

Supplement (ISIT-2020): Online Variational Message Passing in Hierarchical Autoregressive Models

Albert Podusenko, Wouter. M Kouw, Bert de Vries

AR node

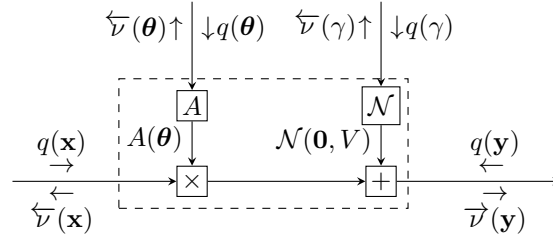


Figure 1: Autoregressive (AR) node.

Derivations

Before proceeding, we need to address the issue of invertability of covariance matrix V with $\epsilon = 0$, i.e.,

$$V = \begin{bmatrix} \frac{1}{\gamma} & 0 & 0 & \dots & 0 \\ 0 & \epsilon & 0 & \dots & \vdots \\ 0 & 0 & \epsilon & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \end{bmatrix}$$

To tackle this problem we assume $\epsilon > 0$, which allows to introduce matrix $W = V^{-1}$ (Appendix D [1]). In this way, our AR node function can be represented as follows:

$$f(\mathbf{y}, \mathbf{x}, \boldsymbol{\theta}, \gamma) = \mathcal{N}(\mathbf{y} \mid A(\boldsymbol{\theta})\mathbf{x}, W^{-1})$$

where

$$W = \begin{bmatrix} \gamma & 0 & 0 & \dots & 0 \\ 0 & \frac{1}{\epsilon} & 0 & \dots & \vdots \\ 0 & 0 & \frac{1}{\epsilon} & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \end{bmatrix} \quad (1)$$

Note that the introduced precision matrix Eq. (1) enforces AR node function to be a proper distribution [1]. Therefore, vector \mathbf{y} doesn't have merely copied components of vector \mathbf{x} , i.e. if $\mathbf{x} = (x_1, x_2, \dots, x_M)$, then

$$\mathbf{y} = \left(\boldsymbol{\theta}^\top \mathbf{x}, x_1 + \mathcal{N}(0, \epsilon), \dots, x_{M-1} + \mathcal{N}(0, \epsilon) \right) = \left(\boldsymbol{\theta}^\top \mathbf{x}, x'_1, \dots, x'_{M-1} \right)$$

The expectation of matrix W :

$$\mathbb{E}_W [W] = \mathbb{E}_\gamma [W] = \begin{bmatrix} m_\gamma & 0 & 0 & \dots & 0 \\ 0 & \frac{1}{\epsilon} & 0 & \dots & \vdots \\ 0 & 0 & \frac{1}{\epsilon} & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \end{bmatrix}$$

The product $A(\boldsymbol{\theta})\mathbf{x}$ can be separated in the shifting operator $\mathbf{S}\mathbf{x}$ and the inner vector product $\mathbf{c}\mathbf{x}^\top \boldsymbol{\theta}$ in the following way:

$$A(\boldsymbol{\theta})\mathbf{x} = \mathbf{S}\mathbf{x} + \underbrace{\mathbf{c}\mathbf{x}^\top \boldsymbol{\theta}}_{A(\boldsymbol{\theta})} \quad (2)$$

where

$$\mathbf{S} = \begin{bmatrix} \mathbf{0}^\top \\ \mathbf{I}_{M-1} & \mathbf{0} \end{bmatrix} \quad \mathbf{c} = (1, 0, \dots, 0)^\top$$

Owing the factorization introduced in Eq. 2 and specific form of matrix W (Eq. 1), our recognition distribution takes the form:

$$q(\mathbf{y}, \mathbf{x}, \boldsymbol{\theta}, \gamma) = q(\boldsymbol{\theta})q(\mathbf{x})q(\mathbf{y})q(\gamma) \quad (3)$$

where

$$\begin{aligned} q(\boldsymbol{\theta}) &= \mathcal{N}(m_\theta, V_\theta) \\ q(\mathbf{x}) &= \mathcal{N}(m_\mathbf{x}, V_\mathbf{x}) \\ q(\mathbf{y}) &= \mathcal{N}(m_\mathbf{y}, V_\mathbf{y}) \\ q(\gamma) &= \Gamma(\alpha, \beta) \end{aligned}$$

$\mathcal{N}(m, V)$ denote a Gaussian distribution with mean vector m and covariance matrix V , while $\Gamma(\alpha, \beta)$ - gamma distribution with shape-rate parametrization. For the sake of brevity, in the following paragraphs, we replace $A(\boldsymbol{\theta})$ and $f(\mathbf{y}, \mathbf{x}, \boldsymbol{\theta}, \gamma)$ with \mathbf{A} and f respectively.

