Note: these slides are a general outline of what was discussed in class. There was a lot of drawing on the board to illustrate these models!

Intro to Computational Models of Cognition

CSP 502

Wednesday Bushong

“All models are wrong, but some are useful.”

-George Box

Why computational modeling?

- Formalizes theories to make precise, quantitative predictions about data
- Forces us to be ***explicit*** about our theoretical assumptions
  - both of these also have the positive side effect of preventing post-hoc, hand-wavey analysis

Marr's Levels

- Computational
- Algorithmic
- Implementational

computational modeling usually (but not always) lives somewhere in here

models also help us to bridge the three levels

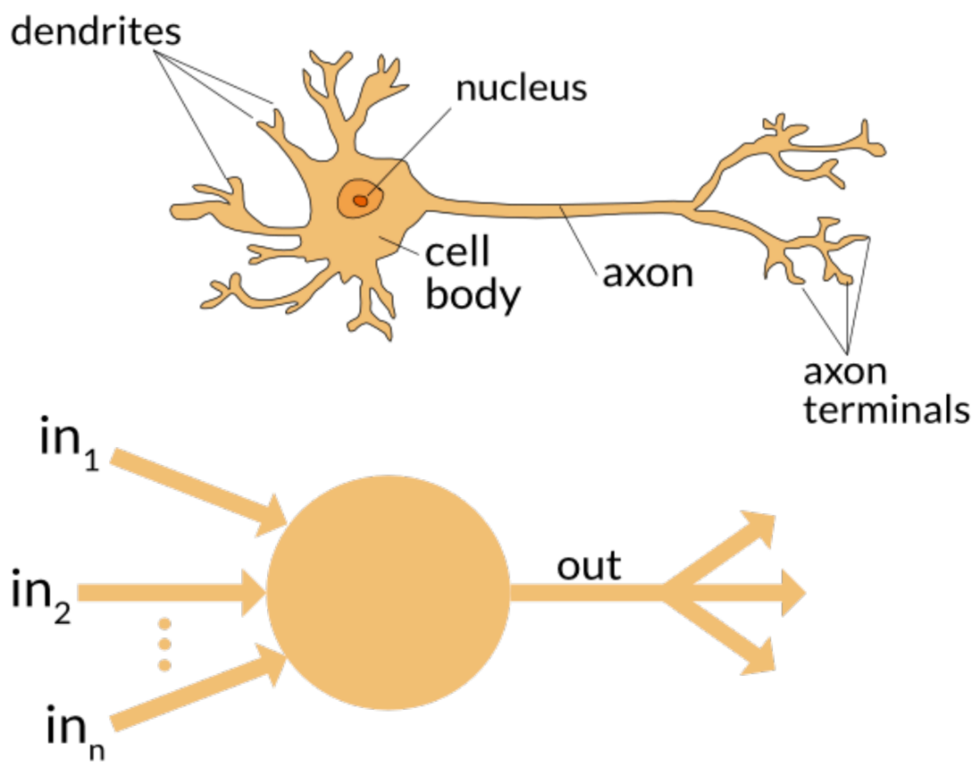
How complex should your model be?

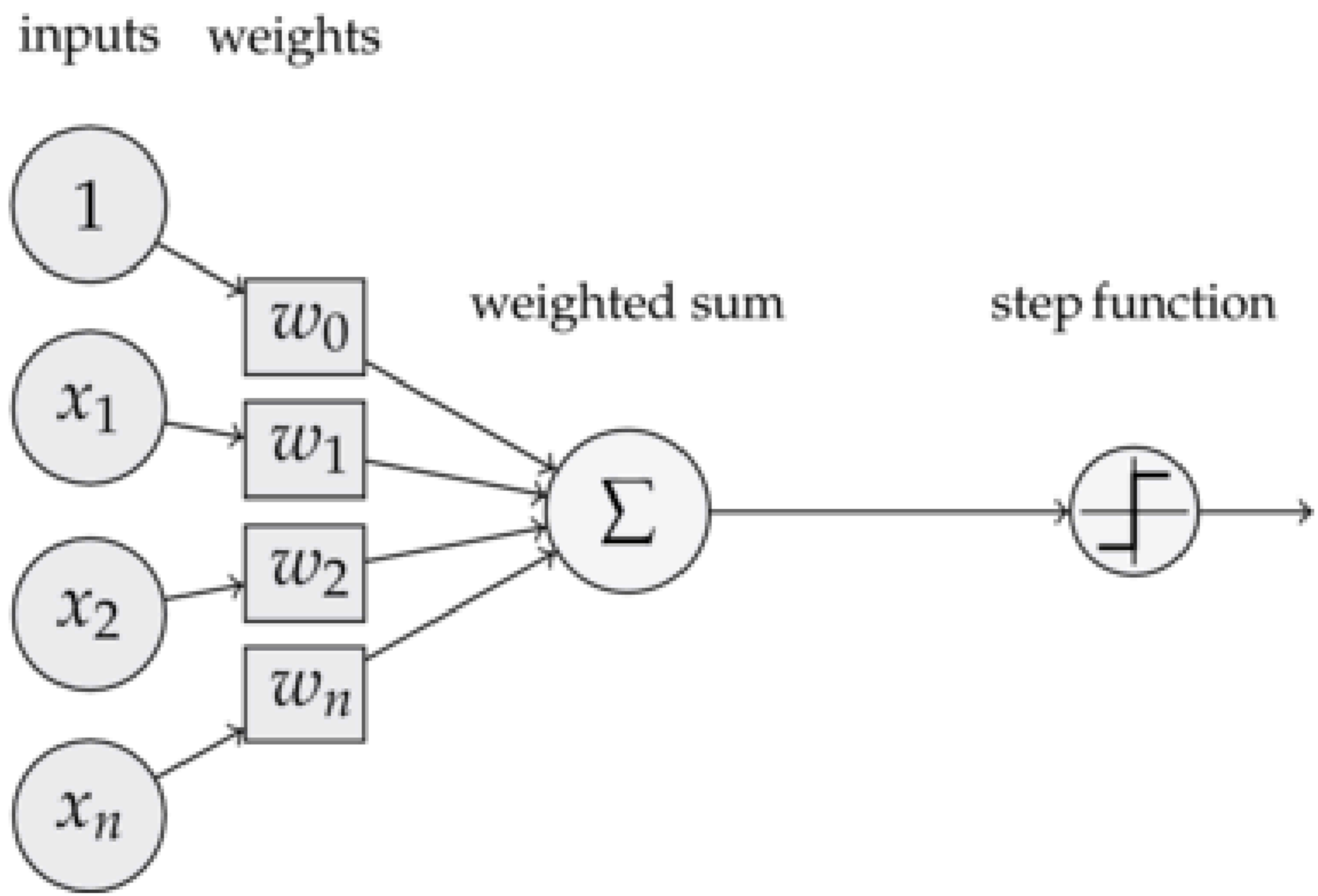
- Balance between simplicity & explanatory power
- What is the goal?
  - predict behavioral response patterns?
  - predict neural responses?
  - predict long-term outcomes?

