# Breakdown of fast-slow analysis in an excitable system with channel noise<sup>1</sup>

#### Paul C Bressloff

Department of Mathematics, University of Utah

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<sup>&</sup>lt;sup>1</sup>Collaborators: Jay Newby and Jim Keener

Part I. Neural excitability

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# THE ACTION POTENTIAL

- Generation and propagation of an action potential based on nonlinearities associated with active membrane conductances.
- Recordings of the current flowing through single ion channels indicate that channels fluctuate rapidly between open and closed states in a stochastic fashion.



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# ION CHANNELS I

- Usually assume that there are a large number of approximately independent channels of each type law of large numbers
- The conductance for an ion channel of type *i*

$$g_i = \bar{g}_i X_i$$

where  $\bar{g}_i$  is the density of channels in the membrane multiplied by the conductance of a single channel and  $X_i$  is the fraction of open channels.



# ION CHANNELS II

• Model kinetics of *X* in terms of voltage-dependent transitions between an open and closed state:

$$\frac{dX}{dt} = \alpha_X(v)(1-X) - \beta_X(v)X,$$

where

$$C(\text{closed}) \underset{\beta_X(v)}{\overset{\alpha_X(v)}{\rightleftharpoons}} O(\text{open}).$$

- From basic thermodynamics, the opening and closing rates are expected to be exponential functions of the voltage.
- Kinetics can be rewritten in the alternative form

$$\tau_X(v)\frac{\mathrm{d}X}{\mathrm{d}t}=a_X(v)-X,$$

where

$$\tau_{\mathrm{X}}(v) = \frac{1}{\alpha_{\mathrm{X}}(v) + \beta_{\mathrm{X}}(v)}, \qquad a_{\mathrm{X}}(v) = \alpha_{\mathrm{X}}(v)\tau_{\mathrm{X}}(v).$$

It follows that *X* approach the asymptotic value  $a_X(v)$  exponentially with time constant  $\tau_X(v)$ ,

MORRIS-LECAR MODEL OF NEURAL EXCITABILITY

• Morris-Lecar (ML) model describes voltage dynamics driven by fast sodium (Na) (or Ca) and slow potassium (*K*) channels

$$\begin{aligned} \frac{dv}{dt} &= a(v)f_{\mathrm{Na}}(v) + wf_{\mathrm{K}}(v) - g(v)\\ \frac{dw}{dt} &= \frac{w_{\infty}(v) - w}{\tau_w(v)}, \end{aligned}$$

- Here *f<sub>i</sub>*(*v*) = *ḡ<sub>i</sub>*(*v<sub>i</sub>* − *v*) and *w* represents the fraction of open K<sup>+</sup> channels.
- The fraction of Na<sup>+</sup> channels is assumed to be in quasi steady-state.
- Analyze the generation of action potentials using a fast/slow analysis

# FAST/SLOW ANALYSIS OF EXCITABILITY

- Fast variable *v* has a cubic-like nullcline and slow variable *w* has a monotonically increasing nullcline
- Assume nullclines have a unique intersection point stable resting state
- Excitable system: sufficiently large perturbations of the resting state result in a time-dependent trajectory taking a prolonged excursion through state space before returning to the resting state the action potential (AP)
- Rapid transition ( $w \approx \text{constant}$ ) during initiation of AP



# FUNDAMENTAL ISSUES

- For fixed *w*, 1D system is bistable with a well-defined threshold for initiation of an AP
- How does one analyze the effects of sodium ion channel fluctuations on spontaneous action potential (SAP) generation? first passage time problem
- Is the fast/slow decomposition still valid when potassium ion channel fluctuations are taken into account?
- How does one formulate spontaneous action potential generation for an excitable system in terms of a first passage time problem there is no well-defined separatrix for escape from the resting state?

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# Part II. First passage time problem for SAP formation

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#### STOCHASTIC ION CHANNEL MODEL

• Let n, n = 0, ..., N be the number of open sodium channels:

$$\frac{dv}{dt} = F(v, n) \equiv \frac{1}{N}f(v)n - g(v),$$
  
with  $f(v) = g_{Na}(V_{Na} - v)$  and  $g(v) = -g_{eff}[V_{eff} - v] + I_{ext}$ .

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

$$n \rightarrow n+1, \quad n \rightarrow n-1$$

at rates

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

Take

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

for constants  $\beta$ ,  $v_1$ ,  $v_2$ .

