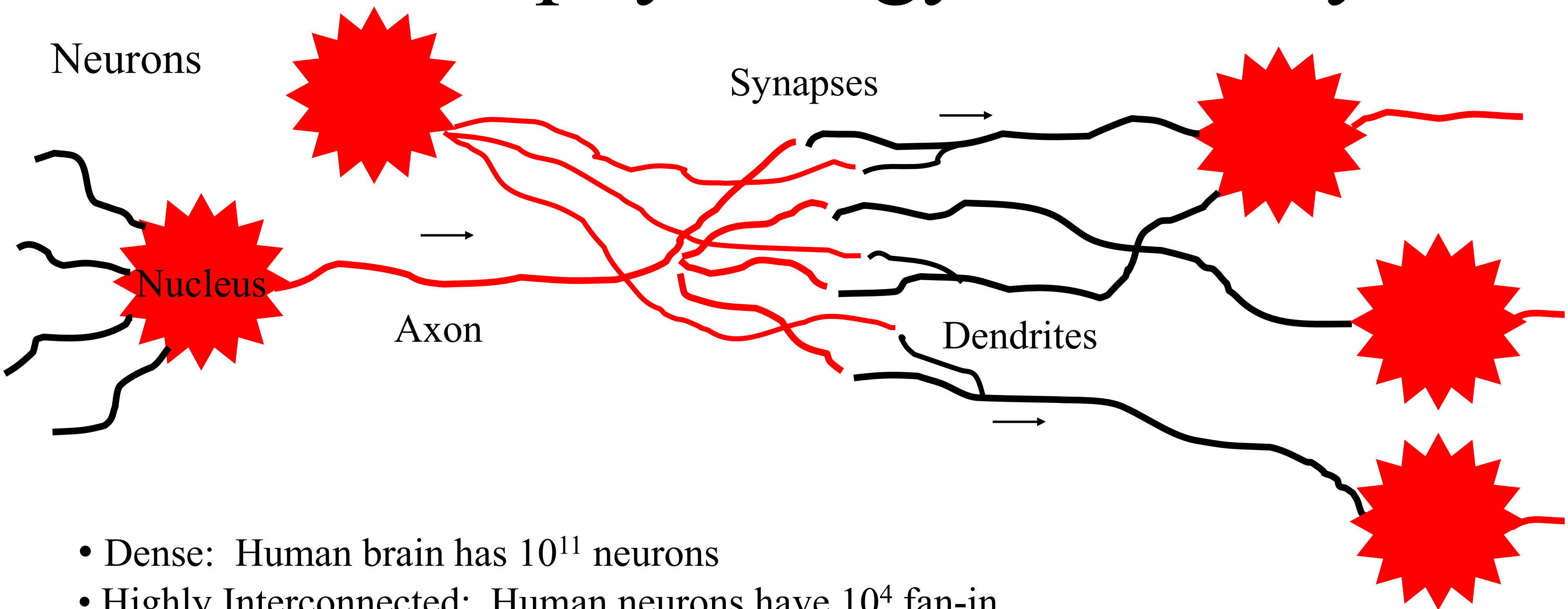
Neural Coding

CS786

August 12th and 13th 2024

Neurophysiology Summary

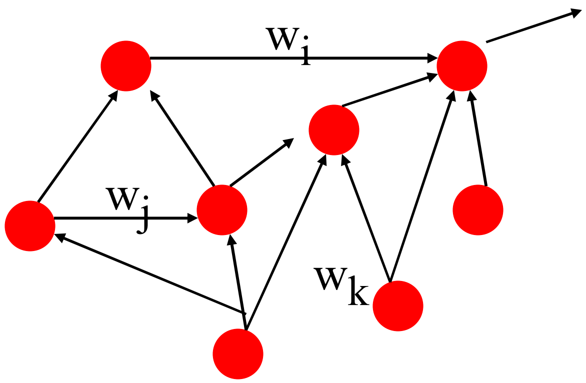


- Dense: Human brain has 10^{11} neurons
- Highly Interconnected: Human neurons have 10^4 fan-in.
- Neurons firing: send action potentials (APs) down the axons when sufficiently stimulated by SUM of incoming APs along the dendrites.
- Neurons can either stimulate or inhibit other neurons.
- Synapses vary in transmission efficiency

Development: Formation of basic connection topology

Learning: Fine-tuning of topology + Major synaptic-efficiency changes.

