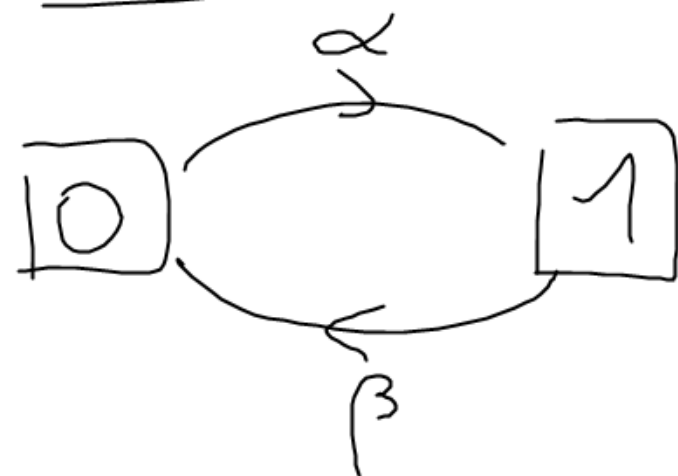


Lesson 9 - January 20th

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PDP

Toy Model.



$$X_t^i \quad i = 1, \dots, N$$

Doors: i 1 2 3 ... N
 X_t^i

Door i is open at time t
 if $X_t^i = 1$
 is closed if $X_t^i = 0$.

$m_N(t) =$ number of open doors.

$$m_N(t) = \sum_{i=1}^N X_t^i$$

$$u_N(t) = \frac{1}{N} m_N(t)$$

the proportion of open doors.

$$\forall t \geq 0, u_N(t) \in \left\{ 0, \frac{1}{N}, \frac{2}{N}, \dots, \frac{k}{N}, \dots, \frac{N-1}{N}, 1 \right\}$$

Result: we can prove that $(u_N(t))_{t \geq 0}$ is a continuous time Markov Process.

The process jumps from 1 state to its 2 neighbors.

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For a small δ , we have.

$$\mathbb{P}\left(u_N(t+\delta) = \frac{l}{N} \mid u_N(t) = \frac{k}{N}\right) \leq C \delta^{|l-k|}$$

So if $|l-k| \geq 2$

$$\frac{1}{\delta} \mathbb{P}\left(u_N(t+\delta) = \frac{l}{N} \mid u_N(t) = \frac{k}{N}\right) \xrightarrow{\delta \rightarrow 0} 0$$

$$P\left(u_N(t+\delta) = \frac{k+1}{N} \mid u_N(t) = \frac{k}{N}\right) = (N-k)\alpha\delta$$

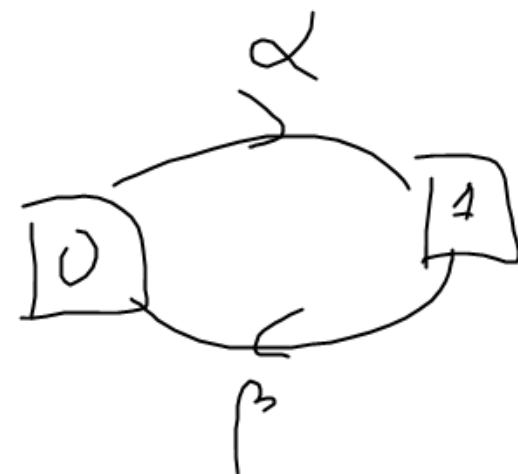
1
0
1
0
1
0
0
0
1
0
1

At time t , there exists exactly k labels i such that $X_t^i = 1$
 $N-k$ ——— i such that $X_t^i = 0$.

If At time $t+\delta$ $u_N(t+\delta) = \frac{k+1}{N}$, it means that during the time interval $[t, t+\delta]$, one of the closed door jump from 0 to 1.

