

Tutorial 4

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7:23 PM

7.1

7.1.a.

$$\begin{aligned}
 x^T A x &= (x_1, x_2, \dots, x_N) \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1N} \\ \vdots & & & \vdots \\ a_{N1} & \dots & \dots & a_{NN} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix} = (x_1, x_2, \dots, x_N) \begin{pmatrix} \sum_{j=1}^N a_{1j} x_j \\ \vdots \\ \sum_{j=1}^N a_{Nj} x_j \end{pmatrix} = \\
 &= \sum_{i=1}^N \sum_{j=1}^N x_i a_{ij} x_j = \\
 &= x_e^2 a_{ee} + \sum_{i \neq e}^N x_i a_{ie} x_e + \sum_{j \neq e}^N x_e a_{ej} x_j + \sum_{j \neq e}^N \sum_{i \neq e}^N x_i x_j a_{ij} \\
 &= 2x_e a_{ee} + \sum_{i \neq e}^N a_{ie} x_i + \sum_{j \neq e}^N a_{ej} x_j = \sum_{i=1}^N a_{ie} x_i + \sum_{j=1}^N a_{ej} x_j \\
 \frac{\partial(x^T A x)}{\partial x_e} &= 2x_e a_{ee} + \sum_{i \neq e}^N a_{ie} x_i \Rightarrow \frac{\partial(x^T A x)}{\partial x} = \begin{pmatrix} \sum_{i=1}^N a_{i1} x_i \\ \vdots \\ \sum_{i=1}^N a_{iN} x_i \end{pmatrix} + \begin{pmatrix} \sum_{j=1}^N a_{1j} x_j \\ \vdots \\ \sum_{j=1}^N a_{Nj} x_j \end{pmatrix} \\
 &= \underbrace{\begin{pmatrix} a_{11} & a_{21} & \dots & a_{N1} \\ \vdots & & & \vdots \\ a_{1N} & \dots & \dots & a_{NN} \end{pmatrix}}_{A^T} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix} + \underbrace{\begin{pmatrix} a_{11} & \dots & a_{1N} \\ \vdots & & \vdots \\ a_{N1} & \dots & a_{NN} \end{pmatrix}}_A \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix} \\
 &= (A^T + A)x.
 \end{aligned}$$

7.1.b.

$$\frac{\partial \mathbf{x}^T \mathbf{A} \mathbf{x}}{\partial \mathbf{A}} = \frac{\partial \left(\sum_{i=1}^N \sum_{j=1}^N a_{ij} x_i x_j \right)}{\partial a_{ek}} = x_e x_k$$

$$\Rightarrow \frac{\partial \mathbf{x}^T \mathbf{A} \mathbf{y}}{\partial \mathbf{A}} = \begin{pmatrix} x_1^2 & x_1 x_2 & \dots & x_1 x_N \\ \vdots & \vdots & & \vdots \\ x_1 x_N & \dots & \dots & x_N^2 \end{pmatrix}$$

$$= \begin{pmatrix} x_1 \\ \vdots \\ x_N \end{pmatrix} (x_1 \dots x_N) = \mathbf{x} \mathbf{x}^T.$$

7.1.c.

$$\frac{\partial \det \mathbf{A}}{\partial \mathbf{A}} = \det(\mathbf{A}) (\mathbf{A}^{-1})^T$$

the determinant $\det(\mathbf{A}) = \sum_{i=1}^N a_{ij} (-1)^{i+j} M_{ij}$

$$\frac{\det(\mathbf{A})}{\partial a_{ij}} = (-1)^{i+j} M_{ij} = \text{adj}(\mathbf{A})_{ij}$$

$$\Rightarrow \frac{\det(\mathbf{A})}{\partial \mathbf{A}} = \text{adj}(\mathbf{A})$$

$$\mathbf{A}^{-1} = \frac{(\text{adj}(\mathbf{A}))^T}{\det(\mathbf{A})}$$

$$\frac{\det(\mathbf{A})}{\partial \mathbf{A}} = \det(\mathbf{A}) (\mathbf{A}^{-1})^T$$

(Laplace's Formula)

M_{ij} is a minor. determinant of a matrix that is \mathbf{A} without row i and column j .

