Hidden markov model

Victor Kitov

Markov model

- $z_1, z_2, ...z_N$ - some random sequence

$$p(z_1, z_2, ...z_N) = p(z_1)p(z_2|z_1)p(z_3|z_1, z_2)...p(z_N|z_1...z_{N-1})$$

- Markov model of order k:

$$p(z_n|z_1, ...z_{n-1}) = p(z_n|z_{n-k}...z_{n-1})$$

  - it is simpler
  - but easier to estimate

- Markov model of order k corresponds to Markov model of order 1, if we consider sequences of length k:

$$z_{n-1} \to \tilde{z}_{n-1} = (z_{n-1}, ...z_{n-k})$$

So its enough to consider only Markov sequences of order 1 (with larger set of states).

Hidden Markov model

At $t=1$ HMM is in some random state with probability

$$p(y_1=i)=\pi_i$$

For each time $t=1,2,...$ HMM:

- is in some hidden state $y_t\in\{1,2,...S\}$
- generates some observable output x_t with probability $p(x_t|y_t)=b_{y_t}(x_t)$
- From t to $t+1$ HMM changes state with probability transition matrix $A=\{a_{ij}\}_{i,j=1}^S$:

$$a_{ij}=p(y_{t+1}=j|y_t=i)$$

Definitions

- We will consider $x_t \in \{1, 2, ...R\}$, then $b_y(x)$ corresponds to matrix $B = \{b_{ir}\}_{i=1,...S}^{r=1,...R}$
- Parameters of HMM $\theta = \{\pi, A, B\}$.
- Suppose our HMM process lasted for T periods.
- Define:
    - $X := x_1 x_2 ... x_T$, $Y := y_1 y_2 ... y_T$
    - $X_{[i,j]} := x_i x_{i+1} ... x_j$, $Y_{[i,j]} := y_i y_{i+1} ... y_j$

Probability calculation

Then

$$p(X|Y) = \prod_{t=1}^{T} b_{y_t}(x_t)$$

$$p(Y) = \pi_{y_1} \prod_{t=1}^{T-1} a_{y_t y_{t+1}}$$

Together these two formulas give

$$p(Y,X) = p(Y)p(X|Y) = \pi_{y_1} \prod_{t=1}^{T-1} a_{y_t y_{t+1}} \prod_{t=1}^{T} b_{y_t}(x_t)$$

Problems occur when we need to calculate $P(X) = \sum_Y p(X, Y)$, because this contains exponentially rising with T number of terms.

Forward algorithm

- Define $\alpha_t(i, X) := p(y_t = i, x_1 ... x_t)$
- We can calculate α_t recursively:

$$\alpha_1(j, X) = p(y_1 = j,\, x_1) = p(y_1 = j)p(x_1 | y_1 = j) = \pi_j b_j(x_1)$$

$$\begin{aligned}
\alpha_{t+1}(j, X) = p(y_{t+1} = j, x_1 ... x_{t+1}) &= \sum_{i=1}^{S} p(y_t = i, y_{t+1} = j, x_1 ... x_t x_{t+1}) \\
&= \sum_{i=1}^{S} p(y_t = i, x_1 ... x_t) p(y_{t+1} = j | y_t = i) p(x_{t+1} | y_{t+1} = j) \\
&= \sum_{i=1}^{S} \alpha_t(i, X) a_{ij} b_j(x_{t+1})
\end{aligned}$$

Forward algorithm

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$$\begin{aligned}\alpha_{t+1}(j, X) = p(y_{t+1} = j, x_1 ... x_{t+1}) &= \sum_{i=1}^{S} p(y_t = i, y_{t+1} = j, x_1 ... x_t x_{t+1}) \\ &= \sum_{i=1}^{S} p(y_t = i, x_1 ... x_t)p(y_{t+1} = j|y_t = i)p(x_{t+1}|y_{t+1} = j) \\ &= \sum_{i=1}^{S} \alpha_t(i, X) a_{ij} b_j(x_{t+1})\end{aligned}$$

- Now its trivial to calculate $P(X) = \sum_{i=1}^{S} \alpha_T(i, X)$.
- Computational complexity of full forward pass $X(TS^2)$.
  - for $t = 1, 2, ... T$ summation over S terms for each of S states.
  - It can be reduced to TM where M is the number of non-zero entries in A if we set apriori some transitions as impossible.

Backward algorithm

Define

$$\beta_t(i, X) := p(X_{t+1}X_{t+2}...X_T|y_t = i)$$

As probability of empty event:

$$\beta_T(i, X) = p(\emptyset|y_T = i) = 1 \quad i = 1, 2, ...S$$

We can calculate β_t recursively:

$$\begin{aligned}\beta_t(i, X) &= p(x_{t+1}...x_T|y_t = i) \\ &= \sum_{j=1}^{S} p(y_{t+1} = j|y_t = i)p(x_{t+1}|y_{t+1} = j)\times \\ &\quad \times p(x_{t+2}...x_T|y_{t+1} = j) \\ &= \sum_{j=1}^{S} a_{ij}b_j(x_{t+1})\beta_{t+1}(j, X)\end{aligned}$$

Properties of forward-backward calculation

$$\sum_{i=1}^{S}\alpha_t(i,X)\beta(i,X)=p(X)\quad\forall t=1,2,...T$$

$$p(y_t=i|X)=\frac{\alpha_t(i,X)\beta_t(i,X)}{p(X)}$$

$$p(y_t=i,y_{t+1}=j|X)=\frac{\alpha_t(i,X)a_{ij}b_j(x_{t+1})\beta_{t+1}(j,X)}{p(X)}$$

- This calculation leads to numerical underflow as $\alpha_t(j,X)\to 0$ and $\beta_t(j,X)\to 0$ as $T\to\infty$.
  - We can introduce new $\alpha_t'(j,X)$ and $\beta_t'(j,X)$ that don't tend to zero.