For any i_0 such that $X_t^{i_0} = 0$, we know that

$$P(X_{t+\delta}^{i_0} = 1 \mid X_t^{i_0} = 0) = \alpha \delta$$



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But $N - k$ doors are closed at time t ,

so the probability to have $k+1$ open doors at time $t+\delta$

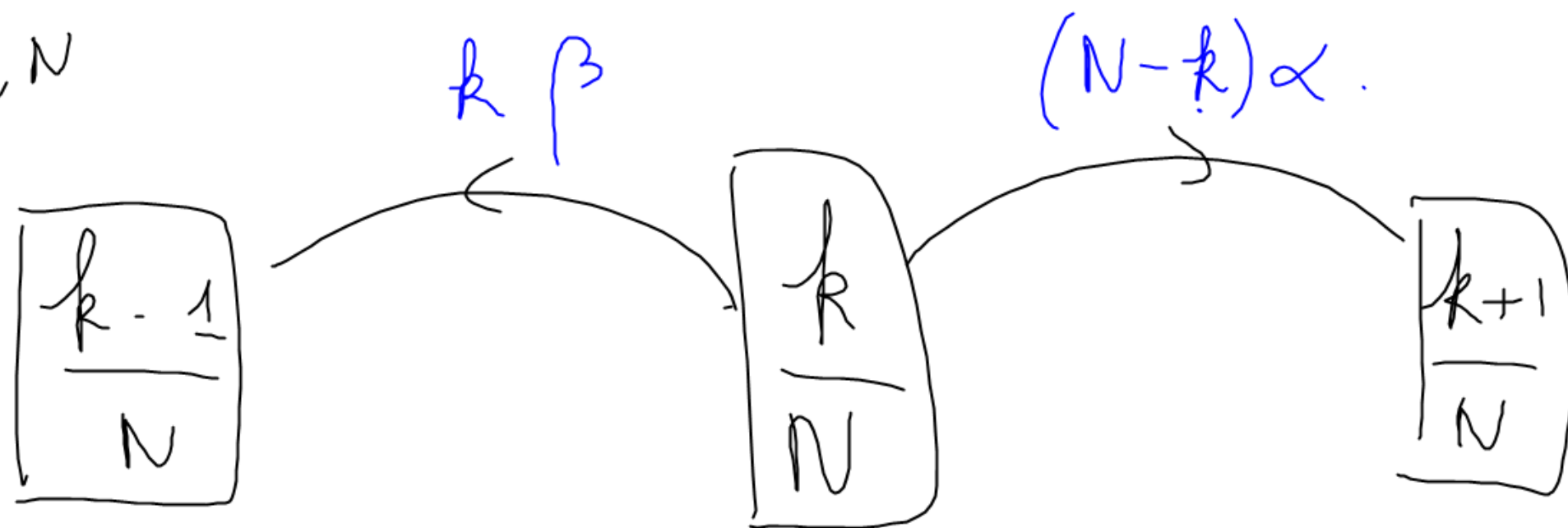
is. $(N - k) \alpha \delta$

Symmetrically,

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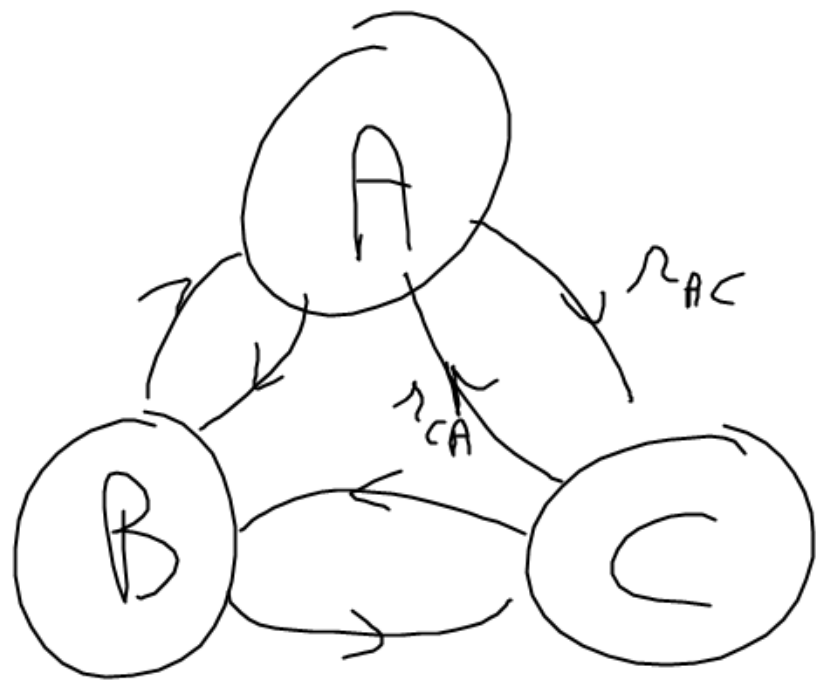
$$P\left(u_N(t+\delta) = \frac{k-1}{N} \mid u_N(t) = \frac{k}{N}\right) = k\beta\delta$$

