

9. Unsupervised learning: EM algorithm for HMMs

Given: i.i.d. training data $\mathcal{T} = \{x^j \in F^n \mid j=1, \dots, m\}$

Task: $u^* \in \arg \max_u \frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \log \sum_{s \in K^n} p_u(x, s)$

Recall EM-algorithm

$$\begin{aligned} L(u) &= \frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \log \sum_{s \in K^n} p_u(x, s) = \\ &= \frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \log \sum_{s \in K^n} \frac{\alpha(s|x)}{\alpha(s|x)} p_u(x, s) \end{aligned}$$

where $\alpha(s|x) \geq 0$, $\sum_{s \in K^n} \alpha(s|x) = 1 \quad \forall x \in \mathcal{T}$

Using concavity of \log , we get a lower bound

$$\begin{aligned} L(u) &\geq L_B(u) = \frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \sum_{s \in K^n} \alpha(s|x) \log p_u(x, s) - \\ &\quad - \frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \sum_{s \in K^n} \alpha(s|x) \log \alpha(s|x) \end{aligned}$$

Maximising it by block-coordinate ascent w.r.t. to α -s and u -s gives the EM-algorithm:

Start with some $u^{(0)}$ and iterate

E-step: set $\alpha^{(t)}(s|x) = p_{u^{(t)}}(s|x) \quad \forall s \in K^n, \forall x \in \mathcal{T}$

M-step: set

$$u^{(t+1)} \in \arg \max_u \frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \sum_{s \in K^n} \alpha^{(t)}(s|x) \log p_u(x, s)$$

Let us analyse the M-step for exponential families and for HMMs in particular. The objective is

$$\frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \sum_{s \in K^n} \alpha^{(+)}(s|x) \langle \Phi(x,s), \mu \rangle - \log Z(\mu) \rightarrow \max_{\mu}$$

Denoting $\Psi = \frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \sum_{s \in K^n} \alpha^{(+)}(s|x) \Phi(x,s)$, we get

the task

$$\langle \Psi, \mu \rangle - \log Z(\mu) \rightarrow \max_{\mu}$$

It is equivalent to the supervised learning task analysed in Sec. 7. We know how to solve it, provided we know how to compute Ψ .

Computing Ψ :

- For each $x \in \mathcal{T}$ we have to compute

$$\Psi^i(x) = \sum_{s \in K^n} \alpha^{(+)}(s|x) \Phi^i(x,s) = \sum_{s \in K^n} p_{\mu^{(+)}}(s|x) \Phi^i(x,s)$$

i.e. we have to compute posterior pairwise marginals

$P(s_{i-1}, s_i | x) \forall i=2, \dots, n$ and $\forall s_{i-1}, s_i \in K$. This can

be done by an algorithm similar to the one discussed in Sec. 5 (see also Assignment 1 from Seminar 3)

- The components of Ψ are then obtained by averaging the components of $\Psi^i(x)$ over all $x \in \mathcal{T}$, i.e.

$$\Psi = \frac{1}{|\mathcal{T}|} \sum_{x \in \mathcal{T}} \Psi^i(x)$$

Theorem 1 (w/o proof)

The sequence $L(u^{(t)})$ is monotonously increasing and the sequence $\alpha^{(t)}$ is convergent.