

Large deviations in stochastic hybrid systems

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OUTLINE OF TALK

Part I. Stochastic hybrid systems in biology

Part II. Analysis of first passage time problems

Part III. Stochastic ion channels

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Part I. Stochastic hybrid systems in biology

1D STOCHASTIC HYBRID SYSTEM

- Consider the piecewise deterministic system

$$\frac{dx}{dt} = \frac{1}{\tau_x} F_n(x), \quad x \in \mathbb{R}, \quad n = 1, \dots, K$$

- $n(t)$ is a discrete Markov process with transition rates $W_{nm}(x)/\tau_n$.
- Set $\tau_x = 1$ and introduce the small parameter $\epsilon = \tau_n/\tau_x$
- Chapman-Kolmogorov (CK) equation for $p_n(x, t) = \mathbb{E}[p(x, t)\mathbf{1}_{n(t)=n}]$ is

$$\frac{\partial p_n}{\partial t} = -\frac{\partial[F_n(x)p_n(x, t)]}{\partial x} + \frac{1}{\epsilon} \sum_{m=1}^K A_{nm}(x)p_m(x, t)$$

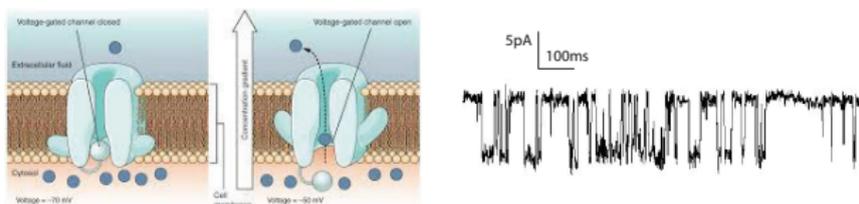
where

$$A_{nm}(x) = W_{nm}(x) - \sum_{k=1}^K W_{kn}(x)\delta_{m,n}.$$

- Assume that there exists a unique stationary density $\rho_n(x)$ with

$$\sum_m A_{nm}(x)\rho_m(x) = 0$$

[A] STOCHASTIC CONDUCTANCE-BASED MODEL



- Suppose a neuron has $n \leq N$ open Na^+ channels and $m \leq M$ open K^+ channels
- Voltage $V(t)$ evolves according to piecewise deterministic dynamics

$$\frac{dv}{dt} = F(v, m, n) \equiv \frac{n}{N} f_{\text{Na}}(v) + \frac{m}{M} f_{\text{K}}(v) - g(v).$$

with $f_i(v) = \bar{g}_i(v_i - v)$

- Assume each channel satisfies the simple kinetic scheme



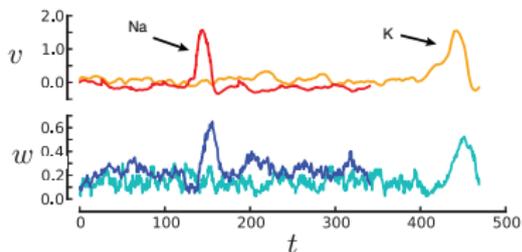
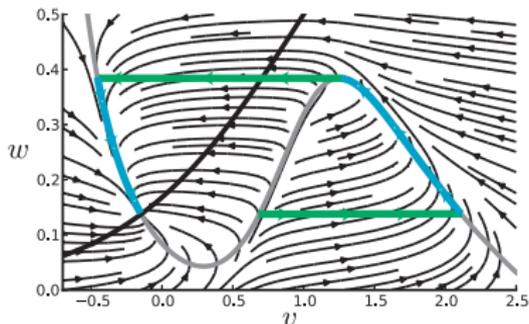
[A] MORRIS-LECAR MODEL OF NEURAL EXCITABILITY

- In the limit of fast Na⁺ channels and infinite K⁺ channels ($M \rightarrow \infty$) we obtain the deterministic Morris-Lecar (ML) model

$$\frac{dv}{dt} = \frac{\alpha_{Na}(v)}{\alpha_{Na}(v) + \beta_{Na}(v)} f_{Na}(v) + w f_K(v) - g(v)$$

