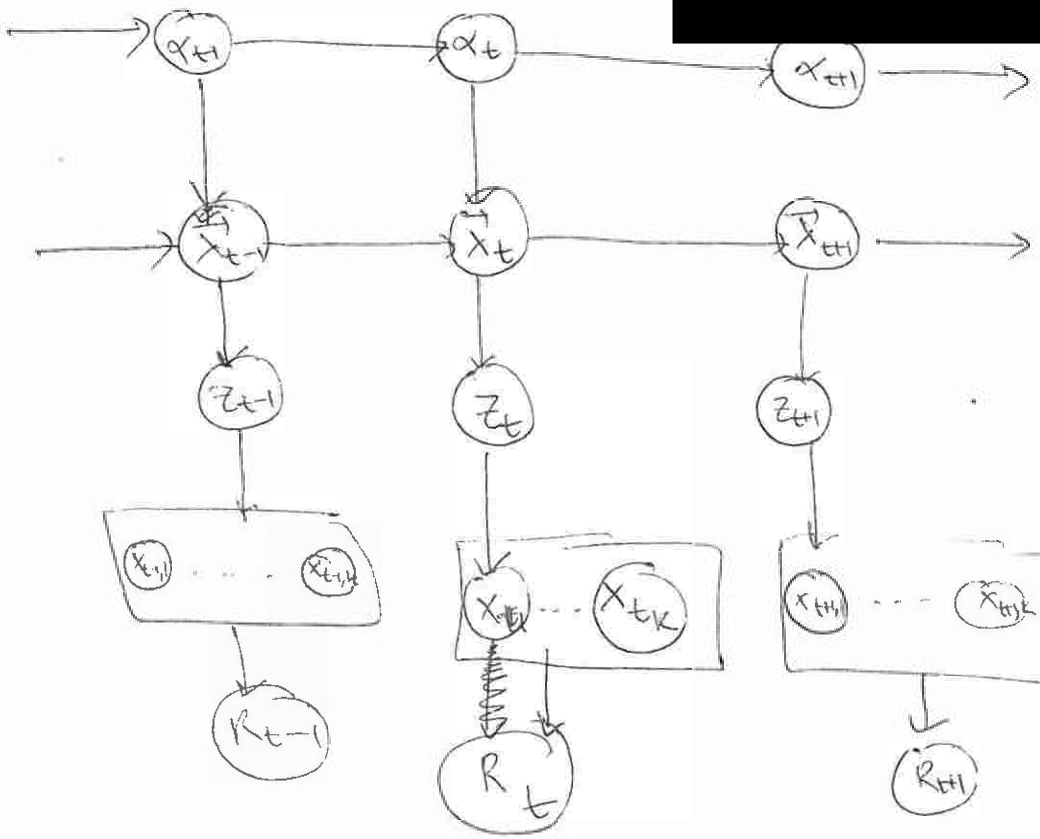
Rational Bayesian Account [redacted]

$|R_t$



$$\lambda_t = \left\{\lambda_t^L, \lambda_t^R, \lambda_t^N\right\} \quad \text{where} \quad \lambda_t^L + \lambda_t^R + \lambda_t^N = 1$$

$$b(\vec{\lambda}_{t+1} \mid \vec{\lambda}_t, \alpha_t) = (1-\alpha_t)\,\delta(\vec{\lambda}_{t+1} = \vec{\lambda}_t) + \alpha_t P_0(\vec{\lambda}_{t+1})$$

α_t = Hazard Rate ~~Probability~~ P_0 is a Dirichle distributi

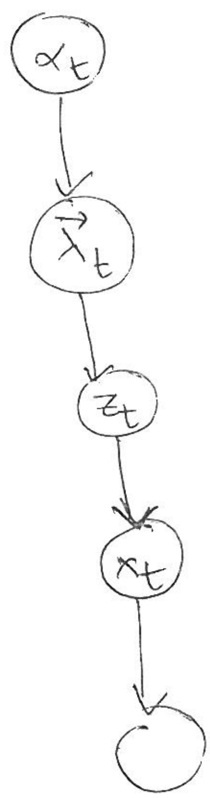
= $Pr(\vec{\lambda}_{now}$ will switch $|\ \vec{\lambda}$ has not switched yet$)$

