1 Introduction

This vignette contains the descriptions of the main algorithms used in the seqHMM (Helske and Helske, 2019) package. First, a forward-backward algorithm is presented, followed by a Viterbi algorithm, and the derivations of the gradients for the numerical optimisation routines.

2 Forward–Backward Algorithm

Following Rabiner (1989), the forward variable

\[
\alpha_t(s) = P(y_{i1}, \ldots, y_{it}, z_t = s|M)
\]

is the joint probability of partial observation sequences for subject \(i\) until time \(t\) and the hidden state \(s\) at time \(t\) given the model \(M\). Let us denote \(b_s(y_{it}) = b_s(y_{i1}) \cdots b_s(y_{itC})\), the joint emission probability of observations at time \(t\) in channels \(1, \ldots, C\) given hidden state \(s\). The forward variable can be solved recursively for subject \(i = 1, \ldots, N\):

1. Initialization: For \(s = 1, \ldots, S\), compute

\[
\alpha_{i1}(s) = \pi_s b_s(y_{i1})
\]

2. Recursion: For \(t = 1, \ldots, T - 1\), compute

\[
\alpha_{i(t+1)}(s) = \left[ \sum_{r=1}^{S} \alpha_{it}(r) a_{rs} \right] b_s(y_{i(t+1)}), \quad s = 1, \ldots, S
\]

3. Termination: Compute the likelihood

\[
P(Y_i|M) = \sum_{s=1}^{S} \alpha_{iT}(s)
\]
The **backward variable**

\[
\beta_{it}(s) = P(y_{i(t+1)}, \ldots, y_{iT}|z_t = s, \mathcal{M})
\]

is the joint probability of the partial observation sequence after time \(t\) and hidden state \(s\) at time \(t\) given the model \(\mathcal{M}\). For subject \(i = 1, \ldots, N\), the backward variable can be computed as

1. **Initialization**: For \(s = 1, \ldots, S\), set
   \[
   \beta_{iT}(s) = 1
   \]

2. **Recursion**: For \(t = T - 1, \ldots, 1\), compute
   \[
   \beta_{it}(s) = \sum_{r=1}^{S} a_{sr} b_r(y_{i(t+1)}) \beta_{i(t+1)}(r), \quad s = 1, \ldots, S
   \]

   In practice the forward-backward algorithm is prone to numerical instabilities. Typically we scale the forward and backward probabilities, as follows (Rabiner, 1989). For subject \(i = 1, \ldots, N\),

   1. **Initialization**: For \(s = 1, \ldots, S\), compute
      \[
      \alpha_{i1}(s) = \pi_s b_s(y_{i1}),
      \]
      \[
      c_{i1} = 1/\sum_{s=1}^{S} \alpha_{i1}(s),
      \]
      \[
      \hat{\alpha}_{i1} = c_{i1} \alpha_{i1}
      \]

   2. **Recursion**: For \(t = 1, \ldots, T - 1\), compute (as before)
      \[
      \alpha_{i(t+1)}(s) = \left[ \sum_{r=1}^{S} \alpha_{it}(r) a_{rs} \right] b_s(y_{i(t+1)}), \quad s = 1, \ldots, S
      \]
      and scale as
      \[
      c_{i(t+1)} = 1/\sum_{s=1}^{S} \alpha_{i(t+1)}(s),
      \]
      \[
      \hat{\alpha}_{i(t+1)} = c_{i(t+1)} \alpha_{i(t+1)}
      \]

   3. **Termination**: Compute the log-likelihood
      \[
      \log P(Y_i|\mathcal{M}) = -\sum_{t=1}^{T} c_{it}
      \]

   The scaling factors \(c_{it}\) from the forward algorithm are commonly used to scale also the backward variables, although other scaling schemes are possible as well. In seqHMM, the scaled backward variables for subject \(i = 1, \ldots, N\) are computed as
1. Initialization: For $s = 1, \ldots, S$, compute

$$\hat{\beta}_{iT}(s) = c_{iT}$$

2. Recursion: For $t = T - 1, \ldots, 1$, and $r = 1, \ldots, S$, compute and scale

$$\beta_{it}(s) = \sum_{r=1}^{S} [a_{sr} b_r(y_{i(t+1)}) \beta_{i(t+1)}(r)], \quad s = 1, \ldots, S$$

$$\hat{\beta}_{it}(s) = c_{it} \beta_{it}(s)$$

Most of the times this scaling method described works well, but in some ill-conditioned cases it is possible that the default scaling still produces underflow in backward algorithm. For these cases, seqHMM also supports the computation of the forward and backward variables in log-space. Although numerically more stable, the algorithm is somewhat slower due repeated use of log-sum-exp trick.

3 **Viterbi Algorithm**

We define the score

$$\delta_{it}(s) = \max_{z_{i1} \cdots z_{it-1}} P(z_{i1} \cdots z_{it} = s, y_{i1} \cdots y_{it}|M),$$

which is the highest probability of the hidden state sequence up to time $t$ ending in state $s$. By induction we have

$$\delta_{it+1}(r) = \left[ \max_s \delta_{it}(s) a_{sr} \right] b_r(y_{i(t+1)}). \quad (1)$$

We collect the arguments maximizing Equation 1 in an array $\psi_{it}(r)$ to keep track of the best hidden state sequence. The full Viterbi algorithm can be stated as follows:

