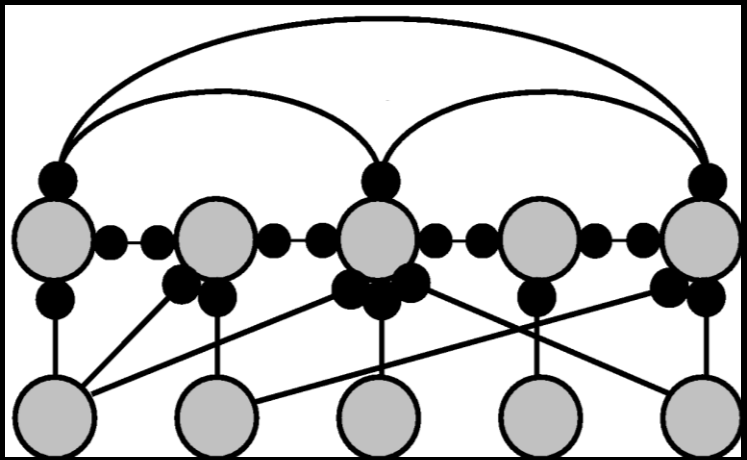
CSE/NB 528

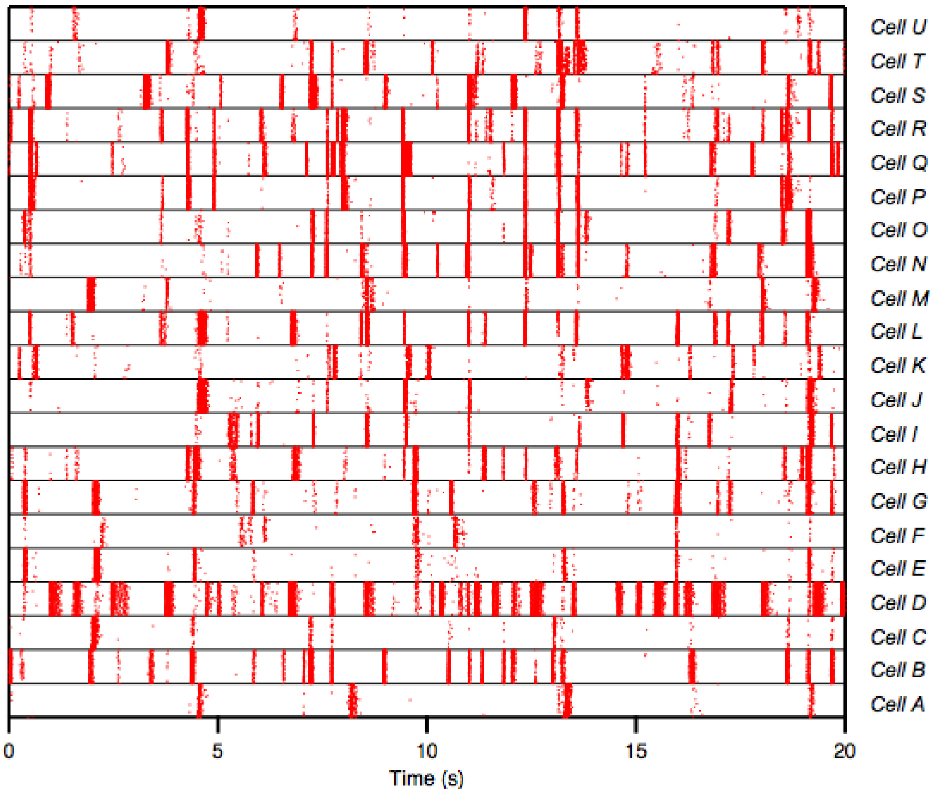
Final Lecture: All Good Things Must…



Course Summary

- **Where have we been?**
  - Course Highlights
- **Where do we go from here?**
  - Challenges and Open Problems
- **Further Reading**

What *is* the neural code?



What is the nature of the code?

Representing the spiking output:

single cells vs populations

rates vs spike times vs intervals

What features of the stimulus does the neural system represent?

Encoding and decoding neural information

Encoding: building functional models of neurons/neural systems and predicting the spiking output given the stimulus

Decoding: what can we say about the stimulus given what we observe from the neuron or neural population?