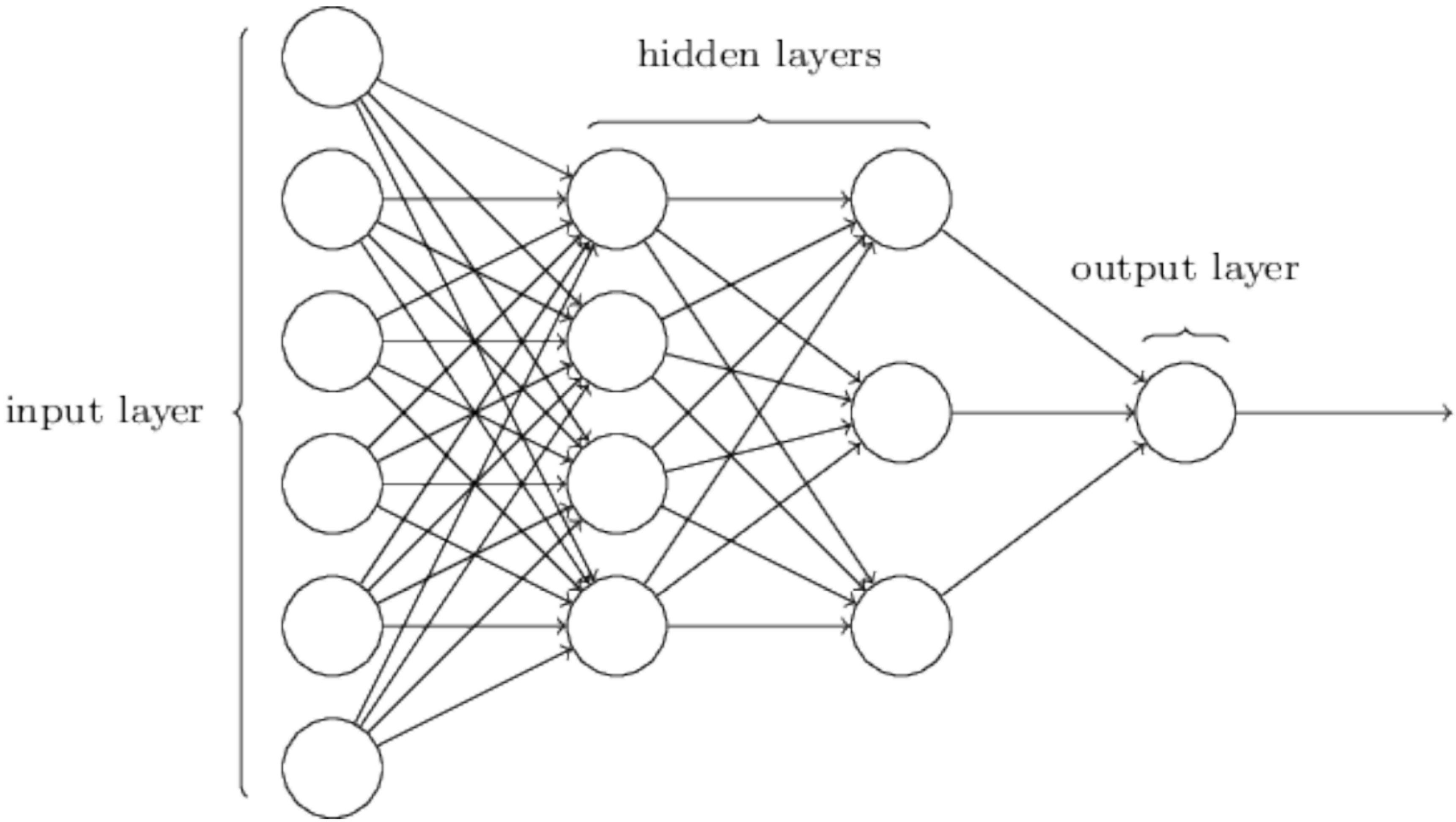
2 major classes of computational modeling in cognitive science

