`osl-dynamics`: HMM Cost Function

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Abstract

We describe the calculation of the cost function used to update the observation model parameters (state means and covariances) in the `osl-dynamics` implementation of a Hidden Markov Model (HMM). We also describe the calculation of the variational free energy for this model.

1 Variational Free Energy

In variational Bayesian inference we learn a posterior distribution for model parameters, $q(.)$, by minimising the *variational free energy*, $\mathcal{F}$, given some data we have observed, $\boldsymbol{x}_t$. For the HMM, our model parameters are:

- The hidden state at each time point, s_t.
- The state transition probability matrix, $\boldsymbol{A}$, where the elements of this matrix are the transition probabilities, $A_{ij} = P(s_t = j | s_{t-1} = i)$.
- The initial state probabilities, $\boldsymbol{\pi}_1$.
- The observation model parameters, θ_{obs}.

If we were being Bayesian on all of these model parameters, we would minimise the following variational free energy[1] [1]

$$\mathcal{F} = \iiiint q(s_{1:T}) q(\boldsymbol{A}) q(\boldsymbol{\pi}_1) q(\theta_{\text{obs}}) \log \left[\frac{q(s_{1:T}) q(\boldsymbol{A}) q(\boldsymbol{\pi}_1) q(\theta_{\text{obs}})}{p(x_{1:T}, s_{1:T}, \boldsymbol{A}, \boldsymbol{\pi}_1, \theta_{\text{obs}})} \right] ds_{1:T} d\boldsymbol{A} d\boldsymbol{\pi}_1 d\theta_{\text{obs}}, \tag{1}$$

where $s_{1:T}$ and $x_{1:T}$ denote $s_1, ..., s_T$ and $\boldsymbol{x}_1, ..., \boldsymbol{x}_T$ respectively. However, in the `osl-dynamics` implementation of an HMM, we will only be Bayesian on the hidden states, $s_{1:T}$. We will learn point estimates for all the other parameters: θ_{obs}, $\boldsymbol{A}$ and $\boldsymbol{\pi}_1$. We learn all of our model parameters by minimising the following variational free energy,

$$\mathcal{F} = \int q(s_{1:T}) \log \left[\frac{q(s_{1:T})}{p(\boldsymbol{x}_{1:T}, s_{1:T})} \right] ds_{1:T}. \tag{2}$$

We will show that Eq. (2) implicitly depends on the point estimates for θ_{obs} below.

[1] We have used the mean field approximation.

2 Generative Model

The denominator in the log function, $p(.)$, is determined by our generative model. For the HMM, if we were being fully Bayesian this would be [1]

$$p(\boldsymbol{x}_{1:T}, s_{1:T}, \boldsymbol{A}, \boldsymbol{\pi}_1, \theta_{\text{obs}}) = p(\boldsymbol{x}_1|s_1, \theta_{\text{obs}})p(s_1|\boldsymbol{\pi}_1)p(\boldsymbol{\pi}_1)p(\theta_{\text{obs}}) \prod_{t=2}^{T} p(\boldsymbol{x}_t|s_t, \theta_{\text{obs}})p(s_t|s_{t-1}, \boldsymbol{A})p(\boldsymbol{A}). \tag{3}$$

However, because we are learning point estimates for most of these parameters $(\theta_{\text{obs}}, \boldsymbol{A}, \boldsymbol{\pi}_1)$ their prior distributions disappear. We will use the following generative model,

$$p(\boldsymbol{x}_{1:T}, s_{1:T}) = p(\boldsymbol{x}_1|s_1, \theta_{\text{obs}})p(s_1) \prod_{t=2}^{T} p(\boldsymbol{x}_t|s_t, \theta_{\text{obs}})p(s_t|s_{t-1}), \tag{4}$$

where θ_{obs} is a point estimate. We assume a multivariate normal distribution for the observed data,

$$p(\boldsymbol{x}_t|s_t = k, \theta_{\text{obs}}) = \mathcal{N}(\boldsymbol{m}_k, \boldsymbol{C}_k), \tag{5}$$

where $\boldsymbol{m}_k$ and $\boldsymbol{C}_k$ are the mean and covariance for state k respectively. Our observation model parameters θ_{obs} are the set of state means and covariances, $\theta_{\text{obs}} = \{\boldsymbol{m}_k, \boldsymbol{C}_k\}_{k=1}^{K}$.