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# CHAPMAN-KOLMOGOROV EQUATION I

• Introduce the joint probability density

 $Prob\{v(t) \in (v, v + dv), n(t) = n\} = p(v, n, t | v_0, n_0, 0) dv,$ 

• Differential Chapman-Kolmogorov (CK) equation (dropping the explicit dependence on initial conditions)

$$\begin{split} \frac{\partial p}{\partial t} &= -\frac{\partial [F(v,n)p(v,n,t)]}{\partial v} \\ &+ \frac{1}{\epsilon} [\omega_+(v,n-1)p(v,n-1,t) + \omega_-(n+1)p(v,n+1,t) \\ &- (\omega_+(v,n) + \omega_-(n))p(v,n,t)], \end{split}$$

 Introduced small parameter *ε* - opening and closing of sodium channels much faster than relaxation dynamics of voltage

# CHAPMAN-KOLMOGOROV EQUATION II

• Rewrite CK equation in the more compact form

$$\frac{\partial p}{\partial t} = -\frac{\partial [F(v,n)p(v,n,t)]}{\partial v} + \frac{1}{\epsilon} \sum_{n'} A(n,n';v)p(v,n',t),$$

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

• There exists a unique steady state density  $\rho(v, n)$  for which

$$\sum_{m} A(n,m;v)\rho(v,m) = 0$$

where

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

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# Mean-field limit

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

$$\frac{dv}{dt} = \sum_{n} F(v, n) \rho(v, n) = a(v) f(v) - g(v) \equiv -\frac{d\Psi}{dv},$$

• Assume deterministic system operates in a bistable regime



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## FIRST-PASSAGE TIME (FTP) PROBLEM

- Assume particle starts at stable fixed point *v*<sub>-</sub>
- Absorbing boundary conditions at *v*<sub>\*</sub>:

$$p(v_*, n, t) = 0$$
 for all  $n \le k$ 

such that  $F(v_*, n) < 0$ .

- Let *T* be FPT with density f(t)
- Introduce survival probability

$$S(t) = \int_0^{v_*} \sum_n p(v, n, t) dv \equiv \operatorname{Prob}\{t < T\}.$$

• It follows that

$$f(t) = -\frac{dS}{dt} = -\int_0^{v_*} \sum_n \frac{\partial p}{\partial t}(v, n, t) dv = \sum_n F(v_*, n) p(v_*, n, t),$$

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# SPECTRAL PROJECTION METHOD I (Ward 1998, Newby/Keener 2011, PCB/Newby 2013/2014)

• Introduce the inner product

$$\langle f,g\rangle = \sum_{n=0}^{\infty} \int_0^{v_*} f(v,n)g(v,n)dv$$

• Consider eigenfunctions of CK linear opertor  $\hat{L}$ 

$$\widehat{L}\phi_r(v,n) \equiv \frac{d}{dv}(F(v,n)\phi_r(v,n)) - \frac{1}{\epsilon}\sum_m A(n,m;v)\phi_r(v,n)$$
  
=  $\lambda_r\phi_r(v,n),$ 

together with the boundary conditions

$$\phi_r(v_*, n) = 0$$
, for  $n \le k$ 

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# SPECTRAL PROJECTION METHOD II

• Assume the spectrum of  $\hat{L}$  satisfies the following:

(i)  $\hat{L}$  has a complete orthonormal set of eigenfunctions  $\phi_r$ 

(ii) The eigenvalues  $\lambda_r$  all have positive real part and the smallest eigenvalue  $\lambda_0$  is simple. Thus we can introduce the ordering  $0 < \lambda_0 < \text{Re}[\lambda_1] \leq \text{Re}[\lambda_2] \leq \ldots$ 

(iii)  $\lambda_0$  is exponentially small,  $\lambda_0 \sim e^{-C/\epsilon}$ , whereas  $\operatorname{Re}[\lambda_r] = \mathcal{O}(1)$  for  $r \geq 1$ . In particular,  $\lim_{\epsilon \to 0} \lambda_0 = 0$  and  $\lim_{\epsilon \to 0} \phi_0(v, n) = \rho(v, n)$ .

• Introduce the eigenfunction expansion

$$p(v, n, t) = \sum_{r=1}^{N} C_r \mathrm{e}^{-\lambda_r t} \phi_r(v, n),$$

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# SPECTRAL PROJECTION METHOD III

• At large times we have the quasistationary approximation

$$p(v,n,t) \sim C_0 \mathrm{e}^{-\lambda_0 t} \phi_0(v,n).$$

• Hence

$$f(t) \sim \mathrm{e}^{-\lambda_0 t} \sum_n \phi_0(v_*, n) v(v_*, n), \quad \lambda_1 t \gg 1.$$

• It can be shown that

$$\lambda_0 = \frac{\sum_{n=0}^{\infty} F(v_*, n) \phi_0(v_*, n)}{\langle 1, \phi_0 \rangle}.$$

• Hence, (normalized) first passage time density reduces to

 $f(t) \sim \lambda_0 \mathrm{e}^{-\lambda_0 t}$ 

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and  $\langle T \rangle = \int_0^\infty t f(t) dt \sim 1/\lambda_0$ .

