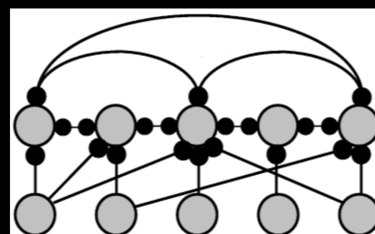
CSE/NB 528

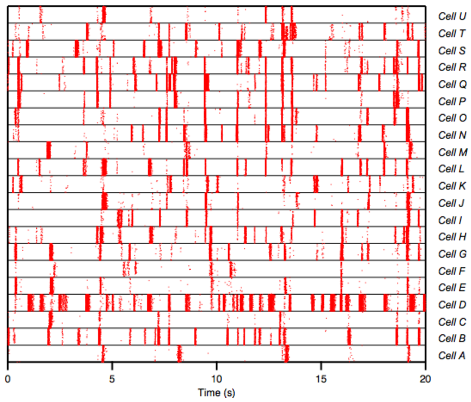
Final Lecture: All Good Things Must…



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

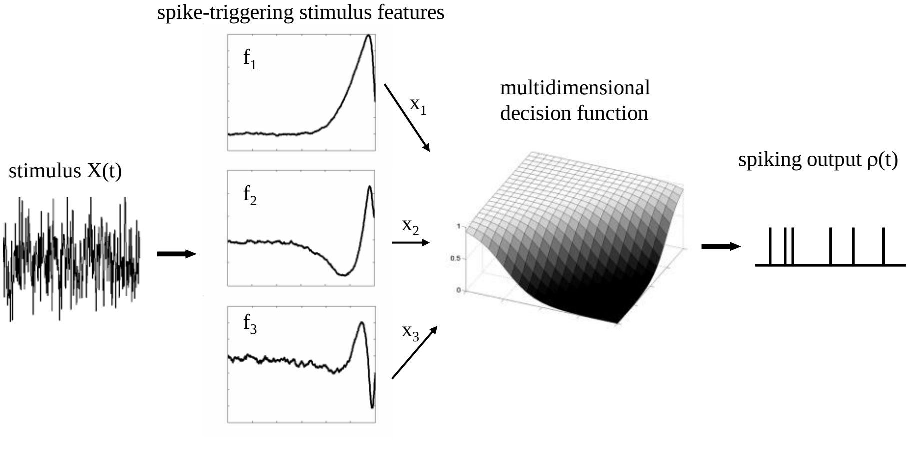
Spike trains are variable

Models are probabilistic

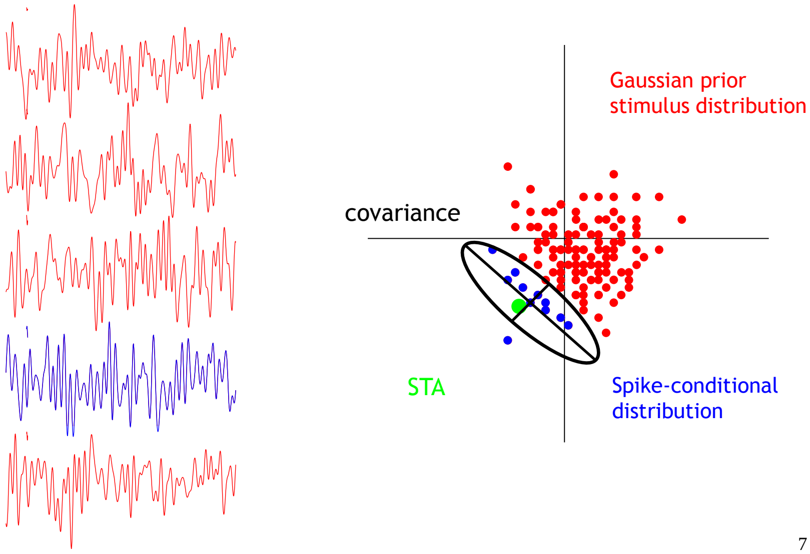
Deviations are close to independent



