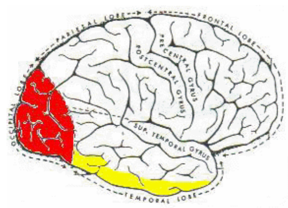
2-2-patterns

Neuropsychological Data

- Agnosia
- Term coined by Sigmund Freud
- From the Greek word for “lack of knowledge”
- The inability to recognize objects when using a given sense (e.g. vision), even though that sense is basically intact (Nolte, 1999)

Agnosia



- Usually involves damage to the occipito-parietal pathway

Patient GS

- Sensory abilities intact
- Language normal
- Unable to name objects

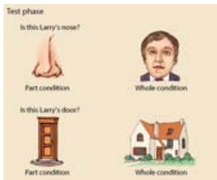
Agnosia

- Apperceptive
  - Object recognition failure due to perceptual processing
  - Difficulty recognizing pictures w/deleted segments
  - Unable to utilize top-down information for pattern recognition
- Associative
  - Perceptual processing intact but subject cannot use information to recognize objects
  - Can draw objects but not say what they are
  - Language otherwise intact
  - Often don’t know other things about object (how it’s used, etc.)

Prosopagnosia

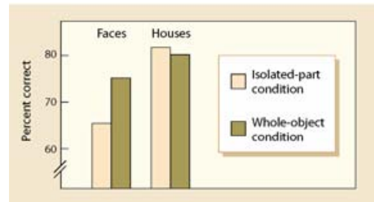
- Specific inability to recognize faces
- Are faces and other objects in the world represented in fundamentally different ways in memory?
- Does face-memory depend on fundamentally different brain systems?

Are Faces Special?



- Subjects presented with a face and asked to represent a face-part
- Subjects presented with a house and asked to represent a house-part

Are Faces Special?



- Houses: similar performance for parts & wholes
- Faces: whole-object advantage

Are Faces Special?

- Objects represented in parts and holistically
- Faces represented holistically

Models of Pattern Recognition

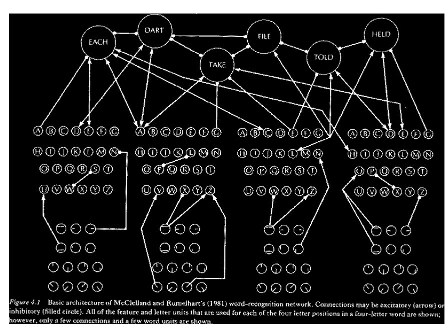
- Template Models
- Feature Models
- Prototype Models
- Neural Network Models

Word Superiority Effect

WORK K

C/K C/K

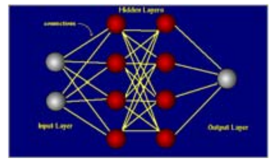
IAC Model



Connectionist (PDP) Models

- Information evaluated in *parallel* and *distributed* throughout the network
- Neurally inspired
  - Neural Networks
- Motivated by problems w/classical architecture

Neural Network Models

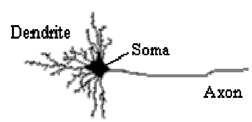


- Nodes
- Connections
- Activation Rules
- Activation
- Output function
- Learning rule

Problems w/Classical Architecture

- Slow
- Brittle
- Inflexible

Slow



- 100-step Constraint
  - Active neuron spikes approximately once every 1-3 ms
  - People can perform cognitive tasks in 100-300 ms
  - Cognitive tasks must be performed w/100 serial operations
  - Or, cognitive tasks performed in parallel

Brittle

- 1 damaged symbol halts computation
- 1 missing line of code could be fatal
- In contrast, effects of brain damage, local
  - BD often hard to notice

Inflexible

- Digital
- Hard Constraints
- No Soft Constraints

Connectionism, NNs

- Hardware Matters
- Neurally-inspired cognitive modeling

Perceptron

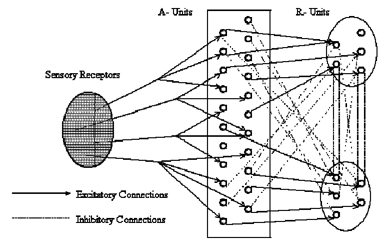


FIGURE 2: Schematization of a Perceptron (Adapted from Rosenblatt, 1958) The receptor units communicate an excitatory signal to the A(ssociation)-units. These then activate the appropriate R(esponse)-unit, which in turn act to inhibit both the other R-units, and their connected A-units. It's a "Winner-Take-All" system, with one layer of modifiable connections, between the A- and R- units.

Biological Nets

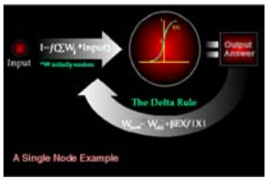
- 10^{10} - 10^{11} neurons
- 10^{5} interconnections per neuron
- Excitatory & Inhibitory
- Learning involves modifying synapses

Connectionist Nets

- Neuron basic processing unit
- Highly interconnected
- Excitatory & Inhibitory
- Learning done by changing strength of connections

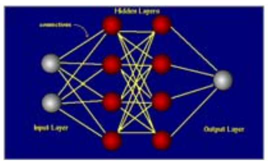
Basics

- Set of processing units
- Input Function
- State of activation
- Output function for each unit



More Basics

- Pattern of Connectivity
- Propagation Rule
- Activation Rule
- Learning Rule
  - Hebb Rule
  - Widrow-Hoff Rule
  - Generalized Delta Rule (back-prop)



The Environment

- Specifying the environment specifies the sorts of problems a particular network addresses
  - Specify Inputs
  - Specify Outputs
- Networks used to model many things
  - Stock Market Predictions
  - Diagnose Heart Attacks
  - Model Cognition
    - Pattern Recognition, Categorization, Memory, Learning

Appeal of Neural Nets

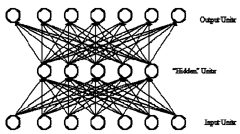


FIGURE 4: A Simple Connectionist Network A three-layer network with two layers of modifiable connections. The fan-in for the hidden units is equal to its fan-out, and connectivity is not localized.

