

# COMS30127: Computational Neuroscience

## Synapses

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# Dr. [your name here]?

- Would you like to do a PhD in computational neuroscience?
- If so there are many good options in the UK and abroad. It's more or less a buyers market (you're buying).
- Here's 3 nice options:
  1. EPSRC DTP with one of Bristol's Computational Neuroscience Unit: Conor Houghton, Nathan Lepora, Naoki Masuda, Rosalyn Moran, Cian O'Donnell. Check out our research webpages and contact us directly if interested.
  2. Bristol's Neural Dynamics PhD program (joint experimental/computational). Webpage: <http://www.bristol.ac.uk/neural-dynamics/>
  3. Rafal Bogacz at Oxford is looking for a PhD student to start Oct 2017. "The topic of research could range from developing a formal theory of information processing in the brain to applying machine learning to the data recorded from the brains of patients."  
Rafal's page: <https://www.ndcn.ox.ac.uk/team/rafal-bogacz>  
PhD advert: <https://www.findaphd.com/search/ProjectDetails.aspx?PJID=83868&LID=1239>

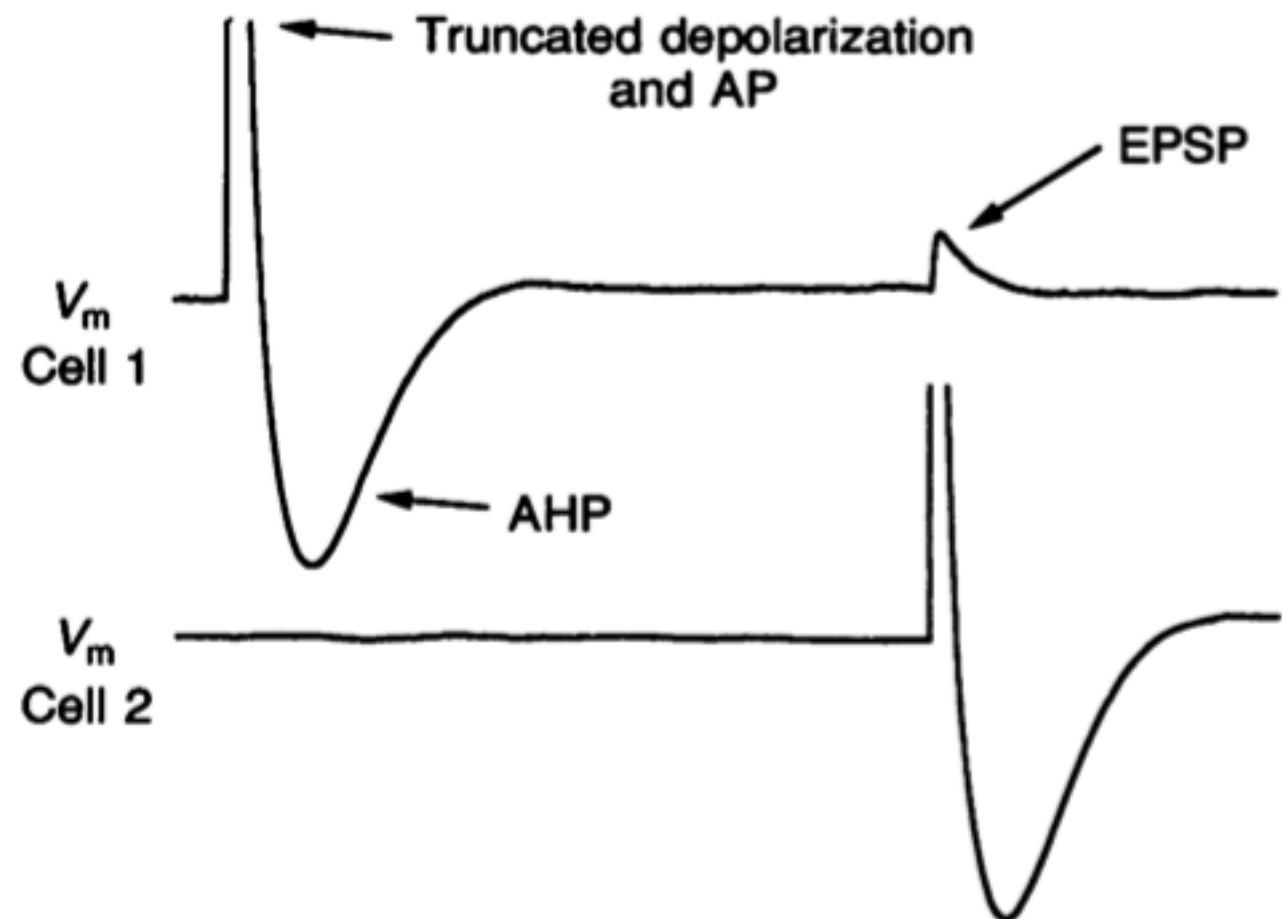
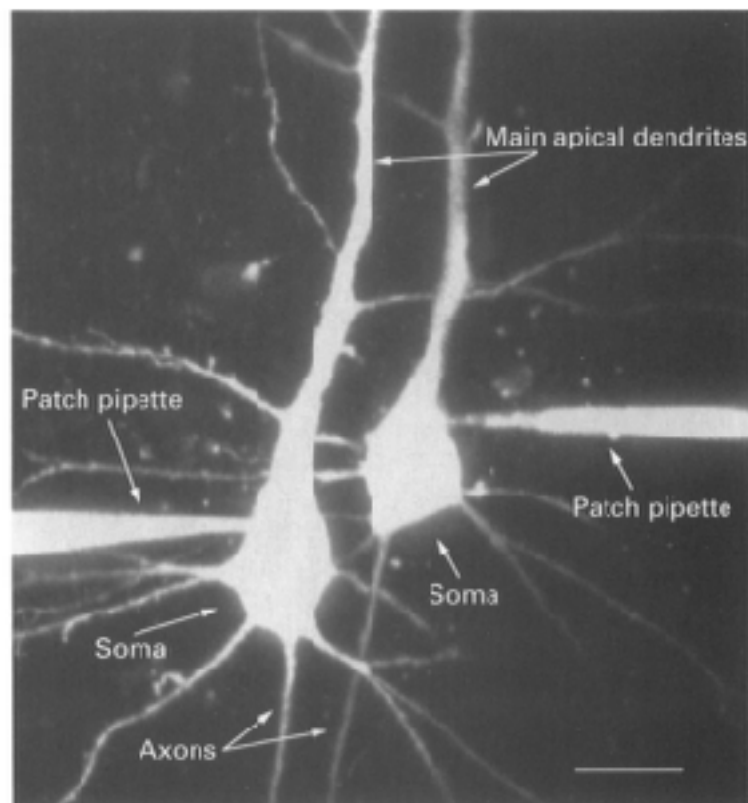
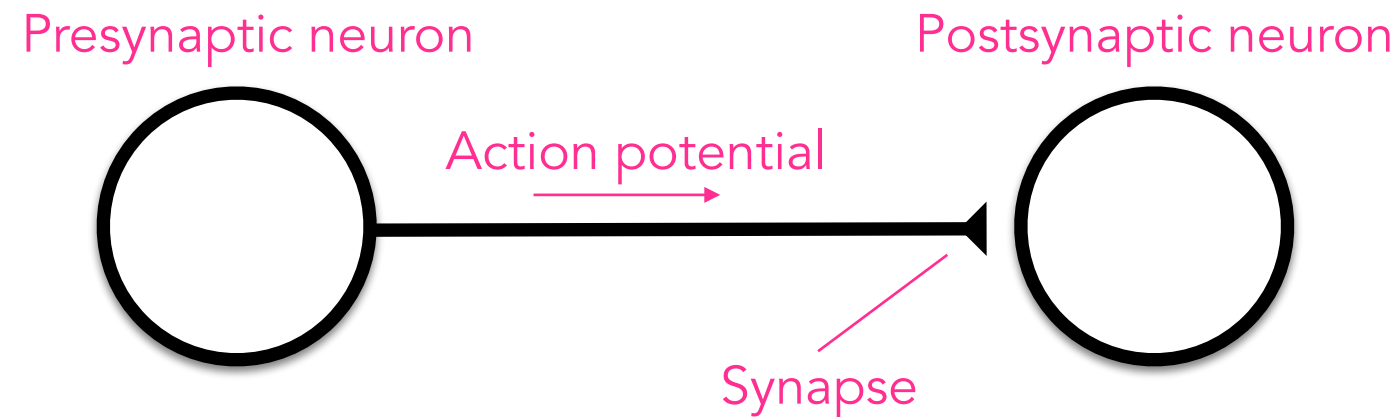
# What we will cover today

- What is a synapse?
- How do synapses work?
- How can we computationally model synapses?