### QUASISTATIONARY DENSITY I

Quasistationary density φ<sub>ε</sub> approximates φ<sub>0</sub> up to exponentially small terms at the boundary

$$\widehat{L}\phi_{\epsilon} = 0, \quad \phi_{\epsilon}(v_*, n) = \mathcal{O}(\mathrm{e}^{-C/\epsilon}).$$

Express λ<sub>0</sub> in terms of the quasistationary density φ<sub>ε</sub> by considering the eigenfunctions of the adjoint operator

$$\widehat{L}^{\dagger}\xi_{r}(v,n) \equiv -F(v,n)\frac{d\xi_{r}(v,n)}{dv} - \frac{1}{\epsilon}\sum_{m}A(m,n;v)\xi_{r}(v,m) = \lambda_{r}\xi_{r}(v,n)$$

and the boundary conditions

$$\xi_r(v_*,n)=0, \quad n>k.$$

• The eigenfunctions  $\{\phi_r\}$  and  $\{\xi_r\}$  form a biorthogonal set:

$$\langle \phi_r, \xi_s \rangle \equiv \int_{-\infty}^{v_*} \sum_n \phi_r(v, n) \xi_s(v, n) dv = \delta_{r,s}$$

# QUASISTATIONARY DENSITY II

• Consider the identity

$$\langle \boldsymbol{\phi}_{\epsilon}, \widehat{L}^{\dagger} \boldsymbol{\xi}_{0} \rangle = \lambda_{0} \langle \boldsymbol{\phi}_{\epsilon}, \boldsymbol{\xi}_{0} \rangle.$$

• Integration by parts then gives

$$\lambda_0 = -\frac{\sum_n \phi_\epsilon(v_*, n) \xi_0(v_*, n) F(v_*, n)}{\langle \phi_\epsilon, \xi_0 \rangle}.$$

• Determine  $\phi_{\epsilon}$  using the WKB method and  $\xi_0$  using matched asymptotics (Keener and Newby 2011, Newby and Chapman 2013).

# WKB METHOD I

• Seek a solution of the form

$$\phi_{\epsilon}(v,n) \sim R(v,n) \exp\left(-\frac{\Phi(v)}{\epsilon}\right)$$

• Substitution yields

$$\sum_{m} \left( A(n,m;v) + \Phi'(v)\delta_{n,m}F(v,m) \right) R(v,m) = \epsilon \frac{dF(v,n)R(v,n)}{dv}$$

- Asymptotic expansions  $R \sim R^{(0)} + \epsilon R^{(1)}$  and  $\Phi \sim \Phi_0 + \epsilon \Phi_1$
- The leading order equation is

$$\sum_{m} A(n,m;v) R^{(0)}(v,m) = -\Phi'_0(v) F(v,n) R^{(0)}(v,n).$$

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# WKB METHOD II

- One positive solution is  $R^{(0)} = \rho$ , for which  $\Phi'_0 = 0$ .
- There exists one other positive solution, for which Φ<sub>0</sub>' = 0 at the determistic fixed points (Newby and Keener 2011)
- Next order in the asymptotic expansion:

$$\sum_{m} \bar{A}(n,m;v) R^{(1)}(v,m) = \frac{dF(v,n)R^{(0)}(v,n)}{dv} - \Phi_1'(v)F(v,n)R^{(0)}(v,n)$$
with

$$\bar{A}(n,m;v) = (A(n,m;v) + \Phi'_0(v)\delta_{n,m}F(v,m))$$

• Matrix operator  $\overline{A}(n, m; v)$  has a 1D null space spanned by the positive WKB solution  $R^{(0)}$ 

# WKB METHOD III

• Fredholm Alternative Theorem yields solvability condition

$$\sum_{n} S(v,n) \left[ \frac{dF(v,n)R^{(0)}(v,n)}{dv} - \Phi_{1}'(v)F(v,n)R^{(0)}(v,n) \right] = 0,$$

$$\sum_{n} S(v,n) \left( A(n,m;v) + \Phi'_0(v) \delta_{n,m} F(v,m) \right) = 0.$$

• Given  $R^{(0)}$ , *S* and  $\Phi_0$ , the solvability condition yields the following equation for  $\Phi_1$ :

$$\Phi_1'(v) = \frac{\sum_n S(v,n) [F(v,n)R^{(0)}(v,n)]'}{\sum_n S(v,n)F(v,n)R^{(0)}(v,n)}.$$