Update of message to \mathbf{y}

$$\begin{aligned}
\log \vec{\nu}(\mathbf{y}) &= \mathbb{E}_{\boldsymbol{\theta}, \mathbf{x}, \gamma} \log f + \text{const} = -\frac{1}{2} \mathbb{E}_{\boldsymbol{\theta}, \mathbf{x}, \gamma} [(\mathbf{y} - \mathbf{Ax})^\top W (\mathbf{y} - \mathbf{Ax})] \\
&\quad + \text{const} \\
&= -\frac{1}{2} \mathbb{E}_{\boldsymbol{\theta}, \mathbf{x}, \gamma} [\mathbf{y}^\top W \mathbf{y} - (\mathbf{Ax})^\top W \mathbf{y} - \mathbf{y}^\top W \mathbf{Ax} + (\mathbf{Ax})^\top W \mathbf{Ax}] \\
&\quad + \text{const}
\end{aligned}$$

As term $(\mathbf{Ax})^\top W \mathbf{Ax}$ doesn't depend on \mathbf{y} , we move it into the *const*. Hence,

$$\begin{aligned}
\log \vec{\nu}(\mathbf{y}) &= -\frac{1}{2} \left[\mathbf{y}^\top m_W \mathbf{y} - (\mathbf{S} m_{\mathbf{x}} + \mathbf{c} m_{\mathbf{x}}^\top m_{\boldsymbol{\theta}})^\top m_W \mathbf{y} - \mathbf{y}^\top m_W \underbrace{(\mathbf{S} m_{\mathbf{x}} + \mathbf{c} m_{\mathbf{x}}^\top m_{\boldsymbol{\theta}})}_{m_{\boldsymbol{\theta}} m_{\mathbf{x}}} \right] \\
&\quad + \text{const} \\
&= -\frac{1}{2} \left[\mathbf{y}^\top m_W \mathbf{y} - \underbrace{(m_{\boldsymbol{\theta}} m_{\mathbf{x}})^\top}_{\mathbf{z}^\top} m_W \mathbf{y} - \mathbf{y}^\top \underbrace{m_W m_{\boldsymbol{\theta}} m_{\mathbf{x}}}_{\mathbf{z}} \right] + \text{const} \\
&= -\frac{1}{2} [\mathbf{y}^\top m_W \mathbf{y} - \mathbf{z}^\top \mathbf{y} - \mathbf{y}^\top \mathbf{z} + \mathbf{z}^\top m_W^{-1} \mathbf{z}] + \text{const} \\
&= -\frac{1}{2} [\mathbf{y}^\top m_W \mathbf{y} - \mathbf{z}^\top m_W^{-1} m_W \mathbf{y} - \mathbf{y}^\top m_W m_W^{-1} \mathbf{z} + \mathbf{z}^\top m_W^{-1} m_W m_W^{-1} \mathbf{z}] \\
&\quad + \text{const} \\
&= -\frac{1}{2} [(\mathbf{y} - m_W^{-1} \mathbf{z})^\top m_W (\mathbf{y} - m_W^{-1} \mathbf{z})] + \text{const} \\
&= -\frac{1}{2} \left[(\mathbf{y} - \underbrace{m_W^{-1} m_W m_{\boldsymbol{\theta}} m_{\mathbf{x}}}_{\mathbf{I}})^\top m_W (\mathbf{y} - m_W^{-1} m_W m_{\boldsymbol{\theta}} m_{\mathbf{x}}) \right] + \text{const} \\
&= -\frac{1}{2} [(\mathbf{y} - m_{\boldsymbol{\theta}} m_{\mathbf{x}})^\top m_W (\mathbf{y} - m_{\boldsymbol{\theta}} m_{\mathbf{x}})] + \text{const}
\end{aligned}$$

Which yields

$$\vec{\nu}(\mathbf{y}) \propto \mathcal{N}(m_{\boldsymbol{\theta}} m_{\mathbf{x}}, m_W^{-1})$$

Update of message to \mathbf{x}

$$\begin{aligned}
\log \overleftarrow{\nu}(\mathbf{x}) &= \mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \log f + \text{const} \\
&= -\frac{1}{2} \mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} [\mathbf{y}^\top W \mathbf{y} - (\mathbf{Ax})^\top W \mathbf{y} - \mathbf{y}^\top W \mathbf{Ax} + (\mathbf{Ax})^\top W \mathbf{Ax}] \\
&\quad + \text{const} \\
&= -\frac{1}{2} \mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} [-\mathbf{x}^\top \mathbf{A}^\top W \mathbf{y} - \mathbf{y}^\top W \mathbf{Ax} + \mathbf{x}^\top \mathbf{A}^\top W \mathbf{Ax}] \\
&\quad + \text{const}
\end{aligned}$$

We split the expression under the expectation into three terms:

I: $\mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \left[-\mathbf{x}^\top \mathbf{A}^\top W \mathbf{y} \right]$

II: $\mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \left[-\mathbf{y}^\top W \mathbf{A} \mathbf{x} \right]$ and

III: $\mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \left[\mathbf{x}^\top \mathbf{A}^\top W \mathbf{A} \mathbf{x} \right]$

Term I:

$$\begin{aligned} \mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \left[-\mathbf{x}^\top \mathbf{A}^\top W \mathbf{y} \right] &= -\mathbf{x}^\top \mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \left[(\mathbf{S} + \mathbf{c} \boldsymbol{\theta}^\top)^\top W \mathbf{y} \right] \\ &= -\mathbf{x}^\top m_{\mathbf{A}}^\top m_W m_{\mathbf{y}} = -(m_{\mathbf{A}} \mathbf{x})^\top m_W m_{\mathbf{y}} \end{aligned}$$