- Models of how a cognitive process is achieved
  - e.g., connectionist models, spreading activation models of memory, process models
  - pros: specific, explicit, give us insight into mechanisms
  - cons: often highly complex and difficult to understand
- Models of *what* the cognitive process being achieved is
  - e.g., Bayesian models, Rescorla-Wagner model of reinforcement
  - pros: simple, based on very few assumptions
  - cons: no explanation of *how* it's implemented

Origins of computational modeling in cog sci: connectionism




inputs
weights
1
x_1
x_2
x_n
w_0
w_1
w_2
w_n
weighted sum
Σ
step function

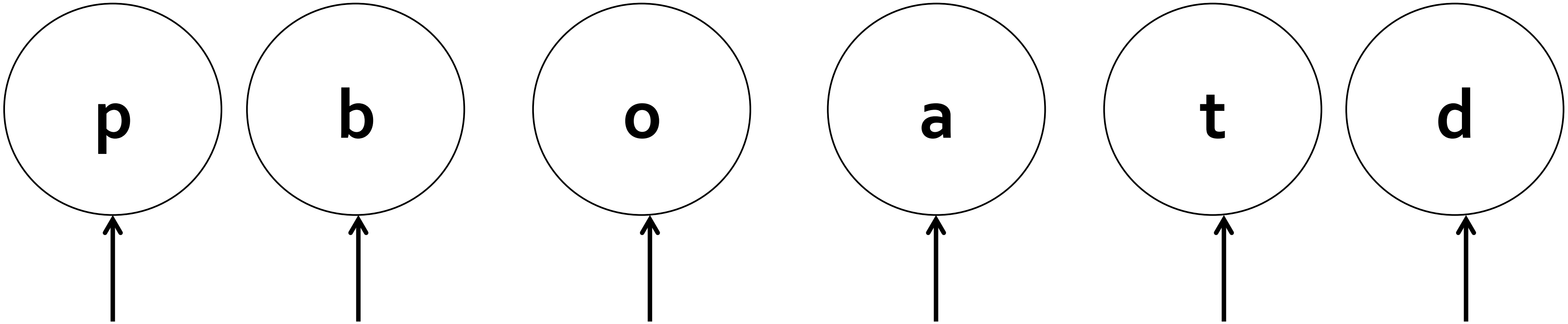

hidden layers
output layer
input layer

Connectionism

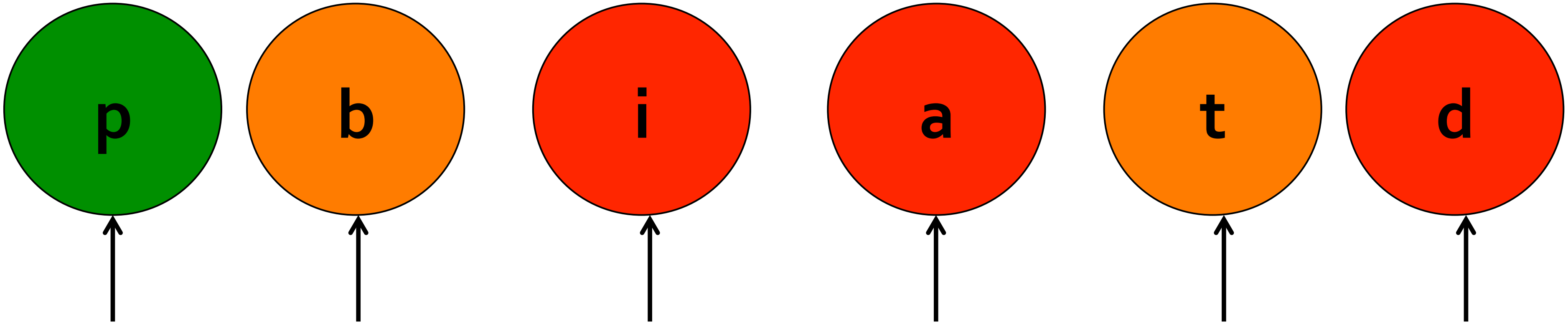
- started with the influential book series Parallel Distributed Processing (McClelland & Rumelhart, 1980s)
  - (cited >25,000 times!)
- central idea: “information processing takes place through the interactions of a large number of simple processing elements”
- running example: TRACE model of speech perception (McClelland & Elman)

- Units aren’t meant to correspond *exactly* to neurons
- Meant as a higher-level explanation of behavior, but draws on the insight that neural information processing is massively distributed and interactive

