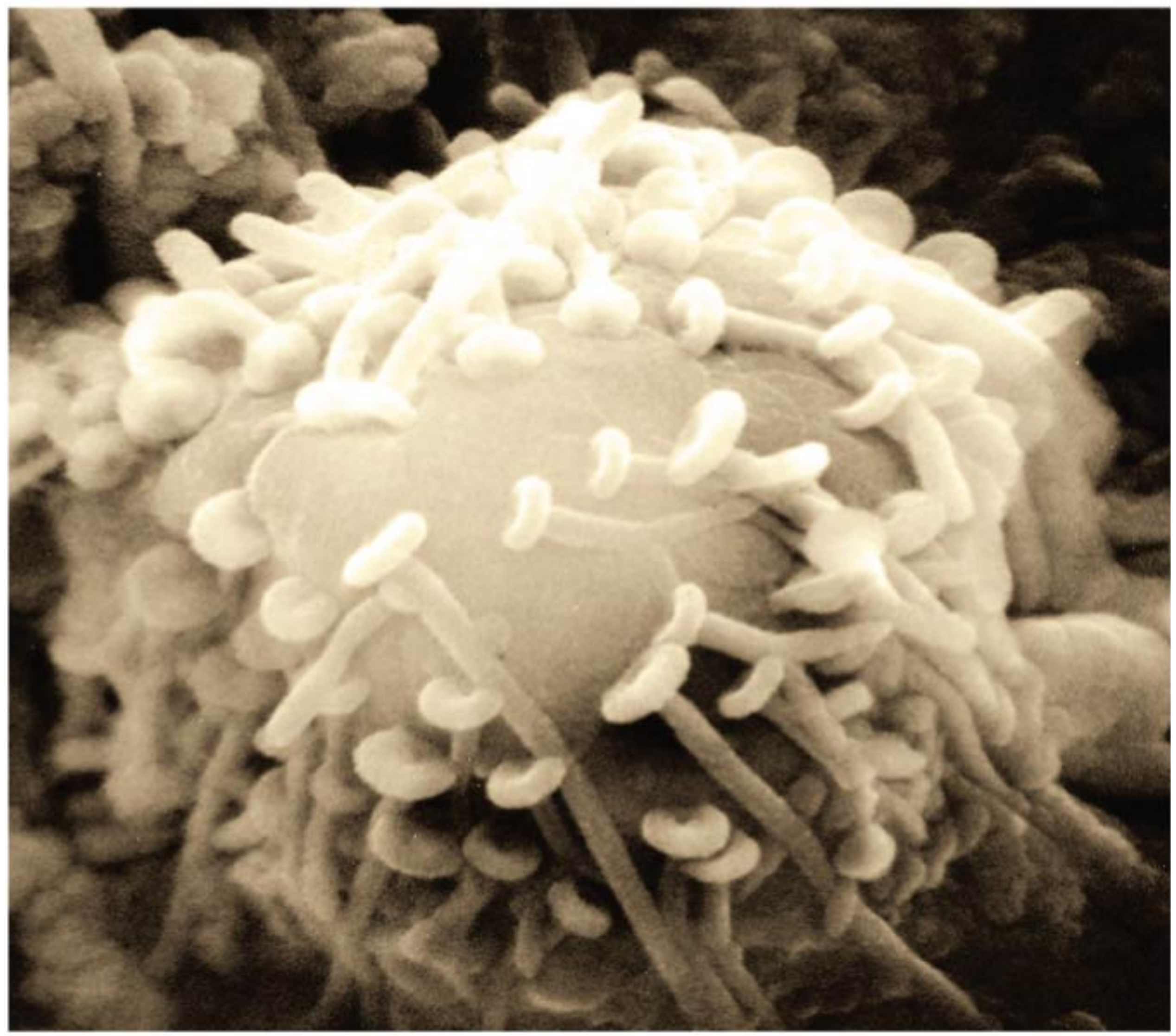
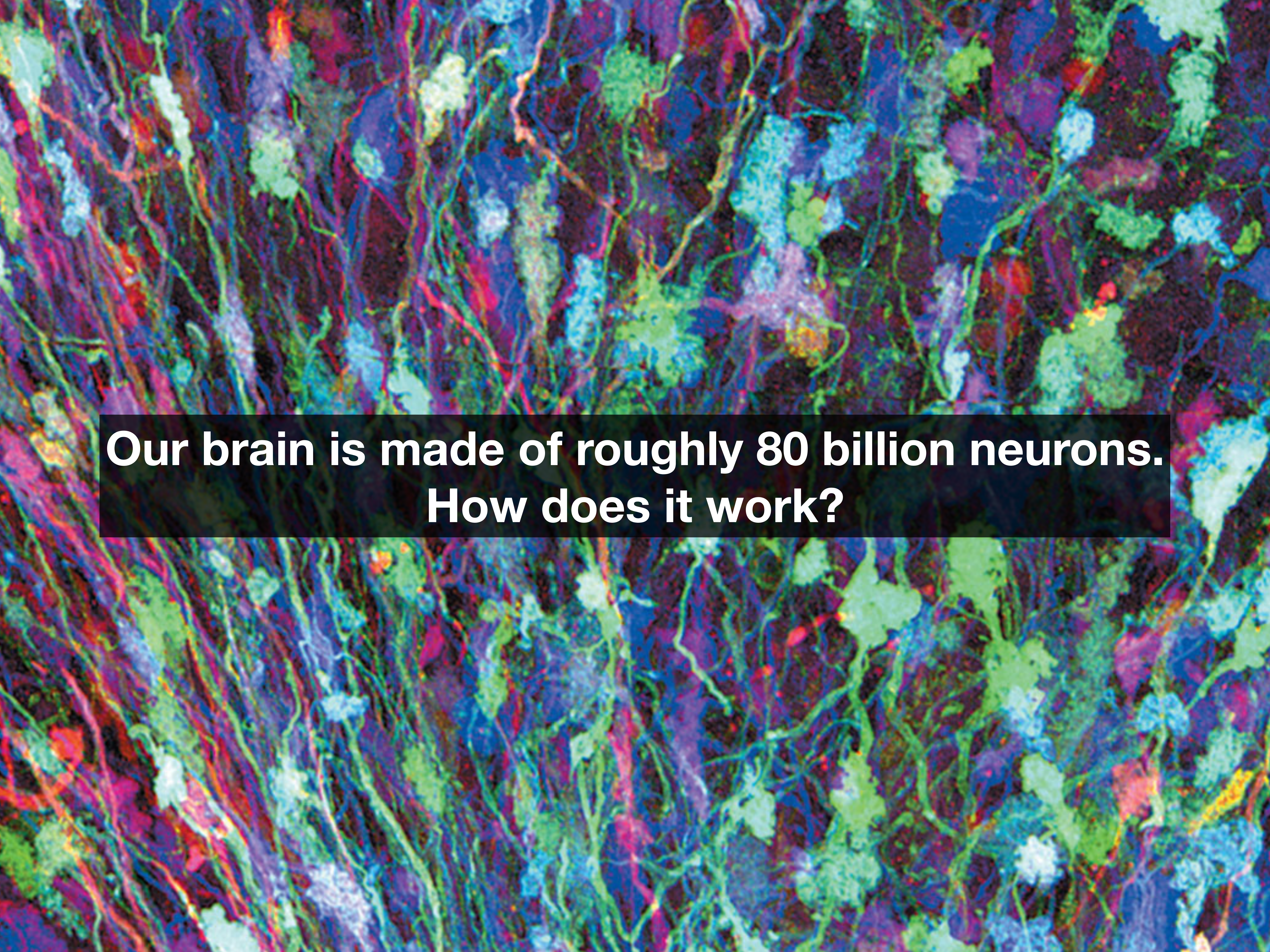
ILAS Seminar - Computer Simulations in Biology