Term II:

$$\mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \left[-\mathbf{y}^\top W \mathbf{A} \mathbf{x} \right] = -m_{\mathbf{y}}^\top m_W m_{\mathbf{A}} \mathbf{x}$$

Term III:

$$\begin{aligned} \mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \left[\mathbf{x}^\top \mathbf{A}^\top W \mathbf{A} \mathbf{x} \right] &= \mathbb{E}_{\boldsymbol{\theta}, \gamma} \left[((\mathbf{S} \mathbf{x} + \mathbf{c} \mathbf{x}^\top \boldsymbol{\theta})^\top W (\mathbf{S} \mathbf{x} + \mathbf{c} \mathbf{x}^\top \boldsymbol{\theta})) \right] \\ &= \mathbb{E}_{\boldsymbol{\theta}} \left[(\mathbf{c} \mathbf{x}^\top \boldsymbol{\theta})^\top m_W \mathbf{S} \mathbf{x} + (\mathbf{c} \mathbf{x}^\top \boldsymbol{\theta})^\top m_W \mathbf{c} \mathbf{x}^\top \boldsymbol{\theta} \right] \\ &\quad + \mathbb{E}_{\boldsymbol{\theta}} \left[(\mathbf{S} \mathbf{x})^\top m_W \mathbf{c} \mathbf{x}^\top \boldsymbol{\theta} + (\mathbf{S} \mathbf{x})^\top m_W \mathbf{S} \mathbf{x} \right] \\ &= (\mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}})^\top m_W \mathbf{S} \mathbf{x} + \mathbb{E}_{\boldsymbol{\theta}} \left[\boldsymbol{\theta}^\top \mathbf{x} \mathbf{c}^\top m_W \mathbf{c} \mathbf{x}^\top \boldsymbol{\theta} \right] \\ &\quad + (\mathbf{S} \mathbf{x})^\top m_W \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}} + (\mathbf{S} \mathbf{x})^\top m_W \mathbf{S} \mathbf{x} \end{aligned}$$

where

$$\mathbb{E}_{\boldsymbol{\theta}} \left[\boldsymbol{\theta}^\top \mathbf{x} \mathbf{c}^\top m_W \mathbf{c} \mathbf{x}^\top \boldsymbol{\theta} \right] = \text{tr}(\mathbf{x} \mathbf{c}^\top m_W \mathbf{c} \mathbf{x}^\top V_{\boldsymbol{\theta}}) + m_{\boldsymbol{\theta}}^\top \mathbf{x} \mathbf{c}^\top m_W \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}}$$

Hence,

$$\begin{aligned} &\mathbb{E}_{\boldsymbol{\theta}, \mathbf{y}, \gamma} \left[\mathbf{x}^\top \mathbf{A}^\top W \mathbf{A} \mathbf{x} \right] \\ &= (\mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}})^\top m_W \mathbf{S} \mathbf{x} + \text{tr}(\mathbf{x} \mathbf{c}^\top m_W \mathbf{c} \mathbf{x}^\top V_{\boldsymbol{\theta}}) + m_{\boldsymbol{\theta}}^\top \mathbf{x} \mathbf{c}^\top m_W \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}} \\ &\quad + (\mathbf{S} \mathbf{x})^\top m_W \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}} + (\mathbf{S} \mathbf{x})^\top m_W \mathbf{S} \mathbf{x} \\ &= (\mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}})^\top m_W \mathbf{S} \mathbf{x} + \mathbf{x}^\top V_{\boldsymbol{\theta}} \mathbf{c}^\top m_W \mathbf{c} \mathbf{x} + m_{\boldsymbol{\theta}}^\top \mathbf{x} \mathbf{c}^\top m_W \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}} \\ &\quad + (\mathbf{S} \mathbf{x})^\top m_W \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}} + (\mathbf{S} \mathbf{x})^\top m_W \mathbf{S} \mathbf{x} \\ &= \underbrace{(\mathbf{S} \mathbf{x} + \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}})^\top m_W \mathbf{S} \mathbf{x}}_{m_{\mathbf{A}} \mathbf{x}} + (\mathbf{S} \mathbf{x} + \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}})^\top m_W \mathbf{c} \mathbf{x}^\top m_{\boldsymbol{\theta}} \\ &\quad + \mathbf{x}^\top V_{\boldsymbol{\theta}} \underbrace{\mathbf{c}^\top m_W \mathbf{c}}_{m_{\gamma}} \mathbf{x} \\ &= (m_{\mathbf{A}} \mathbf{x})^\top m_W m_{\mathbf{A}} \mathbf{x} + \mathbf{x}^\top V_{\boldsymbol{\theta}} m_{\gamma} \mathbf{x} \end{aligned}$$

