

# 1 Gaussian Model

We consider a model in which  $x \rightarrow y \rightarrow z$  forms a Markov chain,  $p(x) \propto 1$  has a flat prior, and each conditional distribution is Gaussian. It follows that the posterior distribution has form

$$p(x, y | z) \triangleq \mathcal{N}(\mu^*, \Sigma), \quad (1)$$

where  $\mu^* = (\mu_x^*, \mu_y^*)^\top$  and  $\Sigma$  has blocks  $\Sigma_{xx}$ ,  $\Sigma_{xy}$ , and  $\Sigma_{yy}$ , and these means and covariances depend on the observation  $z$ . From Barber [eqn. 8.6.11] we know the conditionals have the form

$$p(x | z, y) = \mathcal{N}(x; \mu_x^* + \Sigma_{xy}\Sigma_{yy}^{-1}(y - \mu_y^*), \Sigma_{xx} - \Sigma_{xy}\Sigma_{yy}^{-1}\Sigma_{yx}), \quad (2)$$

$$p(y | z, x) = \mathcal{N}(y; \mu_y^* + \Sigma_{yx}\Sigma_{xx}^{-1}(x - \mu_x^*), \Sigma_{yy} - \Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy}). \quad (3)$$

This gives the form of the CAVI variational factors

$$q^{(t+1)}(x) = \mathcal{N}(x; \mu_x^* + \Sigma_{xy}\Sigma_{yy}^{-1}(\hat{\mu}_y^{(t)} - \mu_y^*), \Sigma_{xx} - \Sigma_{xy}\Sigma_{yy}^{-1}\Sigma_{yx}), \quad (4)$$

$$q^{(t+1)}(y) = \mathcal{N}(y; \mu_y^* + \Sigma_{yx}\Sigma_{xx}^{-1}(\hat{\mu}_x^{(t)} - \mu_x^*), \Sigma_{yy} - \Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy}). \quad (5)$$

Where  $\hat{\mu}^{(t)}$  are the variational means at the  $t$ -th iteration. Hence

$$\hat{\mu}_x^{(t+1)} - \mu_x^* = \Sigma_{xy}\Sigma_{yy}^{-1}(\hat{\mu}_y^{(t)} - \mu_y^*) = \Sigma_{xy}\Sigma_{yy}^{-1}\Sigma_{yx}\Sigma_{xx}^{-1}(\hat{\mu}_x^{(t)} - \mu_x^*) \quad (6)$$

$$\hat{\mu}_y^{(t+1)} - \mu_y^* = \Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy}\Sigma_{yy}^{-1}(\hat{\mu}_y^{(t)} - \mu_y^*) \quad (7)$$

Note that if  $\lambda$  is an operator of one of these matrices, i.e.  $\Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy}\Sigma_{yy}^{-1}v = \lambda v$ , then

$$\Sigma_{xy}\Sigma_{yy}^{-1}\Sigma_{yx}\Sigma_{xx}^{-1}(\Sigma_{xy}\Sigma_{yy}^{-1}v) = \lambda(\Sigma_{xy}\Sigma_{yy}^{-1}v),$$

and similarly in the other direction, so the spectra of these matrices coincide. Let  $\gamma = \|\Sigma_{xy}\Sigma_{yy}^{-1}\Sigma_{yx}\Sigma_{xx}^{-1}\|_2 = \|\Sigma_{yx}\Sigma_{xx}^{-1}\Sigma_{xy}\Sigma_{yy}^{-1}\|_2$ , so the rate of convergence of each variational mean is

$$\|\hat{\mu}_x^{(t+1)} - \mu_x^*\|_2 \leq \gamma \|\hat{\mu}_x^{(t)} - \mu_x^*\|_2 \quad (8)$$

$$\|\hat{\mu}_y^{(t+1)} - \mu_y^*\|_2 \leq \gamma \|\hat{\mu}_y^{(t)} - \mu_y^*\|_2 \quad (9)$$

Hence the rate of convergence for the whole algorithm is  $\gamma$ , since

$$\|(\hat{\mu}_x^{(t+1)}, \hat{\mu}_y^{(t+1)}) - (\mu_x^*, \mu_y^*)\|_2^2 = \|\hat{\mu}_x^{(t+1)} - \mu_x^*\|_2^2 + \|\hat{\mu}_y^{(t+1)} - \mu_y^*\|_2^2 \quad (10)$$

$$\leq \gamma^2 \|\hat{\mu}_x^{(t)} - \mu_x^*\|_2^2 + \gamma^2 \|\hat{\mu}_y^{(t)} - \mu_y^*\|_2^2 \quad (11)$$

$$= \gamma^2 \|(\hat{\mu}_x^{(t)}, \hat{\mu}_y^{(t)}) - (\mu_x^*, \mu_y^*)\|_2^2 \quad (12)$$

This rate  $\gamma$  matches the rate of convergence of the corresponding block Gibbs sampler [Sahu & Roberts, 1998, theorem 1].