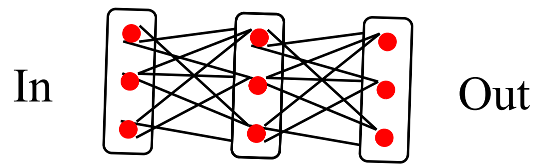
NeuroComputing



- Nodes fire when sum (weighted inputs) > threshold.
  - Other varieties common: unthresholded linear, sigmoidal, etc.
- Connection topologies vary widely across applications
- Weights vary in magnitude & sign (stimulate or inhibit)
- Learning = Finding proper topology & weights
  - Search process in the space of possible topologies & weights
  - Most ANN applications assume a fixed topology.
- The matrix **IS** the learning machine!

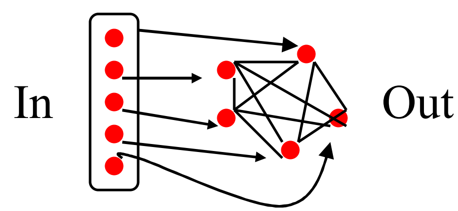
Tasks & Architectures

- Supervised Learning



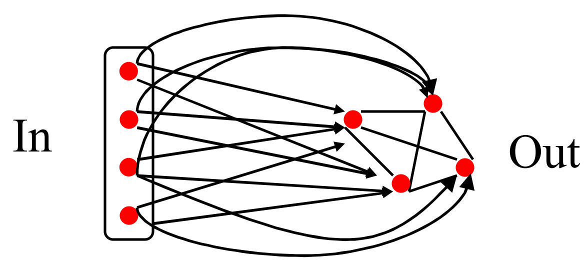
  - Feed-Forward networks
    - Concept Learning: Inputs = properties, Outputs = classification
    - Controller Design: Inputs = sensor readings, Outputs = effector actions
    - Prediction: Inputs = previous X values, Outputs = predicted future X value
  - Learn proper weights via back-propagation

- Unsupervised Learning
  - Pattern Recognition
    - Hopfield Networks



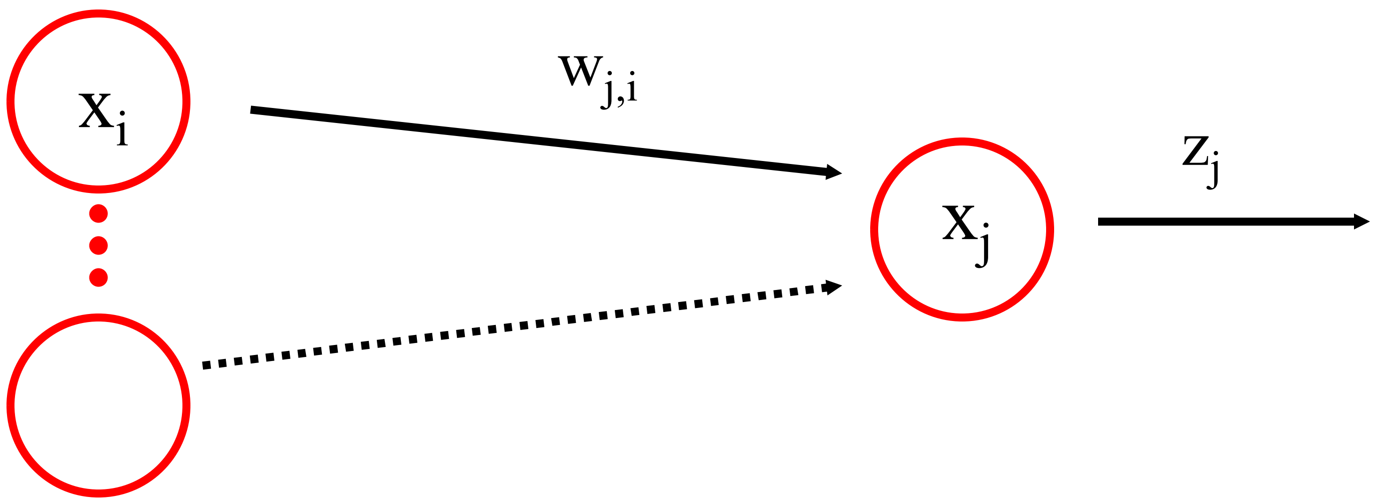
Excitatory & Inhibitory Arcs in the Clique

