

Single neuron models

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Biophysics

- Biological neuron

- Biophysics

- Ionic currents

- Passive properties

- Active properties

Typology of models

- Compartmental models

- Differential models

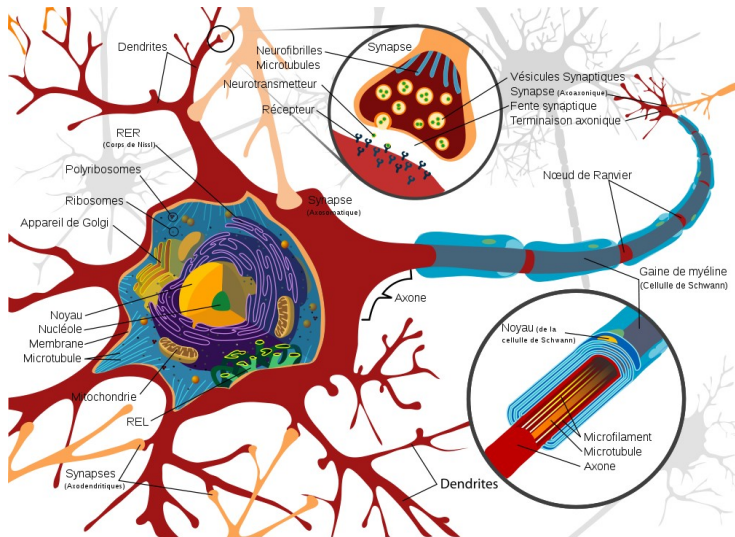
- Hybrid models

- Discrete state automata

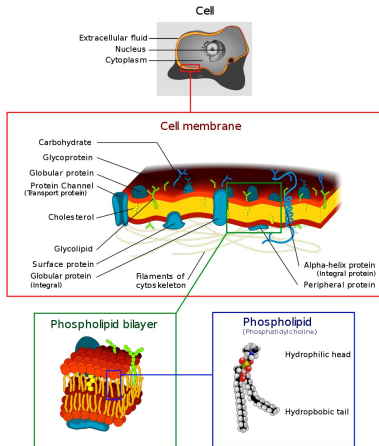
Models of synapses

- Models of synapses

Biological neuron



The membrane



Models of the electrophysiology of excitability

Electro-diffusion laws

Fick's law:

$$J_d = -D \frac{\partial c}{\partial x}$$

Ohm's law:

$$J_e = -\mu z c \frac{\partial V}{\partial x}$$

Einstein's relation:

$$D = \frac{\mu k_B T}{q}$$

Nernst-Planck equation

Ionic form:

$$J = -\left(\mu z c \frac{\partial V}{\partial x} + \frac{\mu k_B T}{q} \frac{\partial c}{\partial x}\right)$$

Molar form:

$$\mathbf{J} = J/\mathcal{N} = -\left(uzc \frac{\partial V}{\partial x} + u \frac{RT}{\mathcal{F}} \frac{\partial c}{\partial x}\right)$$

Current density:

$$I = \mathbf{J} \cdot z\mathcal{F} = -\left(uz^2\mathcal{F}c \frac{\partial V}{\partial x} + uzRT \frac{\partial c}{\partial x}\right)$$

Nernst's equation

At equilibrium ($I=0$):

$$V_2 - V_1 = -\frac{RT}{z\mathcal{F}} \ln\left(\frac{c_2}{c_1}\right)$$

Conventions of electrophysiology:

1. $V_m = V_i - V_e = V$
2. Positive currents: from inside to outside

Equilibrium potential for an ion (k):

$$E_k = V(I_k = 0) \quad \text{thus} \quad E_k = \frac{RT}{z\mathcal{F}} \ln\left(\frac{c_e}{c_i}\right)$$

Ionic distributions

Cell of Mammal ($T = 37^{\circ}\text{C}$):

Ions	c_i	c_e	E_k
K^+	140	5	$\approx -90\text{ mV}$
Na^+	from 5 to 15	145	$\approx 60\text{ to }90\text{ mV}$
Cl^-	4	110	$\approx -90\text{ mV}$

Gradients maintenance:

- ▶ Active processes: pump (ATP-ases), exchanger, co-transporters
- ▶ Donnan's equilibrium

Membrane potential is the result of a stationary regime of exchanges based on transmembrane ionic currents

Ionic currents

Ionic channels:

- ▶ Non-gated channels
- ▶ Gated channels

Models:

- ▶ Electrodiffusion
- ▶ Barriers models
- ▶ State models (kinetics and stochastics)

Characteristic:

- ▶ I-V curve

Goldman-Hodgkin-Katz model

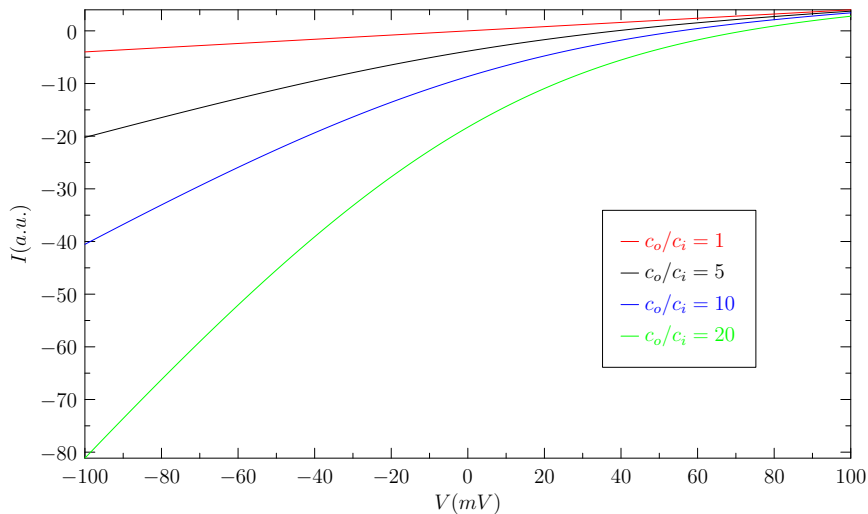
Hypothesis:

1. Electrodiffusion in the membrane
2. No interaction between ions
3. Constant electric field ($dV/dx = V/l$)

Current $I(V)$:

$$I_k = P_k z \mathcal{F} \xi \frac{c_i - c_e e^{-\xi}}{1 - e^{-\xi}} \quad \text{et} \quad \xi = \frac{z \mathcal{F} V}{RT}$$

I-V curves for GHK model

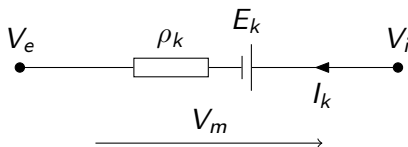


Ohmic (linear) model

Hypothesis:

1. Equivalent circuit
2. Currents follow Ohm's law

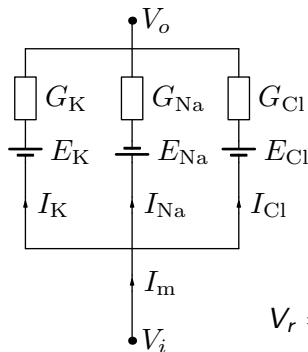
Equivalent circuit:



Current $I(V)$:

$$I_k = \gamma_k (V - E_k) \quad \text{with} \quad \gamma_k = 1/\rho_k$$

Resting potential



Linear model:

$$V_r = \frac{G_{Na}E_{Na} + G_K E_K + G_{Cl}E_{Cl}}{G_{Na} + G_K + G_{Cl}}$$

Constant field (GHK):

$$V_r = -\frac{RT}{\mathcal{F}} \ln \left(\frac{P_K[K]_i + P_{Na}[Na]_i + P_{Cl}[Cl]_e}{P_{Na}[Na]_e + P_K[K]_e + P_{Cl}[Cl]_i} \right)$$

$$I_m = I_{Na} + I_K + I_{Cl} = 0$$

Passive and active currents

Definitions:

1. *Passive* currents have a *constant* conductance
2. *Active* currents have a *variable* conductance (voltage, stimulus or chemical sensitive). They are the basis of *cell excitability*.

Formalism:

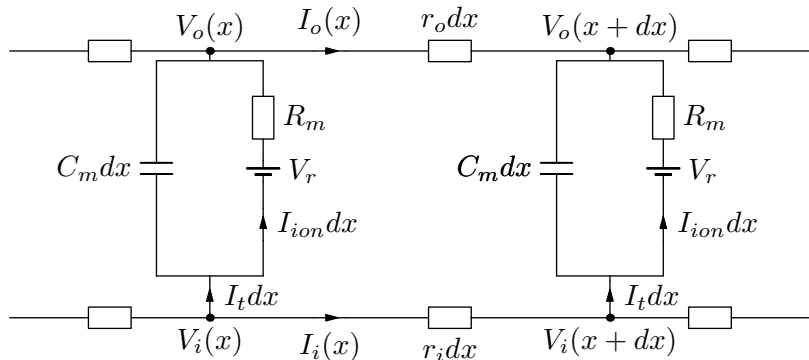
1. Passive:

$$I_k = g_k(V - E_k)$$

2. Active:

$$I_k = \bar{g}_k p(\cdot)(V - E_k)$$

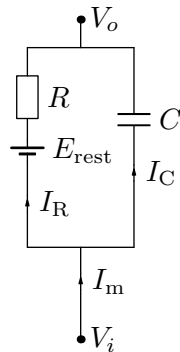
Cable equation (Rall, 1957-1969)



$$\tau_m \frac{\partial V}{\partial t} + R_m I_{ion} = \lambda_m^2 \frac{\partial^2 V}{\partial x^2}$$

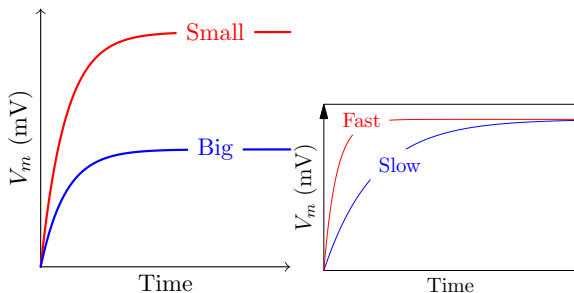
with: $\tau_m = R_m C_m$ and $\lambda_m = \sqrt{\frac{R_m d}{4R_c}}$

Temporal properties

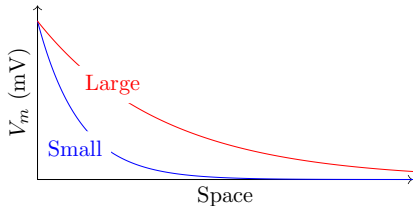
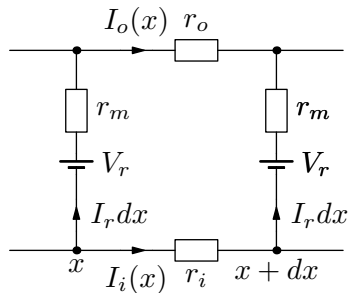


$$\tau \frac{dV}{dt} = V_r + RI - V \quad \text{with} \quad \tau = R_m C_m$$

$$V(t) = V_r + RI(1 - e^{-t/\tau}) \quad \text{and} \quad R = R_m/S$$



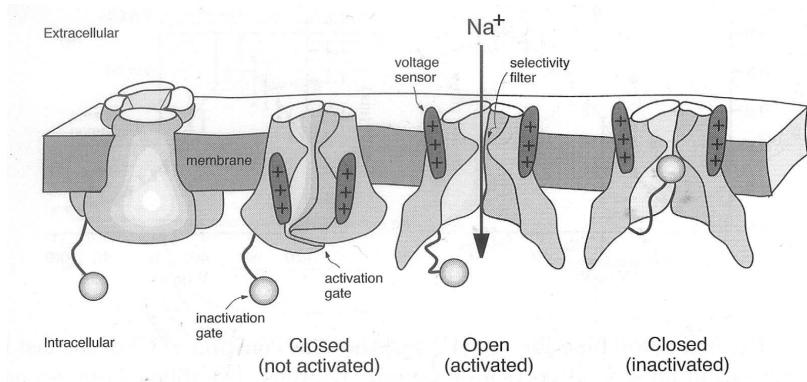
Spatial properties



$$\lambda^2 \frac{d^2 V}{dx^2} = V(x) - V_r$$

$$V_m(x) = V_r + V_\infty e^{-x/\lambda}$$

Sodium gated channel



Formalism for gated channels

$$I_k = \bar{g}_k p(\cdot) (V - E_k) = \bar{g}_k m^a h^b (V - E_k)$$

- ▶ Probability of opening for *activation* (m) and *inactivation* (h) gates.
- ▶ Number of *activation* (a) and *inactivation* (b) gates
- ▶ Independence of the gates:

$$p(\cdot) = \underbrace{m \times m \times \cdots \times m}_a \times \underbrace{h \times h \times \cdots \times h}_b$$

- ▶ *Open / activated channel:*

$$m = 1 \text{ (partially activated: } 0 < m < 1) \text{ and } h = 1.$$

- ▶ *Closed channel:*

- ▶ Not activated: $m = 0$ and $h = 1$
- ▶ Inactivated: $m = 1$ and $h = 0$

Action potential

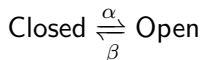
Hodgkin & Huxley (1952):

Experimental analysis and theoretical model that explains the genesis of action potential in the squid giant axon.