# What is a synapse?

- Synapses are the connections between neurons.
- They convert the action potential from one neuron's axon into a 'post-synaptic-potential' in the dendrite of another neuron.
- Although both a synapse's input and output signals are electrical, the most common type of synapse converts the signal into chemical form at an intermediate stage.
- There are also purely electrical synapses (called 'gap junctions') but in this course we will focus on chemical synapses.
- From a functional point of view, synapses are interesting for two reasons:
  1. they are nonlinear, so can perform computations.
  2. they are plastic, so can store information (memories).

# What is a synapse?

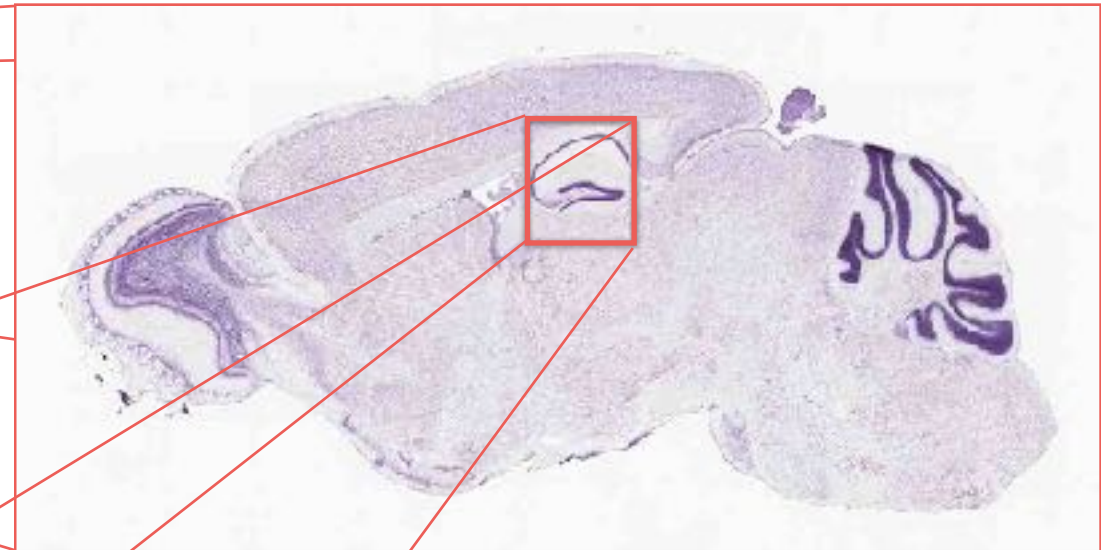
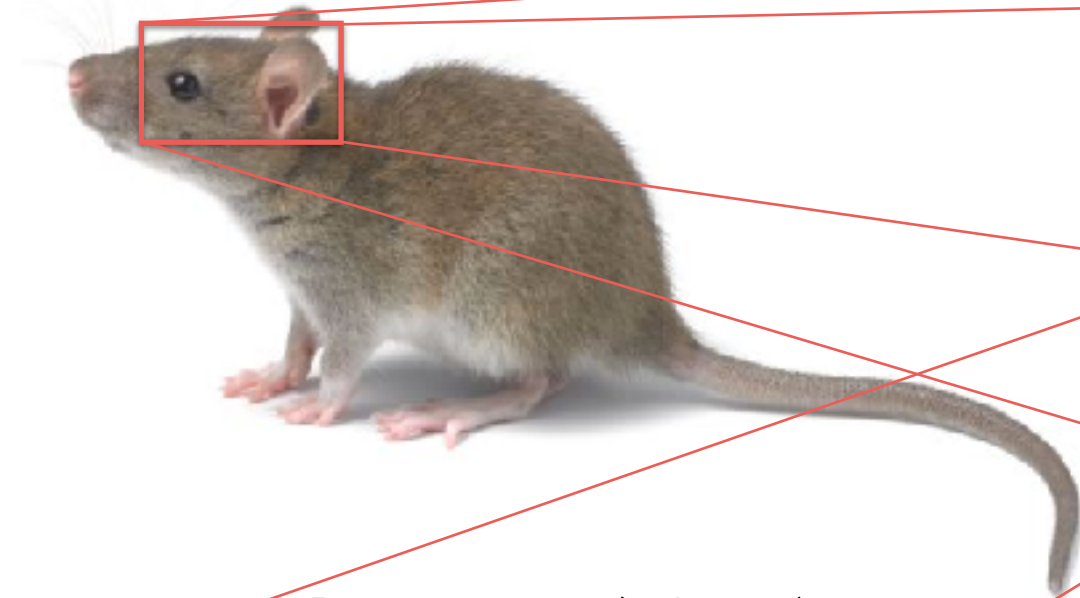




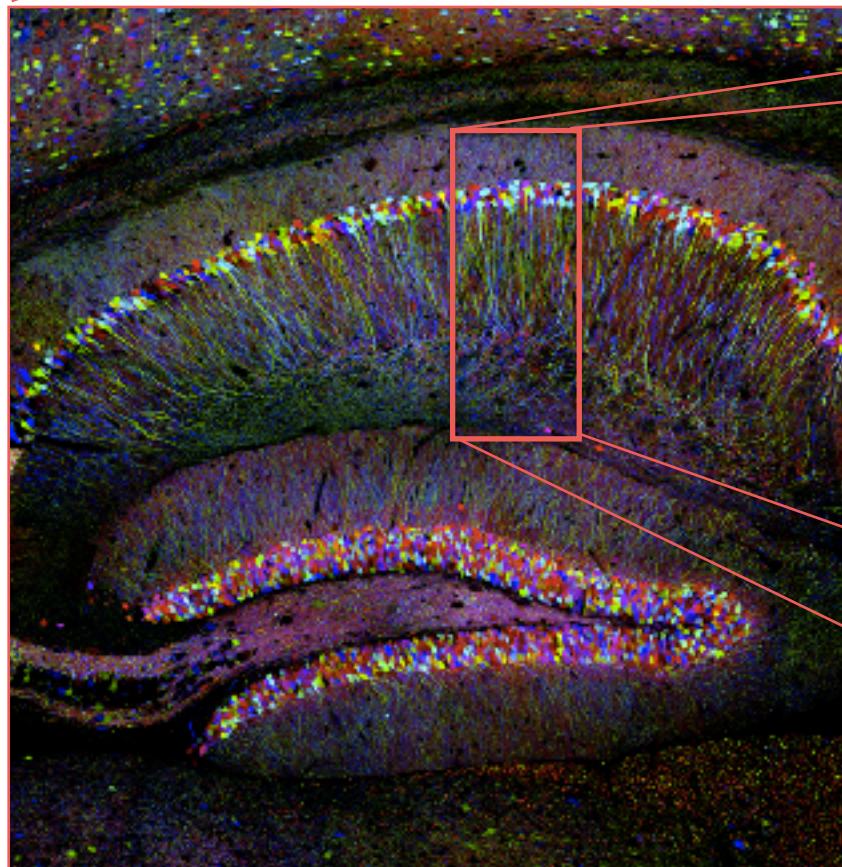
# Zooming in on synapses

Brain (~1 cm)

