

Exercise sheet 06

(1.a)

$$X = \{\vec{x}_1, \dots, \vec{x}_n\}, \hat{X} = \vec{w}_x X$$

$$Y = \{\vec{y}_1, \dots, \vec{y}_n\}, \hat{Y} = \vec{w}_y Y$$

$$\text{Cov}(\hat{X}, \hat{Y}) = \mathbb{E}[(\vec{w}_x X - \underbrace{\mathbb{E}(\vec{w}_x X)}_{=0})(\vec{w}_y Y - \underbrace{\mathbb{E}(\vec{w}_y Y)}_{=0})^T] =$$

$$= \mathbb{E}[(\vec{w}_x X)(\vec{w}_y Y)^T]$$

$$\text{Var}(\hat{X}) = \mathbb{E}[(\vec{w}_x X)^2]$$

$$\text{Var}(\hat{Y}) = \mathbb{E}[(\vec{w}_y Y)^2]$$

$$\text{Corr}(\hat{X}, \hat{Y}) = \frac{\mathbb{E}[(\vec{w}_x X)(\vec{w}_y Y)^T]}{\sqrt{\mathbb{E}[(\vec{w}_x X)^2]} \sqrt{\mathbb{E}[(\vec{w}_y Y)^2]}} =$$

$$= \frac{\frac{1}{N} \sum_i (\vec{w}_x x_i)(\vec{w}_y y_i)}{\sqrt{\frac{1}{N} \sum_i (\vec{w}_x x_i)^2} \sqrt{\frac{1}{N} \sum_i (\vec{w}_y y_i)^2}} =$$

Note:

$$\Sigma = \begin{bmatrix} \Sigma_{xx} & \Sigma_{xy} \\ \Sigma_{yx} & \Sigma_{yy} \end{bmatrix}$$

$$= \frac{\vec{w}_x^T \Sigma_{xy} \vec{w}_y}{\sqrt{\vec{w}_x^T \Sigma_{xx} \vec{w}_x} \sqrt{\vec{w}_y^T \Sigma_{yy} \vec{w}_y}}$$

$$\Rightarrow \max_{\vec{w}_x, \vec{w}_y} \vec{w}_x^T \Sigma_{xy} \vec{w}_y$$

$$\text{s.t.: } \vec{w}_x^T \Sigma_{xx} \vec{w}_x = \vec{w}_y^T \Sigma_{yy} \vec{w}_y = 1$$

(1.b)

$$f(\vec{w}_x, \vec{w}_y) = \vec{w}_x^T \Sigma_{xy} \vec{w}_y$$

$$g_x(\vec{w}_x) = \vec{w}_x^T \Sigma_{xx} \vec{w}_x - 1$$

$$g_y(\vec{w}_y) = \vec{w}_y^T \Sigma_{yy} \vec{w}_y - 1$$

$$\begin{aligned} \mathcal{L}(\vec{w}_x, \vec{w}_y, \alpha, \beta) &= f(\vec{w}_x, \vec{w}_y) - \alpha g_x(\vec{w}_x) - \beta g_y(\vec{w}_y) = \\ &= \vec{w}_x^T \Sigma_{xy} \vec{w}_y - \alpha (\vec{w}_x^T \Sigma_{xx} \vec{w}_x) - \beta (\vec{w}_y^T \Sigma_{yy} \vec{w}_y) \end{aligned}$$

$$\frac{\partial \mathcal{L}}{\partial \vec{w}_x} = \Sigma_{xy} \vec{w}_y - 2\alpha \Sigma_{xx} \vec{w}_x = 0$$

$$\Rightarrow \Sigma_{xx}^{-1} \Sigma_{xy} \vec{w}_y = 2 \cdot \alpha \cdot \vec{w}_x$$

$$\frac{\partial \mathcal{L}}{\partial \vec{w}_y} = \Sigma_{xy}^T \vec{w}_x - 2\beta \Sigma_{yy} \vec{w}_y = 0$$

$$\Rightarrow \Sigma_{yy}^{-1} \Sigma_{xy}^T \vec{w}_x = 2 \cdot \beta \cdot \vec{w}_y$$