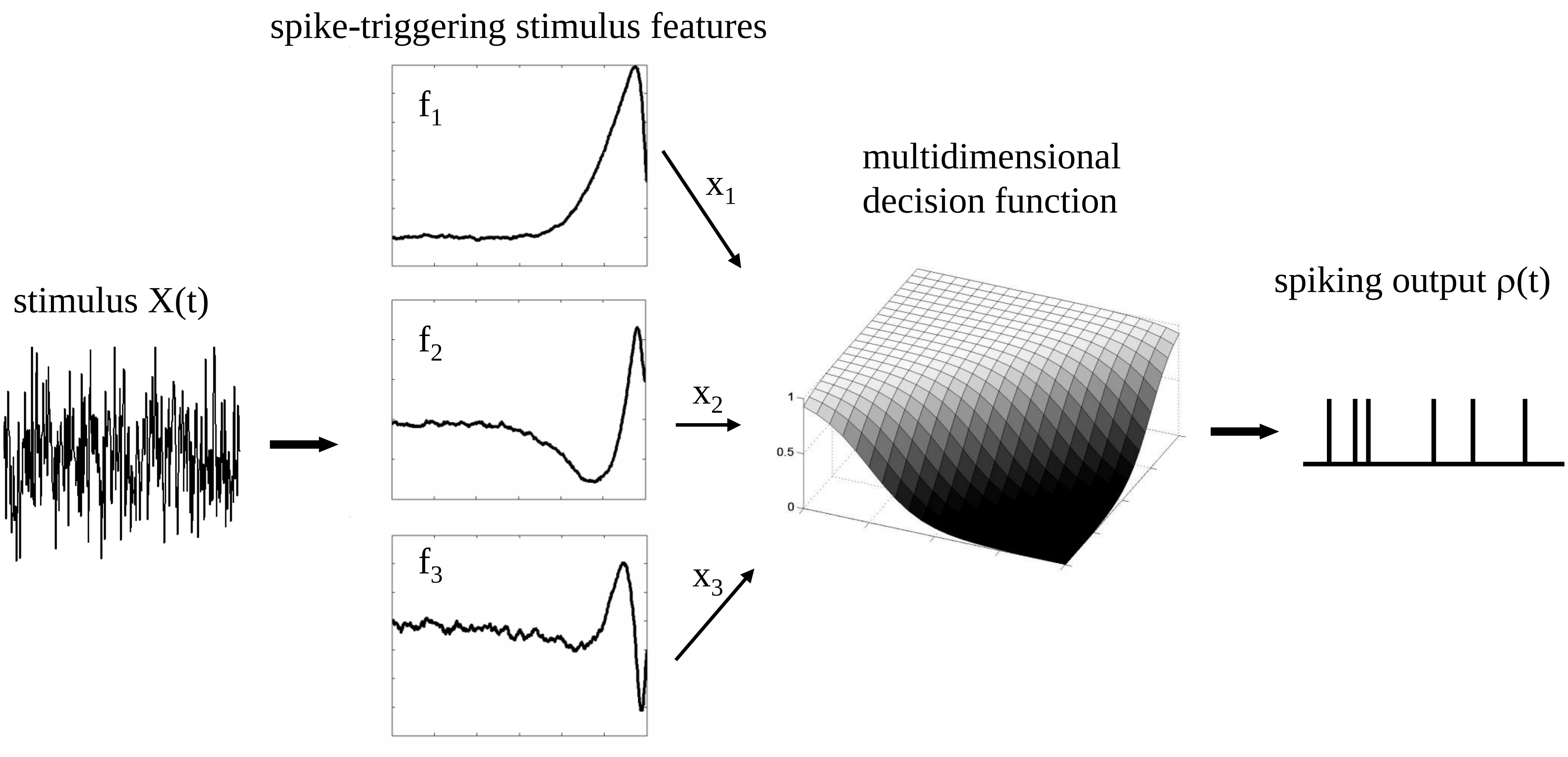
Key concepts: Poisson & Gaussian

Spike trains are variable

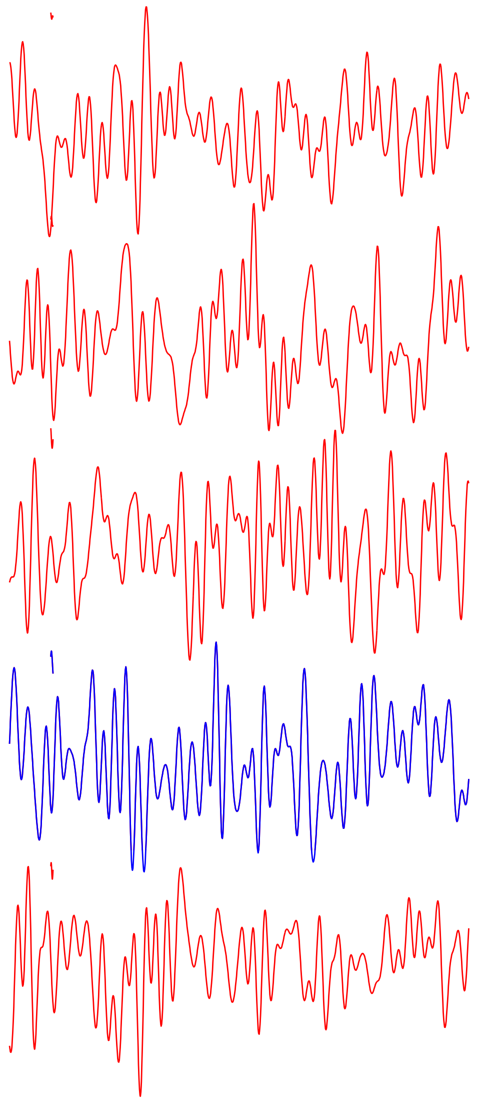
Models are probabilistic

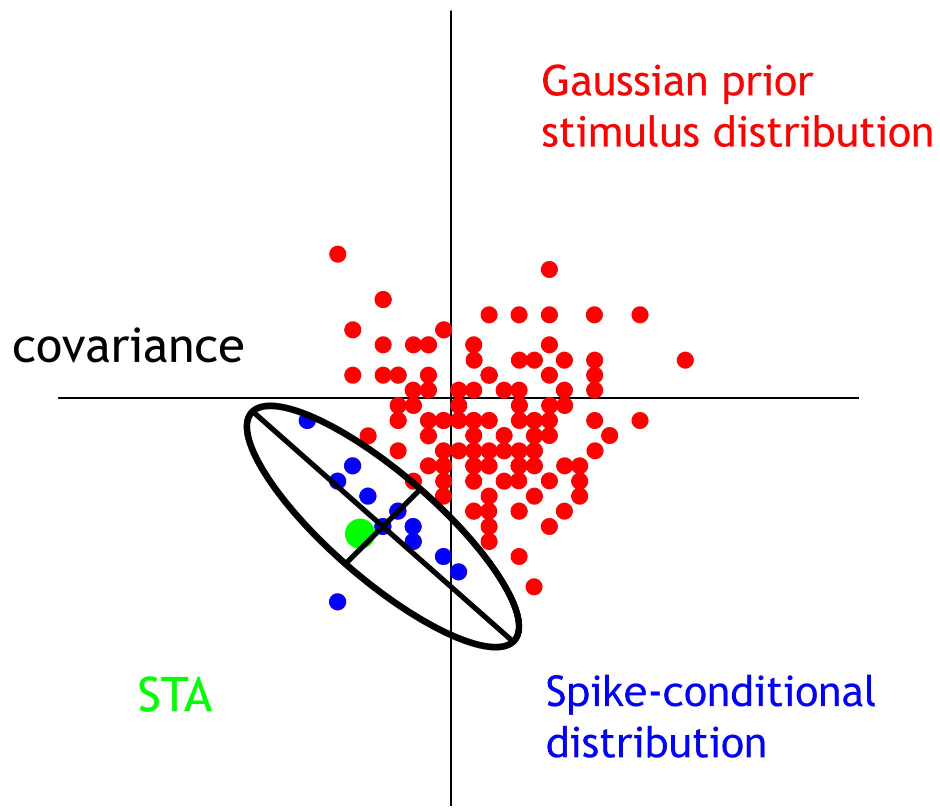
Deviations are close to independent

Highlights: Neural Encoding

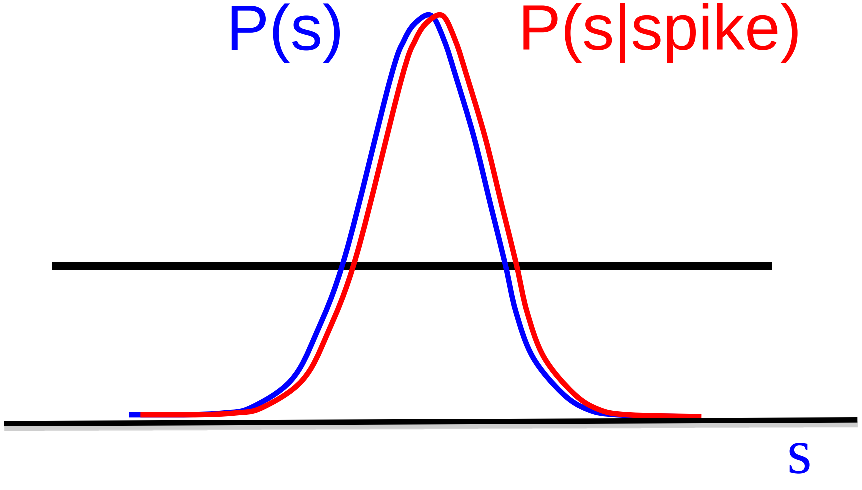


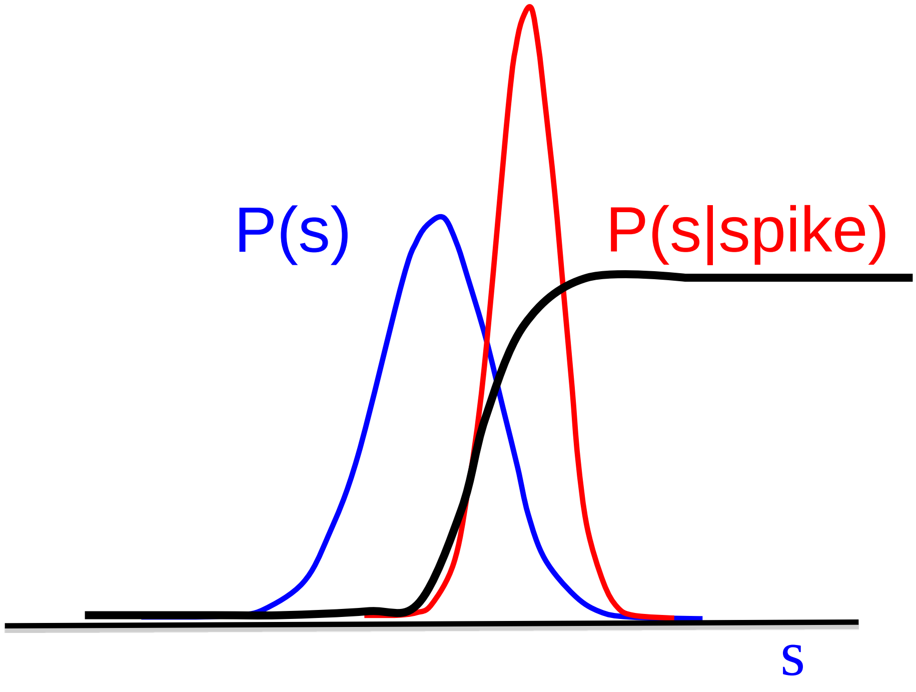
Highlights: Finding the feature space of a neural system