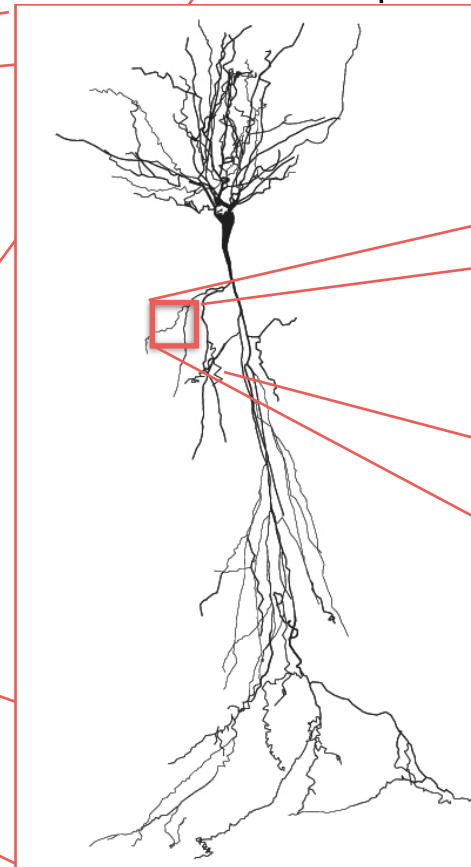
Animal (~10 cm)



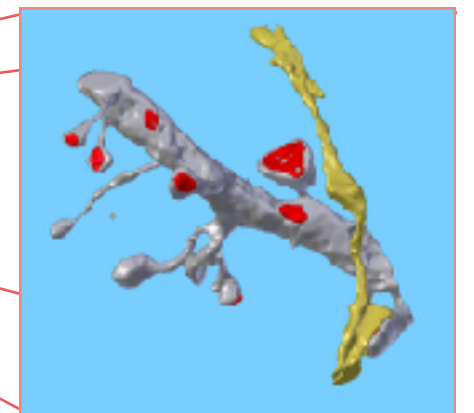
Brain region (~1 mm)



Neuron (~100  $\mu\text{m}$ )

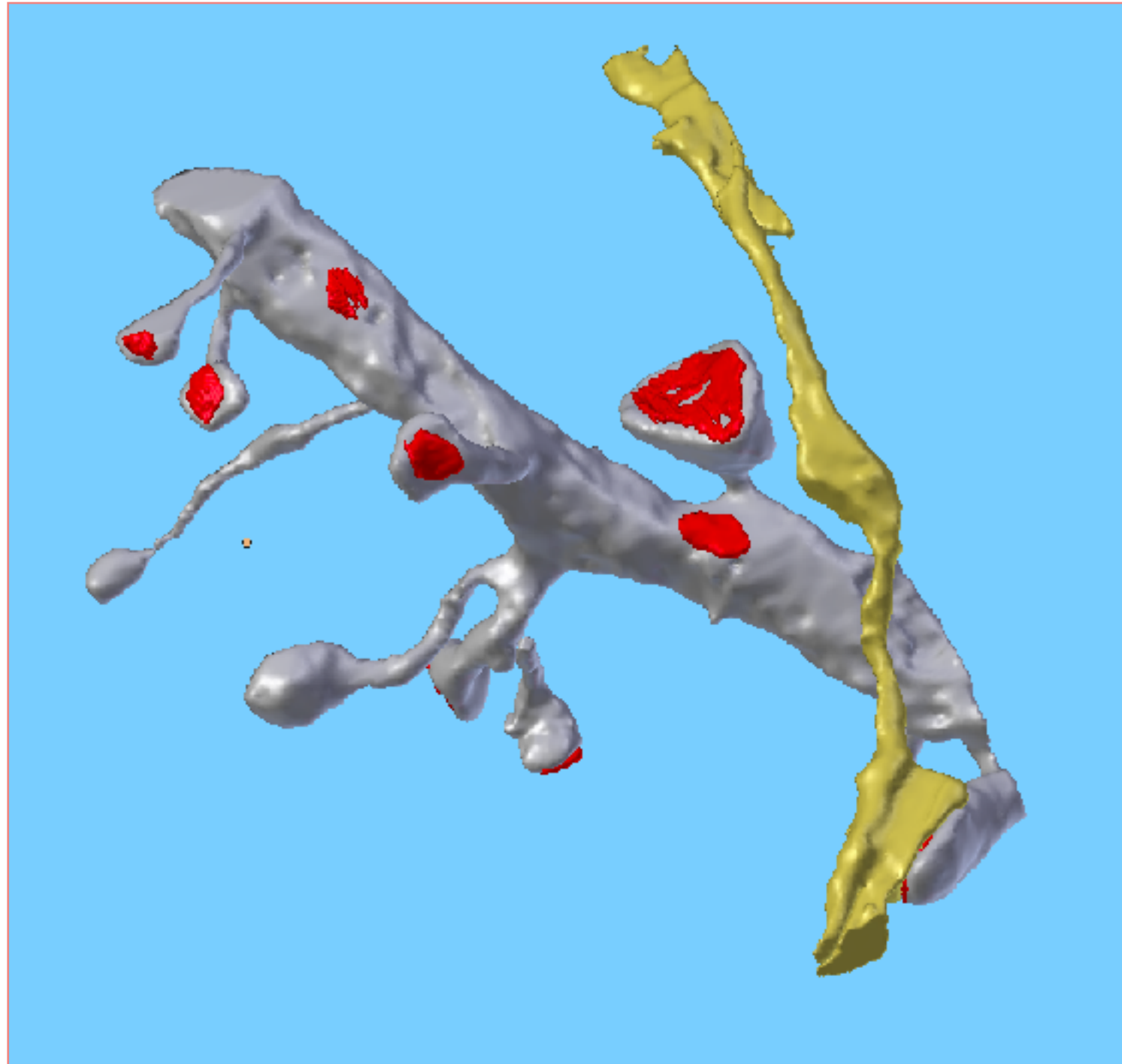


Synapses (~1  $\mu\text{m}$ )



# What is a synapse?

Dendrite and axon from mouse somatosensory cortex.



Electron microscopy data from Graham Knott (EPFL)

Blender demo & Youtube video (<https://www.youtube.com/watch?v=FZT6c0V8fW4&t>)