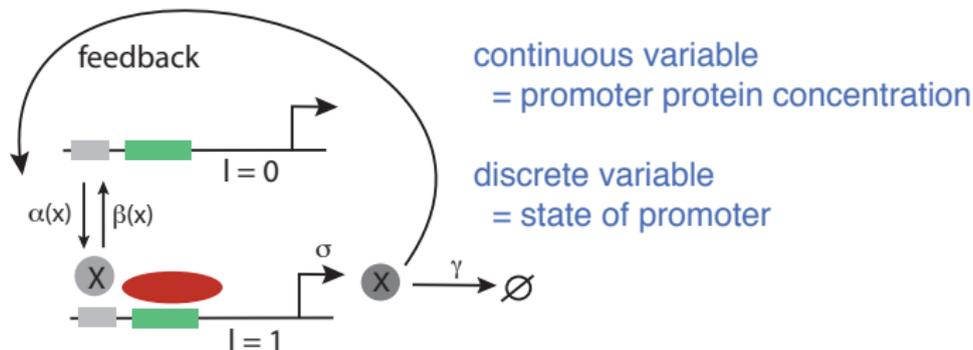
$$\frac{dw}{dt} = \alpha_K(v)(1 - w) - \beta_K(v)w,$$

- Examine excitability using slow/fast analysis
- Require large perturbations (rare events) to induce an action potential



- Ion channel fluctuations can induce spontaneous action potentials.

[B] AUTOREGULATORY GENE NETWORK



- Protein concentration x and promoter state $n \in \{0, 1\}$:

$$\frac{dx}{dt} = F_n(x) = n\sigma + \sigma_0 - x$$

- Promoter transition rates

$$\text{(off)} \xrightleftharpoons[\beta(x)]{\alpha(x)} \text{(on)} \quad \alpha(x) = \alpha_0 x^2, \quad \beta(x) = \beta_0,$$

[B] AUTOREGULATORY GENE NETWORK

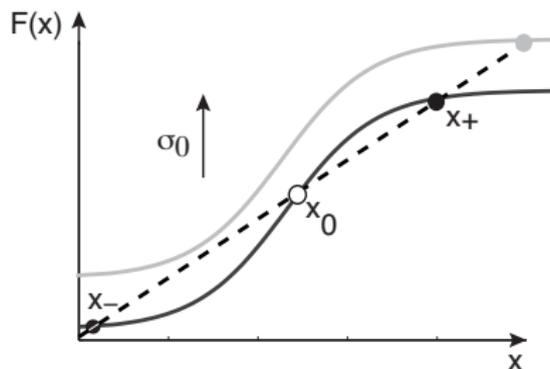
- In the fast switching limit $\varepsilon \rightarrow 0$, we obtain the deterministic equation

$$\dot{x} = \sum_{l=0,1} \rho_l(x) F_l(x) \equiv -x + F(x).$$

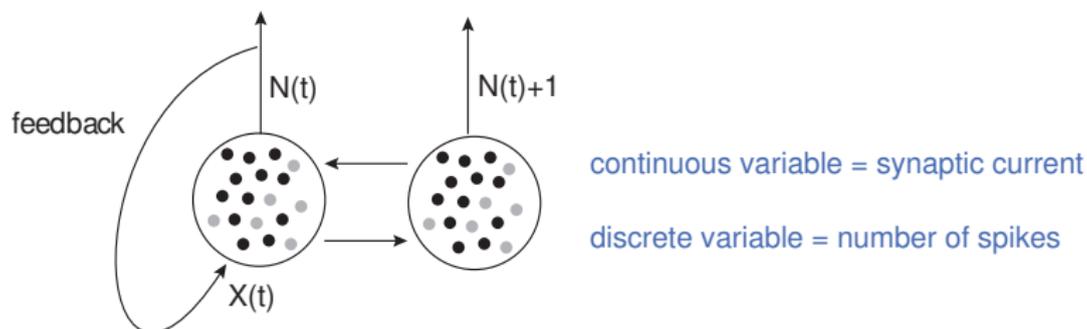
where

$$\rho_0(x) = \frac{\beta(x)}{\alpha(x) + \beta(x)} = 1 - \rho_1(x), \quad F(x) = \sigma_0 + \frac{\sigma \alpha_0 x^2}{\alpha_0 x^2 + \beta_0}.$$