3 Cost Function for Learning $\theta_{\text{obs}} = \{m_k, C_k\}$

We update our point estimate for θ_{obs} by minimising Eq. (2). We separate Eq. (2) into the following terms[2]

$$\mathcal{F} = -\int q(s_{1:T}) \log\left[p(\boldsymbol{x}_{1:T}, s_{1:T})\right] ds_{1:T} + \int q(s_{1:T}) \log\left[q(s_{1:T})\right] ds_{1:T}. \tag{6}$$

Only the first term depends on θ_{obs} so the second term can be ignored. Substituting Eq. (4) into the first term, we have

$$\mathcal{F} \propto -\int q(s_{1:T}) \log\left[p(\boldsymbol{x}_1|s_1, \theta_{\text{obs}})p(s_1) \prod_{t=2}^{T} p(\boldsymbol{x}_t|s_t, \theta_{\text{obs}})p(s_t|s_{t-1})\right] ds_{1:T}. \tag{7}$$

Again, only retaining the factors that depend on θ_{obs}, we have

$$\begin{aligned} \mathcal{F} &\propto -\int q(s_{1:T}) \log\left[\prod_{t=1}^{T} p(\boldsymbol{x}_t|s_t, \theta_{\text{obs}})\right] ds_{1:T} \\ &\propto -\sum_{t=1}^{T} \int q(s_{1:T}) \log\left[p(\boldsymbol{x}_t|s_t, \theta_{\text{obs}})\right] ds_{1:T} \end{aligned} \tag{8}$$

To evaluate this, we rewrite the posterior as

$$q(s_{1:T}) = q(s_t, s_\tau), \tag{9}$$

where τ denotes the all of the time points excluding t. Now we can marginalise s_τ,

$$\begin{aligned} \mathcal{F} &\propto -\sum_{t=1}^{T} \iint q(s_t, s_\tau) \log\left[p(\boldsymbol{x}_t|s_t, \theta_{\text{obs}})\right] ds_t ds_\tau \\ &\propto -\sum_{t=1}^{T} \int q(s_t) \log\left[p(\boldsymbol{x}_t|s_t, \theta_{\text{obs}})\right] ds_t = \mathcal{L}. \end{aligned} \tag{10}$$

[2]We have used $\int q(\xi) d\xi = 1$ to evaluate some of the integrals.

Here, we have defined the negative log-likelihood loss, $\mathcal{L}$, which is minimised via stochastic gradient descent to learn the parameters θ_{obs}. $q(s_t)$ is the marginal posterior calculated using the Baum-Welch algorithm, commonly denoted using the symbol $\boldsymbol{\gamma}(t)$. As $q(s_t)$ is a discrete probability distribution for the state, we can evaluate the integral as

$$\begin{aligned}\mathcal{L} &= -\sum_{t=1}^{T}\sum_{k=1}^{K} q(s_t = k)\log\left[p(\boldsymbol{x}_t|s_t = k, \theta_{\text{obs}})\right] \\ &= -\sum_{t=1}^{T}\sum_{k=1}^{K} \gamma_k(t)\log\left[p(\boldsymbol{x}_t|s_t = k, \theta_{\text{obs}})\right],\end{aligned} \tag{11}$$

where K is the number of states and $q(s_t = k) = \gamma_k(t)$ are the elements of the vector $\boldsymbol{\gamma}(t)$, which denote the probability of state k at time t. Substituting Eq. (5) into this we have

$$\mathcal{L} = -\sum_{t=1}^{T}\sum_{k=1}^{K} \gamma_k(t)\log\left[\mathcal{N}(\boldsymbol{x}_t|\boldsymbol{m}_k, \boldsymbol{C}_k)\right], \tag{12}$$

which is the log-likelihood loss function implemented in `osl-dynamics` for inferring the point estimates for the observation model parameters $\theta_{\text{obs}} = \{\boldsymbol{m}_k, \boldsymbol{C}_k\}$.

4 Calculation of the Variational Free Energy

Once we have trained an HMM we may want to evaluate the variational free energy, i.e. Eq. (2). This can be done with the `free_energy` method of the `hmm.Model` class. The method calculates Eq. (2) by first splitting it into three terms:

$$\begin{aligned}\mathcal{F} &= \int q(s_{1:T})\log\left[\frac{q(s_{1:T})}{p(\boldsymbol{x}_{1:T}, s_{1:T})}\right] ds_{1:T}, \\ &= \int q(s_{1:T})\log\left[\frac{q(s_{1:T})}{p(\boldsymbol{x}_1|s_1)p(s_1)\prod_{t=2}^{T} p(\boldsymbol{x}_t|s_t)p(s_t|s_{t-1})}\right] ds_{1:T}, \\ &= -\int q(s_{1:T})\log\left[\prod_{t=1}^{T} p(\boldsymbol{x}_t|s_t)\right] ds_{1:T} + \int q(s_{1:T})\log\left[\frac{q(s_{1:T})}{p(s_1)\prod_{t=2}^{T} p(s_t|s_{t-1})}\right] ds_{1:T}, \\ &= -\int q(s_{1:T})\log\left[\prod_{t=1}^{T} p(\boldsymbol{x}_t|s_t)\right] ds_{1:T} + \int q(s_{1:T})\log\left[q(s_{1:T})\right] ds_{1:T} \\ &\qquad - \int q(s_{1:T})\log\left[p(s_1)\prod_{t=2}^{T} p(s_t|s_{t-1})\right] ds_{1:T}, \\ &= -LL + E - P,\end{aligned} \tag{13}$$