## Highlights: Neural Encoding

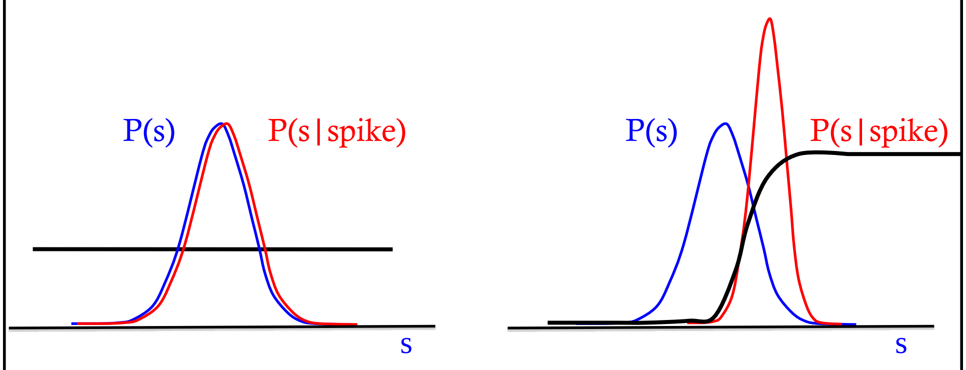


## Highlights: Finding the feature space of a neural system

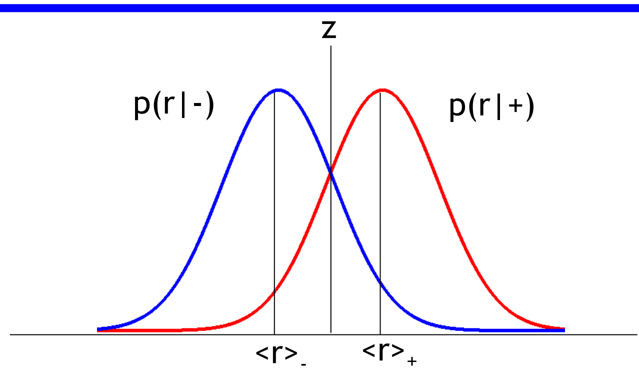





## Highlights: Finding an interesting tuning curve



## Decoding: Signal detection theory



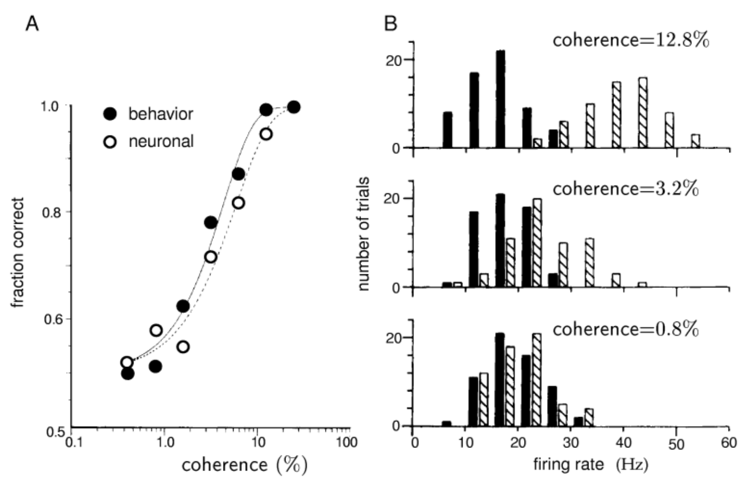

Decoding corresponds to comparing test to threshold.

