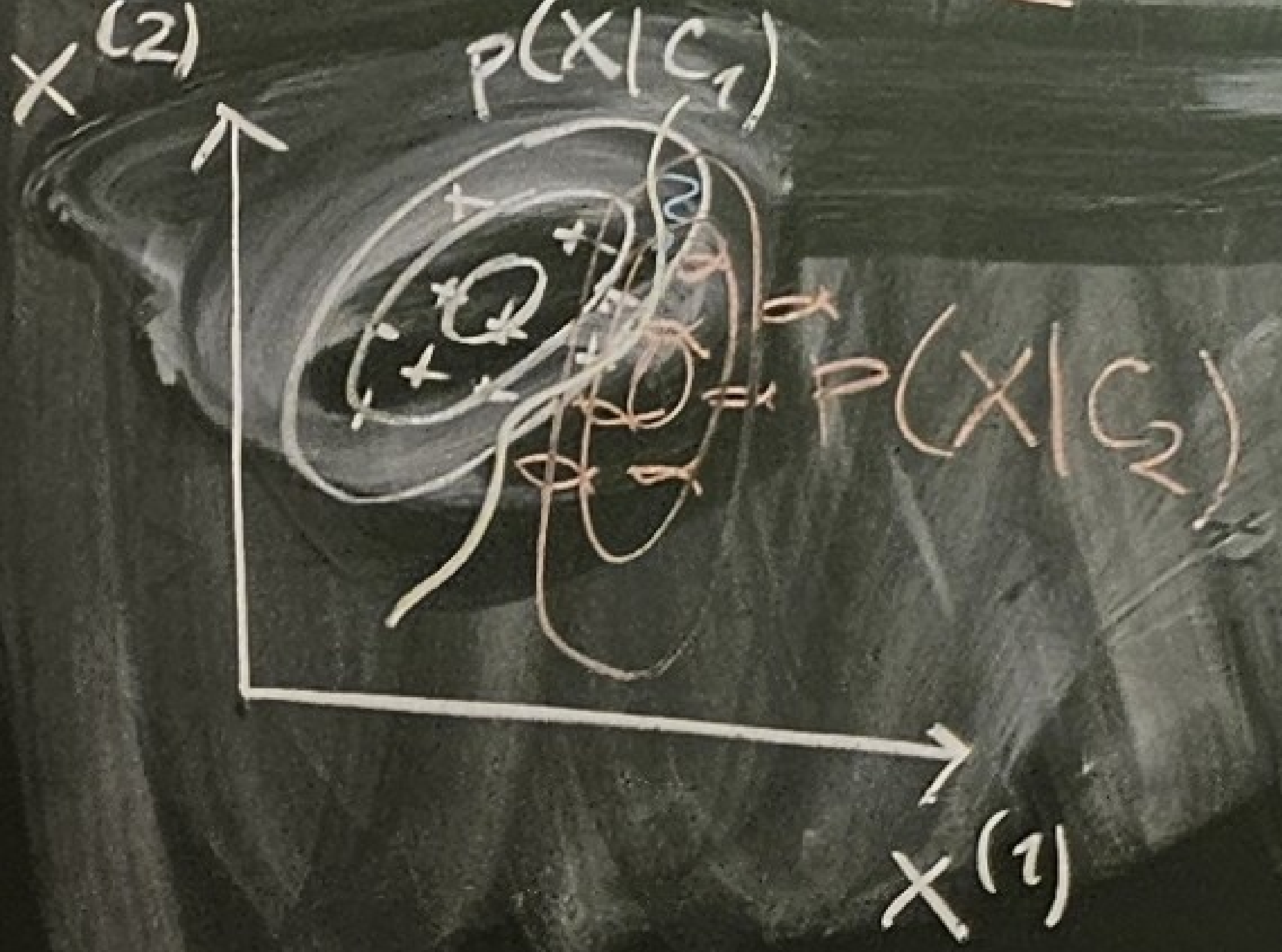
$\boxed{\text{ad } 1^\circ}$

$$\Theta = \left(\frac{1}{\sigma_Z^2}XX^T + \frac{1}{\sigma_\Theta^2}I\right)^{-1}\left(\frac{1}{\sigma_Z^2}XY^T + \frac{1}{\sigma_\Theta^2}\mu\right)$$

$$= \left(XX^T + \left(\frac{\sigma_Z}{\sigma_\Theta}\right)^2 I\right)^{-1}\left(XY^T + \left(\frac{\sigma_Z}{\sigma_\Theta}\right)^2 \mu\right)$$

