

EQUATION 1.

$$P(Y_{tn} | X_t = k) = \text{Bin}(M_{tn} | M_{tn} + U_{tn}, E_{kn}) \quad 1.1$$
$$= E_{Kn}^{M_{tn}} (1 - E_{kn})^{U_{tn}} \quad 1.1.2$$

$X_t = ?$ > REGULAR DISCRETE LIKELIHOOD

$$\hookrightarrow P(Y_n | X_t) = \prod_k P(Y_{tn} | X_t = k)^{\mathbb{1}[X_t = k]} \quad 1.2$$

$$\mathbb{E}_Q(\mathbb{1}[X_t = k]) = \delta_{kt} \quad \therefore \delta \text{ COMES FROM FORWARD/BACK} \quad 1.2.1$$

COMPLETE LIKELIHOOD

$$P(Y | X) = \prod_{tn} P(Y_{tn} | X_t) \quad 1.3$$

GIVEN $X_t = K$ THE LIKELIHOOD FOR AN INDIVIDUAL POSITION
& CELL

ON 1.3 log

$$\log(P(Y | X)) = \sum_{tn} \log(P(Y_{tn} | X_t)) \quad 1.2$$
$$= \prod_K P(Y_{tn} | X_t = K)^{\mathbb{1}[X_t = K]} \quad 1.1.2$$
$$= E_{Kn}^{M_{tn}} (1 - E_{kn})^{U_{tn}}$$

1.4

$$\log(P(Y | X)) = \sum_{tn} \sum_K \frac{\mathbb{1}[X_t = K]}{M_{tn}} M_{tn} \log E_{kn} + U_{tn} (1 - E_{kn})$$

1.2.1 = δ_{kt}

EXPECT $\rightarrow \mathbb{E}_Q \log(P(Y | X)) = \sum_{tn} \sum_K \delta_{kt} M_{tn} \log E_{kn} + U_{tn} (1 - E_{kn})$

MAXIMIZATION WRT E_{kn}

$$\frac{\partial}{\partial E_{kn}} \mathbb{E}_Q(\log(P(Y | X))) = 0 \quad 1.5$$

$$\frac{\partial}{\partial E_{kn}} \sum_{kt} \gamma_{kt} M_{tn} \log E_{kn} + U_{tn} (1 - E_{kn}) \quad 1.6$$

$$= \sum_t \gamma_{kt} \left(\frac{M_{tn}}{E_{kn}} - \frac{U_{tn}}{1 - E_{kn}} \right) \quad 1.7$$

SOLVE FOR E_{kn} IN 1.7

$$\sum_t \gamma_{kt} \left(\frac{M_{tn}}{E_{kn}} \right) = \sum_t \gamma_{kt} \left(\frac{U_{tn}}{1 - E_{kn}} \right)$$

$$\sum_t \gamma_{kt} \left(\frac{M_{tn}}{E_{kn}} \right) E_{kn} = \sum_t \gamma_{kt} \left(\frac{U_{tn}}{1 - E_{kn}} \right) E_{kn}$$

$$\sum_t \gamma_{kt} (M_{tn}) = \sum_t \gamma_{kt} \left(\frac{U_{tn}}{1 - E_{kn}} \right) (1/E_{kn}) (E_{kn})$$

$$(1 - E_{kn}) \sum_t \gamma_{kt} (M_{tn}) = E_{kn} \sum_t \gamma_{kt} (U_{tn}) \quad 1.8$$

IN TERMS OF E_{kn} IN 1.8

$$E_{kn} \sum_t \gamma_{kt} (U_{tn}) + E_{kn} \sum_t \gamma_{kt} (M_{tn}) = \sum_t \gamma_{kt} (M_{tn})$$

$$E_{kn} (\sum_t \gamma_{kt} U_{tn} + \sum_t \gamma_{kt} M_{tn}) = \sum_t \gamma_{kt} M_{tn}$$

$$E_{kn} = \frac{\sum_t \gamma_{kt} M_{tn}}{(\sum_t \gamma_{kt} U_{tn} + \sum_t \gamma_{kt} M_{tn})} \quad 1.9$$

