From J&M chapter 7 -- Jason Eisner's ice cream / weather HMM example.

Model

 $\begin{array}{c} \textbf{Start}_0 \\ \textbf{8} \\ \textbf{HOT}_1 \\ \textbf{2} \\ \textbf{3} \\ \textbf{COLD}_2 \\ \textbf{4} \\ \textbf{P(1 | HOT)} \\ \textbf{P(2 | HOT)} \\ \textbf{P(2 | HOT)} \\ \textbf{P(3 | HOT)} \end{bmatrix} = \begin{bmatrix} 2\\ 4\\ 4\\ 1 \end{bmatrix}$

Figure 7.3 A hidden Markov model for relating numbers of ice creams eaten by Jason (the observations) to the weather (H or C, the hidden variables).

This is Eisner ---> (Associate Professor, John Hopkins University)



Viterbi algorithm

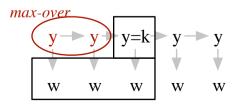
Figure 7.10 The Viterbi trellis for computing the best path through the hidden state space for the ice-cream eating events 3 1 3. Hidden states are in circles, observations in squares. White (unfilled) circles indicate illegal transitions. The figure shows the computation of $v_t(j)$ for two states at two time steps. The computation in each cell follows Eq. 7.19: $v_t(j) = \max_{1 \le j \le N-1} v_{t-1}(i) \ a_{ij} \ b_j(o_t)$. The resulting probability expressed in each cell is Eq. 7.18: $v_t(j) = P(q_0, q_1, \dots, q_{t-1}, o_1, o_2, \dots, o_t, q_t = j | \lambda)$.

Declaratively:

$$V_t[k] = \max_{y_1...y_{t-1}} P(y_t = k, y_1..y_{t-1}, w_1..w_t)$$

Algorithm, for each t=1..N,

$$V_t[k] := \max_{j=1..K} \left(V_{t-1}[j] \ P_{trans}(j \to k) \ P_{emit}(w_t|k) \right)$$



Forward algorithm

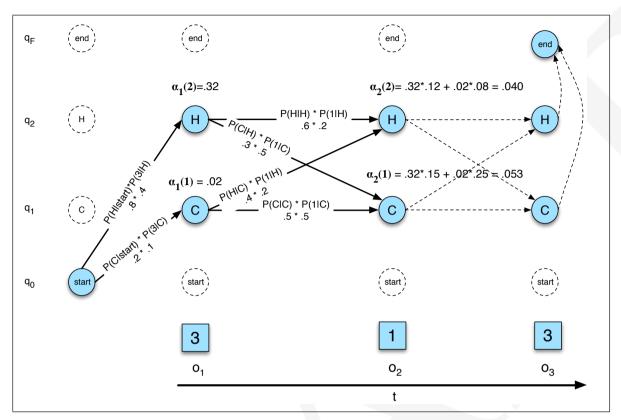
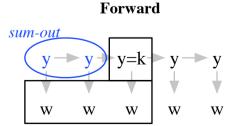


Figure 7.7 The forward trellis for computing the total observation likelihood for the ice-cream events 3 1 3. Hidden states are in circles, observations in squares. White (unfilled) circles indicate illegal transitions. The figure shows the computation of $\alpha_t(j)$ for two states at two time steps. The computation in each cell follows Eq. 7.14: $\alpha_t(j) = \sum_{i=1}^{N} \alpha_{t-1}(i)a_{ij}b_j(o_t)$. The resulting probability expressed in each cell is Eq. 7.13: $\alpha_t(j) = P(o_1, o_2 \dots o_t, q_t = j | \lambda)$.

Declaratively:

$$\alpha_t[k] = \sum_{y_1...y_t} P(y_t = k, w_1..w_t, y_1...y_{t-1})$$



Algorithm, for each t=1..N,

$$\alpha_t[k] := \sum_{j=1..K} \left(\alpha_{t-1}[j] \ P_{trans}(j \to k) \ P_{emit}(w_t|k) \right)$$