Hypothesis:

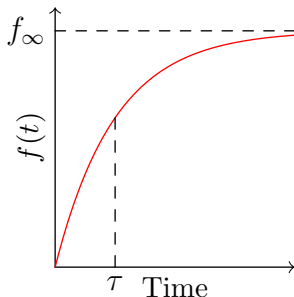
1. No spatial dependency
2. Ohmic currents
3. Sodium, potassium and leak
4. First order kinetics for activation and inactivation gates

First order kinetics

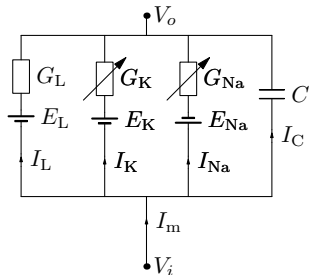


$$\frac{df}{dt} = \alpha(1 - f) - \beta f$$

$$f(t) = f_{\infty}(1 - e^{-t/\tau}) \quad \text{with} \quad f_{\infty} = \frac{\alpha}{\alpha + \beta} \quad \text{and} \quad \tau = \frac{1}{\alpha + \beta}$$



Circuit for Hodgkin and Huxley model



$$I = I_{\text{Na}} + I_{\text{K}} + I_{\text{L}} + I_{\text{C}}$$

$$= I_{\text{Na}} + I_{\text{K}} + G_{\text{L}}(V - E_{\text{L}}) + C \frac{dV}{dt}$$

Active currents:

- ▶ *Transient sodium current:*

$$I_{\text{Na}} = \bar{g}_{\text{Na}} m^3 h (V - E_{\text{Na}})$$

- ▶ *Persistent potassium current:*

$$I_{\text{K}} = \bar{g}_{\text{K}} n^4 (V - E_{\text{K}})$$

Historical Hodgkin-Huxley model

$$C\dot{V} = I - \bar{g}_{\text{Na}}m^3h(V - E_{\text{Na}}) - \bar{g}_{\text{K}}n^4(V - E_{\text{K}}) - g_{\text{L}}(V - E_{\text{L}})$$

$$\dot{m} = \alpha_m(V)(1 - m) - \beta_m(V)m$$

$$\dot{h} = \alpha_h(V)(1 - h) - \beta_h(V)h$$

$$\dot{n} = \alpha_n(V)(1 - n) - \beta_n(V)n$$

and

$$\alpha_n(V) = 0.01 (10 - V)/(\exp((10 - V)/10) - 1)$$

$$\beta_n(V) = 0.125 \exp(-V/80)$$

$$\alpha_m(V) = 0.1 (25 - V)/(\exp((25 - V)/10) - 1)$$

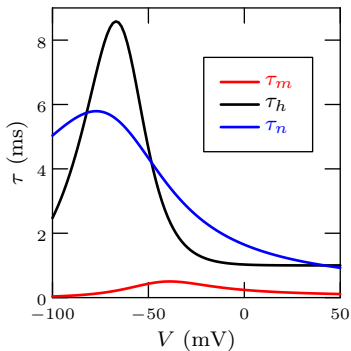
$$\beta_m(V) = 4 \exp(-V/18)$$

$$\alpha_h(V) = 0.07 \exp(-V/20)$$

$$\beta_h(V) = 1 / (\exp((30 - V)/10) + 1)$$

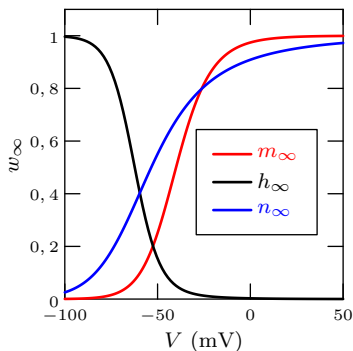
Potential dependence of kinetics parameters

Time constant



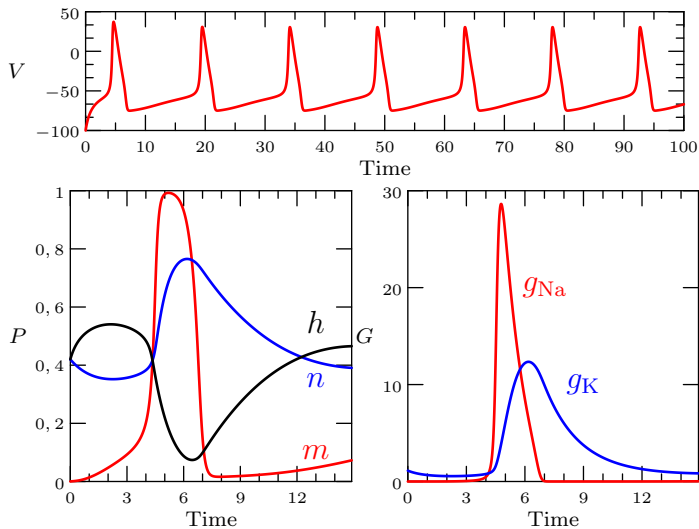
$$\tau_x(V) = \frac{1}{\alpha_x(V) + \beta_x(V)}$$

Asymptotic value



$$x_\infty(V) = \frac{\alpha_x(V)}{\alpha_x(V) + \beta_x(V)}$$

Hodgkin-Huxley model



Standard Hodgkin-Huxley model

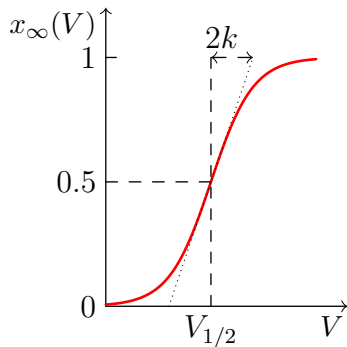
$$C\dot{V} = I - \bar{g}_{\text{Na}}m^3h(V - E_{\text{Na}}) - \bar{g}_{\text{K}}n^4(V - E_{\text{K}}) - g_{\text{L}}(V - E_{\text{L}})$$

$$\dot{m} = (m_{\infty}(V) - m) / \tau_m(V)$$

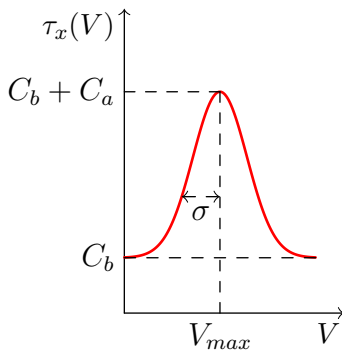
$$\dot{h} = (h_{\infty}(V) - h) / \tau_h(V)$$