= α for exponential ~~but differentiators~~ time varying otherwise

$$\boxed{p(x_{t,k} \mid z_t) = \eta_{z_t}^{x_{t,k}} (1-\eta_{z_t})^{(1-x_{t,k})}}$$

$$b(z_t^L \mid \vec{\lambda}_t) = \frac{\lambda_t^L}{8} \qquad b(d_t = L \mid \vec{\lambda}_t) = \lambda_t^L + \lambda$$

$$b(z_t^U \mid \vec{\lambda}_t) = \lambda_t^U \qquad b(d_t = R \mid \vec{\lambda}_t) = \lambda_t^R + \frac{\lambda}{2}$$



α_t
$\vec{\lambda}_t$
z_t
x_t

$$\cancel{b(x_{t_k} \mid x_{t_{k-1}}, \ldots, x_{t_0}, Z_t, \sigma^2)}$$

$$\cancel{= b(x_{t_k} \mid x_{t_{k-1}}, Z_t, \sigma^2) = N(c Z_t, \sigma^2).}$$

$$\cancel{b(x_{t_0} \mid \quad)}$$

$\cancel{b(x_t}$

d_t = direction left / right.

$$\cancel{b(d_{t_k} \mid x_{t_1 \ldots k}) \propto b(x_{t_k} \mid d_{t_k})}$$

$$\cancel{b(d_{t_k} \mid x_{t_1}, \ldots x_{t_k}, R_1 \ldots R_{t-1})}$$

$$\cancel{\propto b(x_{t_k} \mid d_{t_k}) \sum_{d_{t_{k-1}}} b(d_{t_k} \mid d_{t_{k-1}})}$$

$$\qquad\qquad = 1_{d_{t_k} = d_{t_{k-1}}}$$

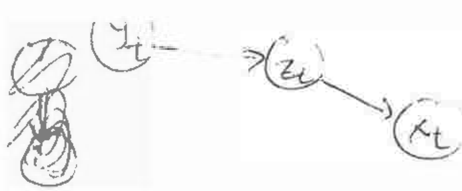
$$b(d_{t_k} \mid x_{t_1}, \ldots x_{t_k}, R_1, \ldots R_{t-1}) \propto b(x_{t_k} \mid d_{t_k}) \sum_{d_{t_{k-1}}} \Big[\underbrace{b(d_{t_k} \mid d_{t_{k-1}})}_{= 1_{d_{t_k} = d_{t_{k-1}}}} \underline{b(d_{t_{k-1}})}$$

$$b(x_{t_k} \mid d_{t_k}) = \sum_{Z_t} \underbrace{b(x_{t_k} \mid Z_t)}_{\text{move this}} \underbrace{P(Z_t \mid d_{t_k})}_{= \left(\left(\frac{\lambda_{m, \gamma_t}}{8} + \frac{\lambda_{0,m}}{2}\right) / \cancel{\text{normalization}}\right.} \quad m = L \text{ or } R$$

$$b(d_{t_0} \mid R_1 \ldots R_{t-1}) = \cancel{b(d_{t_0} \mid Z_t) \, b(Z_t)}$$

$$= \sum_j b(d_{t_0} = i \mid \gamma_{t-1} = j) \, P(\gamma_{t} = j \mid \vec{R}_{t-1})$$

$$b(d_{t_0} = i \mid \gamma_{t-1} = j) = \lambda_{+\gamma_t} \delta_{ij} + \frac{\lambda_{0\gamma_t}}{2} + \lambda_{\bar{\gamma}_t}(1 - \delta_{ij})$$

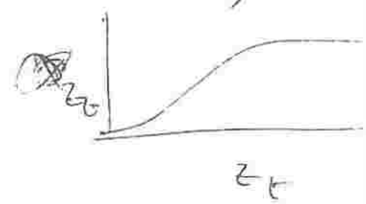


$x_{tk} \in \{0, 1\}$

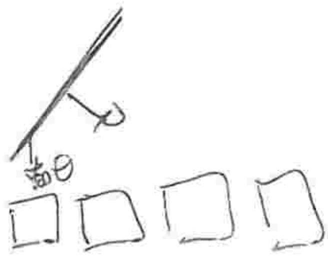
L U R

the
cue $z_t \in \{-9, -8, \ldots, 0, 1, 2 \ldots 9\}$

$; \; \alpha_{z_t} = \sigma(c z_t)$



Context
$y_t \in \{-1, 0, 1\}$
L U R



$$p(z_t \mid y, \lambda_{y_t}) = \begin{cases} \frac{\lambda_{-1, y_t}}{8} ; & z_t = -9, \ldots -1 \\ \lambda_{0, y_t} ; & z_t = 0 \\ \frac{\lambda_{+1, y_t}}{8} ; & z_t = 1, 2 \ldots 9 \end{cases}$$