$\forall k=0, \dots, N$



Reminders of Continuous time Markov chains.

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$$r_{AC} = \lim_{\delta \rightarrow 0} \frac{1}{\delta} P(Y_{t+\delta} = C \mid Y_t = A)$$

$$r_{AC} \geq 0$$

At time $t + \delta$

$$P(Y_{t+\delta} = C \mid Y_t = A) = r_{AC} \delta$$

$$P(Y_{t+\delta} = B \mid Y_t = A) = r_{AB} \delta$$

$$P(Y_{t+\delta} = A \mid Y_t = A) =$$

$$1 - (r_{AC} + r_{AB}) \delta$$

Question : What happens if the number of rows is very large?

Simulation

$$t=0 \quad \frac{\sum \left(\alpha \text{ if } X_0^1 = 0 \right)}{\sum \left(\beta \text{ if } X_0^1 = 1 \right)} \left(1 - X_t^1 \right)$$

$$\frac{\sum \left(\alpha \text{ if } X_0^i = 0 \right)}{\sum \left(\beta \text{ if } X_0^i = 1 \right)} \left(1 - X_t^i \right)$$

one
i.i.d

X_0^i

X_0^N

If $T^2 < T^1$, the Markov Chain $u_N(t)$ is constant on $[0, T^2)$ and $u_N(T^2) = \frac{k+1}{N}$

$$\frac{k}{N} = u_N(0) \xrightarrow{T^1 = E(\beta^k)} \frac{k-1}{N}$$

$$\xrightarrow{T^2 = E(\alpha(N-k))} \frac{k+1}{N}$$

If $T^1 < T^2$, the Markov Chain $u_N(t)$ is constant on $[0, T^1)$ and $u_N(T^1) = \frac{k-1}{N}$

Alternative.

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We can prove that, the 1st jumping time, that is

$\text{Min}(\tau^1, \tau^2)$ follows an exponential distribution

with parameter $k\beta + (N-k)\alpha$.

At this time, u_N jumps to state $\frac{k-1}{N}$ with proba $\frac{k\beta}{k\beta + (N-k)\alpha}$

$$\mathcal{B}\left(\frac{(N-k)\alpha}{k\beta + (N-k)\alpha}\right)$$

Bernoulli n.v.

$\frac{k+1}{N}$ with proba $\frac{(N-k)\alpha}{k\beta + (N-k)\alpha}$

What is the asymptotic as $N \rightarrow \infty$.

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$$U_N(t) = \frac{1}{N} \sum_{i=1}^N X_t^i$$

The strong law of large numbers gives.

$$U_N(t) \xrightarrow{N \rightarrow \infty} \mathbb{E}[X_t^1]$$

$$\begin{aligned} \mathbb{E}[X_t^i] &= 1 \cdot \mathbb{P}(X_t^i = 1) + 0 \cdot \mathbb{P}(X_t^i = 0) \\ &= \mathbb{P}(X_t^1 = 1) = v(1, t) \end{aligned}$$

$$\begin{aligned} v(0, t) &= \mathbb{P}(X_t^1 = 0) \\ &= 1 - v(1, t) \end{aligned}$$

