Derivations for NARMAX node

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NARMAX system

Let y_k be an output of and u_k be an input to a system at time k. Consider the following set of dynamics:

$$y_k = f_\theta\left(y_{k-1}, \dots, y_{k-M_1}, u_k, u_{k-1}, \dots, u_{k-M_2}, e_{k-1}, \dots, e_{k-M_3}\right) + e_k \tag{1}$$

where $e_k \sim \mathcal{N}(0, \gamma^{-1})$ is a zero mean zero auto-correlation Gaussian noise component. The function f, parameterized by θ, is a nonlinear regression from input, output and noise components unto the current output. The constants M_1, M_2, and M_3 refer to the delays, for a total model order of $M = M_1 + 1 + M_2 + M_3$.

Generative model

We cast the NARMAX system equation to a likelihood:

$$\begin{aligned} p(y_k \ &| \ \theta, y_{k-1}, \dots, y_{k-M_1}, u_k, \dots, u_{k-M_2}, \tau) = \\ &\mathcal{N}\Big(y_k \mid f_\theta\left(y_{k-1}, \dots, y_{k-M_1}, u_k, \dots, u_{k-M_2}, e_{k-1}, \dots, e_{k-M_3}\right), \tau^{-1}\Big) . \end{aligned} \tag{2}$$

Using the following priors

$$p(\theta) \triangleq \mathcal{N}\big(\theta \mid \mu_0, \Lambda_0^{-1}\big) , \qquad p(\tau) \triangleq \mathit{\Gamma}\big(\tau \mid \alpha_0, \beta_0\big) , \tag{3}$$

we form the generative model for the entire time-series:

$$p(y_{1:T}, u_{1:T}, \theta, \tau) = \underbrace{p(\theta)p(\tau)}_{\text{priors}} \prod_{k=1}^{T} \underbrace{p(y_k \mid \theta, y_{k1}, .. \, y_{kM_1}, u_k, .. \, u_{kM_2}, \tau)}_{\text{likelihood}} . \tag{4}$$

Recognition model

We define the following recognition distributions:

$$q(\theta) = \mathcal{N}(\theta \mid \mu, \Lambda^{-1}) , \qquad q(\tau) = \Gamma(\tau \mid \alpha, \beta) . \tag{5}$$

Message Computation

The NARMAX factor node sends out variational messages to its coefficients θ and its precision parameter τ. The general mathematical formula for a variational message in a factor graph is [1]:

$$\nu(x_i) \propto \exp\big(\mathbb{E}_{q(x_{j\neq i})}\big[\log p(x_i, \dots)\big]\big)\,, \tag{6}$$

where $p(x_i, \dots)$ represents the factor node function, which in our case is the likelihood (Equation 2).

Note that, in order to compute variational messages, we must be able to compute expected values with respect to the recognition distributions. In NARMAX models, the coefficients θ are part of a nonlinear function, which makes it challenging to compute expected values. In our paper, we employ a Taylor approximation of the nonlinear function f_θ to be able to compute expectations.

Taylor approximation

First-order Taylor approximation of f_θ at point μ:

$$f_\theta(x) \approx f_\mu(x) + J_\theta^\top(\theta - \mu)\,, \tag{7}$$

where J_θ represents the gradient of g with respect to θ evaluated at the approximating point:

$$J_\theta = \frac{\partial f_\theta(x)}{\partial\theta}|_{\theta=\mu}\,. \tag{8}$$

The expectation of the first moment of the function is:

$$\mathbb{E}_{q(\theta)}\big[f_\theta(x)\big] = f_\mu(x) + J_\theta^\top \underbrace{(\mu-\mu)}_{=0} = f_\mu(x)\,. \tag{9}$$

The expectation of the second moment of the function is:

$$\begin{aligned}
&\mathbb{E}_{q(\theta)}\big[f_\theta(x)^2\big] \\
&\quad= \mathbb{E}_{q(\theta)}\Big(f_\mu(x) + J_\theta^\top(\theta-\mu)\Big)\Big(f_\mu(x) + J_\theta^\top(\theta-\mu)\Big) && \text{(10a)}\\
&\quad= \mathbb{E}_{q(\theta)}\Big(f_\mu(x)^2 + 2f_\mu(x)J_\theta^\top(\theta-\mu) + J_\theta^\top(\theta-\mu)(\theta-\mu)^\top J_\theta\Big) && \text{(10b)}\\
&\quad= f_\mu(x)^2 + 2f_\mu(x)J_\theta^\top(\mu-\mu) && \text{(10c)}\\
&\qquad\qquad + \mathbb{E}_{q(\theta)}\Big[J_\theta^\top\big(\theta\theta^\top - \mu\theta^\top - \theta\mu^\top + \mu\mu^\top\big)J_\theta\Big] && \text{(10d)}\\
&\quad= f_\mu(x)^2 + J_\theta^\top\big(\mathbb{E}_{q(\theta)}\big[\theta\theta^\top\big] - \mu\mu^\top - \mu\mu^\top + \mu\mu^\top\big)J_\theta && \text{(10e)}\\
&\quad= f_\mu(x)^2 + J_\theta^\top\big(\Lambda^{-1} - \mu\mu^\top\big)J_\theta && \text{(10f)}
\end{aligned}$$

