



28 June 2022

Incorporating  
chemical dynamics

**12%** of the population suffers from migraines.

Risk of dementia **doubles** every 5 years after age 65.

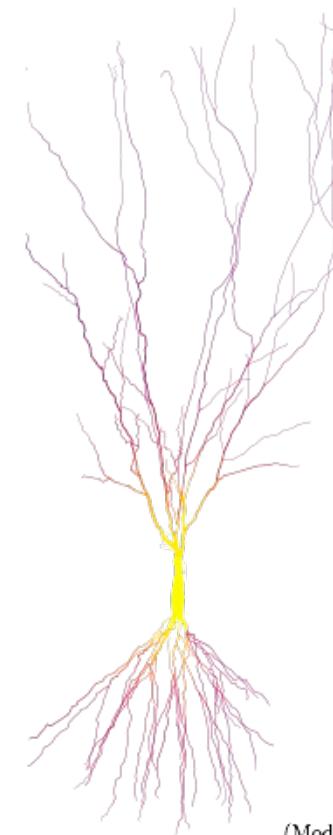
Stroke is the **#2 cause of death** worldwide.

<https://my.clevelandclinic.org/health/diseases/5005-migraine-headaches>

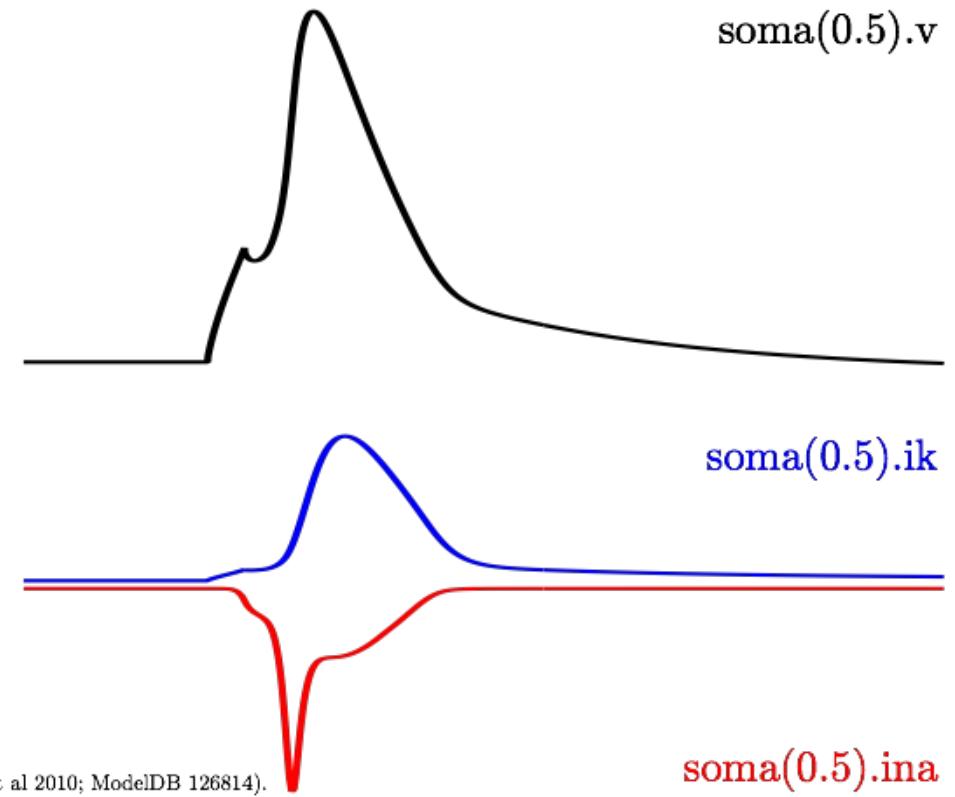
<https://www.sciencedaily.com/releases/2019/10/191029084315.htm>

[http://www9.who.int/gho/mortality\\_burden\\_disease/en/](http://www9.who.int/gho/mortality_burden_disease/en/)

Action potentials arise from ions moving across the membrane



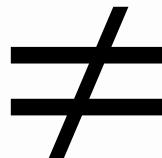
(Model from Saifulina et al 2010; ModelDB 126814).



## Questions

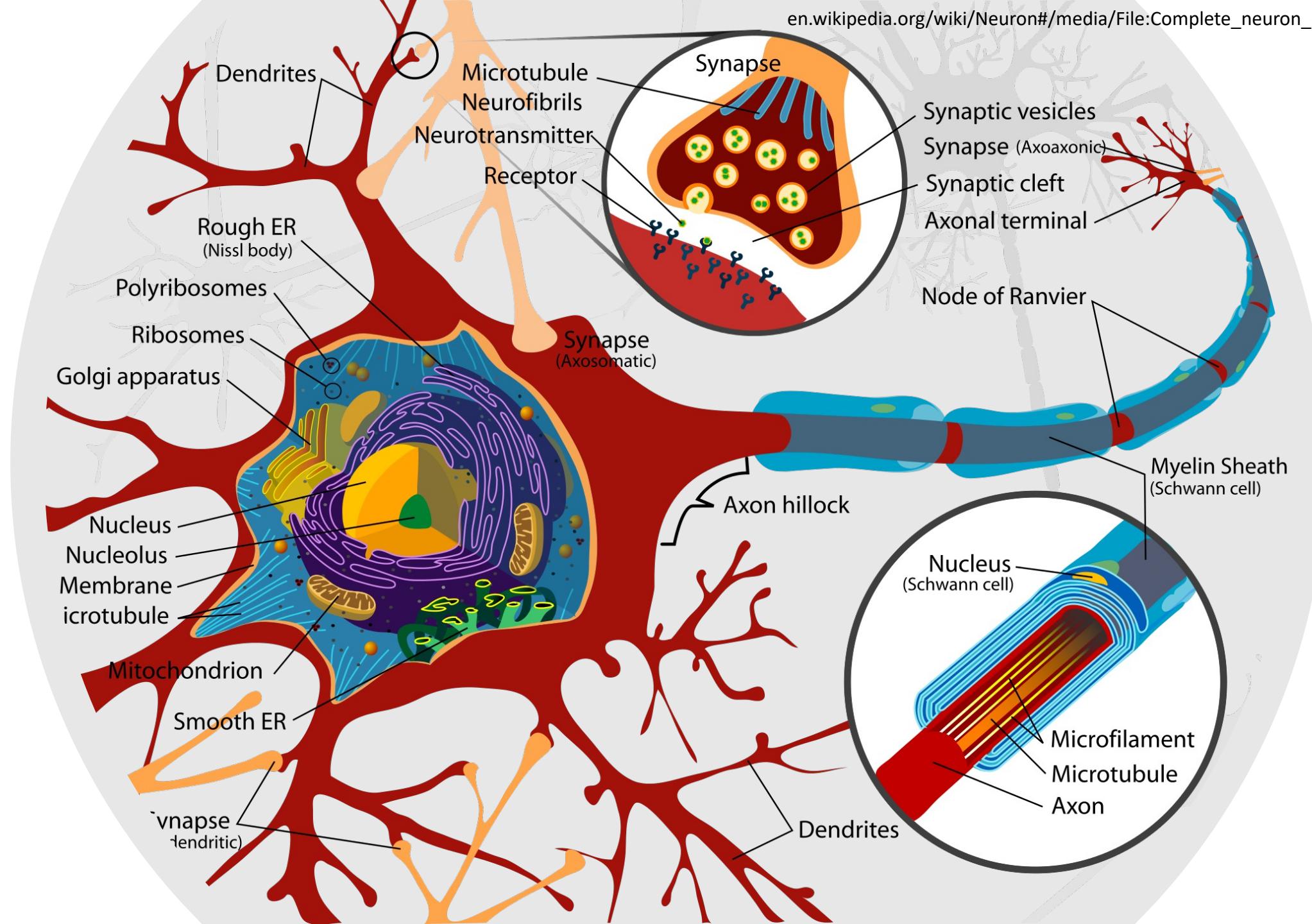
- What's the relationship between sodium current and intracellular concentration?
  - $I = \Delta Q / \Delta t$
  - $F \approx 96485.3 \text{ C mol}^{-1}$
  - $\Delta[\text{Na}] = \frac{10000 I_{\text{Na}} (\text{area})}{(F)(\text{volume})}$  ← in NEURON's units in 1 ms
- What's a typical intracellular sodium concentration for a squid giant axon?
- What about potassium?
- How are things different if it's calcium instead of sodium?

# A neuron is not a transistor



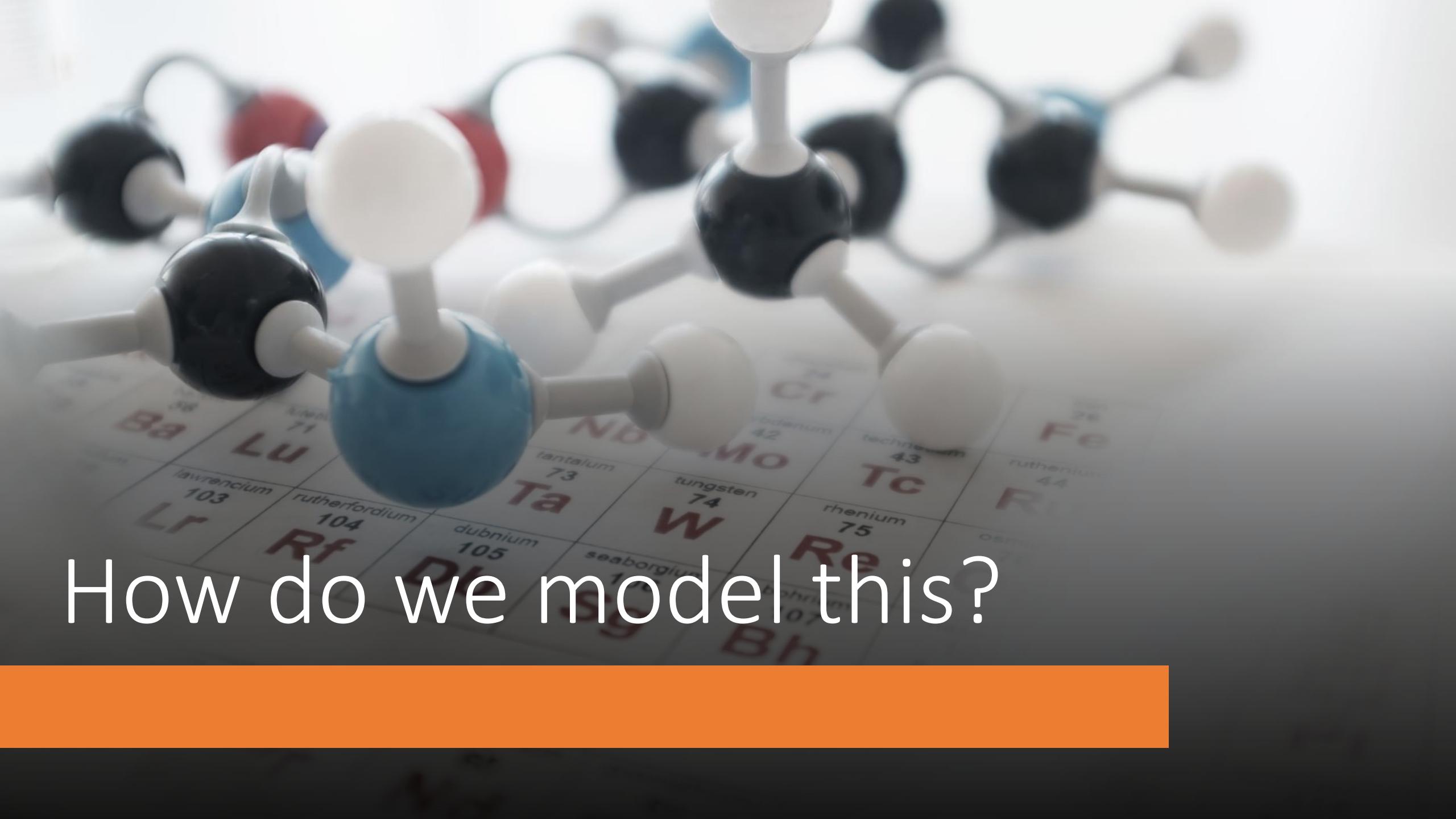
<https://commons.wikimedia.org/wiki/File:Bc635-transistor.png>

Neuron reconstruction from Pyapali et al 1998 via [http://neuromorpho.org/neuron\\_info.jsp?neuron\\_name=n123](http://neuromorpho.org/neuron_info.jsp?neuron_name=n123); rendered with NEURON.