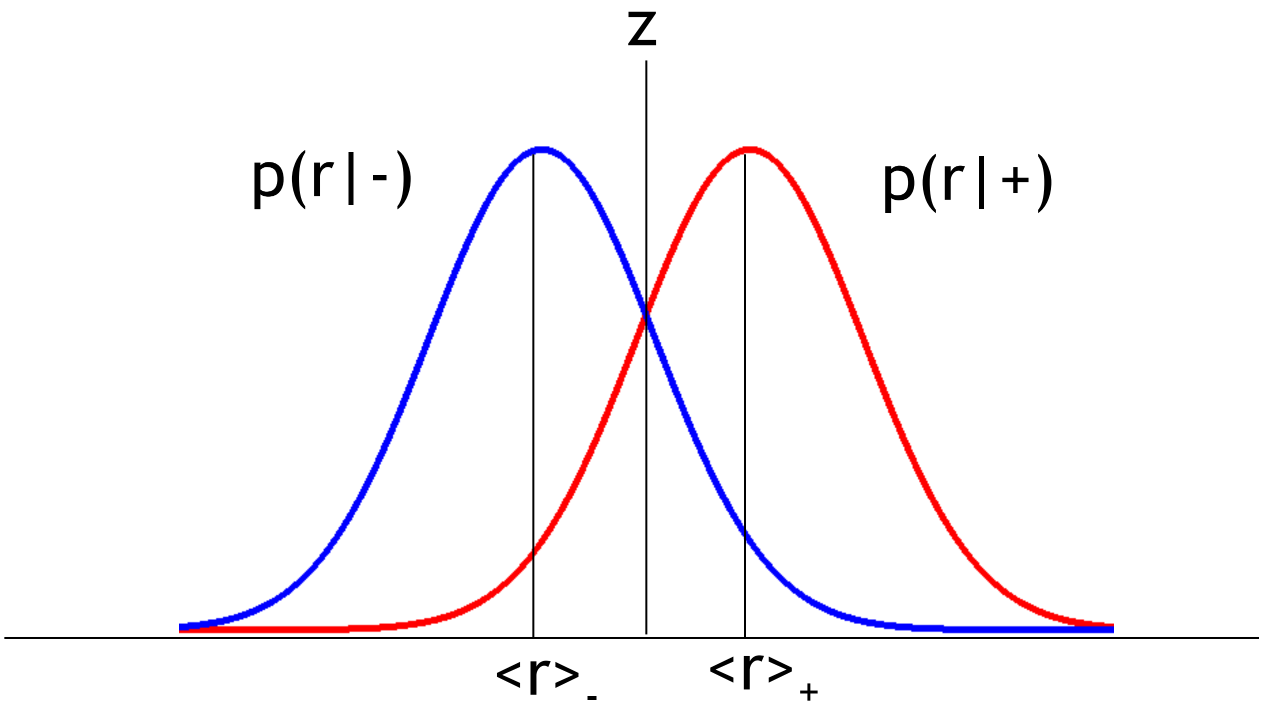


Highlights: Finding an interesting tuning curve





Decoding: Signal detection theory

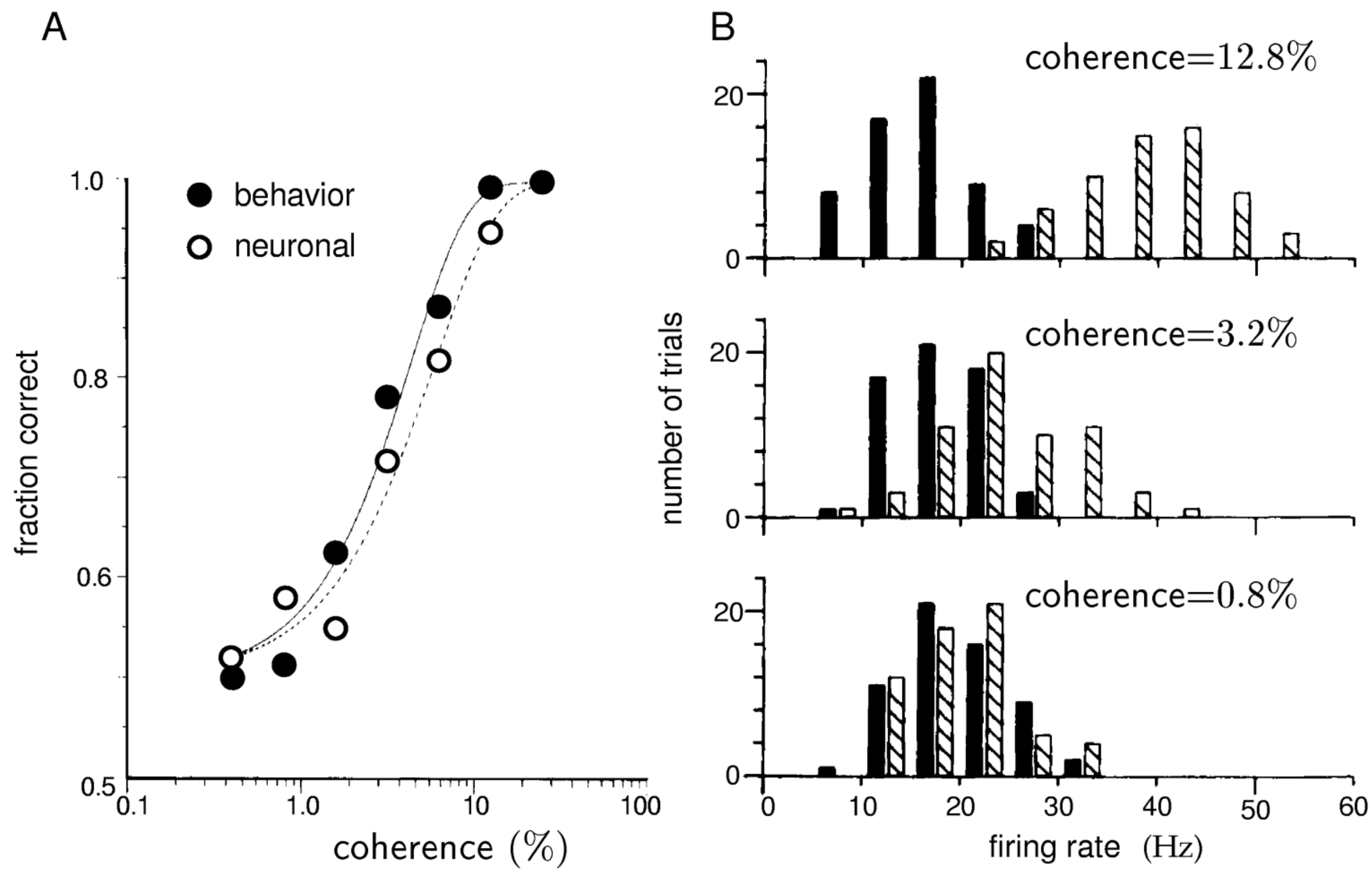


Decoding corresponds to comparing test to threshold.

$\alpha(z) = P[\ r \geq z|-]$ false alarm rate, "size"

$\beta(z) = P[\ r \geq z|+]$ hit rate, "power"

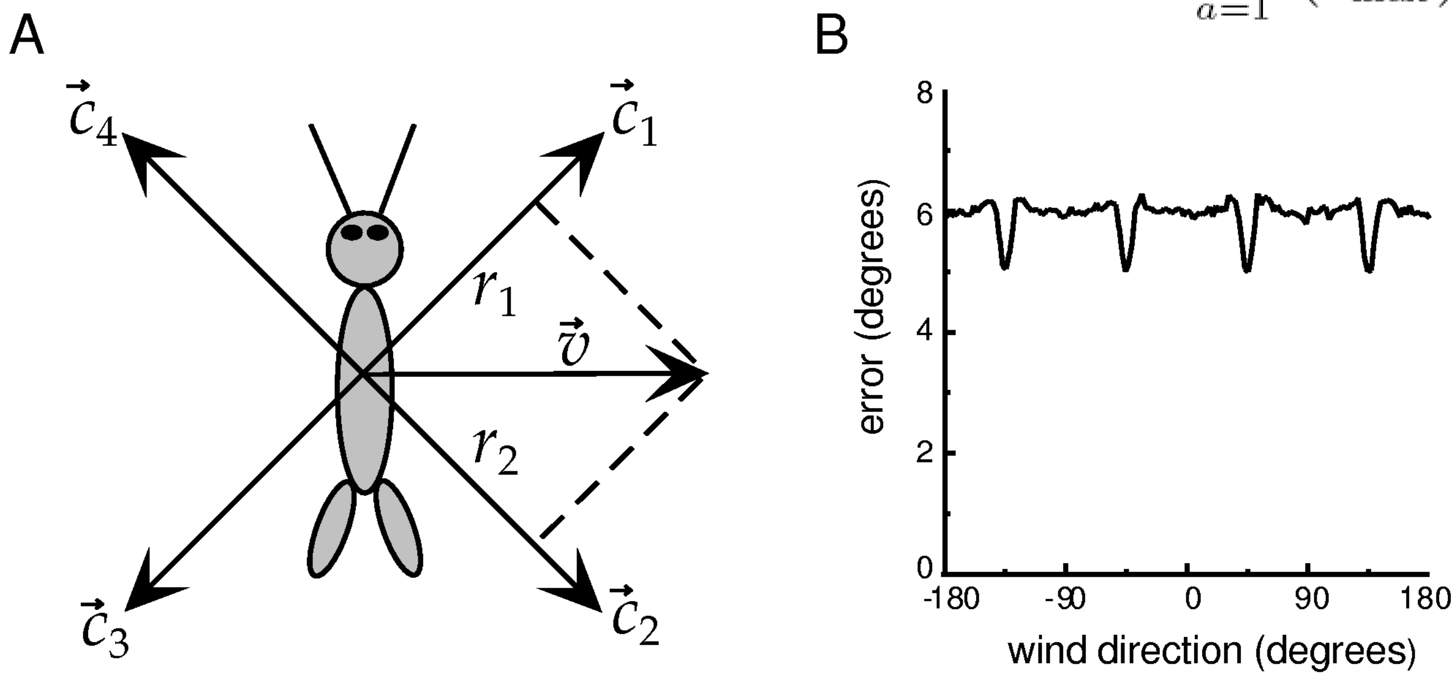
Highlights: Neurometric curves



Decoding from a population

e.g. cosine tuning curves

$$\vec{v}_{\text{pop}} = \sum_{a=1}^{4} \left(\frac{r}{r_{\max}}\right)_a \vec{c}_a$$



RMS error in estimate

Theunissen & Miller, 1991

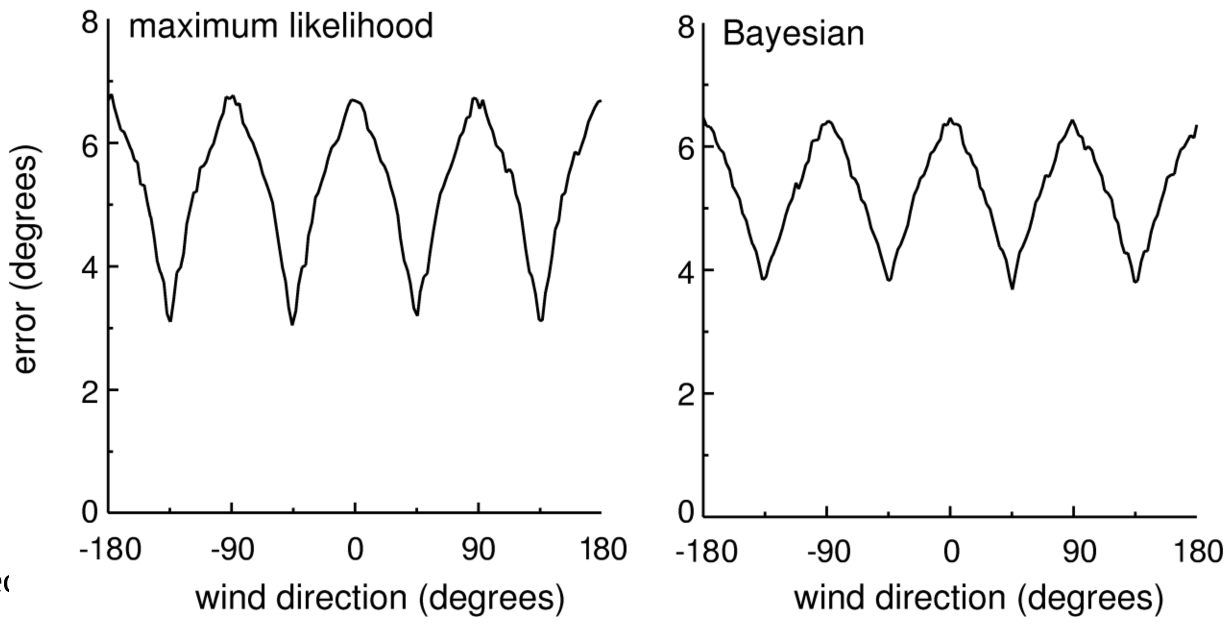
More general approaches: MAP and ML

MAP: s* which maximizes p[s|r]