$$\dot{n} = (n_{\infty}(V) - n) / \tau_n(V)$$

Standard kinetic parameters

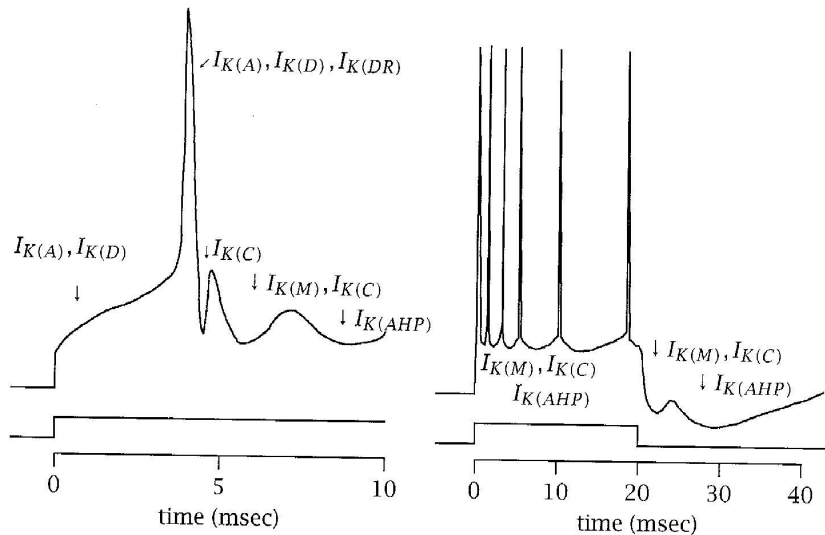


$$x_{\infty}(V) \approx \frac{1}{1 + e^{\frac{V_{1/2}-V}{k}}}$$



$$\tau_x(V) \approx C_b + C_a e^{\frac{-(V_{max}-V)^2}{\sigma^2}}$$

"Zoology" of ion channels



Neuronal models

Criteria:

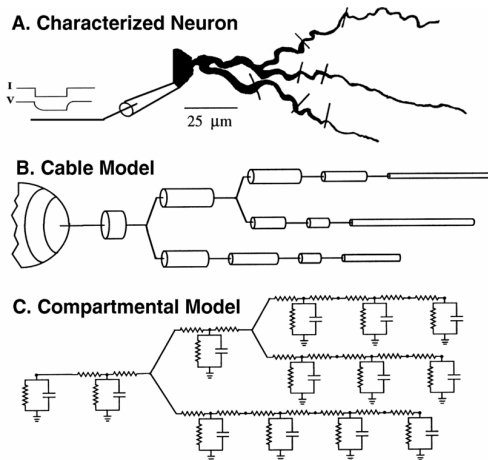
1. Biological plausibility
2. Computational load

Categories:

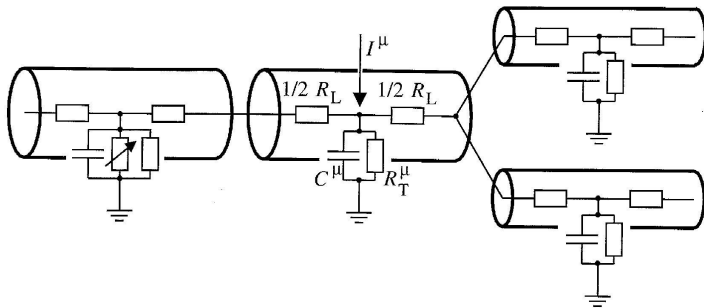
1. Compartmental models
2. Differential models (simplified HH)
3. Hybrid models
4. Discrete state automata

Compartmental models

Principle:



Compartmental models



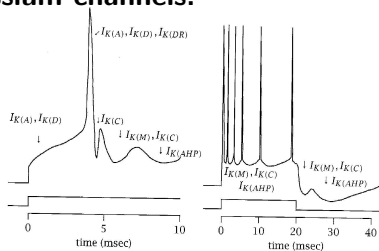
Simulation environments:
NEURON, GENESIS

Zoology of channels

Channels types:

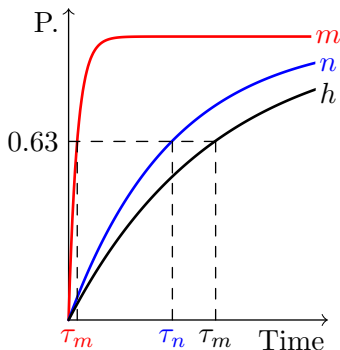
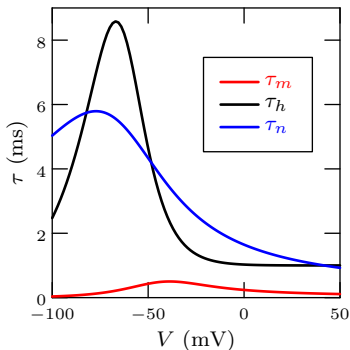
- ▶ $I_{Na}(\text{fast})$, $I_{Na}(\text{slow})$, $I_{Ca}(L)$, $I_{Ca}(T)$, $I_{Ca}(N)$, $I_{Ca}(P)$, $I_{K}(DR)$, $I_{K}(A)$, $I_{K}(D)$, $I_{K}(M)$
- ▶ I_Q , I_h , I_f , $I_{K}(IR)$, $I_{Cl}(V)$
- ▶ $I_{K}(C)$, $I_{K}(AHP)$, $I_{Cl}(Ca)$
- ▶ $I_{K}(L)$, I_{Cl} , $I_{K}(ATP)$, $I_{K}(Na)$

Potassium channels:



Reduction of Hodgkin-Huxley model: step 1

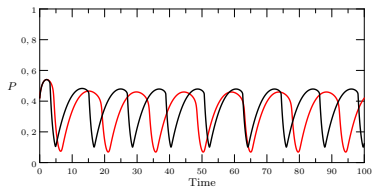
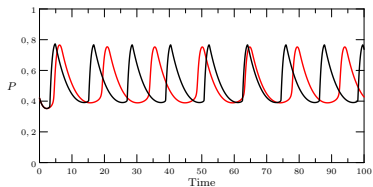
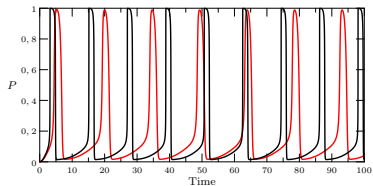
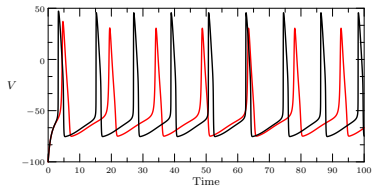
Separation of time scales: $m = m_{\infty}(V)$