Neurons have state and are affected by the brain's state

- Protein oscillations in the SCN
- Hyperpolarization-activated graded persistent activity in the PFC (e.g. Winograd et al., 2008)
- Intracellular calcium dynamics
- Synaptic pathways
- Ischemia



How do we model this?

“**Reaction–diffusion systems** are mathematical models which explain how the **concentration** of one or more substances distributed in space changes under the influence of two processes: **local chemical reactions** in which the substances are transformed into each other, and **diffusion** which causes the substances to spread out across space.”

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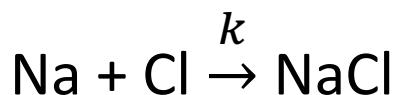
# Mass-Action kinetics

## The model

- A reaction's product is formed at a rate proportional to the concentration of the reactants.

## Example

- Consider the reaction



- Then:

$$[\text{Na}]' = -k[\text{Na}][\text{Cl}]$$

$$[\text{Cl}]' = -k[\text{Na}][\text{Cl}]$$

$$[\text{NaCl}]' = k[\text{Na}][\text{Cl}]$$

### Conservation of mass.

Matter is neither created nor destroyed by reactions.

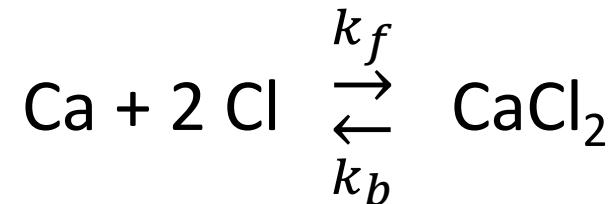
In our equations, this means:

$$[\text{Na}] + [\text{NaCl}] = \text{constant}$$

$$[\text{Cl}] + [\text{NaCl}] = \text{constant}$$

# Example

Every reaction can go both ways, so there is always some possibility for the reaction to reverse. So more realistic kinetics look like:



With corresponding equations:

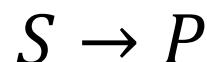
$$[\text{Ca}]' = -k_f[\text{Ca}][\text{Cl}]^2 + k_b[\text{CaCl}_2]$$

$$[\text{Cl}]' = -2k_f[\text{Ca}][\text{Cl}]^2 + 2k_b[\text{CaCl}_2]$$

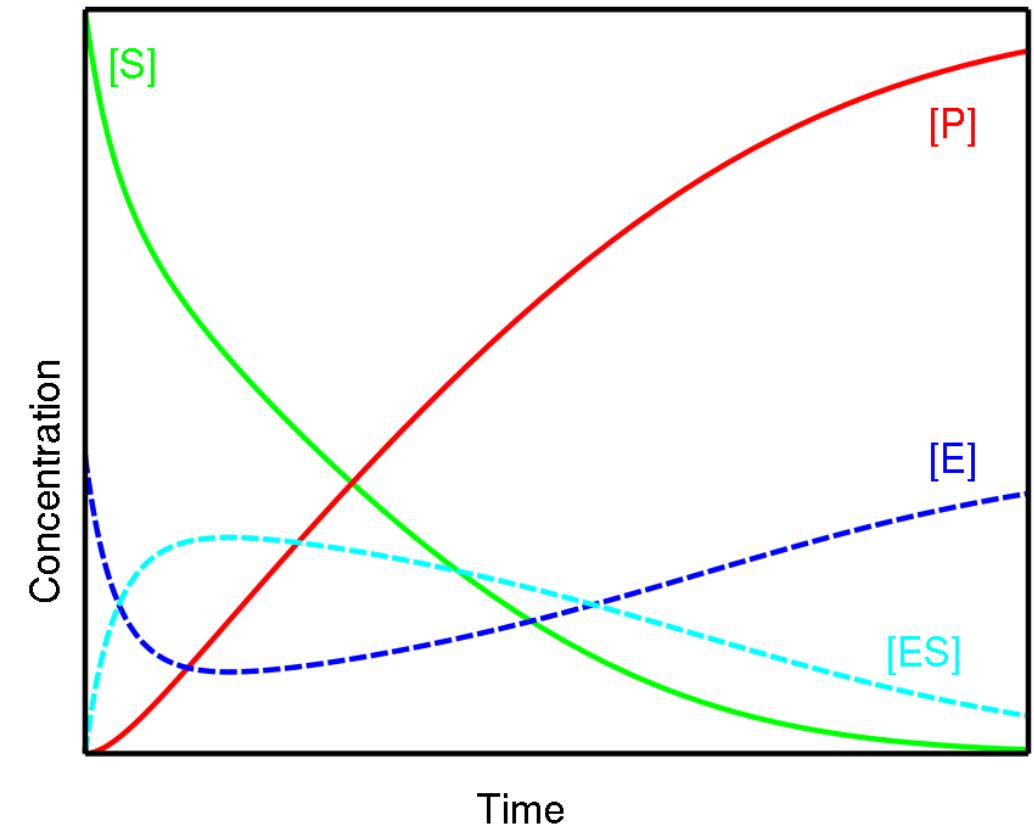
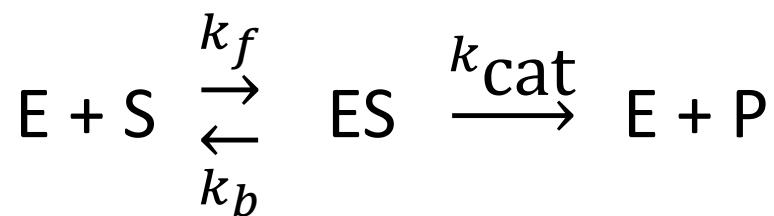
$$[\text{CaCl}_2]' = k_f[\text{Ca}][\text{Cl}]^2 - k_b[\text{CaCl}_2]$$

# Enzyme kinetics

It is generally **not** the case that a substrate transforms directly into a product:



Instead, an enzyme is often involved:



# Michaelis-Menten

If we can assume either:

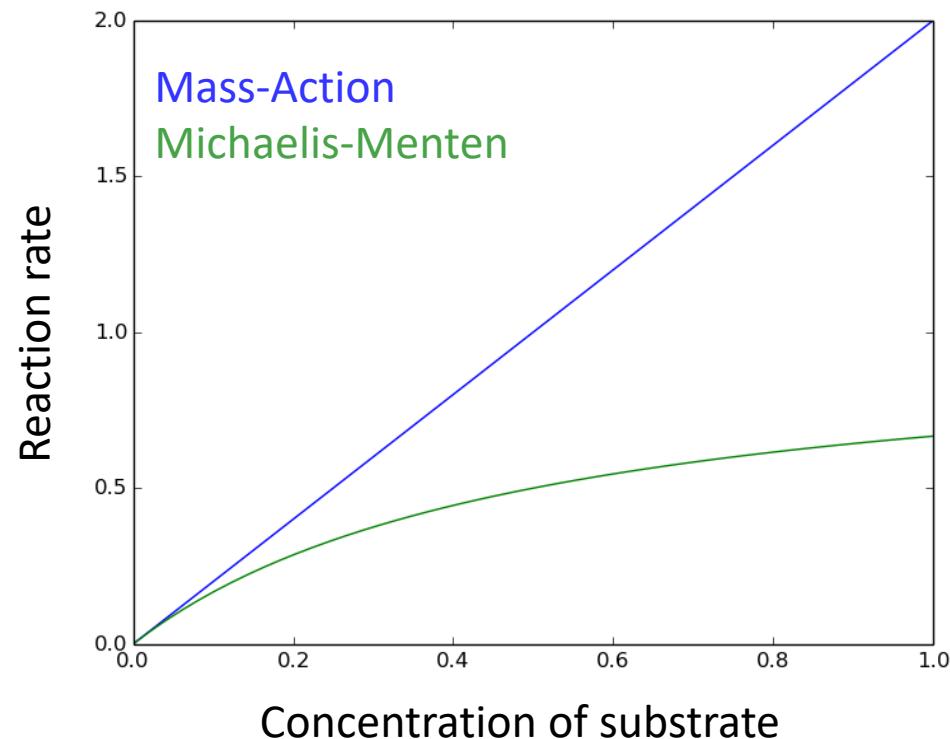
- the substrate ( $S$ ) and the complex ( $ES$ ) are in instantaneous equilibrium, or
- the concentration of the complex ( $ES$ ) does not change on the time-scale of product formation

Then the rate of the enzymatic reaction reduces to:

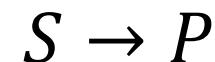
$$\frac{V_{max} [S]}{K_M + [S]}$$

$K_M$  is called the *Michaelis constant*. It is the concentration at which the reaction proceeds at half its maximum rate.