- Parallel
  - Not subject to 100-step constraint
- Distributed Representations
  - Less Brittle
- Graded Rules
  - More Flexible

Buzzwords

- Spontaneous Generalization
- Graceful Degradation
- Mutual Constraint Satisfaction
- Capacity for Learning and Self-Organization
- Biologically Plausible (?)

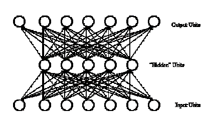
Example

- 3-layer
- Input Layer: Hidden Layer, fully interconnected
- Hidden Layer: Output Layer, fully interconnected
- Train with BackProp

Possibilities

- Input
- Home Team
  - Quarterback Rating
  - Rushing Yards
  - Receiving Yards
  - Field Goals Made
  - Field Goals Attempted
- Away Team

- Output
- Home Team
  - Points
- Away Team
  - Points



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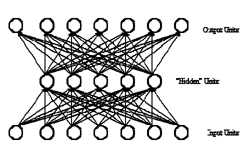
Features

- Incorporates information about context
- Doesn't assume variables are independent
- Captures higher-order statistical regularities



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Tri-Level Hypothesis

- Not symbolic
  - Yes, **sub-symbolic**
- Yes, information processing

"...dissimilarities do not imply that brains are not computers, but only that brains are not serial, digital computers." –Churchland, Koch, Sejnowski

Computational Level

- What problem is the network solving?
- Use of formal methods to
  - Determine limits of networks
  - Determine limits of learning rules

Algorithmic Level

- How do they do those crazy things they do?
- Neural networks blur the structure/process distinction
- Architecture/Program

Implementation Level

- Biological Plausibility
  - Only capture computationally relevant properties (cognitive modelling)
  - Closely model particular brain systems (computational neuroscience)

IAC Model

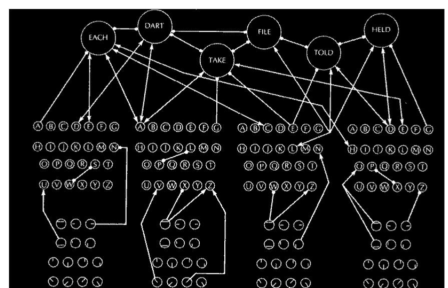


Figure 4.1 Basic architecture of McClelland and Rumelhart's (1981) word-recognition network. Connections may be excitatory (arrow) or inhibitory (filled circle). All of the feature and letter units that are used for each of the four letter positions in a four-letter word are shown; however, only a few connections and a few word units are shown.

Words versus Letters

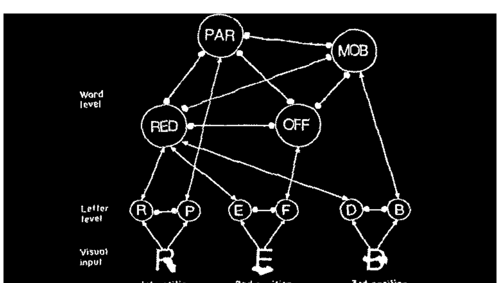


FIGURE 15.2 Illustration of a constraint-satisfaction network that could allow recognition of words (from Holyoak, 1990).

Word Superiority Effect

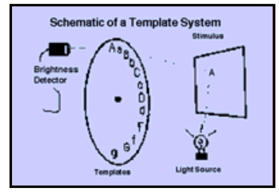
- WORD and WORK both begin to get activated because of WOR
- Activations feedback and activate K and D nodes
- But only K gets bottom-up activation
- D gets top-down activation that gets inhibited
- Letters presented alone don't get top-down activation from word level!

IAC Model Evaluation

- Illustrates important principles
- Doesn't hold up to 21st century standards
  - Scope too narrow
  - No learning mechanism
  - Too many feature units

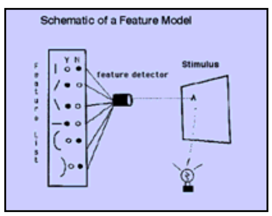
Template Theories of Pattern Recognition

- Template theories: a miniature copy or template of each known pattern is stored in long-term memory
  - straightforward template theory
  - normalized template theory
- Problems
  - not adaptable
  - impose large storage requirements

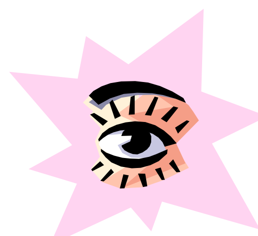


Feature Theories of Pattern Recognition

- Feature theories: patterns consist of a set of specific features or attributes
- Advantages:
  - elementary features can combine to form multiple objects
  - Features can be used to describe novel objects
- Problems:
  - context effects in perception
  - recognition can take place when features are occluded



Pattern Recognition



- Pattern Recognition requires Feature Analysis
  - Break down pattern into primitives
  - Recognize combination of features
- Integration of bottom-up and top-down processing