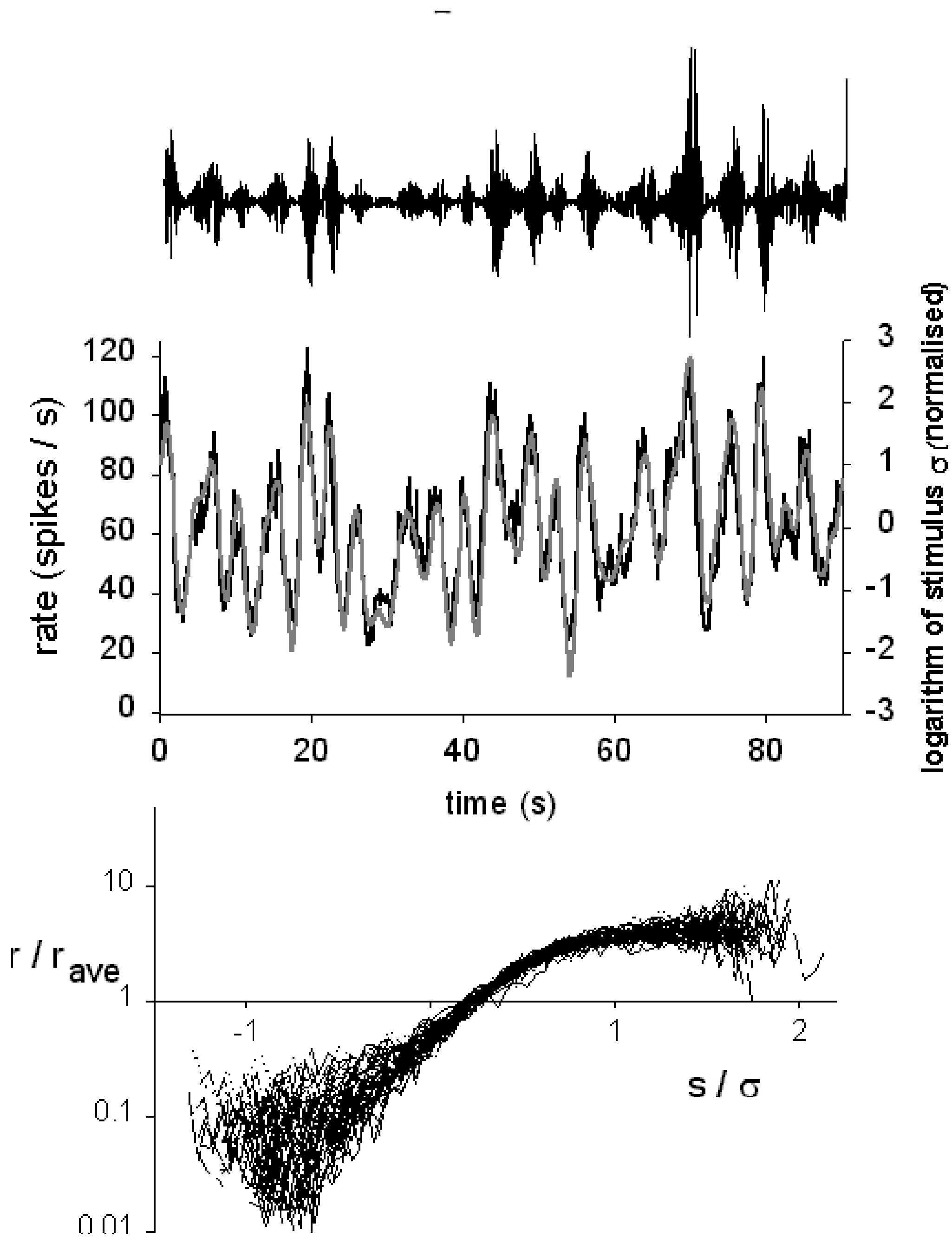
ML: s* which maximizes p[r|s]

Difference is the role of the prior: differ by factor p[s]/p[r]

For cercal data:



Highlights:
Information maximization
as a design principle of the nervous system

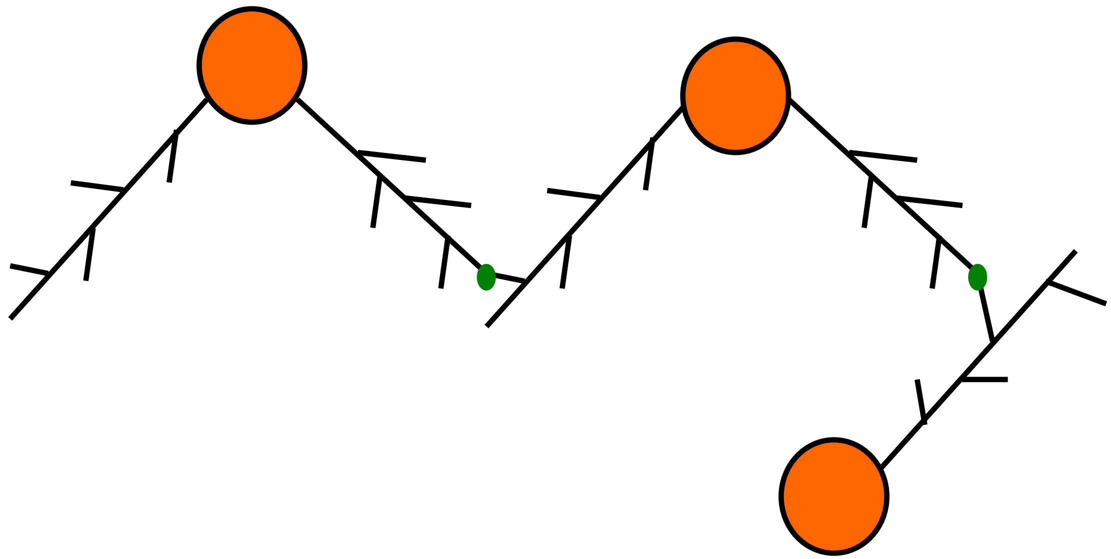


Encoding and decoding neural information

Encoding: building functional models of neurons/neural systems and predicting the spiking output given the stimulus

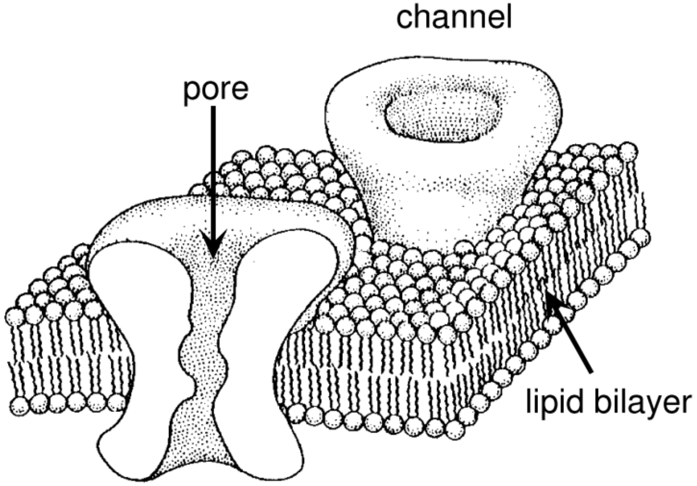
Decoding: what can we say about the stimulus given what we observe from the neuron or neural population?

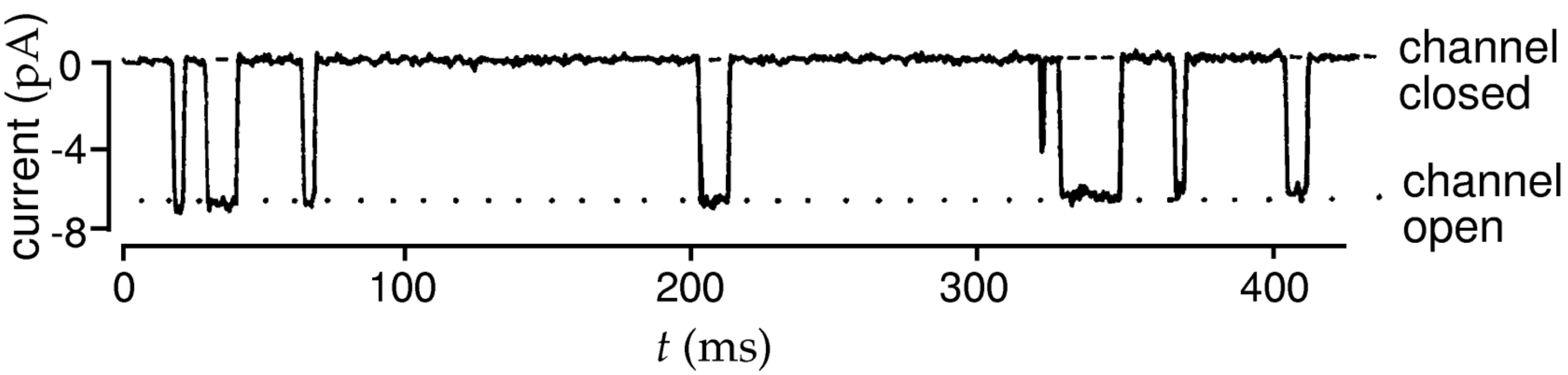
The biophysical basis of neural computation



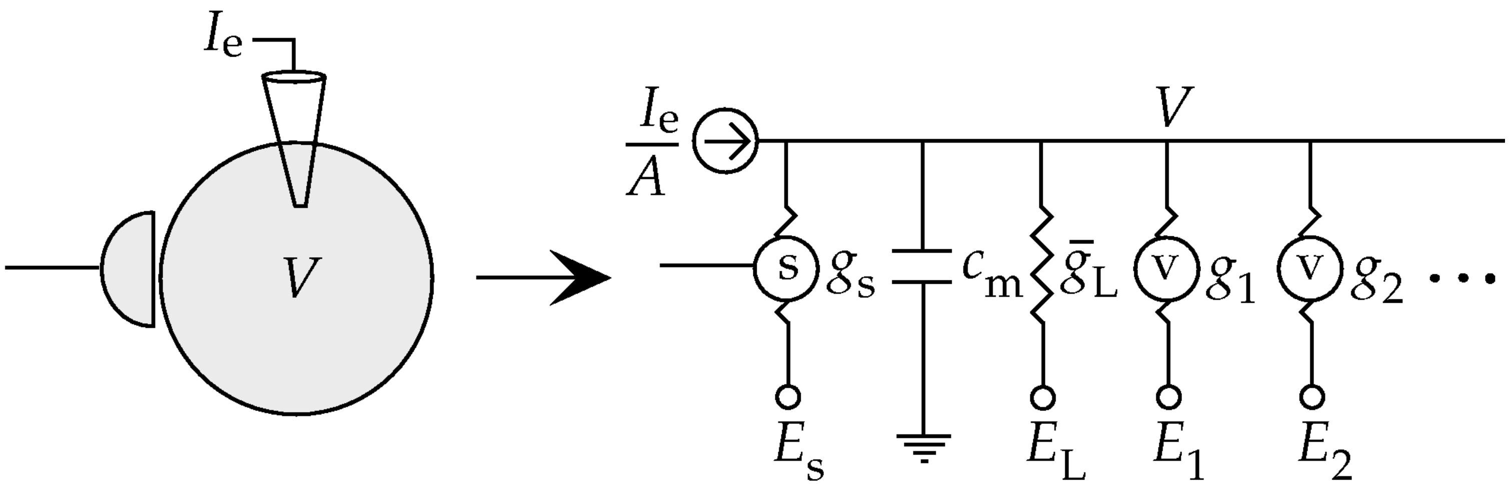
Excitability is due to the properties of ion channels

- Voltage dependent
- transmitter dependent (synaptic)
- Ca dependent





Highlights: The neural equivalent circuit



Ohm's law: $V = IR$ and Kirchhoff's law

$$\boxed{-C_m \frac{dV}{dt}} = \boxed{\sum_i g_i(V - E_i)} + \boxed{I_e}$$

Capacitive current

Ionic currents

Externally applied current

Simplified neural models

A sequence of neural models of increasing complexity that approach the behavior of real neurons

