

COURSEWORK 2

IMPERIAL COLLEGE LONDON

DEPARTMENT OF COMPUTING

495 - Advanced Statistical Machine Learning and Pattern Recognition Coursework 2

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1 Exercise I

1.a

fdss

1.b

(ii) fsds

2 Exercise II

(i) N sequences, T observations per sequence, 5 states

Estimate $\theta = \{\pi, A\}$

$\pi = \{\pi_1 \dots \pi_5\}$

for $l = 1 \dots N : D_l = \{x_1^l \dots x_T^l\}$

$A = [a_{ij}]$

$$A = \begin{bmatrix} 0 & a_{12} & 0 & 0 & 0 \\ 0 & a_{22} & a_{22} & 0 & 0 \\ 0 & 0 & a_{33} & a_{34} & a_{34} \\ 0 & 0 & 0 & a_{44} & a_{45} \\ 0 & 0 & 0 & 0 & a_{55} \end{bmatrix} \quad (1)$$

$$x_t^l = \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\} \quad (2)$$

Maximise $p(D_1 \dots D_N | \theta)$

$$p(D_1 \dots D_N | \theta) \quad (3)$$

$$= \prod_{l=1}^N p(D_l | \theta) \quad (4)$$

Because

$$p(D_1 | \theta) \quad (5)$$

$$= p(x_1^l \dots x_T^l | \theta) \quad (6)$$

$$= p(x_1^l) \prod_{t=2}^T p(x_t^l | x_{t-1}^l) \quad (7)$$

$$= \prod_{k=1}^5 \pi_k^{x_{1k}^l} \prod_{T=2}^T \prod_{j=1}^5 \prod_{k=1}^5 a_{jk}^{x_{t-1j}^l x_{tk}^l} \quad (8)$$

so

$$p(D_1 \dots D_N | \theta) \quad (9)$$

$$= \prod_{l=1}^N \prod_{k=1}^5 \pi_k^{x_{1k}^l} \prod_{T=2}^T \prod_{j=1}^5 \prod_{k=1}^5 a_{jk}^{x_{t-1j}^l x_{tk}^l} \quad (10)$$

Take the log

$$\ln(p(D_1 \dots D_N | \theta)) \quad (11)$$

$$= \sum_{l=1}^N \sum_{k=1}^5 x_{1k}^l \ln(\pi_k) + \sum_{l=1}^N \sum_{T=2}^T \sum_{j=1}^5 \sum_{k=1}^5 x_{t-1j}^l x_{tk}^l \ln(a_{jk}) \quad (12)$$

Now we take

$$N_k^l = \sum_{l=1}^N x_{1k}^l \quad (13)$$

$$N_{jk} = \sum_{l=1}^N \sum_{T=2}^T x_{t-1j}^l x_{tk}^l \quad (14)$$

so

$$\ln(p(D_1 \dots D_N | \theta)) \quad (15)$$

$$= \sum_{l=1}^N N_k^l \ln(\pi_k) + \sum_{j=1}^5 \sum_{k=1}^5 N_{jk} \ln(a_{jk}) \quad (16)$$

When maximising $\ln(p(D_1 \dots D_N | \theta))$, we put constraints:

$$\sum_{k=1}^K \pi_k = 1 \quad (17)$$

$$\sum_{k=1}^K a_{jk} = 1 \quad (18)$$

So

$$L(\pi, A) = \sum_{l=1}^N N_k^l \ln(\pi_k) + \sum_{j=1}^5 \sum_{k=1}^5 N_{jk} \ln(a_{jk}) - \lambda \left(\sum_{k=1}^K \pi_k - 1 \right) - \gamma \left(\sum_{k=1}^K a_{jk} - 1 \right) \quad (19)$$

Maximise $L(\pi, A)$:

$$\frac{\partial L(\pi, A)}{\partial \pi_k} = \frac{N_k^l}{\pi_k} - \lambda \quad (20)$$

$$\frac{\partial L(\pi, A)}{\partial \pi_k} = 0 \quad (21)$$

$$\lambda = \frac{N_k^l}{\pi_k} \quad (22)$$

$$\sum_{k=1}^K \pi_k = 1 = \sum_{k=1}^K \frac{N_k^l}{\lambda} \quad (23)$$

$$\lambda = \sum_{k=1}^K N_k^l \quad (24)$$

$$\pi_k = \frac{N_k^l}{\sum_{k=1}^K N_k^l} \quad (25)$$

$$\frac{\partial L(\pi, A)}{\partial a_{jk}} = \frac{N_{jk}}{a_{jk}} - \gamma \quad (26)$$