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

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



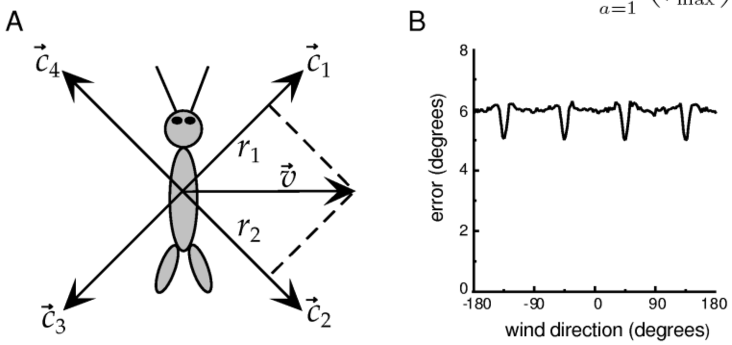
## Highlights: Neurometric curves



## 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



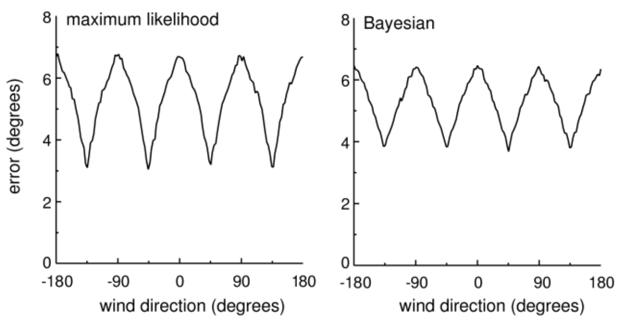
## More general approaches: MAP and ML

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

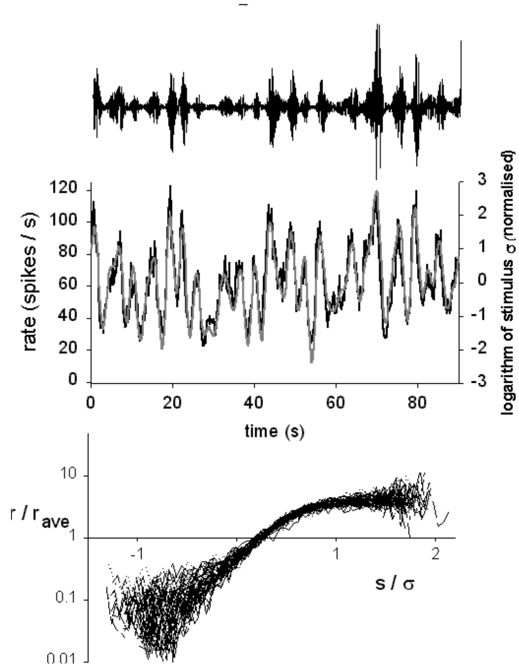
ML: s* which maximizes p[r|s]

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

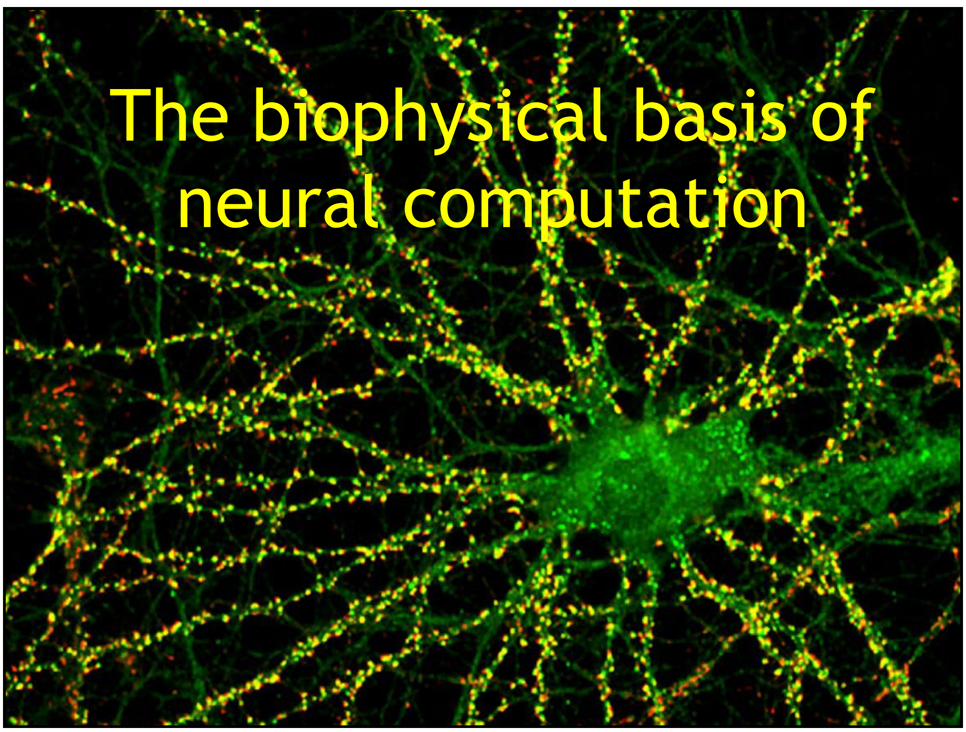
For cercal data:



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



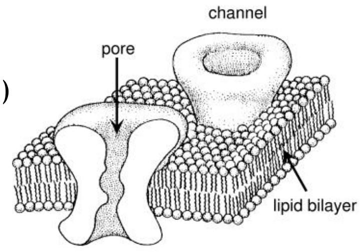


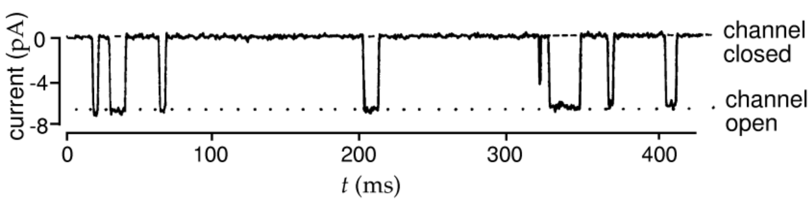



# The biophysical basis of neural computation

## Excitability is due to the properties of ion channels

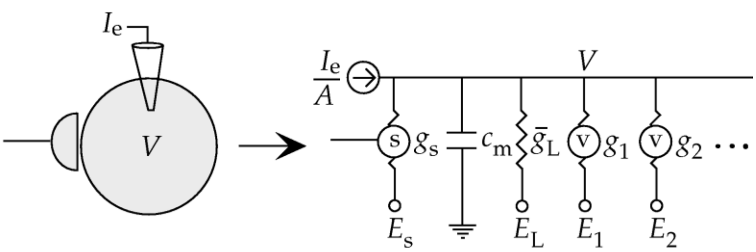
- Voltage dependent
- transmitter dependent (synaptic)
- Ca dependent






## 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:*

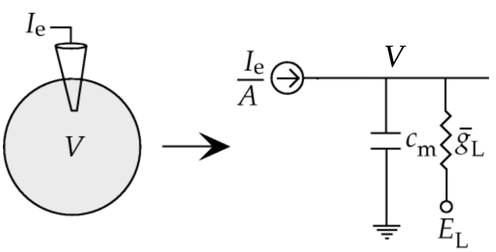
subthreshold, arbitrary kernel
spiking is due to an imposed threshold at $V_T$
postspike, incorporates afterhyperpolarization

*Simple model:*

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



## Simplified models: integrate-and-fire

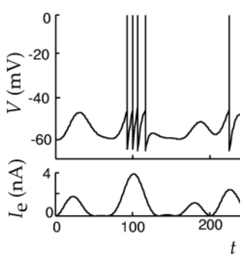



Integrate-and-Fire Model

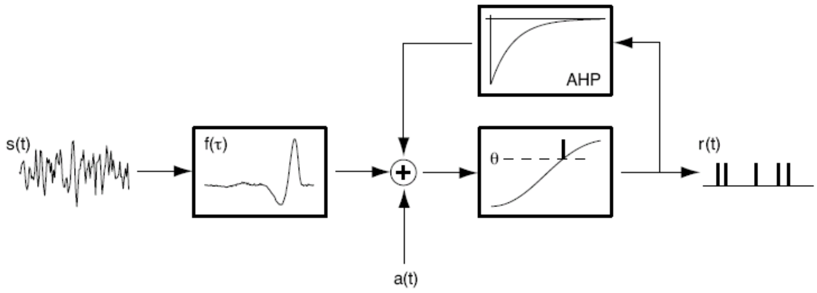
$$\tau_m \frac{dV}{dt} = -(V - E_L) + I_e R_m$$

If V > $V_{threshold}$ → Spike

Then reset: V = $V_{reset}$



## Simplified models: spike response model

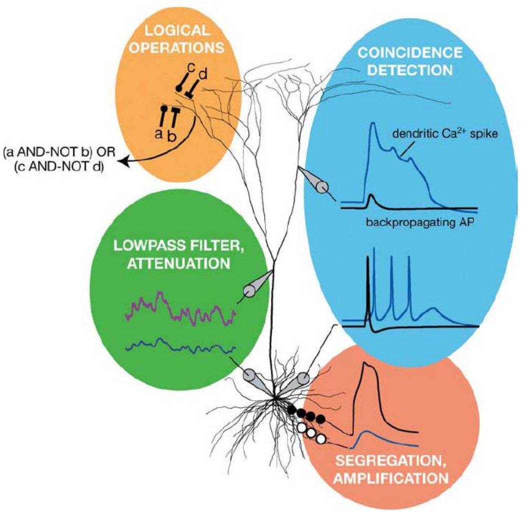



Gerstner; Keat et al. 2001



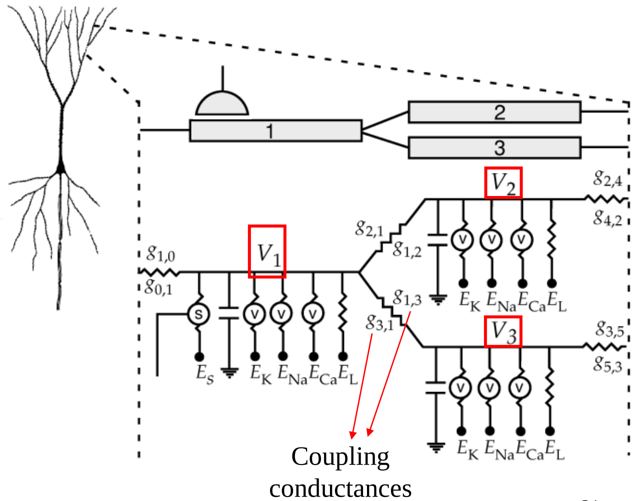
## Highlights: Dendritic computation

Filtering
Shunting
Delay lines
Information segregation
Synaptic scaling
Direction selectivity