# WKB METHOD IV

• Define

$$k(v) = \exp\left(-\int_{v_-}^v \Phi_1'(y)dy\right),\,$$

• To leading order in  $\epsilon$ ,

$$\phi_{\epsilon}(v,n) \sim \mathcal{N}k(v) \exp\left(-\frac{\Phi_0(v)}{\epsilon}\right) R^{(0)}(v,n),$$

Normalization

$$\mathcal{N} = \left[\int_0^{v_*} k(v) \exp\left(-\frac{\Phi_0(v)}{\epsilon}\right) dv\right]^{-1}.$$

• Laplace's method gives

$$\mathcal{N} \sim rac{1}{k(v_-)} \sqrt{rac{|\Phi_0''(v_-)|}{2\pi\epsilon}} \exp\left(rac{\Phi_0(v_-)}{\epsilon}
ight).$$

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# ADJOINT EIGENFUNCTION I

• Leading order adjoint equation

$$\epsilon F(v,n)\frac{d\xi_0(v,n)}{dv} + \sum_m A(m,n;v)\xi_0(v,m) = 0,$$

with boundary conditions

$$\xi_0(v_*, n) = 0, \quad n > k.$$

• Boundary layer: set  $v = v_* - \epsilon z$  and  $Q(z, n) = \xi_0(u_* - \epsilon z)$ :

$$F(v_*, n)\frac{dQ(z, n)}{dz} + \sum_m A(m, n; v_*)Q(z, m) = 0$$

• Inner solution has to be matched with the outer solution  $\xi_0 = 1$ 

$$\lim_{z \to \infty} Q(z, n) = 1$$

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## ADJOINT EIGENFUNCTION II

• Consider the eigenvalue equation

$$\sum_{n} \left( A(n,m;v) - \mu_r(v) \delta_{n,m} v(u,m) \right) S_r(v,n) = 0,$$

 $S_0(v,n) = 1, \ \mu_0 = 0, \quad S_1(v,n) = S(v,n), \ \mu_1(v) = -\Phi_0'(v)$ 

- Zero eigenvalue is degenerate at v = v<sub>\*</sub>, since Φ'<sub>0</sub>(v<sub>\*</sub>) = 0.
- Introduce the generalized eigenfunction expansion

$$Q(z,n) = c_0 + c_1(\widehat{S}(v_*,n) - z) + \sum_{r \ge 2} c_r S_r(v_*,n) e^{-\mu_r(v_*)z}$$

$$\sum_{n} A(n,m;v_*)\widehat{S}(v_*,n) = -F(v_*,m).$$

# ADJOINT EIGENFUNCTION III

• Eliminate secular term  $-c_1 z$  using an alternative scaling in the boundary layer of the form (Newby and Chapman 2013)

$$x = x_* + \epsilon^{1/2} z$$

• Find that

$$c_1 \sim \sqrt{\frac{2|\Phi_0''(v_*)|}{\pi}} + \mathcal{O}(\epsilon^{1/2}), \quad c_r = \mathcal{O}(\epsilon^{1/2}) \text{ for } r \ge 2$$

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• Only need  $c_1$ , since the quasistationary approximation  $\phi_{\epsilon}$  is proportional to  $R^{(0)}$ , which is orthogonal to all eigenvectors  $S_r$ ,  $r \neq 1$ .

# PRINCIPLE EIGENVALUE

• Principal eigenvalue is

$$\begin{aligned} \lambda_0 &\sim \quad \frac{1}{\pi} \frac{k(v_*)B(v_*)}{k(v_-)} \sqrt{\Phi_0''(v_-)|\Phi_0''(v_*)|} \exp\left(-\frac{\Phi_0(v_*) - \Phi_0(v_-)}{\epsilon}\right). \\ B(v_*) &= -\sum_n \widehat{S}(v_*, n) v(u_*, n) \rho(v_*, n) \end{aligned}$$

$$\sum_{m} A(n,m;v)R^{(0)}(v,m) = -\Phi'_{0}(v)F(v,n)R^{(0)}(v,n).$$
$$\sum_{n} S(v,n) \left(A(n,m;v) + \Phi'_{0}(v)\delta_{n,m}F(v,m)\right) = 0.$$
$$\sum_{n} A(n,m;v_{*})\widehat{S}(v_{*},n) = -F(v_{*},m).$$

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# CALCULATION OF PRINCIPAL EIGENALUE

• Find eigenfunction  $R^{(0)}(v, n)$  and eigenvalue  $\mu(v) = -\Phi'_0(v)$ .

$$R^{(0)}(v,n) = \frac{N!}{(N-n)!n!} \frac{(f(v) - g(v))^{N-n} g(v)^n}{f(v)^N}$$

and

$$\mu(v) = N \frac{\alpha(v)f(v) - (\alpha(v) + \beta)g(v)}{g(v)(f(v) - g(v))},$$

