

# Dynamical systems in neuroscience

Pacific Northwest Computational Neuroscience Connection  
October 1-2, 2010

# What do I mean by a *dynamical system*?

- Set of state *variables*
- Law that governs *evolution* of state variables in time
- Often takes the form of *differential equations*

ex:  $\frac{dV}{dt} = V(a - V)(V - 1) - w + I$

$$\frac{dw}{dt} = bV - cw$$

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ex:  $\frac{dV}{dt} = V(a - V)(V - 1) - w + I$  state variables  
 $\frac{dw}{dt} = bV - cw$  parameters

# Dynamical systems arise as models for single neurons

ex: Hodgkin-Huxley equations

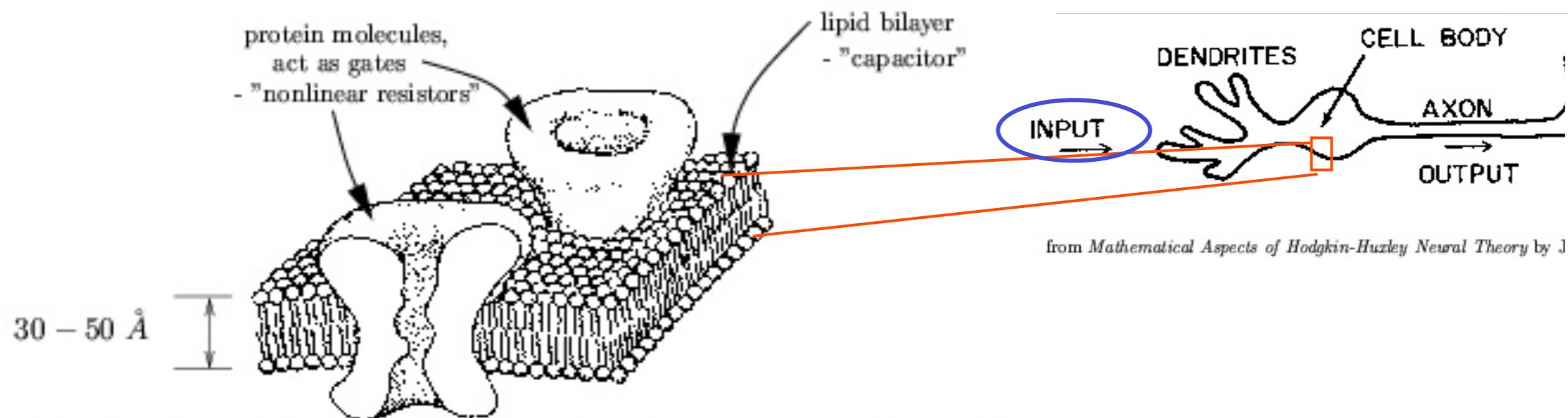
$$C \frac{dV}{dt} = I - g_K n^4 (V - E_K) - g_{Na} m^3 h (V - E_{Na}) - g_L (V - E_L)$$

$$\frac{dn}{dt} = (n_\infty(V) - n) / \tau_n(V)$$

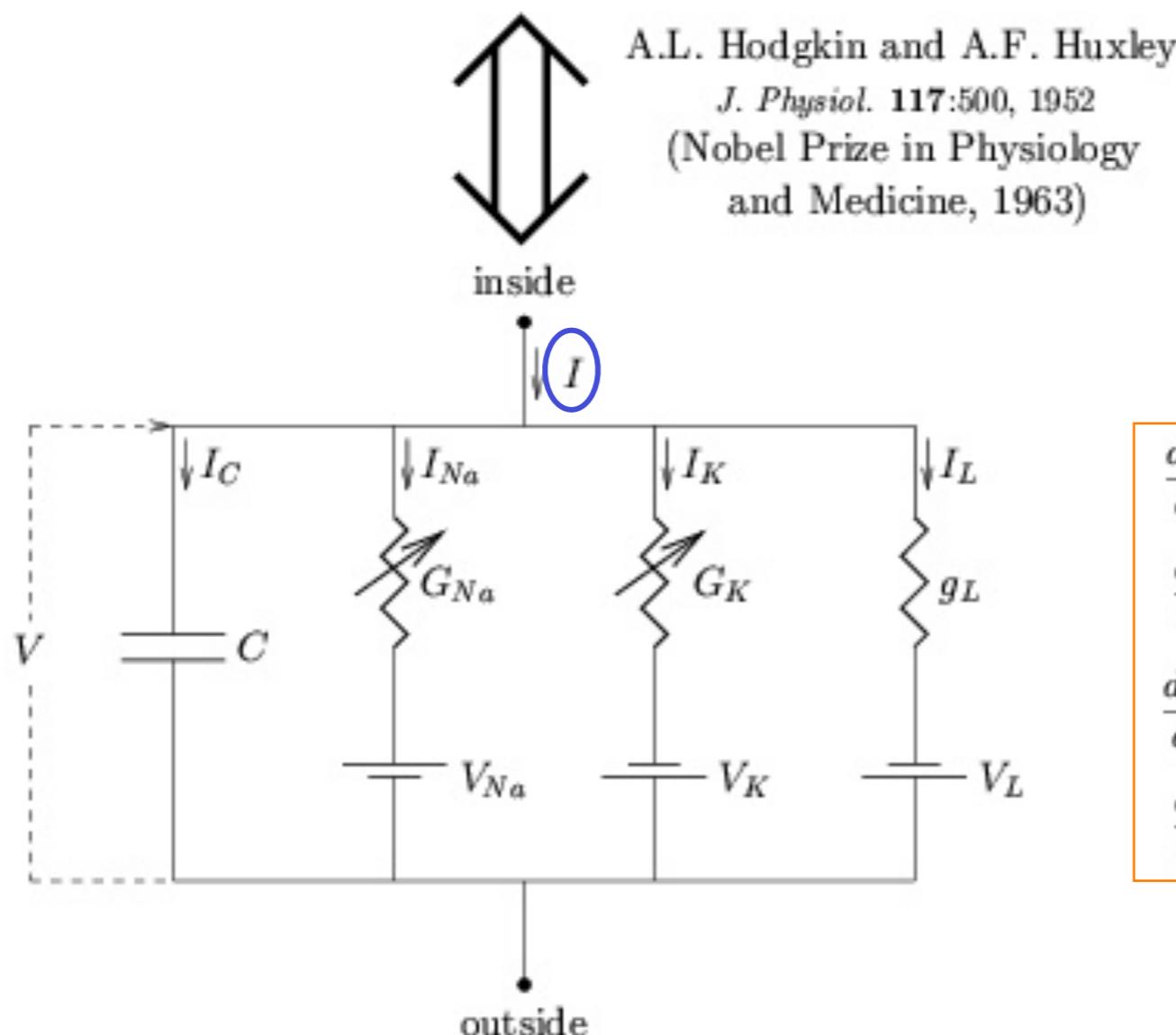
$$\frac{dm}{dt} = (m_\infty(V) - m) / \tau_m(V)$$

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# Hodgkin and Huxley's circuit model of a neuronal membrane:

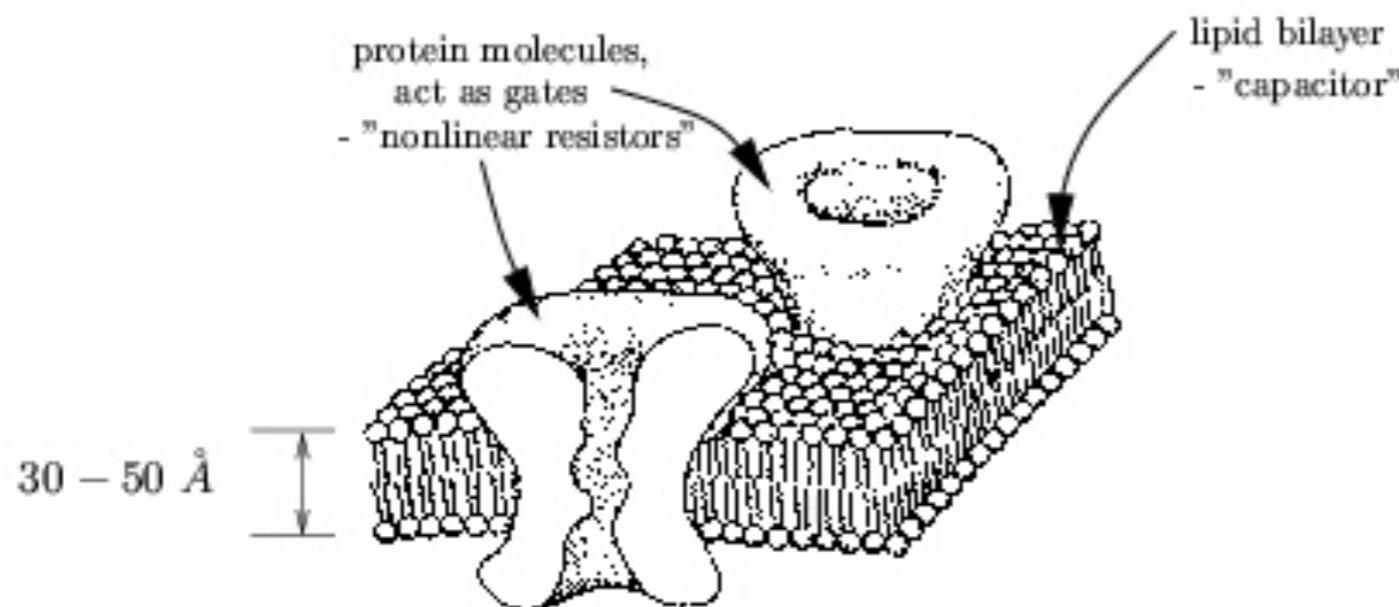


from *Biophysics of Computation: Information Processing in Single Neurons*, by C. Koch, 1999

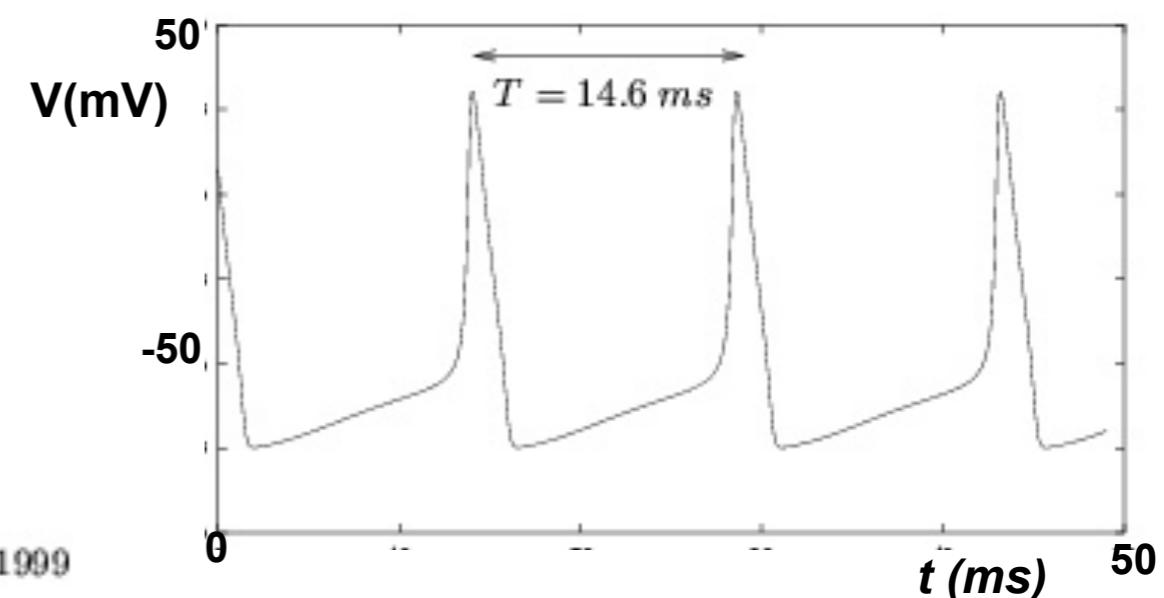


$$\frac{dV}{dt} = [I - \bar{g}_{Na}m^3h(V - V_{Na}) - \bar{g}_K n^4(V - V_K) - g_L(V - V_L)]/C,$$
$$\frac{dn}{dt} = \alpha_n(V)(1 - n) - \beta_n(V)n,$$
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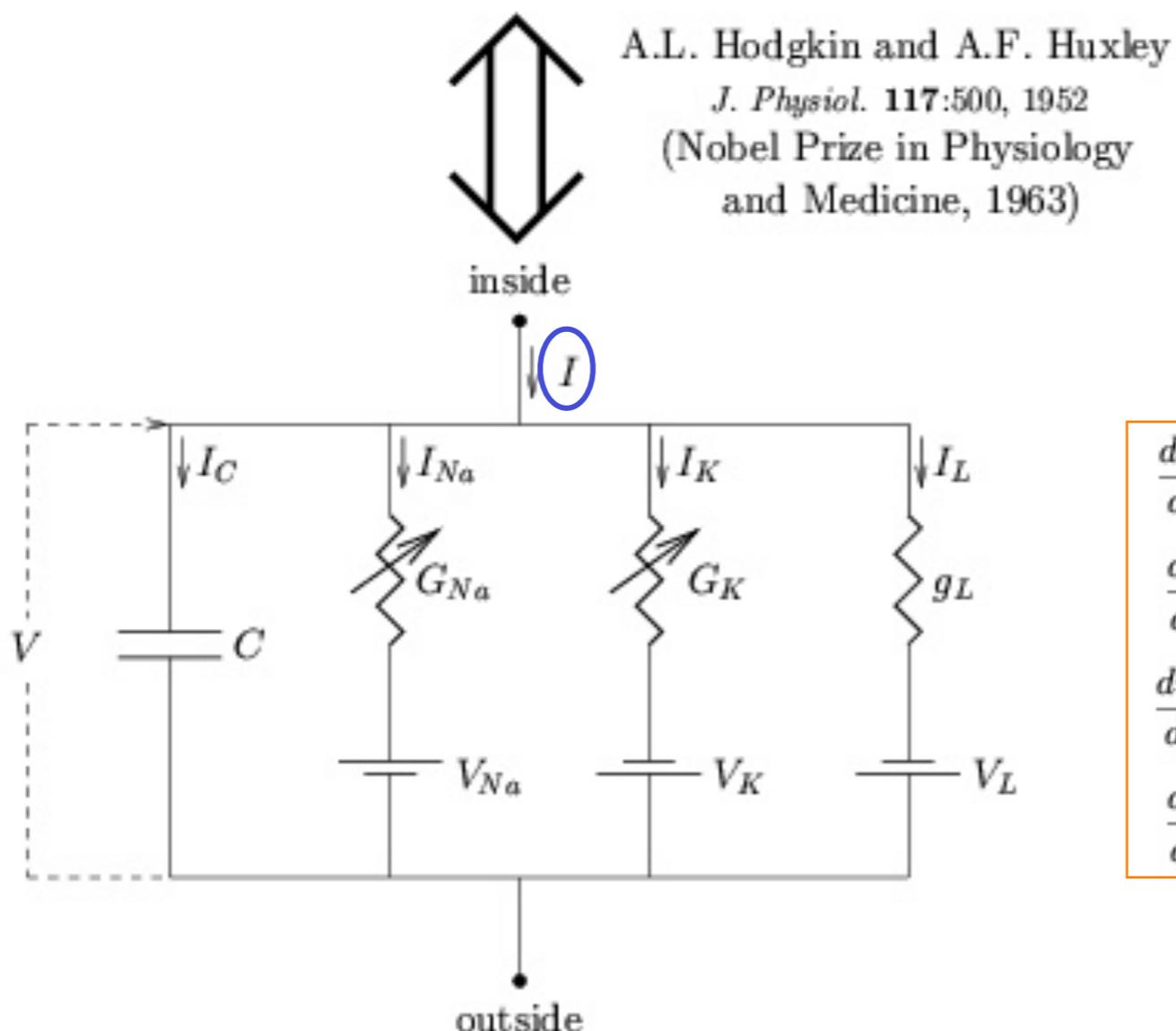
# Hodgkin and Huxley's circuit model of a neuronal membrane:



Voltage response to input current  $10 \mu\text{A}/\text{cm}^2$



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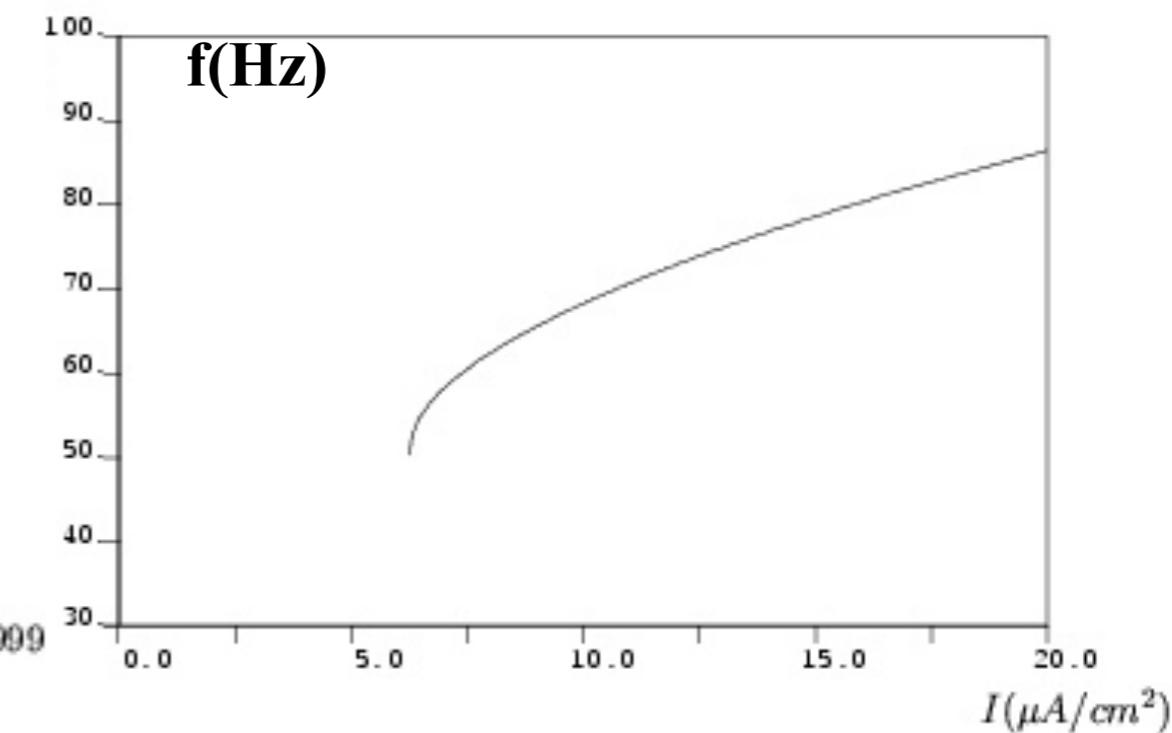
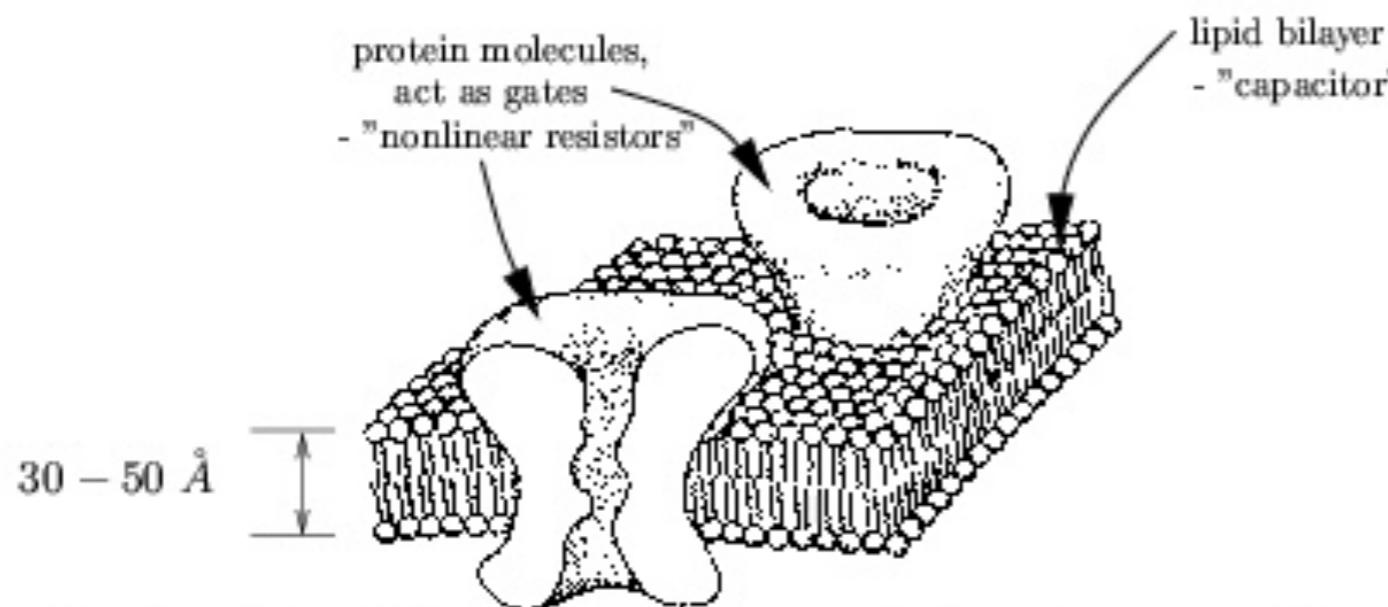