- Hill function $F(x)$ supports bistability



[C] RECURRENT EXCITATORY NEURAL NETWORK



- Consider a large population of excitatory neurons
- $N(t)$ is number of spiking neurons, and $X(t)$ is synaptic current

$$\tau \frac{dx}{dt} = F_n(x) = -x(t) + wn$$

- Birth-death process $N(t) \rightarrow N(t) \pm 1$ with transition rates

$$\Omega_+ = \frac{F(X)}{\tau_a}, \quad \Omega_- = \frac{N(t)}{\tau_a}.$$

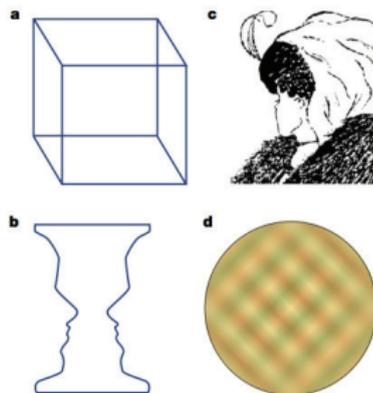
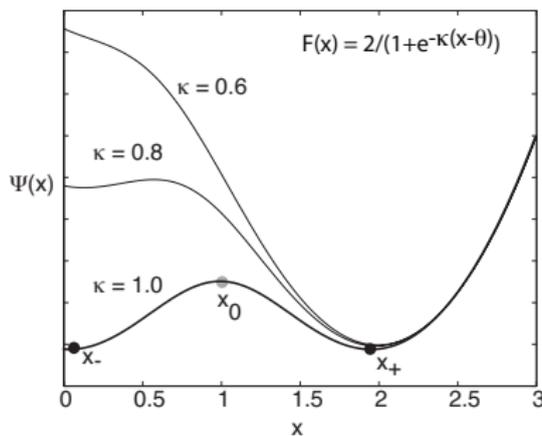
[C] RECURRENT EXCITATORY NEURAL NETWORK

- Stationary density is a Poisson distribution,

$$\rho_n(x) = \frac{[F(x)]^n e^{-F(x)}}{n!},$$

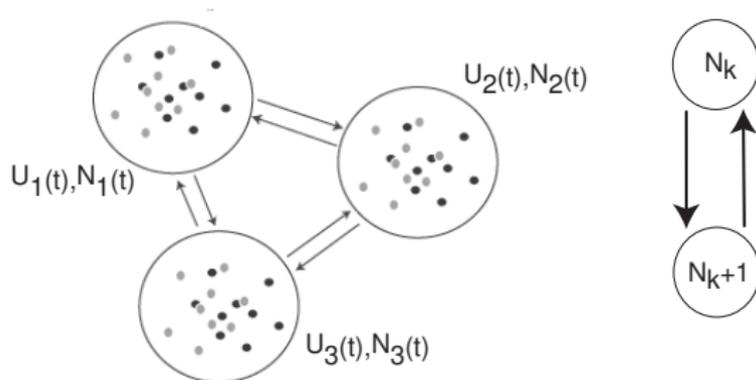
- In the limit $\epsilon \rightarrow 0$, we obtain the mean-field equation

$$\frac{dx}{dt} = \sum_{n=0}^{\infty} F_n(x) \rho_n(x) = -x + wF(x) \equiv V(x) = -\frac{d\Psi}{dx}$$



Ambiguous perception and bistability

[C] EXTEND TO MULTIPLE POPULATIONS



- Consider M homogeneous networks labelled $k = 1, \dots, M$, each containing N identical neurons
- $N_k(t)$ is number of spiking neurons, and $U_k(t)$ is synaptic current