**②** Calculate the prefactor k(v) from the null eigenfunction

$$S(v,n) = \left(\frac{b(v)g(v)}{a(v)(f(v) - g(v)))}\right)^n$$

• Calculate the generalized eigenfunction  $\widehat{S}(v^*, n)$ :

$$\widehat{S}(v^*, n) = \frac{f(v_*)}{N(\alpha(v_*) + \beta)}n.$$

• Calculate the factor B(v\*):

$$B(v_*) = \frac{f(v_*)^2 \alpha(v_*)\beta}{N(\alpha(v_*) + \beta)^2}$$

COMPARISON WITH NUMERICS (KEENER AND NEWBY 2011)

- Compare analytical results with Monte Carlo simulations
- Good agreement in super threshold and sub threshold regimes
- A corresponding diffusion approximation breaks down in the sub threshold regime



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Part III. Breakdown of fast/slow analysis

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#### STOCHASTIC MORRIS-LECAR MODEL

• Take  $n \leq N$  open Na<sup>+</sup> channels and  $m \leq M$  open K<sup>+</sup> channels:

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

• Each channel satisfies the kinetic scheme

$$C \stackrel{\alpha_i(v)}{\underset{\beta_i(v)}{\leftrightarrow}} O, \quad i = \text{Na}, \text{ K},$$

- The Na<sup>+</sup> channels fast relative to voltage and K<sup>+</sup> dynamics.
- Chapman–Kolmogorov (CK) equation,

$$\frac{\partial p}{\partial t} = -\frac{\partial (Fp)}{\partial v} + \mathbb{L}_{K}p + \mathbb{L}_{Na}p.$$

• The jump operators  $\mathbb{L}_j$ , j = Na, K, are defined according to

$$\mathbb{L}_j = (\mathbb{E}_n^+ - 1)\omega_j^+(n, v) + (\mathbb{E}_n^- - 1)\omega_j^-(n, v),$$

with  $\mathbb{E}_n^{\pm} f(n) = f(n \pm 1)$ ,  $\omega_j^-(n, v) = n\beta_j$  and  $\omega_j^+(n, v) = (N - n)\alpha_j(v)$ .

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# $K^+$ channel fluctuations can induce SAPs

- The deterministic ML model is recovered in the limit  $\beta_{Na} \to \infty$ ,  $M \to \infty$  with  $\lambda_M = \beta_{Na}/M$  fixed.
- Find spontaneous SAPs can be generated for finite *M* and/or finite  $\beta_{Na}$



# SMALL NOISE LIMIT

• Introduce a small parameter  $\epsilon \ll 1$  such that (in dimensionless units)

$$\beta_{Na}^{-1} = \epsilon, \quad M^{-1} = \lambda_M \epsilon,$$

- Set w = m/M and write  $(m \pm 1)/M = w \pm M^{-1}$
- Perturbation expansion in  $\epsilon$  combines a **system size expansion** with a **slow/fast analysis**
- We would like to determine the most probable or optimal paths of escape from the resting state in the (v, w)-plane for small ε
- For chemical master equations, the **quasipotential** of the WKB approximation satisfies a **Hamilton-Jacobi equation** the optimal paths given by solutions to an effective **Hamiltonian dynamical system**
- There is an underlying **variational principle** derived using **large deviation theory** or **path-integrals**

#### OPTIMAL PATHS



• (a) Deterministic trajectories converging to a stable fixed point **x**<sub>S</sub>. Boundary of basin of attraction formed by a union of separatrices

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• (b) Noise-induced paths of escape

# WKB APPROXIMATION

• Introduce quasistationary solution of the form

$$\phi_{\epsilon}(v, w, n) = R(n|v, w) \exp\left(-\frac{1}{\epsilon}\Phi(v, w)\right),$$

where  $\Phi(v, w)$  is the **quasipotential** 

• To leading order,

 $\left[\mathbb{L}_{Na}+p_{v}+h(v,w,p_{w})\right]R(n|v,w)=0,$ 

where

$$p_v = \frac{\partial \Phi}{\partial v}, \quad p_w = \frac{\partial \Phi}{\partial w}$$

and

$$h(v,w,p_w) = \frac{\beta_K}{M\lambda_M} \left[ (e^{-\lambda_M p_w} - 1)\omega_K^+(Mw,v) + (e^{\lambda_M p_w} - 1)\omega_K^-(Mw,v) \right]$$

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# HAMILTON-JACOBI EQUATION

• Introducing the ansatz

$$R_n(v,w) = \frac{\Lambda(v,w)^n}{(N-n)!n!},$$

yields a **Hamilton-Jacobi** equation for  $\Phi$ :

$$0 = \mathcal{H}(v, w, p_w, p_v) \equiv (a(v)f_{Na}(v) + g(v))p_v + h(v, w, p_w) - \frac{b(v)}{N} \left[ ((2g(v) + f_{Na}(v))p_vh(v, w, p_w) + (f_{Na}(v) + g(v))g(v)p_v^2 + h(v, w, p_w)^2 \right) \right]$$