$$\gamma = \sum_{k=1}^K N_{jk} \quad (27)$$

$$a_{jk} = \frac{N_{jk}}{\sum_{k=1}^K N_{jk}} \quad (28)$$

Given our matrix A , we know that:

$$a_{12} = 1 \quad (29)$$

$$a_{22} = \frac{N_{22}}{\sum_{k=1}^K N_{2k}} \quad (30)$$

$$a_{23} = 1 - a_{22} = \frac{N_{22}}{\sum_{k=1}^K N_{2k}} \quad (31)$$

$$a_{33} = \frac{N_{33}}{\sum_{k=1}^K N_{3k}} \quad (32)$$

$$a_{34} = \frac{N_{34}}{\sum_{k=1}^K N_{3k}} \quad (33)$$

$$a_{35} = 1 - a_{34} - a_{33} = 1 - \frac{N_{33} + N_{34}}{\sum_{k=1}^K N_{3k}} \quad (34)$$

$$a_{44} = \frac{N_{44}}{\sum_{k=1}^K N_{4k}} \quad (35)$$

$$a_{45} = 1 - a_{44} = 1 - \frac{N_{44}}{\sum_{k=1}^K N_{4k}} \quad (36)$$

$$a_{55} = 1 \quad (37)$$

$$\pi_k = \frac{N_k^l}{\sum_{k=1}^K N_k^l} \quad (38)$$

(ii) K latent states, N sequences, T observations per sequence, 5 Observation state

$$p(z_1^l | \pi) = \prod_{c=1}^K \pi_k^{z_{1c}^l} \quad (39)$$

$$p(z_t^l | z_{t-1}^l, A) = \prod_{j=1}^K \prod_{k=1}^K a_{jk}^{z_{t-1j}^l z_{tk}^l} \quad (40)$$

$$p(z_{1k}^l = 1) = \pi_k \quad (41)$$

$$\pi = \{\pi_1 \dots \pi_5\} \quad (42)$$

$$A = [a_{ij}] \quad (43)$$

$$p(x_t^l | z_t^l) = \prod_{j=1}^5 \prod_{k=1}^K b_{kj}^{x_{t-1j}^l x_{tk}^l} \quad (44)$$

$$\text{Estimate } \theta = \{\pi, A, B\} \quad (45)$$

$$\text{for } l = 1..N : D_l = \{x_1^l \dots x_T^l\} \quad (46)$$

Maximise $p(D_1 \dots D_N, Z_1 \dots Z_N | \theta)$

$$x_t^l = \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} \right\} \quad (47)$$

$$p(D_1 \dots D_N, Z_1 \dots Z_N | \theta) = \prod_{l=1}^N p(x_1^l \dots x_T^l, z_1^l \dots z_T^l | \theta) \quad (48)$$

$$= \prod_{l=1}^N \prod_{t=1}^T p(x_t^l | z_t^l) p(z_1^l) \prod_{t=2}^T p(z_t^l | z_{t-1}^l) \quad (49)$$

$$= \prod_{l=1}^N \prod_{t=1}^T \prod_{j=1}^5 \prod_{k=1}^K b_{kj}^{x_{tj}^l z_{tk}^l} \prod_{k=1}^K \pi_k^{z_{1k}^l} \prod_{t=2}^T \prod_{j=1}^K \prod_{k=1}^K a_{jk}^{z_{t-1j}^l z_{tk}^l} \quad (50)$$

Take the log of this posterior

$$\ln(p(D_1 \dots D_N, Z_1 \dots Z_N | \theta)) \quad (51)$$

$$= \sum_{l=1}^N \sum_{t=1}^T \sum_{j=1}^5 \sum_{k=1}^K x_{tj}^l z_{tk}^l \ln(b_{kj}) + \sum_{l=1}^N \sum_{k=1}^K z_{1k}^l \ln(\pi_k) + \sum_{l=1}^N \sum_{t=2}^T \sum_{j=1}^K \sum_{k=1}^K z_{t-1j}^l z_{tk}^l \ln(a_{jk}) \quad (52)$$