(-1)^T

$$\frac{d\ln \det(A)}{dA} = \frac{\partial \ln \det(A)}{\partial \det(A)} \frac{\partial \det(A)}{\partial A} = \frac{1}{\det(A)} (\det(A) (A^{-1})^T) = (A^{-1})^T$$

7.1.d.

$$\frac{\partial \ln \det(A)}{\partial A^{-1}} = - \left(\frac{-\partial \ln(\det(A))}{\partial A^{-1}} \right) = - \left(\frac{\partial \ln(\det(A^{-1}))}{\partial A^{-1}} \right) = - (A)^T$$

7.1.e.

(7.4)

#impulses counted during interval D .

N different cells and using identical stimuli

2 different type of cells $S_n=1$ with p_1
 $S_n=2$ with p_2

$$x = \begin{pmatrix} x_1 \\ \vdots \\ x_n \\ \vdots \\ x_N \end{pmatrix}$$

$$P(x_n=x_n | S_n=i) = \frac{e^{-ciD} (ciD)^{x_n}}{x_n!} \quad i \in \{1, 2\}. \quad ci \text{ (counts/s) depend only on } S_n$$

Use EM

$$\max_{\{c_1, c_2\}}$$

$$\sum_{i=1}^N \log(P(x_n=x_n | c_1, c_2)) = \sum_{i=1}^N \log(p_1 \frac{e^{-c_1 D} (c_1 D)^{x_i}}{x_i!} + p_2 \frac{e^{-c_2 D} (c_2 D)^{x_i}}{x_i!})$$

$-c_1 D, -c_2 D$

(\cdot)^T.

$\{c_1, c_2\}$

$$Q(c_1, c_2 | c_1^{(t)}, c_2^{(t)}) = \sum_{i=1}^N \left(P(S_i=1 | X_i=x_i, c_1^{(t)}, c_2^{(t)}) \log \left(p_1 \cdot \frac{e^{-c_1 D} (c_1 D)^{x_i}}{x_i!} \right) \right. \\ \left. + P(S_i=2 | X_i=x_i, c_1^{(t)}, c_2^{(t)}) \log \left(p_2 \cdot \frac{e^{-c_2 D} (c_2 D)^{x_i}}{x_i!} \right) \right)$$

$$P(S_n=i | X_n=x_n) P(X_n=x_n) = P(X_n=x_n | S_n=i) P(S_n=i)$$

$$P(S_n=i | X_n=x_n) = \frac{P(X_n=x_n | S_n=i)}{P(X_n=x_n)} \quad \text{★} P(S_n=i) \gamma_{i,1}^{(t)} \triangleq P(S_i=1 | X_i=x_i, c_1^{(t)}, c_2^{(t)})$$

$$Q(c_1, c_2 | c_1^{(t)}, c_2^{(t)}) = \sum_{i=1}^N \left(\gamma_{i,1}^{(t)} \log \left(p_1 \frac{e^{-c_1 D} (c_1 D)^{x_i}}{x_i!} \right) + \gamma_{i,2}^{(t)} \log \left(p_2 \frac{e^{-c_2 D} (c_2 D)^{x_i}}{x_i!} \right) \right) \\ = \sum_{i=1}^N \left(\gamma_{i,1}^{(t)} \left(-\log(x_i!) + \log(p_1) - c_1 D + x_i \log(c_1 D) \right) \right. \\ \left. + \gamma_{i,2}^{(t)} \left(-\log(x_i!) + \log(p_2) - c_2 D + x_i \log(c_2 D) \right) \right) \\ Q(c_1, c_2 | c_1^{(t)}, c_2^{(t)}) = \sum_{i=1}^N \left(\gamma_{i,1}^{(t)} (x_i \log(c_1 D) - c_1 D) + \gamma_{i,2}^{(t)} (x_i \log(c_2 D) - c_2 D) \right)$$

$$c_1^{(t+1)} := \arg \max_{c_1} \sum_{i=1}^N \left(\gamma_{i,1}^{(t)} (x_i \log(c_1 D) - c_1 D) \right)$$

$$\Rightarrow \sum_{i=1}^N \gamma_{i,1}^{(t)} \left(x_i \frac{D}{c_1 D} - D \right) = 0$$

$$\sum_{i=1}^N \gamma_{i,1}^{(t)} x_i - c_1 \sum_{i=1}^N \gamma_{i,1}^{(t)} D = 0.$$

