

Bayesian Inference for Switching Linear Dynamical Systems

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1 Model description

A switching linear dynamical system – also known as *switching state space model* – is defined, borrowing the notation from Linderman et al. [3], by the set of discrete-time stochastic equations

$$x_t = A_{z_t} x_{t-1} + b_{z_t} + v_t, \quad (1)$$

$$y_t = C_{z_t} x_t + d_{z_t} + w_t, \quad (2)$$

where $v_t \in \mathbb{R}^M$ and $w_t \in \mathbb{R}^N$ are Gaussian-distributed random vectors with mean zero and variance Q_{z_t} , S_{z_t} respectively. The vectors $y_t \in \mathbb{R}^N$, $t = 1, \dots, T$ may represent a time series of observations, while the $x_t \in \mathbb{R}^M$ are a set of continuous latent states linked together by linear dynamics defined by the matrices $A_k \in \mathbb{R}^{M \times M}$ and bias vectors $b_k \in \mathbb{R}^M$. The transformation between x and y is also linear, through the matrices $C_k \in \mathbb{R}^{N \times M}$ and bias vectors $d_k \in \mathbb{R}^N$.

The linear parameters A_k , b_k , C_k , d_k form a discrete set of K elements, and a discrete latent variable $z_t \in \{1, \dots, K\}$ sets the specific instances in use at time step t . The variable z evolves over time as a Markov process, meaning that z_t is conditionally independent of all previous states except for its immediate predecessor z_{t-1} :

$$p(z_t \mid z_{t-1}, z_{t-2}, \dots, z_1) = p(z_t \mid z_{t-1}). \quad (3)$$

We will denote the probability to transition from $z_{t-1} = j$ to $z_t = k$ with π_{jk} . The transition $z_{t-1} \rightarrow z_t$ effectively modifies the linear dynamics from x_{t-1} to x_t and the linear transformation from x_t to y_t , *switching* from one regime to another.

Given a set of data points y_t , the goal is then to infer the posterior distribution of the parameter set

$$\vartheta = \{\pi_k, A_k, b_k, Q_k, C_k, d_k, S_k\}, \quad (4)$$

where $x_{1:T}$ denotes the whole sequence x_1, x_2, \dots, x_T , and π_k the k th row of the transition matrix.

2 Implementation in Stan

To set up a Monte Carlo sampling scheme, we chose to work with the Stan [5] programming language and its implementation in R through the package `rstan` [4]. Sampling in Stan is done by default using a variant of the Hamiltonian Monte Carlo scheme called ‘No-U-Turn sampler’ or NUTS [1].

The model cannot be implemented directly as it is, in the sense of specifying a categorical likelihood for the transition $z_t \rightarrow z_{t+1}$ and Gaussian likelihoods for $x_t \mid x_{t-1}$ and $y_t \mid x_t$, because Stan does not allow the definition of integer parameters: so, one should marginalize over the hidden discrete states. Besides Stan’s limitations in this regard, the resulting strategy – known in the literature as *forward algorithm* – is more efficient than the straightforward implementation in sampling low-probability states, and is commonly used in similar inference problems involving hidden Markov models or other state space models [2].

The basic idea behind the forward algorithm is to exploit a recursive relationship to build the full likelihood: indeed, consider the quantity

$$\Gamma_t(k) := p(z_t = k, x_{1:t}, y_{1:t}). \quad (5)$$

By summing over the z states at $t-1$ first and then using the chain rule repeatedly, we can write

$$\begin{aligned} \Gamma_t(k) &= \sum_{j=1}^K p(z_t = k, z_{t-1} = j, x_{1:t}, y_{1:t}) \\ &= p(y_t \mid z_t = k, x_t) p(x_t \mid z_t = k, x_{t-1}) \\ &\quad \cdot \sum_{j=1}^K \pi_{jk} p(z_{t-1} = j, x_{1:t-1}, y_{1:t-1}), \end{aligned} \quad (6)$$

where we have recognized the conditional probability $p(z_t = k \mid z_{t-1} = j, x_{1:t-1}, y_{1:t-1}) = p(z_t = k \mid z_{t-1} = j)$ as the element (j, k) of the transition matrix π . The first two terms outside the sum are the likelihoods of y_t and x_t , and because of the model definition they only depend on z_t , x_t and x_{t-1} . Also, they are simply Gaussian densities:

$$\mathcal{L}_k(y_t) := p(y_t \mid z_t = k, x_t) = \mathcal{N}(C_k x_t + d_k, S_k), \quad (7)$$

$$\mathcal{L}_k(x_t) := p(x_t \mid z_t = k, x_{t-1}) = \mathcal{N}(A_k x_{t-1} + b_k, Q_k). \quad (8)$$

Then, the remaining terms in the sum in (6) are nothing else than $\Gamma_{t-1}(j)$, giving us the recursive relation we needed:

$$\Gamma_t(k) = \mathcal{L}_k(y_t) \mathcal{L}_k(x_t) \sum_{j=1}^K \pi_{jk} \Gamma_{t-1}(j). \quad (9)$$

Indeed, to retrieve the full joint likelihood of the sequences $x_{1:T}$ and $y_{1:T}$ we only need to marginalize the Γ at the last time step T over the discrete states $k = 1, 2, \dots, K$:

$$p(x_{1:T}, y_{1:T}) = \sum_{k=1}^K p(z_T = k, x_{1:T}, y_{1:T}) = \sum_{k=1}^K \Gamma_T(k). \quad (10)$$

To recursively build Γ_t up to time T we need $\mathcal{O}(TK^2)$ operations, because of the double marginalization over z_t and z_{t-1} . To initialize the recursion,

$$\begin{aligned}\Gamma_1(k) &= p(z_1 = k, x_1, y_1) \\ &= \mathcal{L}_1(y_1) p(x_1 | z_1 = k) p(z_1 = k).\end{aligned}\quad (11)$$

The last two terms are the prior distributions on x_1 and z_1 . We chose a multivariate Gaussian for the first and a uniform distribution over the K states for the second.

At this point, we also need the prior distributions for the dynamical parameters. Following the suggestion from Linderman et al. [3], we chose matrix-normal-inverse-Wishart priors:

$$(A_k, b_k), Q_k \sim \text{MNIW}(M_x, \Omega_x, \Psi_x, \nu_x) \quad (12)$$

$$(C_k, d_k), S_k \sim \text{MNIW}(M_y, \Omega_y, \Psi_y, \nu_y). \quad (13)$$

Here $M_x \in \mathbb{R}^{M \times M+1}$ and $M_y \in \mathbb{R}^{N \times (M+1)}$ are the mean matrices of the matrix normals, $\Omega_x, \Omega_y \in \mathbb{R}^{(M+1) \times (M+1)}$ their between-column covariance matrices, while $\Psi_x \in \mathbb{R}^{M \times M}$ and $\Psi_y \in \mathbb{R}^{N \times N}$ are the scale matrices of the inverse Wisharts and ν_x, ν_y their degrees of freedom. The returned random matrices with $M+1$ columns are then split between the matrices A_k and C_k and their corresponding bias vectors b_k and d_k .

References

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