INCORPORATING $\beta(2,2)$ PRIOR IN 1.9

$$\alpha=2 \quad \beta=2$$

$$\log \text{Beta}(E|\alpha, \beta) = (\alpha-1) \log E + (\beta-1) \log (1-E) + C$$

$$\log \text{Beta}(E|2,2) = \log E + \log(1-E) + C \quad 2.0$$

$$1.5 \quad \mathbb{E}_Q [\log P(Y|X)] + \log \text{Beta}[E|2,2] =$$

$$\sum_{t|Kn} \gamma_{kt} (M_{tn} \log E_{kn} + U_{tn} \log (1-E_{kn}) +$$

$$2.0 \longrightarrow \log E_{kn} + \log (1-E_{kn})$$

$$E_{kn} = \frac{\sum_t \gamma_{kt} M_{tn} + 1}{(\sum_t \gamma_{kt} U_{tn} + \sum_t \gamma_{kt} M_{tn}) + 2}$$

$\beta(2,2)$
SUCCESS

$\beta(2,2)$
SUCCESS +
FAILURE.

EQUATION 2.

DERIVATION

$$z_{tj} = P(\underline{y_t^{\text{MISS}} = j} \mid Y_{\text{OBS}}, E, T) \quad \begin{matrix} \text{PREDICTOR VAR} \\ \downarrow \\ \text{STATE } i \end{matrix}$$

IN TERMS OF $E_{tj} = P(Y_{tj}=1 \mid X_t = i)$ PROB MATRIX

$$\text{AND } \delta_{ti} = P(X_t = i \mid Y_{\text{OBS}})$$

y_t^{MISS} AT TIME t TAKES j VAL y_{tj} IS 1 IF $X_t = i$
IN time

Y_{OBS} INFLUENCES THE PRED VAR ON δ_{ti}

↳ SO IT HELPS TO INFORM THE PROBS OF π

$$z_{ti} = \sum_j P(\underline{y_t^{\text{MISS}} = j}, \underline{X_t = i} \mid Y_{\text{OBS}})$$

ALL OVER STATES

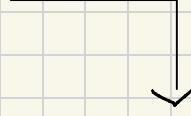
BOTH DEPEND ON Y_{OBS}
THROUGH δ_{ti} AND OUR
MATRIX

CONDITIONAL PROB

$$z_{ti} = \sum_i P(\underline{y_t^{\text{MISS}} = j} \mid X_t = i, Y_{\text{OBS}}) \cdot P(X_t = i \mid Y_{\text{OBS}})$$

y_t^{MISS} IS COND IND? OF Y_{OBS} GIVEN X_t ?

$$z_{ti} = \sum_i E_{ij} \delta_{ti}$$



$$\begin{aligned} P(Y^M, X_t \mid Y^o) &= P(Y^M \mid Y^o) P(X_t \mid Y^o) \\ &= P(Y^M \mid X_t, Y^o) P(X_t \mid Y^o) \end{aligned}$$

CONDITIONAL INDEPENDENCE.

$$\begin{aligned} P(A \mid B, C) &= P(A \mid C) \\ P(A, B \mid C) &= P(A \mid C) P(B \mid C) \\ &= P(A \mid B, C) P(B \mid C) \end{aligned}$$

IF I KNOW C, THEN B TELLS ME NOTHING
ABOUT A
 $A \perp\!\!\!\perp B \mid C$

$$P(Y^M \mid X_t, Y^o) = P(Y^M \mid Y^o)$$

EQUATION 3.

$$L = - \sum_{j=1}^J \sum_{t=1}^{T-1} \log \text{Bin}(M_{t+1,j} | M_{t+1,j} + U_{t+1,j}, p_{tj})$$

↗ ADDING LOSSES IN ALL CELLS
 ↙ LOSSES PER POSITION IN CELL j

where

p_{tj} = RNN OUTPUT

'LOSS IS FOR SCENARIOS WHERE WE PREDICT SEQ DATA'

t = POSITION

j = CELL

?

$$\text{Bin}(x | n, p) = \binom{n}{x} p^x (1-p)^{n-x}$$

APPLYING LOG

$$= \log(p^x) \log((1-p)^{n-x})$$

$$= (x \log p) + (n-x \log(1-p))$$

$$= M_{t+1,j} \log p_{tj} + (M_{t+1,j} + U_{t+1,j} - M_{t+1,j} \log(1-p_{tj}))$$

$$= M_{t+1,j} \log p_{tj} + U_{t+1,j} \log(1-p_{tj})$$

$$= - \sum_{j=1}^J \sum_{t=1}^{T-1} M_{t+1,j} \log p_{tj} + U_{t+1,j} \log(1-p_{tj})$$