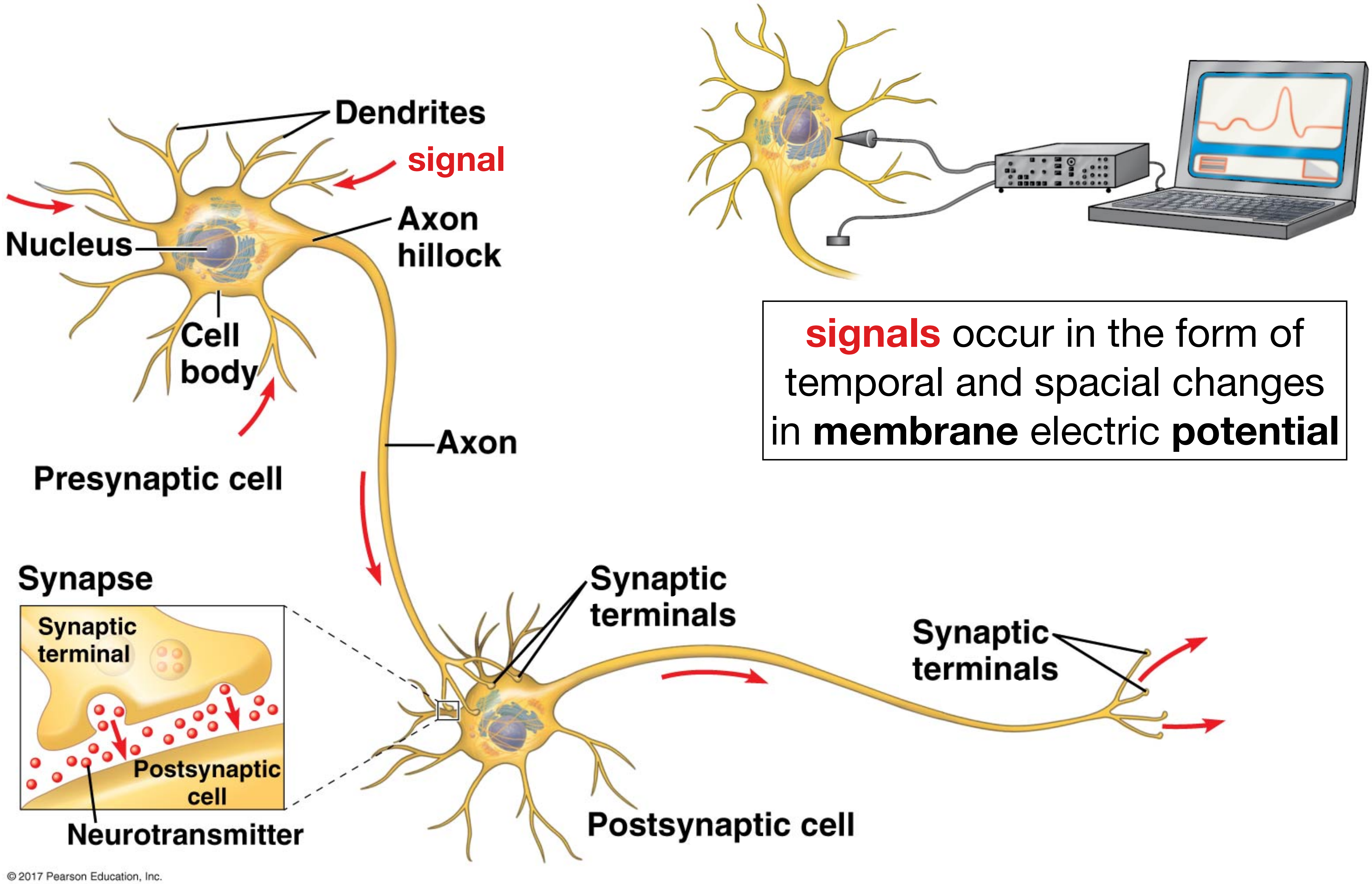
Neuroscience



Giovanni Brandani

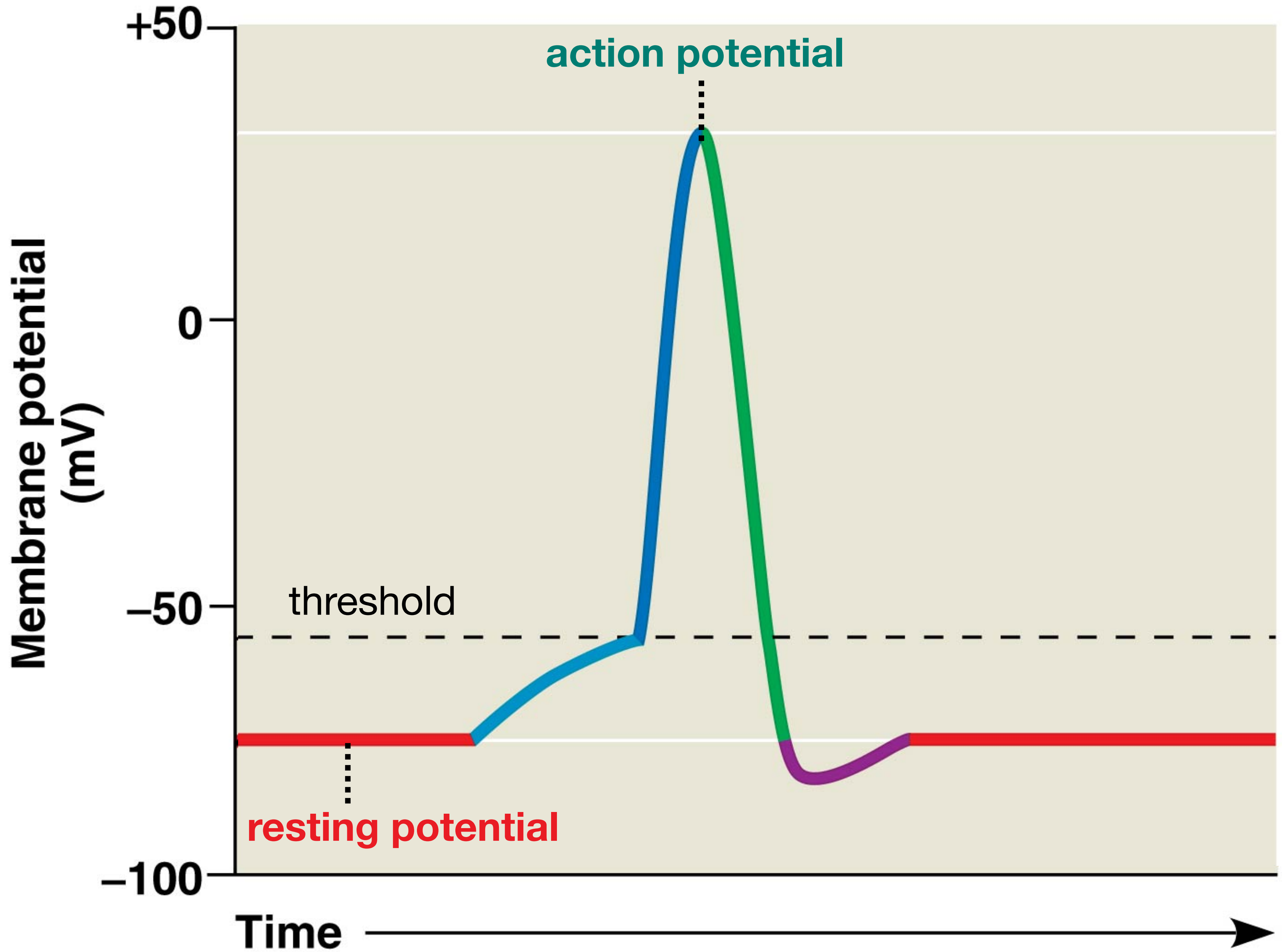

Our brain is made of roughly 80 billion neurons.
How does it work?

Brain function is based on the transmission of signals between neurons

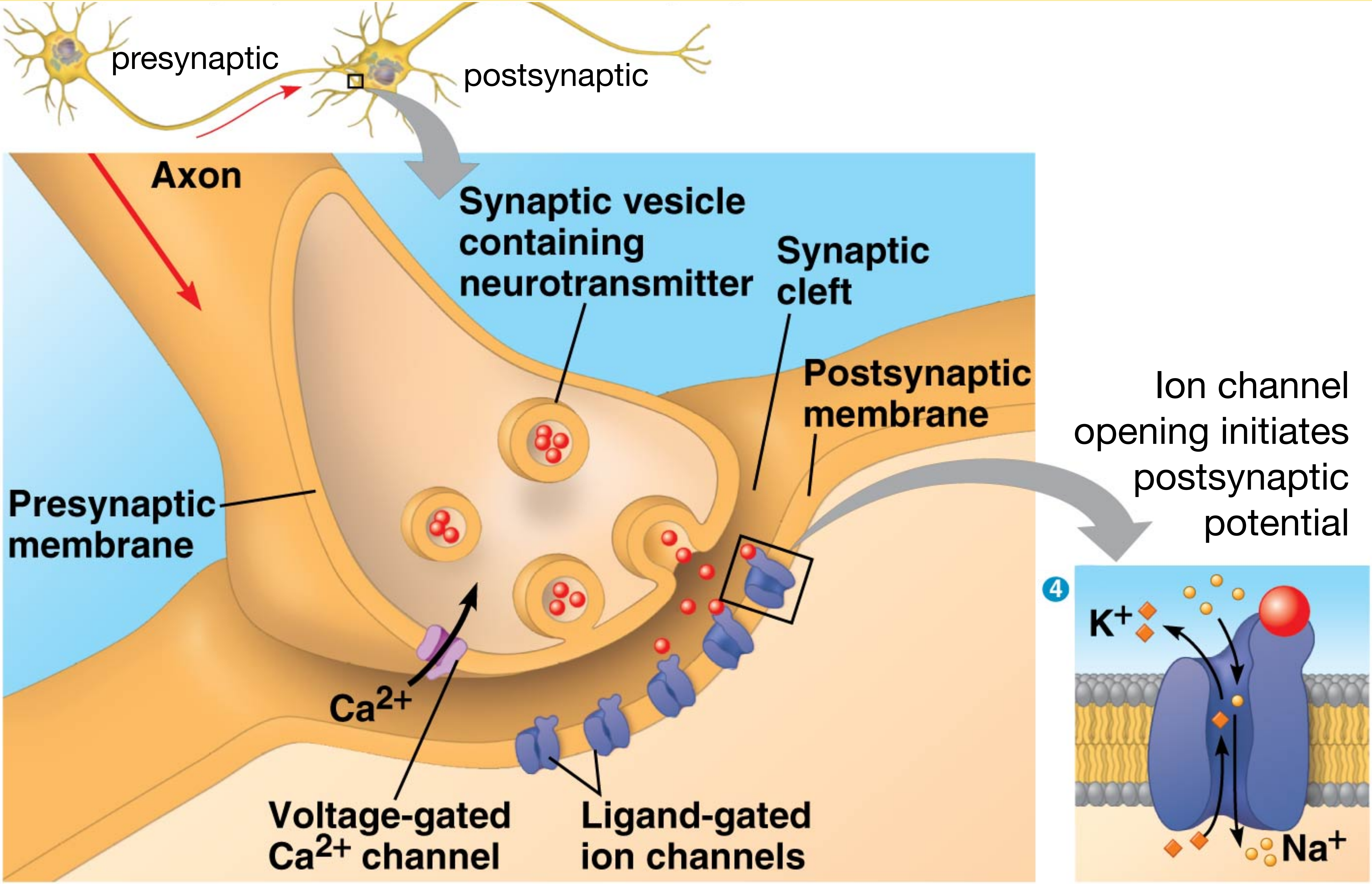


signals occur in the form of temporal and spacial changes in **membrane** electric **potential**