• Solve for Φ using method of characteristics. Satisfy Hamilton's equations

$$\dot{\mathbf{x}} = \nabla_{\mathbf{p}} \mathcal{H}(\mathbf{x}, \mathbf{p}), \quad \dot{\mathbf{p}} = -\nabla_{\mathbf{x}} \mathcal{H}(\mathbf{x}, \mathbf{p}).$$

for  $\mathbf{x} = (v, w)$  and  $\mathbf{p} = (p_v, p_w)$ 

• Interpret  $\Phi(t)$  as the **action** with  $\dot{\Phi}(t) = \mathbf{p}(t) \cdot \dot{\mathbf{x}}(t)$ , is a strictly increasing function of *t*, and the **quasipotential** is given by  $\Phi(v, w) = \Phi(t)$  at the point  $(v, w) = \mathbf{x}(t)$ .

# RESULTS I: SOLUTIONS OF HJ EQUATION



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

# **RESULTS II**

- Φ takes the shape of a potential well in a neighborhood of resting state with convex level curves.
- Once Φ reaches a threshold, a **caustic** is formed along which every point is connected to two equally likely metastable trajectories
- Most probable paths of escape dip significantly below the resting value for *w*, indicating a **breakdown** of the deterministic slow/fast decomposition.
- Escape trajectories pass through a narrow region of state space that acts like a **bottleneck or stochastic saddle node**
- Hence, although there is no well-defined **separatrix** for an excitable system, one can formulate an escape problem by determining the MFPT to reach the bottleneck from the resting state.
- Curves that don't pass through SN are bounded by a curve (S) that acts like a **stochastic separatrix**.

# **RESULTS III**

- Identify SAP trajectories as those metastable trajectories that cross the separatrix.
- SAP trajectories begin at the fixed point as a single trajectory and then fan out just before reaching the metastable separatrix.
- Result confirmed by Monte-Carlo simulations



# SUMMARY OF RESULTS

- Fluctuations in the slow recovery dynamics of K<sup>+</sup> channels significantly affect spontaneous activity in the ML model.
- The maximum likelihood trajectory during initiation of a SAP drops below the voltage nullcline so that *w* is not constant breakdown of fast/slow analysis
- SAP initiation mechanisms is a burst of simultaneously-closing K<sup>+</sup> channels that causes *v* to increase.
- Constraining the paths by fixing *w* alters the effective energy barrier for SAP initiation, which significantly affects determination of the spontaneous firing rate.
- There is an effective metastable separatrix that can be used to formulate an FPT problem for an excitable system

Part IV. Dendritic NMDA spikes

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# NMDA SPIKES IN THIN DENDRITES

- A pyramidal neuron has a thick apical dendrite and various thin dendrites. The latter support the initiation of dendritic NMDA spikes
- A strong glutamatergic input can trigger a dendritic plateau potential of duration 100 msec.
- The plateau potential consists of several dendritic conductances, the most predominant being due to NDMAR channels. Pharmacologically blocking *Na* and *Ca* channels reveals the pure dendritic NMDA spike



#### VOLTAGE CHARACTERISTICS OF DENDRITIC MEMBRANE

- Following strong stimulation and removal of the Mg<sup>+</sup> block, the maximum conductance *g*<sub>max</sub> of the NMDARs is high so that the N-shaped I-V curve has only a stable depolarized fixed point.
- As *g*<sub>max</sub> decreases due to glutamate unbinding, two additional fixed points arise via an SN bifurcation bistability
- As  $g_{\max}$  is further reduced, a second SN bifurcation results in a rapid return to the resting state.



#### DETERMINISTIC CONDUCTANCE-BASED MODEL

• The dendritic voltage *v* evolves as

 $C\frac{dv}{dt} = g_x(t)a_x(v)(V_x-v) + \bar{g}_ya_y(v)(V_y-v) + \bar{g}_L(V_L-v),$ 

where x, y label NMDA and Na channels, respectively, and C is the membrane capacitance.