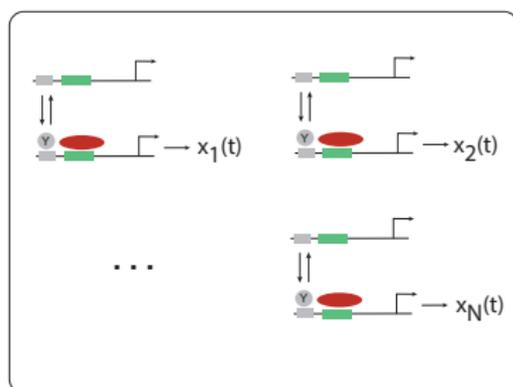
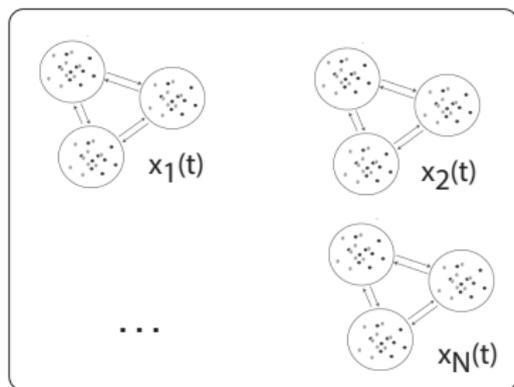
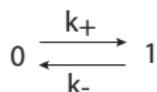
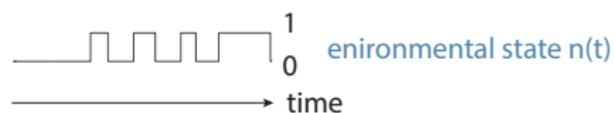
$$\tau \frac{dU_k(t)}{dt} = -U_k(t) + \sum_{k=1}^M w_{kl} N_l(t), \quad N_k(t) \rightarrow N_k(t) \pm 1.$$

with transition rates

$$\Omega_+ = \frac{F(U_k)}{\tau_a}, \quad \Omega_- = \frac{n_k}{\tau_a}.$$

[D] METAPOPOPULATIONS IN RANDOMLY SWITCHING ENVIRONMENTS

- Consider a metapopulation of uncoupled neural or gene networks labeled $\ell = 1, \dots, N$ with state variables $x_\ell(t)$, all being driven by the same external or environmental dichotomous noise $n(t)$



[D] METAPOPOPULATIONS IN RANDOMLY SWITCHING ENVIRONMENTS

- The state $x_\ell(t)$ could be multi-dimensional, deterministic or stochastic. For concreteness we take $x_\ell \in \mathbb{R}$ and

$$\frac{dx_\ell}{dt} = F_{n(t)}(x_\ell)$$

for $\ell = 1, \dots, \mathcal{M}$, with the stochastic variable $n(t)$ independent of ℓ and evolving according to a continuous Markov chain with generator \mathbf{A} .

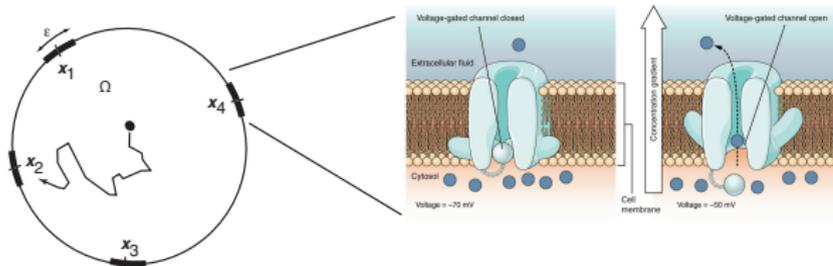
- Take the thermodynamic limit $N \rightarrow \infty$, and let $P(x, t)$ denote the density of networks in state x at time t given a particular realization $\sigma(t) = \{n(\tau), 0 \leq \tau \leq t\}$ of the Markov chain.
- The population density evolves according to the stochastic Liouville equation

$$\frac{\partial}{\partial t} P(x, t) = \left[-\frac{\partial}{\partial x} F_{n(t)}(x) \right] P(x, t),$$

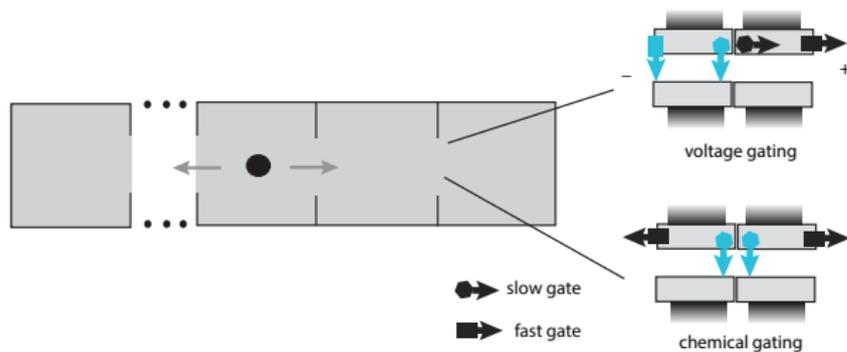
with $P(x, 0) = p_0(x)$.