Putting terms I, II and III together

$$\begin{aligned}
& \log \overleftarrow{\nu}(\mathbf{x}) \\
&= -\frac{1}{2} \left[-(m_{\mathbf{A}}\mathbf{x})^\top m_W m_{\mathbf{y}} - m_{\mathbf{y}}^\top m_W m_{\mathbf{A}}\mathbf{x} + (m_{\mathbf{A}}\mathbf{x})^\top m_W m_{\mathbf{A}}\mathbf{x} + \mathbf{x}^\top V_{\boldsymbol{\theta}} m_{\gamma} \mathbf{x} \right] \\
&\quad + \text{const} \\
&= -\frac{1}{2} \left[-\mathbf{x}^\top \underbrace{m_{\mathbf{A}}^\top m_W m_{\mathbf{y}}}_{\mathbf{z}} - \underbrace{m_{\mathbf{y}}^\top m_W m_{\mathbf{A}}}_{\mathbf{z}^\top} \mathbf{x} + \mathbf{x}^\top \underbrace{(m_{\mathbf{A}}^\top m_W m_{\mathbf{A}} + V_{\boldsymbol{\theta}} m_{\gamma})}_{\mathbf{D}} \mathbf{x} \right] + \text{const} \\
&= -\frac{1}{2} \left[\mathbf{x}^\top \mathbf{D} \mathbf{x} - \mathbf{x}^\top \mathbf{z} - \mathbf{z}^\top \mathbf{x} + \mathbf{z}^\top \mathbf{D}^{-1} \mathbf{z} \right] + \text{const} \\
&= -\frac{1}{2} \left[\mathbf{x}^\top \mathbf{D} \mathbf{x} - \mathbf{x}^\top \mathbf{D} \mathbf{D}^{-1} \mathbf{z} - \mathbf{z}^\top \mathbf{D}^{-1} \mathbf{D} \mathbf{x} + \mathbf{z}^\top \mathbf{D}^{-1} \mathbf{D} \mathbf{D}^{-1} \mathbf{z} \right] + \text{const} \\
&= -\frac{1}{2} \left[(\mathbf{x} - \mathbf{D}^{-1} \mathbf{z})^\top \mathbf{D} (\mathbf{x} - \mathbf{D}^{-1} \mathbf{z}) \right] + \text{const}
\end{aligned}$$

Therefore,

$$\overleftarrow{\nu}(\mathbf{x}) \propto \mathcal{N}(\mathbf{D}^{-1} \mathbf{z}, \mathbf{D}^{-1})$$

where

$$\begin{aligned}
\mathbf{D} &= m_{\mathbf{A}}^\top m_W m_{\mathbf{A}} + V_{\boldsymbol{\theta}} m_{\gamma} \\
\mathbf{z} &= m_{\mathbf{A}}^\top m_W m_{\mathbf{y}}
\end{aligned}$$

Update of message to $\boldsymbol{\theta}$

$$\begin{aligned}
\log \overleftarrow{\nu}(\boldsymbol{\theta}) &= \mathbb{E}_{\mathbf{x}, \mathbf{y}, \gamma} \log f + \text{const} \\
&= -\frac{1}{2} \mathbb{E}_{\mathbf{x}, \mathbf{y}, \gamma} \left[\mathbf{y}^\top W \mathbf{y} - (\mathbf{A} \mathbf{x})^\top W \mathbf{y} - \mathbf{y}^\top W \mathbf{A} \mathbf{x} + (\mathbf{A} \mathbf{x})^\top W \mathbf{A} \mathbf{x} \right] \\
&\quad + \text{const} \\
&= -\frac{1}{2} \mathbb{E}_{\mathbf{x}, \mathbf{y}, \gamma} \left[-(\mathbf{A} \mathbf{x})^\top W \mathbf{y} - \mathbf{y}^\top W \mathbf{A} \mathbf{x} + (\mathbf{A} \mathbf{x})^\top W \mathbf{A} \mathbf{x} \right] + \text{const} \\
&= -\frac{1}{2} \left[-m_{\mathbf{x}}^\top \mathbf{A}^\top m_W m_{\mathbf{y}} - m_{\mathbf{y}}^\top m_W \mathbf{A} m_{\mathbf{x}} \right] \\
&\quad - \frac{1}{2} \left[\text{tr}(\mathbf{A}^\top m_W \mathbf{A} V_{\mathbf{x}}) + (\mathbf{A} m_{\mathbf{x}})^\top m_W \mathbf{A} m_{\mathbf{x}} \right] \\
&\quad + \text{const}
\end{aligned}$$

We seek for a quadratic form of vector $\boldsymbol{\theta}$, therefore recalling Eq. 2, we obtain:

$$\begin{aligned}\log \overleftarrow{\nu}(\boldsymbol{\theta}) = & -\frac{1}{2} [-(\mathbf{S}m_{\mathbf{x}} + \mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})^{\top}m_Wm_{\mathbf{y}} - m_{\mathbf{y}}^{\top}m_W(\mathbf{S}m_{\mathbf{x}} + \mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})] \\ & -\frac{1}{2} \left[\text{tr} \left[m_W(\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^{\top})V_{\mathbf{x}}(\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^{\top})^{\top} \right] \right] \\ & -\frac{1}{2} [(\mathbf{S}m_{\mathbf{x}} - \mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})^{\top}m_W(\mathbf{S}m_{\mathbf{x}} - \mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})] \\ & + \text{const}\end{aligned}$$