A.L. Hodgkin and A.F. Huxley  
*J. Physiol.* **117**:500, 1952  
(Nobel Prize in Physiology  
and Medicine, 1963)

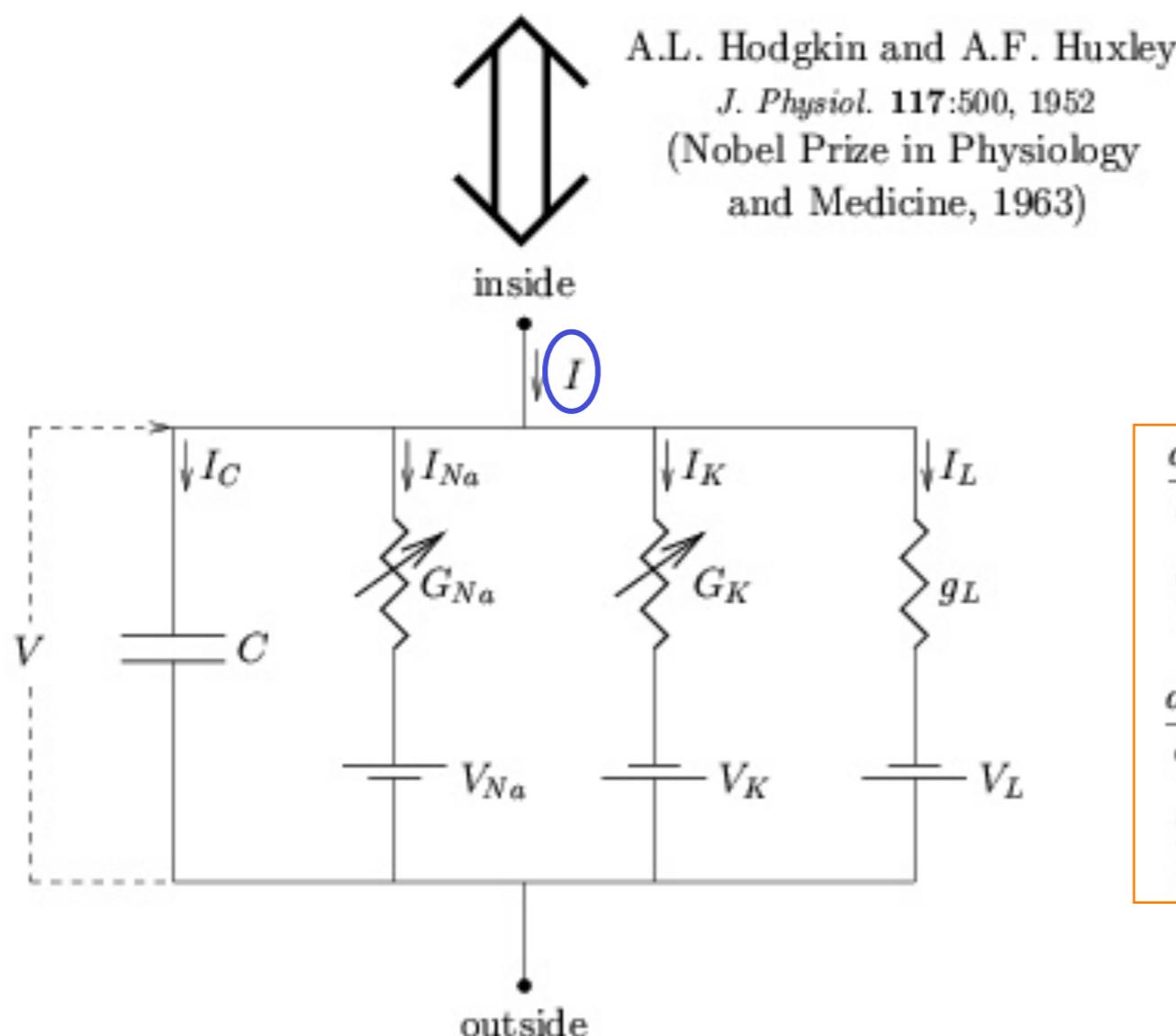


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$$\frac{dV}{dt} = [I - \bar{g}_{Na}m^3h(V - V_{Na}) - \bar{g}_Kn^4(V - V_K) - g_L(V - V_L)]/C$$
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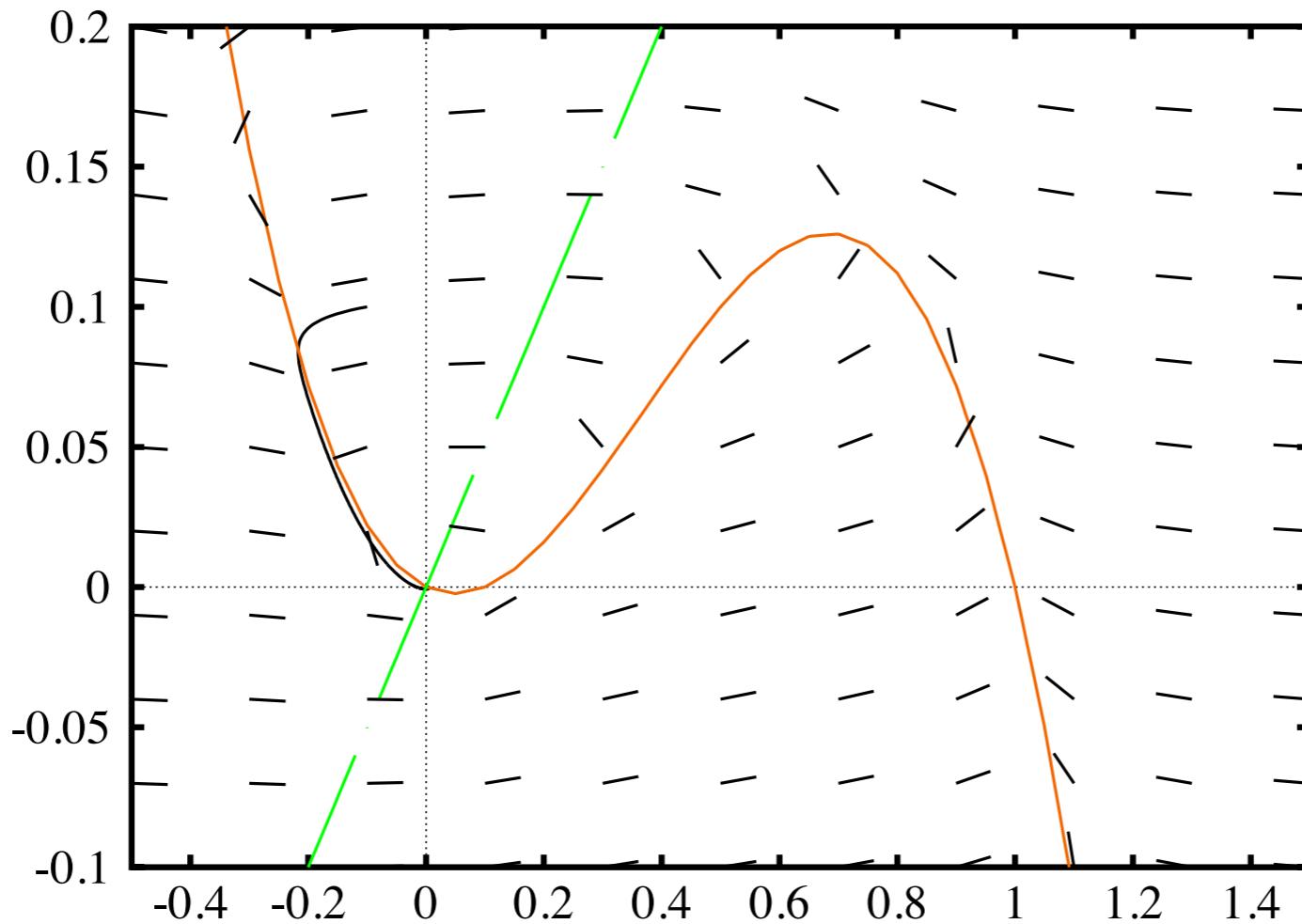
$$\frac{dn}{dt} = (n_\infty(V) - n) / \tau_n(V)$$

$$\frac{dm}{dt} = (m_\infty(V) - m) / \tau_m(V) \quad \Rightarrow \quad \frac{d\mathbf{V}}{dt} = \mathbf{F}(\mathbf{V})$$

$$\frac{dh}{dt} = (h_\infty(V) - h) / \tau_h(V) \quad \mathbf{V} = (V, n, m, h)$$

**Basic question:** can I get info about solutions by analyzing  $\mathbf{F}(\mathbf{V})$ ?

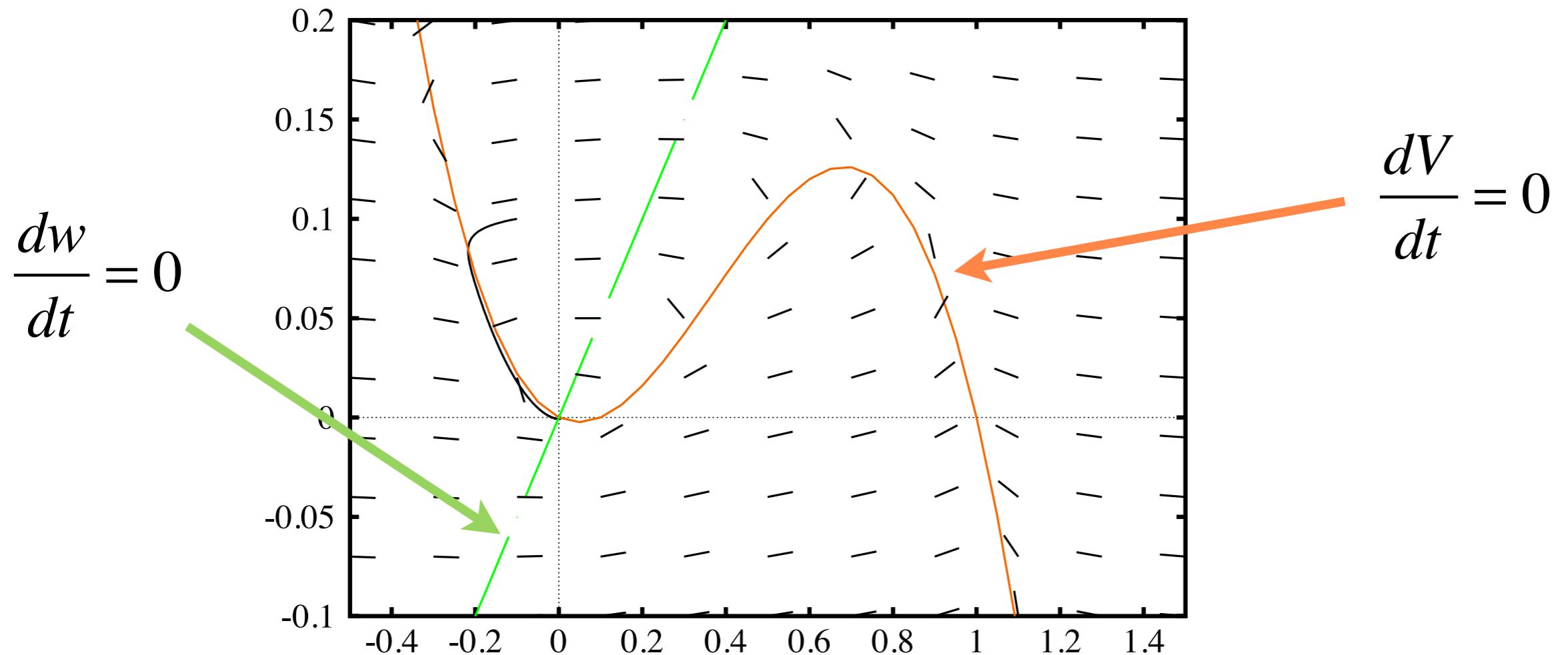
# Phase plane analysis



$$\frac{dV}{dt} = V(a - V)(V - 1) - w + I$$

$$\frac{dw}{dt} = bV - cw$$

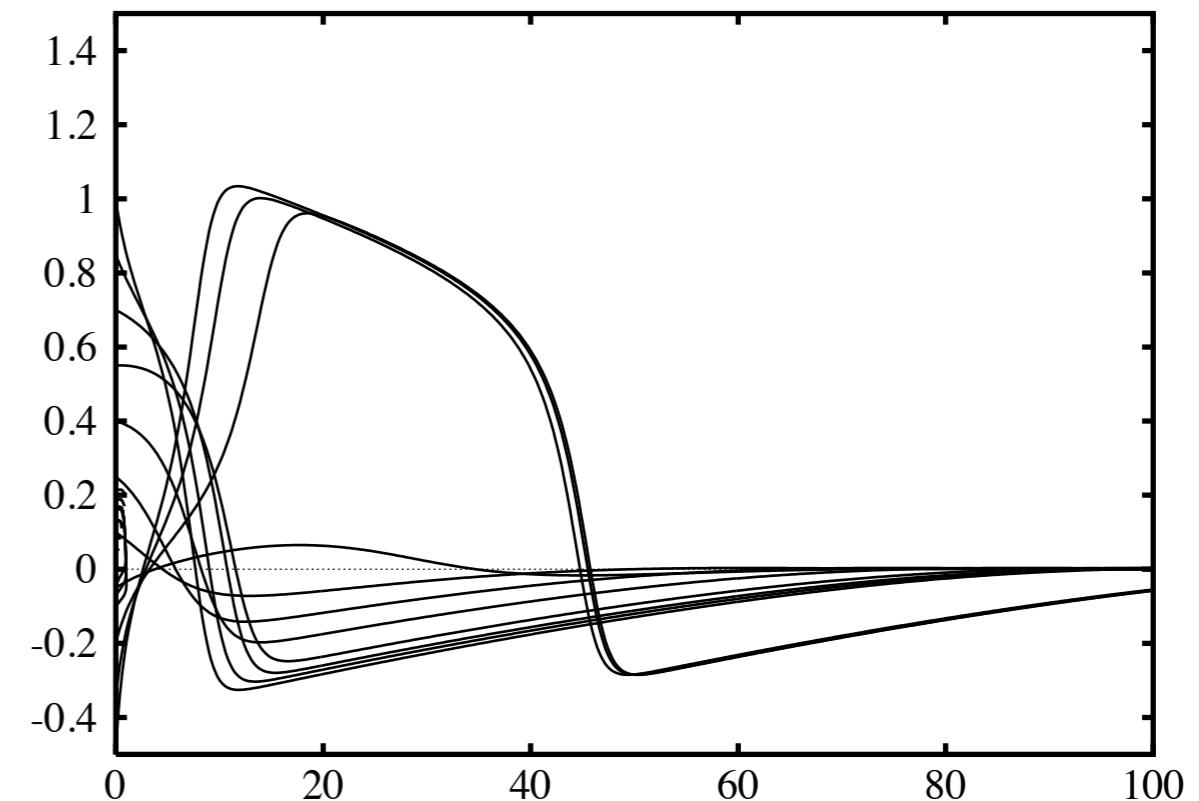
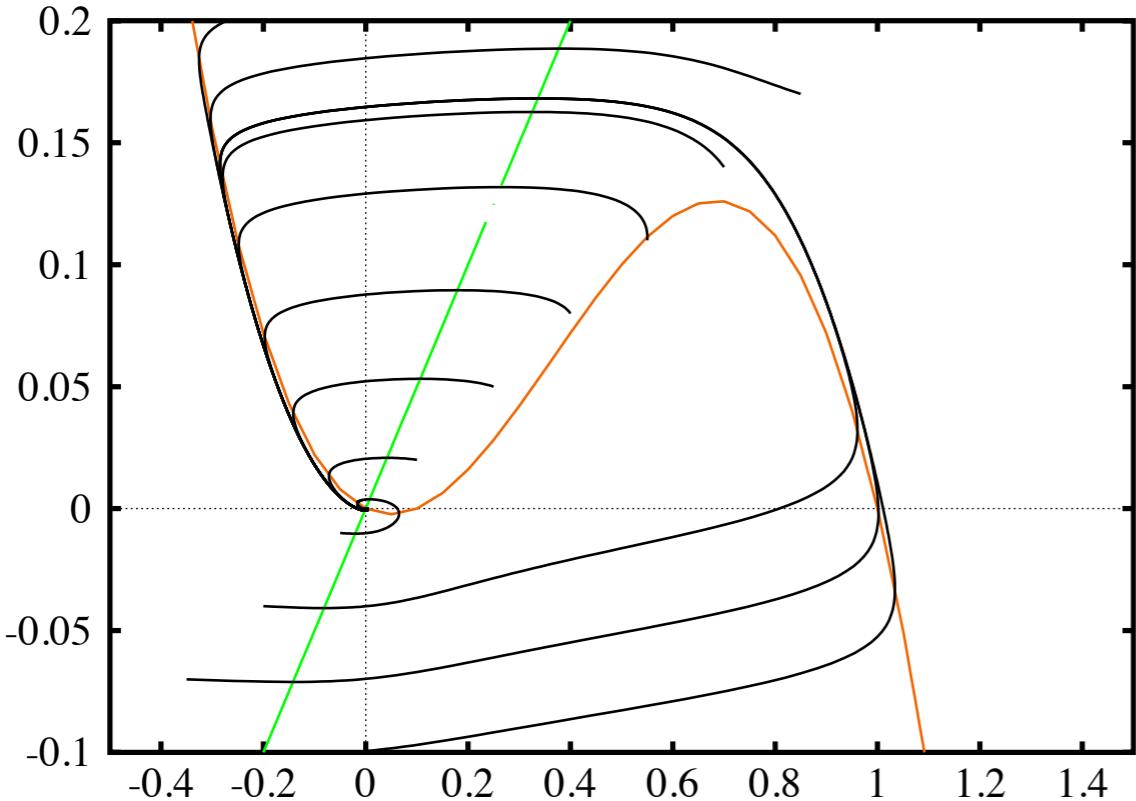
# Phase plane analysis: Nullclines