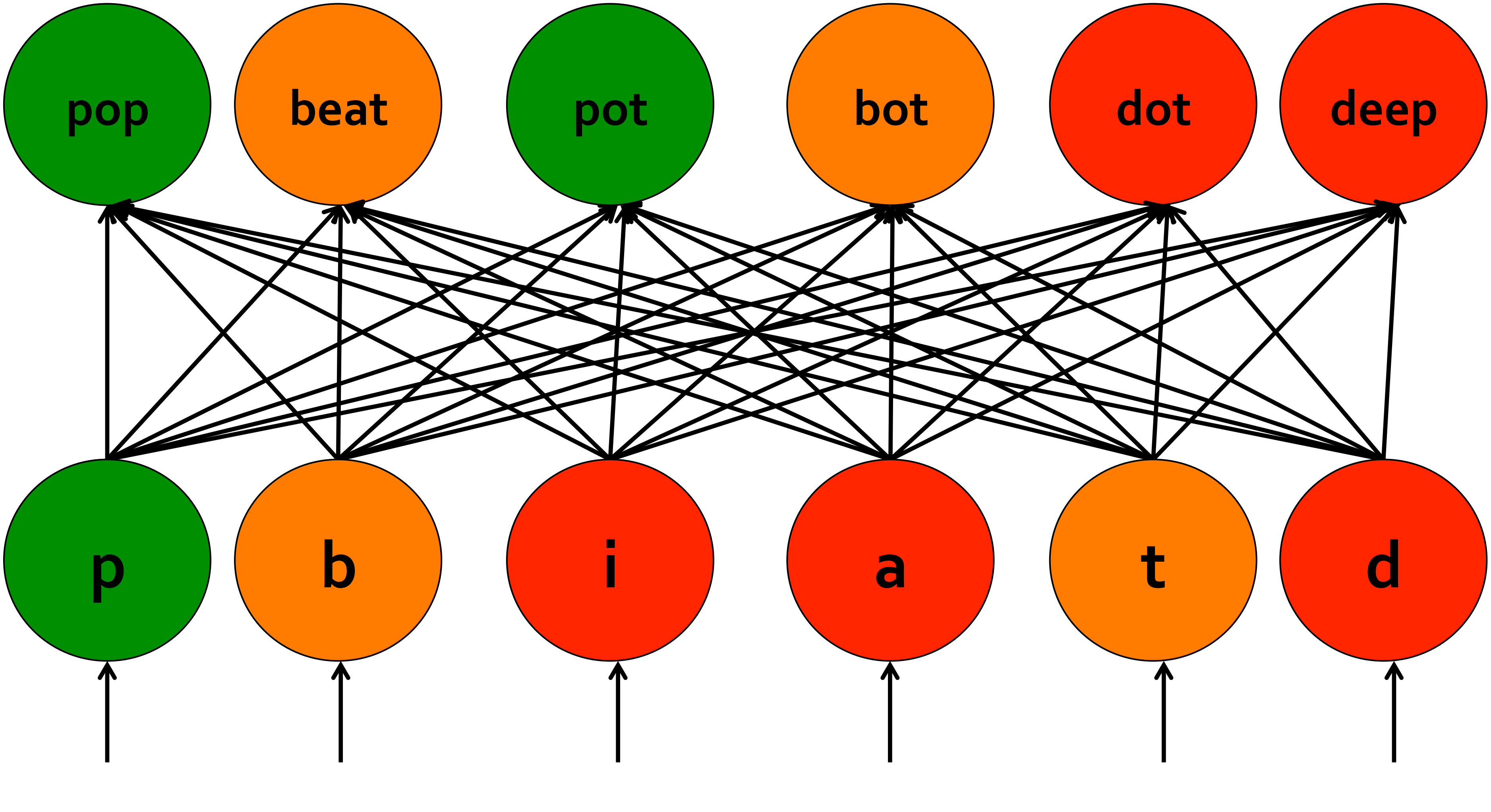
- In typical PDP-style connectionist models, units have some straightforward (usually predetermined) meanings