Integrate and fire neuron:

subthreshold, like a passive membrane
spiking is due to an imposed threshold at V_T

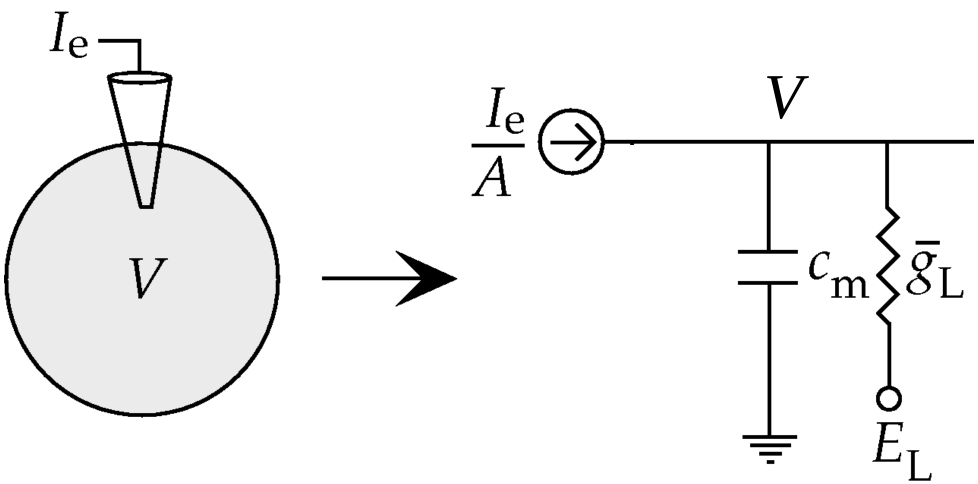
Spike response model:

subthreshold, arbitrary kernel
spiking is due to an imposed threshold at V_T
postspike, incorporates afterhyperpolarization

Simple model:

complete 2D dynamical system
spiking threshold is intrinsic
have to include a reset potential

Simplified models: integrate-and-fire

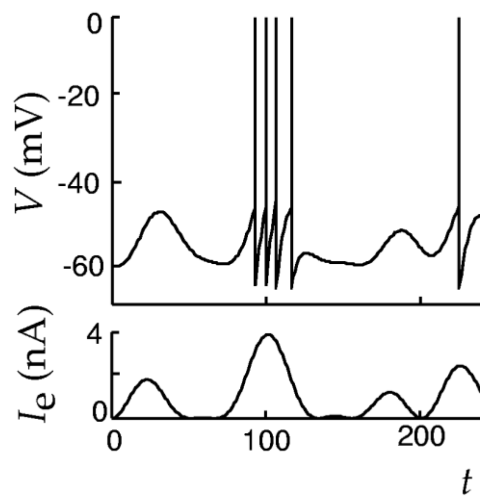


Integrate-and-Fire Model

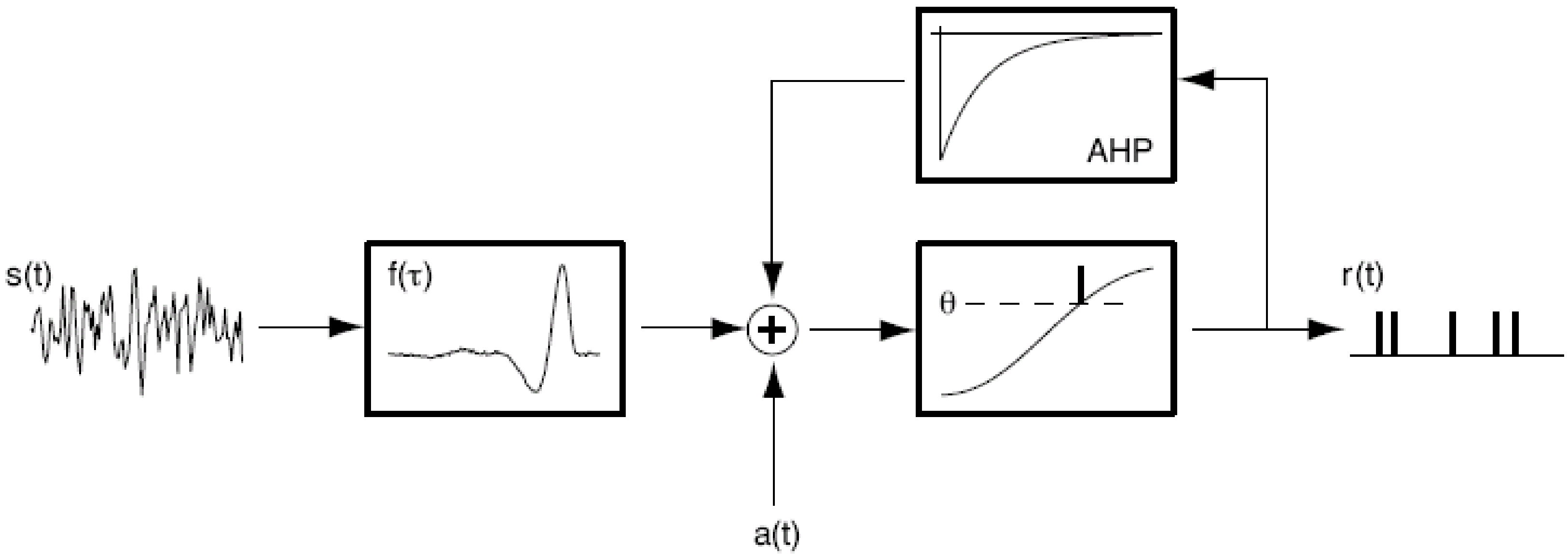
$$\tau_m \frac{dV}{dt} = -(V - E_L) + I_e R_m$$