$\delta > 0$ Dynamics of $V(1, t)$

$$V(1, t + \delta) = \underbrace{\mathbb{P}(X_{t+\delta} = 1 \mid X_t = 1)}_{(1 - \beta\delta)} \underbrace{\mathbb{P}(X_t = 1)}_{V(1, t)} + \underbrace{\mathbb{P}(X_{t+\delta} = 1 \mid X_t = 0)}_{\alpha\delta} \underbrace{\mathbb{P}(X_t = 0)}_{V(0, t) = 1 - V(1, t)}$$

$$= V(1, t) + \delta \left[\alpha(1 - V(1, t)) - \beta V(1, t) \right]$$

$$\frac{V(1, t + \delta) - V(1, t)}{\delta} = \alpha(1 - V(1, t)) - \beta V(1, t) \quad \left| \quad \frac{d}{dt} V(1, t) = \alpha(1 - V(1, t)) - \beta V(1, t) \right.$$

Conclusion

$U_N(t)$ asymptotically solves an Ordinary Differential Equation.

$$\frac{1}{\delta} \mathbb{P} \left(U_N(t+\delta) = \frac{k-1}{N} \mid U_N(t) = \frac{k}{N} \right) = \beta \quad k = N \beta \frac{k}{N}$$

$$\frac{1}{\delta} \mathbb{P} \left(U_N(t+\delta) = \frac{k+1}{N} \mid U_N(t) = \frac{k}{N} \right) = \alpha(N-k) = N \alpha \left(1 - \frac{k}{N} \right)$$

$$\frac{d}{dt} \gamma(1, t) = \alpha(1 - \gamma(1, t)) - \beta \gamma(1, t)$$

if $U_N(t)$ has a jump of size $\frac{1}{N}$ at rate $N\alpha(1-x)$

$$\text{---} - \frac{1}{N} \text{---} N\beta x$$

Γ_t can be generalized.

① Consider a dynamical system given as.

$$\dot{x} = \frac{dx(t)}{dt} = \underline{b(x(t))} \quad \text{with } b \geq 0.$$

You can approximate the solution by the continuous time Markov chain $X^N(t)$.

jump of size $\frac{1}{N}$ at rate $Nb(X^N(t))$

$$X^N(t) \xrightarrow[N \rightarrow \infty]{} x(t)$$

② if $\dot{x} = \frac{dx(t)}{dt} = b_1(x(t)) - b_2(x(t))$ $\frac{b_2}{b_1} \geq 0$