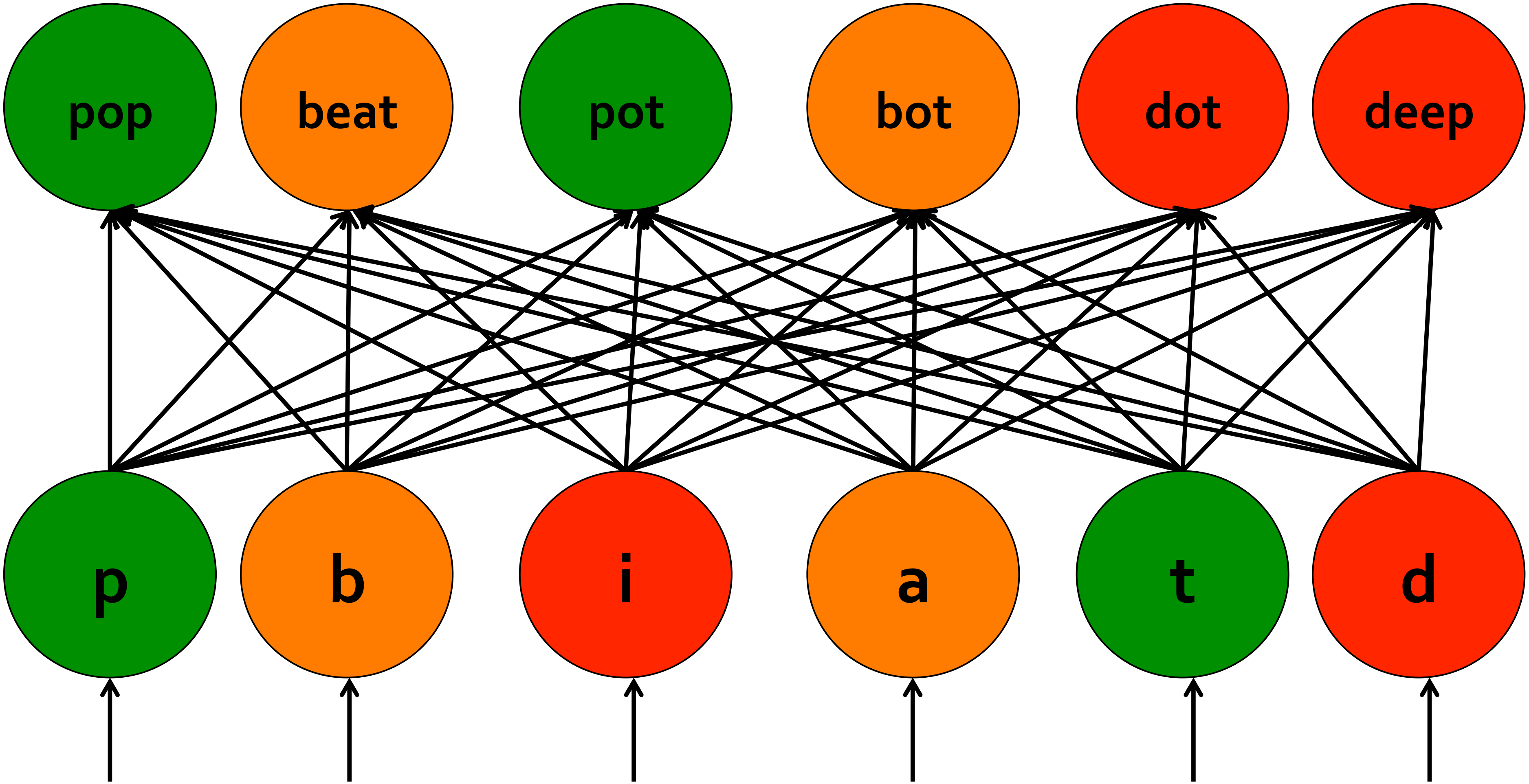
- In typical PDP-style connectionist models, units have some straightforward (usually predetermined) meanings
- The level of activation of these units corresponds to the evidence for that representation/hypothesis



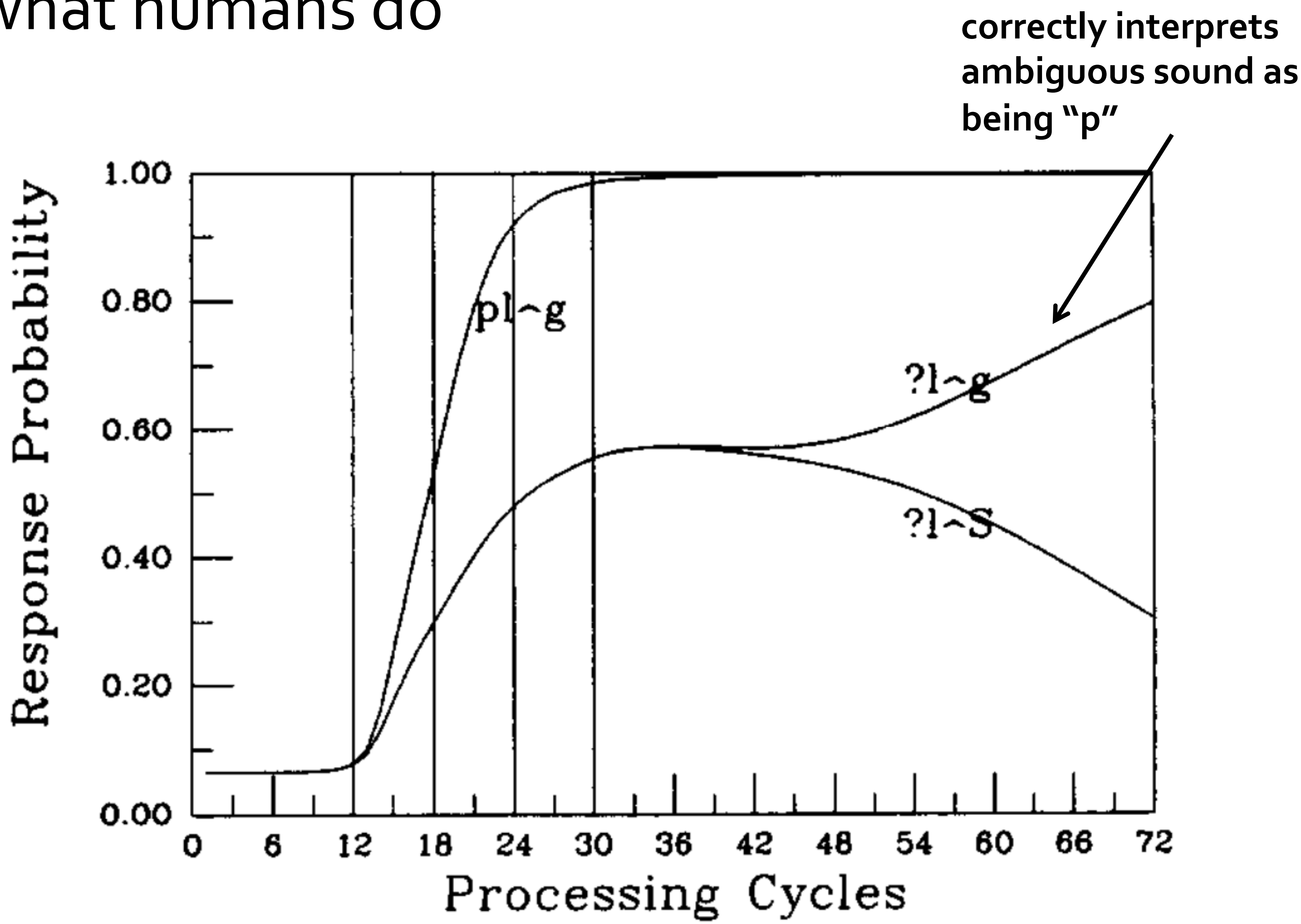
- activation is passed up to other levels