• Substituting both equations yields:

$$\Sigma_{xx}^{-1} \Sigma_{xy} \Sigma_{yy}^{-1} \Sigma_{xy}^T \cdot \vec{w}_x = \lambda \vec{w}_x = l \vec{w}_x$$

$$\Sigma_{yy}^{-1} \Sigma_{xy}^T \Sigma_{xx}^{-1} \Sigma_{xy} \cdot \vec{w}_y = \lambda \vec{w}_y = l \vec{w}_y$$

$$\text{With: } l = 4\alpha\beta$$

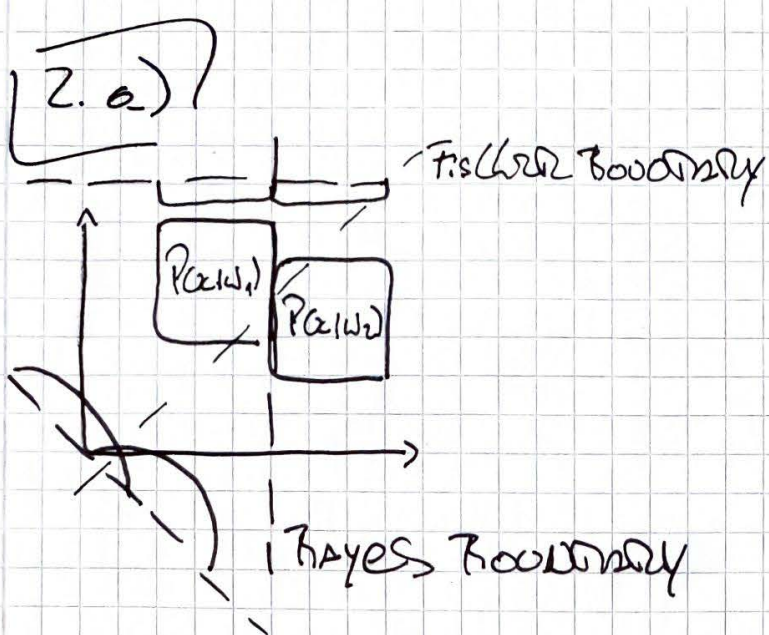
(1.c)

$$\underbrace{\vec{w}_x^T \Sigma_{xy} \vec{w}_y}_{\rightarrow} + \underbrace{\vec{w}_y^T \Sigma_{yx} \vec{w}_x}_{\leftarrow} = 2\alpha \underbrace{\vec{w}_x^T \Sigma_{xx} \vec{w}_x}_{=1} + 2\beta \underbrace{\vec{w}_y^T \Sigma_{yy} \vec{w}_y}_{=1}$$

$$\Rightarrow \vec{w}_x^T \Sigma_{xy} \vec{w}_y = \alpha + \beta$$

Hence, the correlation coefficient at an optimum:

$$\text{Corr} = \alpha + \beta$$



(2.b)

$$P_1(x|w_1) = \mathcal{N}(\mu_1, \Sigma_1)$$

$$P_2(x|w_2) = \mathcal{N}(\mu_2, \Sigma_2)$$

$$g_1(x) = \log(P(x|w_1)) + \log(P(w_1))$$

$$g_2(x) = \log(P(x|w_2)) + \log(P(w_2))$$

$$\psi(x) = g_1(x) - g_2(x) - \log(P(w_1)) + \log(P(w_2))$$

$$= \log P(x|w_1) - \log P(x|w_2)$$

$$= -\log\left(\sqrt{(2\pi)^d |\Sigma_1|}\right) - \frac{1}{2}(x - \mu_1)^T \Sigma_1^{-1} (x - \mu_1) + \log\left(\sqrt{(2\pi)^d |\Sigma_2|}\right) - \frac{1}{2}(x - \mu_2)^T \Sigma_2^{-1} (x - \mu_2)$$