Let us work out the term $\text{tr} \left[m_W(\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^{\top})V_{\mathbf{x}}(\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^{\top})^{\top} \right]$ separately.

$$\begin{aligned}\text{tr} \left[m_W(\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^{\top})V_{\mathbf{x}}(\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^{\top})^{\top} \right] \\ = \text{tr}[m_W\mathbf{S}V_{\mathbf{x}}\mathbf{S}^{\top} + m_W\mathbf{c}\boldsymbol{\theta}^{\top}V_{\mathbf{x}}\mathbf{S}^{\top} + m_W\mathbf{c}\boldsymbol{\theta}^{\top}V_{\mathbf{x}}\boldsymbol{\theta}\mathbf{c}^{\top} + m_W\mathbf{S}V_{\mathbf{x}}\boldsymbol{\theta}\mathbf{c}^{\top}] \quad (4) \\ = \text{tr}(m_W\mathbf{S}V_{\mathbf{x}}\mathbf{S}^{\top}) + \boldsymbol{\theta}^{\top}V_{\mathbf{x}}\mathbf{S}^{\top}m_W\mathbf{c} + \mathbf{c}^{\top}m_W\mathbf{c}\boldsymbol{\theta}^{\top}V_{\mathbf{x}}\boldsymbol{\theta} + \mathbf{c}^{\top}m_W\mathbf{S}V_{\mathbf{x}}\boldsymbol{\theta}\end{aligned}$$

Owing that $\mathbf{S}^{\top}\boldsymbol{\Sigma}\mathbf{c} = \mathbf{0}$ and $\mathbf{c}^{\top}\boldsymbol{\Sigma}\mathbf{S} = \mathbf{0}^{\top}$, where $\boldsymbol{\Sigma}$ is an arbitrary diagonal matrix.

$$\begin{aligned}\log \overleftarrow{\nu}(\boldsymbol{\theta}) = & -\frac{1}{2} \left[-(\mathbf{S}m_{\mathbf{x}})^{\top}m_Wm_{\mathbf{y}} - (\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})^{\top}m_Wm_{\mathbf{y}} - m_{\mathbf{y}}^{\top}m_W\mathbf{S}m_{\mathbf{x}} \right. \\ & - m_{\mathbf{y}}^{\top}m_W\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta} + \text{tr}(m_W\mathbf{S}V_{\mathbf{x}}\mathbf{S}^{\top}) + \underbrace{\boldsymbol{\theta}^{\top}V_{\mathbf{x}}\mathbf{S}^{\top}m_W\mathbf{c}}_0 \\ & + \mathbf{c}^{\top}m_W\mathbf{c}\boldsymbol{\theta}^{\top}V_{\mathbf{x}}\boldsymbol{\theta} + \underbrace{\mathbf{c}^{\top}m_W\mathbf{S}V_{\mathbf{x}}\boldsymbol{\theta}}_0 \\ & + (\mathbf{S}m_{\mathbf{x}})^{\top}m_W\mathbf{S}m_{\mathbf{x}} - \underbrace{(\mathbf{S}m_{\mathbf{x}})^{\top}m_W\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta}}_0 \\ & \left. - \underbrace{(\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})^{\top}m_W\mathbf{S}m_{\mathbf{x}}}_0 + (\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})^{\top}m_W\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta} \right] + \text{const} \\ = & -\frac{1}{2} \left[-(\mathbf{S}m_{\mathbf{x}})^{\top}m_Wm_{\mathbf{y}} - (\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})^{\top}m_Wm_{\mathbf{y}} - m_{\mathbf{y}}^{\top}m_W\mathbf{S}m_{\mathbf{x}} \right. \\ & - m_{\mathbf{y}}^{\top}m_W\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta} + \text{tr}(m_W\mathbf{S}V_{\mathbf{x}}\mathbf{S}^{\top}) + \mathbf{c}^{\top}m_W\mathbf{c}\boldsymbol{\theta}^{\top}V_{\mathbf{x}}\boldsymbol{\theta} \\ & \left. + (\mathbf{S}m_{\mathbf{x}})^{\top}m_W\mathbf{S}m_{\mathbf{x}} + (\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta})^{\top}m_W\mathbf{c}m_{\mathbf{x}}^{\top}\boldsymbol{\theta} \right] + \text{const}\end{aligned}$$

We move terms which do not depend on θ to the *const*, hence

$$\begin{aligned}
\log \zeta(\theta) &= -\frac{1}{2} \left[-(cm_x^\top \theta)^\top m_W m_y - m_y^\top m_W cm_x^\top \theta + c^\top m_W c \theta^\top V_x \theta \right. \\
&\quad \left. + (cm_x^\top \theta)^\top m_W cm_x^\top \theta \right] + \text{const} \\
&= -\frac{1}{2} \left[\theta^\top \underbrace{(V_x c^\top m_W c + m_x c^\top m_W cm_x^\top)}_{\mathbf{D}} \theta - \underbrace{m_y^\top m_W cm_x^\top}_{z^\top} \theta \right. \\
&\quad \left. - \theta^\top \underbrace{m_x c^\top m_W m_y}_{z} \right] + \text{const} \\
&= -\frac{1}{2} \left[\theta^\top \mathbf{D} \theta - z^\top \theta - \theta^\top z + z^\top \mathbf{D}^{-1} z \right] + \text{const} \\
&= -\frac{1}{2} \left[(\theta - \mathbf{D}^{-1} z)^\top \mathbf{D} (\theta - \mathbf{D}^{-1} z) \right] + \text{const}
\end{aligned}$$