$$\frac{dV}{dt} = V(a - V)(V - 1) - w + I$$

$$\frac{dw}{dt} = bV - cw$$

# Phase plane analysis: Equilibria and stability

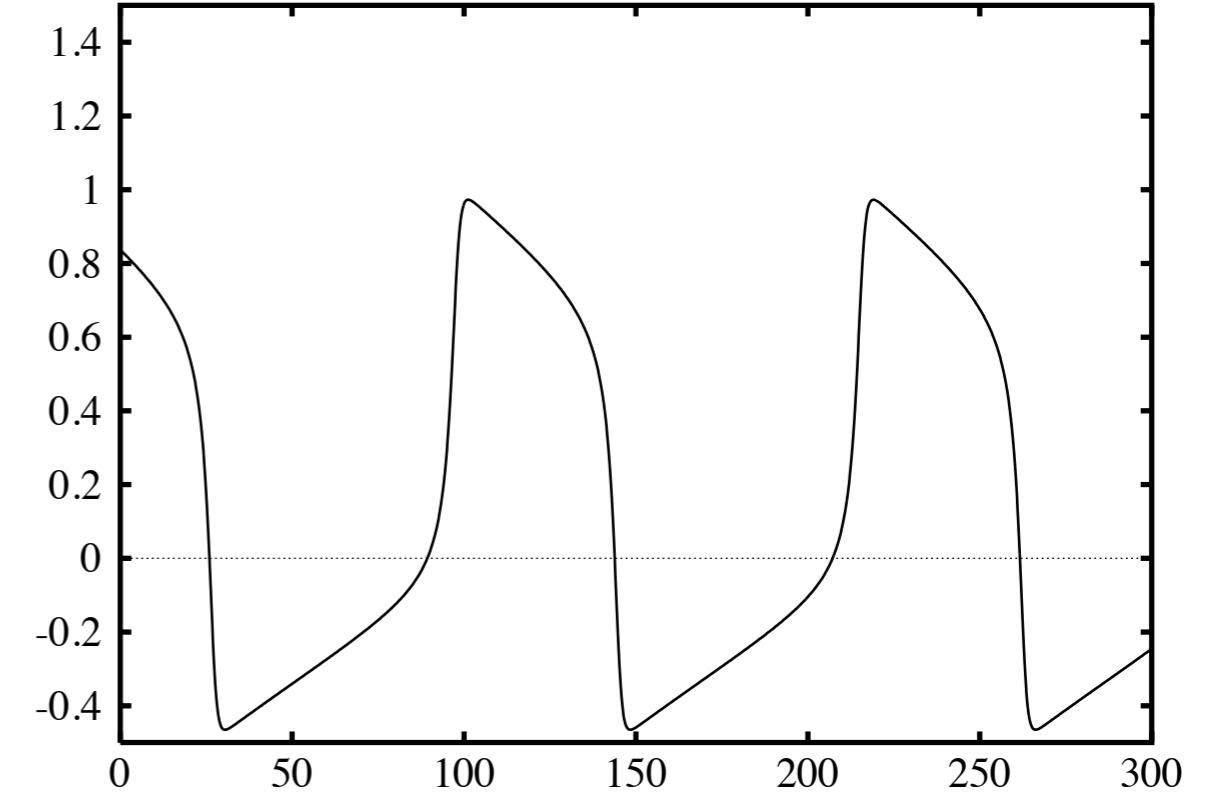
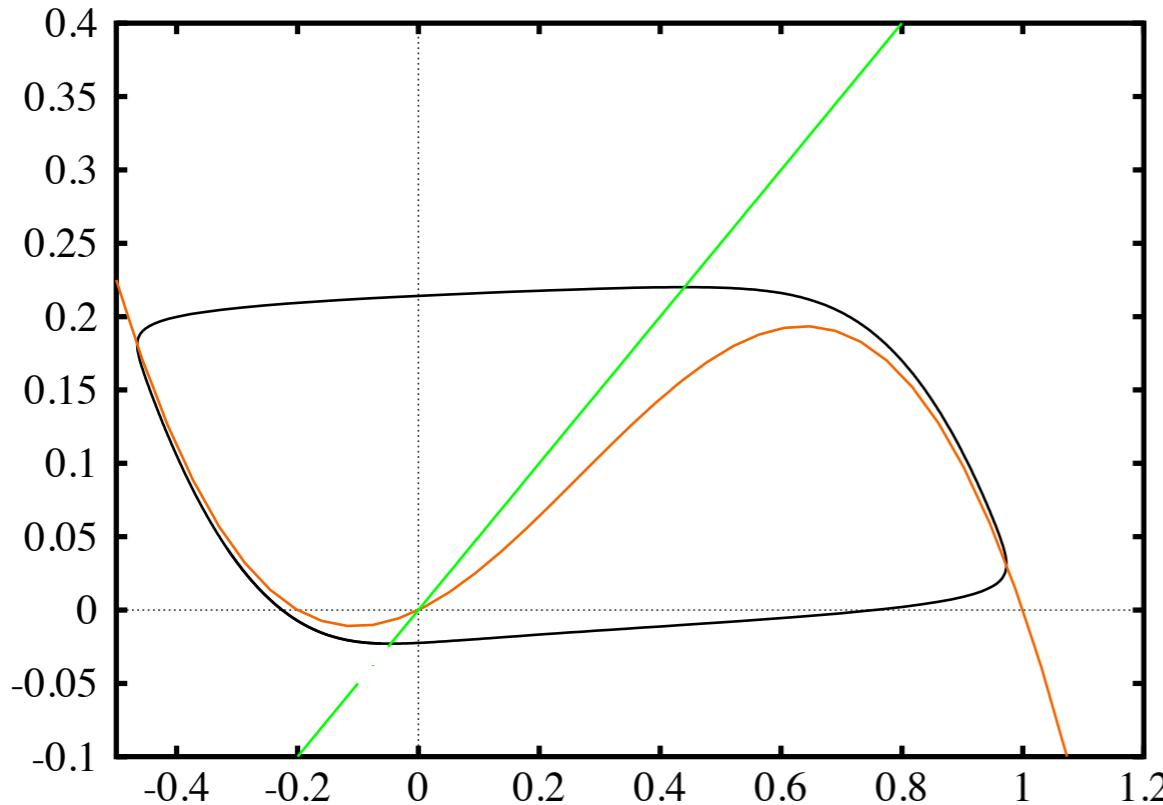


$$\frac{dV}{dt} = V(a - V)(V - 1) - w + I$$

$$\frac{dw}{dt} = bV - cw$$

$$a=.1, b=.01, c=.02, I=0$$

# Phase plane analysis: Equilibria and stability

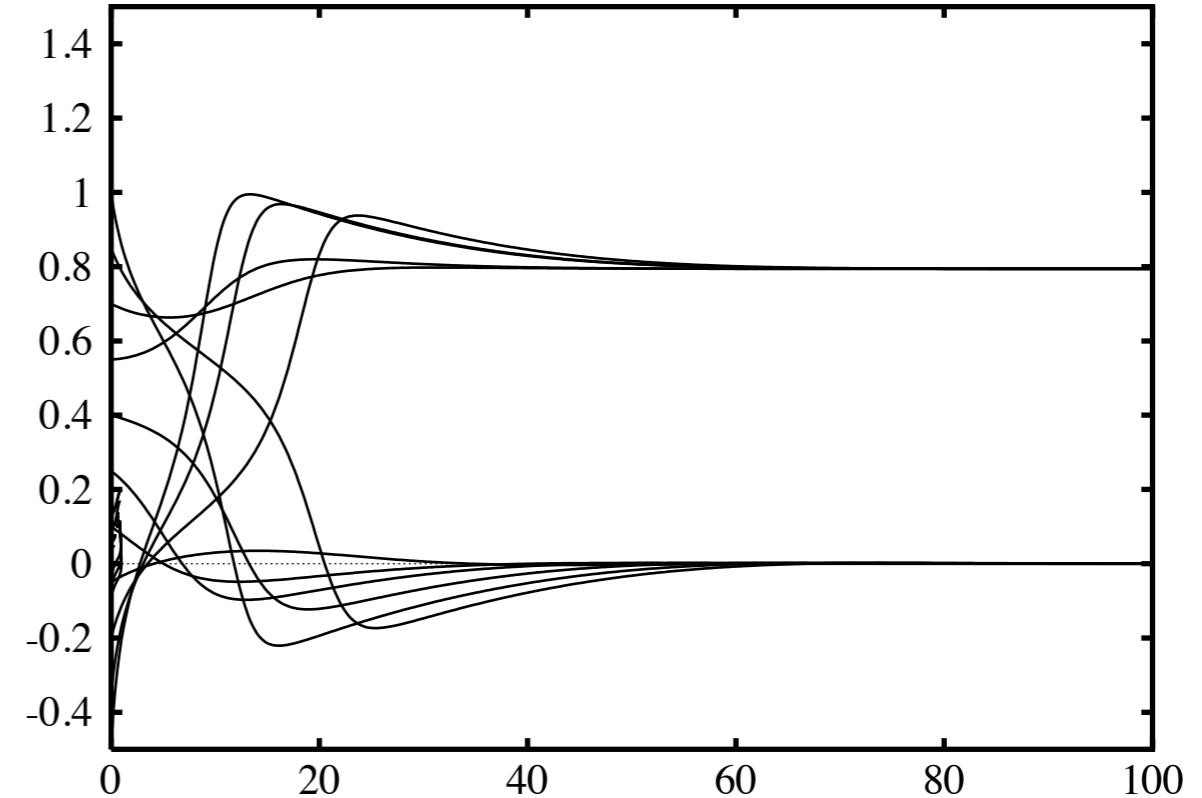
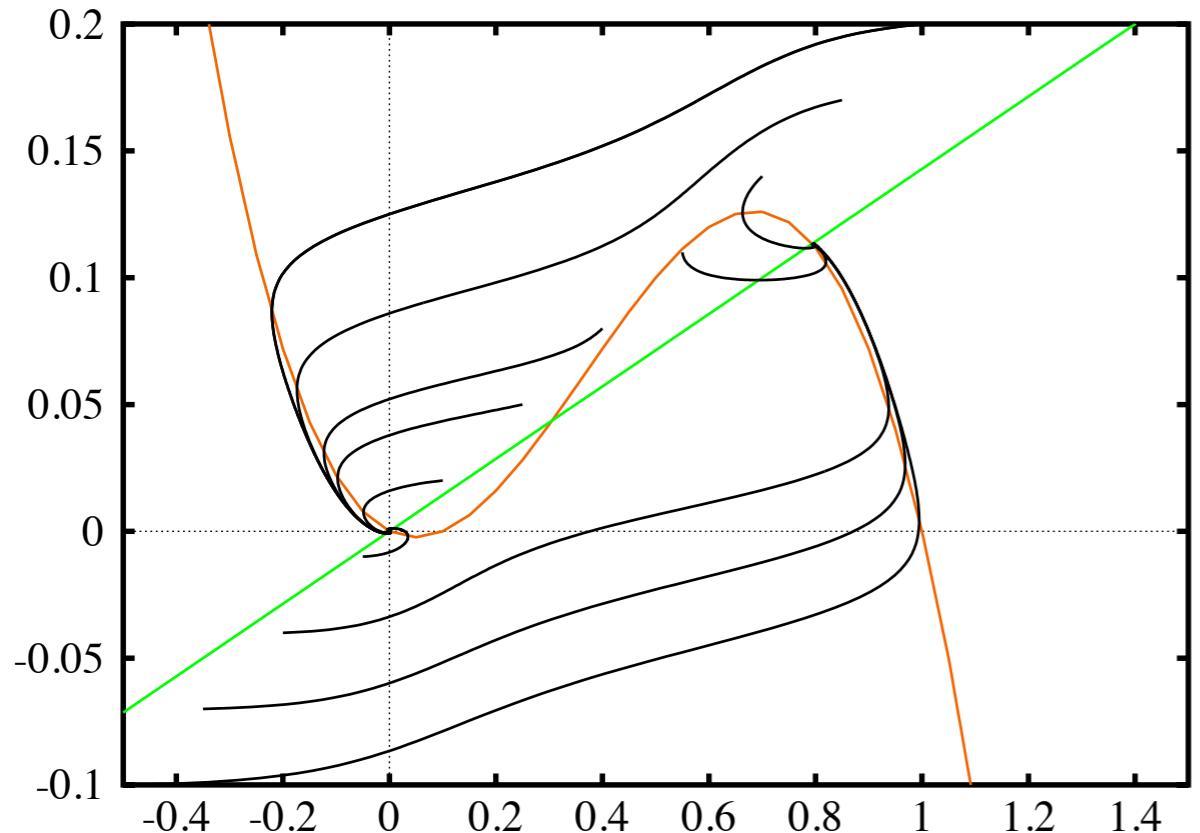