[D] MANY OTHER EXAMPLES OF SWITCHING ENVIRONMENTS

[A] Diffusion in domains with stochastically gated boundaries



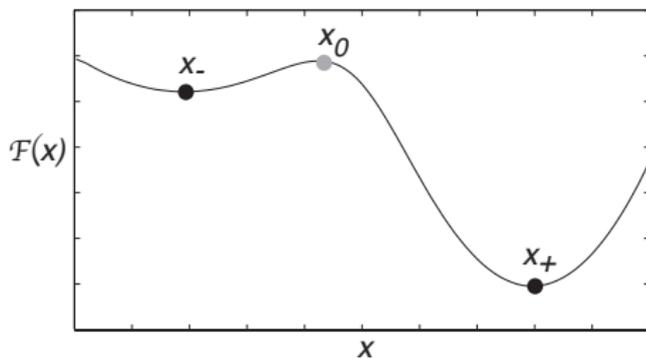
[B] Diffusively coupled cells with stochastically gated gap junctions



Part II. Analysis of first passage time problems

FIRST-PASSAGE TIME (FTP) PROBLEM I

- Suppose that mean field equation is bistable



- Let $T(x)$ be the stochastic time for system to exit at x_0 starting at x
- Introduce the survival probability $\mathbb{P}(x, t)$ that the particle has not yet exited at time t :

$$\mathbb{P}(x, t) = \int_0^{x_0} \sum_n p_n(x', t|x, 0) dx'$$

and define the first passage time (FPT) density

$$f(x, t) = -\frac{\partial \mathbb{P}(x, t)}{\partial t}.$$

FIRST-PASSAGE TIME (FTP) PROBLEM II

- The mean first passage time (MFPT) $\tau(x)$ is

$$\tau(x) = \langle T(x) \rangle \equiv \int_0^\infty f(x, t) t dt = \int_0^\infty \mathbb{P}(x, t) dt,$$

- In limit $\epsilon \rightarrow 0$, expect MFPT to have the Arrhenius-like form

$$\tau(x_-) = \frac{2\pi\Gamma(x_0, x_-)}{\sqrt{|\Phi''(x_0)|\Phi''(x_-)}} e^{[\Phi(x_0) - \Phi(x_-)]/\epsilon}.$$

where $\Phi(x)$ is a **quasipotential** and Γ is a prefactor.

- Determine $\Phi(x)$ using large deviation theory/path integrals/WKB

PATH-INTEGRAL REPRESENTATION (PCB/NEWBY)

- Consider the eigenvalue equation

$$\sum_m [A_{nm}(x) + q\delta_{n,m}F_m(x)] R_m^{(s)}(x, q) = \lambda_s(x, q) R_n^{(s)}(x, q),$$

and let $\xi_m^{(s)}$ be the adjoint eigenvector.

- Perron-Frobenius theorem shows that there exists a real, simple Perron eigenvalue labeled by $s = 0$, say, such that $\lambda_0 > \text{Re}(\lambda_s)$ for all $s > 0$
- Path-integral representation of PDF

$$P(x, \tau) = \int_{x(0)=x_*}^{x(\tau)=x} \exp\left(-\frac{1}{\epsilon} \int_0^\tau [p\dot{x} - \lambda_0(x, p)] dt\right) \mathcal{D}[p] \mathcal{D}[x]$$