Thus:

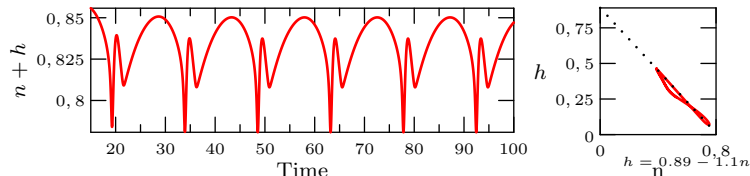
$$C\dot{V} = I - \bar{g}_{\text{Na}} m_{\infty}(V)^3 h(V - E_{\text{Na}}) - \bar{g}_{\text{K}} n^4(V - E_{\text{K}}) - g_{\text{L}}(V - E_{\text{L}})$$
$$\dot{h} = (h_{\infty}(V) - h)/\tau_h(V) \quad \text{and} \quad \dot{n} = (n_{\infty}(V) - n)/\tau_n(V)$$

Comparison of HH models: 4D vs. 3D



Reduction of Hodgkin-Huxley model: step 2

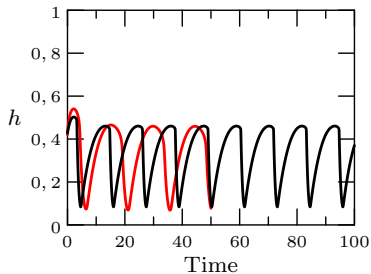
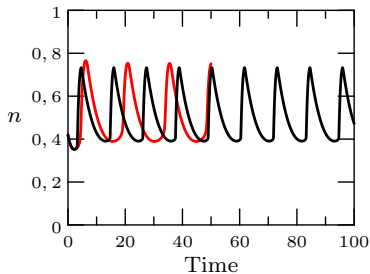
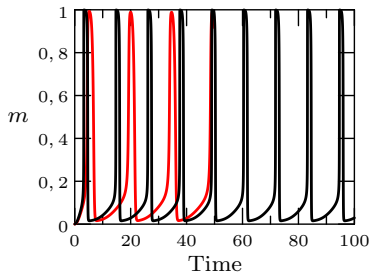
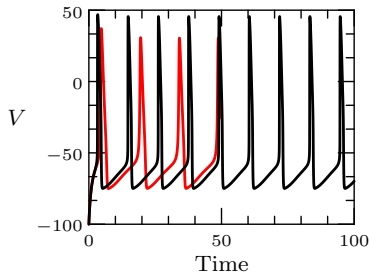
Comparison of h and n : $h + n \approx 0.8$



Thus:

$$\begin{aligned} C\dot{V} &= I - \bar{g}_{\text{Na}} m_{\infty}(V)^3 (0.8 - n)(V - E_{\text{Na}}) - \bar{g}_{\text{K}} n^4 (V - E_{\text{K}}) \\ &\quad - g_{\text{L}}(V - E_{\text{L}}) \\ \dot{n} &= (n_{\infty}(V) - n) / \tau_n(V) \end{aligned}$$

Comparison of HH models: 4D vs. 2D



Two-dimensional models

Morris-Lecar model:

$$\begin{aligned}C\dot{V} &= I - \bar{g}_{\text{Ca}}m_{\infty}(V)(V - E_{\text{Ca}}) - \bar{g}_{\text{K}}n(V - E_{\text{K}}) - g_{\text{L}}(V - E_{\text{L}}) \\ \dot{n} &= (n_{\infty}(V) - n)/\tau_n(V)\end{aligned}$$

INa,p+IK model:

$$\begin{aligned}C\dot{V} &= I - \bar{g}_{\text{Na}}m_{\infty}(V)(V - E_{\text{Na}}) - \bar{g}_{\text{K}}n(V - E_{\text{K}}) - g_{\text{L}}(V - E_{\text{L}}) \\ \dot{n} &= (n_{\infty}(V) - n)/\tau_n(V)\end{aligned}$$

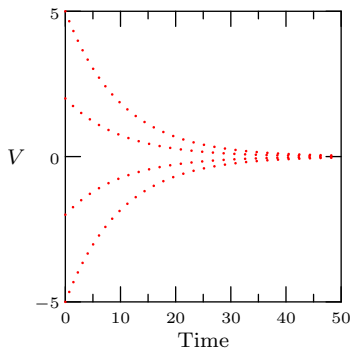
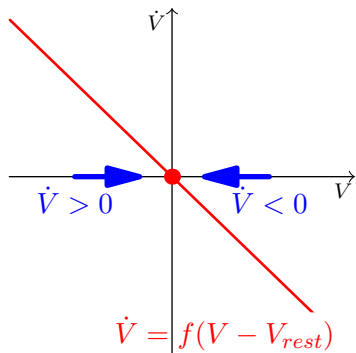
Fitzhugh-Nagumo model:

$$\begin{aligned}\dot{x} &= x(a - x)(x - 1) - y + I \\ \dot{y} &= bx - cy\end{aligned}$$

Qualitative analysis of dynamical systems

Example of 1D linear system:

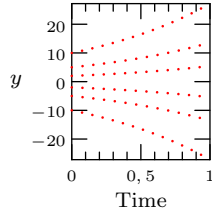
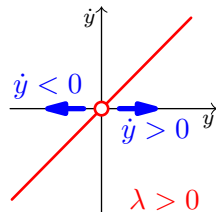
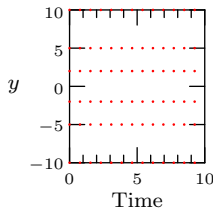
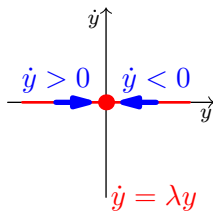
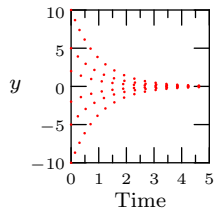
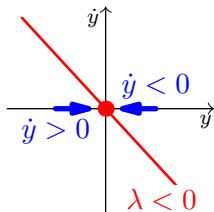
$$C \frac{dV}{dt} = -G(V - V_{rest}) = C\dot{V}$$



Qualitative analysis of dynamical systems

General 1D linear system:

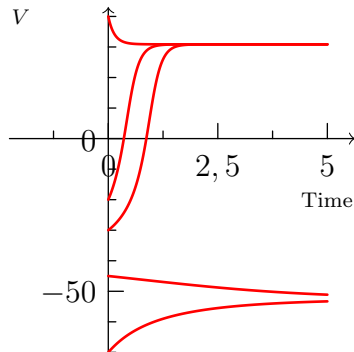
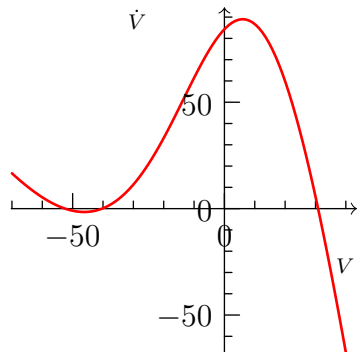
$$\dot{y}(t) = \lambda y(t) \quad \text{Solution: } y(t) = y_0 e^{\lambda t}$$



Qualitative analysis of dynamical systems

Example of 1D nonlinear system: persistent sodium model.