# Michaelis-Menten vs Mass-Action

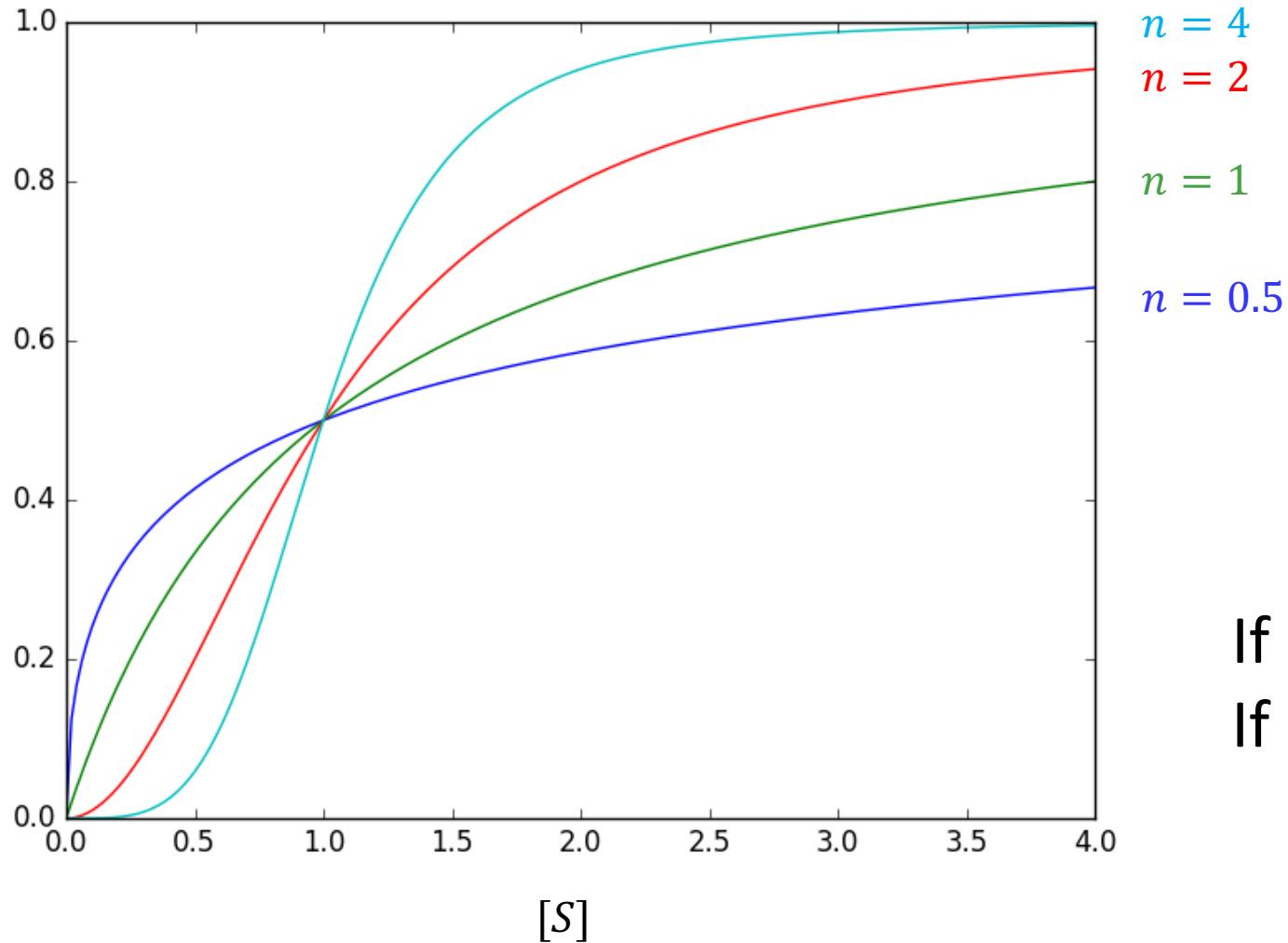


$$y = 2x \quad y = \frac{x}{x + 0.5}$$



Both curves on the left have the same rate of reaction when the substrate concentration is low, but the Michaelis-Menten rate levels off (due to limited enzyme availability) as concentrations increase.

# Hill equation: cooperative binding

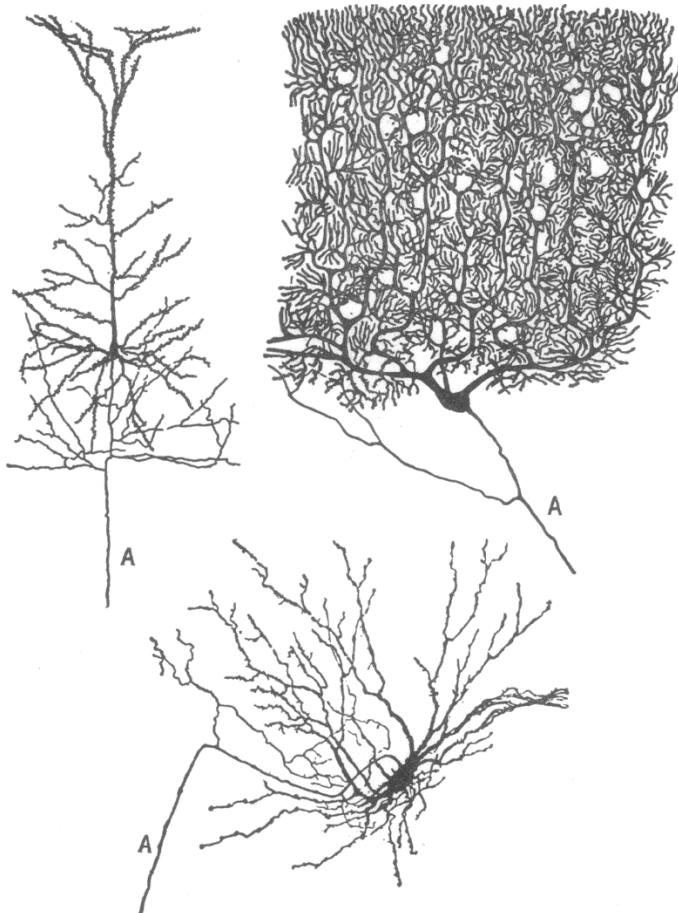


$n = 4$   
 $n = 2$   
 $n = 1$   
 $n = 0.5$

$$\frac{V_{max} [S]^n}{[k_A]^n + [S]^n}$$
$$\frac{[S]^n}{1^n + [S]^n}$$

If  $n > 1$ , positive cooperativity.  
If  $n < 1$ , negative cooperativity.

# Neurons have spatial extent



Effects of non-point-ness:

- Ion and protein concentrations vary with space.
- Cellular mechanisms (ER, ion channels, etc) vary with space.

Concentrations at different locations affect each other:

- Transport
- Diffusion

# Fick's Laws

*The mathematics of diffusion*

## Fick's First Law:

- Diffusive flux is proportional to the concentration gradient.

$$J = -D\nabla\varphi$$

- Here  $D$  is called the *diffusion coefficient*.

## Fick's Second Law (the diffusion equation):

$$\frac{\partial\varphi}{\partial t} = \nabla \cdot (D\nabla\varphi) = D \nabla^2\varphi$$

where the last equality only holds if  $D$  is constant.

# Where does diffusion occur?

## Cytosol

- But not full cross section because of organelles

## Organelles

- e.g. endoplasmic reticulum

## Extracellular space

- Tortuosity
- Anisotropy
- Volume fraction

# Practical limits of pure diffusion

The expected time  $E[t]$  for a molecule with diffusion constant  $D$  to diffuse a distance  $x$  is:

$$E[t] = \frac{x^2}{2D}$$

So in particular, if

$$D = 1 \text{ } \mu\text{m}^2/\text{ms} \text{ and}$$

$$x = 100 \text{ } \mu\text{m},$$

Then

$$E[t] = \frac{100^2}{2} = 5000 \text{ ms.}$$

# Reaction-Diffusion in NEURON

```
from neuron import rxd
```

---

Developer Builds

**USER DOCUMENTATION:**

NEURON Python documentation

NEURON HOC documentation

Python tutorials

## Python RXD tutorials

Changing initial conditions and parameters

Reaction-Diffusion tutorial

Restricting reactions to certain sections

basic-initialization

calcium waves

circadian

combining currents from mod files with rxd

degradable\_buffer

extracellular

ip3-demo

thresholds

## How to use CoreNEURON

**DEVELOPER DOCUMENTATION:**

NEURON SCM and Release

NEURON Development topics

C/C++ API

[Home](#) » Python RXD tutorials[Edit on GitHub](#)

## Python RXD tutorials

- [Changing initial conditions and parameters](#)
- [Reaction-Diffusion tutorial](#)
- [Restricting reactions to certain sections](#)
- [basic-initialization](#)
- [calcium waves](#)
- [circadian](#)
- [combining currents from mod files with rxd](#)
- [degradable\\_buffer](#)
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# Why use NEURON's rxd module?

## Reduces typing

- **In two lines:** declare a domain, declare a molecule, allow it to diffuse, and respond to flux from ion channels.

```
cyt = rxd.Region(soma.wholetree(), nrn_region="i")
ca = rxd.Species(cyt, name="ca", d=1, charge=2)
```

- **Reduces** the risk for **errors** from typos or misunderstandings.

## Allow arbitrary domains

- By default, NEURON only has two domains for chemical concentrations – just inside and just outside the plasma membrane. The `rxd` module allows you to declare your own regions of interest (e.g. ER, mitochondria, etc).

# rxd module overview

- **Where** do the dynamics occur?

- Cytosol
- Endoplasmic reticulum
- Mitochondria
- Extracellular Space

- **Who** are the actors?

- Ions
- Proteins

- **What** are the reactions?

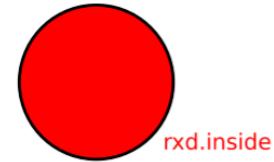
- Buffering
- Degradation
- Phosphorylation

## Interface design principle

- Reaction-diffusion model specification is independent of:
  - Deterministic or stochastic
  - 1D or 3D

# Declaring a region: rxd.Region

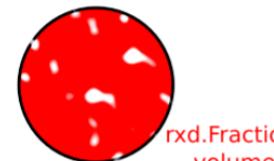
geometry:



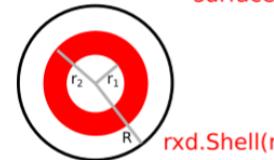
rx.d.inside



rx.d.membrane



rx.d.FractionalVolume(  
volume\_fraction= $f_1$ ,  
surface\_fraction= $f_2$ )



rx.d.Shell( $r_1/R$ ,  $r_2/R$ )

Adapted from:  
McDougal et al 2013.

## Basic usage

```
cyt = rxd.Region(seclist)
```

seclist may be any iterable of sections; e.g. a Python list or h.allsec() or...

## Identify with a standard region

```
cyt = rxd.Region(seclist, nrn_region="i")
```

nrn\_region may be I or o, corresponding to the locations of e.g. nai vs nao

## Specify the cross-sectional shape

```
cyt = rxd.Region(seclist, geometry=rxd.Shell(0.5, 1))
```

The default geometry is rxd.inside.

The geometry and nrn\_region arguments may both be specified.

# rxd.Region tips

## Specify nrn\_region if concentration interact with NMODL

- If NMODL mechanism (ion channels, point processes, etc) depend on or affect the concentration of a species living in a given region, that region must declare a nrn\_region (**typically 'i'**)

## To declare a region that exists on all sections

- `r = rxd.Region(h.allsec())`

## Use list comprehensions to select sections

- `r = rxd.Region([sec for sec in h.allsec()  
if 'apical' in str(sec)])`

# Ions and proteins: rxd.Species

## Basic usage

```
protein = rxd.Species(region, d=16)
```

- d is the diffusion constant in  $\mu\text{m}^2/\text{ms}$ ; region is either an rxd.Region or an iterable of Region objects

## Initial conditions

```
protein = rxd.Species(region, initial=value)
```

- value is in mM. It may be a constant or a function of the node.

## Connecting with NMODL, InterViews graphics, etc...

```
ca = rxd.Species(region, name='ca', charge=2)
```

- If the nrn\_region of region is 'i', the concentrations of this species will be stored in cai, and its concentrations will be affected by ica.

protein.initial can be read and set, to allow exploration of the role of initial conditions

# Variable step integration tolerances

Tip:

NEURON's variable step solver has a default absolute tolerance of 0.001.