$\underbrace{\quad}_{\text{... } (t)_x}.$

$$\Rightarrow \sum_{i=1}^N \gamma_{i,1}^{(t)} \left(x_i \frac{v}{C_1 D} - D \right) = 0$$

similarly for $c_2 = \frac{\sum_{i=1}^N \gamma_{i,2}^{(t)} x_i}{\sum_{i=1}^N \gamma_{i,2}^{(t)} D}$

$$= \frac{\sum_{i=1}^N (1 - \gamma_{i,1}^{(t)}) x_i}{\sum_{i=1}^N (1 - \gamma_{i,1}^{(t)}) D}$$

$$c_1 = \frac{\sum_{i=1}^N \gamma_{i,1}^{(t)} x_i}{\sum_{i=1}^N \gamma_{i,1}^{(t)} D}$$

★

$$\begin{aligned} P(S_n=i | X_n=x_n) &= \frac{P(X_n=x_n | S_n=i) P(S_n=i)}{P(X_n=x_n)} \\ &= \frac{p_i e^{-c_i D} (c_i D)^{x_n}}{x_n!} \\ &= \frac{p_1 e^{-c_1 D} (c_1 D)^{x_n}}{x_n!} + \frac{p_2 e^{-c_2 D} (c_2 D)^{x_n}}{x_n!} \end{aligned}$$

7.5.

observable $\underline{x} = (x_1, \dots, x_t, \dots)$
 $\underline{u} = (u_1, \dots, u_t, \dots)$
 $\underline{v} = (v_1, \dots, v_t, \dots)$

↑

non observable.

$$u_0 = 0$$

$$u_t = \begin{cases} +1 & u_{t-1} + v_t \geq 0 \\ -1 & u_{t-1} + v_t < 0 \end{cases}$$

z)

recall: $P(a,b,c) = P(a|b,c)P(b|c)P(c)$.

$\underbrace{v_1, \dots, v_T, \dots}_{\underline{v} = (v_1, \dots, v_T, \dots)}$ $\underbrace{w_1, \dots, w_T, \dots}_{\underline{w} = (w_1, \dots, w_T, \dots)}$

$\overbrace{x_1, \dots, x_T}^{x_1, \dots, x_T}$

$$\begin{aligned}
 P(\underline{v}, \underline{x} | \lambda, c) &= P(v_1, \dots, v_T, x_1, \dots, x_T | \lambda, c) = \\
 &= P(v_T, x_T | v_{T-1}, \dots, v_1, x_{T-1}, \dots, x_1, \lambda, c) P(v_{T-1}, x_{T-1} | v_{T-2}, \dots, \\
 &\quad \dots) \\
 P(v_i, x_i | v_{i-1}, \dots, v_1, x_{i-1}, \dots, x_1, \lambda, c) &= \\
 &= P(x_i | v_i, v_{i-1}, \dots, v_1, x_{i-1}, \dots, x_1, \lambda, c) P(v_i | v_{i-1}, \dots, \\
 &= P(x_i | v_i, c) P(v_i | v_{i-1}) \\
 \Rightarrow P(\underline{v}, \underline{x} | \lambda, c) &= \left(\prod_{t=2}^T \underbrace{P(x_t = x_t | v_t = v_t)}_{N(c|v_t, \lambda^2)} \cdot P(v_t | v_{t-1}) \right)
 \end{aligned}$$

..

