## Kernel Bayes' Rule: Toy Example

Ta-Chu Kao<sup>1,@</sup>

<sup>1</sup>Gatsby Computational Neuroscience Unit <sup>©</sup>Correspondence: c.kao@ucl.ac.uk

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In this short note, I derive the analytic solution to the problem presented in 5.1 of Fukumizu et al., 2011.

For random variables  $X, Y \in \mathbb{R}^d$ , we are given the joint distribution  $P(X, Y) = \mathcal{N}(\mu, \Sigma)$ , where

$$\mu = \begin{bmatrix} \mathbf{0}_d \\ \mathbf{1}_d \end{bmatrix}$$
 and  $\mathbf{\Sigma} = \begin{bmatrix} \mathbf{\Sigma}_{XX} & \mathbf{\Sigma}_{XY} \\ \mathbf{\Sigma}_{YX} & \mathbf{\Sigma}_{YY} \end{bmatrix}$ . (1)

This means we can easily write down the likelihood

$$P(Y|X) = \mathcal{N}\left(\mathbf{1}_d + \mathbf{\Sigma}_{YX}\mathbf{\Sigma}_{XX}^{-1}X, \mathbf{\Sigma}_{YY} - \mathbf{\Sigma}_{YX}\mathbf{\Sigma}_{XX}^{-1}\mathbf{\Sigma}_{XY}\right). \tag{2}$$

The aim is to find the posterior mean of Q(X|Y) with likelihood P(Y|X) and prior  $\Pi(X) = \mathcal{N}(\mathbf{0}_d, \Sigma_{XX}/2)$ . We can easily write down the joint distribution  $Q(X, Y) = P(Y|X)\Pi(X)$  as a multivariate Gaussian distribution given by:

$$Q(X,Y) = \mathcal{N}(\mu_Q, \Sigma_Q)$$
 (3)

where

$$\mu_Q = \begin{bmatrix} \mathbf{0}_d \\ \mathbf{1}_d \end{bmatrix} \text{ and } \mathbf{\Sigma}_Q = \begin{bmatrix} \mathbf{\Sigma}_{XX}/2 & \mathbf{\Sigma}_{XX}^{-1} \mathbf{\Sigma}_{XY} \\ \mathbf{\Sigma}_{YX} \mathbf{\Sigma}_{XX}^{-1} & \mathbf{\Sigma}_{YY} - \mathbf{\Sigma}_{YX} \mathbf{\Sigma}_{XX}^{-1} \mathbf{\Sigma}_{XY}/2 \end{bmatrix}.$$
(4)

And thus the posterior mean of Q(X|Y) is given by

$$\boldsymbol{\Sigma}_{XX}^{-1} \boldsymbol{\Sigma}_{XY} \left( \boldsymbol{\Sigma}_{YY} - \boldsymbol{\Sigma}_{YX} \boldsymbol{\Sigma}_{XX}^{-1} \boldsymbol{\Sigma}_{XY} / 2 \right)^{-1} \left( \boldsymbol{Y} - \mathbf{1}_d \right). \tag{5}$$

## References

Kenji Fukumizu, Le Song, and Arthur Gretton. Kernel bayes' rule. Advances in neural information processing systems, 24, 2011.