Since NEURON measures concentration in mM and some cell biology concentrations (e.g. calcium) are in  $\mu$ M, this tolerance may be too high. Compensate by using an `atolscale` in the constructor, e.g.

```
ca = rxd.Species(cyt, atolscale=1e-6)
```

Example:

## Initial value as a function of distance from a point

```
def my_initial(node):
    # compute the distance
    distance = h.distance(soma(0.5), node)
    # return a certain function of the distance
    return 2 * h.tanh(distance / 1000.)

cyt = rxd.Region(soma.wholetree(), name='cyt', nrn_region='i')

ip3 = rxd.Species(cyt, name='ip3', charge=2, initial=my_initial)
```

Example:

## Initial value as a function of spatial position

```
def my_initial(node):
    # return a certain function of the x-coordinate
    return 1 + h.tanh(node.x3d / 100.)

cyt = rxd.Region(h.allsec(), name='cyt', nrn_region='i')

ip3 = rxd.Species(cyt, name='ip3', charge=2, initial=my_initial)
```

Tip:

## rxd.Parameter

- Use `rxd.Parameter` objects to represent things that vary either spatially or across different simulations. They use the same specification as `rxd.Species`.
- e.g.

```
 $\alpha$  = rxd.Parameter(cyt, initial=0.3)
```

Tip:

## rxd.Parameter

Use short-hand to avoid repeatedly writing rxd.Parameter boilerplate;  
e.g.

```
def declare_parameters(r, **kwargs):
    '''enables clean declaration of parameters in top namespace'''
    for key, value in kwargs.items():
        globals()[key] = rxd.Parameter(r, name=key, initial=value)
```

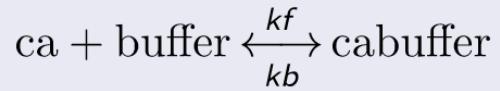
Can then, e.g.:

```
declare_parameters(r,
    vsP=1.1 * nM / hour,
    KmP=0.2 * nM,
    ksP=0.9 / hour)
```

- Units come from: `from neuron.units import nM, hour`

# Specifying dynamics: rxd.Reaction

## Mass-action kinetics

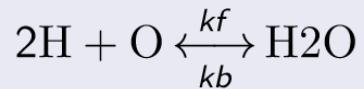


buffering = rxd.Reaction(ca + buffer, cabuffer, kf, kb)

kf is the forward reaction rate, kb is the backward reaction rate. kb may be omitted if the reaction is unidirectional.

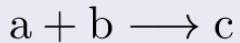
In a mass-action reaction, the reaction rate is proportional to the product of the concentrations of the reactants.

## Repeated reactants



water\_reaction = rxd.Reaction(2 \* H + O, H2O, kf, kb)

## Arbitrary reaction formula, e.g. Hill dynamics



hill\_reaction = rxd.Reaction(a + b, c, a ^ 2 / (a ^ 2 + k ^ 2), mass\_action=False)

Hill dynamics are often used to model cooperative reactions.

# rxd.Rate and rxd.MultiCompartmentReaction

## rxd.Rate

Use rxd.Rate to specify an explicit contribution to the rate of change of some concentration or state variable.

$$\text{ip3degradation} = \text{rxd.Rate(ip3, -k * ip3)}$$

## rxd.MultiCompartmentReaction

Use rxd.MultiCompartmentReaction when the dynamics span multiple regions; e.g. a pump or channel.

$$\text{ip3r} = \text{rxd.MultiCompartmentReaction(ca[er], ca[cyt], kf, kb, membrane=cyt\_er\_membrane)}$$

The rate of these dynamics is proportional to the membrane area.

# Manipulating nodes

## Getting a list of nodes

- nodelist = protein.nodes
- nodes\_in\_region = protein.nodes(region)
- nodes\_in\_sec\_and\_region = protein.nodes(sec)(region)

## Working with concentrations and values

- nodelist.concentration = value
- values = nodelist.concentration
- ca\_timeseries =  
h.Vector().record(ca(er)(soma(0.5)).\_ref\_concentration)
- for node in state\_var.nodes:  
    node.value \*= 2

## Other operations

- surface\_areas = nodelist.surface\_area
- volumes = nodelist.volume
- first\_node = nodelist[0]

# Concentration pointers

node.\_ref\_concentration

If there's only one node in a nodelist, you can also use:

nodelist.\_ref\_concentration

## Recording traces:

```
cai = h.Vector().record(  
    ca.nodes(soma(0.5))._ref_concentration  
)
```

## Plotting in an h.Graph:

```
g = h.Graph()  
g.addvar('ca[er](dend(0.5))',  
    ca[er].nodes(dend(0.5))._ref_concentration)  
  
h.graphList[0].append(g)
```

Remember, you can use e.g. `dir(ca.nodes)` to find out what methods exist.

Example:

# Calcium buffering\*

Consider calcium buffering with a degradable buffer:

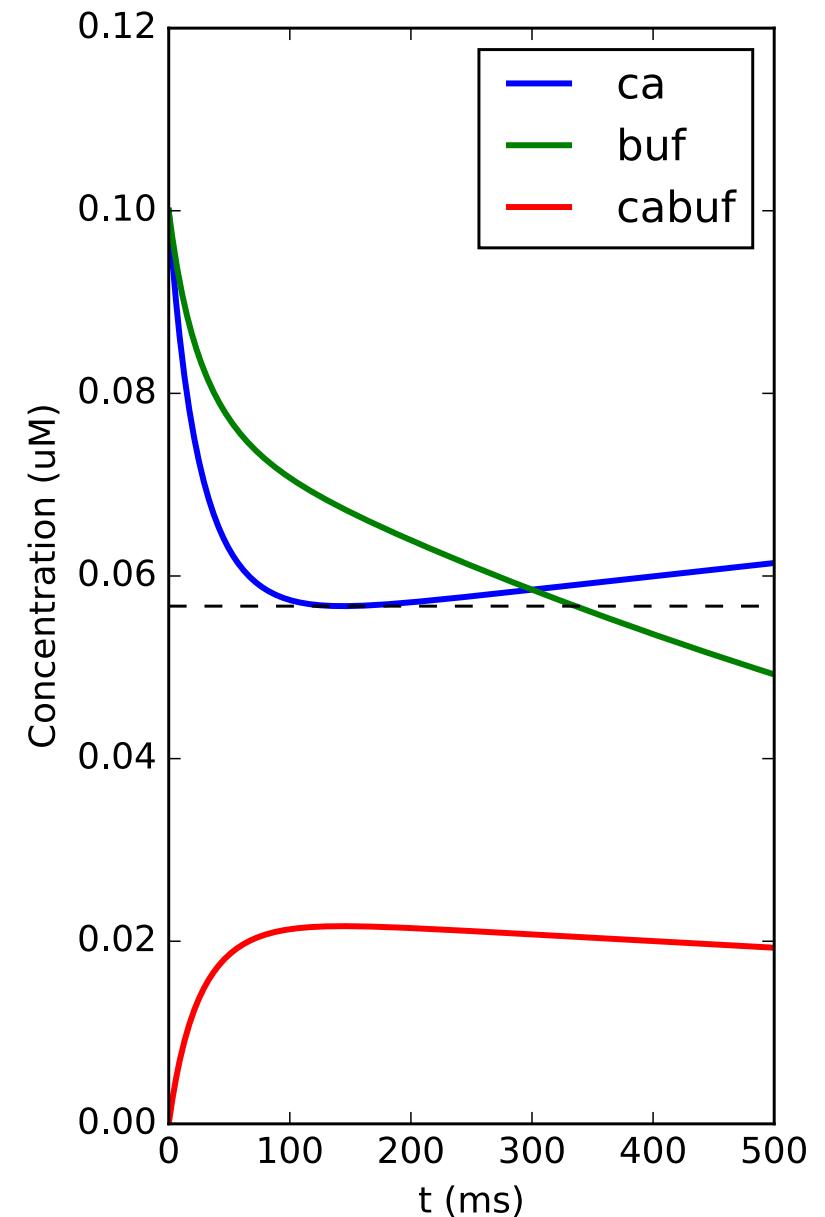


```
from neuron import h, rxd
from neuron.units import nM

# where
soma = h.Section(name="soma")
cyt = rxd.Region([soma], nrn_region="i")

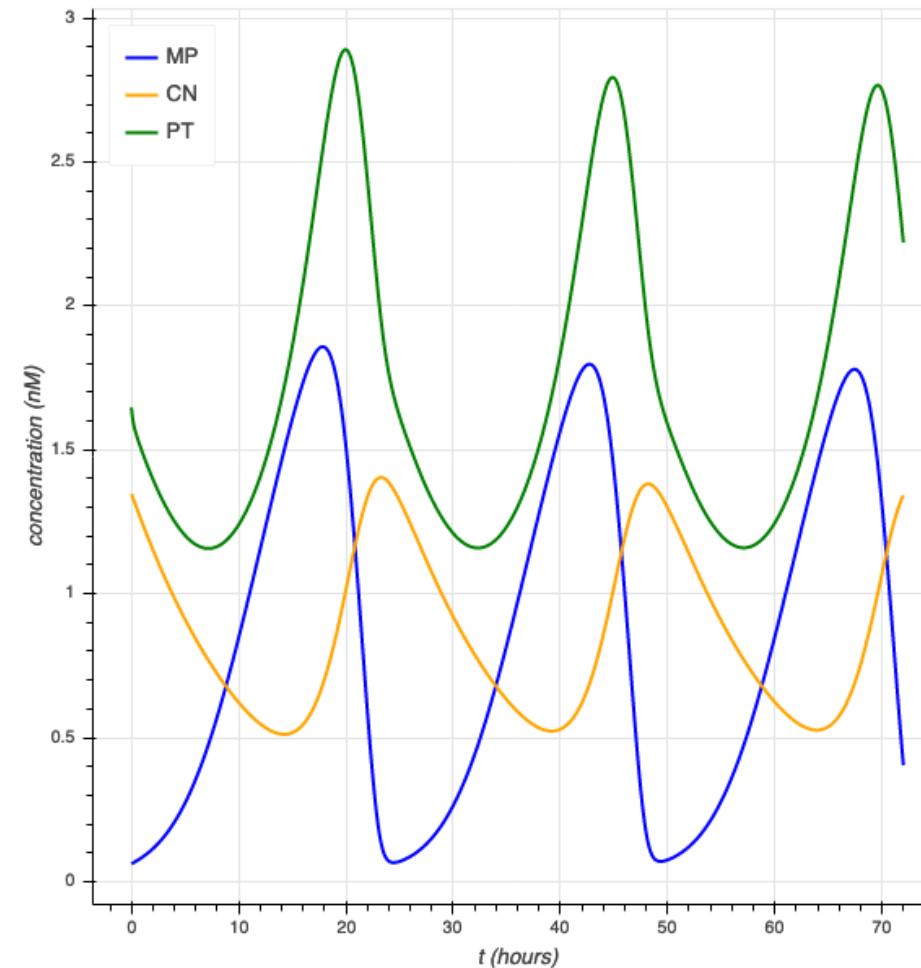
# who
ca = rxd.Species(cyt, name="ca", charge=2, initial=100*nM)
buf = rxd.Species(cyt, name="buf", initial=100*nM)
cabuf = rxd.Species(cyt, name="cabuf", initial=0)

# what
buffering = rxd.Reaction(2 * ca + buf, cabuf, 1e6, 1e-2)
degradation = rxd.Rate(buf, 1e-3 * buf)
```



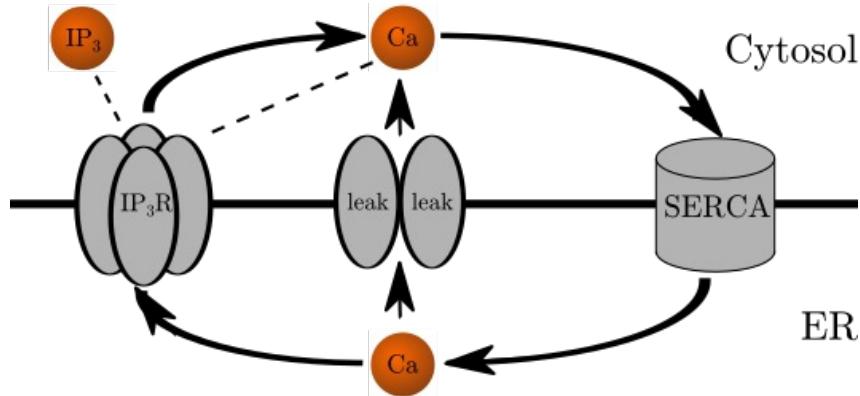
Example:

# Leloup, Gonze, Goldbeter 1999



Example:

# CICR



$$\frac{\partial \text{Ca}_{\text{cyt}}^{2+}}{\partial t} = d_{\text{Ca}_{\text{cyt}}^{2+}} \cdot \Delta \text{Ca}_{\text{cyt}}^{2+} + \frac{J_{\text{IP3R}} - J_{\text{SERCA}} + J_{\text{leakER}}}{f_{\text{cyt}}} + c_{\text{ionic}},$$

$$\frac{\partial \text{Ca}_{\text{ER}}^{2+}}{\partial t} = d_{\text{Ca}_{\text{ER}}^{2+}} \cdot \Delta \text{Ca}_{\text{ER}}^{2+} - \frac{J_{\text{IP3R}} - J_{\text{SERCA}} + J_{\text{leakER}}}{f_{\text{ER}}},$$

$$\frac{\partial \text{IP}_3}{\partial t} = d_{\text{IP}_3} \cdot \Delta \text{IP}_3,$$

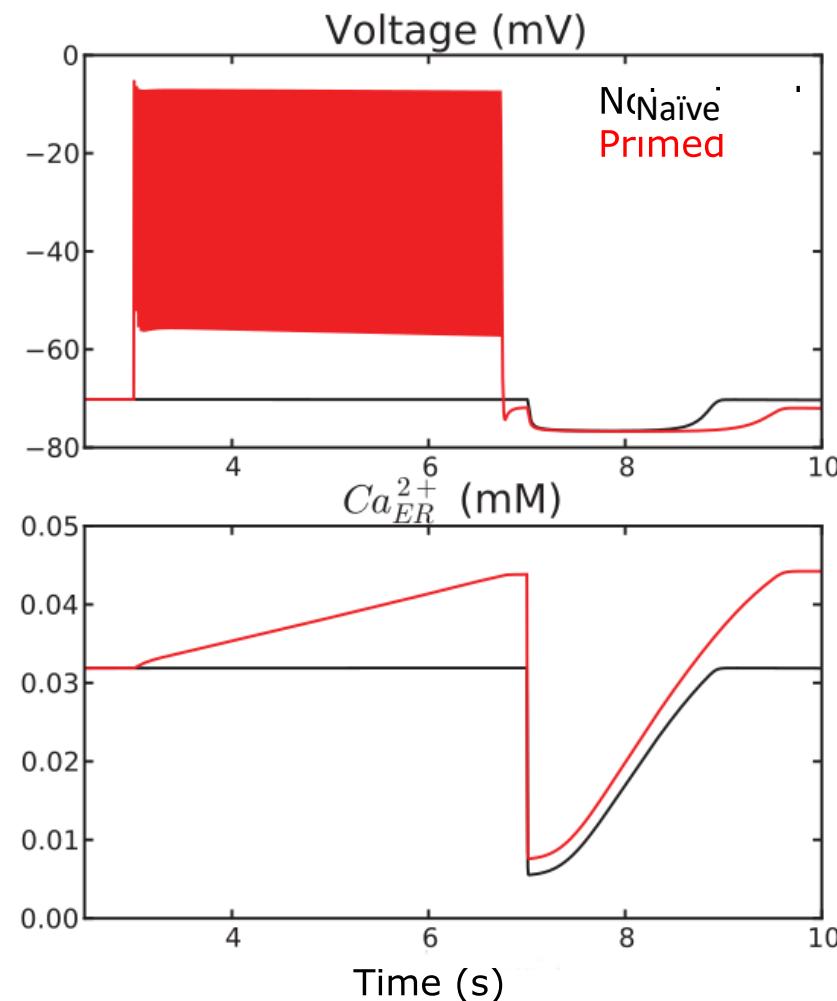
$$J_{\text{IP3R}} = \bar{p}_{\text{IP}_3\text{R}} \cdot m_{\text{IP}_3\text{R}}^3 \cdot n_{\text{IP}_3\text{R}}^3 \cdot h_{\text{IP}_3\text{R}}^3 \cdot (\text{Ca}_{\text{ER}}^{2+} - \text{Ca}_{\text{cyt}}^{2+}) / \Xi,$$

$$J_{\text{SERCA}} = -\frac{\bar{p}_{\text{serca}} \cdot \text{Ca}_{\text{cyt}}^{2+2}}{(k_{\text{serca}}^2 + \text{Ca}_{\text{cyt}}^{2+2}) \cdot \Xi},$$

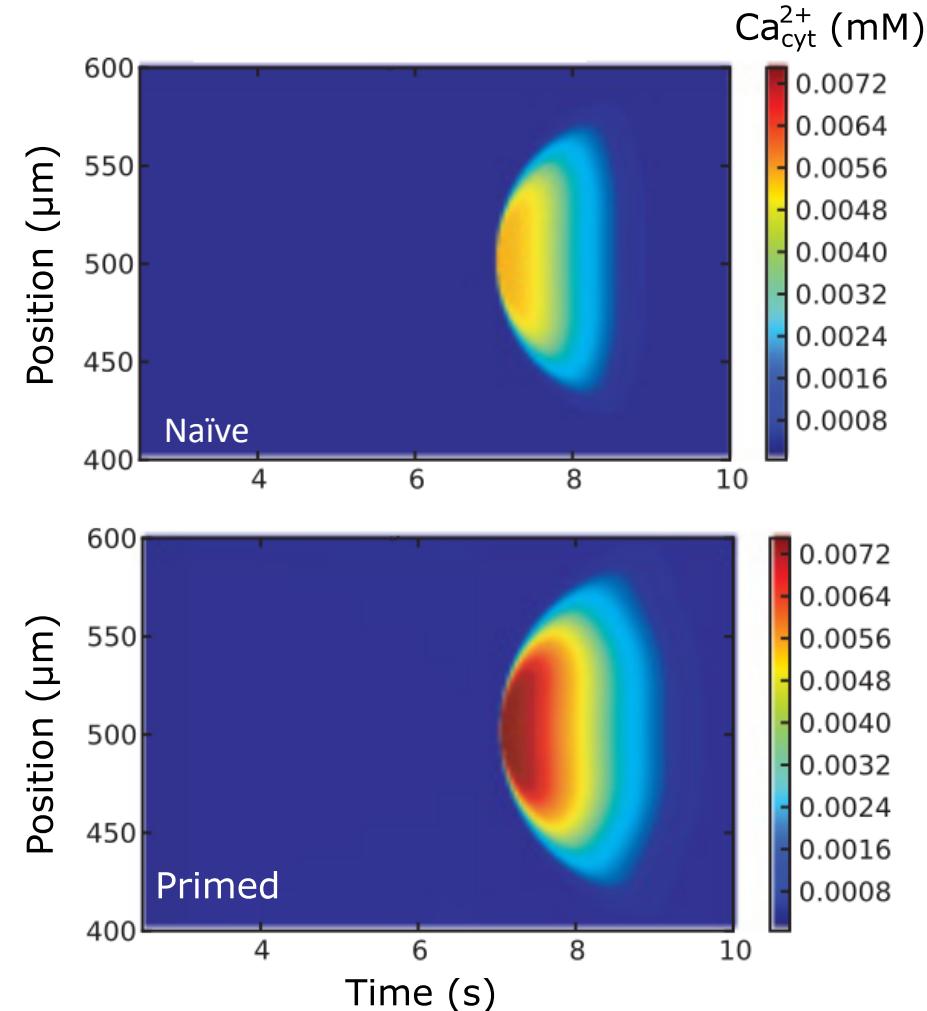
$$J_{\text{leakER}} = \bar{p}_{\text{leakER}} \cdot (\text{Ca}_{\text{ER}}^{2+} - \text{Ca}_{\text{cyt}}^{2+}) / \Xi.$$

Example:

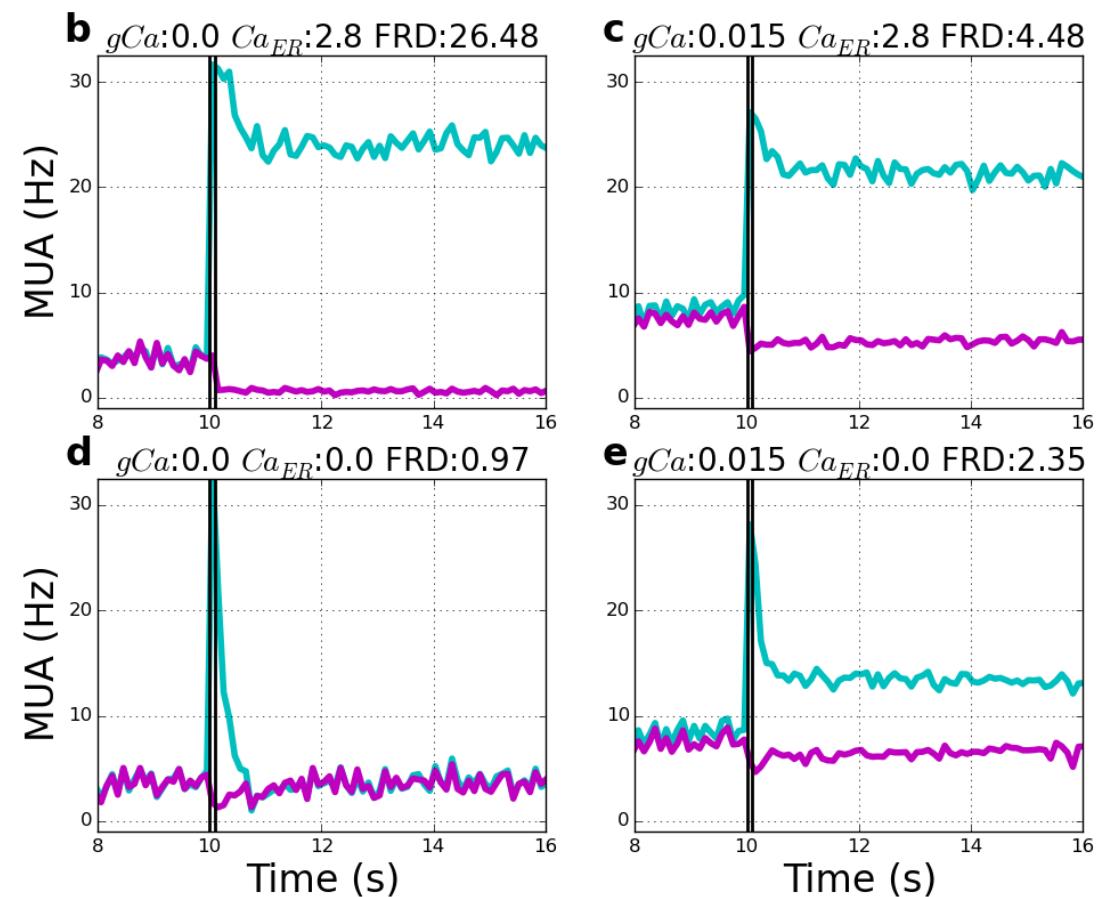
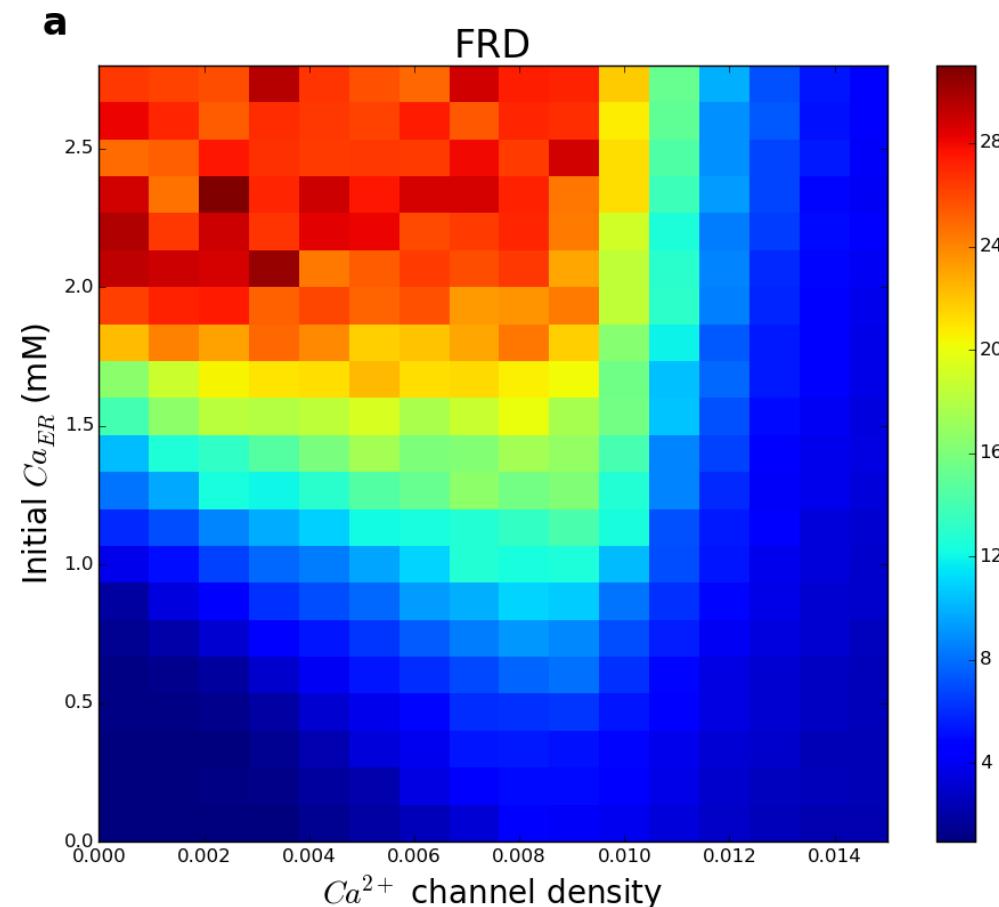
# CICR