Take expectation with respect to posterior

$$E_{[z_{tk}^l]}[\ln(p(D, Z|\theta))] = \sum_{l=1}^N \sum_{t=1}^T \sum_{j=1}^5 \sum_{k=1}^K x_{tj}^l E[z_{tk}^l] \ln(b_{kj}) \quad (53)$$

$$+ \sum_{l=1}^N \sum_{k=1}^K E[z_{1k}^l] \ln(\pi_k) + \sum_{l=1}^N \sum_{t=2}^T \sum_{j=1}^K \sum_{k=1}^K E[z_{t-1j}^l z_{tk}^l] \ln(a_{jk}) \quad (54)$$

To maximise it we need to put constraints

$$\sum_{k=1}^5 b_{jk} = 1 \quad (55)$$

$$\sum_{k=1}^5 \pi_k = 1 \quad (56)$$

$$\sum_{k=1}^K a_{jk} = 1 \quad (57)$$

So

$$L(\pi, \mathbf{A}, \mathbf{B}) = \sum_{l=1}^N \sum_{t=1}^T \sum_{j=1}^5 \sum_{k=1}^K x_{tj}^l E[z_{tk}^l] \ln(b_{kj}) + \sum_{l=1}^N \sum_{k=1}^K E[z_{1k}^l] \ln(\pi_k) \quad (58)$$

$$+ \sum_{l=1}^N \sum_{t=2}^T \sum_{j=1}^K \sum_{k=1}^K E[z_{t-1j}^l z_{tk}^l] \ln(a_{jk}) - \lambda \left(\sum_{k=1}^5 b_{jk} - 1 \right) - \gamma \left(\sum_{k=1}^5 \pi_k - 1 \right) - \mu \left(\sum_{k=1}^K a_{jk} - 1 \right) \quad (59)$$

Maximise $L(\pi, \mathbf{A}, \mathbf{B})$:

$$\frac{\partial L(\pi, \mathbf{A}, \mathbf{B})}{\partial b_{jk}} = \frac{\sum_{l=1}^N \sum_{t=1}^T E[z_{tk}^l]}{b_{jk}} - \lambda = 0 \quad (60)$$

$$\lambda = \frac{\sum_{l=1}^N \sum_{t=1}^T E[z_{tk}^l]}{b_{jk}} \quad (61)$$

$$b_{jk} = \frac{\sum_{l=1}^N \sum_{t=1}^T x_{tj}^l E[z_{tk}^l]}{\sum_{l=1}^N \sum_{t=1}^T \sum_{j=1}^K E[z_{tk}^l]} \quad (62)$$

$$\frac{\partial L(\pi, \mathbf{A}, \mathbf{B})}{\partial \pi_k} = \frac{\sum_{l=1}^N \sum_{k=1}^K E[z_{1k}^l]}{\pi_k} - \gamma = 0 \quad (63)$$

$$\gamma = \frac{\sum_{l=1}^N \sum_{k=1}^K E[z_{1k}^l]}{\pi_k} \quad (64)$$

$$\pi_k = \frac{\sum_{l=1}^N E[z_{1k}^l]}{\sum_{l=1}^N \sum_{r=1}^K E[z_{1r}^l]} \quad (65)$$

$$\frac{\partial L(\boldsymbol{\pi}, \mathbf{A}, \mathbf{B})}{\partial a_{jk}} = \frac{\sum_{l=1}^N \sum_{t=2}^T E[z_{t-1j}^l z_{tk}^l]}{a_{jk}} - \mu = 0 \quad (66)$$

$$a_{jk} = \frac{\sum_{l=1}^N \sum_{t=2}^T E[z_{t-1j}^l z_{tk}^l]}{\sum_{l=1}^N \sum_{t=2}^T \sum_{r=1}^K E[z_{t-1j}^l z_{tr}^l]} \quad (67)$$

Answer is

$$b_{jk} = \frac{\sum_{l=1}^N \sum_{t=1}^T x_{tj}^l E[z_{tk}^l]}{\sum_{l=1}^N \sum_{t=1}^T \sum_{j=1}^K E[z_{tk}^l]} \quad (68)$$

$$\pi_k = \frac{\sum_{l=1}^N E[z_{1k}^l]}{\sum_{l=1}^N \sum_{r=1}^K E[z_{1r}^l]} \quad (69)$$

$$a_{jk} = \frac{\sum_{l=1}^N \sum_{t=2}^T E[z_{t-1j}^l z_{tk}^l]}{\sum_{l=1}^N \sum_{t=2}^T \sum_{r=1}^K E[z_{t-1j}^l z_{tr}^l]} \quad (70)$$