  - Data Clustering
    - Competitive Networks



Maxnet: Clique = only inhibitory arcs

Learning = Weight Adjustment

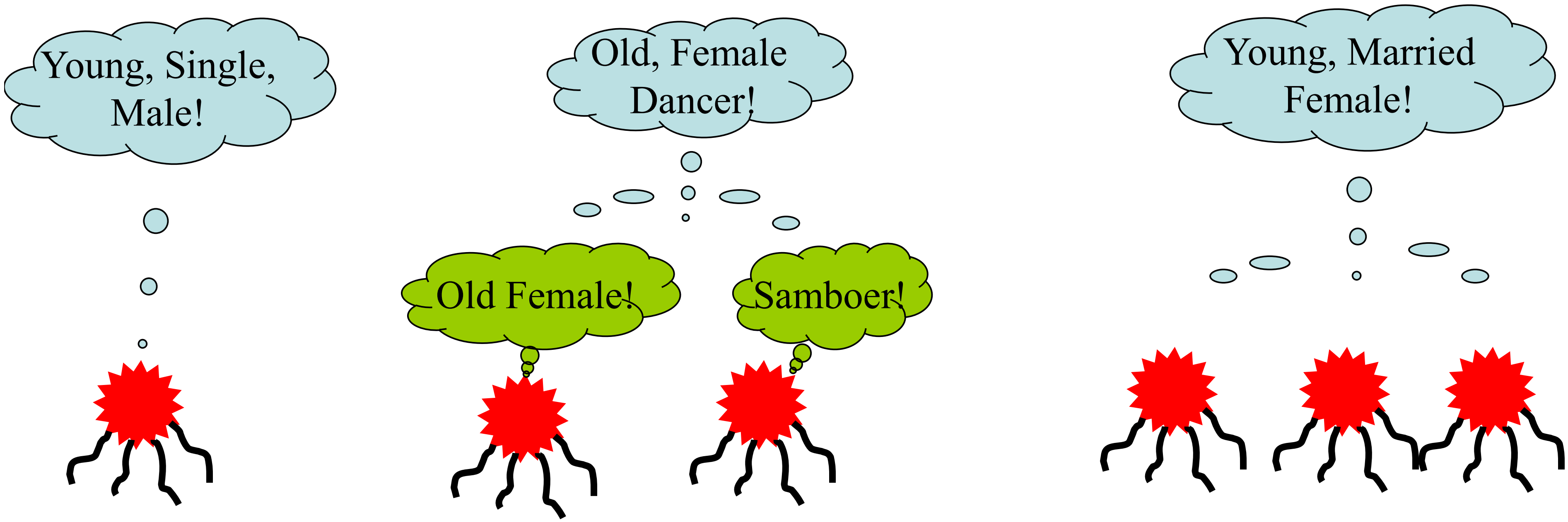


- Generalized Hebbian Weight Adjustment:
  - The sign of the weight change = the sign of the correlation between x_i and z_j:

    $\Delta w_{ji} \propto x_i z_j$
  - z_j is:
    - x_j — Hopfield networks
    - $d_j - x_j$ — Perceptrons (d_j = desired output)
    - $d_j - \sum_i x_i w_{ji}$ — ADALINES " "

Local -vs- Distributed Representations

- Assume examples/concepts have 3 features:
  - Age : {Young, Middle, Old}
  - Sex: {Male, Female}
  - Marital Status: {Single, Dancer, Married}



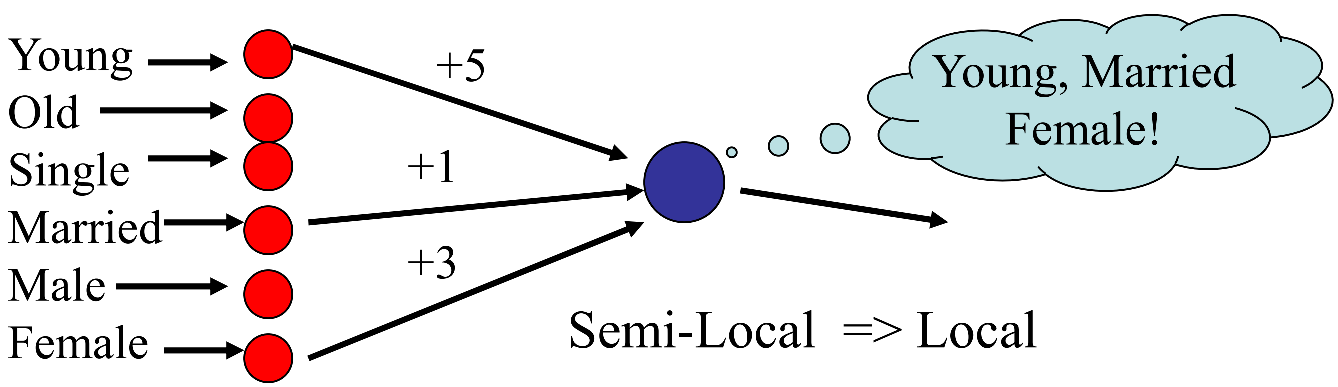
<u>Local:</u> One neuron represents an entire conjuctive concept.