Adapted from Neymotin\*, McDougal\*, et al. (2015). Figure 11.

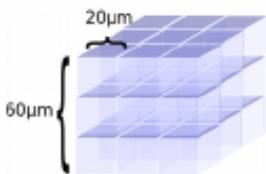


Example:  
CICR



# Extracellular diffusion

- Uses the same simple Python interface



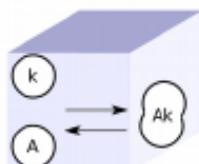
```
ecs = rxd.Extracellular(xlo=-30, ylo=-30, zlo=-30,  
                         xhi=30, yhi=30, zhi=30,  
                         dx=20, tortuosity=1.6,  
                         volume_fraction=0.2)
```

```
astrocytic_buffering = rxd.Reaction(A + k, AK, kf, kb)
```

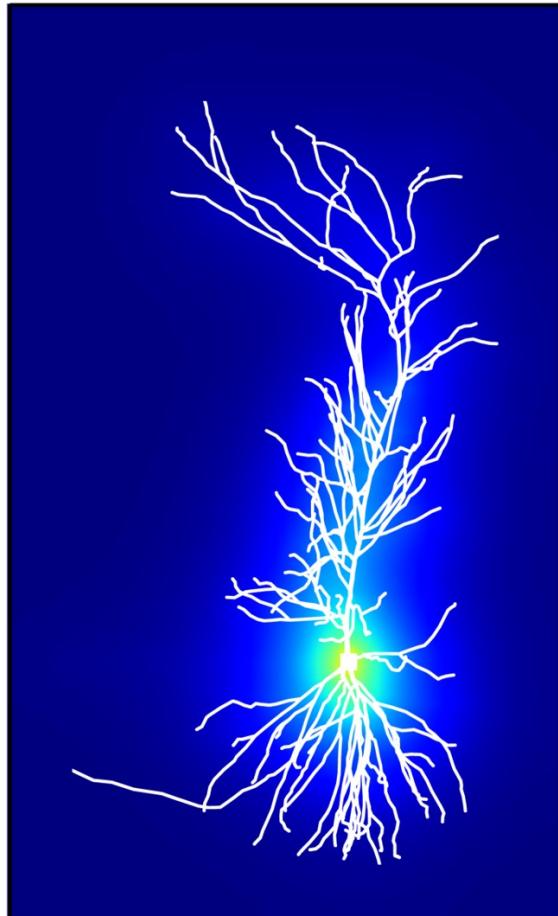
- Rectangular cuboid grid
- Supports
  - anisotropy & heterogeneous tissue characteristics

```
k = rxd.Species(ecs, name='k', d=2.62, charge=1,  
                 initial=lambda nd: 40 if nd.x3d**2 + nd.y3d**2 + nd.z3d**2 < 100**2 else 3.5,  
                 ecs_boundary_conditions=3.5)
```

Tortuosity and volume\_fraction can be either constants or functions of  $(x, y, z)$ .



# Extracellular diffusion



New region type:

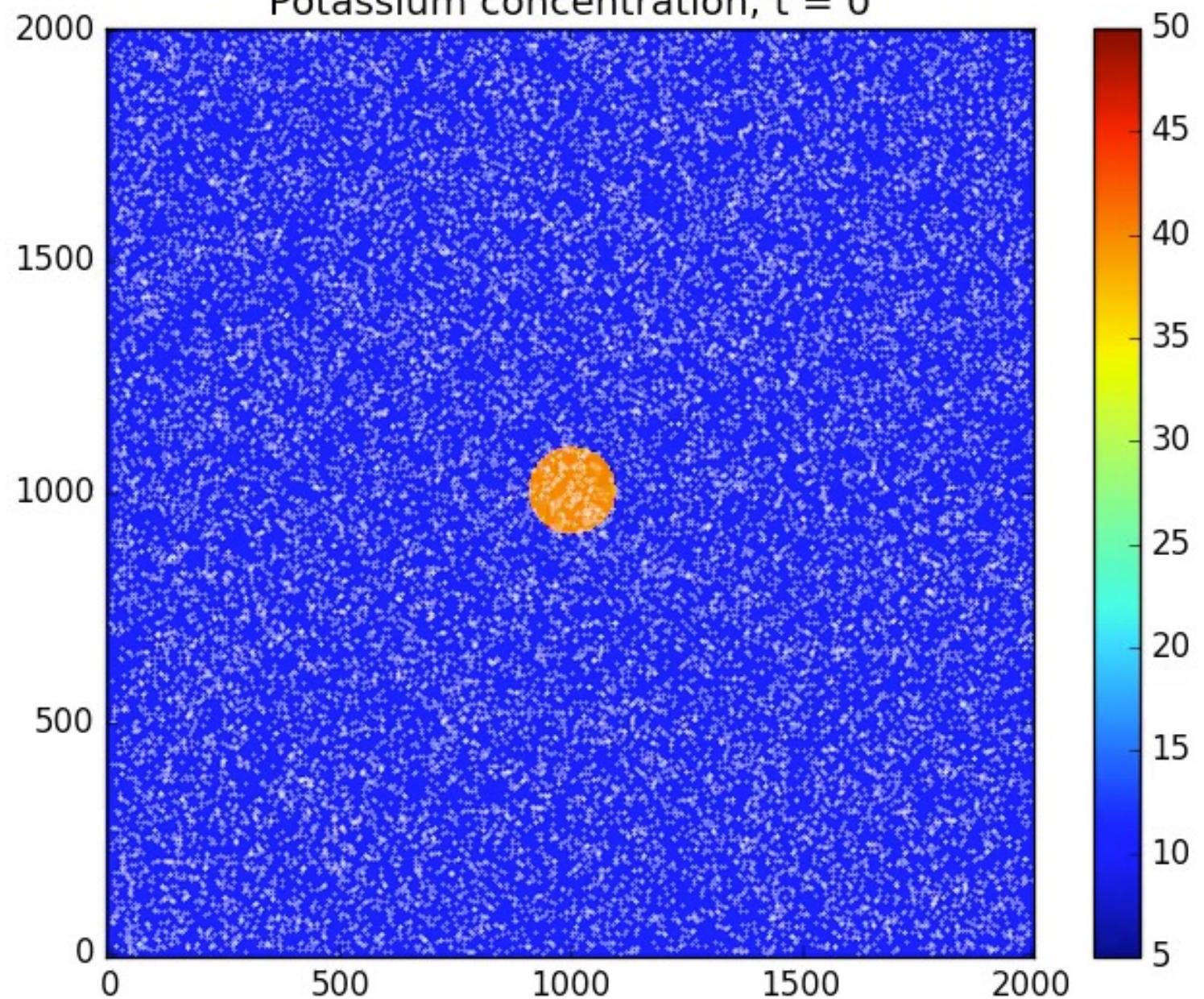
```
ecs = rxd.Extracellular(xlo, ylo, zlo, xhi, yhi, zhi,  
                        dx=dx, tortuosity=1,  
                        volume_fraction=1)
```

Setting/getting extracellular concentrations:

```
ca[ecs].states3d[5:15, 5:15, :] = 1  
pyplot.imshow(ca[ecs].states3d[:, :, 0],  
              interpolation='nearest', vmin=0, vmax=1,  
              extent=ca[ecs].extent('xy'),  
              origin='lower')
```

All 3D simulation in NEURON is done using a parallelized Douglas-Gunn alternating implicit method.

Potassium concentration;  $t = 0$



# 3D Simulations



## Specifying 3D Simulations

Just add one line of code<sup>2</sup>:

```
rxd.set_solve_type(dimension=3)
```

```
all = rxd.Region(h.allsec())
```

```
ca = rxd.Species(all, d=1)
```

```
ca.initial = lambda node: 1 if node.x3d < 50 else 0
```

## Plotting

Get the concentration values expressed on a regular 3D grid via  
nodelist.value\_to\_grid()

```
values = ca.nodes.value_to_grid()
```

Pass the result to a 3d volume plotter, such as Mayavi's VolumeSlicer:

```
graph = VolumeSlicer(data=ca.nodes.value_to_grid())
graph.configure_traits()
```

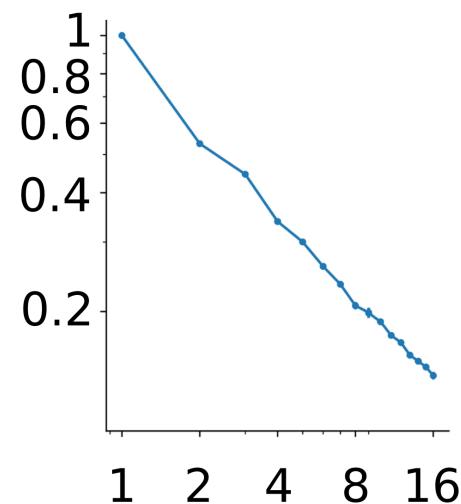
<sup>2</sup> `rxd.set_solve_type` can optionally take a list of sections as its first argument; in that case only the specified sections will be simulated in three dimensions.