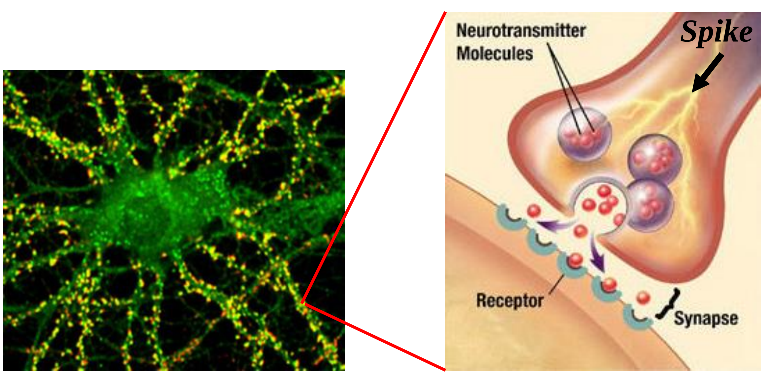
# Highlights: Compartmental models

Neuronal structure can be modeled using electrically coupled compartments



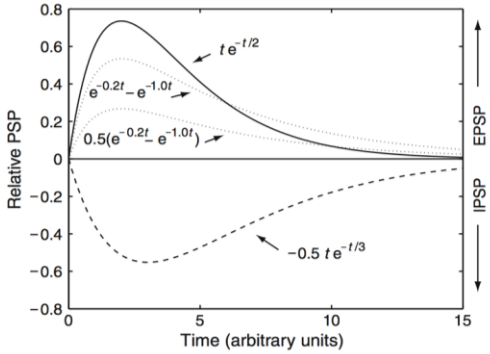



# Connecting neurons: Synapses



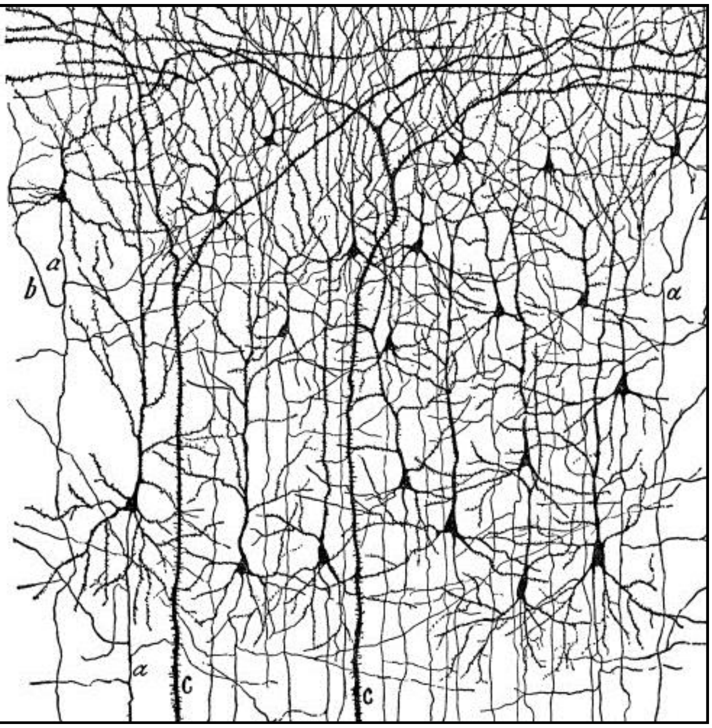

Presynaptic spikes cause neurotransmitters to cross the cleft and bind to postsynaptic receptors, allowing ions to flow in and change postsynaptic potential

## EPSPs and IPSPs

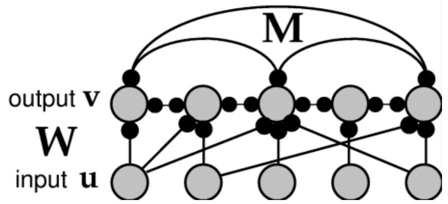



Size of PSP is a measure of synaptic strength
Can vary on the short term due to input history
Long term due to synaptic plasticity (LTP/LTD)