Neurons fire when their membrane potential surpasses a certain threshold



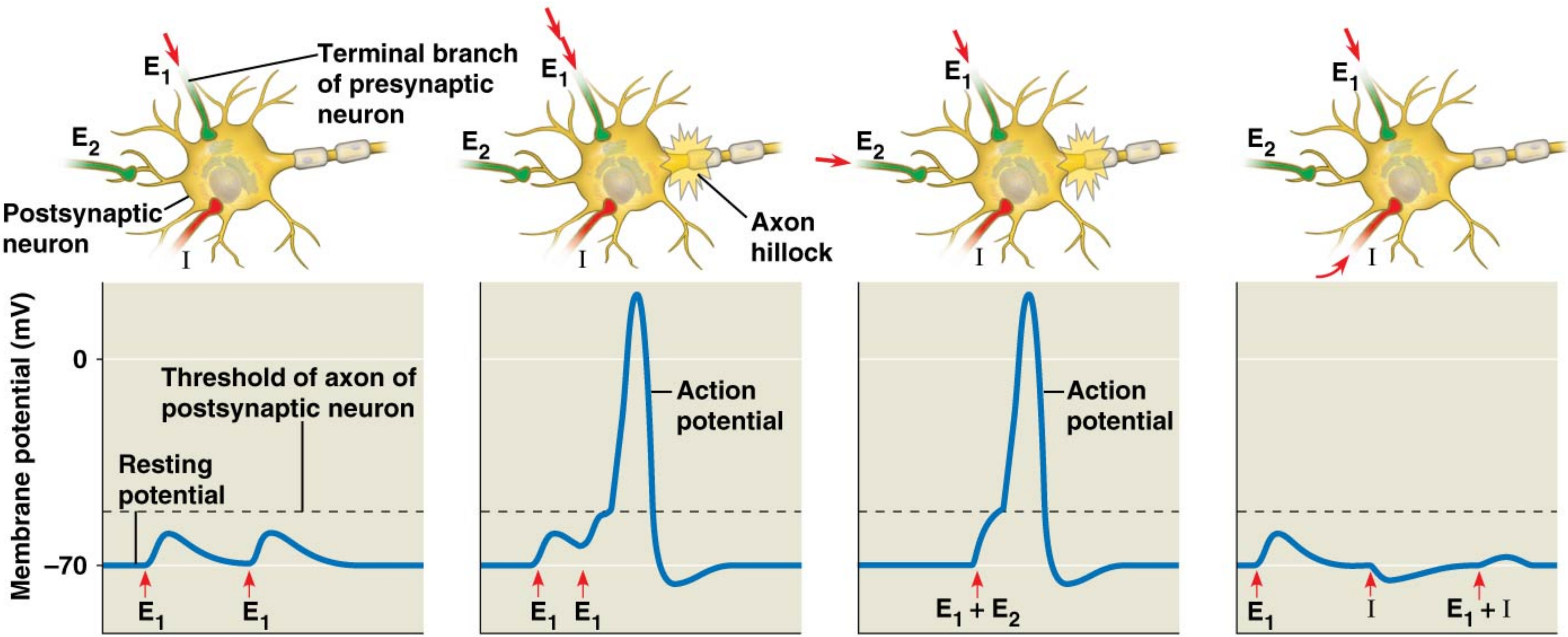
Synaptic connections are based on neurotransmitters that open ion channels on the postsynaptic membrane



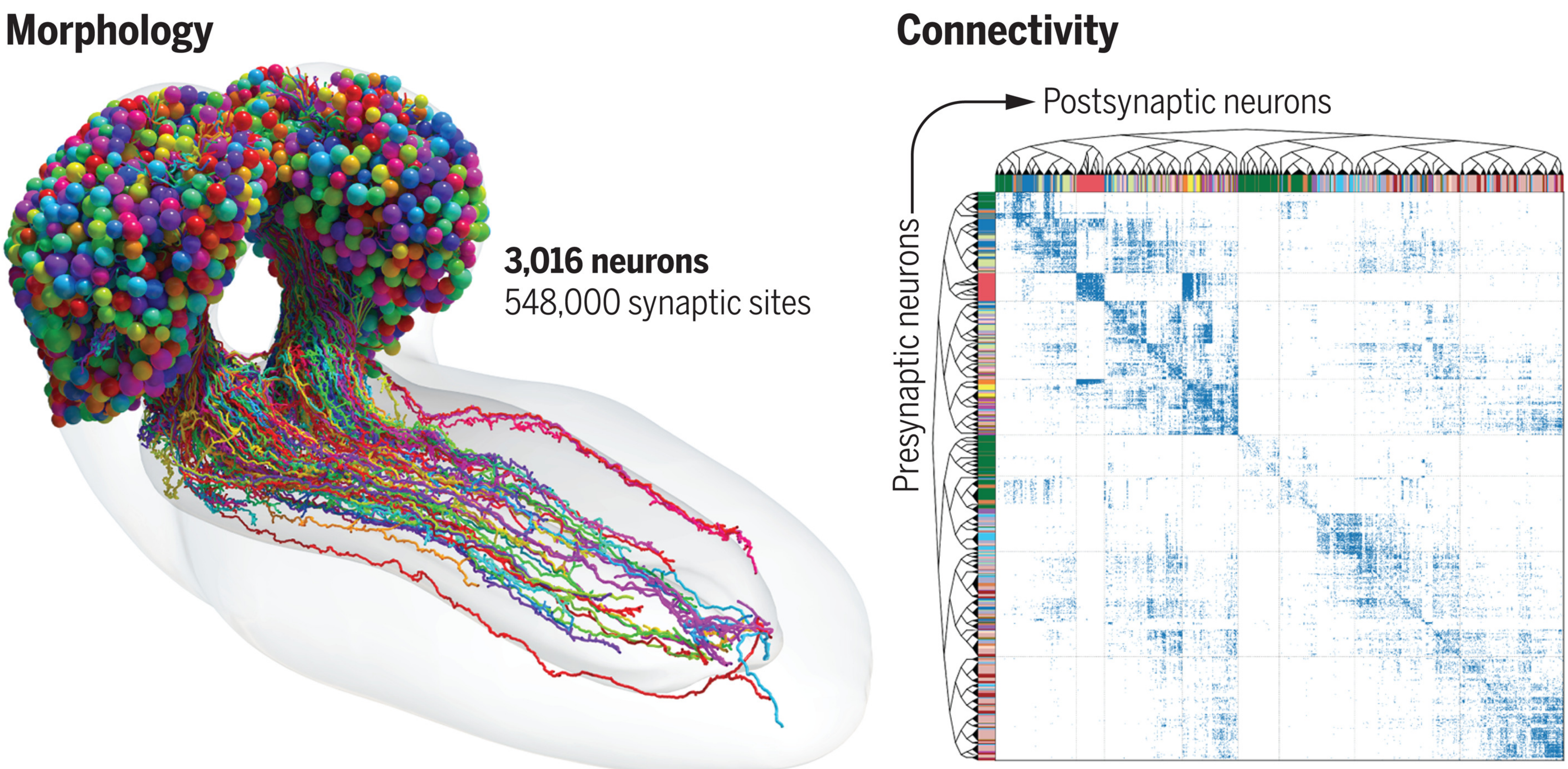
Ion channel opening initiates postsynaptic potential

Postsynaptic potentials can be excitatory or inhibitory depending on the ion channel opened