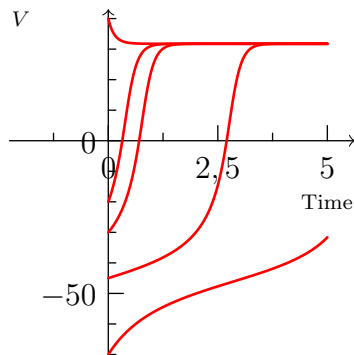
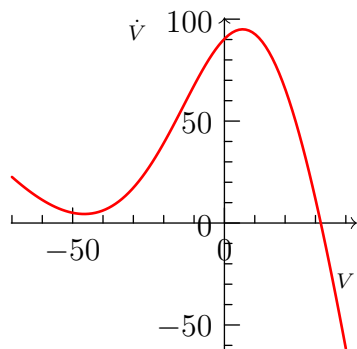
$$C\dot{V} = I - g_L(V - E_L) - g_{Na}m_\infty(V)(V - V_{Na})$$



Qualitative analysis of dynamical systems

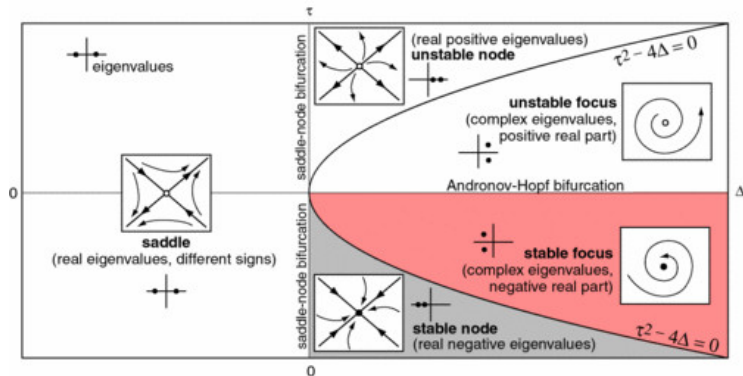
Example of 1D nonlinear system: persistent sodium model
($I = 60$)

$$C\dot{V} = I - g_L(V - E_L) - g_{Na}m_\infty(V)(V - V_{Na})$$



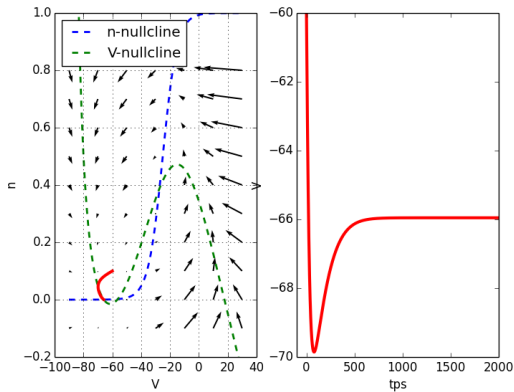
Qualitative analysis of dynamical systems

2D system:



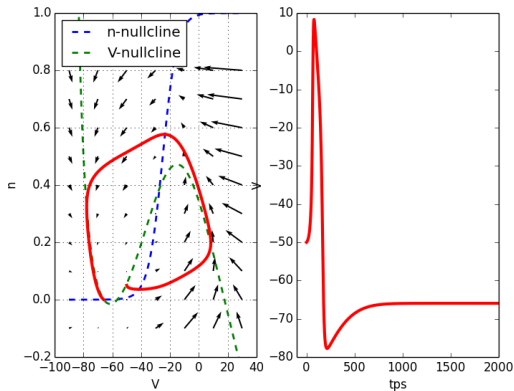
INa,p+IK model: high threshold

General behavior: $I = 0$



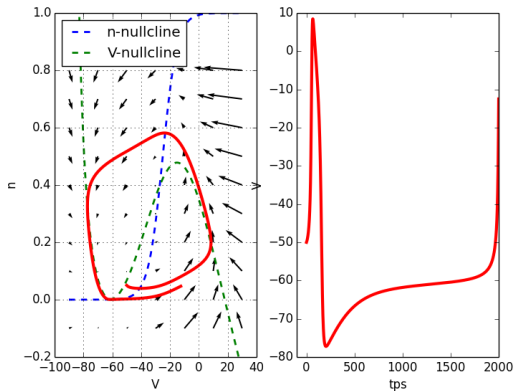
INa,p+IK model: high threshold

General behavior: $I = 0$



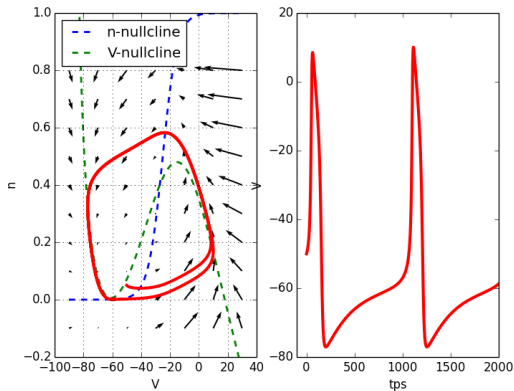
INa,p+IK model: high threshold

Saddle-node bifurcation: $I = 4.75$



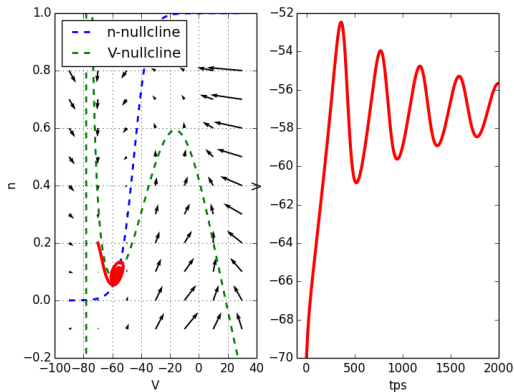
INa,p+IK model: high threshold

Saddle-node bifurcation: $I = 6$



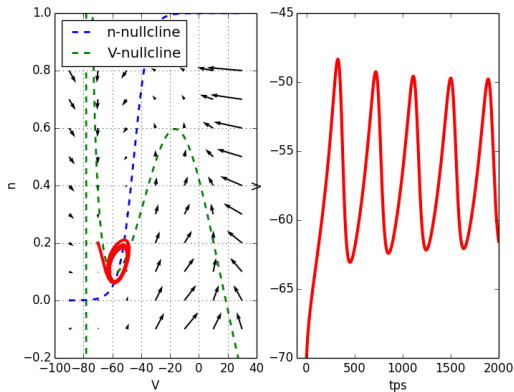
INa,p+IK model: low threshold

Supercritical Hopf bifurcation: $I = 18.5$



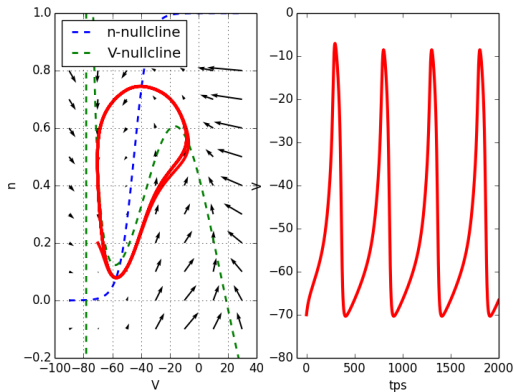
INa,p+IK model: low threshold

Supercritical Hopf bifurcation: $I = 21$



INa,p+IK model: low threshold

Supercritical Hopf bifurcation: $I = 27$



Hodgkin's classification (1948)

Type I neurons:

- ▶ Variable frequency
- ▶ Saddle-node / high threshold

Type II neurons:

- ▶ Constant frequency
- ▶ Hopf / low threshold

Bursting models (3D)

Fast-slow system:

Hindmarsh-Rose model:

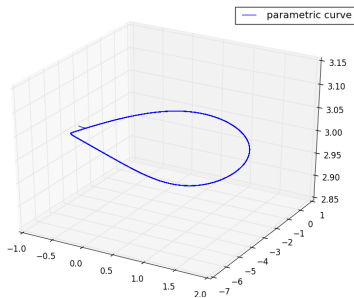
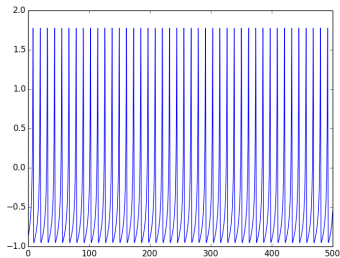
$$\dot{x} = y - ax^3 + by^2 - z + I$$

$$\dot{y} = c - dx^2 - y$$

$$\dot{z} = r[s(x - x_0) - z]$$

Hindmarsh-Rose model (1984)

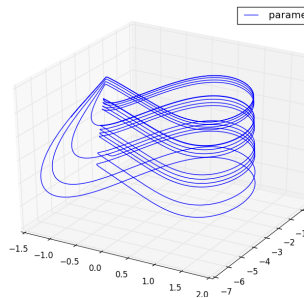
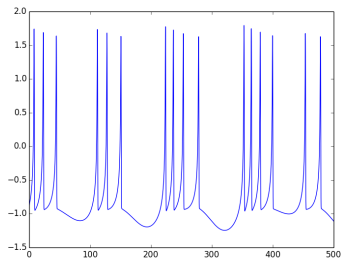
Two-dimensional: $r = 0$



Periodic behavior (limit cycle)

Hindmarsh-Rose model (1984)

Three-dimensional: $r = 0.006$



Chaotic behavior (strange attractor)

Hybrid models

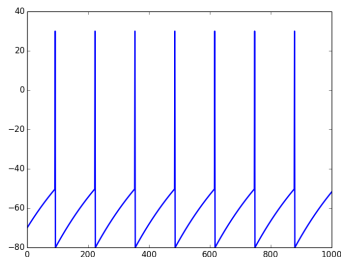
Characteristics:

- ▶ Continuous part
- ▶ Discrete part

Leaky "integrate and fire" (Lapicque, 1909)

$$\tau_m \dot{V} = -V + RI(t)$$

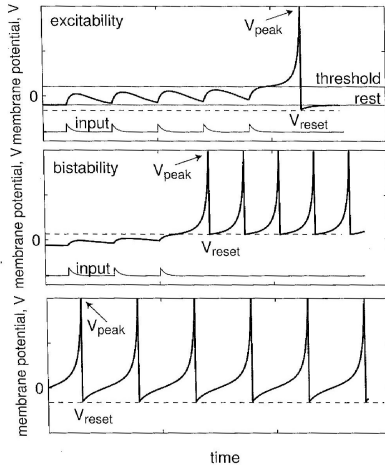
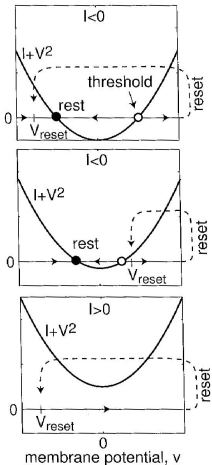
If $V > V_{th}$ then $V \leftarrow V_{reset}$



No spike generation mechanism

Quadratic integrate and fire

$$\tau \dot{V} = V^2 + RI(t)$$

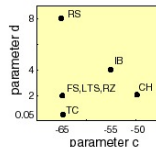
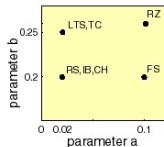
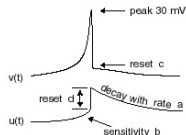


Two-dimensional hybrid model

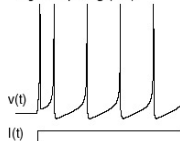
$$v' = 0.04v^2 + 5v + 140 - u + I$$

$$u' = a(bv - u)$$

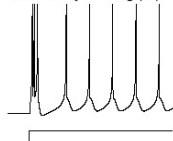
if $v = 30$ mV,
then $v \leftarrow c$, $u \leftarrow u + d$



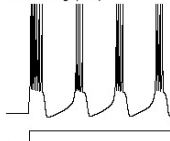
regular spiking (RS)



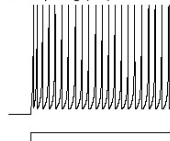
intrinsically bursting (IB)



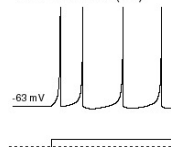
chattering (CH)



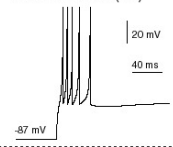
fast spiking (FS)



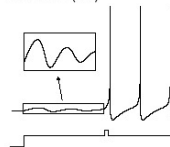
thalamo-cortical (TC)