## Networks



## 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: $\tau_w \frac{d\mathbf{w}}{dt} = \mathbf{u}v$

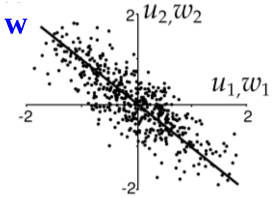
- Average effect over many inputs:

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

- $Q$ is the input correlation matrix:

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

Hebb rule performs principal component analysis (PCA)

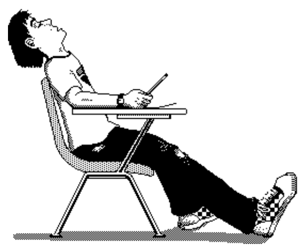


# Highlights: Generative Models

Droning lecture

Lack of sleep

Mathematical derivations





# Highlights: Generative Models and the Connection to Statistics

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

$p[\mathbf{v};G]$ (prior)

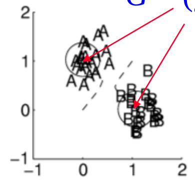
Causes $\mathbf{v}$

$p[\mathbf{v}\,|\,\mathbf{u};G]$ (posterior)

Generative model

Use EM algorithm for learning the parameters $G$

$G = (\mu_{v,}\ \sigma_v)$



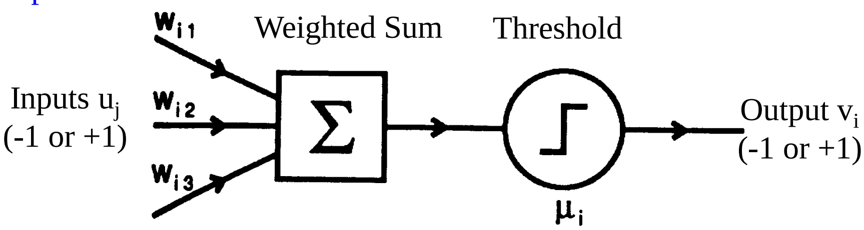
Causes of clustered data

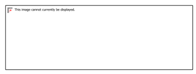
$p[\mathbf{u}\,|\,\mathbf{v};G]$ (data likelihood)

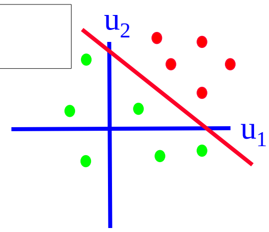
Data $\mathbf{u}$

# Highlights: Supervised Learning: Neurons as Classifiers

Perceptron:




Separating hyperplane: 

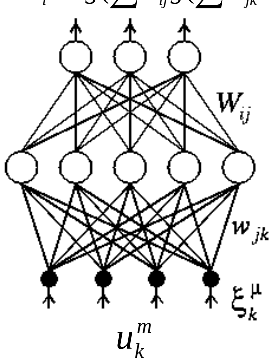





# Highlights: Supervised Learning: Regression

**Backpropagation for Multilayered Networks**

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

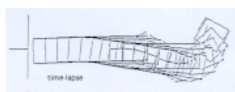



Finds **W** and **w** that minimize errors:

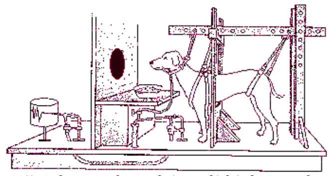
$$E(W_{ij}, w_{jk}) = \frac{1}{2}\sum_{m,i}(d_i^m - v_i^m)^2$$

Desired output

Example: Truck backer upper



## Highlights: Reinforcement Learning

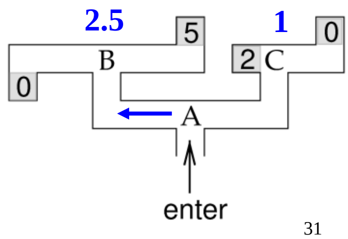


(http://employees.csbsju.edu/tcreed/pb/pdoganim.html)

- 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
- How 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 **Monday, June 10, 10:30am-12:20pm in the same classroom**
- Keep your presentation short: **~8 slides, 8 mins/group**
- Slides:
  - Bring your slides on a USB stick to use the class laptop

  **OR**
  - Bring your own laptop if you have videos etc.
- Projects reports (10-15 pages total) due by **midnight Tuesday, June 11** (by email to both Adrienne and Raj)


Have a great summer!


Au revoir!