$X^N(t)$ is a continuous time Markov chain with

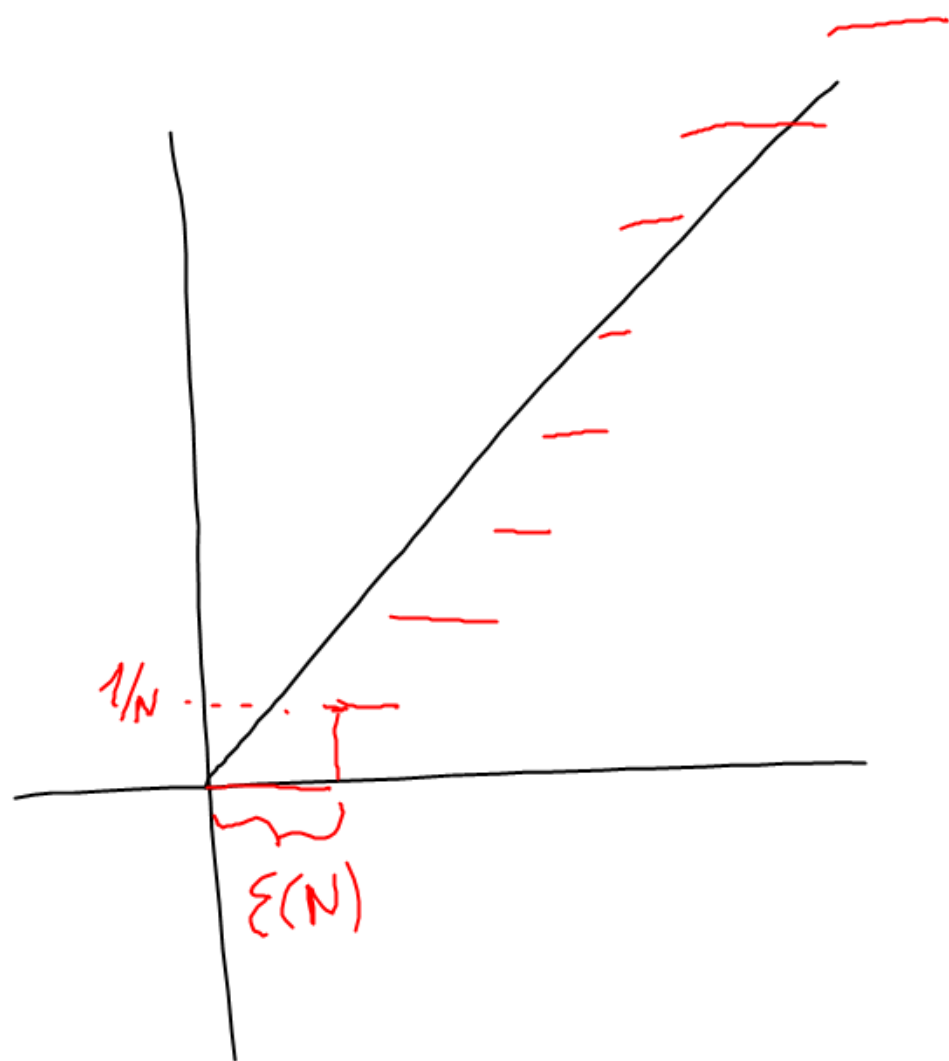
jumps $\frac{1}{N}$ at rate $N b_1(X^N(t))$

$= \frac{1}{N}$ at rate $N b_2(X^N(t))$

$$|X_t^N - x(t)| \xrightarrow[N \rightarrow \infty]{} 0 \quad \text{in probability.}$$

A ~ example

$$b \equiv 1.$$



$$\frac{1}{N} P^N(t)$$

where P^N is a Poisson Process with parameter N , we have

$$\sup_{t \in [0, T]} \left| t - \frac{1}{N} P^N(t) \right| \xrightarrow[N \rightarrow \infty]{} 0 \text{ in probability.}$$

Hodgkin Huxley Dynamics.

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$$C_m \frac{dV_t}{dt} = -g_L (\underbrace{V_t - \bar{E}_L}_{\text{blue}}) - \bar{g}_{Na} \underbrace{(m_t)^3 h_t}_{\text{red}} (\underbrace{V_t - \bar{E}_{Na}}_{\text{blue}}) \\ - \bar{g}_K \underbrace{(n_t)^4}_{\text{red}} (\underbrace{V_t - \bar{E}_K}_{\text{blue}})$$