Signals coming from many pre-synaptic neurons are summed in time and space



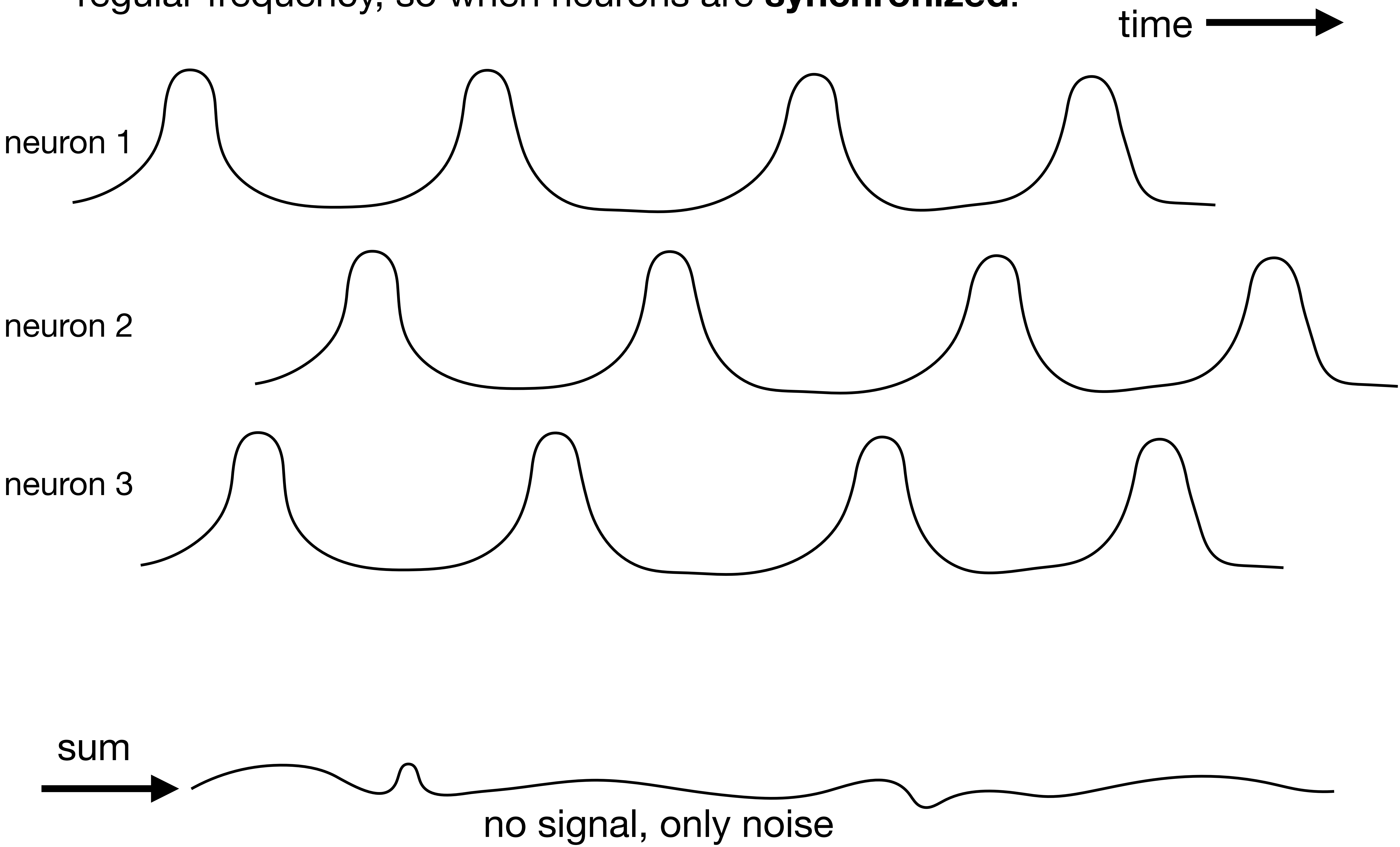
Experiments can now reconstruct the complete map of a brain of complex organisms



Winding et al. "The connectome of an insect brain." Science 379.6636 (2023): eadd9330.

Based on connectivity data from experiments, computer simulations can be used to understand how the brain processes information and how it learns about the world

Problem: understanding the basis of **brain waves**, which occur when groups of neurons fire (emit signal) at the same time at a regular frequency, so when neurons are **synchronized**.