where LL is the posterior expected log-likelihood (same as Eq. (12)), E is the posterior entropy and P is the posterior expected prior probability. To evaluate the terms in the above equation we factorise the posterior as

$$q(s_{1:T}) = q(s_1)\prod_{t=2}^{T} q(s_t|s_{t-1}) = q(s_1)\prod_{t=2}^{T}\frac{q(s_{t-1}, s_t)}{q(s_{t-1})} = q(s_1)\prod_{t=1}^{T-1}\frac{q(s_t, s_{t+1})}{q(s_t)}. \tag{14}$$

The above factorisation is an assumption of the Baum-Welch algorithm. Let's first look at the entropy term,

$$
\begin{aligned}
E &= \int q(s_{1:T}) \log \left[q(s_{1:T}) \right] ds_{1:T}, \\
&= \int q(s_{1:T}) \log \left[q(s_1) \prod_{t=1}^{T-1} \frac{q(s_t, s_{t+1})}{q(s_t)} \right] ds_{1:T}, \\
&= \int q(s_{1:T}) \log \left[\frac{\prod_{t=1}^{T-1} q(s_t, s_{t+1})}{\prod_{t=2}^{T-1} q(s_t)} \right] ds_{1:T}, \\
&= \sum_{t=1}^{T-1} \int q(s_{1:T}) \log q(s_t, s_{t+1}) ds_{1:T} - \sum_{t=2}^{T-1} \int q(s_{1:T}) \log q(s_t) ds_{1:T}.
\end{aligned} \tag{15}
$$

To evaluate the integral we marginalise out the state at times that do not appear inside the log function,

$$
\begin{aligned}
E &= \sum_{t=1}^{T-1} \int q(s_t, s_{t+1}, s_\tau) \log q(s_t, s_{t+1}) ds_t ds_{t+1} ds_\tau - \sum_{t=2}^{T-1} \int q(s_t, s_\tau) \log q(s_t) ds_t ds_\tau. \\
&= \sum_{t=1}^{T-1} \int q(s_t, s_{t+1}) \log q(s_t, s_{t+1}) ds_t ds_{t+1} - \sum_{t=2}^{T-1} \int q(s_t) \log q(s_t) ds_t.
\end{aligned} \tag{16}
$$

This can be calculated using the marginal posterior, $\boldsymbol{\gamma}(t) = q(s_t)$, and joint posterior, $\boldsymbol{\xi}(t) = q(s_t, s_{t+1})$, provided by the Baum-Welch algorithm:

$$
E = \sum_{t=1}^{T-1} \sum_{i,j=1}^{K} \xi_{ij}(t) \log \xi_{ij}(t) - \sum_{t=2}^{T-1} \sum_{i=1}^{K} \gamma_i(t) \log \gamma_i(t), \tag{17}
$$

where $\xi_{ij}(t) = P(s_t = i, s_{t+1} = j)$. Finally, we calculate the posterior expected prior probability as

$$
\begin{aligned}
P &= \int q(s_{1:T}) \log \left[p(s_1) \prod_{t=2}^{T} p(s_t | s_{t-1}) \right] ds_{1:T}, \\
&= \int q(s_1) \prod_{t=1}^{T-1} \frac{q(s_t, s_{t+1})}{q(s_t)} \log \left[p(s_1) \prod_{t=2}^{T} p(s_t | s_{t-1}) \right] ds_{1:T}, \\
&= \int q(s_1) \log p(s_1) ds_1 + \sum_{t=1}^{T-1} \int q(s_t, s_{t+1}) \log p(s_{t+1} | s_t) ds_t ds_{t+1}.
\end{aligned} \tag{18}
$$

Using the marginal and joint posterior provided by the Baum-Welch algorithm and the point estimates for the initial probabilities, $\boldsymbol{\pi}_1$ and transition probability matrix, $\boldsymbol{A}$, this is evaluated as

$$
P = \sum_{i=1}^{K} \gamma_i(1) \log \pi_{1,i} + \sum_{t=1}^{T-1} \sum_{i,j=1}^{K} \xi_{ij}(t) \log A_{ij}. \tag{19}
$$

References

[1] I. Rezek and S. Roberts, Ensemble hidden Markov models with extended observation densities for biosignal analysis. Probabilistic modeling in bioinformatics and medical informatics. Springer, London, 419-450 (2005).