$\lambda_{-1,y_t} + \lambda_{+1, y_t} + \lambda_{0}$

$$p(y_t = i \mid y_{t-1} = j) = \begin{cases} c & \text{if } i = j \\ \frac{1-c}{2} & \text{if } i \neq j \end{cases}$$

$$p(x_{tk} \mid z_t) = \alpha_{z_t}^{x_{tk}} (1 - \alpha_{z_t})^{(1 - x_{tk})}$$

now look
prev. p

$$\overset{b_{tk}}{\overset{\parallel}{b}}\left(y_{tk} \mid \{x_{tk}\}_{k=1}^{K}, \{R_t, \ldots R_1\}\right)$$

$$\propto b(x_{tk} \mid y_{tk}) \sum_{y_{t,k-1}} \left[b(y_{tk} \mid y_{tk-1}) \right] b(y_{t k-1} \ldots)$$

$\sum_{z_t} p(x_{tk} \mid z_t) p(z_t)$

$= \mathbb{1}_{y_{tk}=y}$ since contexts static

b_{tk}
$\parallel$
$b(y_{tk} \ldots)$

$$P(z_t) = \sum_{y_{t_0}} P(z_t \mid y_{t_0}, x_{y_t})\, b(y_{t_0} \mid R_{t-1} \ldots R_1)$$

$P(\text{diff} \mid \text{right})$

$b(y_{tk} \mid \{x_{t,k}\}_{k=1}^{L}, R_1)$

$\boxed{\Theta_{\text{thresh}}}$

Monkey Resp $\bar{R}_t$, $\bar{R}_t^{L,R}$ true solution

$$\frac{\sum_{1}^{j} m_0 Z_t}{N}$$

Ideal Bayesian

$b_{t_0 i_0}$

only thing told

$$b(y_t = i \mid R_{t-1}, R_{t-2}, \ldots R_1)$$

b_{t-1, j_0}

$$\propto \sum_j b(y_{t_0} = i \mid y_{t-1} = j, \{R_{t-1}\})\, b(y_{t-1,0} = j \mid \{R_{t-1}\})$$

$$\propto b(R_{t-1} \mid y_{t_0} = i) \sum_j b(y_{t_0} = i \mid y_{t-1,0} = j)\, b_{t-1,j}$$

$\| \; P(y_t = i \mid y_{t-1} = j) = 1_{ij}$

or

independent of $y_{t-1,0}$

transition $p(y_{t_0} \mid y_{t-1})$

$$\lambda_{R_{t-1}, i} + \frac{\lambda_{0,i}}{2}$$

$$R_t = \{-1, 1\}, \quad i \in \{0, 1\}$$

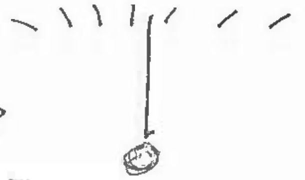
Note that:

$$\sum_{R_t} b(R_t \mid y_{t_0} = i) = \sum_{R_t} \left(\lambda_{R_t, i} + \frac{\lambda_{0,i}}{2}\right)$$

$$= \lambda_{+1,i} + \lambda_{0,i}/2 + \lambda_{-1,i} + \lambda_{0,i}/2 = 1.$$

$0.7\times\frac{1}{3},\ 0.7\times\frac{1}{3},\ 0.7\times\frac{1}{3}$

$0.1\times\frac{1}{2}$



$P(z_t \mid d_t) = P$

$P(x_{tk} \mid d_{tk}) =$

$= \sum_t P(x_{tk} \mid d_{tk}, z_t) \cdot P(z_t \mid d_{tk})$

$0{,}4\cdot\frac{1}{3},\ 0{,}4\frac{1}{3},\ 0{,}4\cdot\frac{1}{3},\ \frac{0{,}2}{\square}$

