

HMM Problem (Jason Eisner's ice creams).

(i) likelihood (forward algorithm)

In each entry we compute $\alpha_t(j) = \Pr(O_{1:t}, q_t=j | \lambda)$

$$= \sum_i \Pr(O_{1:t-1}, q_{t-1}=i | \lambda)$$

$$\cdot \Pr(q_t=j | q_{t-1}=i)$$

$$\cdot \Pr(O_t | q_t=j)$$

$$= \sum_i \alpha_{t-1}(i) A_{ij} B_j(O_t)$$

	1	3	3
HOT	$0.8 \times 0.2 = 0.16$	$0.16 \times 0.6 \times 0.4 + 0.1 \times 0.5 \times 0.4 = 0.0584$	$0.0584 \times 0.6 \times 2.4 + 0.0114 \times 0.5 \times 2.4 = 0.0163$
COLD	$0.2 \times 0.5 = 0.1$	$0.16 \times 0.4 \times 2.1 + 0.1 \times 0.5 \times 2.1 = 0.0114$	$0.0584 \times 0.4 \times 0.1 + 0.0114 \times 0.5 \times 0.1 = 0.002906$

$$\Rightarrow \Pr("133" | \lambda) = \Pr("133", q_3=\text{hot})$$

$$+ \Pr("133", q_3=\text{cold})$$

$$= 0.0163 + 0.002906 = 0.0192.$$

We can also use backward algorithm to compute $\Pr("133" | \lambda)$.

In each entry we compute:

$$\begin{aligned}
 \beta_t(j) &= \Pr(D_{t+1:T} | q_t=j, \lambda) \\
 &= \sum_i \Pr(D_{t+1:T} | q_{t+1}=i, \lambda) \cdot \Pr(q_{t+1}=i | q_t=j) \\
 &\quad \cdot \Pr(D_{t+1} | q_{t+1}=i) \\
 &= \sum_i \beta_{t+1}(i) A_{ji} B_i(D_{t+1})
 \end{aligned}$$

	1	3	3
HOT	$(0.28 \times 0.6 \times 0.1) + (0.25 \times 0.4 \times 0.1) = 0.0772$	$(1 \times 0.6 \times 0.4) + (1 \times 0.4 \times 0.1) = 0.28$	1
COLD	$(0.28 \times 0.5 \times 0.4) + (0.25 \times 0.5 \times 0.1) = 0.0685$	$(1 \times 0.5 \times 0.4) + (1 \times 0.5 \times 0.1) = 0.25$	1

$$\begin{aligned}
 \Rightarrow \Pr("133" | \lambda) &= \pi(\text{hot}) \cdot \Pr("133" | q_1=\text{hot}, \lambda) \\
 &\quad + \pi(\text{cold}) \cdot \Pr("133" | q_1=\text{cold}, \lambda) \\
 &= (0.0772 \times 0.8 \times 0.2) + (0.0685 \times 0.2 \times 0.5) \\
 &= 0.0192 \quad (\text{Same result as we got using forward algorithm})
 \end{aligned}$$

(iii) Decoding : we'll apply Viterbi algorithm to compute:

$$\begin{aligned}
 V_t(\hat{j}) &= \max_{q_{1:t-1}} \Pr(q_{1:t-1}, O_{1:t}, q_t = \hat{j} | \lambda) \\
 &= \max_i \left\{ \max_{q_{1:t-2}} \Pr(q_{1:t-2}, O_{1:t-1}, q_{t-1} = i | \lambda) \cdot \Pr(q_t = \hat{j} | q_{t-1} = i) \right. \\
 &\quad \left. \cdot \Pr(O_t | q_t = \hat{j}) \right\} \\
 &= \max_i \left\{ V_{t-1}(i) A_{ij} B_j(O_t) \right\}.
 \end{aligned}$$

	1	3	3
HOT	$0.8 \times 0.2 = 0.16$	$\max \{ 0.16 \times 0.6 \times 0.4, 0.1 \times 0.5 \times 0.4 \} = 0.0384$	$\max \{ 0.0384 \times 0.6 \times 0.4, 0.0064 \times 0.5 \times 0.4 \} = 0.009216$
COLD	$0.2 \times 0.5 = 0.1$	$\max \{ 0.16 \times 0.4 \times 0.1, 0.1 \times 0.5 \times 0.1 \} = 0.0064$	$\max \{ 0.0384 \times 0.4 \times 0.1, 0.0064 \times 0.5 \times 0.1 \} = 0.001536$

By tracing back those maximal values we got:

$$\max_{q_{1:3}} \Pr("133", q_{1:3} | \lambda) = \text{"hot hot hot"}.$$

(iii) Learning: the Baum-Welch algorithm is quite complicated, and I shall only show the computation for 1 E-step and 1 M-step for A_{hh} and B_h . I'll use parameters in (ii) & (iii) as initial parameters: $\lambda_0 = \{\pi, A, B\}$

① E-step:

- compute $\beta_t(i, j)$: since we've computed α, β in (ii), we could then easily obtain all $\beta_t(i, j)$:

$$\begin{aligned}\beta_t(i, j) &= \Pr(q_t=i, q_{t+1}=j \mid \bar{D} \mid \lambda_0) \\ &= \Pr(D_{1:t} \mid q_t=i \mid \lambda_0) \cdot \Pr(D_{t+1} \mid q_{t+1}=j, \lambda_0) \\ &\quad \cdot \Pr(D_b \mid q_t=i, \lambda_0) \cdot \Pr(q_{t+1}=j \mid q_t=i) \\ &= \alpha_t(i) \beta_{t+1}(j) \cdot A_{ij} B_j(D_t)\end{aligned}$$

$$\begin{aligned}\Rightarrow \beta_1(h, h) &= \alpha_1(h) \beta_2(h) A_{hh} B_h(1) \\ &= 0.16 \times 0.28 \times 0.6 \times 0.2 = 0.005376\end{aligned}$$

$$\begin{aligned}\beta_2(h, h) &= \alpha_2(h) \beta_3(h) A_{hh} B_h(3) \\ &= 0.0584 \times 1 \times 0.6 \times 0.4 = 0.014016\end{aligned}$$

- compute $\gamma_t(h)$:

$$\gamma_1(h) = \alpha_1(h) \beta_1(h) = 0.16 \times 0.0772 = 0.12352$$

$$\gamma_2(h) = \alpha_2(h) \beta_2(h) = 0.0584 \times 0.28 = 0.016352$$

$$\gamma_3(h) = \alpha_3(h) \beta_3(h) = 0.0163 \times 1 = 0.0163$$

- Now, update A_{hh} and B_{hl} :

$$A_{hh} = \frac{\gamma_1(hh) + \gamma_2(hh)}{\gamma_1(h) + \gamma_2(h)} = 0.1386$$

$$B_{hl} = \frac{\gamma_1(h)}{\gamma_1(h) + \gamma_2(h) + \gamma_3(h)} = 0.7909$$

SPP Problem.

Let $U(\alpha, \beta)$ denote the expected utility (return) if the player pays α dollars at first, with the coin having probability β to show its head in each toss:

$$U(\alpha, \beta) = \sum_{k=1}^{\infty} (\sqrt{\alpha \cdot 2^k} - \alpha) \cdot \beta^k$$

$$= \sqrt{\alpha} \left(\frac{\sqrt{2}\beta}{1-\sqrt{2}\beta} \right) - \alpha$$

To obtain maximum return, setting $\frac{\partial U}{\partial \alpha} = 0$ we have:

$$\alpha^*(\beta) = \frac{\beta^2}{2(1-\sqrt{2}\beta)^2}, \text{ and the optimal utility would be:}$$

$$U(\alpha^*(\beta), \beta) = \frac{\beta^2}{2(1-\sqrt{2}\beta)^2}$$

For a fair coin, by taking $\beta = \frac{1}{2}$ we have:

$$U(\alpha^*(\frac{1}{2}), \frac{1}{2}) = \frac{3+2\sqrt{2}}{4} \approx 1.457.$$

$$\alpha^*(\frac{1}{2}) = \frac{3+2\sqrt{2}}{4} \approx 1.457.$$

As we can see, $U(\alpha^*(\beta), \beta) = \frac{\beta^2}{2(1-\sqrt{2}\beta)^2} > 0$, so a rational player would always have positive expected return, and the bookies will lose in expectation (since this is a zero-sum game). Now suppose the bookies covertly use a coin with $\alpha\beta < \frac{1}{2}$, but they

shall still claim that the coin is fair. Hence, all players, if acting rationally, would still pay $\alpha^*(\frac{1}{2}) = 1.457$ dollars at each round. Their expected utility would then actually be:

$$U(\alpha^*(\frac{1}{2}), \beta) = \sqrt{\alpha^*(\frac{1}{2})} \left(\frac{\sqrt{2}\beta}{1-\sqrt{2}\beta} \right) - \alpha^*(\frac{1}{2}).$$

Setting $U(\alpha^*(\frac{1}{2}), \beta) = 0$ we have:

$$\beta_0 = \frac{\sqrt{\alpha^*(\frac{1}{2})}}{\sqrt{2}(1 + \sqrt{\alpha^*(\frac{1}{2})})} \approx 0.387.$$

Hence, if the bookmakers covertly set $\beta < \beta_0$, they'll have positive expected return (and players will lose in expectation).

Now if an info-broker sells the following info:

"the bookies are using a coin with $\beta=0.3$ secretly"

the players would, of course, adjust their strategies (since if they still pay $\alpha^*(\frac{1}{2})$ dollars at each round, they'll have negative expected return). Taking $\beta=0.3$, the optimal pay $\alpha^*(\beta)$ is:

$$\alpha^*(0.3) = 0.1358$$

$$\Rightarrow U(\alpha^*(0.3), \beta=0.3) = \alpha^*(0.3) = 0.1358$$

Hence, the price for this information would be the difference between: 1) the optimal return after the players know

that the bookies are cheating ; and 2) their expected return when they don't know this conspiracy :

If the players don't know the bookies are cheating, they'll pay $\alpha^*(\frac{1}{2})$ at each round, their expected return would be:

$$U(\alpha^*(\frac{1}{2}), 0.3) = \sqrt{\alpha^*(\frac{1}{2})} \left(\frac{\sqrt{2} \cdot 0.3}{1 - \sqrt{2} \cdot 0.3} \right) - \alpha^*(\frac{1}{2}) \\ \approx -0.568$$

Then the price would be :

$$p = U(\alpha^*(0.3), 0.3) - U(\alpha^*(\frac{1}{2}), 0.3) \\ \approx 0.7038.$$