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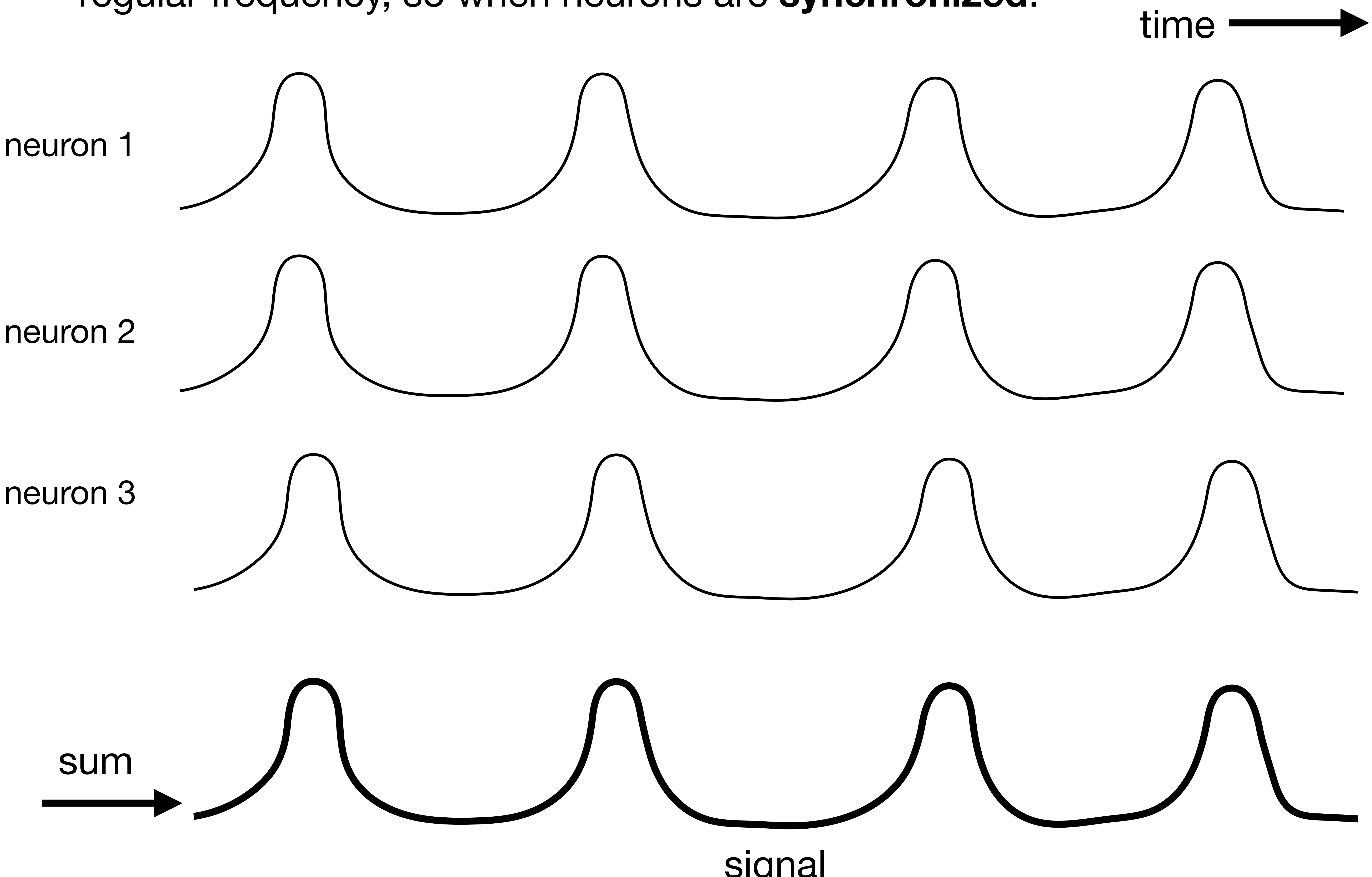
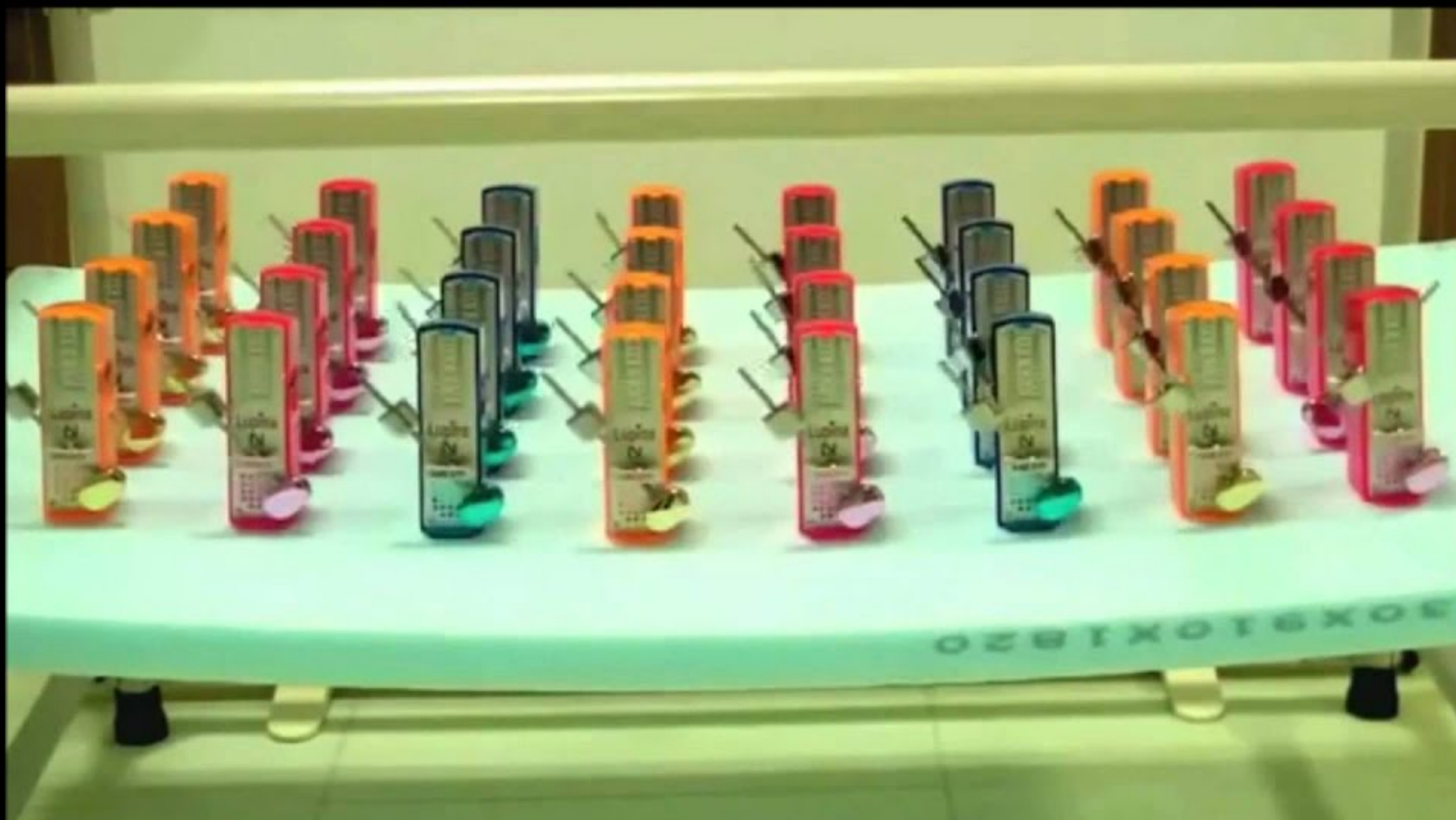
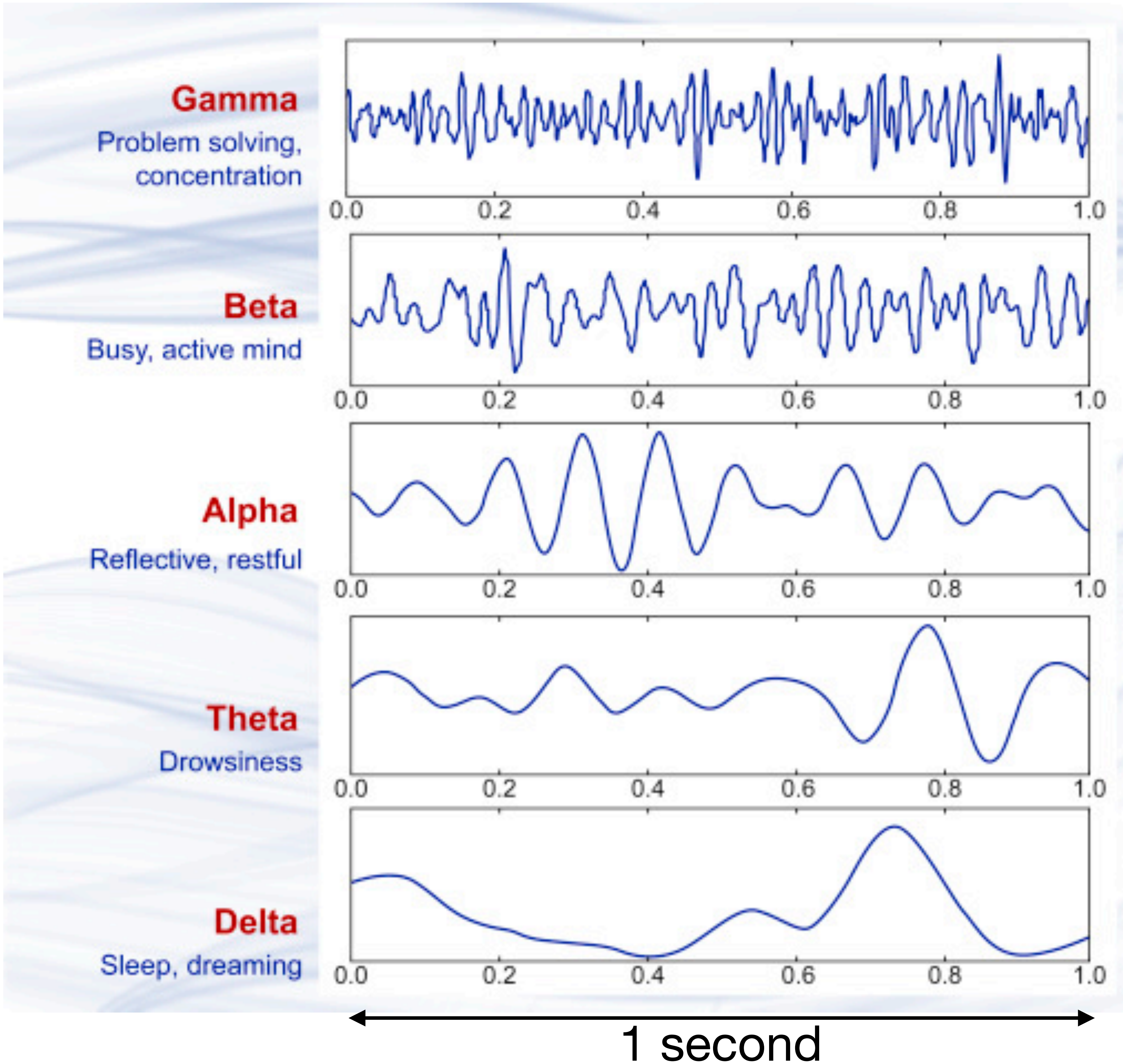


Synchronization occurs even in non-biological systems, and in fact the mechanism is very similar!



https://www.youtube.com/watch?v=5v5eBf2KwF8

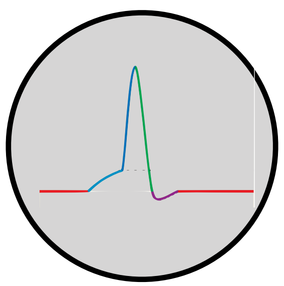
Brain wave frequency is related to the task performed



Abhang et al. “Introduction to EEG-and speech-based emotion recognition.” Academic Press, 2016.