<u>Semi-Local:</u> Together they rep a conjunctive concept, and each neuron reps one or a few conjuncts - i.e. concept broken into clean pieces.

<u>Distributed:</u> Together they rep a conjunctive concept, but the individual conjuncts cannot necessarily be localized to single neurons

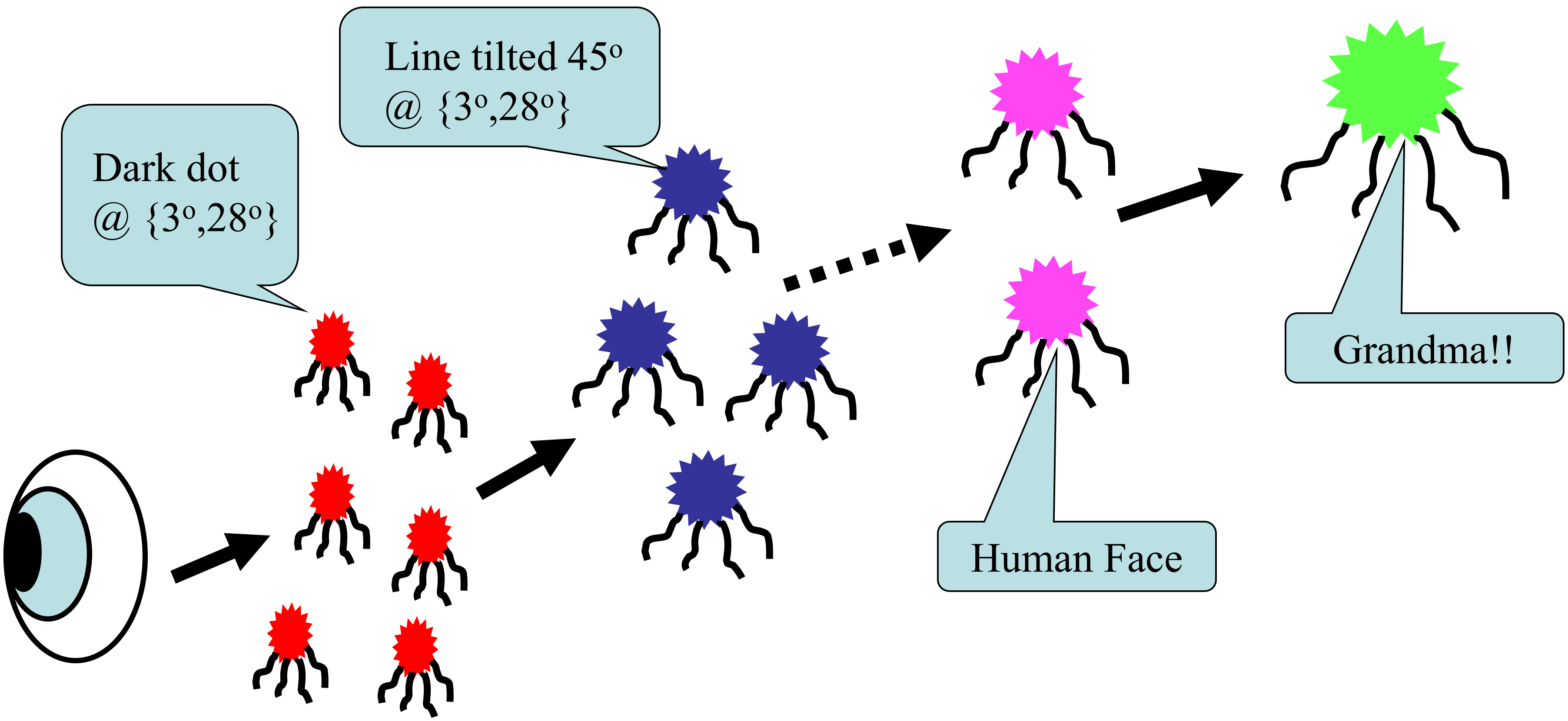
Local -vs- Distributed (2)