$$\frac{dV}{dt} = V(a - V)(V - 1) - w + I$$

$$\frac{dw}{dt} = bV - cw$$

a=.2, b=.01, c=.02, I=0

# Phase plane analysis: Bistability

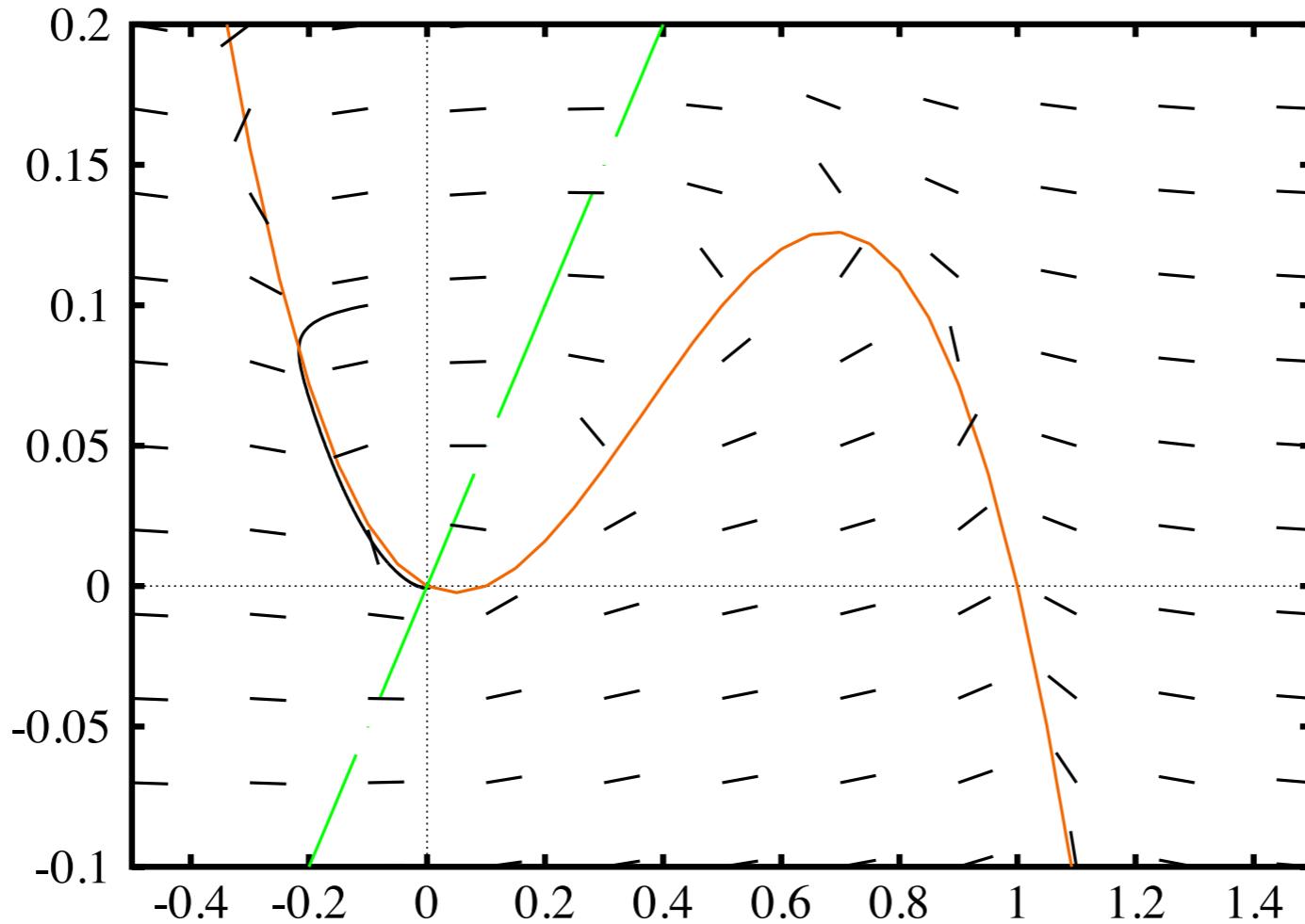


$$\frac{dV}{dt} = V(a - V)(V - 1) - w + I$$

$$\frac{dw}{dt} = bV - cw$$

$$a = .1, b = .01, c = .07, I = 0$$

# Bifurcations: a qualitative change in behavior

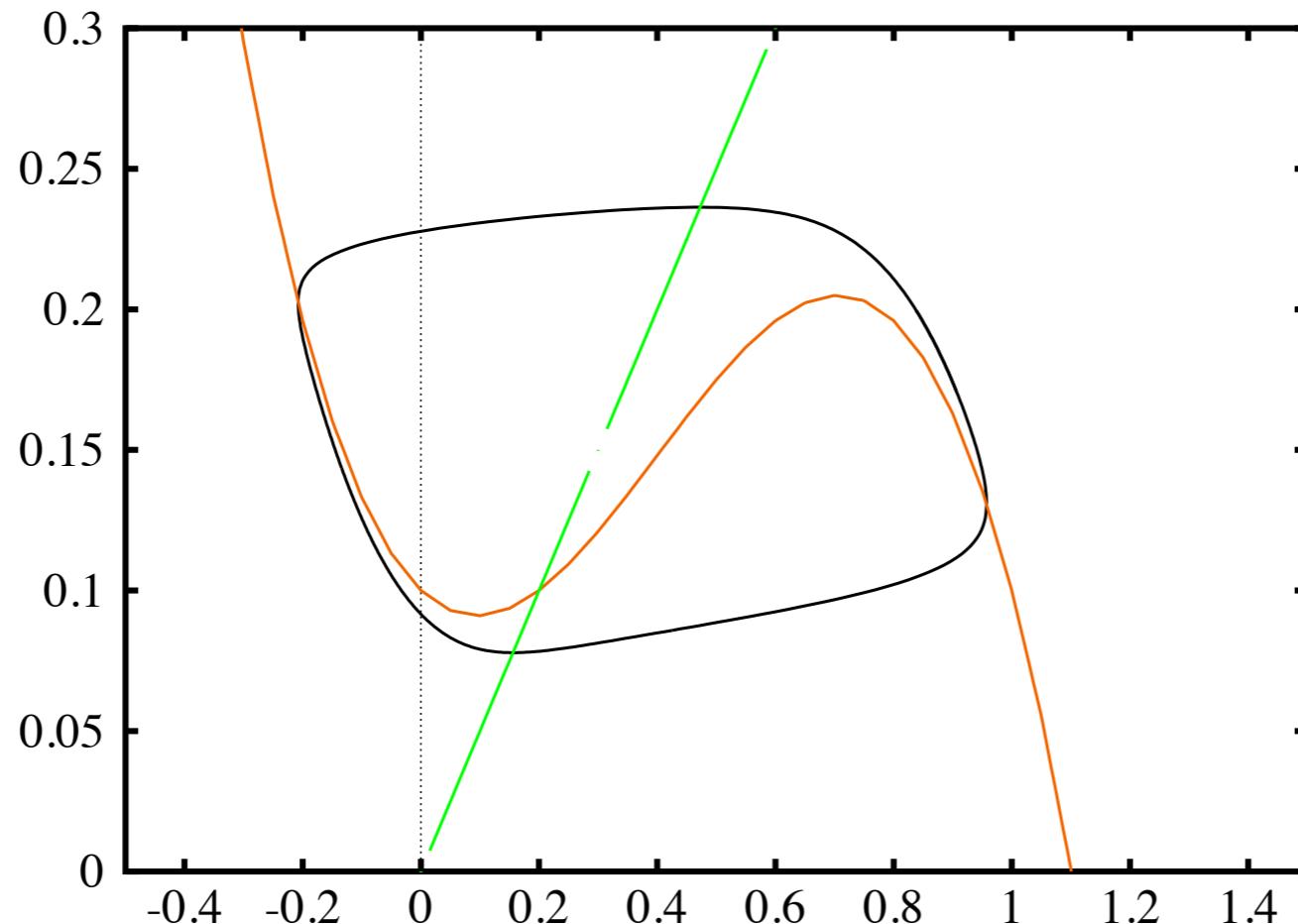


$$\frac{dV}{dt} = V(a - V)(V - 1) - w + \textcolor{red}{I}$$

$$\frac{dw}{dt} = bV - cw$$

$$\textcolor{red}{I} = 0$$

# Bifurcations: a qualitative change in behavior

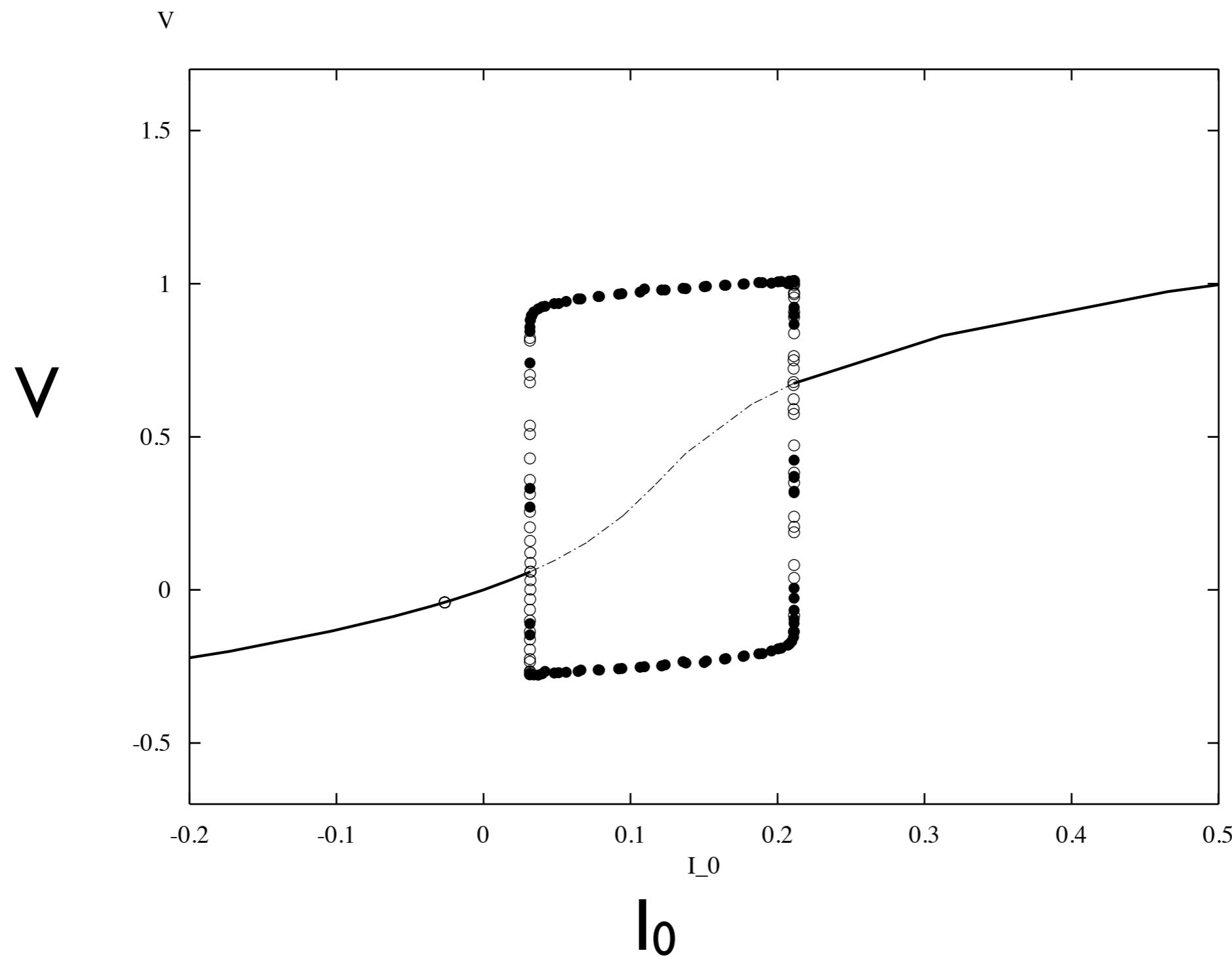


$$\frac{dV}{dt} = V(a - V)(V - 1) - w + I$$

$$\frac{dw}{dt} = bV - cw$$

$$I = 1$$

# Bifurcation diagrams: an example

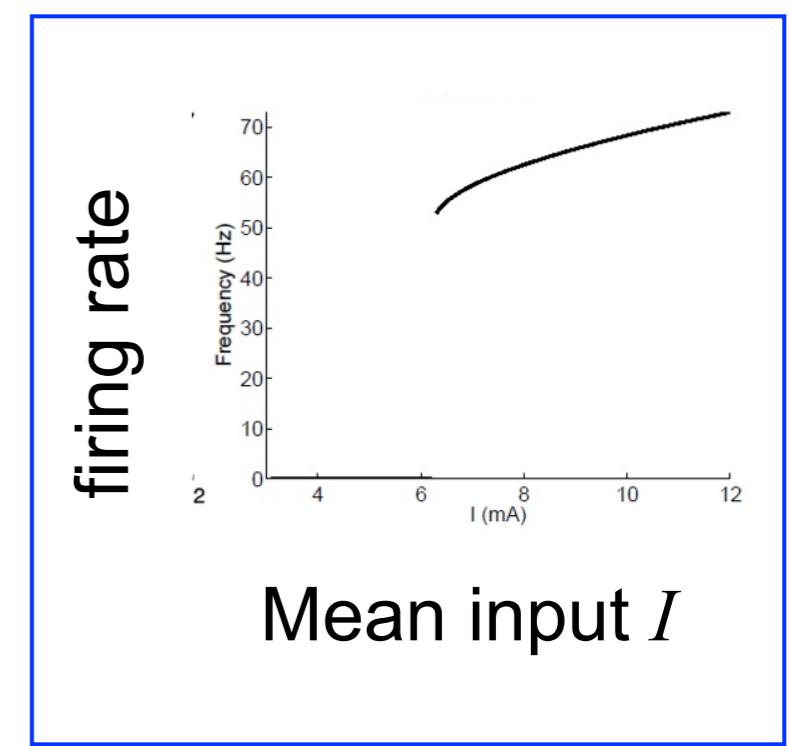
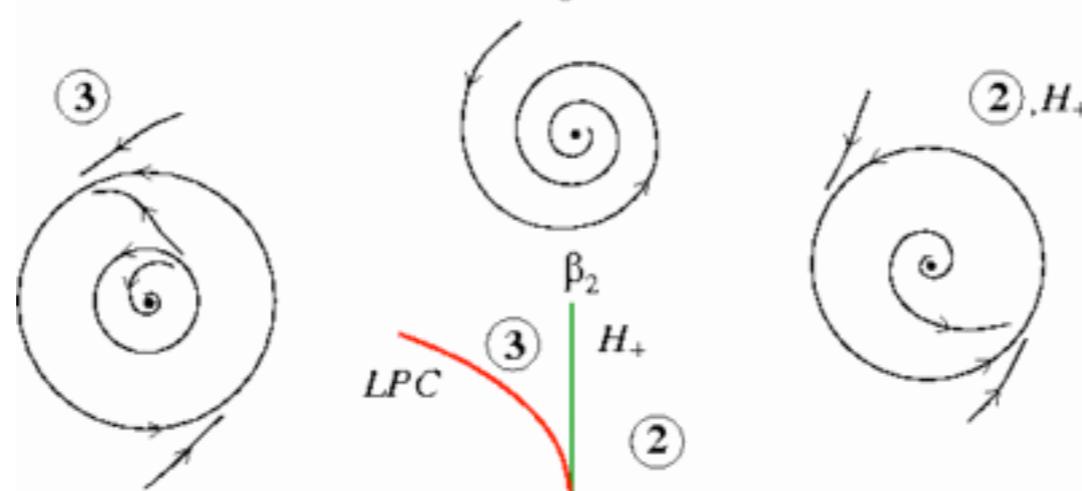
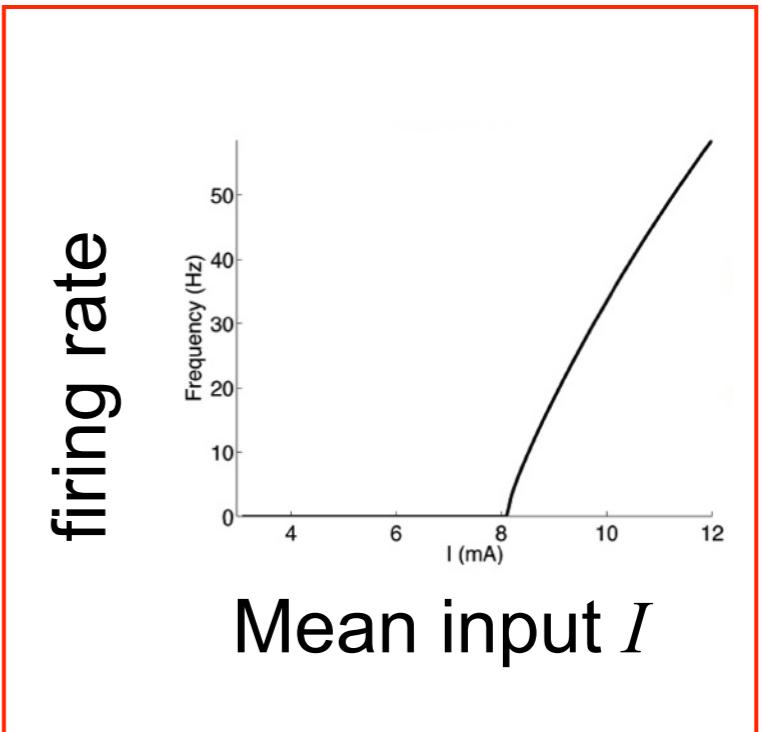
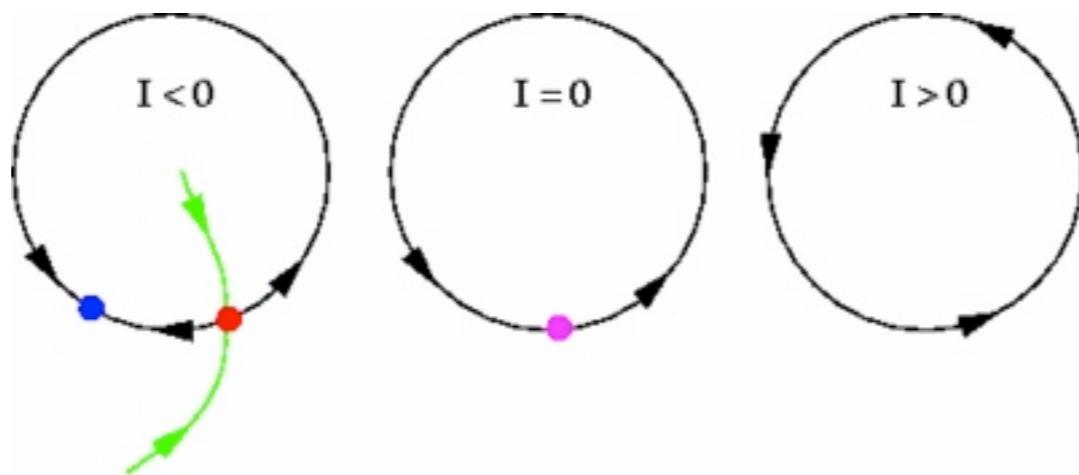


# Two types of bifurcations: Type I vs. Type II (or Class 1 vs. Class 2)

saddle  
node on  
invariant  
circle

“Class 1  
excitability”

subcritical  
Hopf:  
“Class 2  
excitability”

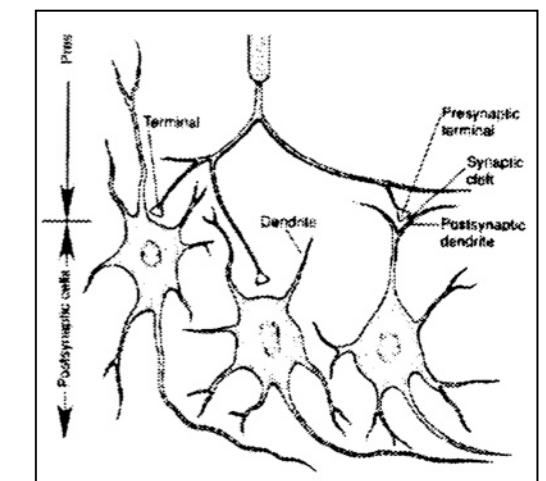
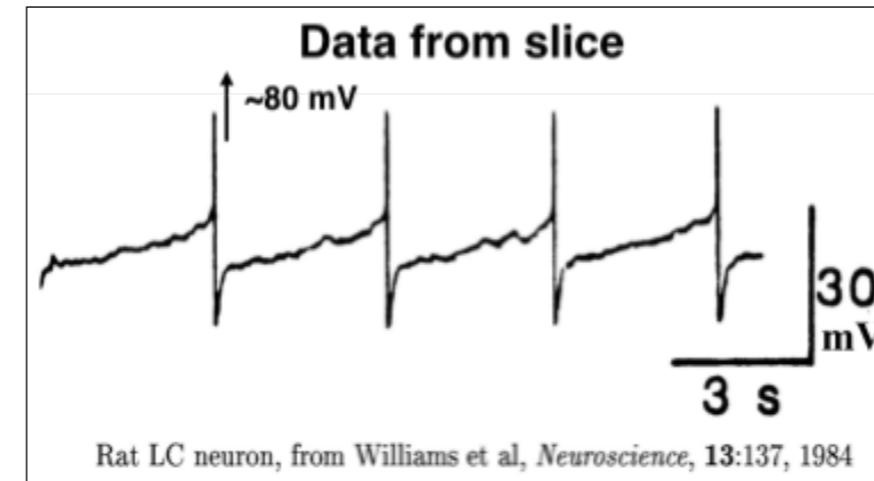


# Some simplified models

- Phase model
- Integrate-and-fire
- Firing rate models

# Reduction of neurons to phases:

## 1. Brain recordings: voltage spikes via ionic currents



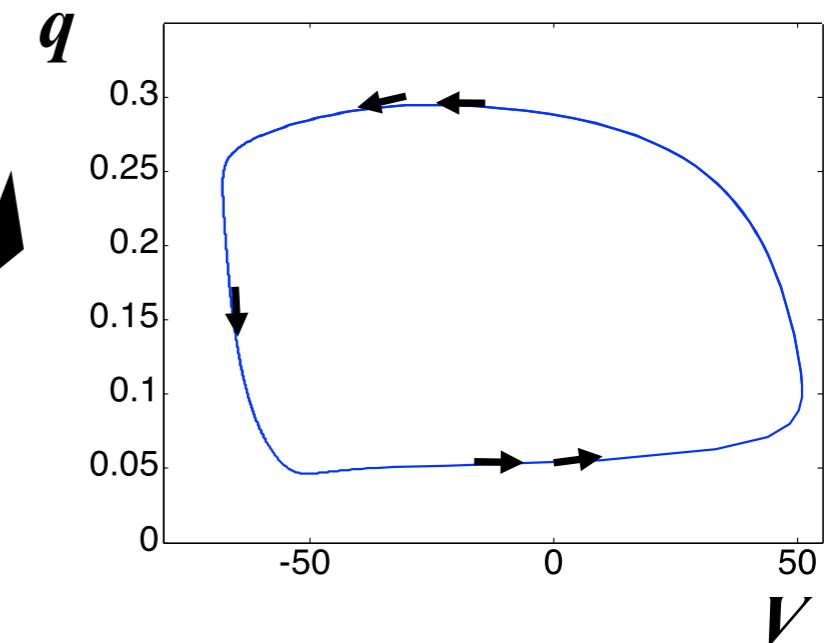
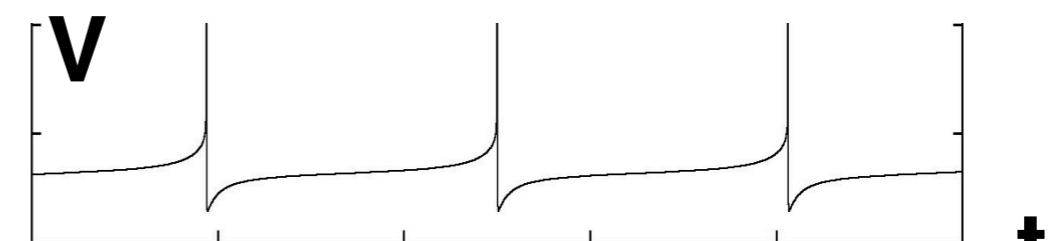
## 2. Nonlinear oscillator eqn. for each neuron

$$\begin{aligned}\dot{v}_i &= [I_i^b - g_{Na}m_\infty(v_i)^3(-3(q_i - Bb_\infty(v_i)) + 0.85)(v_i - v_{Na}) \\ &\quad - g_Kq_i(v_i - v_K) - g_L(v_i - v_L) + I_i^{ext}]/C \\ \dot{q}_i &= (q_\infty(v_i) - q_i)/\tau_q(v_i).\end{aligned}$$