Feasible calculation

Define

$$\alpha'_t(i,X) := p(y_t = i|X_{[1,t]})$$
$$\eta(i,X) := p(y_t = i, x_t|X_{[1,t-1]})$$
$$\eta(X) := p(x_t|X_{[1,t-1]})$$

Then

$$\eta_1(i,X) = p(y_1 = i, x_1) = \pi_i b_i(x_1)$$
$$\eta_1(X) = p(x_1) = \sum_{s=1}^{S} \eta_1(s,X)$$
$$\alpha'_1(i,X) = \frac{\eta_1(i,X)}{\eta_1(X)}$$

Feasible calculation

For $t = 1, 2, ... T - 1$:

$$\eta_{t+1}(i, X) = \sum_{j=1}^{S} \alpha'(i, X) a_{ij} b_j(x_{t+1})$$

$$\eta_{t+1}(X) = \sum_{i=1}^{S} \eta(i, X)$$

$$\alpha'_{t+1}(i, X) = \frac{\eta_{t+1}(i, X)}{\eta_{t+1}(X)}$$

Feasible calculation

Define

$$\beta'(i,X) := \frac{p(X_{[t+1,T]}|y_t = i)}{p(X_{[t+1,T]}|X_{[1,T]})}$$

These values can be calculated recursively

$$\beta'_T(i,X) = 1$$

$$\beta'_t(i,X) = \frac{\sum_{j=1}^{S} a_{ij} b_j(x_{t+1}) \beta'_{t+1}(j,X)}{\eta_{t+1}(X)}, \quad t = T-1, ...1.$$

Feasible calculation

$$p(y_t = i|X) = \alpha'_t(i, X)\beta'_t(i, X)$$

$$p(y_t = i, y_{t+1} = j|X) = \frac{\alpha'_t(i, X)a_{ij}b_j(x_{t+1})\beta'_{t+1}(j, X)}{\eta_{t+1}(X)}$$

Viterbi algorithm

- Problem: for given $X_{[1,T]}$ find maximum probable $Y_{[1,T]}$.
  - full search considers S^T variants, impractical!
- Define

$$y_1^*, ...y_T^* := \arg\max_{y_1,...y_T} p(y_1, ...y_T, x_1, ...x_T)$$

$$\varepsilon_t(i, X) := \max_{y_1,...y_{t-1},} p\left(y_1...y_{t-1}y_t = i, x_1...x_t\right)$$

$$v_t(i, X) := \arg\max_j p(y_1...y_{t-2}, y_{t-1} = j, y_t = i, x_1...x_t)$$

- Viterbi algorithm:
  - based on dynamic programming approach
  - forward pass: calculation of $\varepsilon_t(i, X)$ for all $t = 1, 2, ...T$ and $i = 1, 2, ...S$.
  - backward pass: calculation of y_T^* and recursively y_t^* for $t = T-1, T-2, ...1$.

Viterbi algorithm: forward pass

Definitions:

$$\varepsilon_t(i,X) := \max_{y_1,\dots y_{t-1},} p\left(y_1 \dots y_{t-1} y_t = i, x_1 \dots x_t\right)$$
$$v_t(i,X) := \arg\max_j p(y_1 \dots y_{t-2}, y_{t-1} = j, y_t = i, x_1 \dots x_t)$$

Init:

$$\varepsilon_1(i,X) = p(x_1, y_1 = i) = \pi_i b_i(x_1)$$

For $t = 1, \dots T-1$:

$$\begin{aligned}
\varepsilon_{t+1}(i,X) &= \max_{y_1 \dots y_{t-1}, j} p(x_1 \dots x_t x_{t+1}, y_1 \dots y_{t-1} y_t = j, y_{t+1} = i) \\
&= \max_j \max_{y_1 \dots y_{t-1}} p(y_1 \dots y_{t-1} y_t = j, x_1 \dots x_t) p(x_{t+1} y_{t+1} = i | y_1 \dots y_{t-1} y_t = j, x_1 \dots x_t) \\
&= \max_j \max_{y_1 \dots y_{t-1}} p(y_1 \dots y_{t-1} y_t = j, x_1 \dots x_t) p(x_{t+1} y_{t+1} = i | y_t = j) \\
&= \max_j \max_{y_1 \dots y_{t-1}} p(y_1 \dots y_{t-1} y_t = j, x_1 \dots x_t) p(y_{t+1} = i | y_t = j) p(x_{t+1} | y_{t+1}) \\
&= \max_j \varepsilon_t(j,X) a_{ji} b_i(x_t) \\
v_{t+1}(i,X) &= \arg\max_j \varepsilon_t(j,X) a_{ji}
\end{aligned}$$

Viterbi algorithm: backward pass

Definitions

$$y_1^*,...y_T^* := \arg\max_{y_1,...y_T} p(y_1,...y_T,x_1,...x_T)$$

$$\varepsilon_t(i,X) := \max_{y_1,...y_{t-1},} p\left(y_1...y_{t-1}y_t = i, x_1...x_t\right)$$

$$v_t(i,X) := \arg\max_j p(y_1...y_{t-2},y_{t-1} = j, y_t = i, x_1...x_t)$$

Init:

$$p^*(X) = \max_j \varepsilon(j,X)$$

$$y_T^*(X) = \arg\max_j \varepsilon(j,X)$$

For $t = T-1, T-2, ...1$:

$$y_t^*(X) = v_{t+1}(y_{t+1}^*(X))$$