

# Tree HMM Derivation

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## Contents

<b>1</b>	<b>Setup</b>	<b>1</b>
1.1	Backwards Messages	1
<b>2</b>	<b>Forward-Backward (E-step) Derivation</b>	<b>2</b>
2.1	Forward Messages	2
2.2	Smoother Posteriors	2
2.3	Jax implementation	2
<b>3</b>	<b>M Step</b>	<b>2</b>

## 1 Setup

Suppose (for illustration only- method will be fully general) that cell  $r$  has daughters  $n, m$ , with division at time  $\tilde{t}$ . Assume:

$$z_{r,1} \sim \text{Cat}(\pi_0) \quad \text{initial distribution of root}$$

$$z_{r,t+1}|z_{r,t} = k \sim \text{Cat}(\pi_k) \quad \text{Markov transitions}$$

Identically

$$z_{r,p+1}|z_{r,p} = k \sim \text{Cat}(\pi_k) \quad \text{for } p > \tilde{t} + 1$$

Assume likelihood identical for parents and children, conditional on latent  $z$ :

$$p(x_{r,t}|z_{r,t}, x_{r,t-1}) := \ell_t^{(r)},$$

above is probably just typical AR(1) Gaussian emission.

Finally, assume that:

$$(z_{n,\tilde{t}+1}|z_{r,\tilde{t}}) = k \sim \text{Cat}(\tilde{\pi}_k)$$

### 1.1 Backwards Messages

Initialize for all cells at their "endpoint"-  $\beta_t^{(c)} = \mathbf{1}_k$  For a cell  $r$  at time  $t$ , backwards message is given by:

$$\beta_t^{(r)} = \bigodot_{c \in C(r)} \left[ P_c^T (\beta_{t+1}^{(c)} \odot \ell_{t+1}^{(c)}) \right].$$

Here, if  $C(r) = \{r\}$ , then  $P_c = P$ . If  $C(r) = \{n, m\}$ , then  $P_c = \tilde{P}$ .

That is, the backwards message is from the immediate children, and propagates up the tree so that  $\beta_1^{(r)}$  includes the messages from all children.

## 2 Forward-Backward (E-step) Derivation

### 2.1 Forward Messages

Initialize  $\alpha_1^{(root)} = \pi \odot l_0^{(root)}$ .

$$\alpha_{t+1}^{(c)} = \ell_{t+1}^{(c)} \odot \left[ P_c^T \alpha_t^{(p)} \right].$$

### 2.2 Smoother Posteriors

$$p(z_t^{(n)} | \text{All observations}) \propto \alpha_t^{(n)} \odot \beta_t^{(n)}.$$

### 2.3 Jax implementation

## 3 M Step