## 1. Hidden Markov Models

Definition 1.1 (Hidden Markov Models). A HMM is a Markov process $(X, Y)$ on a $(\mathbb{X} \times \mathbb{Y}, \mathcal{X} \times \mathcal{Y})$ with transition kernel $K\left(x^{\prime}, d y^{\prime}\right) P\left(x, d x^{\prime}\right)$ and initial distribution $K(x, d y) \mu_{0}(d x)$, where $P$ is a probability kernel from $\mathbb{X}$ to $\mathbb{X}, K$ is a probability kernel from $\mathbb{X}$ to $\mathbb{Y}$, and $\mu_{0}$ is a probability measure on $\mathbb{X}$.
Definition 1.2 (Non-degeneracy). A HMM has non-degenerate observations if $K(x, d y)=\lambda(x, y) \phi(d y)$ for some measurable positive function $\lambda$ on $\mathbb{X} \times \mathbb{Y}$ and a probability measure $\phi$ on $\mathbb{Y}$.

Definition 1.3 (Notation). We set $\pi_{k \mid n}=P_{X_{k} \mid Y_{0: n}}, \pi_{k}=\pi_{k \mid k}, \lambda_{k: n}\left(x_{k: n}, y_{k: n}\right)=$ $\prod_{j=k}^{n} \lambda\left(x_{j}, y_{j}\right), P_{k: n}\left(x_{k-1}, d x_{k: n}\right)=\prod_{j=k}^{n} P\left(x_{j-1}, d x_{j}\right)$ for $k \geq 1$, and $P_{0: n}\left(d x_{0: n}\right)=$ $P_{1: n}\left(x_{0}, d x_{1: n}\right) \mu_{0}\left(d x_{0}\right)$. We let $f$ denote an arbitrary bounded measurable function on $\mathbb{X}$.

Theorem 1.4 (Filtering, smoothing, prediction). Let $(X, Y)$ be a HMM with nondegenerate observations as in Definitions 1.1 and 1.2. Then

$$
\begin{aligned}
\pi_{k \mid n}\left(y_{0: n}, f\right) & =\frac{\rho_{k \mid n}\left(y_{0: n}, f\right)}{\rho_{k \mid n}\left(y_{0: n}, 1\right)} \\
\rho_{k \mid n}\left(y_{0: n}, f\right) & =\int f\left(x_{k}\right) \lambda_{0: n}\left(x_{0: n}, y_{0: n}\right) P_{0: k \vee n}\left(d x_{0: k \vee n}\right) .
\end{aligned}
$$

The smoothing densities $\alpha_{k \mid n}=\pi_{k \mid n} / \pi_{k}$ and $\beta_{k \mid n}=\rho_{k \mid n} / \rho_{k}, k \leq n$, satisfy

$$
\begin{aligned}
\alpha_{k \mid n}\left(y_{0: n}, x_{k}\right) & =\frac{\beta_{k \mid n}\left(y_{k+1: n}, x_{k}\right)}{\int \beta_{k \mid n}\left(y_{k+1: n}, x_{k}\right) \pi_{k}\left(y_{0: k}, d x_{k}\right)}, \\
\beta_{k \mid n}\left(y_{k+1: n}, x_{k}\right) & =\int \lambda_{k+1: n}\left(x_{k+1: n}, y_{k+1: n}\right) P_{k+1: n}\left(x_{k}, d x_{k+1: n}\right) .
\end{aligned}
$$

Theorem 1.5 (Recursions). The prediction step for $k \geq n$ is

$$
\begin{aligned}
& \pi_{k+1 \mid n}\left(y_{0: n}, f\right)=\int f\left(x_{k+1}\right) P\left(x_{k}, d x_{k+1}\right) \pi_{k \mid n}\left(y_{0: n}, d x_{k}\right) \\
& \rho_{k+1 \mid n}\left(y_{0: n}, f\right)=\int f\left(x_{k+1}\right) P\left(x_{k}, d x_{k+1}\right) \rho_{k \mid n}\left(y_{0: n}, d x_{k}\right)
\end{aligned}
$$

The correction step for $k \geq 0$ is

$$
\begin{aligned}
& \pi_{k+1}\left(y_{0: k+1}, f\right)=\frac{\int f\left(x_{k+1}\right) \lambda\left(x_{k+1}, y_{k+1}\right) \pi_{k+1 \mid k}\left(y_{0: k}, d x_{k+1}\right)}{\int \lambda\left(x_{k+1}, y_{k+1}\right) \pi_{k+1 \mid k}\left(y_{0: k}, d x_{k+1}\right)} \\
& \rho_{k+1}\left(y_{0: k+1}, f\right)=\int f\left(x_{k+1}\right) \lambda\left(x_{k+1}, y_{k+1}\right) \rho_{k+1 \mid k}\left(y_{0: k}, d x_{k+1}\right)
\end{aligned}
$$

The filtering step is a prediction followed by a correction step. The smoothing step for $k \leq n$ is

$$
\begin{aligned}
\alpha_{k-1 \mid n}\left(y_{0: n}, x_{k-1}\right) & =\frac{\int \lambda\left(x_{k}, y_{k}\right) \alpha_{k \mid n}\left(y_{0: n}, d x_{k}\right) P\left(x_{k-1}, d x_{k}\right)}{\int \lambda\left(x_{k}, y_{k}\right) \alpha_{k \mid n}\left(y_{0: n}, d x_{k}\right) P\left(x_{k-1}, d x_{k}\right) \pi_{k}\left(y_{0: k}, d x_{k}\right)} \\
& =\frac{\int \lambda\left(x_{k}, y_{k}\right) \alpha_{k \mid n}\left(y_{0: n}, d x_{k}\right) P\left(x_{k-1}, d x_{k}\right)}{\int \lambda\left(x_{k}, y_{k}\right) P\left(x_{k-1}, d x_{k}\right) \pi_{k-1}\left(y_{0: k-1}, d x_{k-1}\right)}, \\
\beta_{k-1 \mid n}\left(y_{k: n}, x_{k-1}\right) & =\int \lambda\left(x_{k}, y_{k}\right) \beta_{k \mid n}\left(y_{k+1: n}, x_{k}\right) P\left(x_{k-1}, d x_{k}\right) .
\end{aligned}
$$