$0.7 \quad 0.1 \quad 0.2$

$\lambda_+;\ \lambda_0,\ \lambda_-$

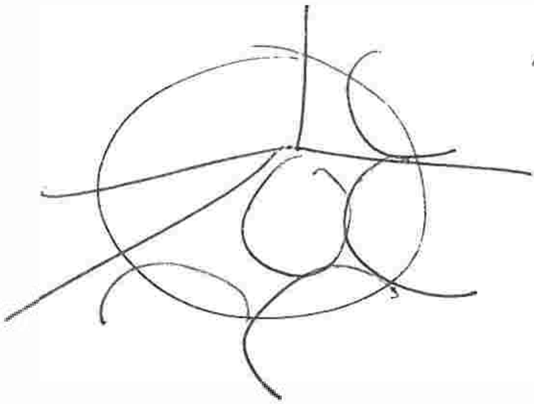
$1\ \frac{1}{3}\ \frac{1}{3}\ \frac{1}{3}$

$P(A) = \sum_b P(A \mid B=b) \cdot P(B=b)$

$\frac{\lambda_+}{3} \ldots,\ \frac{\lambda_0}{2}$

$\frac{1}{8}\ \frac{1}{4}\ \frac{1}{4}\ \frac{1}{4}$

1



$P(z_t \mid \cancel{d_t = 0})$

$p(x_{tk} \mid d_{tk}) = \{$

$\frac{210}{225} + \frac{15}{225}$

$p(z_{tk} \mid d_t)$

$\frac{1}{14} + \frac{1}{14}$

$\frac{2}{15}$

$\{000,\ \frac{x}{2}\ \frac{0{,}5-\frac{x}{2}}{3}\}$

$\frac{3}{000}$

$\{\frac{0{,}5-\frac{x}{2}}{3}$

$p(z_{tk} \mid R)$

$p(z_t \mid$

$\frac{1}{7}\ \frac{1}{7}\ \frac{1}{7}\ \frac{1}{7}\ \frac{1}{7}\ \frac{1}{7}\ \frac{1}{7}$

$p(z_{tk} \mid d_t = R)$

$\frac{\frac{1}{2}}{\frac{1}{3}}$

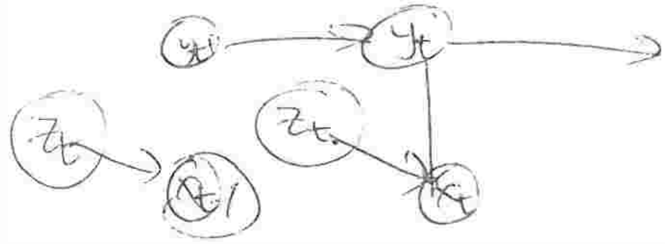
$p(O \mid d_{tk} = R) = 0{,}5$

$p(O \mid d_{tk} = C) = 0{,}5$

$P(z_t \mid d_t) = \{0, 0, 0, \frac{1}{8}, \frac{7}{24}, \frac{7}{24}, \frac{7}{24}\}$

$\frac{1}{7}\quad \frac{1}{14}$

$\frac{1}{7}$



$z_t \in \{-9, \ldots 0, \ldots 9\}$

$x_t \in \{L, R\}$ ($0, 1$)

$y_t \in \{\text{EQ}, \ldots, \text{SR}\}$ ($-1, 0, 1$)