- Size requirements to represent the whole set of 18 3-feature concepts - assuming binary neurons (on/off)
  – Local: 3x3x2 = 18
    - Instance is EXACTLY 1 of 18 neurons being on.
  – Semi-Local: 3+3+2 = 8 (Assume one feature value per neuron)
    - Instance is EXACTLY 3 of 8 neurons being on.
  – Distributed: $\log_2 18 = 5$
    - Instance is any combination of on/off neurons
    - Add 1 bit and DOUBLE the representational capacity, so each concept can be represented by 2 different codes (redundancy).
- The same neural network (artificial or real) may have different types of coding in different regions of the network.



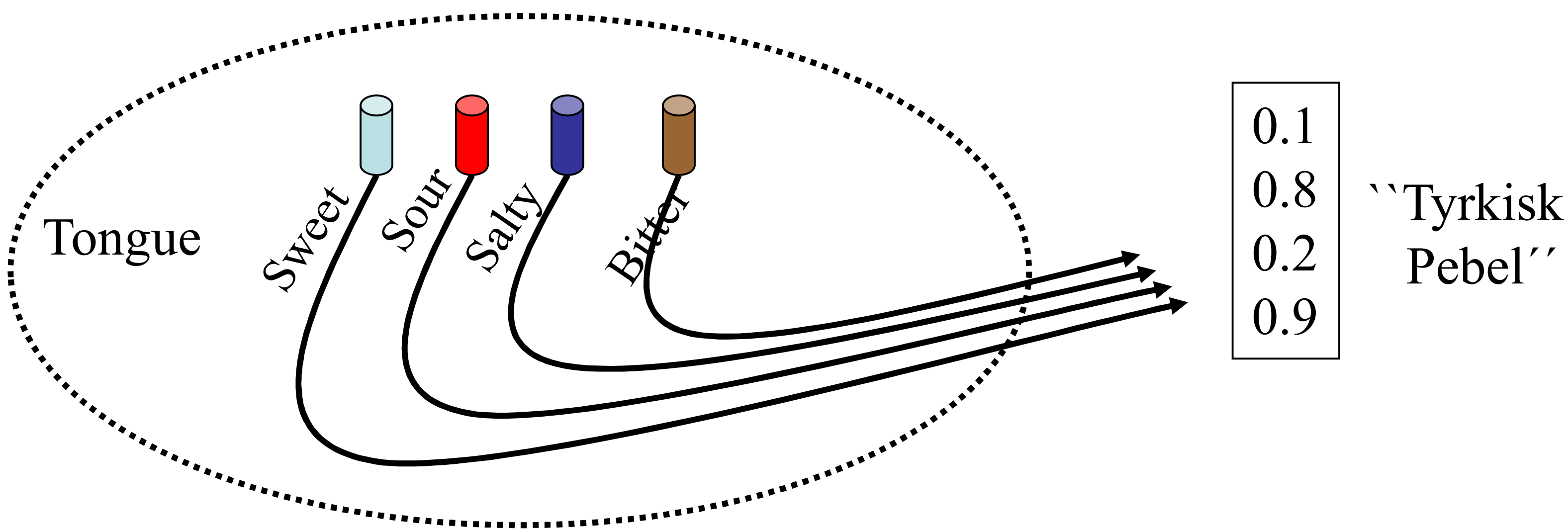
Representational Hierarchies

- In the brain, neurons involved in early processing are often semi-local, while neurons occuring later along the processing path (i.e. higher level neurons), are often local.
- In simpler animals, there appears to be a lot of local coding. In humans, it is still debatable.



Vector Coding

- An organism's sensory apparatus uses vector coding as a representation of its inputs.
- Semi-local coding, since the components of a conjunctive concept are localized to individual neurons.
- A particular color, flavor, sound, etc. = a vector of receptor states (not a single receptor state).
- Combinatorics: n^k possible vector states, k = # receptors, n = # possible receptor states. Note: n > 2 in many cases.
- The fact that humans are much better at disciminating sensory inputs than actually describing them illustrates the relative density of sensory vector space -vs- the sparseness of language.