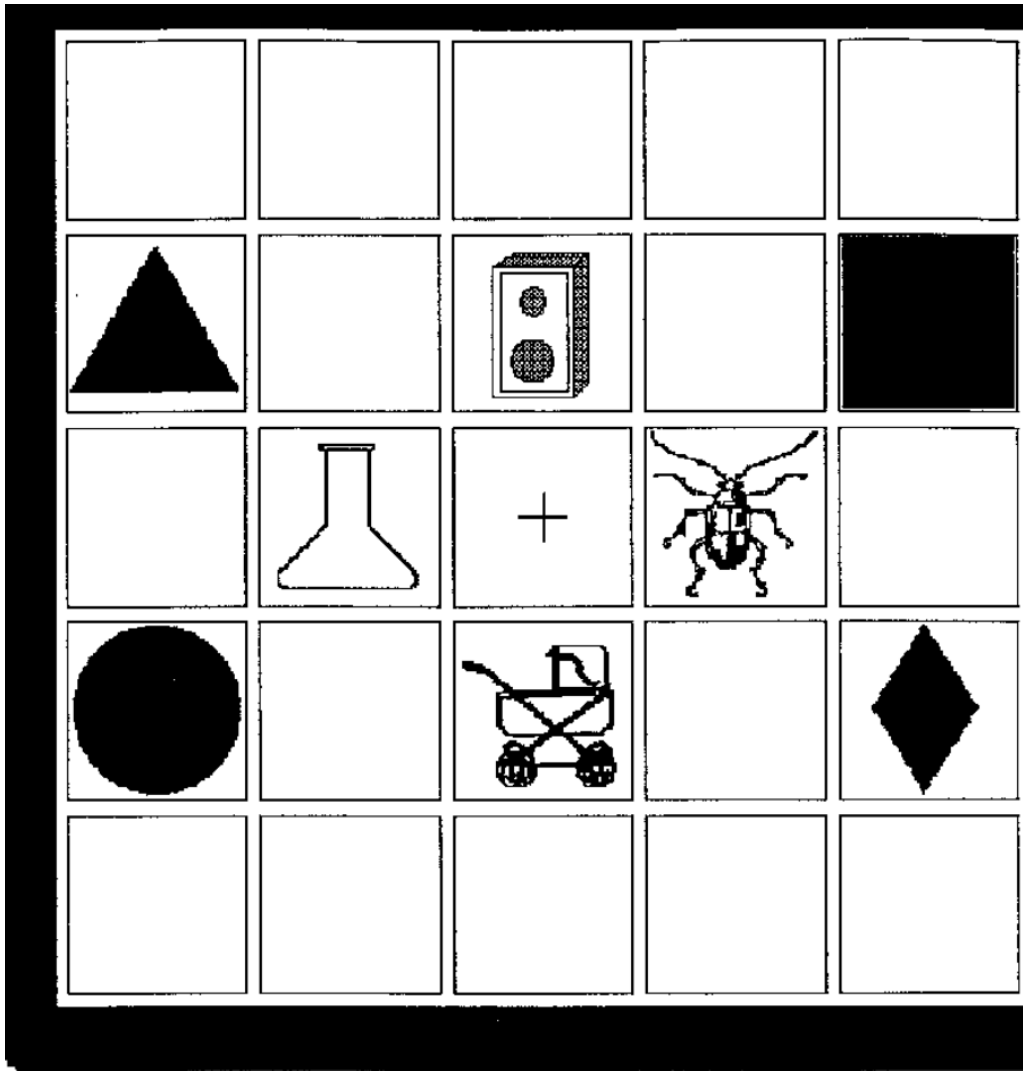
- …but also passed back down from higher levels! (the system is *interactive*)