$\cancel{p(x_t \mid y_t, z}$

$p(x_t^{=L} \mid z_t)$

$$p(x_t \mid y_t, z_t) = \alpha^{x_t}(1-\alpha)^{1-x_t}$$

where

$$\alpha = f(\ldots y_t \ldots z_t)$$

$$\int dy_t \, p(x_t \mid y_t, z_t)\, p(y_t \mid z_t)$$

$$= p(x_t \mid z_t)$$

$\cancel{p(y_t \mid x_t, z_t)}$

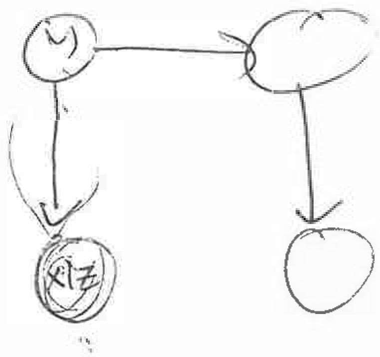
$p(y_t \mid$

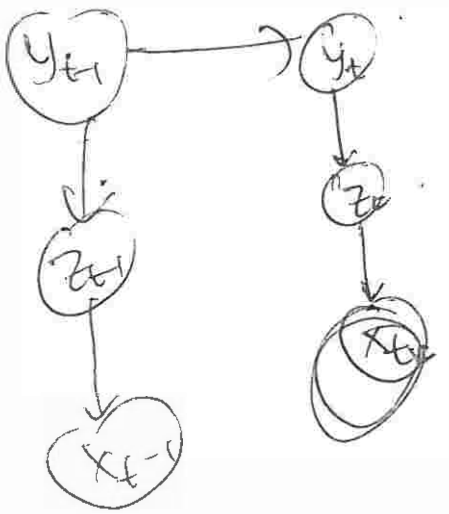
$$p(\overset{\text{L/R}}{x_1}, \ldots \overset{\text{L/R}}{x_T} \mid z_1, \ldots z_T)$$

z = stimulus (−7 7)

x = ~~response~~ L, R

y = state/cite [L, R





Likelihood ratios

$\cancel{b(x_{tk} | z_t}$)

$H_1 \Rightarrow d_t = R$

$H_2 \Rightarrow d_t = L$

$$I_k = \log\left(\prod_k \frac{b(x_{tk} \mid d_t = L)}{b(x_{tk} \mid d_t = R)}\right) = \sum_k \log \frac{b(x_{tk}|}{b(x_{tk}|}$$

$$= \log\left(\frac{b(x_{tk}|d_t=1)}{b(x_{tk}|d_t=1)}\right) \sum_{k-1} \log\left(\frac{b(x_{tk-1}|d}{b(x_{tk-1}|d}\right)$$

$$I_{k-1} + \log\left(\frac{b(x_{tk}|d_t=1)}{b(x_{tk}|d_t=2)}\right)$$

where

$$b(x_{tk} \mid d_t) = \sum_{z_t} b(x_{tk} \mid z_t)\, b(z_t \mid d_t)$$

$$b(x_{tk} \mid z_t) = \alpha_{z_t}^{x_{tk}} (1-\alpha_{z_t})^{1-x_{tk}}$$

Now include bias, see Bogacz et al (2006)

Helena: How LFP depends on dendritic morphology.

Extracellular potential is generated by transmembrane currents

$$\Phi(\vec{r}, t) = \frac{1}{4\pi\sigma} \frac{I_0(t)}{|\vec{r} - \vec{r}_0|}$$

Pyramidal cell.

With random morphology (different placement of dendrites) or ~~uniform~~ standard morphology

Give same stimulus

Compare ↓
LFP generated by 2 different cells

Rory:

Laureline. STDP and DA neuromodulation.

DA in control of syn plasticity

DA = PL : inhib ↓
D1 = AMPAR. ~ NMDAR.

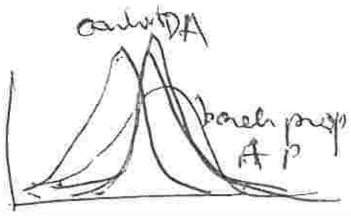
~~Convolve~~ ΔW = eligibility × thresholded postV. increase

Clopath et al 2010.

3 compartment neuron model of larger P neuron. : repeats generalizing behavior ~~PFC~~ pre exc., inh. neurons

DA shifts V voltage trace

~~[illegible]~~ V



Aki: Plasticity w/o sensory presence
Sensory deprivation.

IB & ~~[illegible]~~ RS cell.

Photoexcitation w/ glutamate imaging.

Ainoha. modeling bistable cortical network forming up & down transitions

No correlations indicating UP ~~[illegible]~~ states.

E - I network.

IF + adaptation network

Rainer: Olfactory system

optogenetic stimulation of olfactory bulb.

~~[illegible]~~ Stimulus triggered average : average the data after onset of a particular stimulus.

How many of [illegible] do we need to: ~~[illegible]~~ SVD.

[illegible]

Merel's practice

Race to Mush

Martin Sonter (Ach)

Phasic Ach.

task signal det. least 1/2 trials there is buf signal.