$(U_1, X_{i-1}, \dots, X_1, \lambda, c) =$

$P(X_1 = x_1 | U_1 = u_1^c) P(U_1 = u_1 | U_0 = 0)$

do not depend on c

$$Q(c|c^{(t)}) = \sum_{\substack{\underline{u} \\ \text{all combinations}}} P(\underline{u}=\underline{u} | \underline{X}=\underline{x}) \left(\sum_{t=1}^T \log (P(X_t=x_t | u_t=u_t)) \right)$$

all the terms that do not appear in the summand

$$Q'(c|c^{(t)}) = \sum_{t=1}^T P(u_t=1 | \underline{X}=\underline{x}, c^{(t)}) \log (P(X_t=x_t | u_t=1))$$

$$Q'(c|c^{(t)}) = \sum_{t=1}^T \gamma_{1,t} \log \left(\frac{1}{\sqrt{2\pi\sigma_w}} e^{-\frac{(x_t-c)^2}{2\sigma_w^2}} \right) + \gamma_{2,t} \log$$

Fix log - and ignore parts that do not depend on c

$$-\sum_{t=1}^T \gamma_{1,t} (x_t - c)^2 - \sum_{t=1}^T \gamma_{2,t} (x_t + c)^2$$

$$s(c) \leftarrow \sum_{t=2}^T \log(P(U_t = u_t | U_{t-1} = u_{t-1})) + \log(P(U_1 = u_1 | U_0 = 0))$$

and are marginalized:

$$\dots, c)) + P(U_t = -1 | X = x, c^{(t)}) \log(P(X_t = x_t | U_t = -1, c))$$

$$+ \left(\frac{1}{\sqrt{2\pi w^2}} e^{-\frac{(x_t + c)^2}{2w^2}} \right)$$

over c :

T

$t=1$

$T=1$

concave ✓

take derivative and set to 0 \Rightarrow

$$-\sum_{t=1}^T g_{1,t}(x_t - c) +$$

and therefore:

$$\sum_{t=1}^T (\gamma_{1,t} + \gamma_{2,t}) q_1 = \sum_{t=1}^T (\gamma_{1,t} - \gamma_{2,t}) x_t$$

$\underbrace{\gamma_{1,t} + \gamma_{2,t}}_{\text{each of them}} \quad \text{add to 1}$

$$q_1 = \frac{1}{T} \sum_{t=1}^T \left(\frac{\gamma_{1,t} - \gamma_{2,t}}{x_t} \right)$$

7.7

HMM with GMM's

$$g_{im,t} = P[S_t=i \wedge U_t=m | x, \lambda] = \gamma_{i,t} \cdot \frac{w_{im} g(x_t, f_i)}{\sum_{k=1}^M w_{ik} g(x_t, f_k)}$$

$$\gamma_{i,t} = P(S_t=i | x, \lambda)$$

$$\sum_{t=1}^T \gamma_{2,t} (x_t + c) = 0.$$

$$(\gamma_{1,t} - \gamma_{2,t}) x_t$$

$$\frac{m, C_{im}}{N_{ik}, C_{ik}}$$

$$\gamma_{i,t} = P(S_t = i | x, \lambda)$$

$$P(S_t = i, U_t = m | x, \lambda) = P(S_t = i | U_t = m, x, \lambda) \\ = P(U_t = m | S_t = i, x, \lambda)$$

$$f(x | U_t = m, S_t = i, \lambda) = g(x, \pi^i_m, \zeta^i_m)$$

$$P(U_t = m | S_t = i, x) f(x | S_t = i) = f(x | U_t = m)$$

$$P(U_t = m | S_t = i, x) = \frac{g(x_t, \pi^i_m, \zeta^i_m)}{\sum_{k=1}^M w_k g(x_t, \pi^k_m, \zeta^k_m)}$$

$$\Rightarrow \gamma_{i,t} = \gamma_{i,t}^*$$

$$P(U_t = m | x, \underline{\lambda})$$

$$\geq P(s_t = i | x, \underline{\lambda})$$

$$, s_t = i) P(U_t = m | s_t = i)$$

ω_{im}

(i_k, a_k)