# How do synapses work?

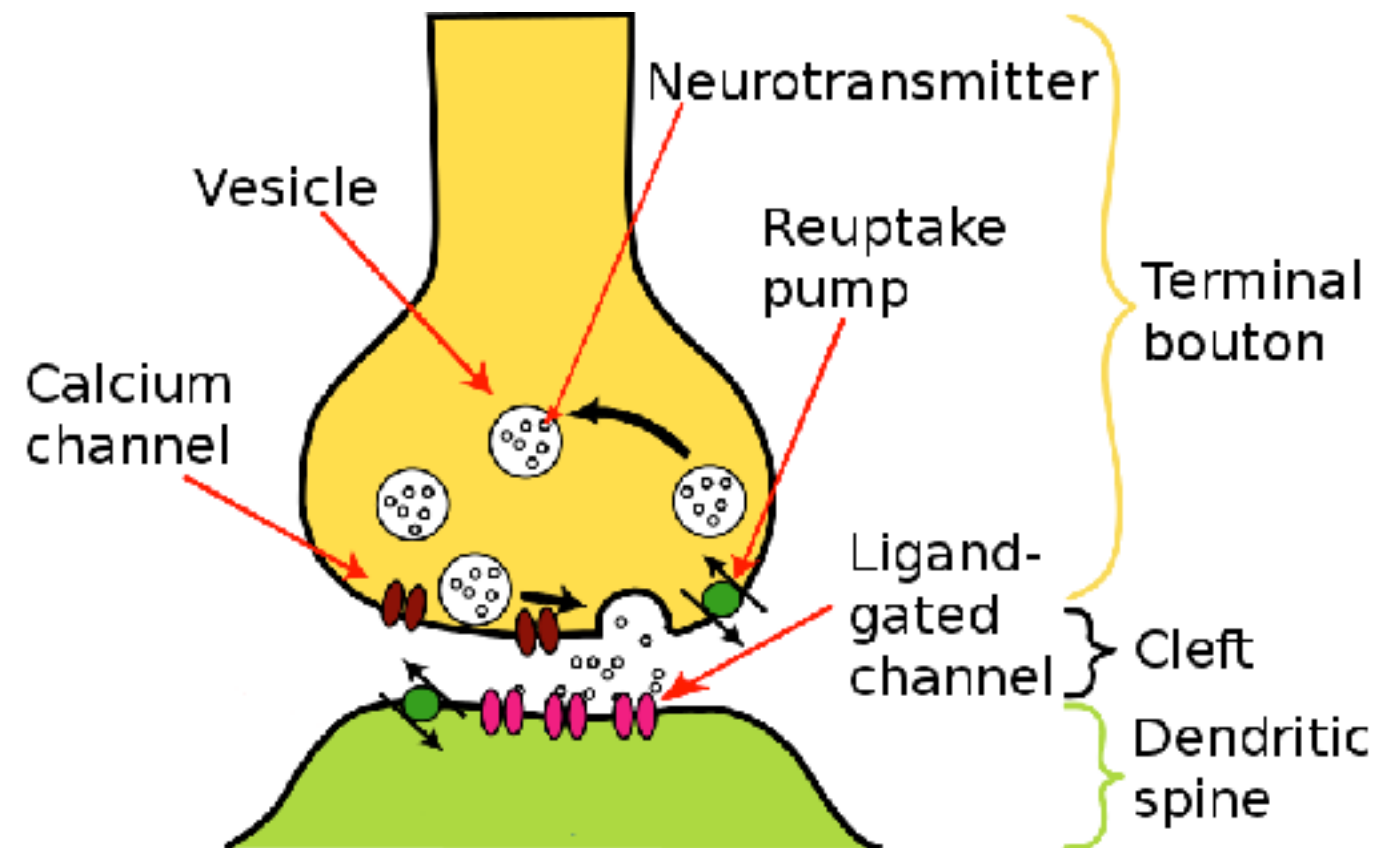
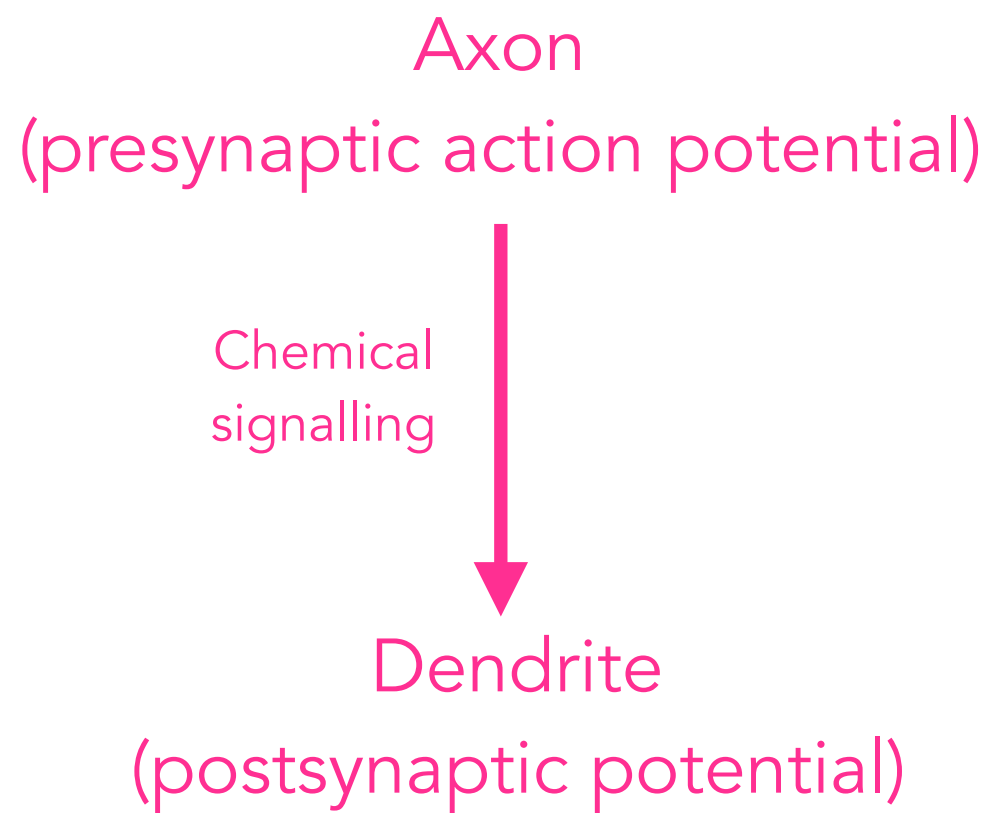
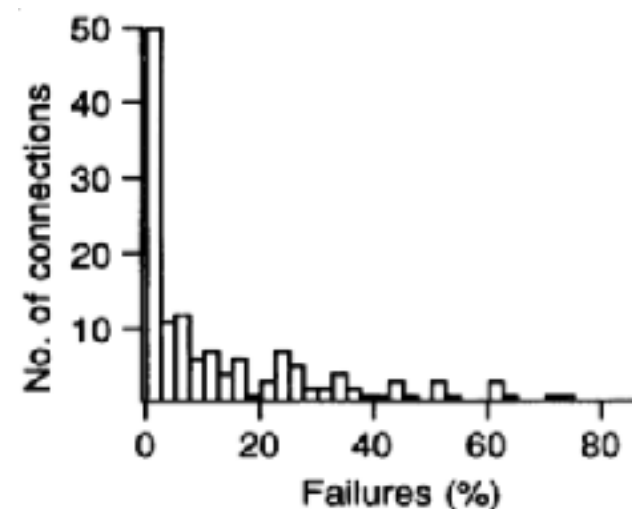
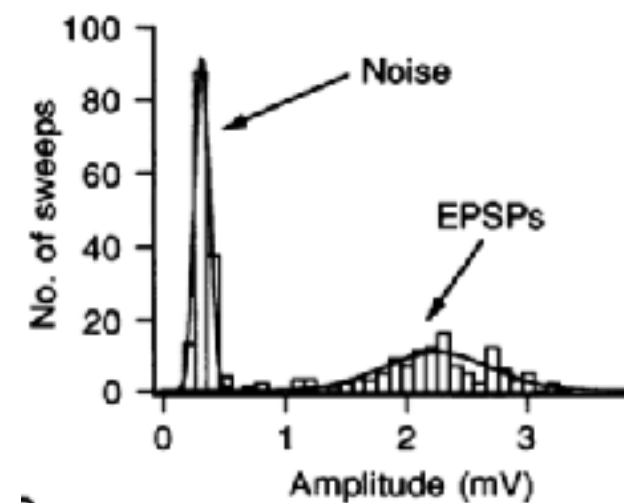
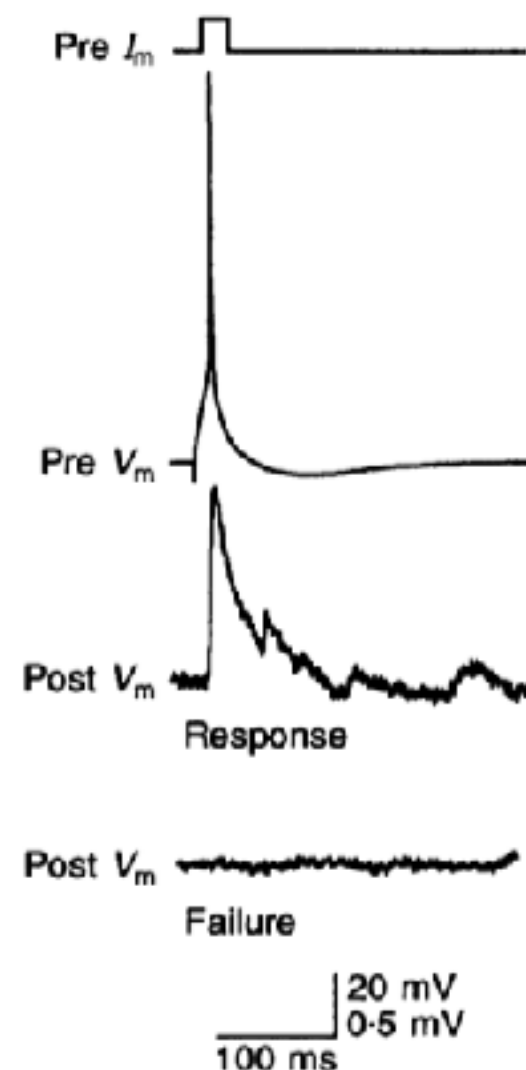