VARIATIONAL PRINCIPLE

- Applying steepest descents to path integral yields a variational principle in which optimal paths minimize the action

$$S[x, p] = \int_0^\tau [p\dot{x} - \lambda_0(x, p)] dt.$$

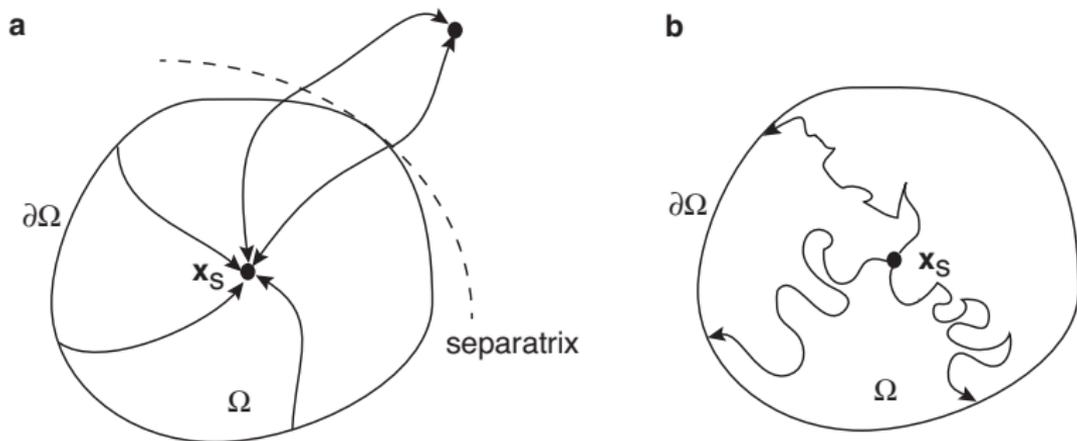
- Hence, we can identify the Perron eigenvalue $\lambda_0(x, p)$ as a Hamiltonian and the optimal paths are solutions to Hamilton's equations

$$\dot{x} = \frac{\partial \mathcal{H}}{\partial p}, \quad \dot{p} = -\frac{\partial \mathcal{H}}{\partial x}, \quad \mathcal{H}(x, p) = \lambda_0(x, p)$$

- Deterministic mean field equations and optimal paths of escape from a metastable state both correspond to zero energy solutions.
- Setting $\lambda_0 = 0$ in eigenvalue equation gives

$$\sum_m [A_{nm}(x) + p\delta_{n,m}F_m(x)] R_m^{(0)}(x, p) = 0$$

"ZERO ENERGY" PATHS



- (a) Deterministic trajectories converging to a stable fixed point x_s .
Boundary of basin of attraction formed by a union of separatrices
- (b) Noise-induced paths of escape

MEAN-FIELD EQUATIONS

- We have the trivial solution $p = 0$ and $R_m^{(0)}(x, 0) = \rho_m(x)$ with

$$\sum_m A_{nm}(x) \rho_m(x) = 0$$

- Differentiating the eigenvalue equation with respect to p and then setting $p = 0$, $\lambda_0 = 0$ shows that

$$\left. \frac{\partial \lambda_0(x, p)}{\partial p} \right|_{p=0} \rho_n(x) = F_n(x) \rho_n(x) + \sum_m A_{nm}(x) \left. \frac{\partial R_m^{(0)}(x, p)}{\partial p} \right|_{p=0}$$

- Summing both sides wrt n and using $\sum_n A_{nm} = 0$,

$$\left. \frac{\partial \lambda_0(x)}{\partial p} \right|_{p=0} = \sum_n F_n(x) \rho_n(x)$$

- Hamilton's equation $\dot{x} = \partial \lambda_0(x, p) / \partial p$ recovers mean-field equation

$$\dot{x} = \sum_n F_n(x) \rho_n(x).$$

MAXIMUM-LIKELIHOOD PATHS OF ESCAPE

- Unique non-trivial solution $p = \mu(x)$ with positive eigenvector $R_m^{(0)}(x, \mu(x)) = \psi_m(x)$:

$$\sum_m [A_{nm}(x) + \mu(x)\delta_{n,m}F_m(x)] \psi_m(x) = 0$$

- Yields quasipotential $\Phi(x)$ with $\Phi'(x) = \mu(x)$ and

$$S[x, p] \equiv \int_{-\infty}^{\tau} [p\dot{x} - \lambda_0(x, p)] dt = \int_{x_s}^x \Phi'(x) dx.$$

- Equivalent to WKB quasipotential obtained using ansatz for quasistationary solutions

$$p_n(x) = R_n(x) \exp\left(-\frac{1}{\epsilon} \Phi(x)\right),$$

Part III. Stochastic ion-channels

REDUCED MORRIS-LECAR MODEL

- Adiabatic approximation: freeze K dynamics and absorb into leak current.
- Let $n, n = 0, \dots, N$ be the number of open sodium channels:

$$\frac{dv}{dt} = F_n(v) \equiv \frac{1}{N}f(v)n - g(v),$$

with $f(v) = g_{\text{Na}}(V_{\text{Na}} - v)$ and $g(v) = -g_{\text{eff}}[V_{\text{eff}} - v] + I_{\text{ext}}$.