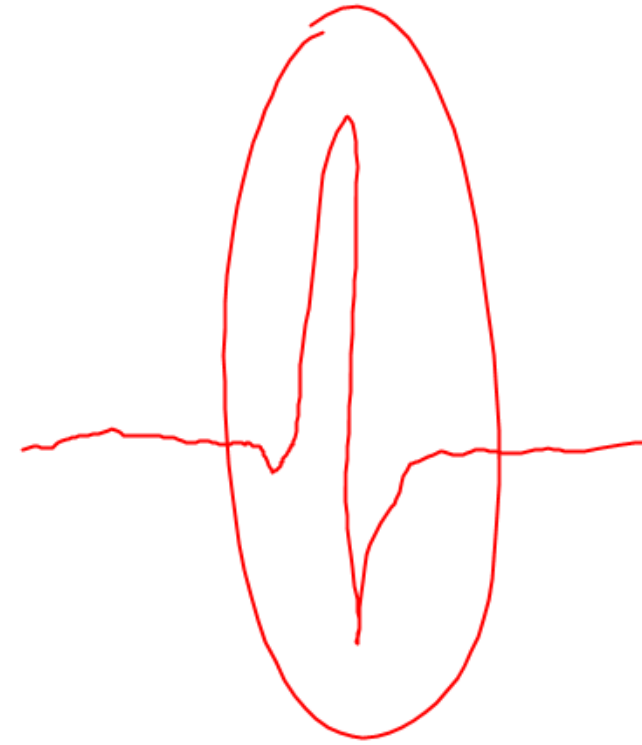
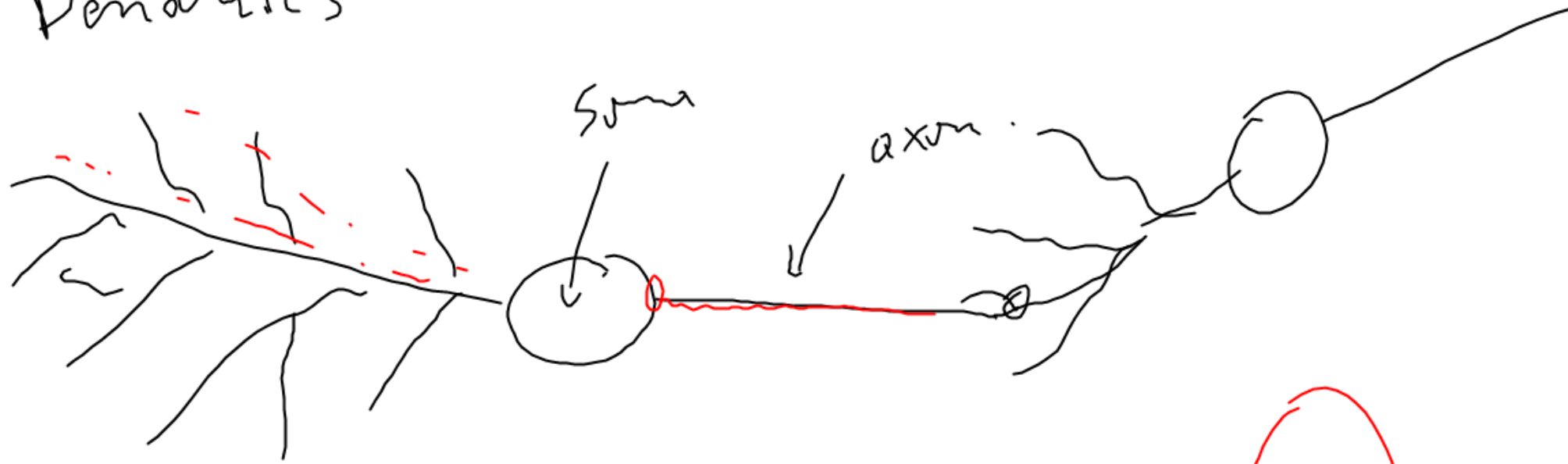
$$\frac{d \underbrace{m_t}_{\text{red}}}{dt} = \alpha_m(V_t) (1 - m_t) - \beta_m(V_t) m_t$$

$$\frac{d \underbrace{h_t}_{\text{red}}}{dt} = \alpha_h(V_t) (1 - h_t) - \beta_h(V_t) h_t$$

$$\frac{d \underbrace{n_t}_{\text{red}}}{dt} = \alpha_n(V_t) (1 - n_t) - \beta_n(V_t) n_t$$

Dendrites

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But a biological neuron has only a finite number of ionic channels.

Starting from Hodgkin Huxley Model, we can construct a PDMP, which is "more realistic" in the sense