- give the model some input and see if it does what humans do

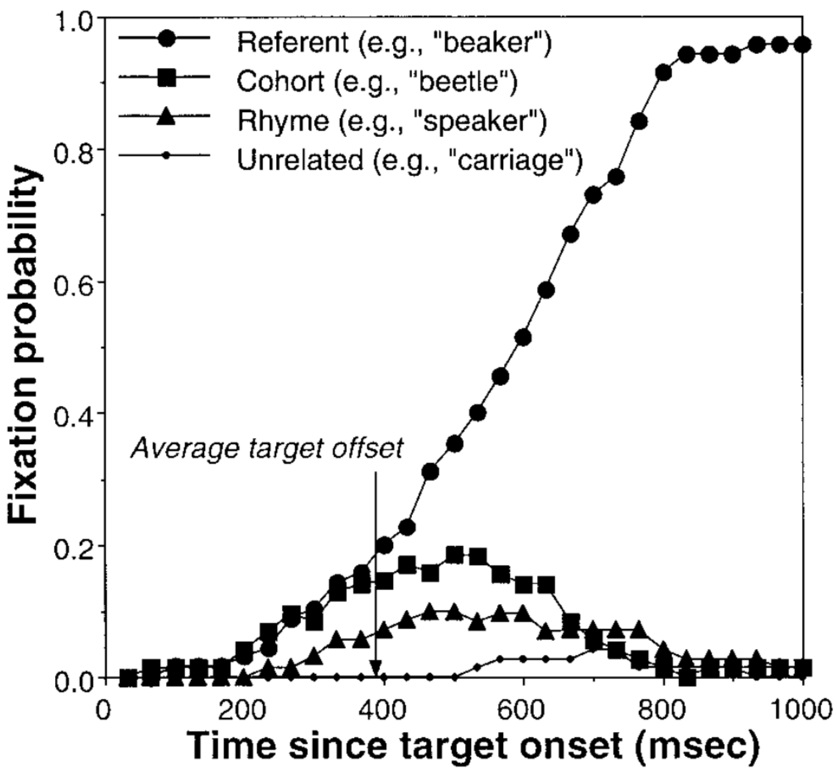


- Over 10 years later, innovations in eye-tracking methodology allow us to test TRACE's predictions in real time!

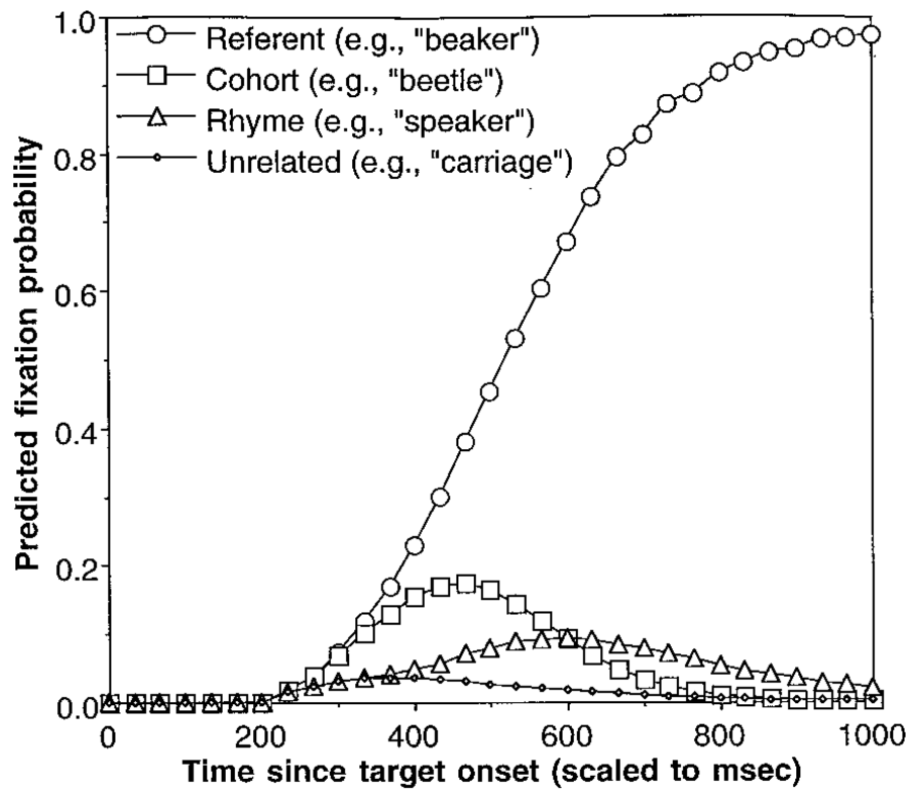


Allopenna et al. (1998)

Humans



TRACE



- Manipulating aspects of network structure & comparing with human behavior can give us insight into mechanisms
  - cascading vs. non-cascading
  - feedforward vs. interactive
  - inhibition within layers or not