Hence,

$$\zeta(\theta) \propto \mathcal{N}(\mathbf{D}^{-1} z, \mathbf{D}^{-1})$$

where

$$\begin{aligned}
z &= m_x c^\top m_W m_y = m_\gamma(m_x \circ m_y) \\
(\circ) &\text{denote Hadamard product} \\
\mathbf{D} &= (V_x c^\top m_W c + m_x c^\top m_W cm_x^\top) = V_x m_\gamma + m_x m_\gamma m_x^\top
\end{aligned}$$

Update of message to γ

$$\begin{aligned}
\log \zeta(\gamma) &= \mathbb{E}_{\mathbf{x}, \mathbf{y}, \theta} \log f + \text{const} \\
&= \log(|W|^{\frac{1}{2}}) - \frac{1}{2} \mathbb{E}_{\mathbf{x}, \mathbf{y}, \theta} [(\mathbf{y} - \mathbf{A}\mathbf{x})^\top W (\mathbf{y} - \mathbf{A}\mathbf{x})] + \text{const} \\
&= \log(|W|^{\frac{1}{2}}) \\
&\quad - \frac{1}{2} \mathbb{E}_{\mathbf{x}, \mathbf{y}, \theta} [\mathbf{y}^\top W \mathbf{y} - \mathbf{x}^\top \mathbf{A}^\top W \mathbf{y} - \mathbf{y}^\top W \mathbf{A} \mathbf{x} + \mathbf{x}^\top \mathbf{A}^\top W \mathbf{A} \mathbf{x}] \\
&\quad + \text{const} \\
&= \log(|W|^{\frac{1}{2}}) - \frac{1}{2} \left[\text{tr}(W V_y) + m_y^\top W m_y - (m_A m_x)^\top W m_y \right. \\
&\quad \left. - m_y^\top W m_A m_x + \mathbb{E}_{\mathbf{x}, \theta} [\mathbf{x}^\top \mathbf{A}^\top W \mathbf{A} \mathbf{x}] \right] + \text{const}
\end{aligned}$$

Let us work out the remaining expectation term separately

$$\mathbb{E}_{\mathbf{x}, \theta} [\mathbf{x}^\top \mathbf{A}^\top W \mathbf{A} \mathbf{x}] = \mathbb{E}_\theta [\text{tr}(\mathbf{A}^\top W \mathbf{A} V_x) + (m_A m_x)^\top W m_A m_x]$$

where

$$\begin{aligned}
\mathbb{E}_{\boldsymbol{\theta}}[\text{tr}(\mathbf{A}^\top W \mathbf{A} V_{\mathbf{x}})] &= \text{tr}(W \mathbb{E}_{\boldsymbol{\theta}}[(\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^\top) V_{\mathbf{x}} (\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^\top)^\top]) \\
&= \text{tr}(W \mathbb{E}_{\boldsymbol{\theta}}[\mathbf{S} V_{\mathbf{x}} \mathbf{S}^\top + \mathbf{c}\boldsymbol{\theta}^\top V_{\mathbf{x}} \mathbf{S}^\top + \mathbf{c}\boldsymbol{\theta}^\top V_{\mathbf{x}} \boldsymbol{\theta} \mathbf{c}^\top + \mathbf{S} V_{\mathbf{x}} \boldsymbol{\theta} \mathbf{c}^\top]) \\
&= \text{tr}(W \mathbf{S} V_{\mathbf{x}} \mathbf{S}^\top) + \underbrace{m_{\boldsymbol{\theta}}^\top V_{\mathbf{x}} \mathbf{S}^\top W \mathbf{c}}_0 + \underbrace{\mathbf{c}^\top W \mathbf{c} m_{\boldsymbol{\theta}}^\top V_{\mathbf{x}} m_{\boldsymbol{\theta}}}_{\gamma} + \underbrace{\mathbf{c}^\top W \mathbf{S} V_{\mathbf{x}} m_{\boldsymbol{\theta}}}_0 \\
&= \text{tr}(\mathbf{S}^\top W \mathbf{S} V_{\mathbf{x}}) + \gamma m_{\boldsymbol{\theta}}^\top V_{\mathbf{x}} m_{\boldsymbol{\theta}}
\end{aligned} \tag{5}$$