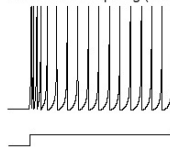
thalamo-cortical (TC)



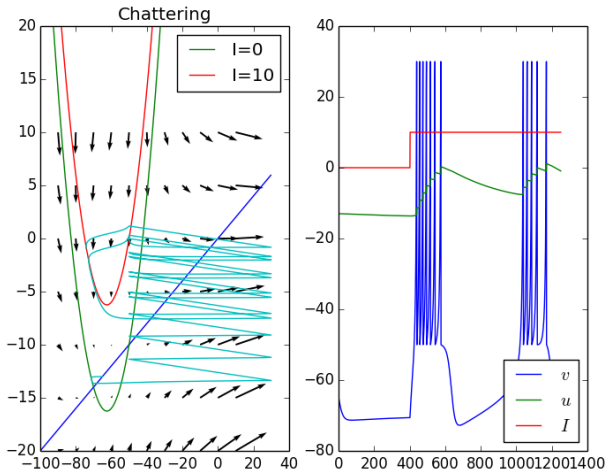
resonator (RZ)



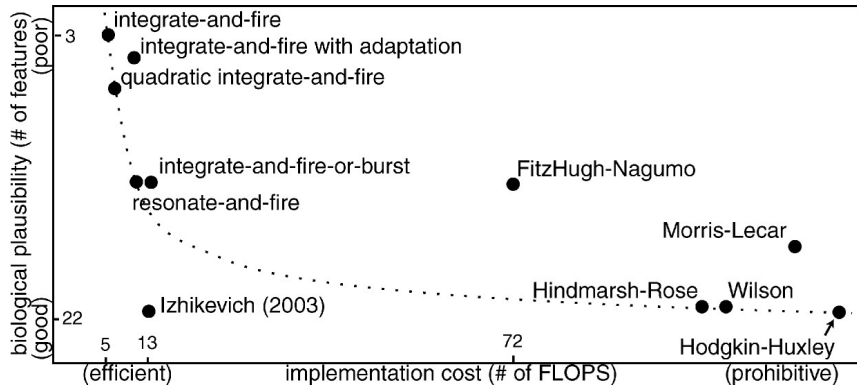
low-threshold spiking (LTS)



Two-dimensional hybrid model



Simplified models



Izhikevich (2004)

Discrete state automata

Binary models:

Excitable systems:

- ▶ Quiescent
- ▶ Active
- ▶ Refractory

Generic models:

Models of synapses

- ▶ Synaptic weights: matrix representation
- ▶ Synaptic currents:
 - ▶ Kinetic models
 - ▶ Simplified models
- ▶ Learning rules:

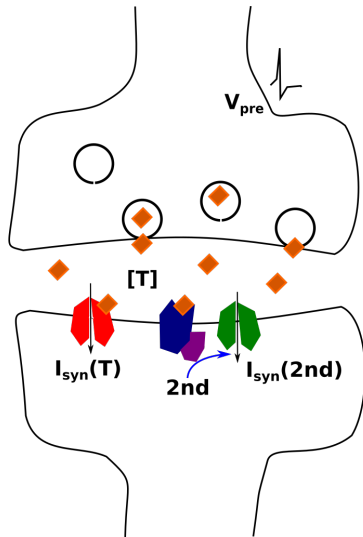
Synaptic weights

$$W = [w_{ij}]$$

- ▶ $w_{ij} > 0$ for excitatory connections.
- ▶ $w_{ij} < 0$ for inhibitory connections.
- ▶ With quantal release (n sites, p probability of release, q size of the quantum):

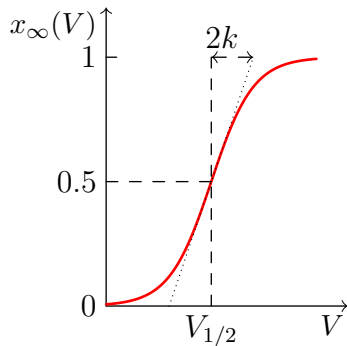
$$w \approx npq$$

Synaptic mechanisms



Transmitter release

$$[T](V_{pre}) = \frac{T_{max}}{1 + e^{\xi}} \quad \text{with} \quad \xi = \frac{-(V_{pre} - v_{1/2})}{K_p}$$



Synaptic currents: kinetic models

$$I_{syn}(t) = g_{syn}(t)(V_m(t) - E_{syn}) \quad \text{with} \quad g_{syn}(t) = \bar{g}_{syn}s(t)$$

- ▶ Dependency to transmitter concentration
- ▶ Kinetics of current changes

Ionotropic receptors



with C for "Closed" and O for "open". We get the equation:

$$\frac{ds}{dt} = \alpha [T] (1 - s) - \beta s \quad (2)$$

$$I_{\text{AMPA}} = \bar{g}_{\text{AMPA}} s (V_m - E_{\text{AMPA}}) \quad (3)$$

$$I_{\text{GABA}_A} = \bar{g}_{\text{GABA}_A} s (V_m - E_{\text{GABA}_A}) \quad (4)$$

$$I_{\text{NMDA}} = \bar{g}_{\text{NMDA}} s M(V) (V - E_{\text{NMDA}}) \quad (5)$$

and:

$$M(V) = \frac{1}{1 + \exp(-0.062 V) [\text{Mg}^{2+}]_o / 3.57} \quad (6)$$

Metabotropic receptors



$$I_{\text{GABA}_B} = \bar{g}_{\text{GABA}_B} \frac{s^n}{s^n + K_d} (V - E_K) \quad \text{with } n = 4 \quad (10)$$

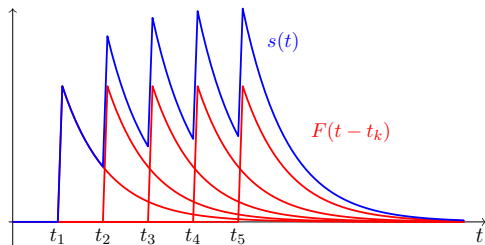
$$\frac{dr}{dt} = K_1 [T] (1 - r) - K_2 r \quad (11)$$

$$\frac{ds}{dt} = K_3 r - K_4 s \quad (12)$$

Synaptic currents: simplified models

$$I_{syn}(t) = g_{syn}(t)(V_m(t) - E_{syn}) \quad \text{with} \quad g_{syn}(t) = \bar{g}_{syn}s(t)$$

$$s(t) = \sum_k F(t - t_k) \quad \text{with} \quad \begin{cases} F(t) = 0 & \text{for } t < 0 \\ F(t) > 0 & \text{otherwise} \end{cases}$$



The α function:

$$F(t) = \frac{f_r f_d}{f_r - f_d} (e^{-f_d t} - e^{-f_r t})$$