# Threading

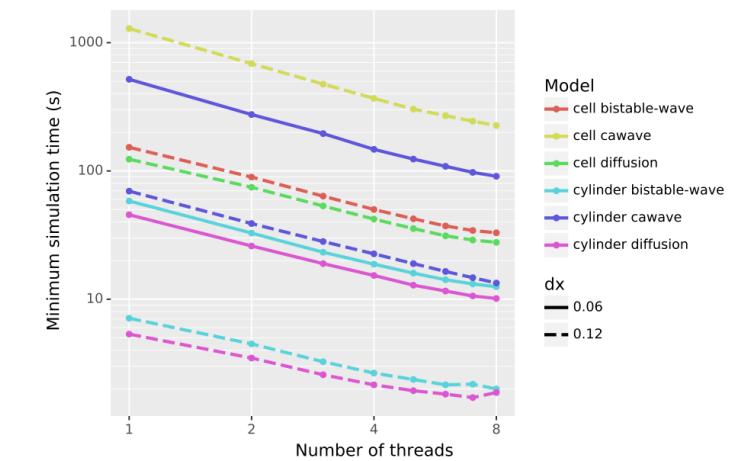
- Extracellular and 3D simulations may be threaded using, e.g.

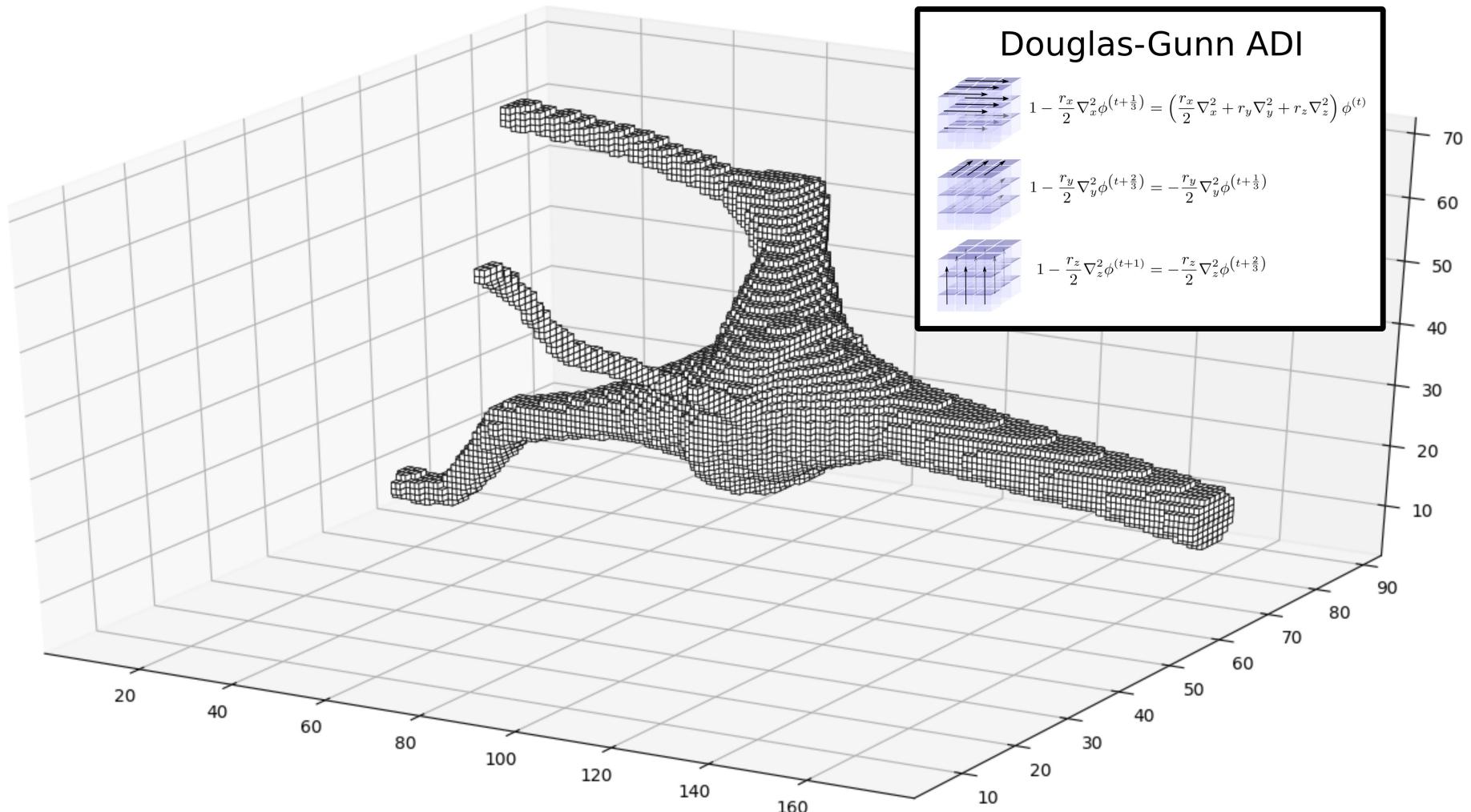
```
rxn.nthread(4) # for four threads
```

- Either electrophysiology or reaction-diffusion can be threaded, but not both.



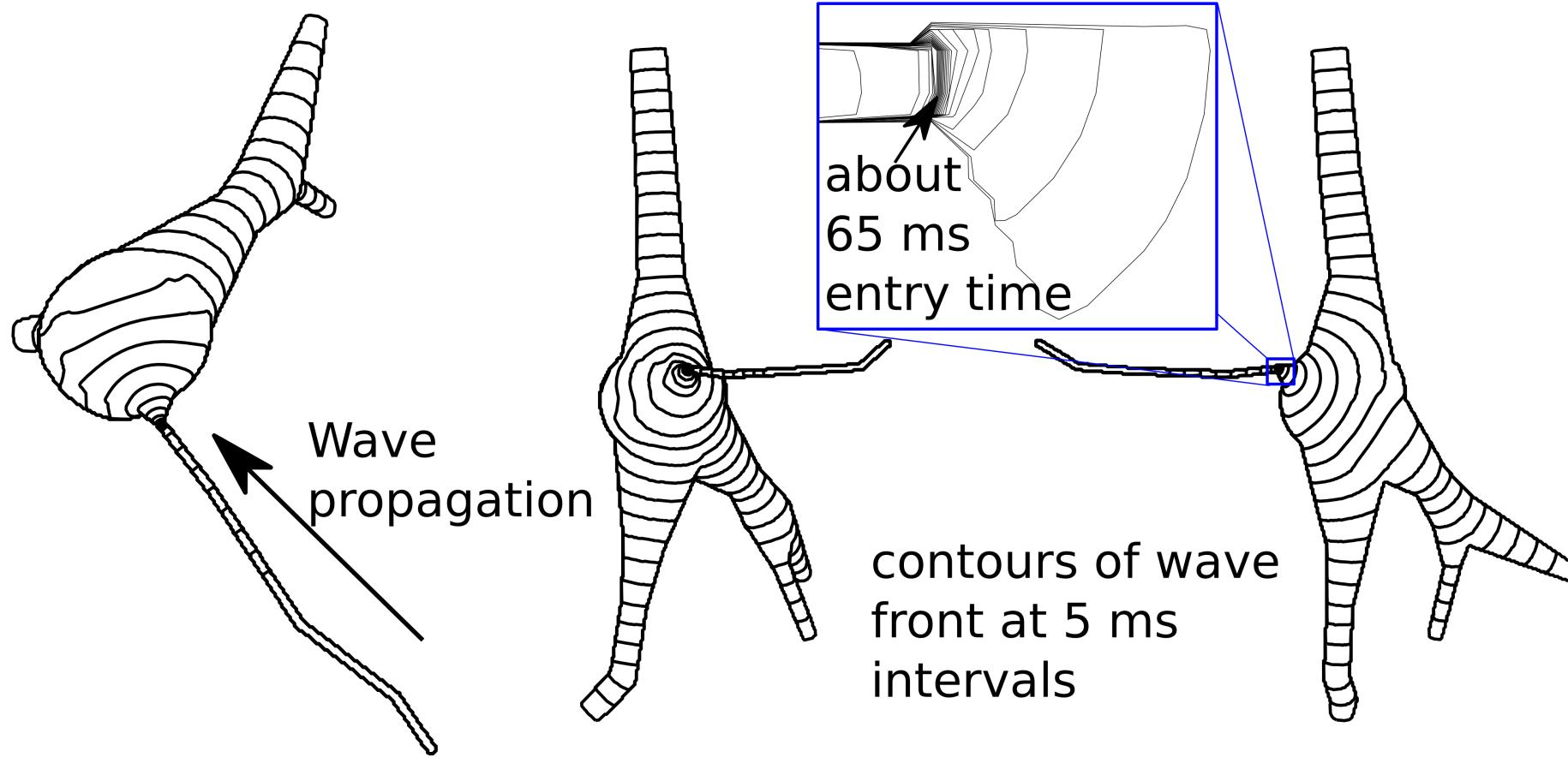
3D extra- (left) and intracellular (right)  
runtime by number of threads.





NEURON 7.7+ uses threaded DG-ADI; previous versions used bicgstab.

# Wave curvature and delays at soma



$$u_t = D \nabla^2 u - \xi u(1-u)(\alpha-u)$$

For a similar example, see:

<https://neuron.yale.edu/neuron/docs/3dhybrid-intracellular-tutorial>

For about 750k voxels, a pre-alpha branch of NEURON 7.7 simulated 300 ms of this ( $dt=0.025\text{ms}$ ) with four threads in 258 s.