Comparison of Coding Forms

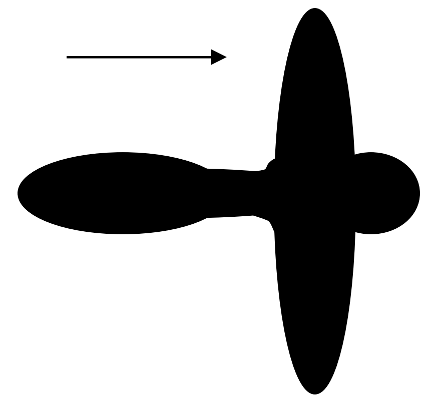
- **Compact Representation:** Local (NO!), Distributed (YES!)
- **Graceful Degredation** (Code works when a few neurons are faulty): Local (NO!), Distributed (Yes- due to redundancy).
- **Binding Problem** (How to represent two concepts that occur simultaneously): Local (EASY! - two active nodes), Distributed (HARD - but may be possible by quick shifts back and forth between the 2 activation patterns)

  In more complex animals, all 3 coding forms are probably present, with local for the ***most salient concepts*** for that organism.

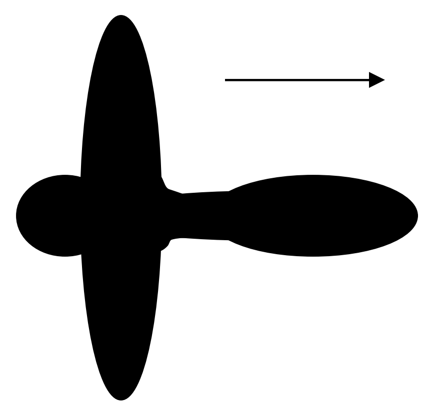
Species-Specific Saliency

- The key stimuli for an organism are often locally or semi-locally encoded, with direct connections from the detector neuron(s) to a motor (action-inducing) neuron.

The movement of this simple pattern ressembles a **hawk** and scares small chickens.

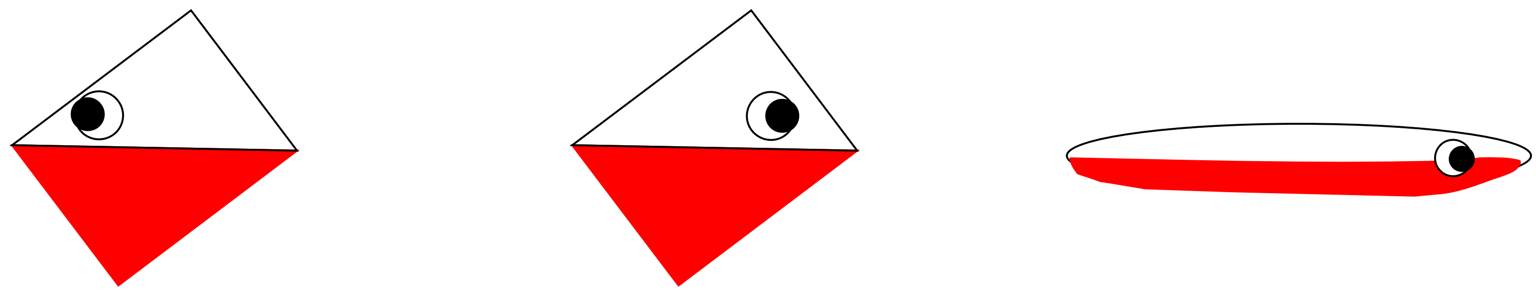


The movement of the reverse pattern ressembles a **goose** and elicits no response from the chicks.