that it takes into account the finite number of channels

We consider doors of type m , h and n

N^m

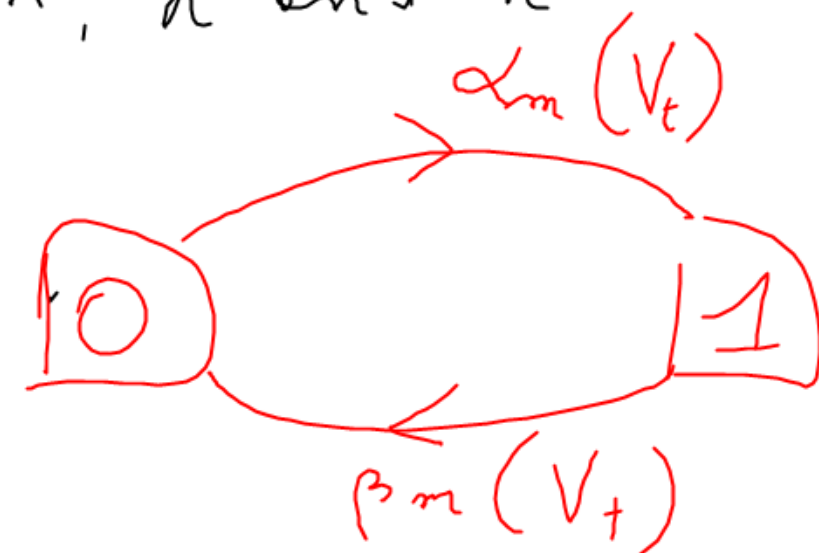
doors of type m

N^h

_____ h

N^n

_____ n



$X_{t,m,i}$

\hat{m}_t = proportion of open doors
of type m

$X_{t,h,i}$
doors of type h .

$X_{t,n,i}$
_____ n

$$\hat{m}_t = \frac{1}{N^m} \sum_{i=1}^{N^m} X_{t,m,i}$$

$$\hat{n}_t = \frac{1}{N^n} \sum_{i=1}^{N^n} X_{t,n,i}$$

$$\hat{h}_t = \frac{1}{N^h} \sum_{i=1}^{N^h} X_{t,h,i}$$

Description of the PDMP.

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The regimes correspond to the values $\left(\frac{k_1^{(m)}}{N^{(m)}}; \frac{k_2^{(d)}}{N^{(d)}}; \frac{k_3^{(m)}}{N^{(m)}} \right)$

The dynamics of (\hat{V}_t) between the jumps is.

$$C_m \frac{d\hat{V}_t}{dt} = -g_L \left(\hat{V}_t - \bar{I}_L \right) - \bar{g}_{Na} \left(\frac{k_1^{(m)}}{N^{(m)}} \right)^3 \frac{k_2^{(d)}}{N^{(d)}} \left(\hat{V}_t - \bar{I}_{Na} \right) - \bar{g}_K \left(\frac{k_3^{(m)}}{N^{(m)}} \right) \left(\hat{V}_t - \bar{I}_K \right)$$

precisely.

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\hat{m}_t

jumps

to $\hat{m}_t - \frac{1}{N^{(m)}}$ at rate

$$N^{(m)} \beta_m(\hat{V}_t) \hat{m}_t$$

to $\hat{m}_t + \frac{1}{N^{(m)}}$ at rate

$$N^{(m)} \alpha_m(\hat{V}_t) (1 - \hat{m}_t)$$

\hat{h}_t

jumps

to

$\hat{h}_t - \frac{1}{N^{(h)}}$ at rate

$$N^{(h)} \beta_h(\hat{V}_t) \hat{h}_t$$

$\hat{h}_t + \frac{1}{N^{(h)}}$ at rate

$$N^{(h)} \alpha_h(\hat{V}_t) (1 - \hat{h}_t)$$

\hat{n}_t

jumps

to

$\hat{n}_t - \frac{1}{N^{(n)}}$ at rate

$$N^{(n)} \beta_n(\hat{V}_t) \hat{n}_t$$

$\hat{n}_t + \frac{1}{N^{(n)}}$ at rate

$$N^{(n)} \alpha_n(\hat{V}_t) (1 - \hat{n}_t)$$

Simulation

1st "Rough" algorithm.

time step δ

During each time step.

$$\hat{V}_{t+\delta} \approx \hat{V}_t + \delta \left[\frac{\partial \hat{V}_t}{\partial t} \right]$$

or I use the exact expression of the solution.