Image from Wikipedia (modified by C Houghton)

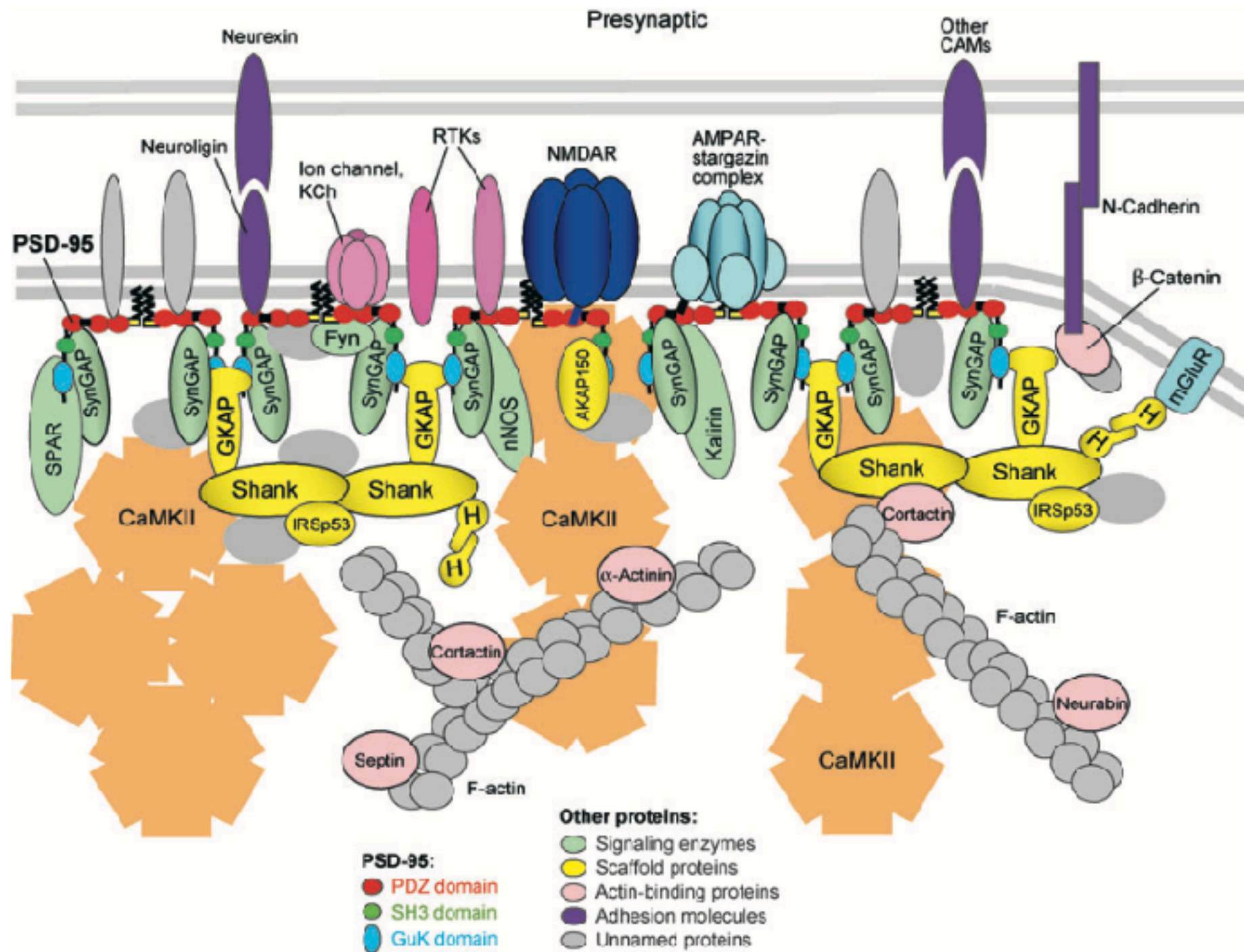


# Synapses are probabilistic

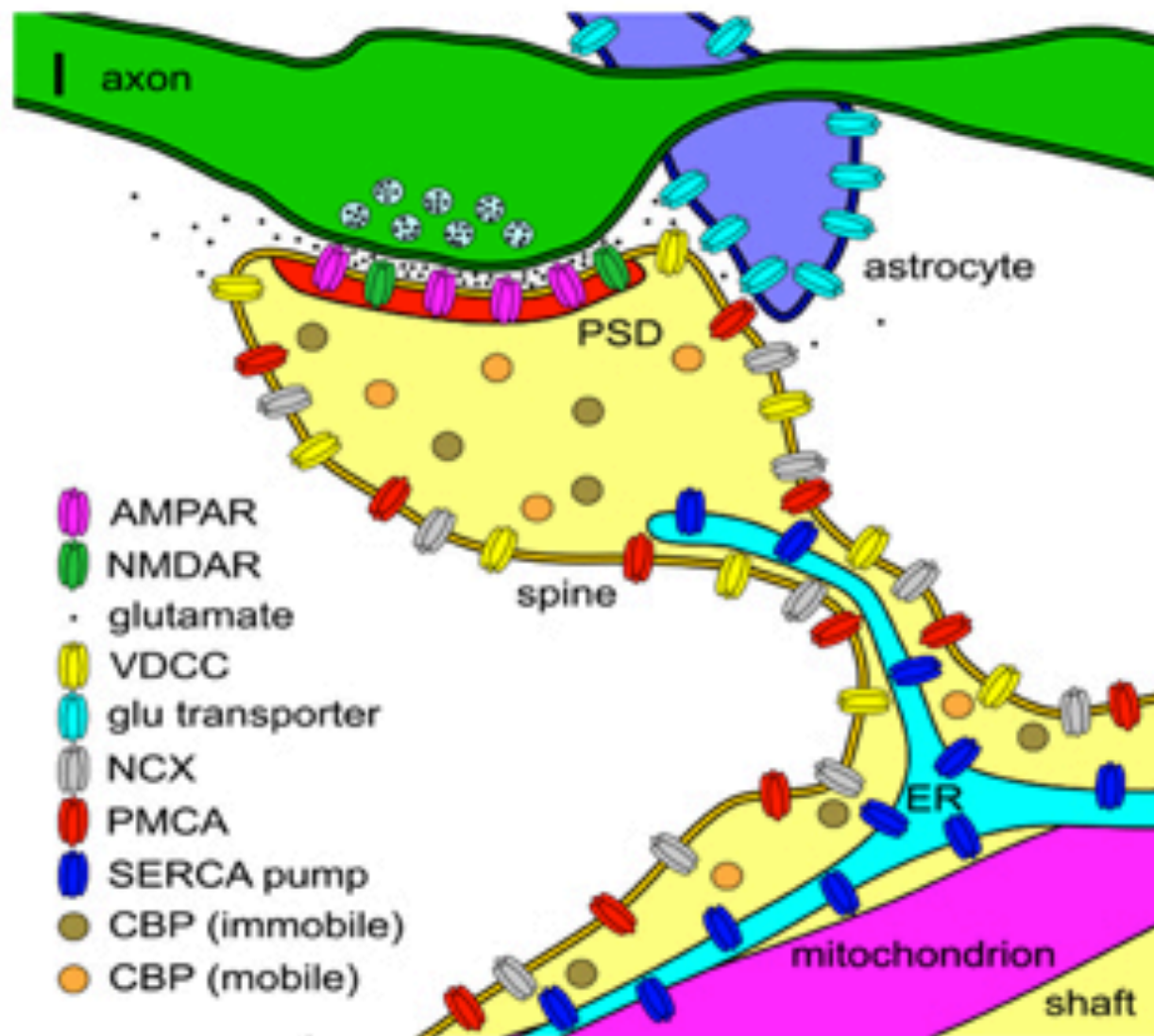
- When an action potential arrives at a synapse, it may or may not lead to release of neurotransmitter.
- The 'release probability'  $p$  is often quantified experimentally,  $0 < p < 1$ .