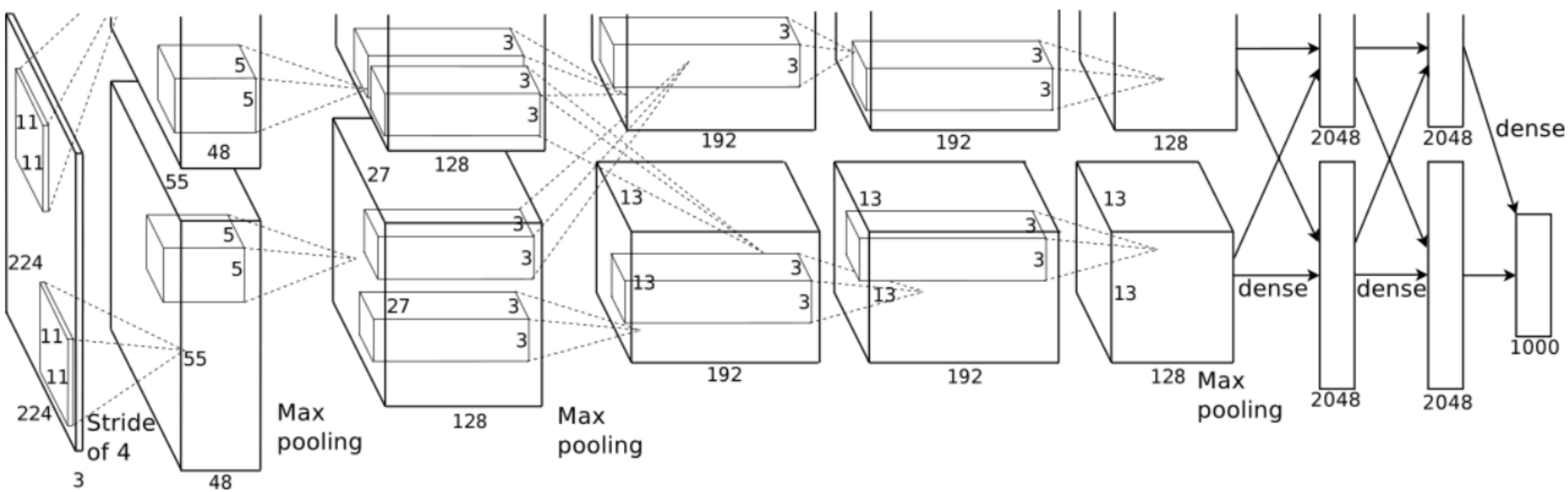
Problems with connectionism

- With increasing complexity, more and more difficult to interpret
- Training input to models was not naturalistic
- Models with more than a few layers (were) computationally intractable
  - models had to be so simplified that it wasn't clear whether they could scale
- Connectionism was largely abandoned for like 20 years…

Model as tool becomes model as theory…the case of deep neural networks

- Google wanted to get better at computer vision/recognizing objects (shocker)

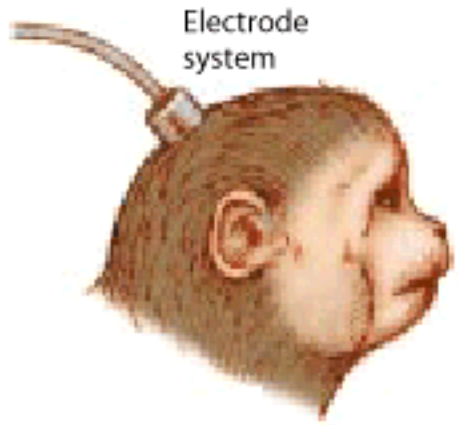
- With their vast resources, development of AlexNet

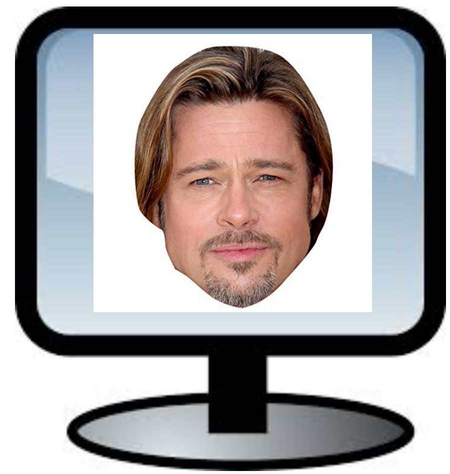


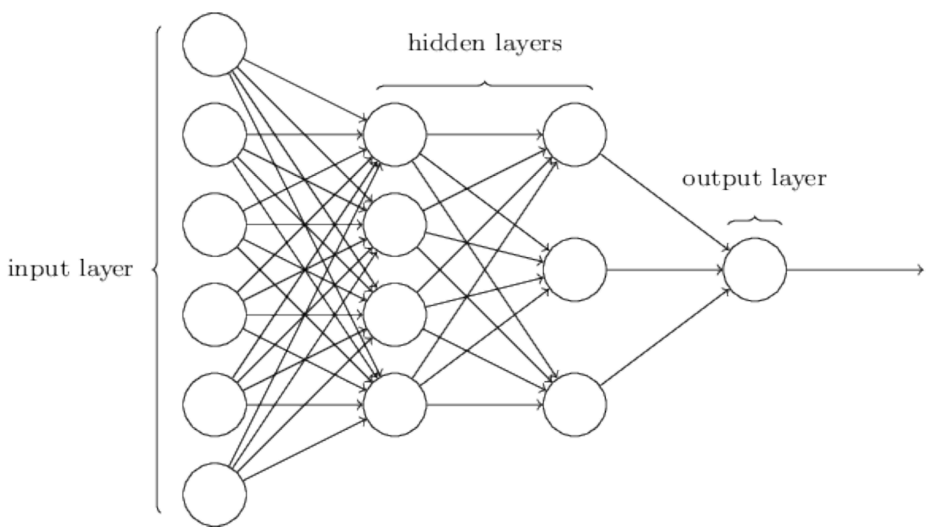
Our Google Overlords, a.k.a
Geoff Hinton, 2012

- After lots of tinkering, high accuracy on image databases
- Researchers start to wonder: might this mirror the brain?

Neural Net 'Receptive Fields'







- Related: comparing performance of networks trained on specific tasks to brain area performance

From highly complex to very simple: the rise of Bayesian modeling

- Describe cognition in terms of general mathematical laws

Examples:

- cue combination
- Kleinschmidt model of speech perception/ adaptation

Cons of Bayesian modeling

- Most modeling efforts are applied to highly specific problems → not clear how everything comes together into one system
- Despite their simplicity, there can be many hidden assumptions
- Possible mechanisms are largely ignored
  - but, some recent efforts to link Bayesian models to neural networks