- The opening and closing of the ion channels is described by a birth-death process according to

$$n \rightarrow n \pm 1,$$

with rates

$$\omega_+(n) = \alpha(v)(N - n), \quad \omega_-(n) = \beta n$$

- Take

$$\alpha(v) = \beta \exp\left(\frac{2(v - v_1)}{v_2}\right)$$

CHAPMAN-KOLMOGOROV EQUATION

- CK equation is

$$\frac{\partial p_n}{\partial t} = -\frac{\partial[F_n(v)p_n(v, t)]}{\partial v} + \frac{1}{\epsilon} \sum_{n'} A_{nm}(v)p_m(v, t),$$

$$A_{n,n-1} = \omega_+(n-1), A_{nn} = -\omega_+(n) - \omega_-(n), A_{n,n+1} = \omega_-(n+1).$$

- There exists a unique steady state density $\rho_n(v)$ for which

$$\sum_m A_{nm}(v)\rho_m(v) = 0$$

where

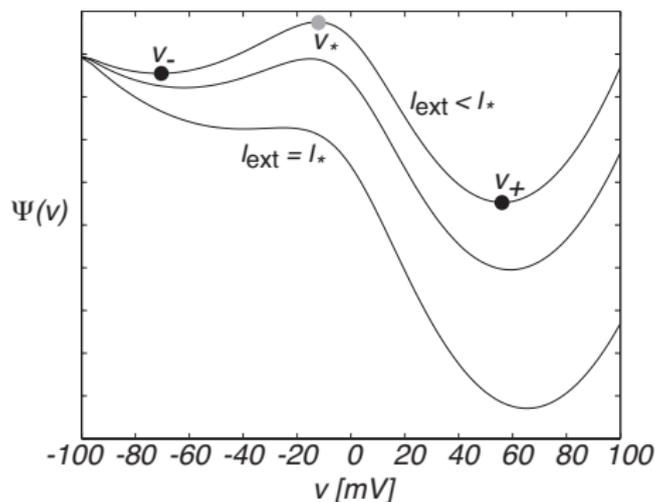
$$\rho_n(v) = \frac{N!}{(N-n)!n!} a(v)^n b(v)^{N-n}, \quad a(v) = \frac{\alpha(v)}{\alpha(v) + \beta}, \quad b(v) = 1 - a(v).$$

MEAN-FIELD LIMIT

- In the limit $\epsilon \rightarrow 0$, we obtain the mean-field equation

$$\frac{dv}{dt} = \sum_n F_n(v) \rho_n(v) = a(v)f(v) - g(v) \equiv -\frac{d\Psi}{dv},$$

- Assume deterministic system operates in a bistable regime



PERRON EIGENVALUE I

- Eigenvalue equation for λ_0 and $R^{(0)} = \psi$:

$$\begin{aligned}(N - n + 1)\alpha\psi_{n-1} - [\lambda_0 + n\beta + (N - n)\alpha]\psi_n + (n + 1)\beta\psi_{n+1} \\ = -p \left(\frac{n}{N}f - g \right) \psi_n\end{aligned}$$

- Consider the trial solution

$$\psi_n(x, p) = \frac{\Lambda(x, p)^n}{(N - n)!n!},$$

- Yields the following equation relating Λ and μ :

$$\frac{n\alpha}{\Lambda} + \Lambda\beta(N - n) - \lambda_0 - n\beta - (N - n)\alpha = -p \left(\frac{n}{N}f - g \right).$$