In the special case of a polynomial function with basis expansion ϕ,

$$f_\theta(x) = \theta^\top\phi(x)\,, \tag{11}$$

the Taylor approximation defaults to:

$$\begin{aligned}
\theta^\top \phi(x) &\approx \mu^\top \phi(x) + \frac{\partial \theta^\top \phi(x)}{\partial \theta}|_{\theta=\mu}(\theta - \mu) && \text{(12a)}\\
&= \mu^\top \phi(x) + \phi(x)^\top (\theta - \mu) && \text{(12b)}\\
&= \theta^\top \phi(x)\,. && \text{(12c)}
\end{aligned}$$

Message to θ

In the following, I use the shorthand $f_\theta = f_\theta(y_{k-1}, \dots, e_{k-M_3})$.

$$\begin{aligned}
\log \nu(\theta) &\propto \mathbb{E}_{q(\tau)} \log \mathcal{N}\Big(y_k \mid f_\theta(y_{k-1}, \dots, e_{k-M_3}), \tau^{-1}\Big) && \text{(13a)}\\
&\propto -\frac{1}{2}\mathbb{E}_{q(\tau)}\big[\tau\big]\Big(y_k - f_\theta\Big)^2 && \text{(13b)}\\
&= -\frac{1}{2}\frac{\alpha}{\beta}\Big(y_k^2 - 2y_k f_\theta + f_\theta^2\Big) && \text{(13c)}\\
&\approx -\frac{1}{2}\frac{\alpha}{\beta}\Big(y_k^2 - 2y_k[f_\mu + J_\theta^\top(\theta-\mu)] + [f_\mu + J_\theta^\top(\theta-\mu)]^2\Big) && \text{(13d)}\\
&= -\frac{1}{2}\frac{\alpha}{\beta}\Big(y_k^2 - 2y_k f_\mu - 2y_k J_\theta^\top \theta + 2y_k J_\theta^\top \mu + \\
&\qquad f_\mu^2 + 2f_\mu J_\theta^\top(\theta-\mu) + J_\theta^\top(\theta-\mu)(\theta-\mu)^\top J_\theta\Big) && \text{(13e)}\\
&= -\frac{1}{2}\frac{\alpha}{\beta}\Big(y_k^2 - 2y_k f_\mu - 2y_k J_\theta^\top \theta + 2y_k J_\theta^\top \mu + \\
&\qquad f_\mu^2 + 2f_\mu J_\theta^\top \theta - 2f_\mu J_\theta^\top \mu + J_\theta^\top(\theta\theta^\top - \mu\theta^\top - \theta\mu^\top + \mu\mu^\top)J_\theta\Big) && \text{(13f)}\\
&\propto -\frac{1}{2}\frac{\alpha}{\beta}\Big(-2y_k J_\theta^\top \theta + 2f_\mu J_\theta^\top \theta + J_\theta^\top \theta\theta^\top J_\theta - 2J_\theta^\top \mu\theta^\top J_\theta\Big) && \text{(13g)}\\
&= -\frac{1}{2}\frac{\alpha}{\beta}\Big(-2(y_k - f_\mu)J_\theta^\top \theta + \theta^\top J_\theta J_\theta^\top \theta - 2J_\theta^\top \mu J_\theta^\top \theta\Big) && \text{(13h)}\\
&= -\frac{1}{2}\Big(-2\underbrace{\frac{\alpha}{\beta}(y_k - f_\mu + J_\theta^\top \mu)J_\theta^\top}_{\psi}\theta + \theta^\top\underbrace{(\frac{\alpha}{\beta}J_\theta J_\theta^\top)}_{\Psi}\theta\Big)\,. && \text{(13i)}
\end{aligned}$$

We recognize both a linear function, $\psi\theta$, and a quadratic function, $\theta^\top \Psi \theta$, in the log-domain. Consider for a moment a multivariate Gaussian $\mathcal{N}(x \mid m, W^{-1})$ (W being the precision matrix) in the log-domain and ignore the normalization terms as well as all terms in the exponent that don't depend on x:

$$-\frac{1}{2}\Big(-2x^\top W m + x^\top W x\Big)\,. \tag{14}$$

With this in the back of our mind, we can recognize a Gaussian distribution in Equation 13i: the term Ψ corresponds to the precision matrix W and the term ψ corresponds to the Wm part. If we left-multiply Wm with the inverse precision W^{-1}, we obtain the mean; $m = W^{-1}Wm$. We can do the same to obtain the mean of the variational message: $\Psi^{-1}\psi$. Overall, this yields:

$$\overleftarrow{\nu}(\theta) \propto \mathcal{N}(\Psi^{-1}\psi, \Psi^{-1})\,. \tag{15}$$

Note that we stick to the mean-covariance parametrization in our $\mathcal{N}(\cdot)$ notation. To be precise: Ψ is the precision and Ψ^{-1} is the covariance matrix.

In the case of a polynomial f_θ, the term f_μ corresponds to $\mu^\top \phi(y_{k-1}, \dots)$ and the term $J_\theta^\top \mu$ corresponds to $\phi(y_{k-1}, \dots)^\top \mu$, which cancel out. Therefore, the parameters default to:

$$\psi = \frac{\alpha}{\beta} y_k \phi(y_{k-1}, \dots)^\top \tag{16a}$$

$$\Psi = \frac{\alpha}{\beta} \phi(y_{k-1}, \dots) \phi(y_{k-1}, \dots)^\top \tag{16b}$$

Message to τ

Free Energy Computation

References

[1] Justin Dauwels. On variational message passing on factor graphs. In *IEEE International Symposium on Information Theory*, pages 2546–2550, 2007.