and

$$\begin{aligned}
\mathbb{E}_{\boldsymbol{\theta}}[(\mathbf{A} m_{\mathbf{x}})^\top W \mathbf{A} m_{\mathbf{x}}] &= \mathbb{E}_{\boldsymbol{\theta}}[\text{tr}(m_{\mathbf{x}}^\top \mathbf{A}^\top W \mathbf{A} m_{\mathbf{x}})] \\
&= \mathbb{E}_{\boldsymbol{\theta}}[\text{tr}(W \mathbf{A} m_{\mathbf{x}} m_{\mathbf{x}}^\top \mathbf{A}^\top)] \\
&= \text{tr}(W \mathbb{E}_{\boldsymbol{\theta}}[(\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^\top) m_{\mathbf{x}} m_{\mathbf{x}}^\top (\mathbf{S} + \mathbf{c}\boldsymbol{\theta}^\top)^\top]) \\
&= \text{tr}(\mathbf{S}^\top W \mathbf{S} m_{\mathbf{x}} m_{\mathbf{x}}^\top) + \gamma m_{\mathbf{x}}^\top V_{\boldsymbol{\theta}} m_{\mathbf{x}} + \gamma m_{\boldsymbol{\theta}}^\top m_{\mathbf{x}} m_{\mathbf{x}}^\top m_{\boldsymbol{\theta}}
\end{aligned} \tag{6}$$

Before proceeding, let us focus on $\mathbf{S}^\top W \mathbf{S}$:

$$\mathbf{S}^\top W \mathbf{S} = \begin{bmatrix} \mathbf{0} & \mathbf{I}_{M-1} \\ \mathbf{0}^\top & \end{bmatrix} \begin{bmatrix} \gamma & 0 & 0 & \dots & 0 \\ 0 & \frac{1}{\epsilon} & 0 & \dots & \vdots \\ 0 & 0 & \frac{1}{\epsilon} & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \end{bmatrix} \begin{bmatrix} \mathbf{0}^\top & \\ \mathbf{I}_{M-1} & \mathbf{0} \end{bmatrix}$$

Obviously, there will be no entry of γ in the resulting matrix. Therefore the terms which incorporate $\mathbf{S}^\top W \mathbf{S}$ can be moved to the *const*.

$$\mathbb{E}_{\mathbf{x}, \boldsymbol{\theta}}[\mathbf{x}^\top \mathbf{A}^\top W \mathbf{A} \mathbf{x}] = \gamma m_{\boldsymbol{\theta}}^\top V_{\mathbf{x}} m_{\boldsymbol{\theta}} + \gamma m_{\mathbf{x}}^\top V_{\boldsymbol{\theta}} m_{\mathbf{x}} + \gamma m_{\boldsymbol{\theta}}^\top m_{\mathbf{x}} m_{\mathbf{x}}^\top m_{\boldsymbol{\theta}} + \text{const}$$

This leads to

$$\begin{aligned}
\log \overleftarrow{\nu}(\gamma) &= \log(|W|^{\frac{1}{2}}) - \frac{1}{2} \left[\text{tr}(W V_{\mathbf{y}}) + m_{\mathbf{y}}^\top W m_{\mathbf{y}} - (m_{\mathbf{A}} m_{\mathbf{x}})^\top W m_{\mathbf{y}} \right. \\
&\quad \left. - m_{\mathbf{y}}^\top W m_{\mathbf{A}} m_{\mathbf{x}} + \gamma m_{\boldsymbol{\theta}}^\top V_{\mathbf{x}} m_{\boldsymbol{\theta}} + \gamma m_{\mathbf{x}}^\top V_{\boldsymbol{\theta}} m_{\mathbf{x}} + \gamma m_{\boldsymbol{\theta}}^\top m_{\mathbf{x}} m_{\mathbf{x}}^\top m_{\boldsymbol{\theta}} \right] \\
&\quad + \text{const}
\end{aligned}$$

As the resulting message should depend solely on γ we need to get rid of all terms which incorporate matrix W . Let us consider these terms separately:

I: $\log(|W|^{\frac{1}{2}})$

II: $\text{tr}(W V_{\mathbf{y}})$

III: $m_{\mathbf{y}}^\top W m_{\mathbf{y}}$

IV: $(m_{\mathbf{A}} m_{\mathbf{x}})^\top W m_{\mathbf{y}}$

$$V: m_{\mathbf{y}}^\top W m_{\mathbf{A}} m_{\mathbf{x}}$$

Term I:

$$\begin{aligned} \log(|W|^{\frac{1}{2}}) &= \frac{1}{2} \log \begin{vmatrix} \gamma & 0 & 0 & \dots & 0 \\ 0 & \frac{1}{\epsilon} & 0 & \dots & \vdots \\ 0 & 0 & \frac{1}{\epsilon} & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \end{vmatrix} \\ &= \frac{1}{2} \log \gamma + \frac{1}{2} (1 - M) \log(\epsilon) = \log \gamma^{\frac{1}{2}} + \text{const} \end{aligned}$$

Term II:

$$\begin{aligned} \text{tr}(W V_{\mathbf{y}}) &= \text{tr} \left(\begin{bmatrix} \gamma & 0 & 0 & \dots & 0 \\ 0 & \frac{1}{\epsilon} & 0 & \dots & \vdots \\ 0 & 0 & \frac{1}{\epsilon} & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \end{bmatrix} V_{\mathbf{y}} \right) \\ &= \gamma V_{\mathbf{y}}^{(1,1)} + \text{const} \end{aligned}$$

where $V_{\mathbf{y}}^{(1,1)}$ is the first element of matrix $V_{\mathbf{y}}$.