L $\frac{\lambda t}{8}$

R $\frac{\lambda . R}{8}$

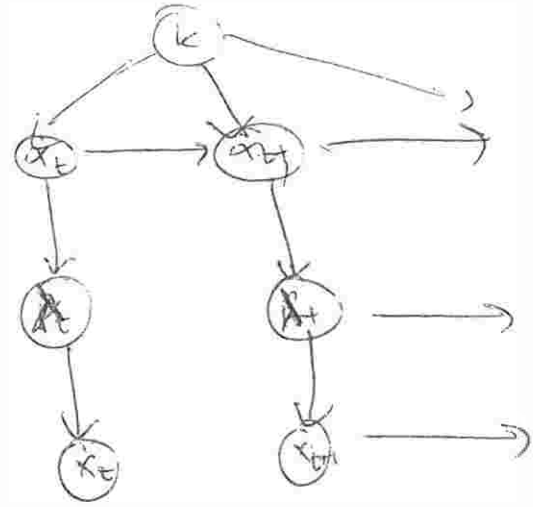
$b(d_{tk} \mid x_{t1 \ldots k})$

R_t

$$\frac{b(d_{tk} \mid x'_{t1 \ldots k})}{b(d_{t0})}$$

Behrens's task

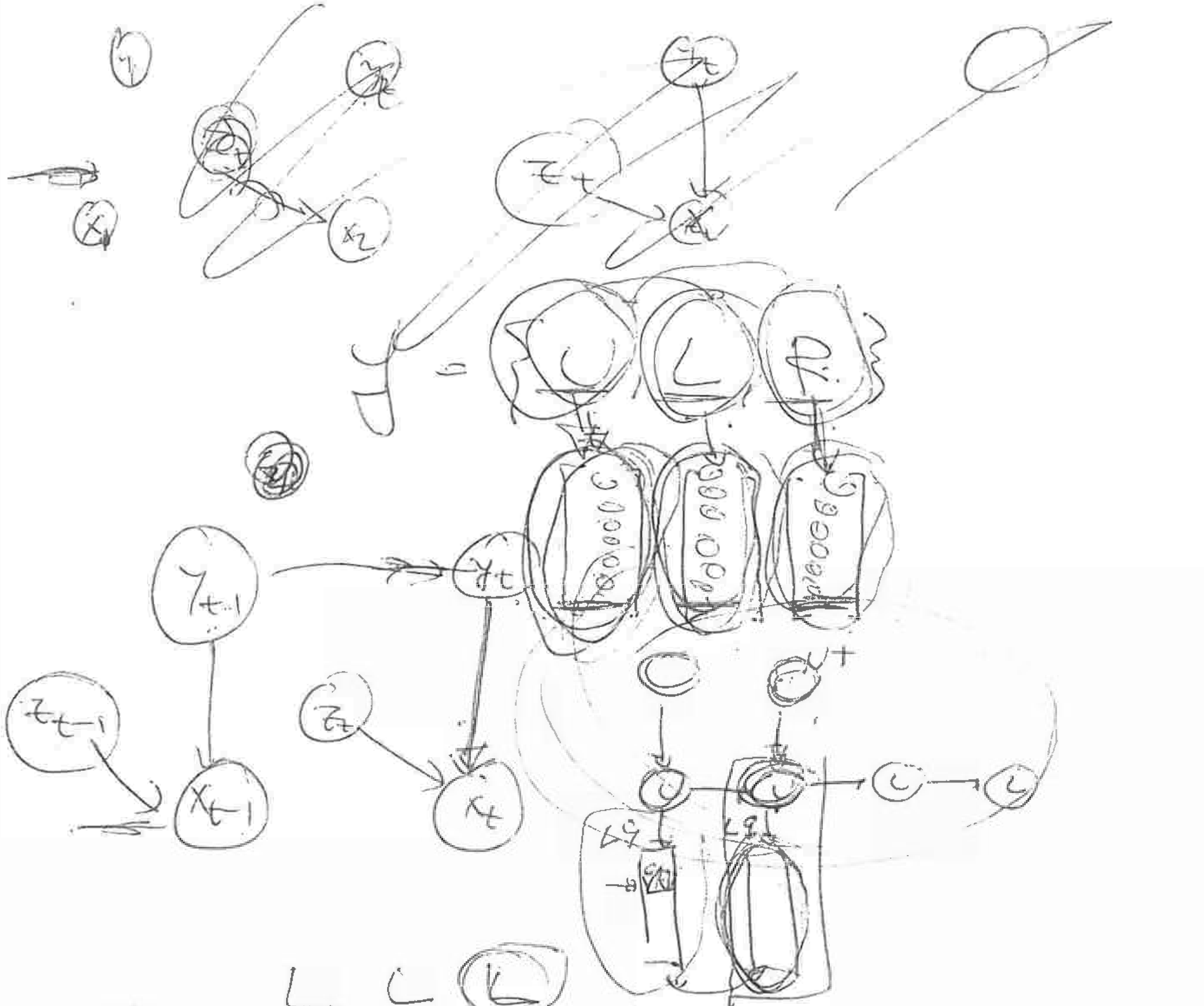
Volatility



~~Volat~~ Volatility itself can change from ~~time~~ trial to ~~trial~~ trial. , whereas in Angela's , it is fixed.

$$p(\lambda_t = \lambda \mid \vec{x}_{t-1}) = \alpha\, p(\lambda_{t-1} = \lambda \mid \vec{x}_{t-1}) + (1-\alpha)\, p_0(\lambda_t = \lambda).$$

$$p(y_t \mid x_1, \dots x_t, z_1, \dots z_t)$$