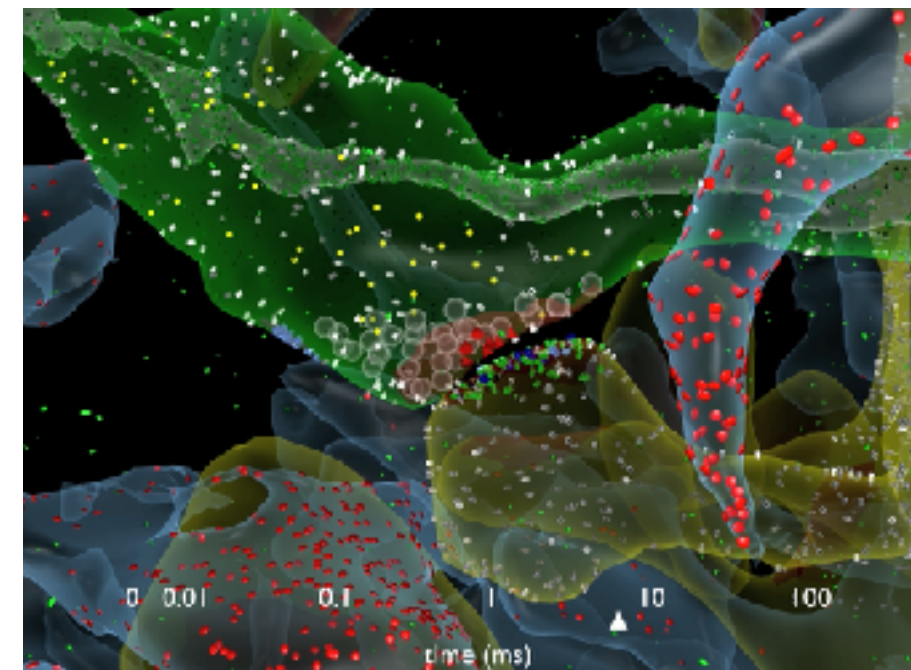
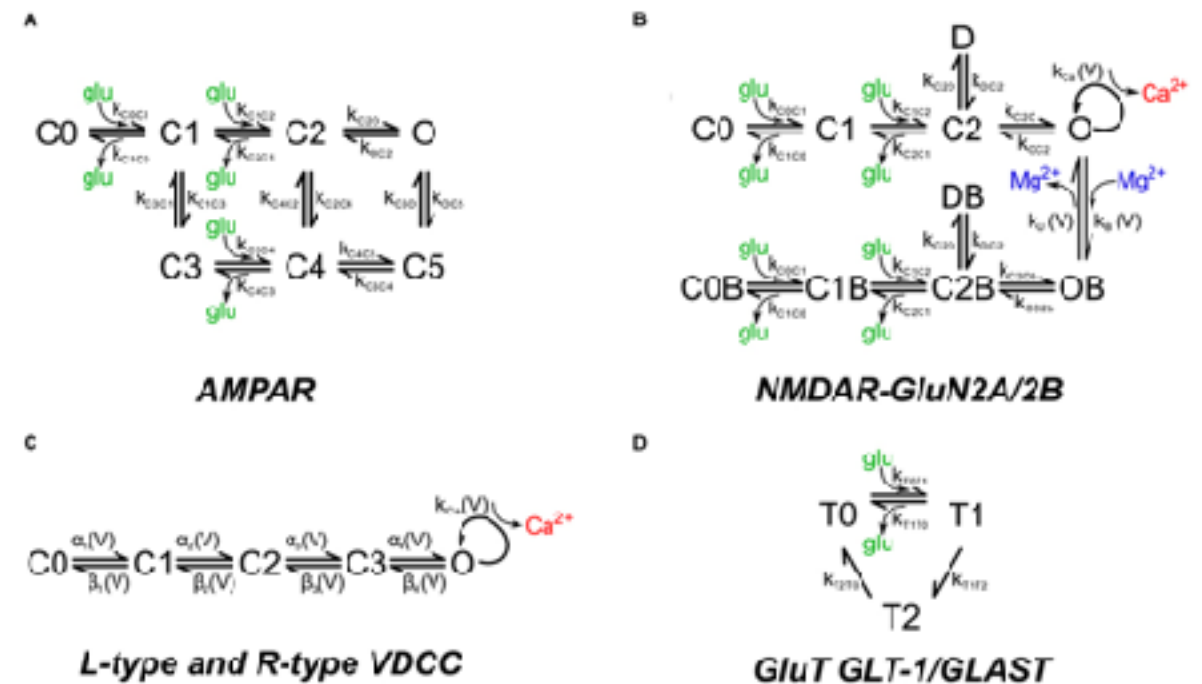
# Synapses are complex



# MCell simulation of synaptic release



Bartol et al, *Frontiers Syn Neuro* (2015)



Video courtesy of Tom Bartol (Salk Institute, California)

# How can we computationally model a synapse?

- We could simulate the dynamics of each molecule involved in the signalling process (like the MCell simulation).
- But since that is (very) computationally expensive, we might instead go for a reduced mass-action chemical-kinetics model.
- However a lot of people still find even that too expensive and parameter heavy, so instead use even simpler phenomenological models that black-box the synapse as a simple input-output system.



# Simple synapse models

The most common way to phenomenologically model a synapse is as a time-dependent conductor in series with a battery.

$$I_s(t) = \bar{g}_s s(t) (E_s - V)$$

The value of  $E_s$  determines whether the synapse is excitatory or inhibitory:

for excitatory synapses  $E_s$  usually = 0 mV

for inhibitory synapses  $E_s$  usually =  $V_{rest}$

But how should we model  $s(t)$ ?