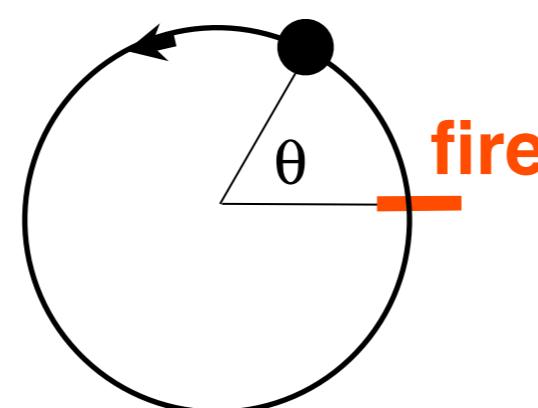
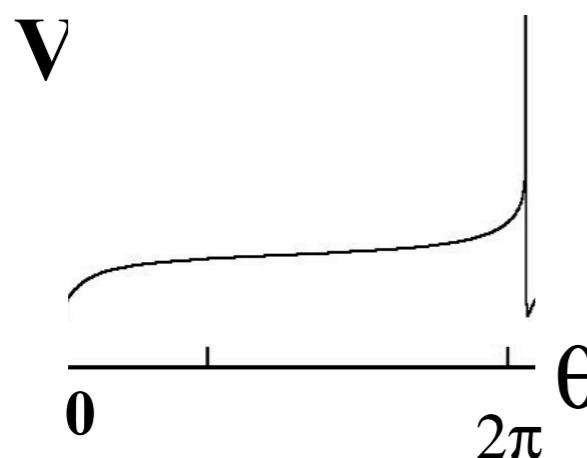
$V$  = *voltage*

$q$  = *conductance*

e.g Rose and Hindmarsh, 1989.  
Hodgkin and Huxley, etc.



## 3. Coordinate change → phase



Winfrey '74, Guckenheimer '75, ...

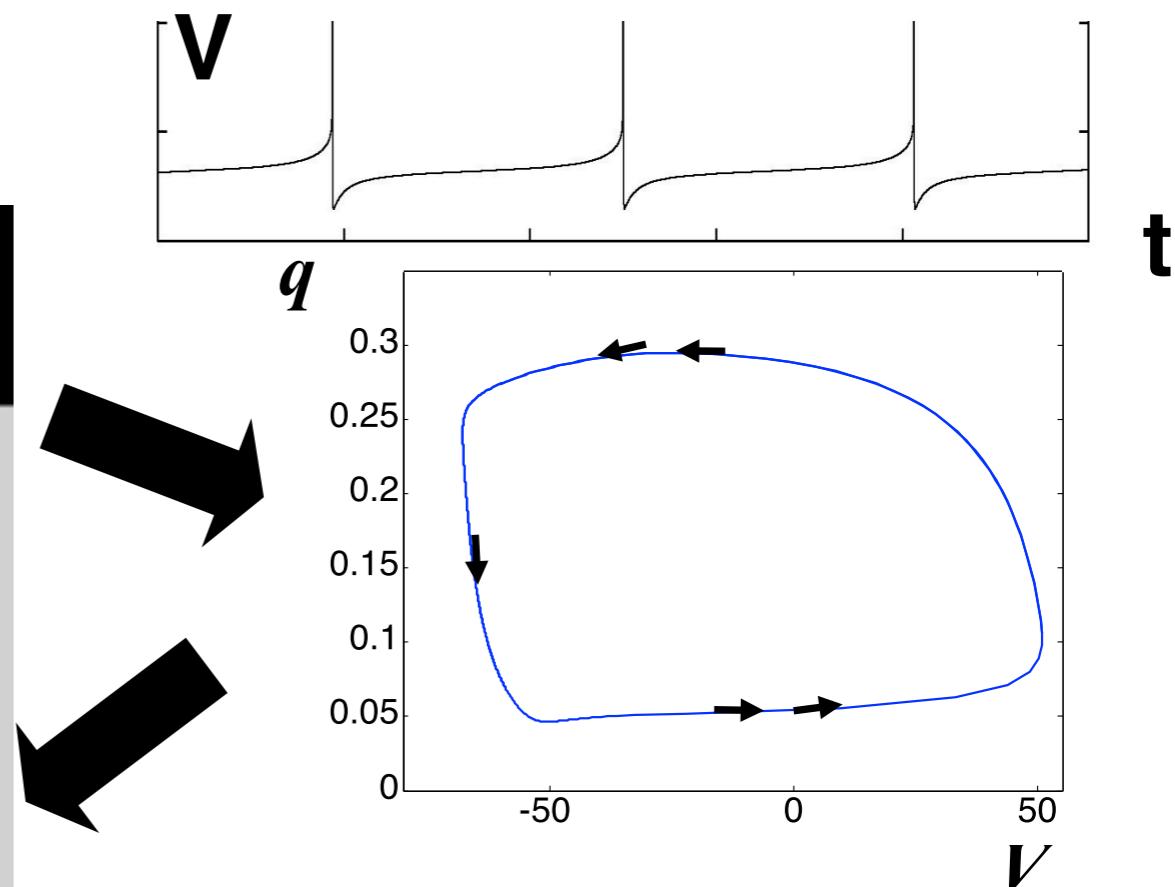
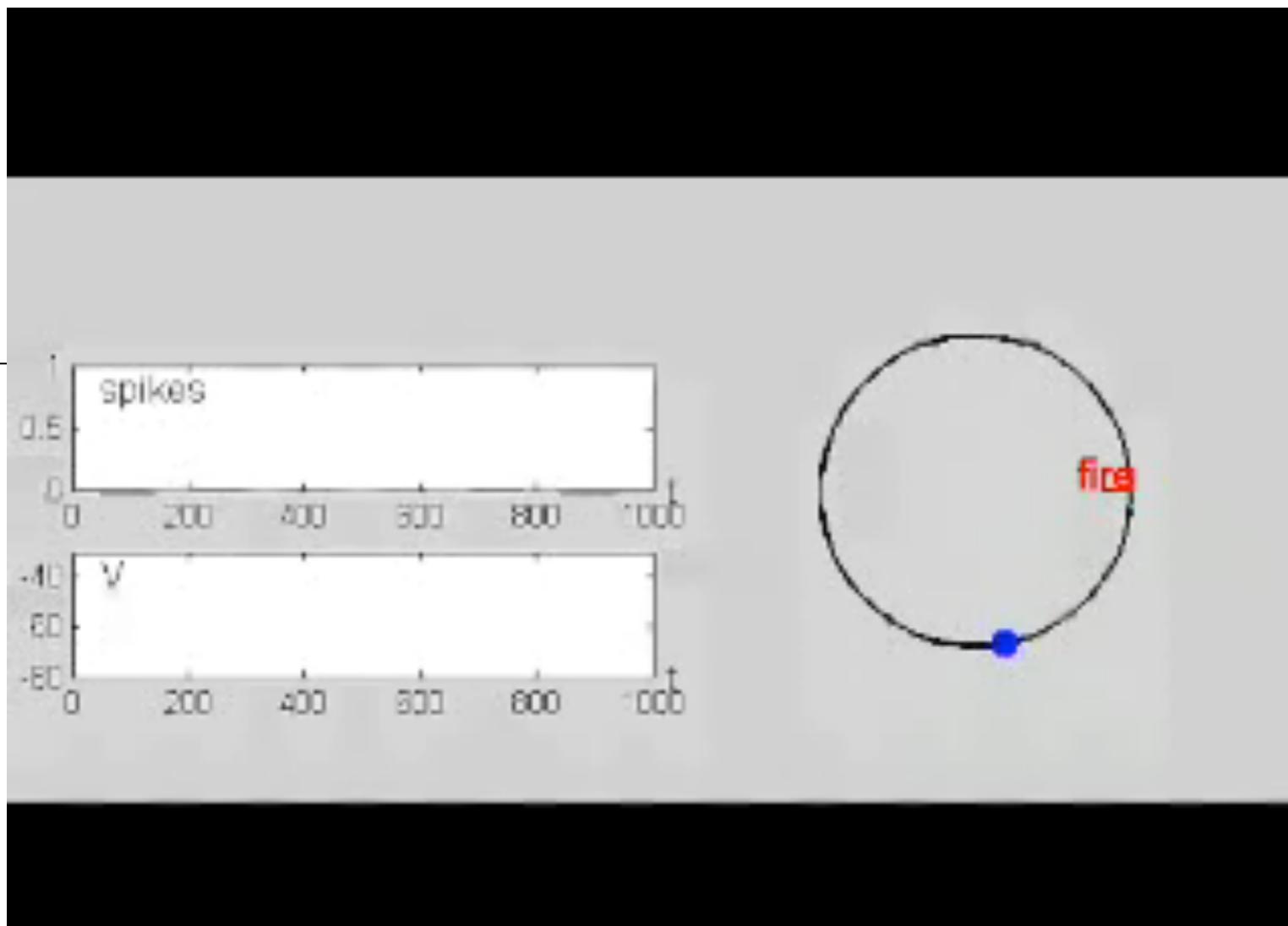
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$V = \text{voltage}$

$q = \text{conductance}$



Winfrey '74, Guckenheimer '75, ...  
25

# Goal: simple phase description

$$\frac{d\theta}{dt} = \omega$$

- Let  $\mathbf{x} = \begin{pmatrix} V \\ q \end{pmatrix}$ . Then we have defined coordinate change so that:

$$\frac{d\mathbf{x}}{dt} = \mathbf{F}(\mathbf{x}) \rightarrow \frac{d\theta}{dt} = \omega$$

where  $\mathbf{F}(\mathbf{x})$  is ‘original’ neural vectorfield giving oscillations at freq.  $\omega$ .

# Goal: simple phase description

$$\frac{d\theta}{dt} = \underline{\omega} + \dots$$

**natural  
frequency**

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- We’re actually interested in effects of additional currents:  $J(\mathbf{x},t)$  “perturbation”

$$\frac{d\mathbf{x}}{dt} = \mathbf{F}(\mathbf{x}) + \begin{pmatrix} J(\mathbf{x},t) \\ 0 \end{pmatrix} \rightarrow \frac{d\theta}{dt} = \frac{\partial \theta}{\partial \mathbf{x}} \cdot \left[ \mathbf{F}(\mathbf{x}) + \begin{pmatrix} J(\mathbf{x},t) \\ 0 \end{pmatrix} \right]$$

$$\frac{d\theta}{dt} = \omega + \boxed{\frac{\partial \theta}{\partial V}} J(\mathbf{x},t)$$

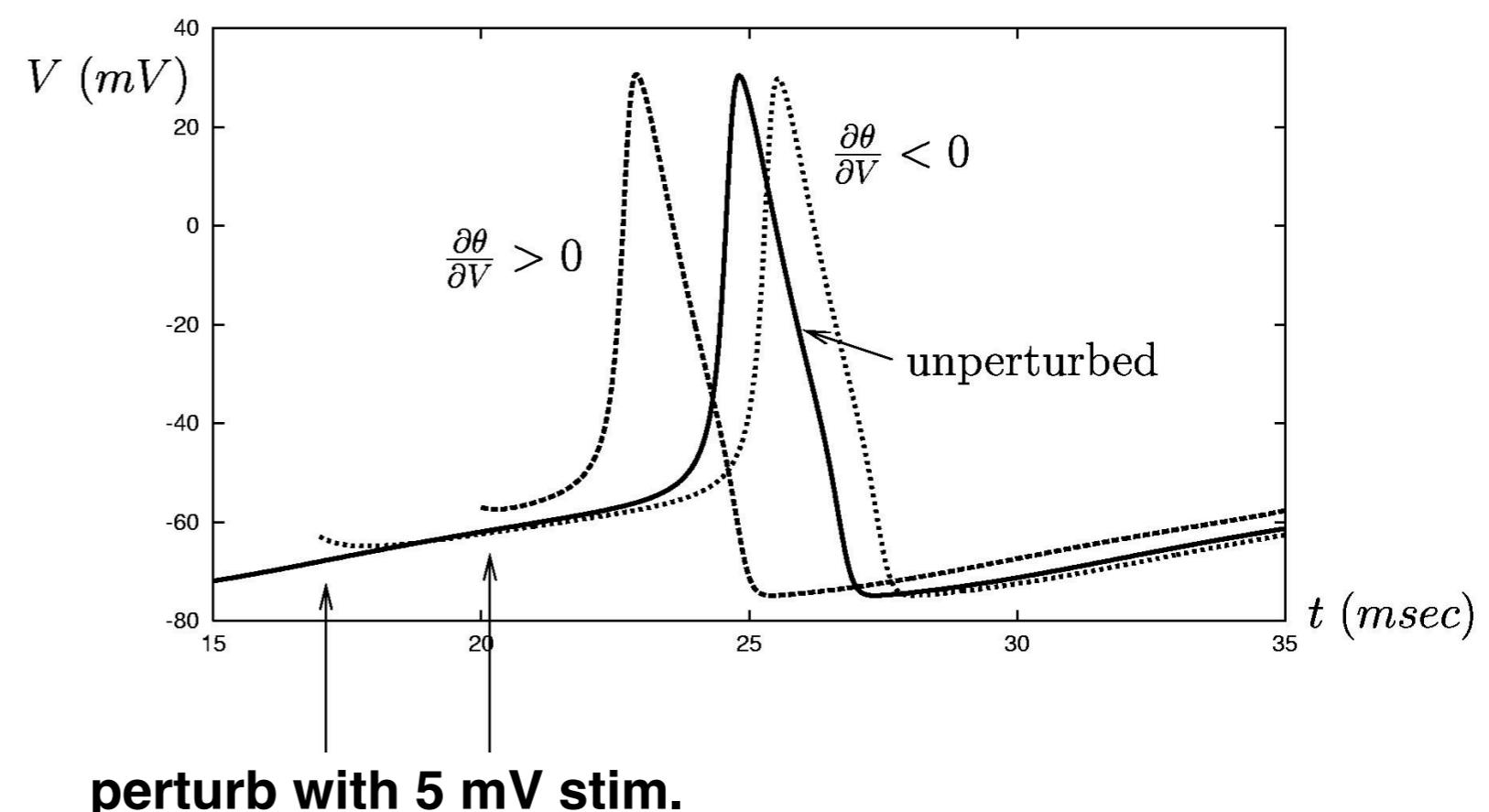
# Finding $\partial\theta / \partial V = z(\theta)$ , the phase response curve:

- Perturb an uncoupled neuron with a brief voltage stimulus  $\Delta V$  at different times in its cycle, parameterized by  $\theta$
- Measure the resulting phase-shift  $\Delta\theta$  with respect to the unperturbed system

For Hodgkin-Huxley neurons with  $I = 10\mu A/cm^2$ :

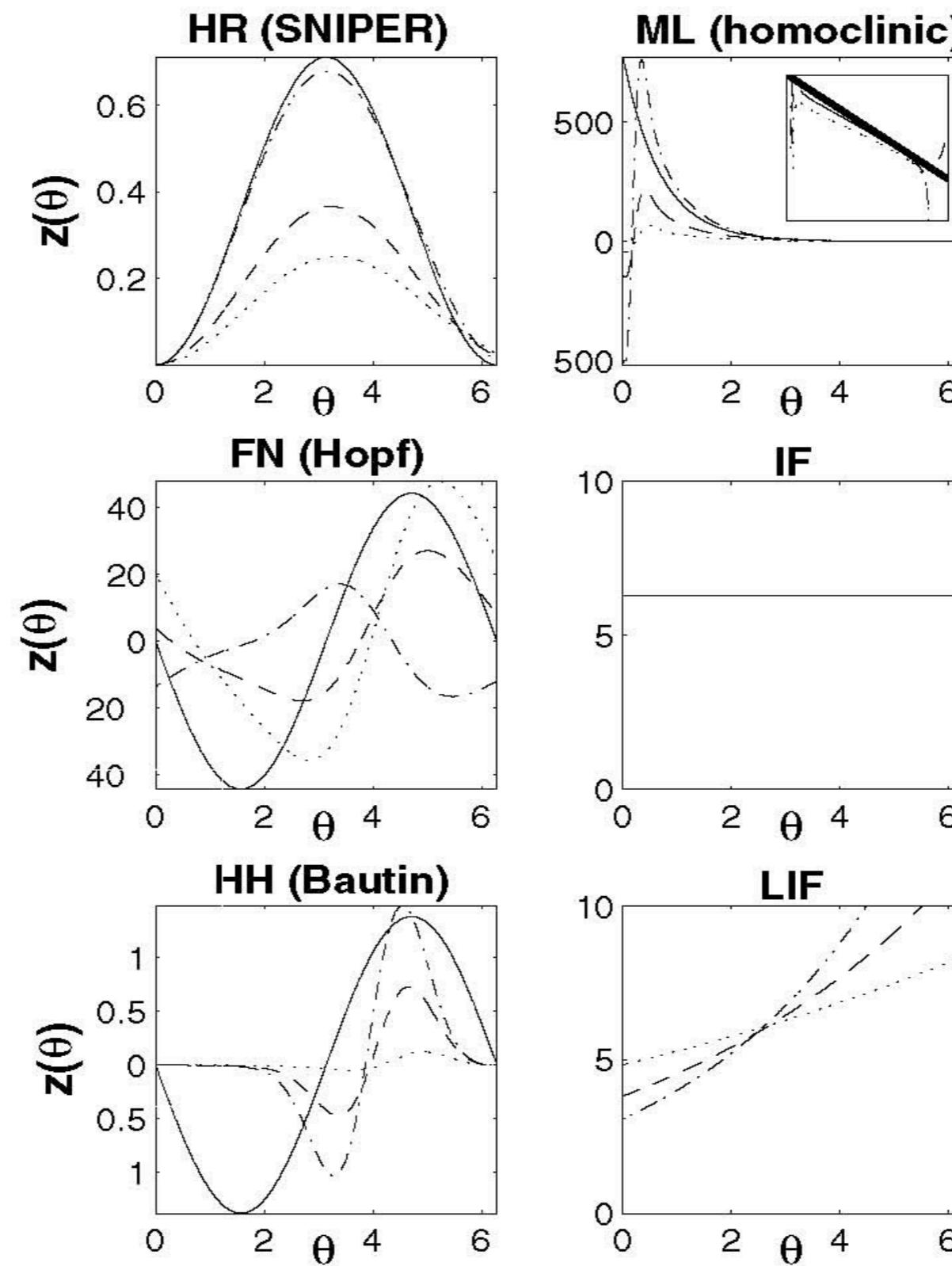
$$z(\theta) = \lim_{\Delta V \rightarrow 0} \frac{\Delta\theta}{\Delta V}$$