If V > $V_{threshold}$ → Spike

Then reset: V = V_{reset}

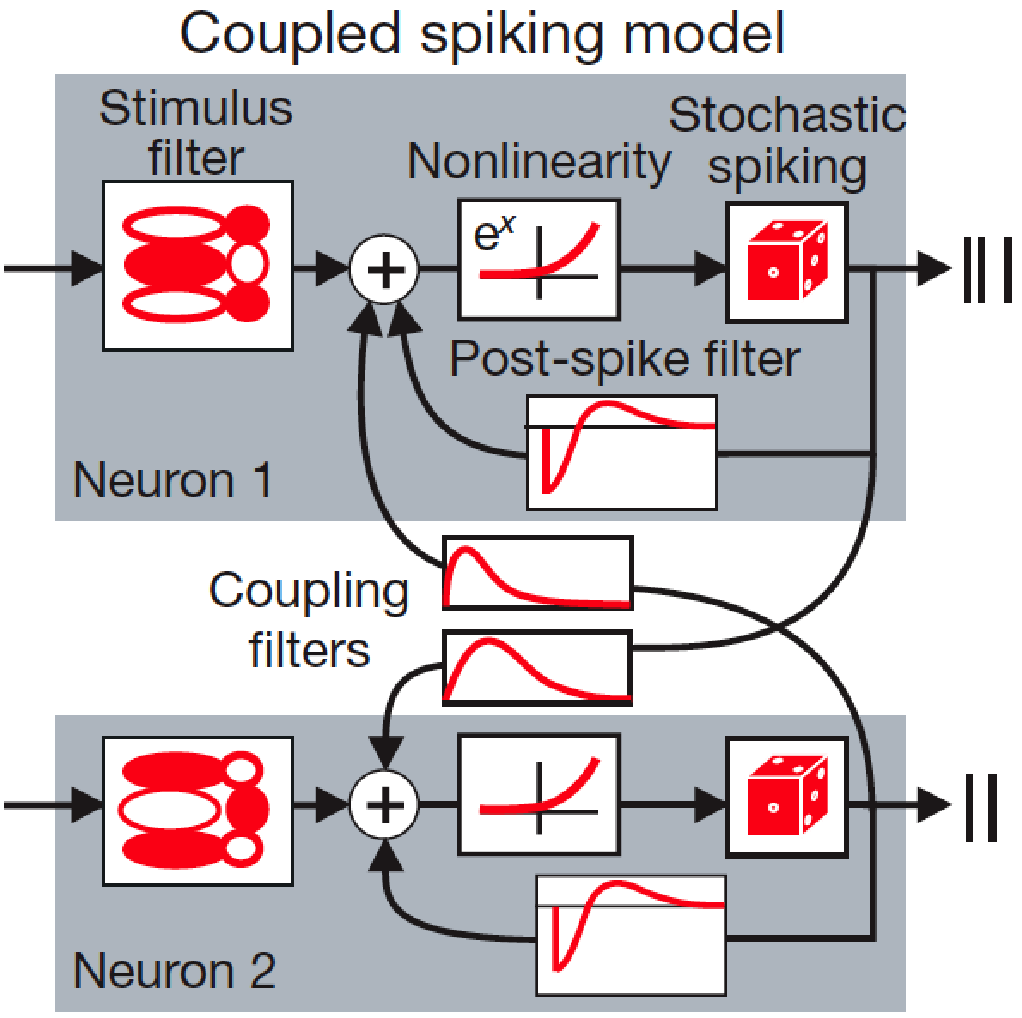


Simplified models: spike response model

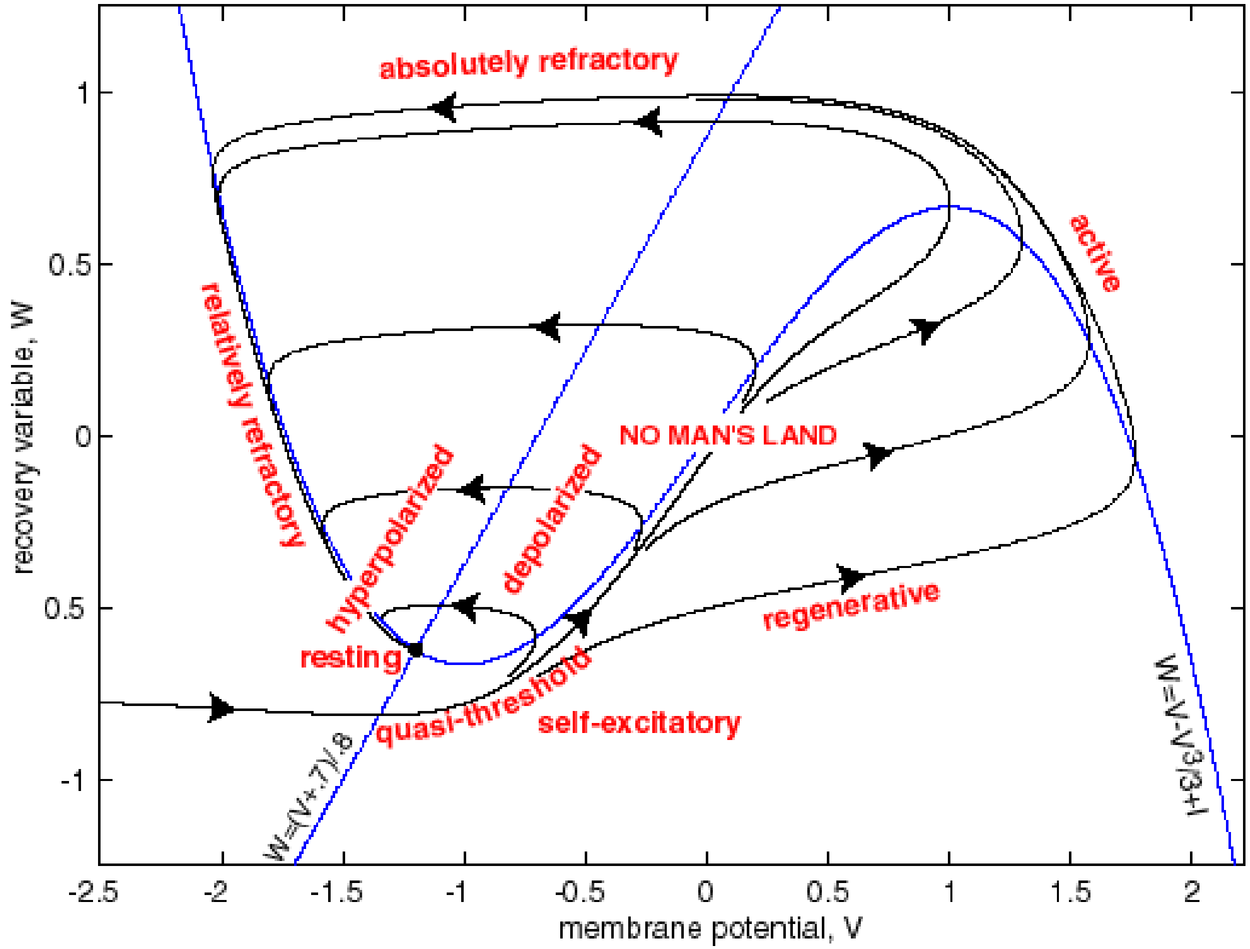


Gerstner; Keat et al. 2001

Simplified models: spike response model

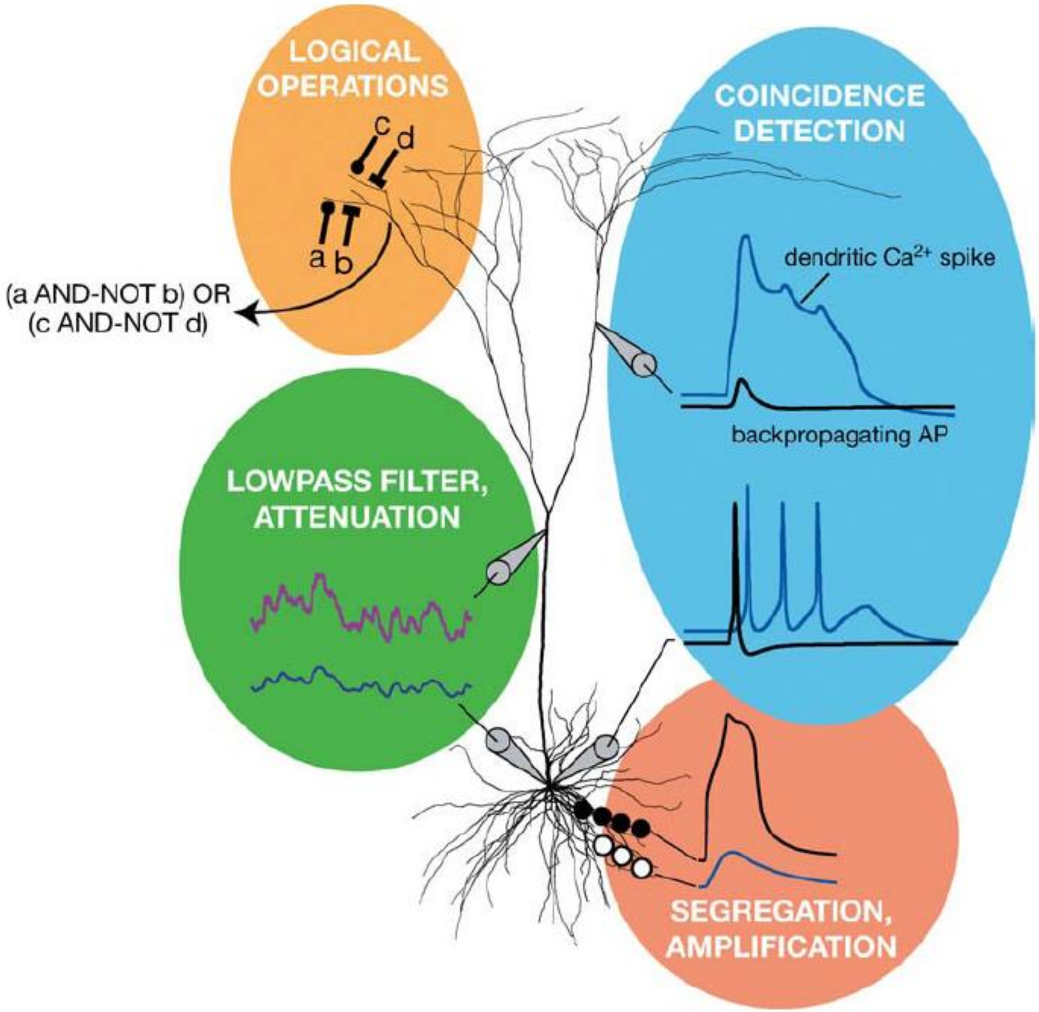


Simplified models: dynamical models



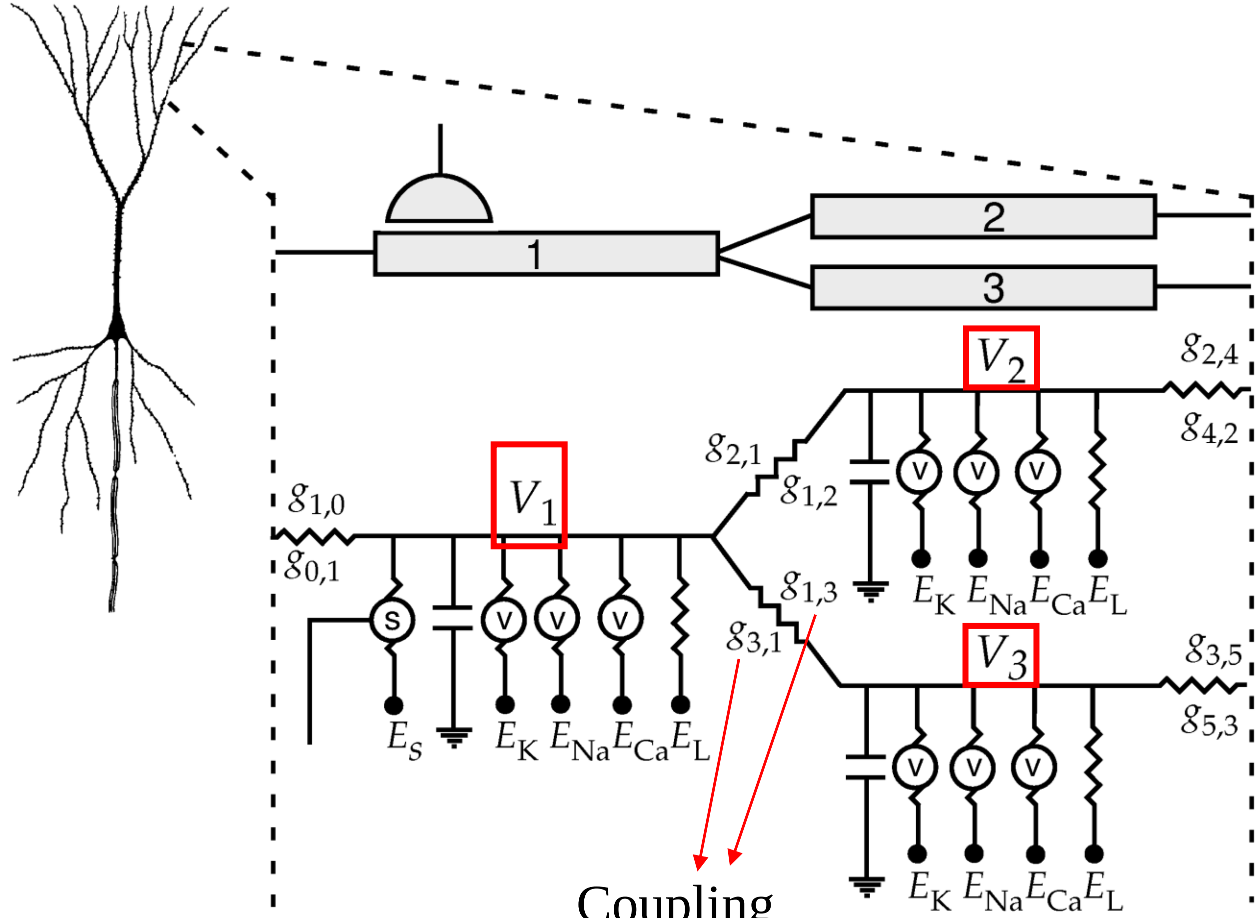
Highlights: Dendritic computation

Filtering
Shunting
Delay lines
Information segregation
Synaptic scaling
Direction selectivity