$$\propto p(x_t \mid y_t, z_t) \sum_{y_{t-1}} p(y_t \mid y_{t-1})\, p(y_{t-1} \mid x_1 \dots x_t)$$



L C L

L9, R2, R4,5, R2, R5

L L

$$p(x_{t+1}, x_{t+2}, \dots x_T \mid z_{t+1}, z_{t+2}, \dots z_T)$$

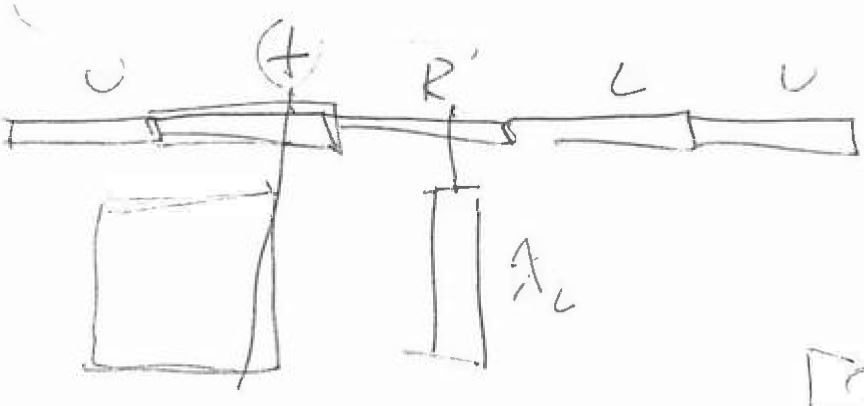
$$P(L \mid \lambda, S) =$$

$$p(1-p)^x$$

$p(x_t | y_1, \dots, y_t, z_1, \dots, z_t)$

$p(x_t^{= \text{LorR}} | z_1, \dots, z_t)$

$= \int^T dy_1 \dots dy_t \; p(x_t | y_1 \dots y_t, z)$
$p(y_1 \dots y_t$



$\lambda_R \quad \begin{bmatrix} \circ & \cdot & \cdot \\ \cdot & \circ & \cdot \\ \cdot & \cdot & \circ \end{bmatrix}$