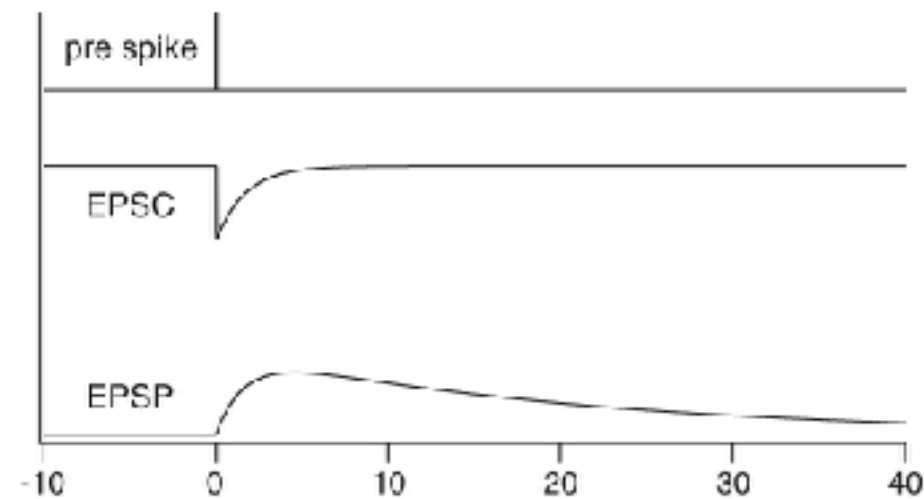


# Simple synapse models

## Single exponential

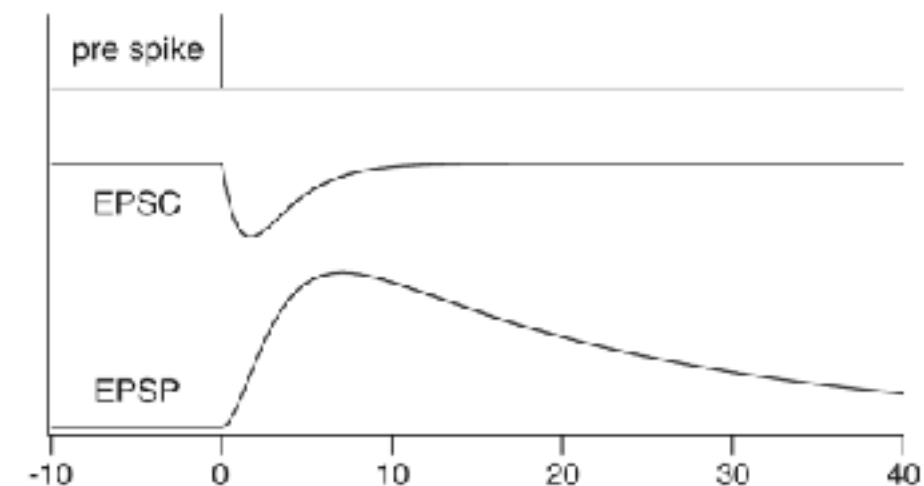
$$s(t) \rightarrow s(t) + 1$$

$$s(t) = e^{-t/\tau_s}$$



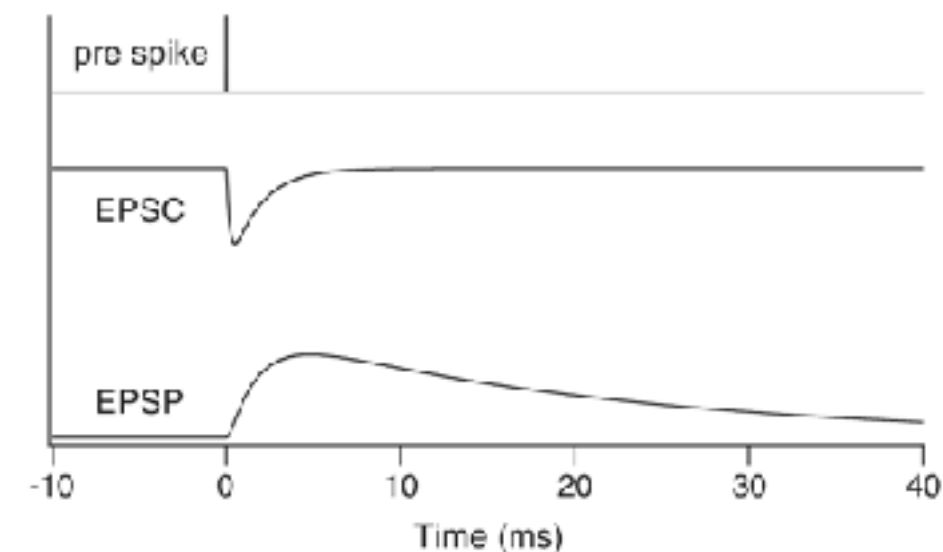
## Alpha function

$$s(t) = te^{-t/\tau_s}$$



## Difference of two exponentials

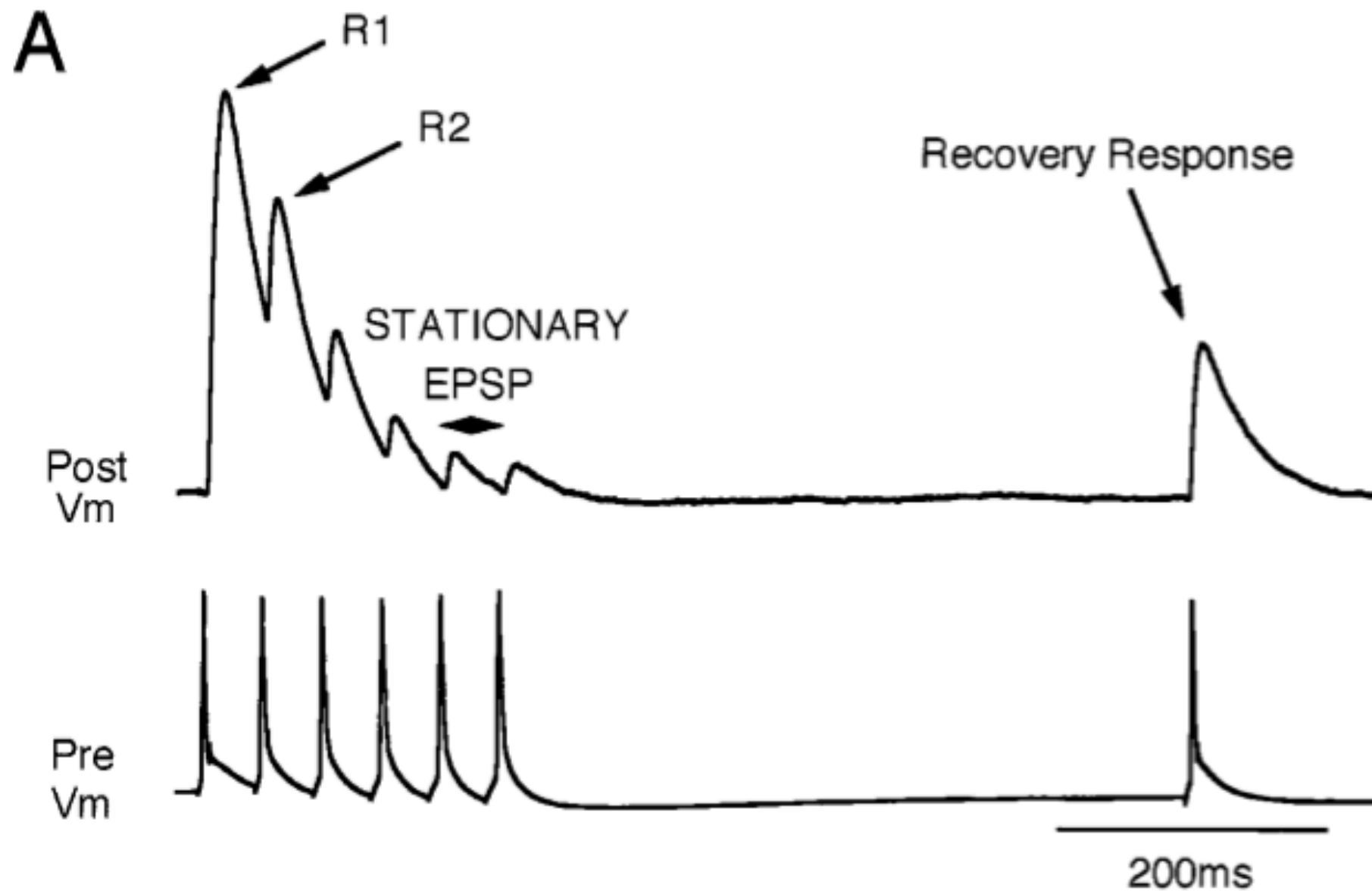
$$s(t) = e^{-t/\tau_{decay}} - e^{-t/\tau_{rise}}$$



# Plastic synapses

- The magnitude of a synapse's electrical response to an action potential can change depending on the activity history of the synapse (known as plasticity).
- These changes can be fast or slow, and short-lasting (ms—s) or long-lasting (hours—years).
- Short-term synaptic plasticity is thought to aid fast cognitive processing (much like the spikes themselves).
- Long-term synaptic plasticity, in contrast, is thought to mediate long-term memory (more on this next lecture).