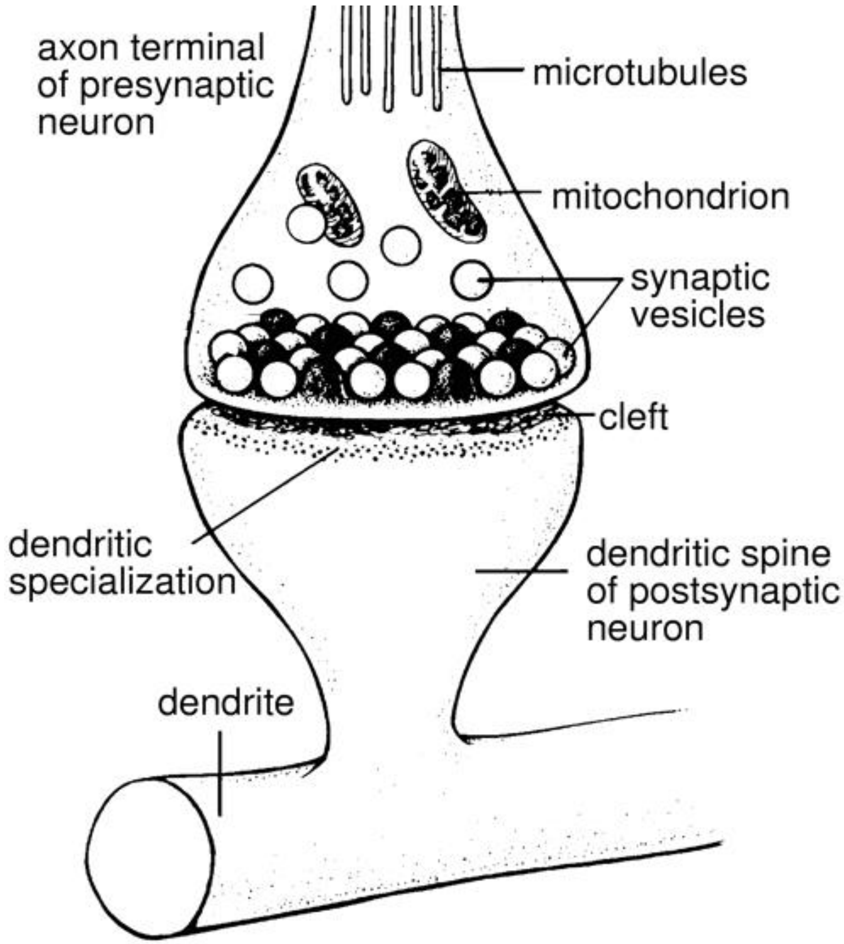
Highlights: Compartmental models

Neuronal structure can be modeled using electrically coupled compartments



Coupling conductances

Connecting neurons: Synapses

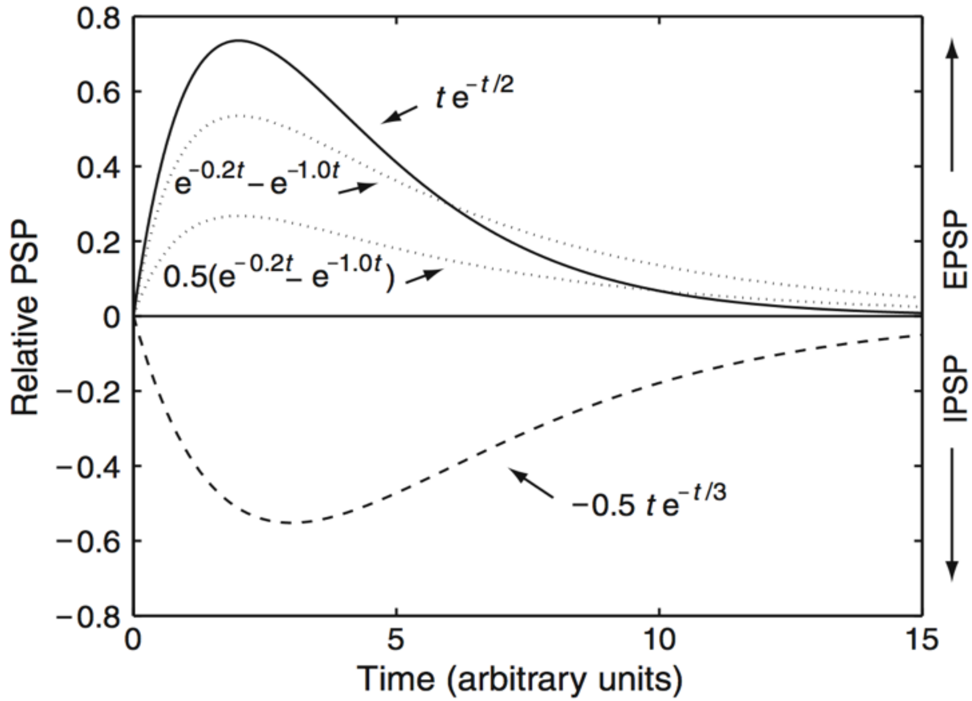


Presynaptic voltage spikes cause neurotransmitter to cross the cleft, triggering postsynaptic receptors allowing ions to flow in, changing postsynaptic potential

Glutamate: excitatory

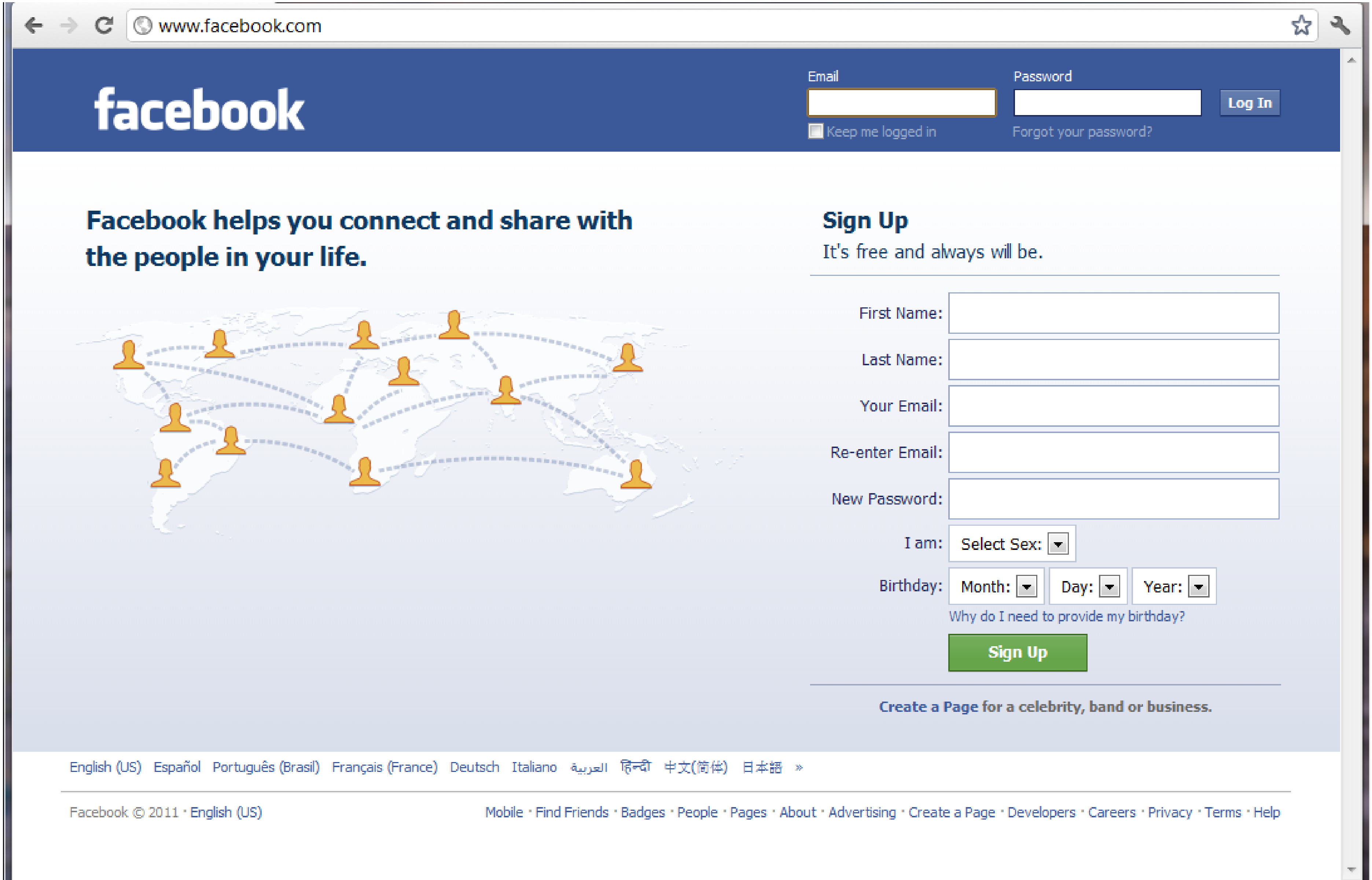
$GABA_A$: inhibitory

Synaptic voltage changes



Size of the PSP is a measure of synaptic strength.
Can vary on the short term due to input history
on the long term due to synaptic plasticity
.. one way to build circuits that learn

Networks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Email
Password
Log In
Keep me logged in
Forgot your password?
Facebook helps you connect and share with the people in your life.
Sign Up
It's free and always will be.
First Name:
Last Name:
Your Email:
Re-enter Email:
New Password:
I am:
Select Sex:
Birthday:
Month:
Day:
Year:
Why do I need to provide my birthday?
Sign Up
Create a Page for a celebrity, band or business.
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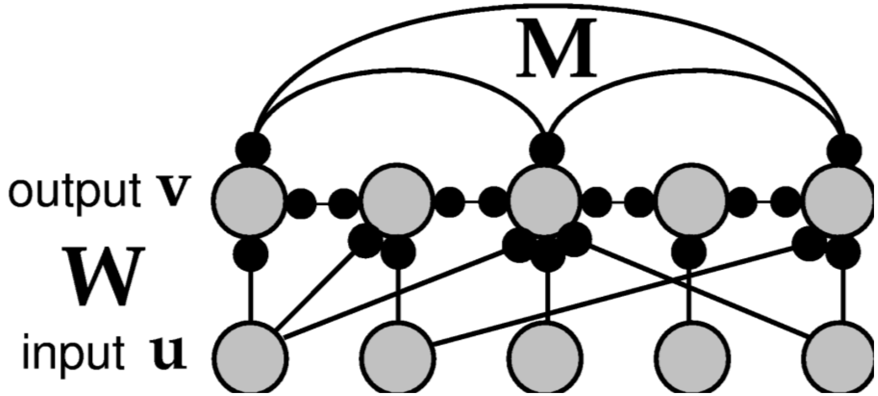
Modeling Networks of Neurons