$p(X|C)$ → $p(X|C_1)$, $p(X|C_2)$

tuń C_1 — łosoś C_2



Jeżeli: $p(x|C_1)\cdot p(C_1) > p(x|C_2)\cdot p(C_2)$

to x jest C_1

w przec. x jest C_2

„Prawie" Optymalny klasyfik. Bayesa

$2♡ + 3♡ = 5♡$

$2\int_0^1 \varepsilon(x)\,dx + 3\int_0^1 \varepsilon(x)\,dx =$

$= 5\int_0^1 \varepsilon(x)\,dx$

2𝄞 + 3𝄞 = 5𝄞

Model — lin. dane

zakł. Gauss R

przekon. μ, H

$$\hat{\Theta}_{MAP} = \left(X R^{-1} X^T + H^{-1}\right)^{-1} \left(X R^{-1} Y^T + H^{-1}\mu\right)$$

$$= \left(\frac{1}{\sigma_Z^2} X X^T + \frac{1}{\sigma_\Theta^2} I\right)^{-1} \left(\frac{1}{\sigma_Z^2} X Y^T + \frac{1}{\sigma_\Theta^2}\mu\right)$$

ad. 1.

$$\left(X X^T + \left(\frac{\sigma_Z}{\sigma_\Theta}\right)^2 I\right)^{-1} \left(X Y^T + \left(\frac{\sigma_Z}{\sigma_\Theta}\right)^2 \mu\right) \to \hat{\Theta}_{MNK}$$

ad. 2.

$$\left(\left(\frac{\sigma_\Theta}{\sigma_Z}\right)^2 X X^T + I\right)^{-1} \left(\left(\frac{\sigma_\Theta}{\sigma_Z}\right)^2 X Y^T + \mu\right) \to \mu$$

$$\hat{\Theta}_{MNK} = \left(X X^T\right)^{-1} X Y^T$$

$R = I \quad H = I \quad \mu = 0_K$

$$R = \begin{bmatrix} \sigma_Z^2 & & 0 \\ & \ddots & \\ 0 & & \sigma_Z^2 \end{bmatrix} = \sigma_Z^2 I \qquad H = \sigma_\Theta^2 I$$

obserwacje — wiedza przek.