• The glutamate-bound NMDA receptors act like sodium channels, with non-ohmic voltage-dependent conductances

$$a_r(v) = \frac{1}{1 + \mathrm{e}^{-\gamma_r(v - \kappa_r)}}, \quad r = x, y.$$

Here  $a_r(v)$  represents the fraction of open ion channels of type r in the limit of fast channel kinetic

• The time-dependent deactivation of the NMDA channels following the binding of glutamate is incorporated by taking the maximal conductance of the NMDA receptors to be a slowly decaying function of time *t*:

$$g_x(t)=\bar{g}_x\mathrm{e}^{-t/\tau},$$

#### STOCHASTIC MODEL

• Fix  $g_x$  and set C = 1. Have a stochastic hybrid system

$$\frac{dV}{dt} = I(V, n_x, n_Y) \equiv \bar{g}_x \frac{n_x(t)}{N} (V_x - V) + \bar{g}_y \frac{n_y(t)}{N} (V_y - V) + \bar{g}_L (V_L - V),$$

• Only holds between jumps in the discrete random variables *n<sub>x</sub>*, *n<sub>y</sub>*: birth-death processes

$$n_r \xrightarrow[]{\omega_+^r(n_r,V)/\epsilon} n_r + 1, \quad n_r \xrightarrow[]{\omega_-^r(n_r)/\epsilon} n_r - 1.$$

• The transition rates are

$$\omega_+^r(n_r, V) = \alpha_r(V)(N - n_r), \quad \omega_-^r(n_r) = \beta_r n_r,$$

after rescaling  $\alpha_i$ ,  $\beta_i$  by a factor  $1/\epsilon$ .

• Introduce the associated probability density

 $p(v, n_x, n_y, t)dv = \mathbb{P}[v \le V(t) \le v + dv, n_x(t) = n_x, n_y(t) = n_y],$ 

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# STOCHASTIC MODEL II

• The differential Chapman-Kolmogorov (CK) equation is

$$\frac{\partial p}{\partial t} = -\frac{\partial}{\partial v} \left[ I(v, n_x, n_y) p(v, n_x, n_y, t) \right] + \frac{1}{\epsilon} \mathbb{L} p(v, n_x, n_y, t),$$

where  $\mathbb{L} = \mathbb{L}_x + \mathbb{L}_y$ ,

 $\mathbb{L}_{r} = (\mathbb{E}_{r}^{+} - 1)\omega_{-}^{r}(n_{r}) + (\mathbb{E}_{r}^{-} - 1)\omega_{+}^{r}(n_{r}, V).$ 

and  $\mathbb{E}_r^{\pm}$  are ladder operators defined according to

 $\mathbb{E}_r^{\pm}F(n_r)=F(n_r\pm 1)$ 

# STOCHASTIC MODEL III

• Can rewrite CK equation as

$$\frac{\partial p}{\partial t} = -\frac{\partial}{\partial v} \left[ I(v, \mathbf{n}) p(v, \mathbf{n}, t) \right] + \frac{1}{\epsilon} \sum_{\mathbf{m}} A(\mathbf{n}, \mathbf{m}; v) p(v, \mathbf{m}),$$

where  $\mathbf{n} = (n_x, n_y)$  and the matrix *A* has the non–zero entries

$$A(n_x, n_y, n_x - 1, n_y; v) = \omega_+^x (n_x - 1, v),$$
  

$$A(n_x, n_y, n_x, n_y - 1; v) = \omega_+^y (n_y - 1, v),$$
  

$$A(n_x, n_y, n_x + 1, n_y; v) = \omega_-^x (n_x + 1),$$
  

$$A(n_x, n_y, n_x, n_y + 1; v) = \omega_-^y (n_y + 1),$$
  

$$A(n_x, n_y, n_x, n_y; v) = - \left[ \omega_-^x (n_x) + \omega_-^y (n_y) + \omega_+^x (n_x, v) + \omega_+^y (n_y, v) \right].$$

• Note that 
$$\sum_{\mathbf{m}} \equiv \sum_{m_x=0}^{N} \sum_{m_y=0}^{N}$$
.

# STOCHASTIC MODEL IV

• The transition matrix satisfies

$$\sum_{\mathbf{n}} A(\mathbf{n}, \mathbf{m}; v) = 0, \quad \sum_{\mathbf{m}} A(\mathbf{n}, \mathbf{m}; v) \rho(v, \mathbf{m}) = 0.$$

• The steady-state density  $\rho$  is

$$\rho(v, n_x, n_y) = \prod_{r=x,y} \frac{N!}{(N-n_r)!n_r!} a_r(v)^{n_r} b_r(v)^{N-n_r}$$

$$a_r(v) = \frac{\alpha_r(v)}{\alpha_r(v) + \beta_r}, \ b_r(v) = \frac{\beta_r}{\alpha_r(v) + \beta_r}.$$

• In the deterministic limit  $\epsilon \rightarrow 0$ 

$$\frac{dv}{dt} = F(v) = \frac{\bar{n}_x}{N} f_x(v) + \frac{\bar{n}_y}{N} f_y(v) - g(v) \equiv -\frac{d\Psi}{dv}$$

where  $\bar{n}_r$  is the mean number of open channels,

$$\bar{n}_r = \sum_{n_x=1}^N \sum_{n_y=1}^N n_r \rho(v, n_x, n_y) = Na_r(v).$$

# WKB APPROXIMATION

• Seek a WKB solution of the form

$$\varphi_{\epsilon}(v, \mathbf{n}) = R(v, \mathbf{n}) \exp\left(-\frac{\Phi(v)}{\epsilon}\right),$$

where  $\Phi(v)$  is the quasipotential.