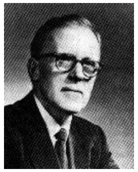


$$\tau \frac{d\mathbf{v}}{dt} = -\mathbf{v} + F(\mathrm{W}\mathbf{u} + \mathrm{M}\mathbf{v})$$

Output Decay Input Feedback

Highlights: Unsupervised Learning

- For linear neuron: $v = \mathbf{w}^T \mathbf{u} = \mathbf{u}^T \mathbf{w}$
- Basic Hebb Rule: $\tau_w \frac{d\mathbf{w}}{dt} = \mathbf{u}v$



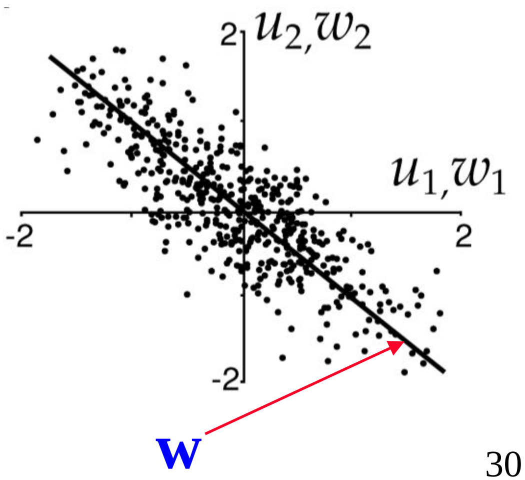
- Average effect over many inputs:

$$\tau_w \frac{d\mathbf{w}}{dt} = \langle \mathbf{u}v \rangle = Q\mathbf{w}$$

- Q is the input correlation matrix:

$$Q = \langle \mathbf{u}\mathbf{u}^T \rangle$$

Hebb rule performs principal component analysis (PCA)



Highlights: The Connection to Statistics

Unsupervised learning = learning the *hidden causes* of input data

Causes **v** $p[\mathbf{v} \mid \mathbf{u}; G]$

(posterior)

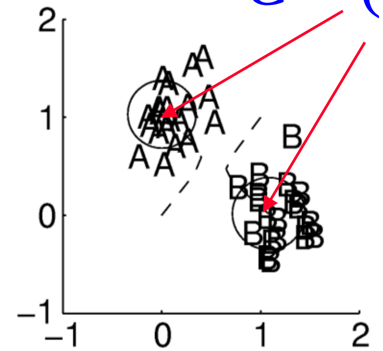
Generative model

Recognition model

Data **u** $p[\mathbf{u} \mid \mathbf{v}; G]$

(data likelihood)

$G = (\boldsymbol{\mu}_{v}, \boldsymbol{\sigma}_{v})$

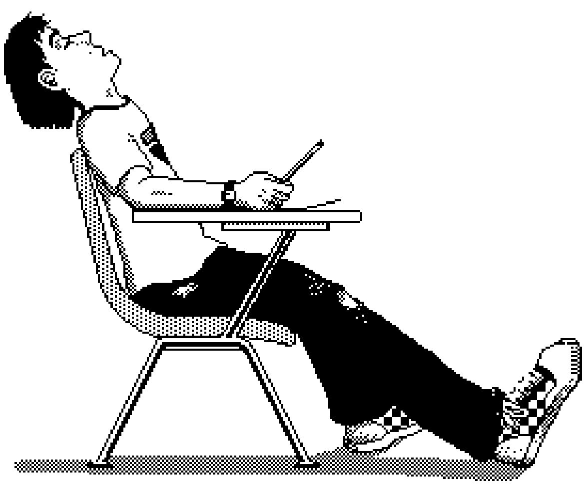


Causes of clustered data

Use EM algorithm for learning

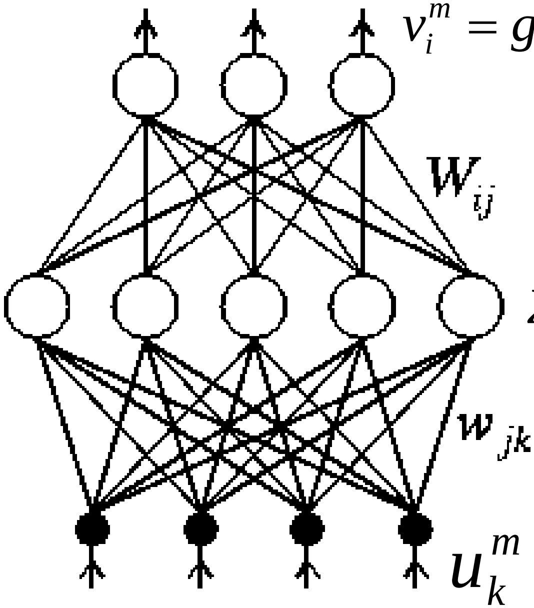
Highlights: Generative Models

Droning lecture   Lack of sleep   Mathematical derivations



Highlights: Supervised Learning

Backpropagation for Multilayered Networks



$$v_i^m = g(\sum_j W_{ij} g(\sum_k w_{jk} u_k^m))$$

Goal: Find **W** and **w** that minimize errors:

$$E(W_{ij}, w_{jk}) = \frac{1}{2}\sum_{m,i}(d_i^m - v_i^m)^2$$

Desired output

Gradient descent learning rules:

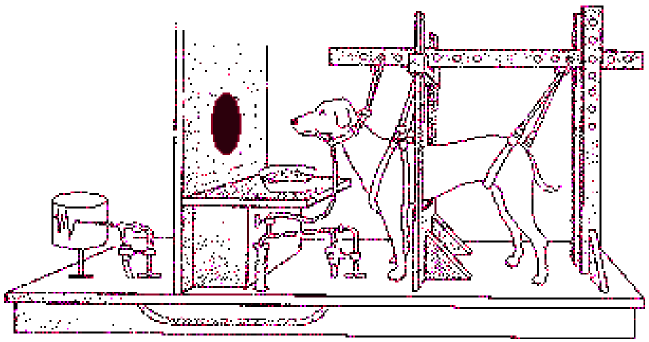
$$W_{ij} \rightarrow W_{ij} - \varepsilon \frac{\partial E}{\partial W_{ij}}$$ (Delta rule)

$$w_{jk} \rightarrow w_{jk} - \varepsilon \frac{\partial E}{\partial w_{jk}} = w_{jk} - \varepsilon \frac{\partial E}{\partial x_j^m} \cdot \frac{\partial x_j^m}{\partial w_{jk}}$$ (Chain rule)

Highlights: Reinforcement Learning

- Learning to predict rewards:

$$w \rightarrow w + \varepsilon(r - v)u$$

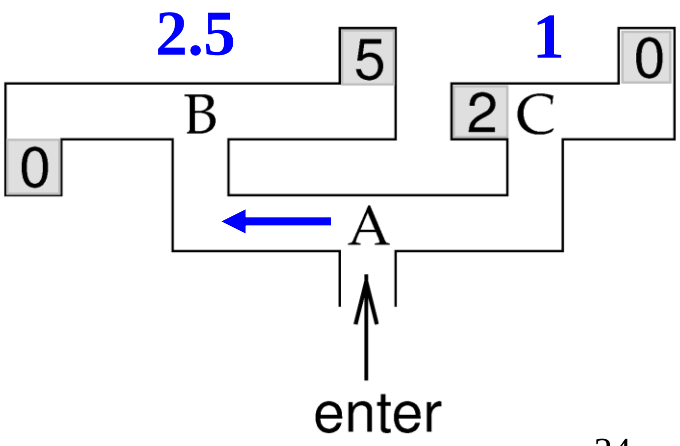


(http://employees.csbsju.edu/tcreed/pb/pdoganim.html)

- Learning to predict **delayed rewards** (TD learning):

$$w(\tau) \rightarrow w(\tau) + \varepsilon[r(t) + v(t+1) - v(t)]u(t-\tau)$$

- Actor-Critic Learning:
  - Critic learns value of each state using TD learning
  - Actor learns best actions based on value of next state (using the TD error)



The Future: Challenges and Open Problems

- How do neurons encode information?
  - **Topics**: Synchrony, Spike-timing based learning, Dynamic synapses
- Does a neuron's structure confer computational advantages?
  - **Topics**: Role of channel dynamics, dendrites, plasticity in channels and their density
- How do networks implement computational principles such as efficient coding and Bayesian inference?
- How do networks learn "optimal" representations of their environment and engage in purposeful behavior?
  - **Topics**: Unsupervised/reinforcement/imitation learning

Further Reading (for the summer and beyond)

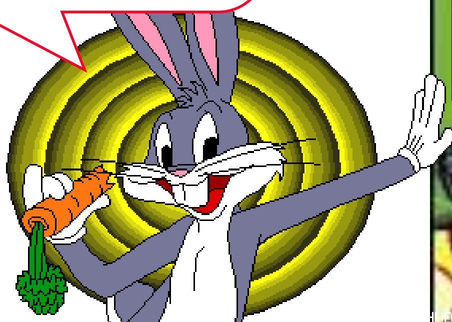
- *Spikes: Exploring the Neural Code,* F. Rieke et al., MIT Press, 1997
- *The Biophysics of Computation,* C. Koch, Oxford University Press, 1999
- *Large-Scale Neuronal Theories of the Brain*, C. Koch and J. L. Davis, MIT Press, 1994
- *Probabilistic Models of the Brain*, R. Rao et al., MIT Press, 2002
- *Bayesian Brain*, K. Doya et al., MIT Press, 2007
- *Reinforcement Learning: An Introduction*, R. Sutton and A. Barto, MIT Press, 1998

Next meeting: Project presentations!

- Project presentations will be on **Thursday, June 9 (10:30am-12:20pm) in the same classroom**
- Keep your presentation short: **~6-8 slides, 8 mins/group**
- Slides:
  - Bring your slides on a USB stick to use the class laptop (Apple)

  OR
  - Bring your own laptop if you have videos etc.
- Projects reports (10-15 pages total) due **June 9** (by email to both Adrienne and Raj before midnight)

Have a great summer!



Au revoir!