- Collecting terms independent of n and terms linear in n yields

$$p = -\frac{N}{f(x)} \left(\frac{1}{\Lambda(x, p)} + 1 \right) (\alpha(x) - \beta(x)\Lambda(x, p)),$$

and

$$\lambda_0(x, p) = -N(\alpha(x) - \Lambda(x, p)\beta(x)) - pg(x).$$

PERRON EIGENVALUE II

- Eliminating Λ from these equation gives

$$p = \frac{1}{f(x)} \left(\frac{N\beta(x)}{\lambda_0(x, p) + N\alpha(x) + pg(x)} + 1 \right) (\lambda_0(x, p) + pg(x))$$

- Obtain a quadratic equation for λ_0 :

$$\lambda_0^2 + \sigma(x)\lambda_0 - h(x, p) = 0.$$

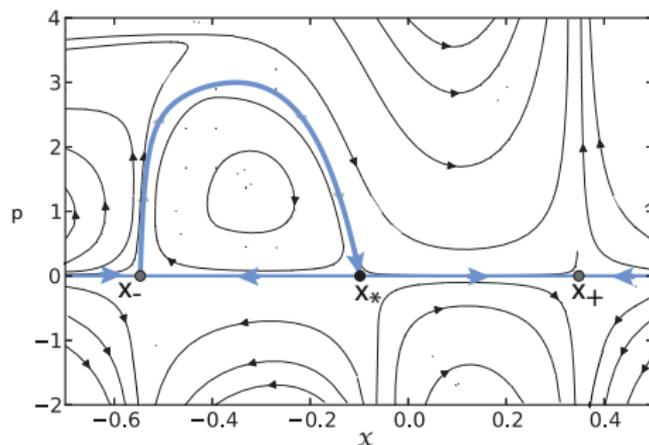
with

$$\sigma(x) = (2g(x) - f(x)) + N(\alpha(x) + \beta(x)),$$

$$h(x, p) = p[-N\beta(x)g(x) + (N\alpha(x) + pg(x))(f(x) - g(x))].$$

- The “zero energy” solutions imply that $h(x, p) = 0$

THE QUASIPOTENTIAL



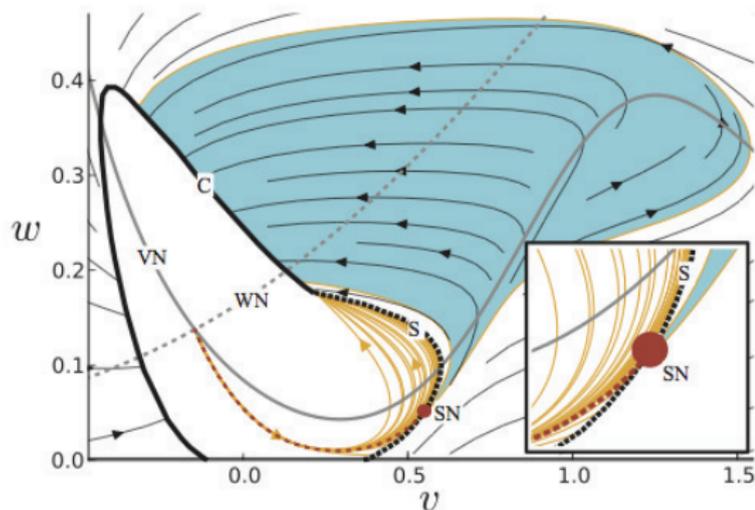
- Non-trivial solution yields

$$p = \mu(x) \equiv N \frac{\alpha(x)f(x) - (\alpha(x) + \beta)g(x)}{g(x)(f(x) - g(x))}.$$

- The corresponding quasipotential Φ is given by

$$\Phi(x) = \int^x \mu(y) dy.$$

STOCHASTIC ML (NEWBY,PCB,KEENER)



Caustic (C),
 v nullcline (VN),
 w nullcline (WN),
metastable separatrix (S),
bottleneck (BN),
caustic formation point (CP)

- Most probable paths of escape dip significantly below the resting value for w , indicating a breakdown of slow/fast decomposition.
- Escape trajectories all pass through a narrow region of state space (bottleneck or stochastic saddle node)
- In spite of no well-defined separatrix for an excitable system, one can formulate an escape problem by determining the mean first passage time to reach the bottleneck from the resting state.

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