# Full 3D simulation (part 1 of 2)

```
from neuron import h, rxd
from neuron.units import um, ms, mV
import matplotlib.pyplot as plt
import numpy as np

h.load_file("stdrun.hoc")

# Create morphology
soma = h.Section(name="soma")
soma.L = soma.diam = 5 * um
soma.nseg = 5
dend = h.Section(name="dend")
dend.L = 15 * um
dend.diam = 1 * um
dend.nseg = 15
dend.connect(soma)

# tell NEURON this cell should be in 3D
rxd.set_solve_type(soma.wholetree(), dimension=3)

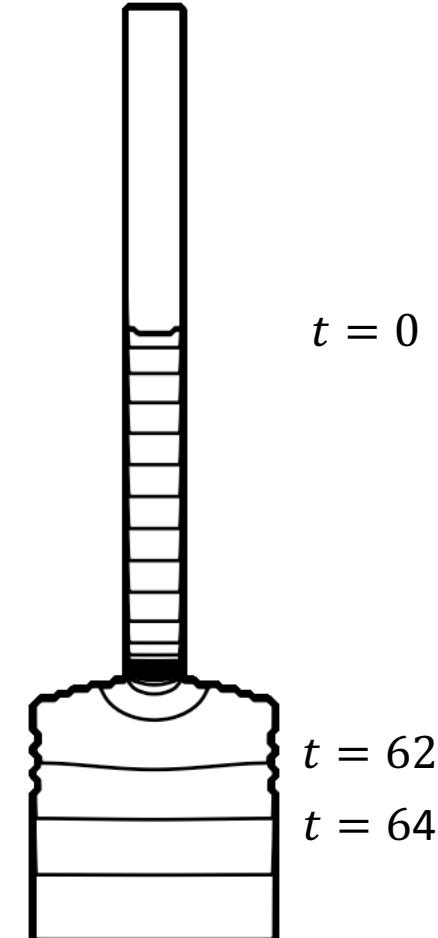
def ca_init(node):
    return 1 if node.sec == dend and node.segment.x > 0.5 else 0
```

# Full 3D simulation (part 2 of 2)

```
r = rxd.Region(soma.wholetree(), dx=0.1 * um)
ca = rxd.Species(r, d=0.3, name="ca", initial=ca_init, charge=2)
bistable_reaction = rxd.Rate(ca, -ca * (1 - ca) * (0.05 - ca))

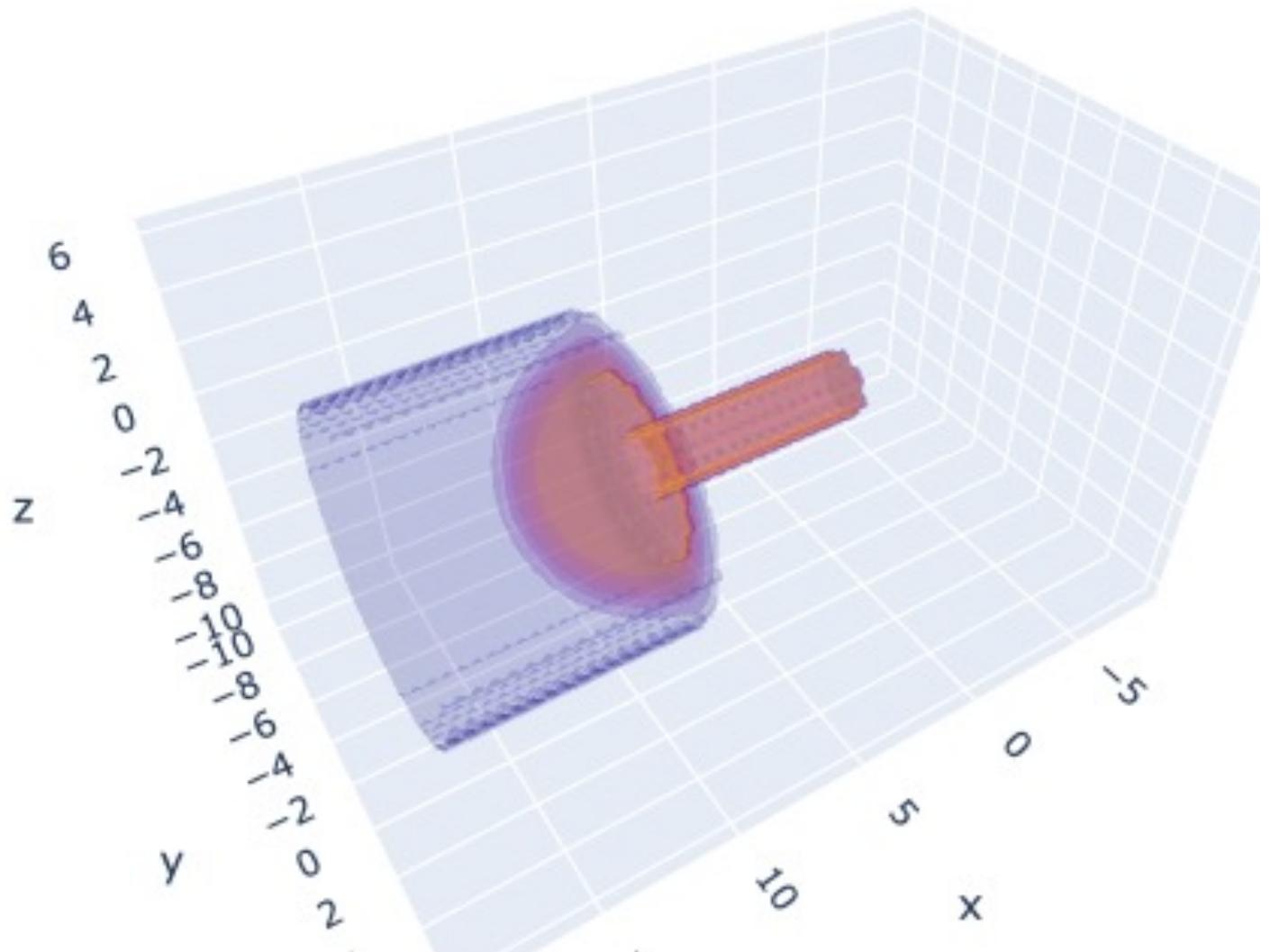
def plot_contours(species):
    g = species.nodes.value_to_grid()
    collapsed = np.max(np.nan_to_num(g), axis=1)
    xs, ys = np.meshgrid(range(collapsed.shape[1]), range(collapsed.shape[0]))
    plt.contour(xs, ys, collapsed, 1, colors="k", linewidths=1)
    plt.axis("equal")
    plt.axis("off")

h.finitialize(-65 * mV)
plt.figure(figsize=(3, 6))
for tstop in range(0, 100 * ms, 2 * ms):
    h.continuerun(tstop)
    print(tstop)
    plot_contours(ca)
    plt.show()
```



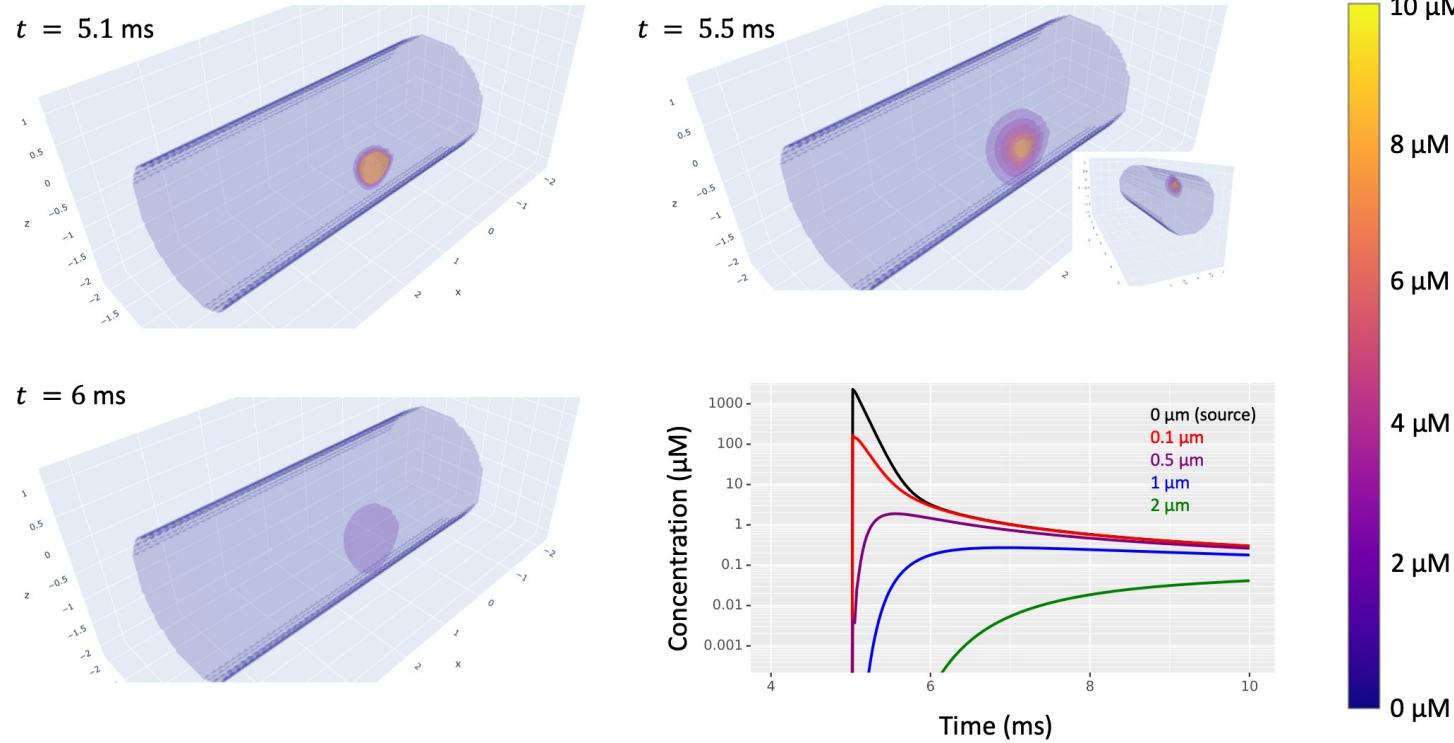
## Example: Wave Curvature

- A regenerative wave front with a reflective boundary will always meet that boundary at a right angle.
- This has the effect of forcing regenerative waves to bend and slow when the geometry widens.
- Here we visualize using plotly's volume renderer.



[tinyurl.com/neuron-wave-curvature](http://tinyurl.com/neuron-wave-curvature)

# Example: 3D point source



```
NEURON {
    POINT_PROCESS RxDSyn
    RANGE tau
}

PARAMETER {
    tau = 1 (ms)
}

STATE { g }

INITIAL { g=0 }

BREAKPOINT { SOLVE state METHOD cnexp }

DERIVATIVE state { g' = -g/tau }
NET_RECEIVE(weight) {
    g = g + weight
}

node.include_flux(r._ref_g)
```

# For more information

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## Journal articles on reaction-diffusion in NEURON

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## Online resources

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- McDougal RA, Hines ML, Lytton WW. (2013). Reaction-diffusion in the NEURON simulator. *Frontiers in Neuroinformatics*, 7.
- McDougal RA, Hines ML, Lytton WW. (2013). Water-tight membranes from neuronal morphology files. *Journal of Neuroscience Methods*, 220(2), 167-178.
- Newton AJH, McDougal RA, Hines ML, Lytton WW. (2018). Using NEURON for reaction-diffusion modeling of extracellular dynamics. *Frontiers in Neuroinformatics*, 12, 41.
- McDougal RA, Conte C, Eggleston L, Newton AJH, Galijasevic H. (2022). Efficient simulations of 3D reaction-diffusion in models of neurons and networks. *Frontiers in Neuroinformatics*.
- 

NEURON forum  
<https://neuron.yale.edu/forum/>

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Programmer's reference  
[http://neuronsimulator.github.io/nrn/py\\_doc/](http://neuronsimulator.github.io/nrn/py_doc/)

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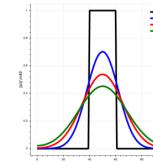
NEURON reaction-diffusion tutorials  
<https://www.neuron.yale.edu/neuron/docs/reaction-diffusion>

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# Exercises

[tinyurl.com/neuron-diffusion-exercise](http://tinyurl.com/neuron-diffusion-exercise)

- Pure diffusion



[tinyurl.com/neuron-regen-signal](http://tinyurl.com/neuron-regen-signal)

- Regenerative signaling

[tinyurl.com/neuron-hh-example-2](http://tinyurl.com/neuron-hh-example-2)

- Hodgkin-Huxley, concentrations, and homeostasis