• Substituting into the equation  $\widehat{L}\phi_{\epsilon} = 0$ , we have

$$\sum_{\mathbf{m}} \left( A(\mathbf{n}\,m;v) + \Phi'(v)\delta_{\mathbf{n},\mathbf{m}}I(v,\mathbf{m}) \right) R(v,\mathbf{m}) = \epsilon \frac{dI(v,\mathbf{n})R(v,\mathbf{n})}{dv},$$

where  $\Phi' = d\Phi/dv$ .

• Introducing the asymptotic expansions  $R \sim R^{(0)} + \epsilon R^{(1)}$  and  $\Phi \sim \Phi_0 + \epsilon \Phi_1$ , the leading order equation is

$$\sum_{\mathbf{m}} A(\mathbf{n}, \mathbf{m}; v) R^{(0)}(v, \mathbf{m}) = -\Phi'_0(v) I(v, \mathbf{n}) R^{(0)}(v, \mathbf{n}).$$

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# CALCULATION OF THE QUASIPOTENTIAL

• Try a normalized positive solution of the form

$$R^{(0)}(v,\mathbf{n}) = \frac{1}{[1+\Lambda_x(v)]^N} \frac{1}{[1+\Lambda_y(v)]^N} \frac{N! [\Lambda_x(v)]^{n_x}}{(N-n_x)! n_x!} \cdot \frac{N! [\Lambda_y(v)]^{n_y}}{(N-n_y)! n_y!},$$
  
$$\sum_{x \in \mathcal{R}^{(0)}(v,\mathbf{n}) = 1 \text{ for all } v} R^{(0)}(v,\mathbf{n}) = 1 \text{ for all } v.$$

with  $\sum_{n_x,n_y} R^{(0)}(v, \mathbf{n}) = 1$  for all v

- Substitute into zeroth order equation and collect terms independent of **n** and terms linear in *n<sub>x</sub>*, *n<sub>y</sub>*
- Three equations in three unknowns  $\Lambda_x, \Lambda_y, \Phi_0$ .
- Find that  $\Lambda_x$  satisfies a quadratic with

$$\Lambda_x^{\pm} = -\frac{b}{2a} \pm \frac{\sqrt{b^2 - 4ac}}{2a}, \quad \Lambda_y = \frac{\alpha_x + \alpha_y - \beta_x \Lambda_x}{\beta_y}$$

with

$$a = \beta_x (f_x + f_y), \quad c = -(\alpha_x + \alpha_y) f_y$$
  
$$b = -(\alpha_x + \alpha_y) (f_x + f_y) + \beta_x f_y - f_x \beta_y$$

• Only one root yields positive solution

EFFECT OF GLUTAMATE UNBINDING ON QUASIPOTENTIAL

- MFPT for spike initiation calculated using similar methods to ML model
- Need to account for glutamate unbinding to determine mean duration of a spike
- Quasipotential is a function of slowly varying maximum NMDA conductance  $g_x(t) = \bar{g}_x e^{-t/\tau}$
- Using an adiabatic approximation, we can take  $\Phi$  to vary slowly with time *t*



# STOCHASTIC PHASE-PLANE ANALYSIS

• With glutamate unbinding have a planar system

$$\begin{aligned} \frac{dv}{dt} &= ha_x(v)(V_x - v)/\tau_x + a_y(v)(V_y - v)/\tau_y + (V_L - v)/\tau_L \equiv J(v, h), \\ \frac{dh}{dt} &= -\frac{h}{\tau}, \quad h(0) = 1. \end{aligned}$$

- Assume a separation of time-scales  $\tau_j \ll \tau$  and use an adiabatic approximation.
- Let  $\lambda_0(t)$  be the MFPT to jump from RH to LH branch given  $h(t) = e^{-t/\tau}$ .



PHASE-PLANE ANALYSIS

- Let  $P(s) = \mathbb{P}(T > s)$  where *T* is the random spike duration.
- The probability that a spike terminates in an infinitesimal time interval  $\delta s$  is  $\lambda_0(s)\delta s$ , so that

$$P(s+\delta s) = P(s)(1-\lambda_0(s)\delta s).$$

• Taking  $\delta s \to 0$  and integrating gives  $P(s) = \exp\left(-\int_0^s \lambda_0(t)dt\right)$ , and