Term III:

$$m_{\mathbf{y}}^\top W m_{\mathbf{y}} = \gamma m_{\mathbf{y}}^{(1)} m_{\mathbf{y}}^{(1)} + \text{const}$$

where $m_{\mathbf{y}}^{(1)}$ is the first element of $m_{\mathbf{y}}$.

Both terms IV and V result into the same scalar, i.e.

$$\begin{aligned} m_{\mathbf{y}}^\top W m_{\mathbf{A}} m_{\mathbf{x}} &= (m_{\mathbf{A}} m_{\mathbf{x}})^\top W m_{\mathbf{y}} \\ &= \left(m_{\boldsymbol{\theta}}^\top m_{\mathbf{x}}, m_{\mathbf{x}}^{(1)}, \dots, m_{\mathbf{x}}^{(M-1)} \right) \begin{bmatrix} \gamma & 0 & 0 & \dots & 0 \\ 0 & \frac{1}{\epsilon} & 0 & \dots & \vdots \\ 0 & 0 & \frac{1}{\epsilon} & \dots & \vdots \\ \vdots & \vdots & \ddots & \ddots & \vdots \end{bmatrix} \begin{bmatrix} m_{\mathbf{y}}^{(1)} \\ m_{\mathbf{y}}^{(2)} \\ \vdots \\ m_{\mathbf{y}}^{(M)} \end{bmatrix} \\ &= m_{\boldsymbol{\theta}}^\top m_{\mathbf{x}} \gamma m_{\mathbf{y}}^{(1)} + \sum_{i=1}^{M-1} \frac{m_{\mathbf{x}}^{(i)}}{\epsilon} m_{\mathbf{y}}^{(i+1)} = \gamma m_{\mathbf{y}}^{(1)} m_{\boldsymbol{\theta}}^\top m_{\mathbf{x}} + \text{const} \end{aligned}$$

Hence

$$\begin{aligned}
\log \overleftarrow{\nu}(\gamma) &= \log \gamma^{\frac{1}{2}} - \frac{1}{2} \left(\gamma V_{\mathbf{y}}^{(1,1)} + \gamma m_{\mathbf{y}}^{(1)} m_{\mathbf{y}}^{(1)} - 2\gamma m_{\mathbf{y}}^{(1)} m_{\boldsymbol{\theta}}^{\top} m_{\mathbf{x}} \right. \\
&\quad \left. + \gamma m_{\boldsymbol{\theta}}^{\top} V_{\mathbf{x}} m_{\boldsymbol{\theta}} + \gamma m_{\mathbf{x}}^{\top} V_{\boldsymbol{\theta}} m_{\mathbf{x}} + \gamma m_{\boldsymbol{\theta}}^{\top} m_{\mathbf{x}} m_{\mathbf{x}}^{\top} m_{\boldsymbol{\theta}} \right) + \text{const} \\
&= \log \gamma^{\frac{1}{2}} - \frac{\gamma}{2} \left(V_{\mathbf{y}}^{(1,1)} + m_{\mathbf{y}}^{(1)} m_{\mathbf{y}}^{(1)} - 2m_{\mathbf{y}}^{(1)} m_{\boldsymbol{\theta}}^{\top} m_{\mathbf{x}} \right. \\
&\quad \left. + m_{\boldsymbol{\theta}}^{\top} V_{\mathbf{x}} m_{\boldsymbol{\theta}} + m_{\mathbf{x}}^{\top} V_{\boldsymbol{\theta}} m_{\mathbf{x}} + m_{\boldsymbol{\theta}}^{\top} m_{\mathbf{x}} m_{\mathbf{x}}^{\top} m_{\boldsymbol{\theta}} \right) + \text{const}
\end{aligned}$$

After exponentiating $\log \overleftarrow{\nu}(\gamma)$ it yields a gamma distribution:

$$\overleftarrow{\nu}(\gamma) \propto \gamma^{\frac{1}{2}} \exp \left\{ -\frac{\gamma}{2} B \right\}$$

or

$$\overleftarrow{\nu}(\gamma) \propto \Gamma \left(\frac{3}{2}, \frac{B}{2} \right)$$

where

$$\begin{aligned}
B &= V_{\mathbf{y}}^{(1,1)} + m_{\mathbf{y}}^{(1)} m_{\mathbf{y}}^{(1)} - 2m_{\mathbf{y}}^{(1)} m_{\boldsymbol{\theta}}^{\top} m_{\mathbf{x}} + m_{\mathbf{x}}^{\top} V_{\boldsymbol{\theta}} m_{\mathbf{x}} \\
&\quad + m_{\boldsymbol{\theta}}^{\top} (V_{\mathbf{x}} + m_{\mathbf{x}} m_{\mathbf{x}}^{\top}) m_{\boldsymbol{\theta}}
\end{aligned}$$

References

- [1] J. Dauwels, A. Eckford, S. Korl, and H.-A. Loeliger, “Expectation maximization as message passing-part I: Principles and gaussian messages,” *arXiv preprint arXiv:0910.2832*, 2009. [Online]. Available: <http://arxiv.org/abs/0910.2832>