**NOTE: this  
technique often  
used in lab  
experiments!**



# Phase response curves for different neurons look very different!

[Ermentrout and Kopell,  
Van-Vreeswick, Bressloff,  
Izhikevich, Moehlis,  
Holmes, S-B]



Hodgkin-Huxley

Leaky  
Integrate and  
Fire

## - With phase dynamics ...

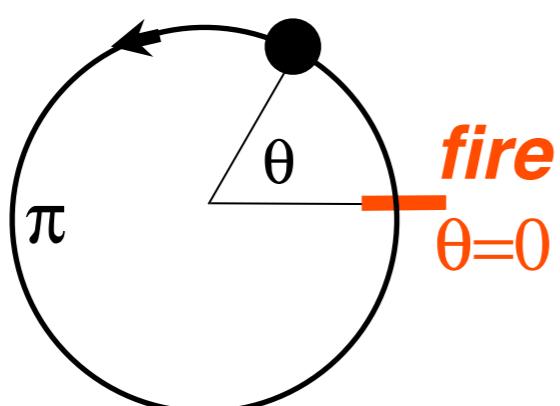
$$\frac{d\theta}{dt} = \omega + z(\theta) \times [I_{syn}(t)]$$

natural frequency

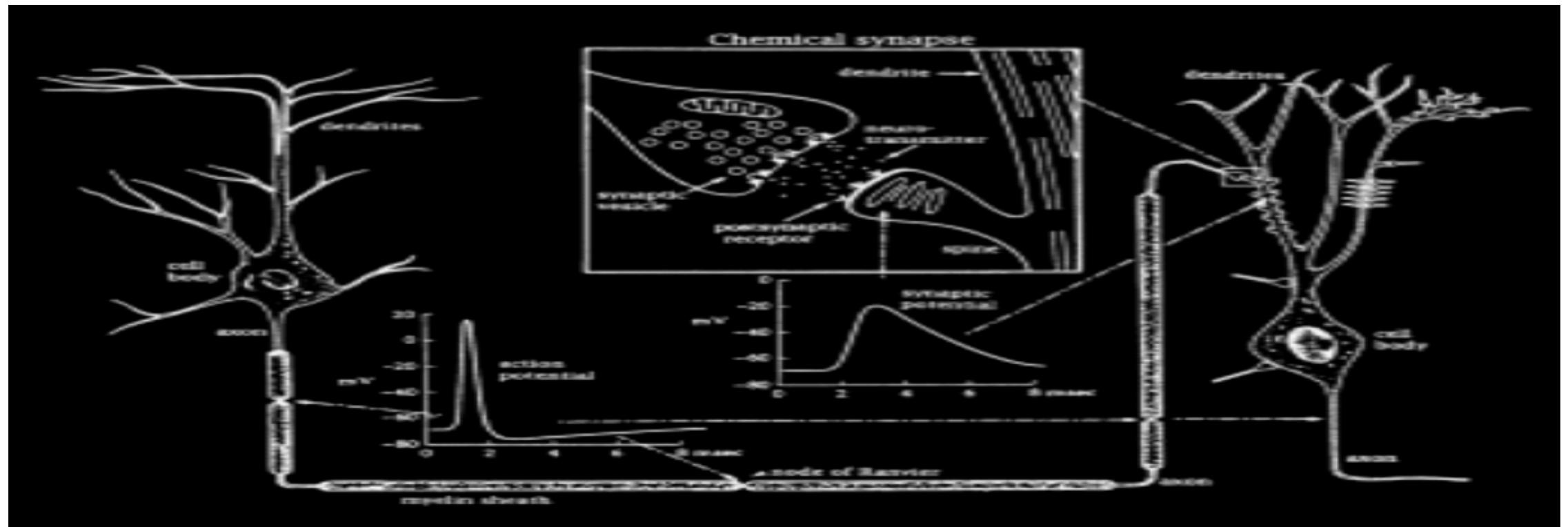
phase response curve

(phase sensitivity curve)

$$z(\theta) = \lim_{\Delta V \rightarrow 0} \frac{\Delta \theta}{\Delta V}$$



# We can study synchrony in “network” of two coupled neurons

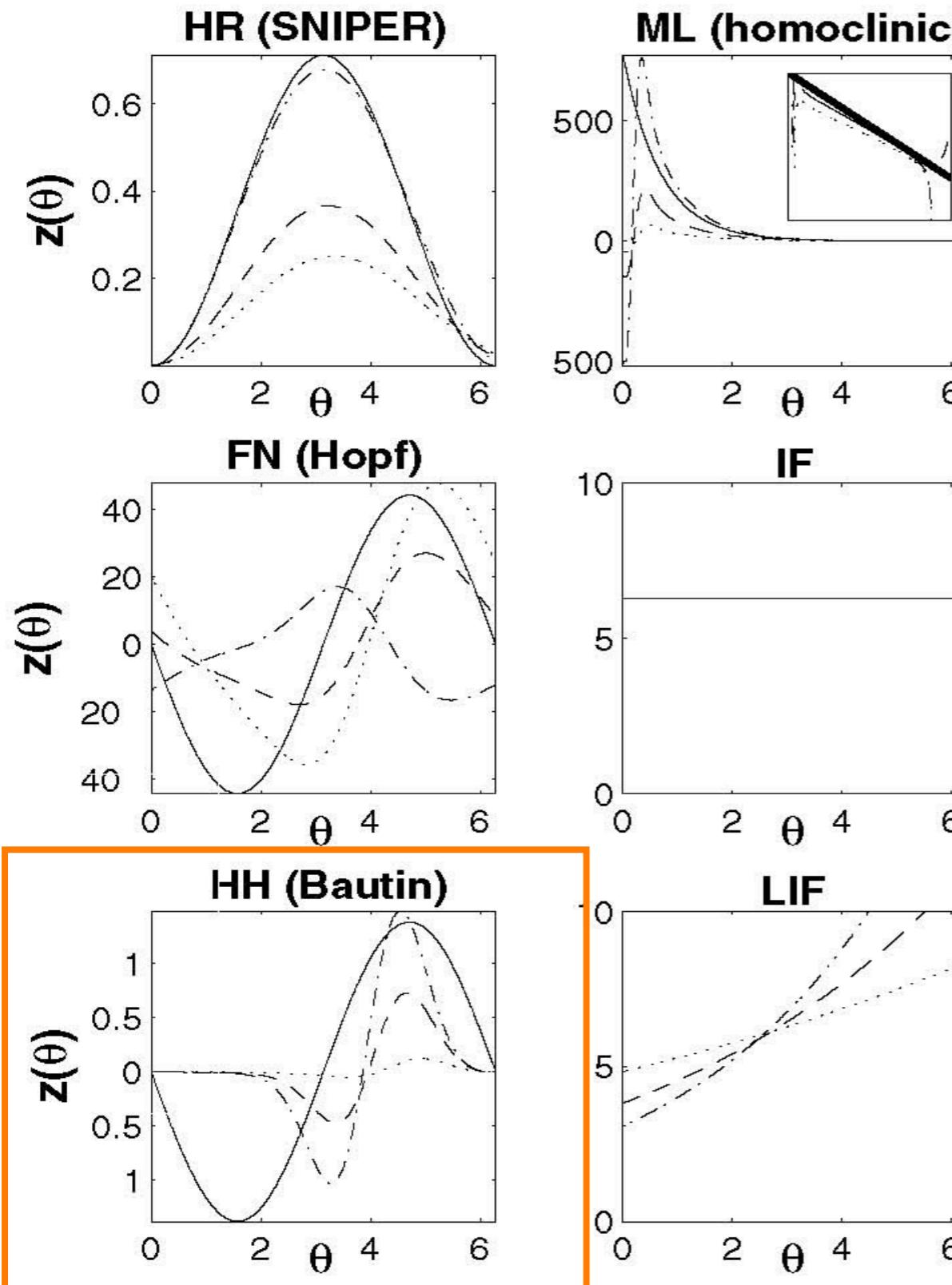


$$I_{\text{syn}}(t)$$

$$\frac{d\theta_1}{dt} = \omega + z(\theta_1) * h\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + z(\theta_2) * h\delta(t - t_1^j)$$

# For example, Hodgkin-Huxley...

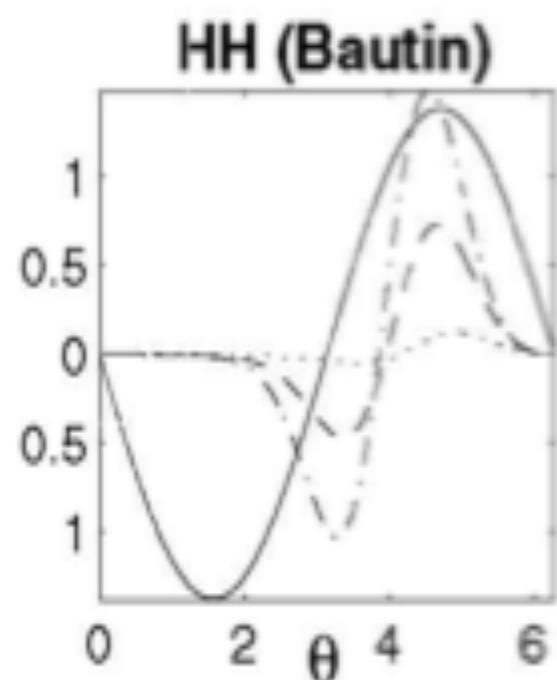


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# The Hodgkin-Huxley model

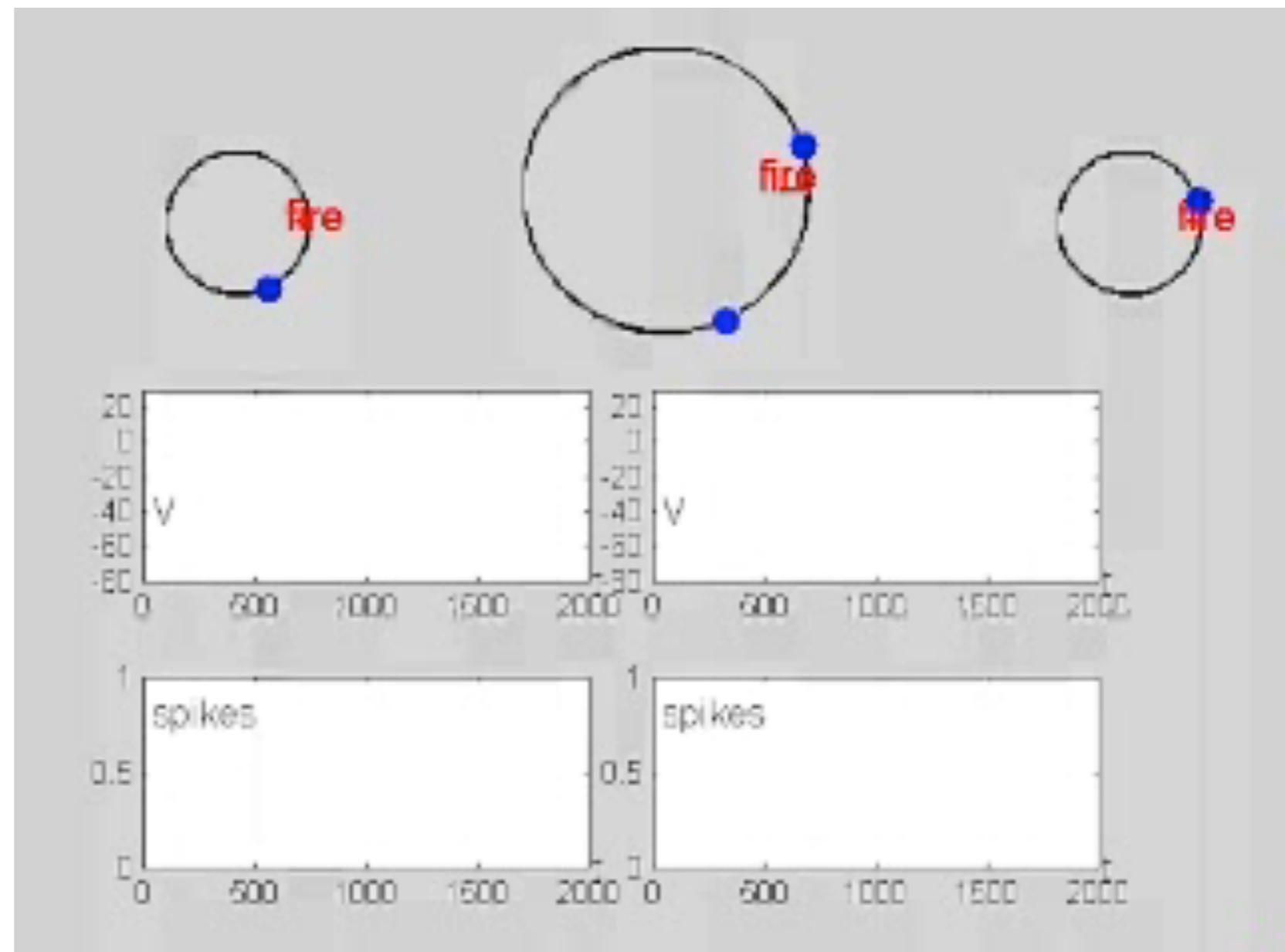
PRC

$z(\theta)$



$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

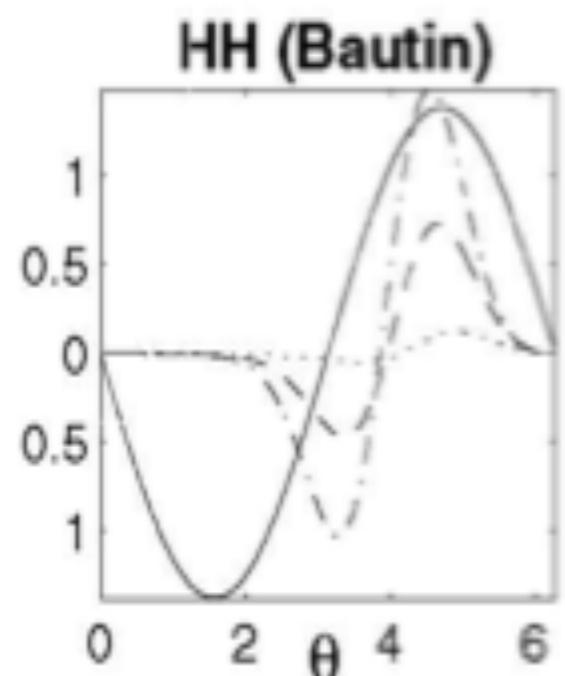
$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$



# The Hodgkin-Huxley model

PRC

$z(\theta)$



$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$

Moral: “Fast” excitatory coupling can synchronize HH neurons ...

# Analyze via Poincare map between firing times of $\theta_1$

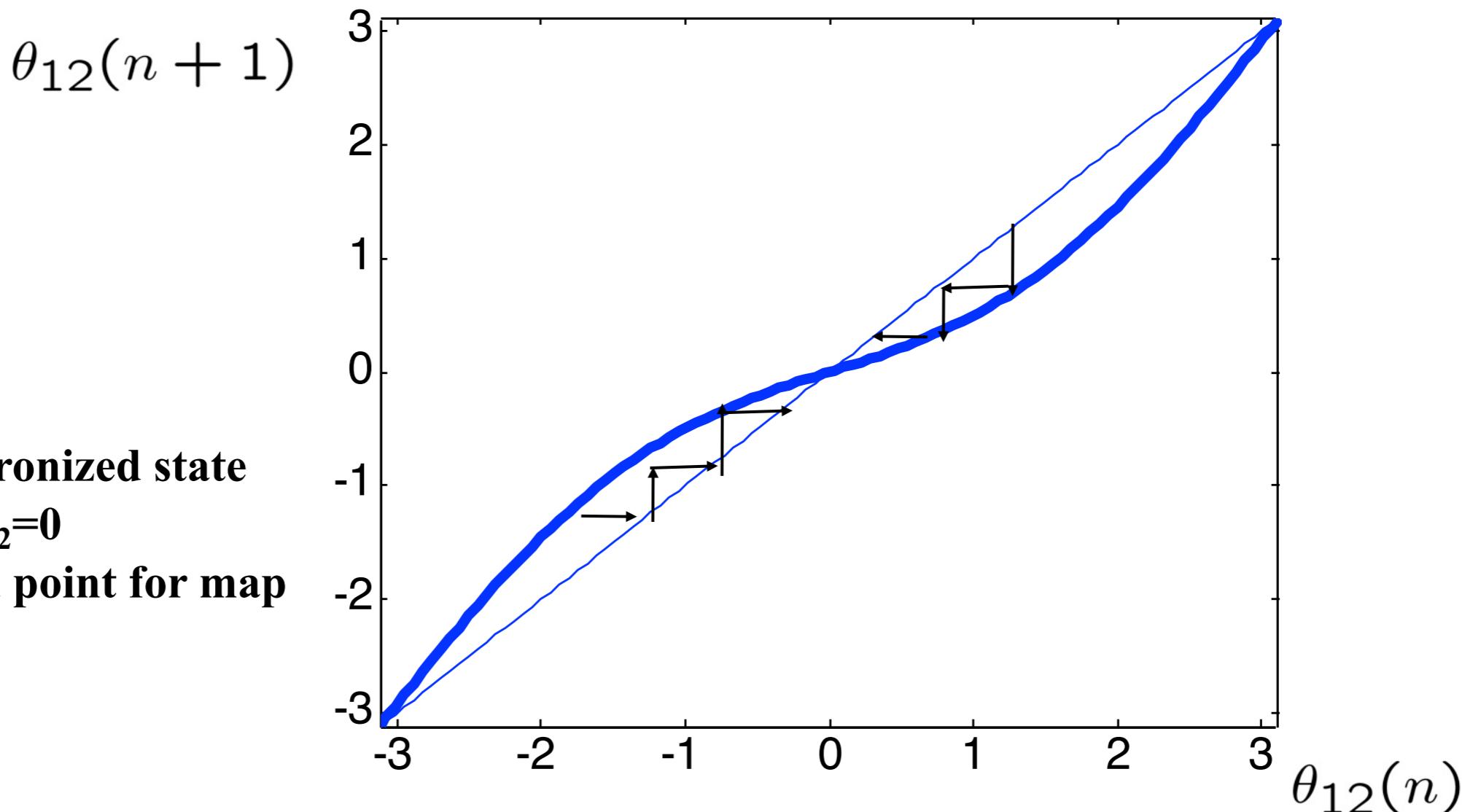
$$\theta_{12} = \theta_1 - \theta_2$$

Nancy Kopell, Bard Ermentrout,  
-- “weak coupling theory”