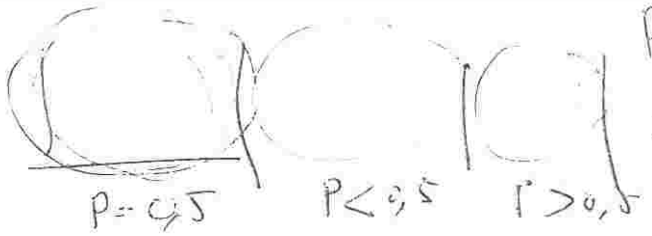
$X_t \quad \lambda_U$

$(\cancel{X_t} | \cancel{Y_t}, Z_t) =$

$(X_t | Y_t, Z_t) = f(\lambda_i$

$\lambda_U =$
$\lambda_L =$
λ_R
$\underline{1}$

$z_t \in \{-9, \ldots, 0, 9\}$ $p(z_t) = -9, \ldots, -1 = p_L$



$p(z_t) = 0 \quad p_N$

$p(z_t) = 1, \ldots, 9 = p_R$

$p_L + p_N + p_R =$

$y_t = L, R$

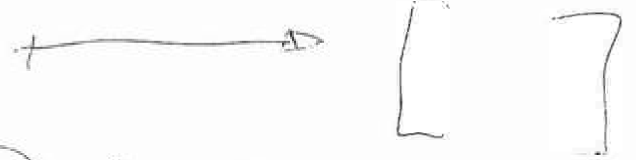
$$p(y_t \mid y_{t-1}, z_{t-1}, y_{t-2}, z_{t-2}, \ldots) \stackrel{?}{=}$$

$$p(x_t = L \mid y_t, z_t) = \alpha(y_t, z_t)$$

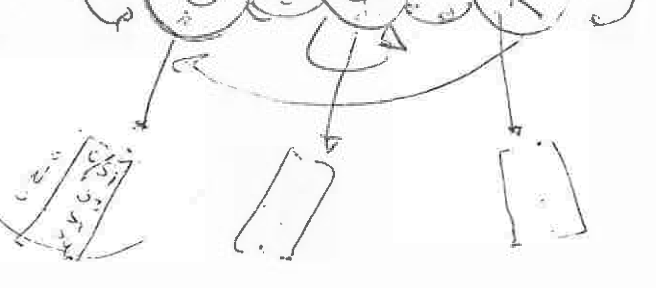
$$p(x_t = R \mid y_t, z_t) = 1 - \alpha(y_t, z_t)$$

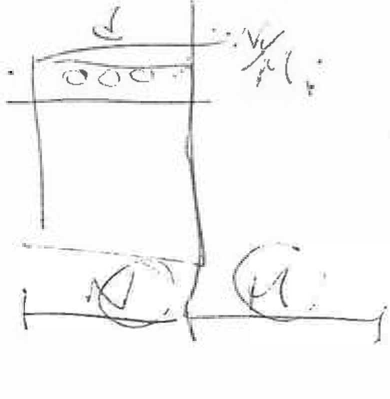
$$\cancel{p(x_t \mid z_t) = \int p(x_t \mid y_t, z_t)\, p(y_t)}$$

$$= \cancel{\int p(x_t \mid z_t)}$$



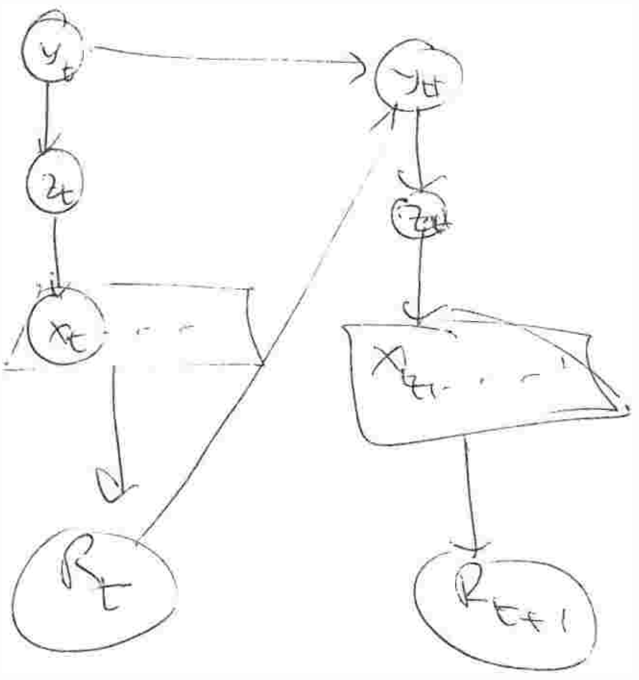
$$= \int p(x_t \mid y_t)\, p(y_t \mid z_t)\, dy_t$$





Any increasing c, w function w ~~makes~~ ~~an~~ exiting early ~~less costly~~ 1. >0 penalise

$$\int_0^t c\,dt = ct.$$



To fit
do
1) VB
2) or sampling

can't do EM
because
of $\underline{y_{t+1} | R_t}$