# Dynamical synapses



Short-term synaptic depression due to a use-dependent decrease in release probability.

# Dynamical synapse models

- Think of the synaptic efficacy as being determined by the available amount of some resource.
- The resource has 3 states: Effective ( $E$ ), Inactive ( $I$ ) and Recovered ( $R$ ).

$$\frac{dR}{dt} = \frac{I}{\tau_{rec}}$$

$$\frac{dE}{dt} = -\frac{E}{\tau_{inact}} + U_{SE} \cdot R \cdot \delta(t - t_{AP})$$

$$I = 1 - R - E,$$

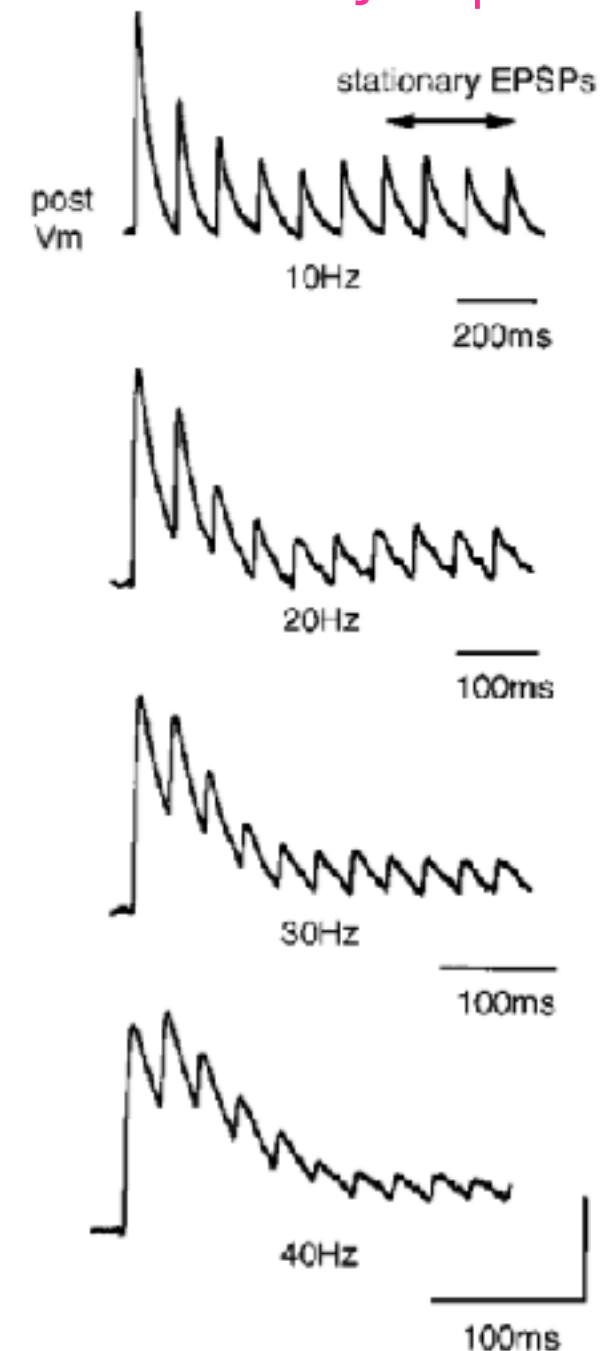
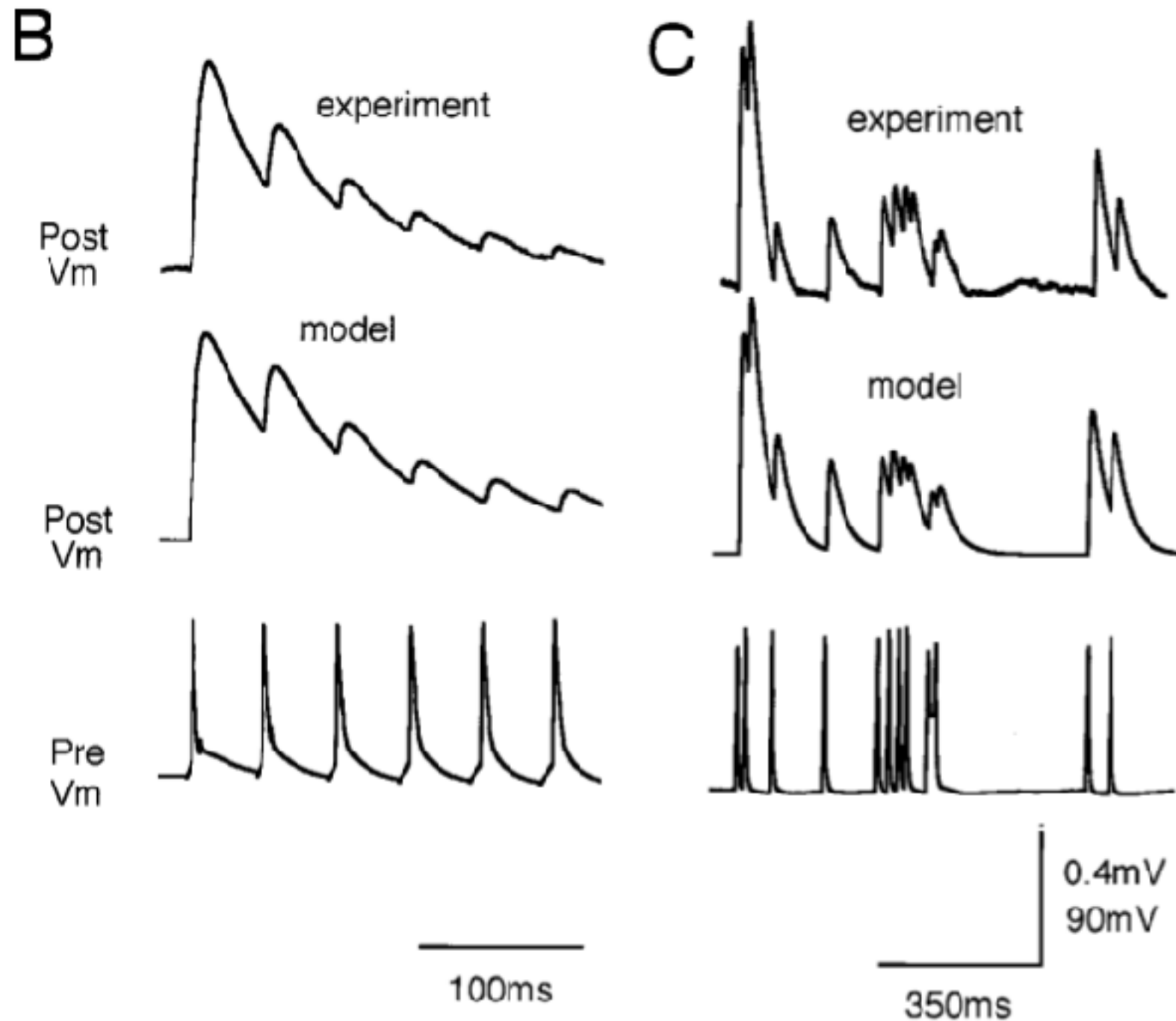
- $U_{SE}$  is a parameter that determines how much resources get depleted with each spike.

$$EPSC_{n+1} = EPSC_n(1 - U_{SE})e^{-\Delta t/\tau_{rec}} + A_{SE}U_{SE}(1 - e^{-\Delta t/\tau_{rec}}),$$

# Dynamical synapses

Model matches data

Faster stimulation =  
weaker synapses





# Summary

- Synapses are the connections between neurons.
- They convert the pre-synaptic action potential to a (excitatory or inhibitory) post-synaptic potential via a chemical intermediate stage.
- They are highly stochastic (noisy).
- They are also complicated molecular machines.
- We can model them at multiple levels of granularity, as appropriate for the task at hand.

End