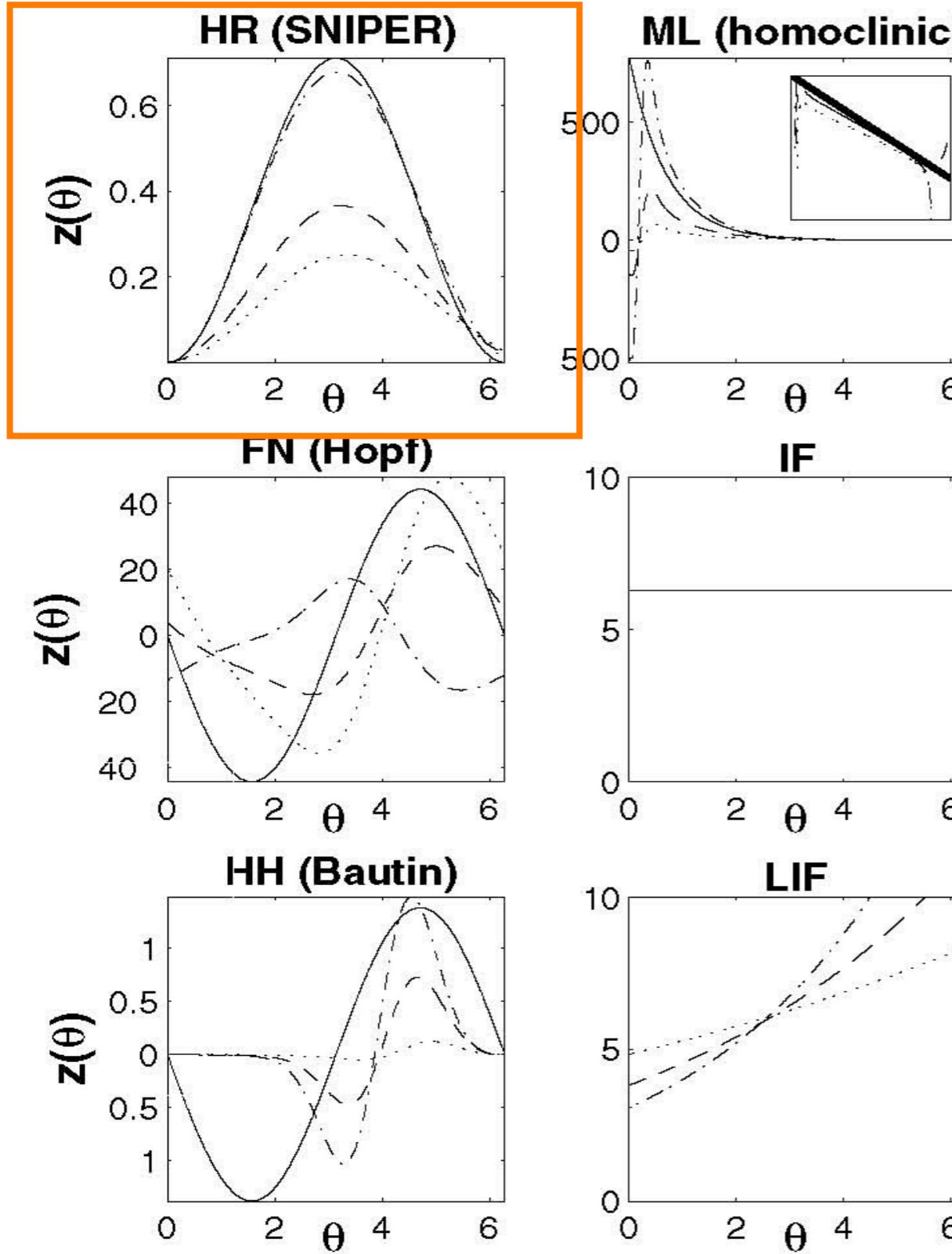
$$\theta_{12}(n+1) = \theta_{12}(n) + h \{z(\theta_{12}(n)) - z(-\theta_{12}(n))\} + \mathcal{O}(h^2)$$

E.g., for HH neuron,  $z(\theta) \sim -\sin(\theta)$ , so

$$\theta_{12}(n+1) \approx \theta_{12}(n) - 2h \sin(\theta_{12})$$



# Let's try Hodgkin-Huxley + A-current



$$C \frac{dV}{dt} = I - g_K n^4 (V - E_K) \\ - g_{Na} m^3 h (V - E_{Na}) - g_L (V - E_L) \\ - g_A a^3 b (V - E_A)$$

$$\frac{dn}{dt} = (n_\infty(V) - n) / \tau_n(V)$$

$$\frac{dm}{dt} = (m_\infty(V) - m) / \tau_m(V)$$

$$\frac{dh}{dt} = (h_\infty(V) - h) / \tau_h(V)$$

$$\frac{da}{dt} = (a_\infty(V) - a) / \tau_a(V)$$

$$\frac{db}{dt} = (b_\infty(V) - b) / \tau_b(V)$$

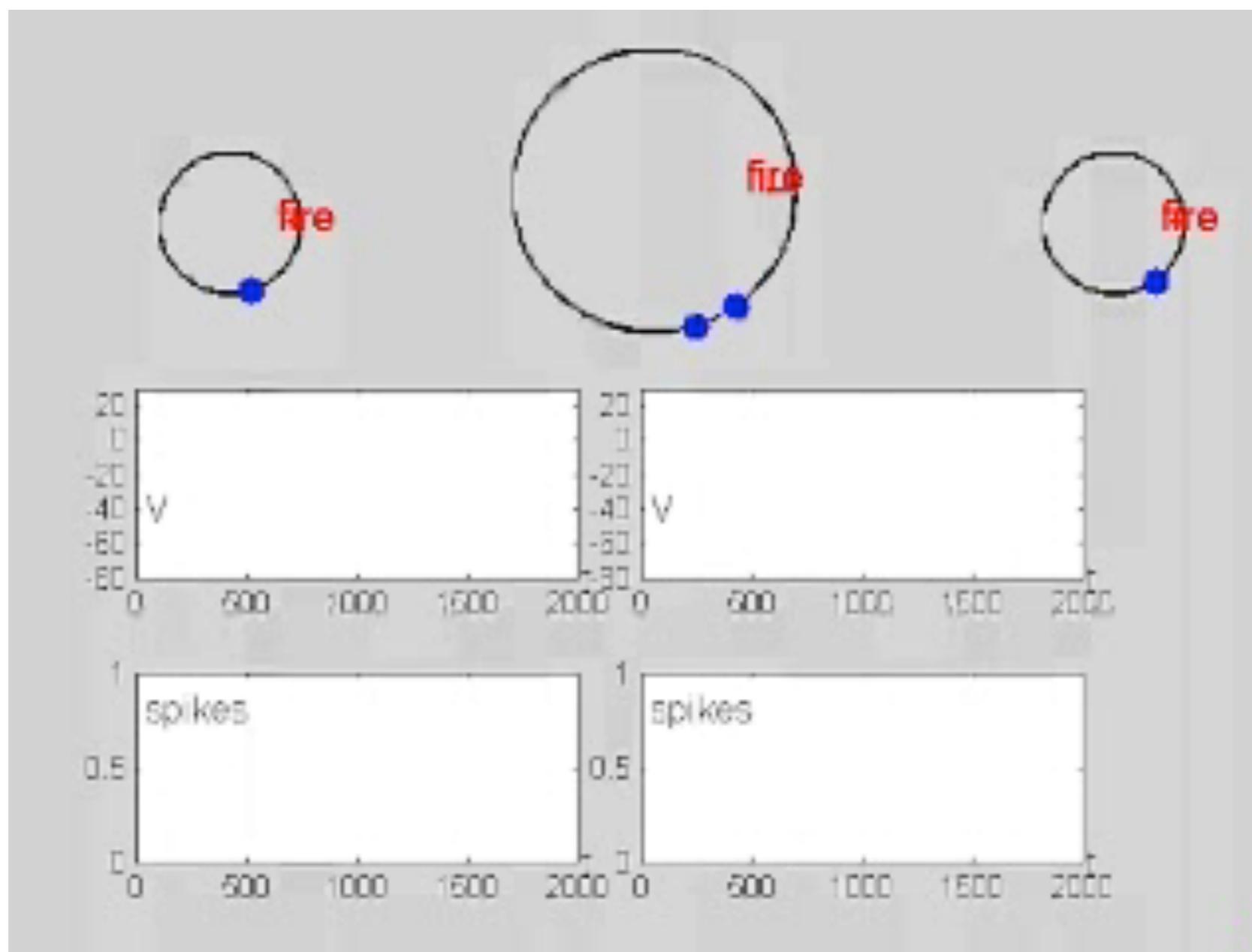
# The “Hodgkin Huxley plus A current” model

**PRC**

**z(θ)**

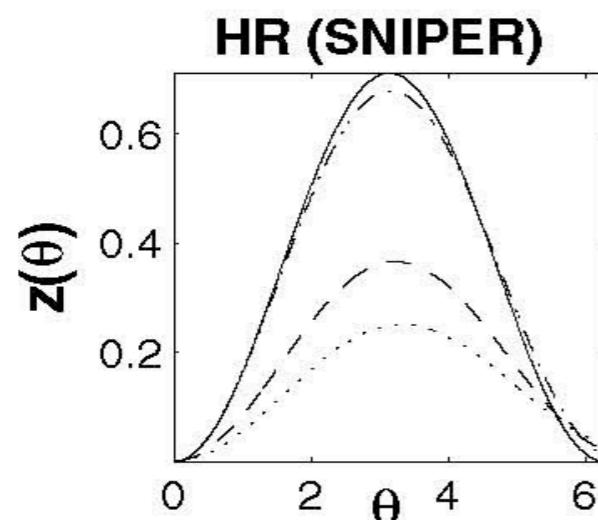
$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$

$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$



# The “Hodgkin Huxley plus A current” model

PRC  
 $z(\theta)$



$$\frac{d\theta_1}{dt} = \omega + h * z(\theta_1)\delta(t - t_2^j)$$
$$\frac{d\theta_2}{dt} = \omega + h * z(\theta_2)\delta(t - t_1^j)$$

**Moral: Excitatory coupling actually  
DEsynchronizes HH neurons with A currents**

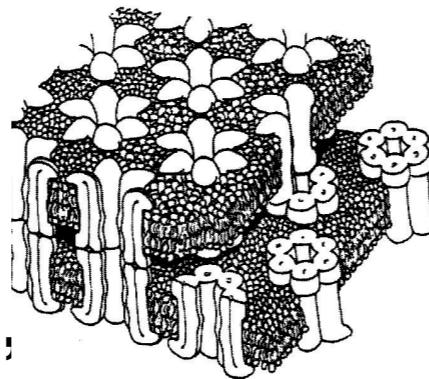
**Stable “anti-synchronized” state**

**However, inhibition *does* synchronize ...**

**“When inhibition, not excitation,  
synchronizes...” Van Vreeswijk et al 1995**

# Beyond impulse coupling

Brain has gap junctions,



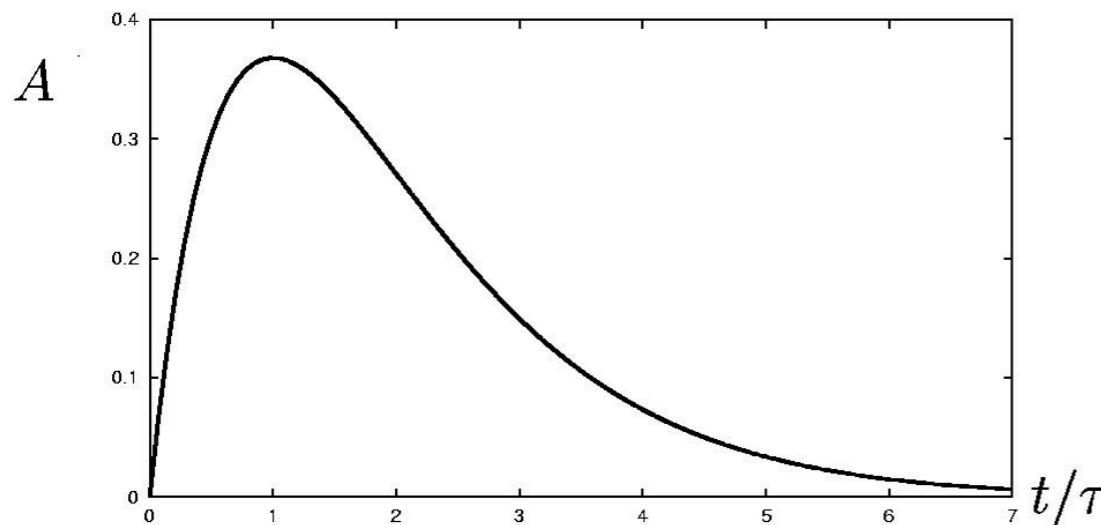
$$\dot{V}_i = \dots + \frac{\alpha_e}{N} \sum_{j=1}^N (V_j - V_i)$$

$N$  = number of neurons

$\alpha_e$  = electrotonic coupling strength

as well as slow chemical synapses.

$$\dot{V}_i = \dots + \frac{\alpha_s}{N} (V_K - V_i) \sum_{j=1}^N A(t - t_j - \tau_d)$$



$$\frac{d\theta}{dt} = \omega + z(\theta) \times [I_{syn}(t)]$$

$$\frac{d\theta_i}{dt} = \omega + z(\theta_i) \sum_{j=1}^n I_j(\theta_j)$$

**Kuramoto, Kopell, Ermentrout -- average coupling functions:**

$$f_{e,s}(\theta) = \frac{1}{2\pi} \int_0^{2\pi} z(\phi) I_{e,s}^{coup}(\theta + \phi) d\phi$$

get a system depending on phase differences only

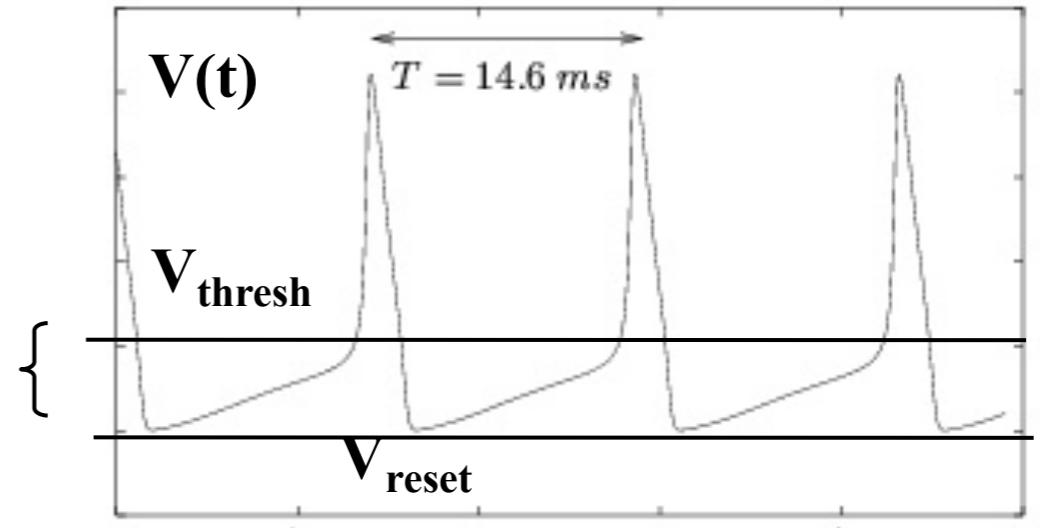
$$\frac{d\theta_i}{dt} = \underbrace{\omega + \frac{\alpha}{N} \sum_j f_e(\theta_j - \theta_i)}_{\text{electrotonic}} + \underbrace{\frac{\beta}{N-1} \sum_{j \neq i} f_s(\theta_j - \theta_i)}_{\text{synaptic}}$$

# Integrate-and-fire models

Hodgkin-Huxley

$$\frac{dV}{dt} = [I - \bar{g}_{Na}m^3h(V - V_{Na}) - \bar{g}_K n^4(V - V_K) - g_L(V - V_L)]/C,$$

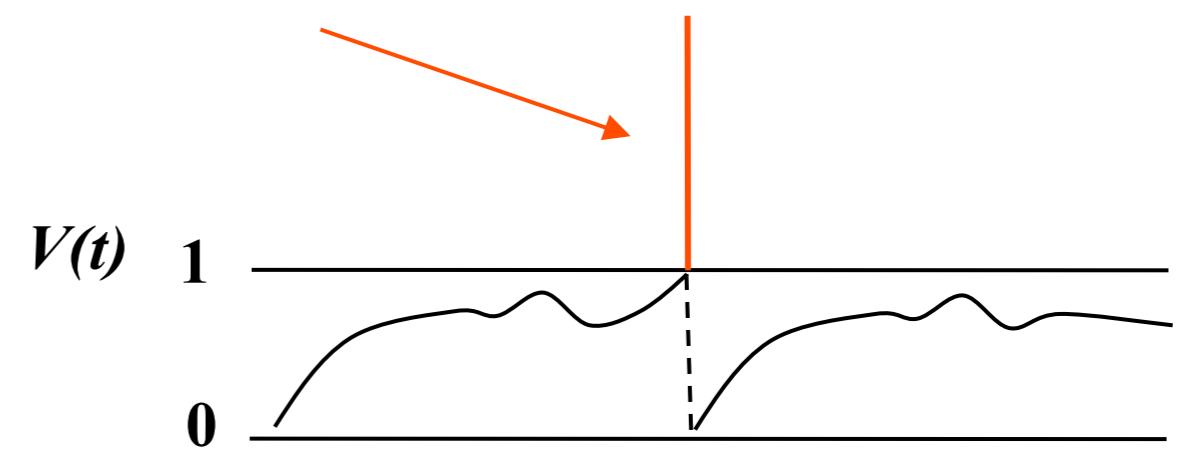
**Claim:** conductances approx. constant in this range  
Above value  $V_{\text{thresh}}$ , “stereotyped” spike takes over



In range  $[V_{\text{reset}}, V_{\text{thresh}}]$ , following rescaling,

$$\tau \frac{dV}{dt} = -V + k_1 + k_2 I \quad ; 0 \leq V \leq 1$$

plus “reset” condition:  $V \rightarrow 0$  and spike when passes 1



INTEGRATE – AND – FIRE MODEL  
OF LAPICQUE  
Gerstner, Abbott, others relate to HH