Building a simple model of the mammalian cortex

We need: 1. A model for individual **neurons**



$$\frac{dv}{dt} = 0.04v^2 + 5v + 140 - u + I$$

$$\frac{du}{dt} = a(bv - u)$$

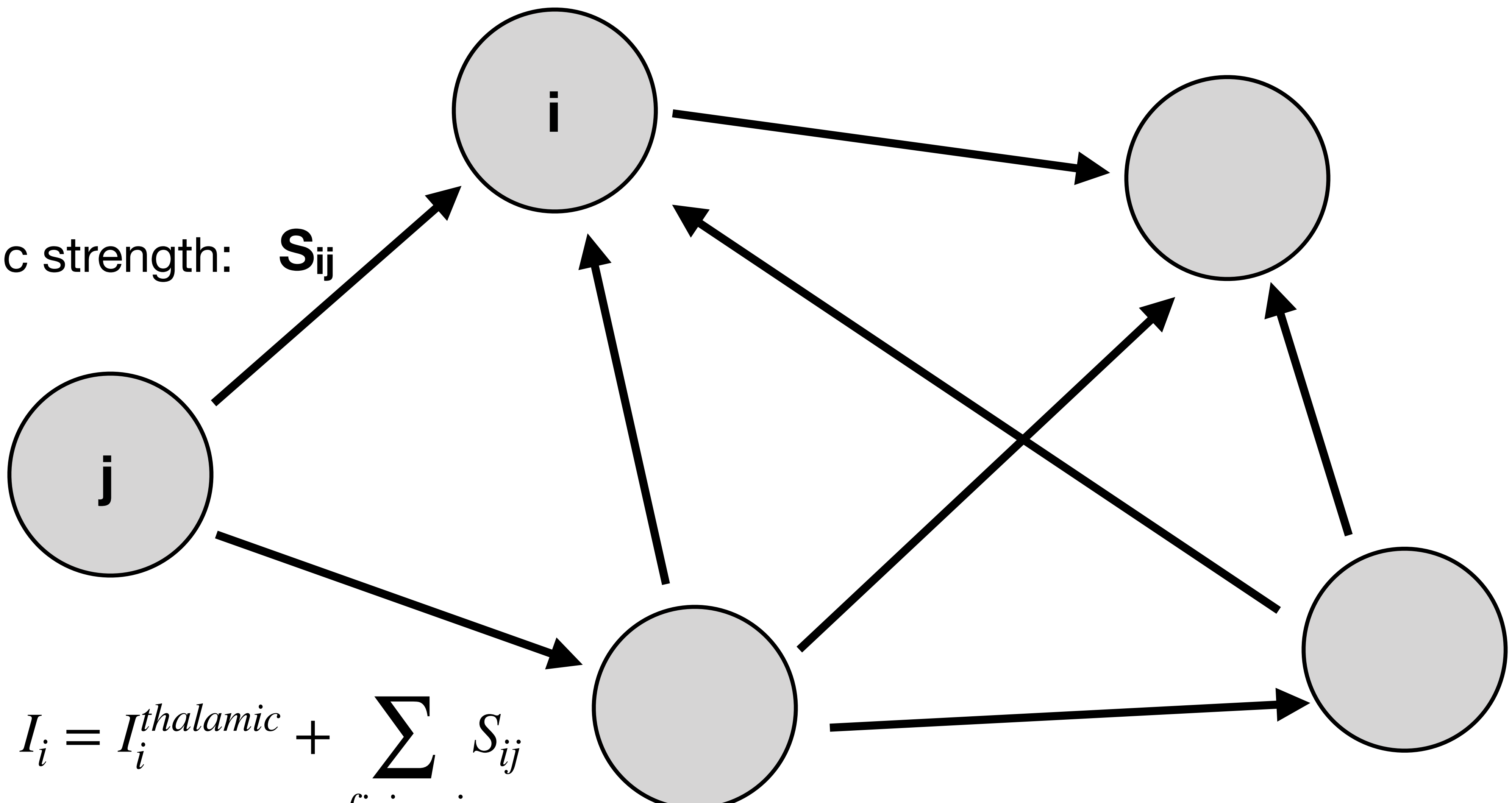
firing: $$\text{if } v \geq 30 \text{ mV, then } \begin{cases} v \leftarrow c \\ u \leftarrow u + d. \end{cases}$$

v is the membrane potential
u is a variable accounting for ion channel opening
a, b, c, and d are parameters representing different neurons
I is the input current from pre-synaptic neurons

Izhikevich, "Simple model of spiking neurons." IEEE Transactions on neural networks 14.6 (2003): 1569-1572.

Building a simple model of the mammalian cortex

We need:
1. A model for individual **neurons**
2. A model for how neurons communicate with each other with **synaptic connections** →



synaptic strength: $\mathbf{S_{ij}}$

input current $$I_i = I_i^{thalamic} + \sum_{firing\ j} S_{ij}$$

the first term is a noisy input coming from another region of the brain (the thalamus), and the second term sums the synaptic connection strengths over the firing neurons

Izhikevich, "Simple model of spiking neurons." IEEE Transactions on neural networks 14.6 (2003): 1569-1572.