1. Initialization
   $$\delta_{i1}(s) = \pi_s b_s(y_{i1}), s = 1, \ldots, S$$
   $$\psi_{i1}(s) = 0$$

2. Recursion
   $$\delta_{it}(r) = \max_{s=1, \ldots, S} (\delta_{i(t-1)}(s)a_{sr})b_r(y_{it}),$$
   $$\psi_{it}(s) = \arg \max_{s=1, \ldots, S} (\delta_{i(t-1)}(s)a_{sr}), s = 1, \ldots, S; t = 2, \ldots, T$$

3. Termination
   $$\hat{P} = \max_{s=1, \ldots, S} (\delta_{iT}(s))$$
   $$\hat{z}_{iT} = \arg \max_{s=1, \ldots, S} (\delta_{iT}(s))$$

4. Sequence backtracking
   $$\hat{z}_{it} = \psi_{it+1}(\hat{z}_{i(t+1)}), t = T - 1, \ldots, 1.$$
4 Gradients

Following Levinson, Rabiner, and Sondhi (1983), by using the scaled forward and backward variables we have

\[
\frac{\partial \log P(Y_i|M)}{\partial \pi_s} = b_s(y_{i1}) \hat{\beta}_{i1}(s),
\]

\[
\frac{\partial \log P(Y_i|M)}{\partial a_{sr}} = \sum_{t=1}^{T-1} \hat{\alpha}_{it}(s) b_t(y_{i(t+1)}) \hat{\beta}_{i(t+1)}(r),
\]

and

\[
\frac{\partial \log P(Y_i|M)}{\partial b_{rc}(m)} = \sum_{t:y_{itc}=m} \sum_{s=1}^{S} \alpha_{1t}(s) a_{sr} \hat{\beta}_{i(t+1)}(r) + I(y_{i1c}=m) \pi_r \hat{\beta}_{i1}(r).
\]

In the direct numerical optimization algorithms used by seqHMM, the model is parameterised using unconstrained parameters \(\pi'_s, a'_{sr}, b'_{rc}(m)\) such that

\[
a_{sr} = \exp(a'_{sr}) / \sum_{k=1}^{S} \exp(a'_{sk}),
\]

and similarly for emission and initial probabilities. This leads to

\[
\frac{\partial \log P(Y_i|M)}{\partial \pi'_s} = \frac{\partial \log P(Y_i|M)}{\partial \pi_s} \pi_s (1 - \pi_s)
\]

\[
\frac{\partial \log P(Y_i|M)}{\partial a'_{sr}} = \frac{\partial \log P(Y_i|M)}{\partial a_{sr}} a_{sr} (1 - a_{sr}),
\]

and

\[
\frac{\partial \log P(Y_i|M)}{\partial b'_{rc}(m)} = \frac{\partial \log P(Y_i|M)}{\partial b_{rc}(m)} b_{rc}(m) (1 - b_{rc}(m)).
\]

4.1 MHMM case

For mixture HMM with \(K\) clusters, we define a full model with \(S = S^1 + \cdots + S^K\) states in a block form with \(\pi_i = (w_{i1}\pi^1, \ldots, w_{iK}\pi^K)\top\), where \(\pi^k, k = 1, \ldots, K\) is the vector of initial probabilities for the submodel \(M^k\) and

\[
w_{ik} = \exp(x_i^\top \gamma_k) / (1 + \sum_{j=2}^{K} \exp(x_i^\top \gamma_j)), \text{ with } \gamma_1 = 0.
\]

First note that the log-likelihood of the HMM for ith subject can be written as

\[
P(Y_i|M) = \sum_{s=1}^{S} \sum_{r=1}^{S} \alpha_{ts} a_{sr} b_r(y_{i(t+1)}) \beta_t(r),
\]

for any \(t = 1, \ldots, T - 1\). Thus for \(t = 1\) we have
\[ P(Y_i|M) = \sum_{s=1}^{S} \sum_{r=1}^{S} \alpha_1(s) a_{sr} b_r(y_{i2}) \beta_2(r) \]

\[ = \sum_{s=1}^{S} \alpha_1(s) \sum_{r=1}^{S} a_{sr} b_r(y_{i2}) \beta_2(r) \]

\[ = \sum_{s=1}^{S} \alpha_1(s) \beta_1(s) \]

\[ = \sum_{s=1}^{S} \pi_is b_s(y_{i1}) \beta_1(s). \]

(2)

Therefore the gradients for the unconstrained parameters \( \pi_s^k \) of the kth cluster are given as

\[ \frac{\partial \log P(Y_i|M)}{\partial \pi^k_s} = \frac{\partial \log P(Y_i|M^k)}{\partial \pi^k_s} \pi^k_s (1 - \pi^k_s) w_{ik}. \]

For \( \gamma^k \), the gradients are of form

\[ \frac{\partial \log P(Y_i|M)}{\partial \gamma^k} = \sum_{s=1}^{S} b_s(y_{i1}) \hat{\beta}_1(s) \pi_{is} \frac{\partial \gamma^k}{\partial \gamma^k} \]

(3)

Now if state \( s \) belongs to cluster \( k \), we have

\[ \frac{\partial \pi_{is}}{\partial \gamma^k} = \pi^k_s \frac{\partial}{\partial \gamma^k} \frac{\exp(x_i^\top \gamma_k)}{\sum_{j=1}^{K} \exp(x_i^\top \gamma_j)} \]

\[ = \pi^k_s x_i^\top w_{ik} (1 - w_{ik}), \]

(4)

and

\[ \frac{\partial \pi_{is}}{\partial \gamma^k} = -\pi^h_s x_i^\top w_{ik} w_{ik}, \]

otherwise, where \( h \) is the index of cluster containing the state \( s \).

References