$$+ \hat{m}_{t+\delta} = \hat{m}_t + \frac{1}{N^{(m)}}$$

with proba $N^{(m)} \alpha_m(\hat{V}_t)(1 - \hat{m}_t)\delta$

$$\hat{h}_{t+\delta} = \hat{h}_t + \frac{1}{N^{(h)}}$$

with proba $N^{(m)} \beta_m(\hat{V}_t) \hat{m}_t \delta$

+ same for $\hat{n}_{t+\delta}$

$$\hat{h}_t - \frac{1}{N^{(h)}}$$

with proba

$$N^{(h)} \alpha_h(\hat{V}_t)(1 - \hat{h}_t)\delta$$

$$N^{(h)} \beta_h(\hat{V}_t) \hat{h}_t \delta$$

$$\begin{aligned}
 C_m \frac{d\hat{V}_t}{dt} = & -g_L (\hat{V}_t - E_L) - \overline{g_{Na}} (\hat{m}_t)^3 \hat{h}_t (\hat{V}_t - E_{Na}) \\
 & - \overline{g_K} (\hat{m}_t) (\hat{V}_t - E_K)
 \end{aligned}$$

$$\begin{array}{lcl}
 + \hat{m}_{t+\delta} & = & \hat{m}_t \quad \text{with proba } 1 - \left[N^{(m)} \alpha_m(\hat{V}_t)(1 - \hat{m}_t) + N^{(m)} \beta_m(\hat{V}_t) \hat{m}_t \right] \delta \\
 & & \hat{m}_t + \frac{1}{N^{(m)}} \quad \text{with proba } N^{(m)} \alpha_m(\hat{V}_t)(1 - \hat{m}_t) \delta \\
 & & \hat{m}_t - \frac{1}{N^{(m)}} \quad \text{with proba } N^{(m)} \beta_m(\hat{V}_t) \hat{m}_t \delta
 \end{array}$$

2] Second alg^s with rejection.

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We know that the first time² we observe a change of regime is characterized by.

$$P[\tau \geq t] = \exp\left(-\int_0^t \sum 6 \text{ terms } d\theta\right)$$

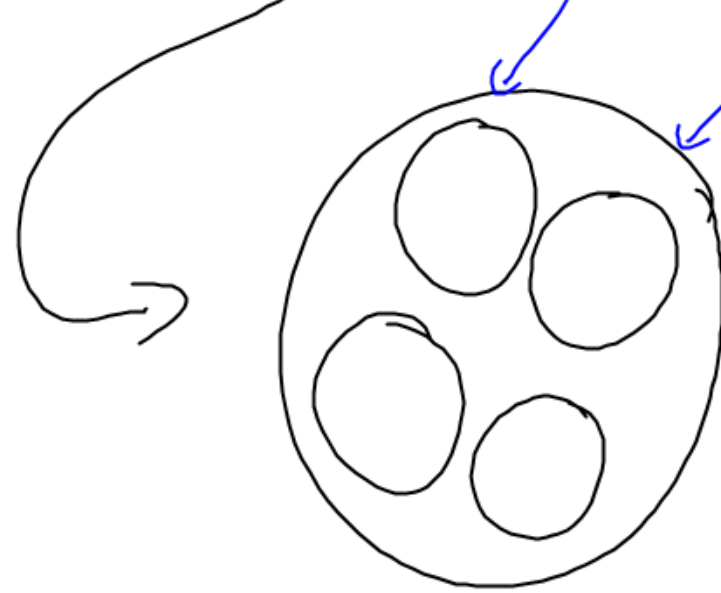
$$N^{(h)} \beta_h(\vec{V}_0) \vec{h}_0 + N^{(h)} \alpha_h(\vec{V}_0) (1 - \vec{h}_0)$$

+ similar for m and n instead of h .

Hodgkin Huxley Dynamics.

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$$C_m \frac{dV_t}{dt} = -g_L (V_t - \bar{E}_L) - \bar{g}_{Na} \underbrace{(m_t)^3 h_t}_{\text{channel}} (V_t - \bar{E}_{Na}) - \bar{g}_K \underbrace{(n_t)^4}_{\text{channel}} (V_t - \bar{E}_K)$$



channel

