

ML2 Sheet 2

1 Exercise 3

1.1 Exercise 3 (a)

The two *min* functions are going to return a large negative value if either $\omega_x^\top C_{xx} \omega_x$ or $\omega_y^\top C_{xx} \omega_y$ or both are large. Therefore, they will subtract away much of the impact of the first term $\omega_x^\top C_{xy} \omega_y$. This means that, dependent on the size of the positive scalar α , the last two terms will impose a “penalty” whenever a large ω_x or ω_y is used, which will mitigate the issue where the maximization is caused by any such large vector, similarly to the constrained CCA.

1.2 Exercise 3 (b)

$$\frac{\partial \phi_x}{\partial \theta_x} = \begin{pmatrix} \frac{\partial \phi_{x_1}}{\partial \theta_{x_1}} & \dots & \frac{\partial \phi_{x_n}}{\partial \theta_{x_1}} \\ & \ddots & \vdots \\ \frac{\partial \phi_{x_{h_1}}}{\partial \theta_{x_1}} & \dots & \frac{\partial \phi_{x_{h_1}}}{\partial \theta_{x_n}} \end{pmatrix}$$

1.a

$$w_x \in \mathbb{R}^{d_1} \quad X \in \mathbb{R}^{d_1 \times N} \quad d_x \in \mathbb{R}^N$$

We can represent $w_x = X \cdot d_x$ as a system of equations

$$\left\{ \begin{array}{l} X_{11} \cdot d_1 + X_{12} \cdot d_2 + \dots + X_{1N} \cdot d_N = w_{x_1} \\ X_{21} \cdot d_1 + X_{22} \cdot d_2 + \dots + X_{2N} \cdot d_N = w_{x_2} \\ X_{31} \cdot d_1 + X_{32} \cdot d_2 + \dots + X_{3N} \cdot d_N = w_{x_3} \\ \vdots \\ \vdots \end{array} \right\} \quad \begin{array}{l} d_1 \\ \vdots \end{array}$$

N

Having N variables and d_1 equations would normally mean that no solutions exist because $N > d_1$, but ~~if~~ considering the condition $N \ll d_1$ system becomes determined (even overdetermined), meaning there exist a solution that lies in the span ~~of~~ of the data.

1.6

$$\begin{bmatrix} 0 & AB \\ BA & 0 \end{bmatrix} \cdot \begin{bmatrix} x \\ y \end{bmatrix} = \rho \begin{bmatrix} A^2 & 0 \\ 0 & B^2 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \quad (1)$$

We can rewrite (1) as

$$AB y = \rho A^2 x$$

$$BA x = \rho B^2 y$$

By setting $w_x = Xx$, $w_y = Yy$ we obtain

$$X^T X Y^T Y y = \rho X^T X X^T X x$$

$$Y^T Y X^T X x = \rho Y^T Y Y^T Y y$$

$$X^T C_{xy} w_y = \rho X^T C_{xx} x$$

$$Y^T C_{yx} w_x = \rho Y^T C_{yy} y$$

After dividing by X^T and Y^T we get

$$C_{xy} w_y = \rho C_{xx} x$$

$$C_{yx} w_x = \rho C_{yy} y$$

which is the original eigenvalue problem.

3.1

3.2

2. a

Original ~~eigenvalue~~ ^{CCA} problem

- 1 Reformulate the problem in terms of dot products

First, set $w_x = X \alpha_x$ $w_y = Y \alpha_y$ - Solution will lie in the space spanned by the data not number of dimensions

Lagrangian looks like that:

$$\mathcal{L} = \alpha_x^T X^T X Y^T Y \alpha_y - \lambda_1 (\alpha_x^T X^T X X^T X \alpha_x - 1) - \lambda_2 (\alpha_y^T Y^T Y Y^T Y \alpha_y - 1)$$

- 2 Replace all dot products with valid kernels

$$K_x = \Phi_1(X) \Phi_1(X)^T, K_y = \Phi_2(Y) \Phi_2(Y)^T \text{ where } \begin{matrix} \phi_1: x \mapsto \phi_1(x) \\ \phi_2: y \mapsto \phi_2(y) \end{matrix}$$

$$\mathcal{L} = \alpha_x^T K_x K_y \alpha_y - \lambda_1 (\alpha_x^T K_x \alpha_x - 1) - \lambda_2 (\alpha_y^T K_y \alpha_y - 1)$$

Original eigenvalue problem.

The course of action is the same as above

$$1 \quad C_{xy} w_y = \lambda_1 C_{xx} w_x \rightarrow X Y^T Y \alpha_y = \lambda_1 X X^T X \alpha_x \quad (1)$$

$$C_{yx} w_x = \lambda_1 C_{yy} w_y \rightarrow Y X^T X \alpha_x = \lambda_1 Y Y^T Y \alpha_y \quad (2)$$

Multiplying both sides by X^T for (1) and Y^T for (2) we get

$$X^T X Y^T Y \alpha_y = \lambda_1 X^T X X^T X \alpha_x$$

$$Y^T Y X^T X \alpha_x = \lambda_1 Y^T Y Y^T Y \alpha_y$$

- 2 Replace dot products with kernels

$$K_x K_y \alpha_y = \lambda_1 K_x \alpha_x$$

$$K_y K_x \alpha_x = \lambda_1 K_y \alpha_y$$

2.6 kCCA computes new ~~transformed~~ coordinate system that is optimal in maximizing correlation between two sets of variables. Each axis is nonlinear combination of variables in corresponding set of variables.

Index of comments

- 3.1 Likely not invertible
- 3.2 What is the original eigenvalue problem?