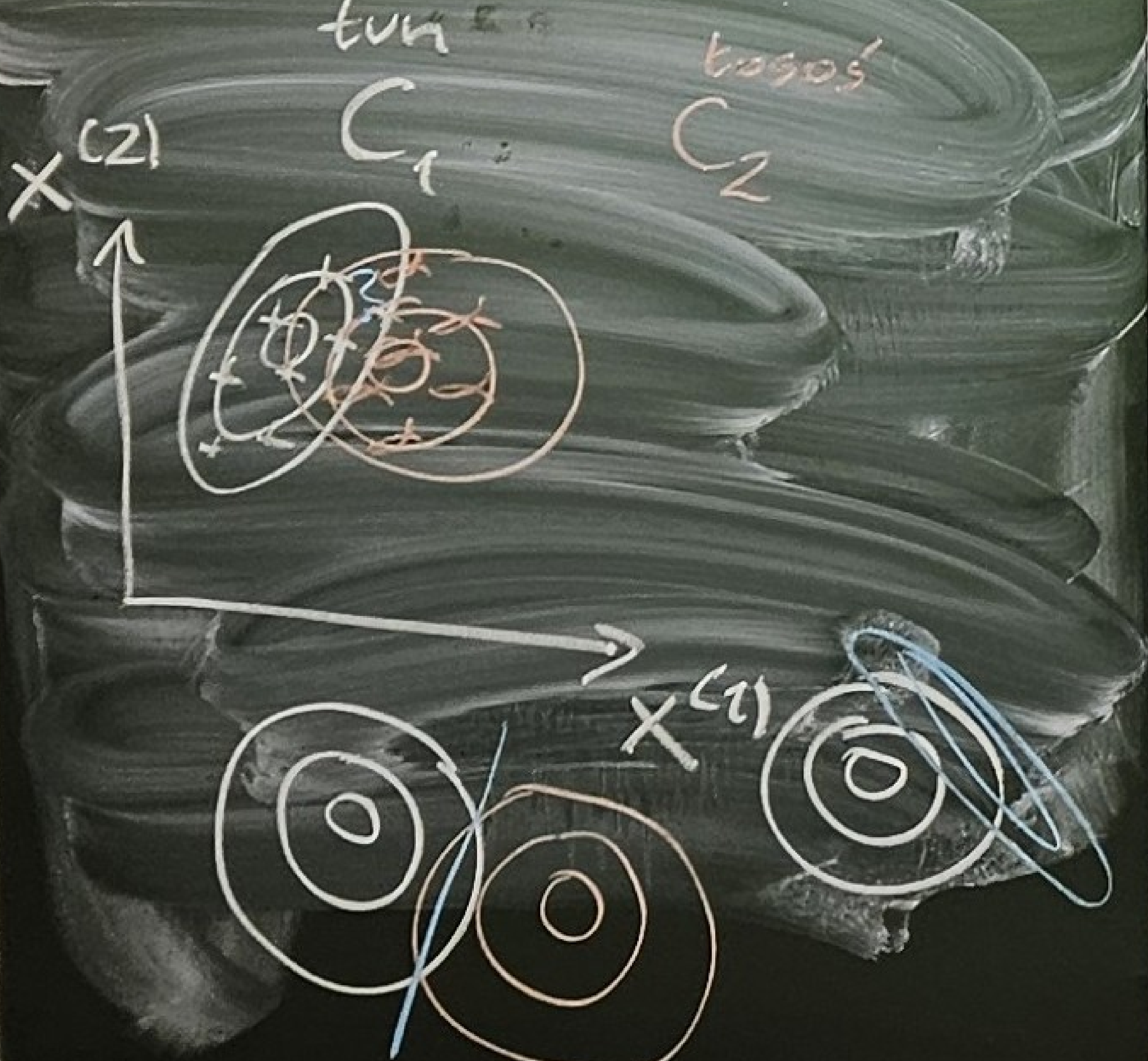
1° Lipna wiedza, dobre obserwacje

$\sigma_Z \ll \sigma_\Theta \qquad \frac{\sigma_Z}{\sigma_\Theta} \to 0$

2° Wiaryg. wiedza, lipne obserw.

$\sigma_Z \gg \sigma_\Theta \qquad \frac{\sigma_\Theta}{\sigma_Z} \to 0$

$P(X|C_1)$ $P(X|C_2)$



jeżeli

$P(x|C_1) > P(x|C_2)$

to C_1

w przec.

C_2

Searle

Chiński Pokój

μ - bliskie rzecz. przekonanie

Dane

1°

$\sigma \ll \lambda$

$\frac{\sigma}{\lambda} \to 0$

2°

$\sigma \gg \lambda$

$\frac{\lambda}{\sigma} \to 0$

$$\hat{\Theta}_{MAP} = (XR^{-1}X^T + H^{-1})^{-1}(XR^{-1}Y^T + H^{-1}\mu)$$

$$R = \begin{bmatrix} \sigma_1^2 & & 0 \\ & \ddots & \\ 0 & & \sigma_N^2 \end{bmatrix} = \sigma^2 I \qquad H = \begin{bmatrix} \lambda_1^2 & & 0 \\ & \ddots & \\ 0 & & \lambda_K^2 \end{bmatrix} = \lambda^2 I$$

$$\hat{\Theta}_{MAM} = \left(\frac{1}{\sigma^2}XX^T + \frac{1}{\lambda^2}I\right)^{-1}\left(\frac{1}{\sigma^2}XY^T + \frac{1}{\lambda^2}\mu\right)$$

1°

2°

$\approx \mu$

$$\hat{\Theta}_{MNK} = (XX^T)^{-1}XY^T$$

$$XR^{-1}X^T + H^{-1} = XX^T$$

$$XR^{-1}Y^T + H^{-1}\mu = XY^T$$

$$XR^{-1}Y^T + (-XR^{-1}X^T + XX^T)\mu = XY^T$$