# Many variations...

$$\tau \frac{dV}{dt} = -V + k_1 + k_2 I \quad ; 0 \leq V \leq 1$$

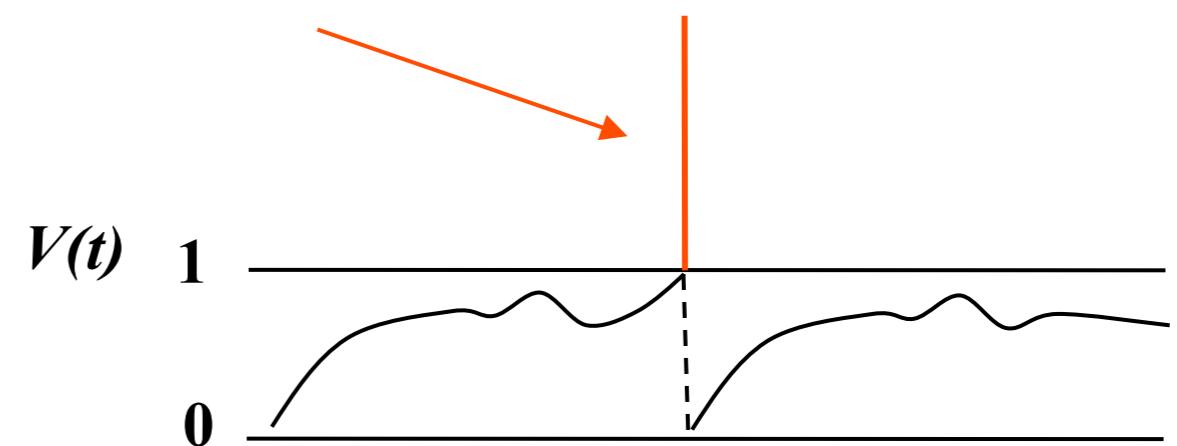
plus “reset” condition:  $V \rightarrow 0$  and spike when passes 1

$$\frac{dV}{dt} = -V + aV^2; \quad V < V_{thresh}$$

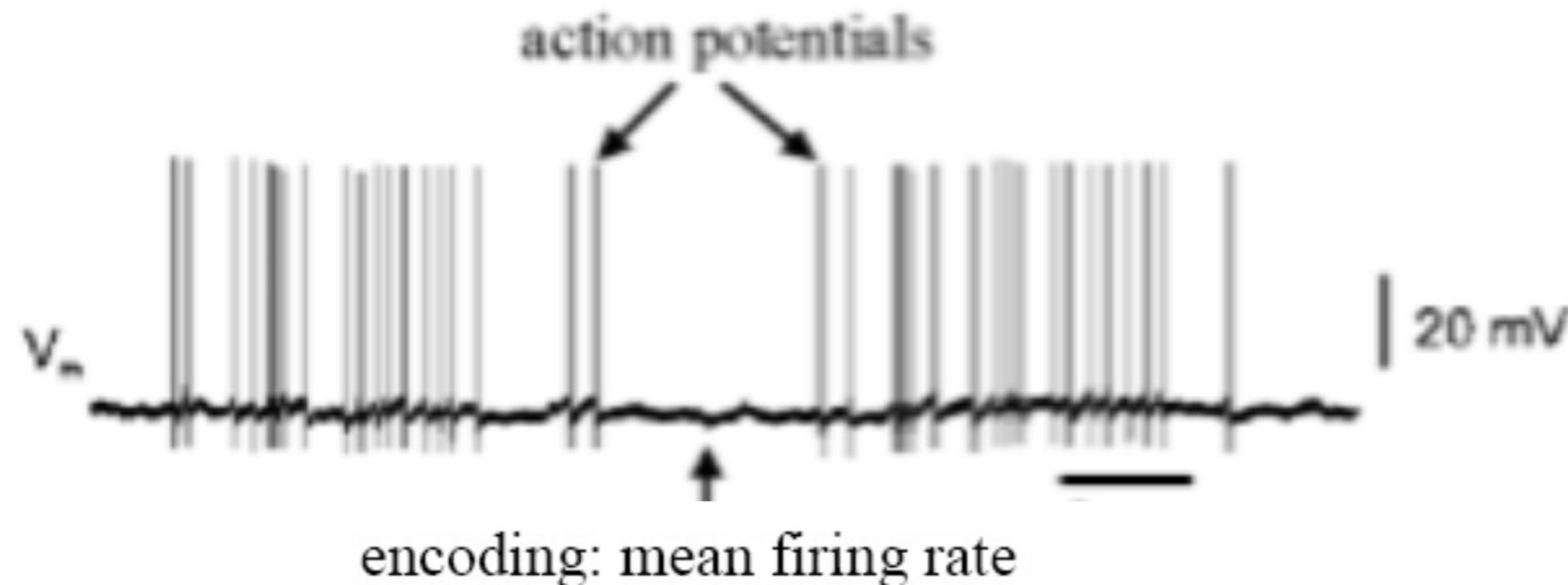
**quadratic integrate  
and fire (QIF)**

$$\frac{dV}{dt} = \frac{1}{\tau_m} \left( E_L - V + \Delta_T e^{(V-V_T)/\Delta_T} \right)$$

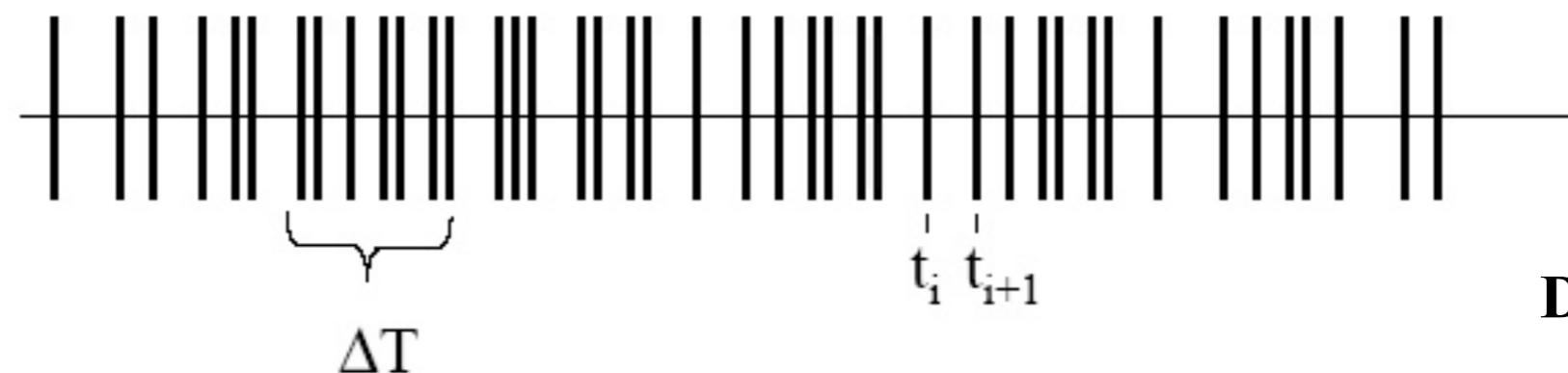
**exponential integrate  
and fire (EIF)**



# Firing rate models

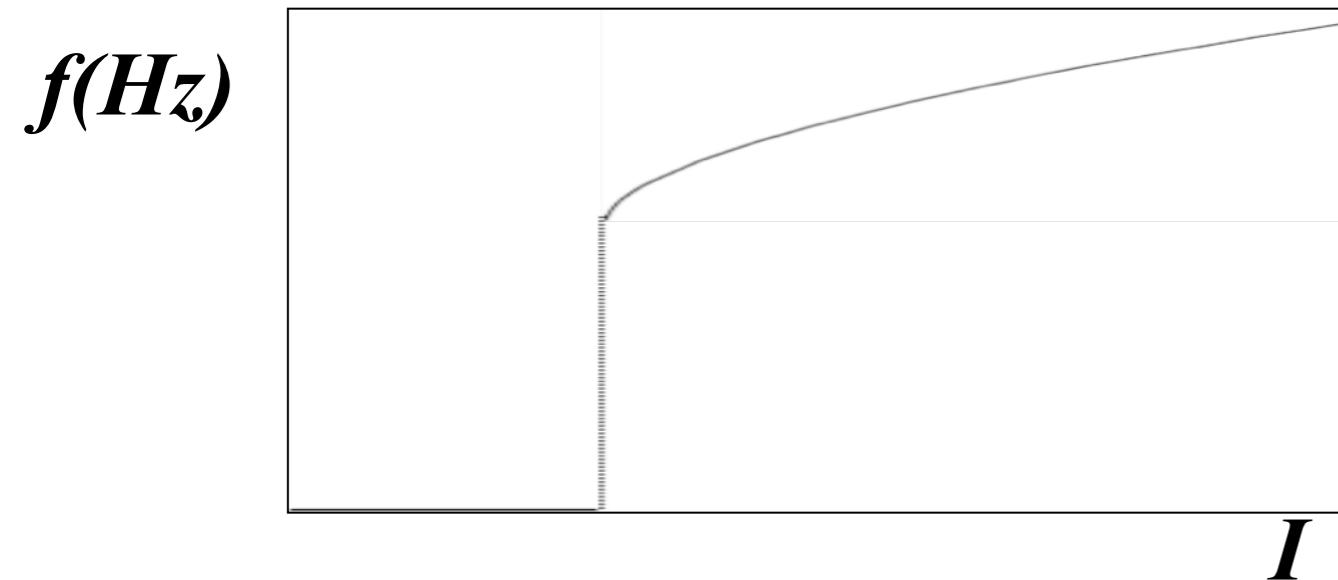


$$f(t) = \frac{1}{\Delta T} \int_t^{t+\Delta T} \sum_{i=1}^{n_i} \delta(t' - t_i) dt'$$

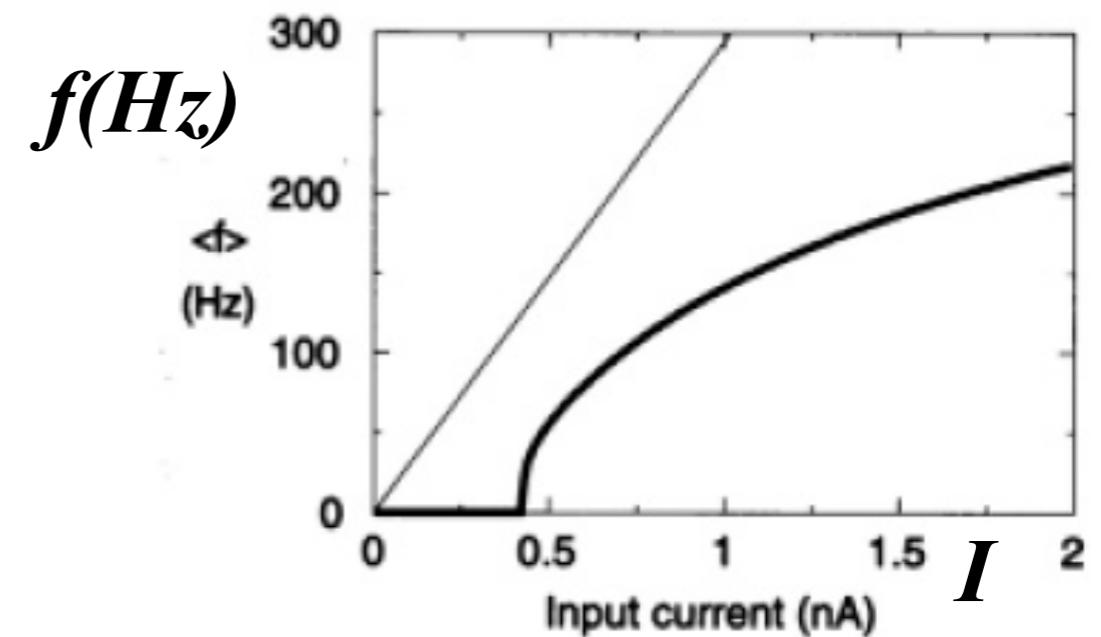


*How does firing rate  $f$  depends on input current  $I$ ?  
via different firing rate vs. current (“ $f$ - $I$ ”) curves*

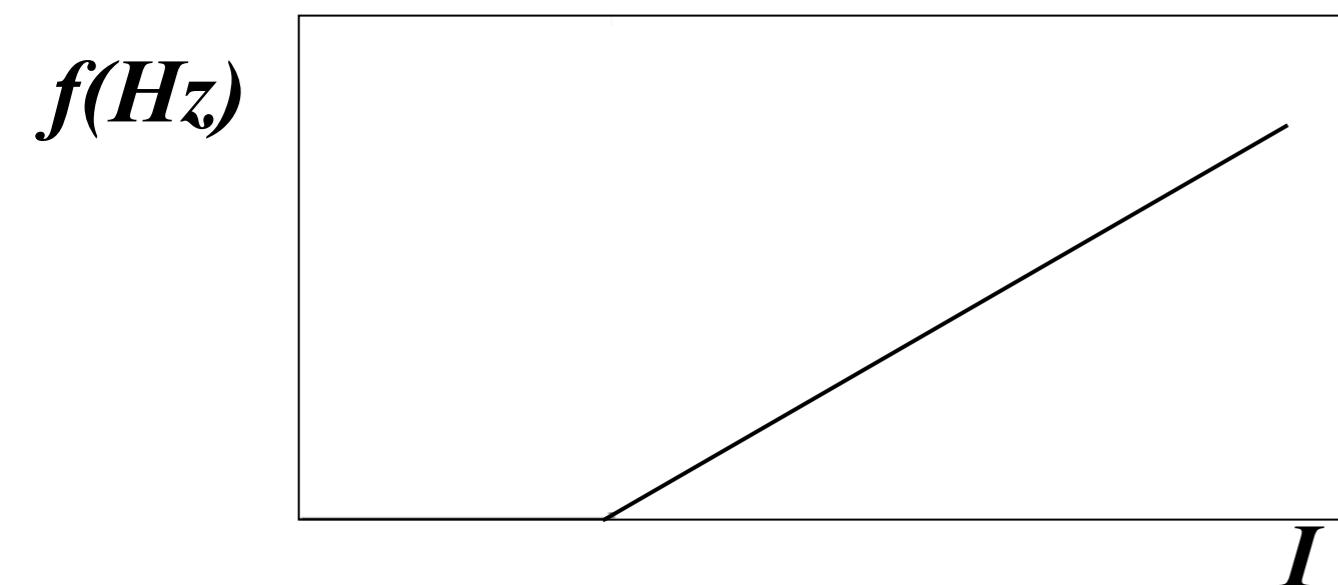
**Hodgkin-Huxley**



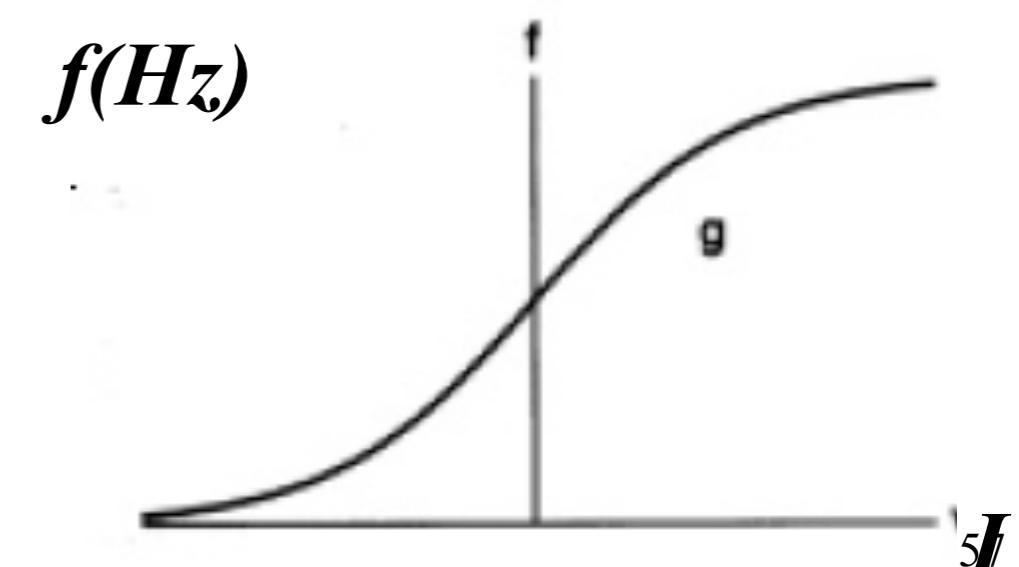
**Integrate + Fire**



**Piecewise linear**



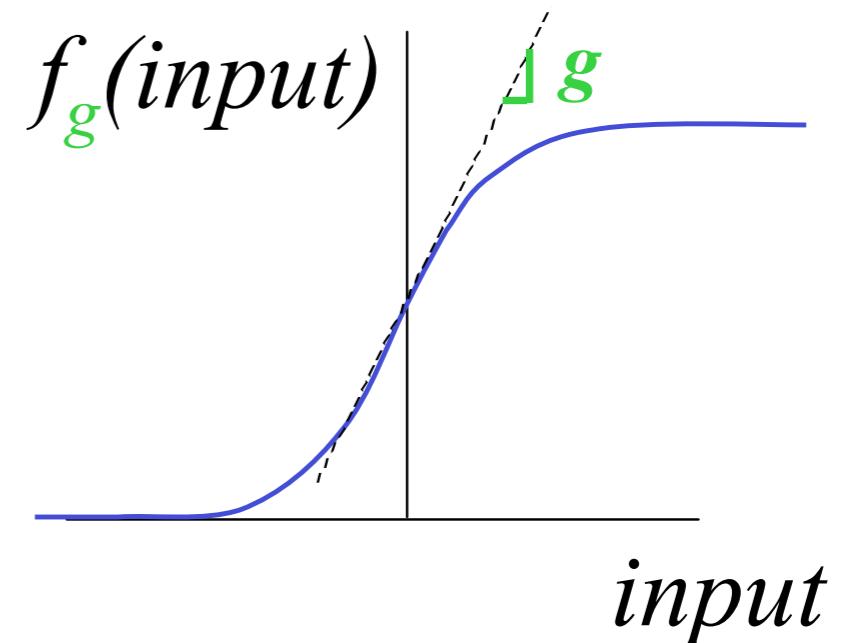
**Sigmoidal, gain  $g$**



# Dynamics?

- Think of neural “units...” described by firing rates  $y$  which approach equilibrium rates  $f(\text{input})$  with time constant  $\tau_m$ .

$$\tau_m \frac{dy}{dt} = -y + f(\text{input})$$



- *nonlinearity of input-output function  $f$*  allows amazing array of “neural network” computations – Hopfield, Grossberg, Cohen
  - *associative memory: recall and learning*
  - *can encode complex input-output functions*

# Computational tools for dynamical systems

- XPP
- AUTO
- MATCONT

# References

- Check website later!
- <http://depts.washington.edu/compsci/>