Pseudo-code for the cortex model (in matlab)

```
% Excitatory neurons    Inhibitory neurons
Ne=800;                 Ni=200;
re=rand(Ne,1);          ri=rand(Ni,1);
a=[0.02*ones(Ne,1);     0.02+0.08*ri];
b=[0.2*ones(Ne,1);      0.25-0.05*ri];
c=[-65+15*re.^2;        -65*ones(Ni,1)];
d=[8-6*re.^2;           2*ones(Ni,1)];
S=[0.5*rand(Ne+Ni,Ne), -rand(Ne+Ni,Ni)];

v=-65*ones(Ne+Ni,1);    % Initial values of v
u=b.*v;                 % Initial values of u
firings=[];             % spike timings

for t=1:1000            % simulation of 1000 ms
  I=[5*randn(Ne,1);2*randn(Ni,1)]; % thalamic input
  fired=find(v>=30);    % indices of spikes
  firings=[firings; t+0*fired,fired];
  v(fired)=c(fired);
  u(fired)=u(fired)+d(fired);
  I=I+sum(S(:,fired),2);
  v=v+0.5*(0.04*v.^2+5*v+140-u+I); % step 0.5 ms
  v=v+0.5*(0.04*v.^2+5*v+140-u+I); % for numerical
  u=u+a.*(b.*v-u);                 % stability
end;
```

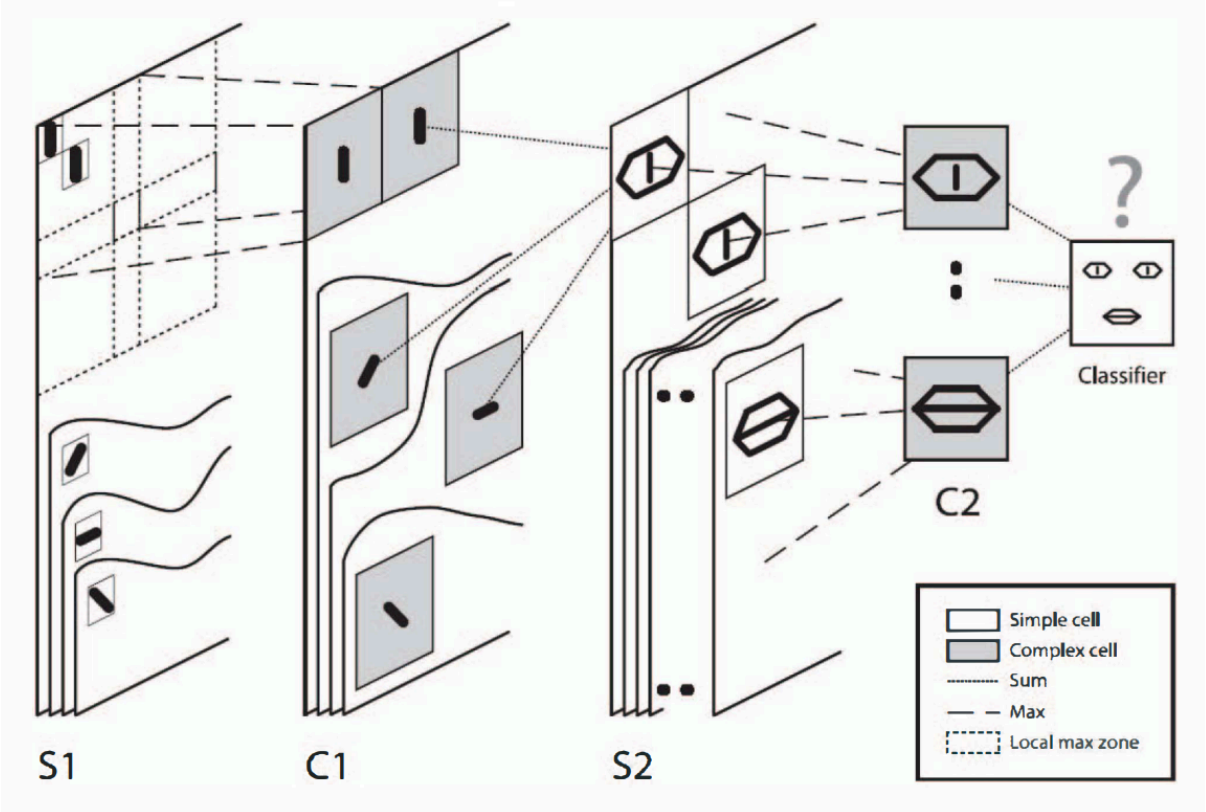
Note that in python, re, ri, a, b, c, d, v, and u should be 1-dimensional arrays, using 2d arrays makes things more complicated

Izhikevich, "Simple model of spiking neurons." IEEE Transactions on neural networks 14.6 (2003): 1569-1572.

Understanding learning

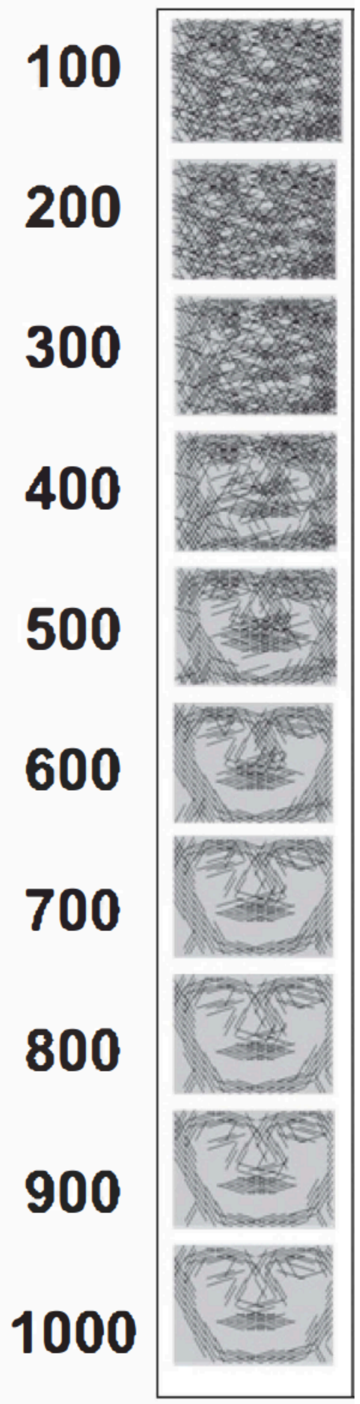
The Izhikevich model can also be extended to study how the brain learns to processes signals from the outside, for example to recognize faces

Tavanaei et al. "Acquisition of visual features through probabilistic spike-timing-dependent plasticity." 2016 International Joint Conference on Neural Networks (IJCNN). IEEE, 2016



The brain can learn through Spike-Timing-Dependent Plasticity:

- when a post-synaptic neuron fires just after (e.g., within 10ms) the firing of a pre-synaptic neuron, the synaptic connection is strengthened, leading to long-term potentiation (LTP)
- Otherwise, firing of the post-synaptic neuron leads to a weakening of the synaptic connection, leading to long-term depression (LTD)



Features learned by network of spiking neurons by exposing it to images of faces

Task:

A. Read the original paper introducing the neuron model (Ref. 1), implement it in python and reproduce the behavior of different types of neurons as reported in the paper.
B. Implement the mammalian cortex model from the same paper and reproduce the results about neuron synchronization (in order to reproduce the results, the model should be implemented <u>exactly</u> as described in the paper, including the timestep of 1ms, comparable to the timescale of an action potential). NOTE: use numpy arrays.

References:

1. Izhikevich, "Simple model of spiking neurons." IEEE Transactions on neural networks 14.6 (2003): 1569-1572.
2. Izhikevich, Eugene M., and Gerald M. Edelman. "Large-scale model of mammalian thalamocortical systems." Proceedings of the national academy of sciences 105.9 (2008): 3593-3598.
3. Connors, Barry W., and Michael J. Gutnick. "Intrinsic firing patterns of diverse neocortical neurons." Trends in neurosciences 13.3 (1990): 99-104.