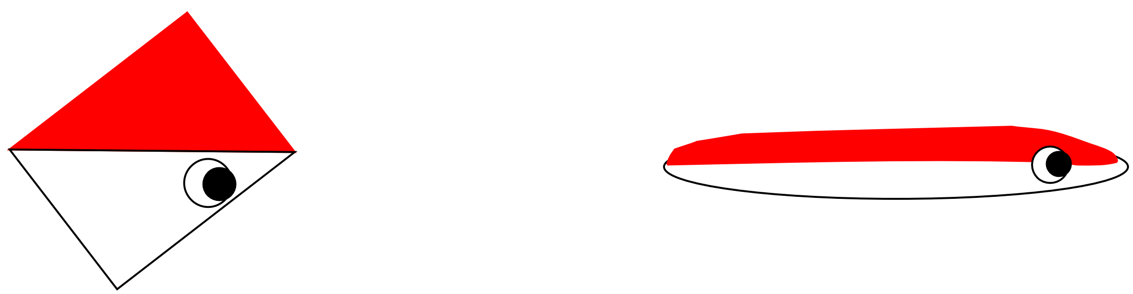


Fish Dinner

- Three-spined sticklebacks respond to these simple stimuli:

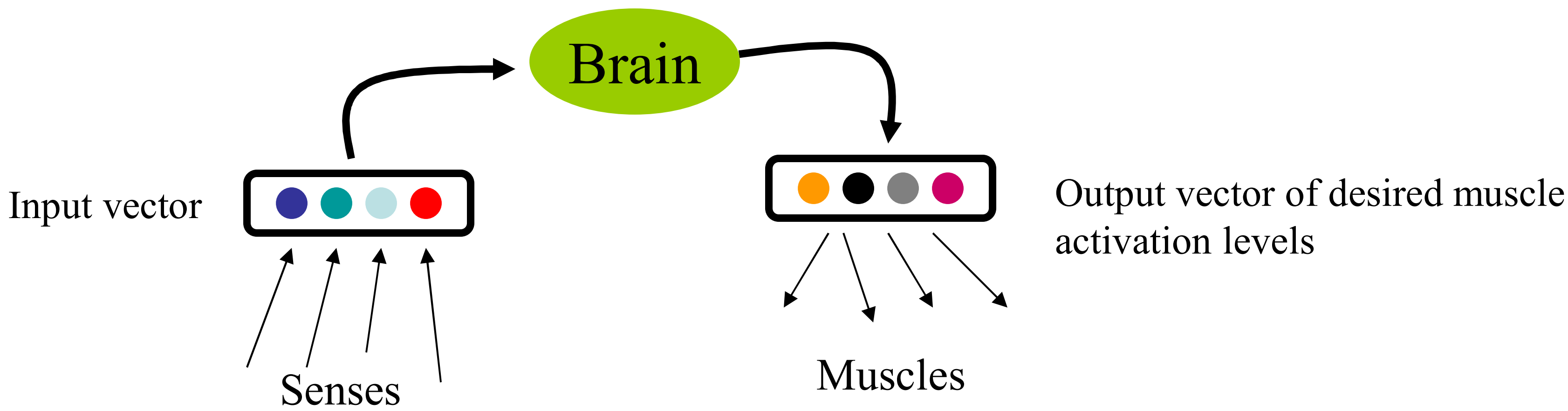


- But not these:

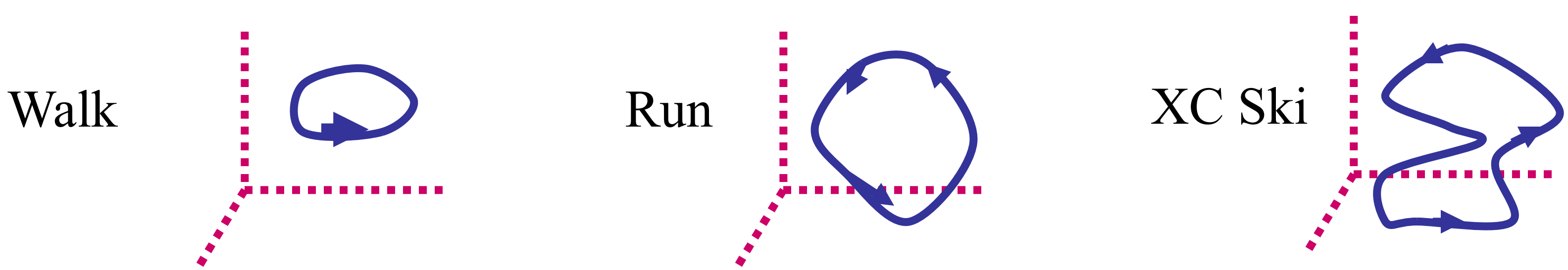


- Salient feature: Red belly!

Sensorimotor Coordination: Mapping Sensations to Actions

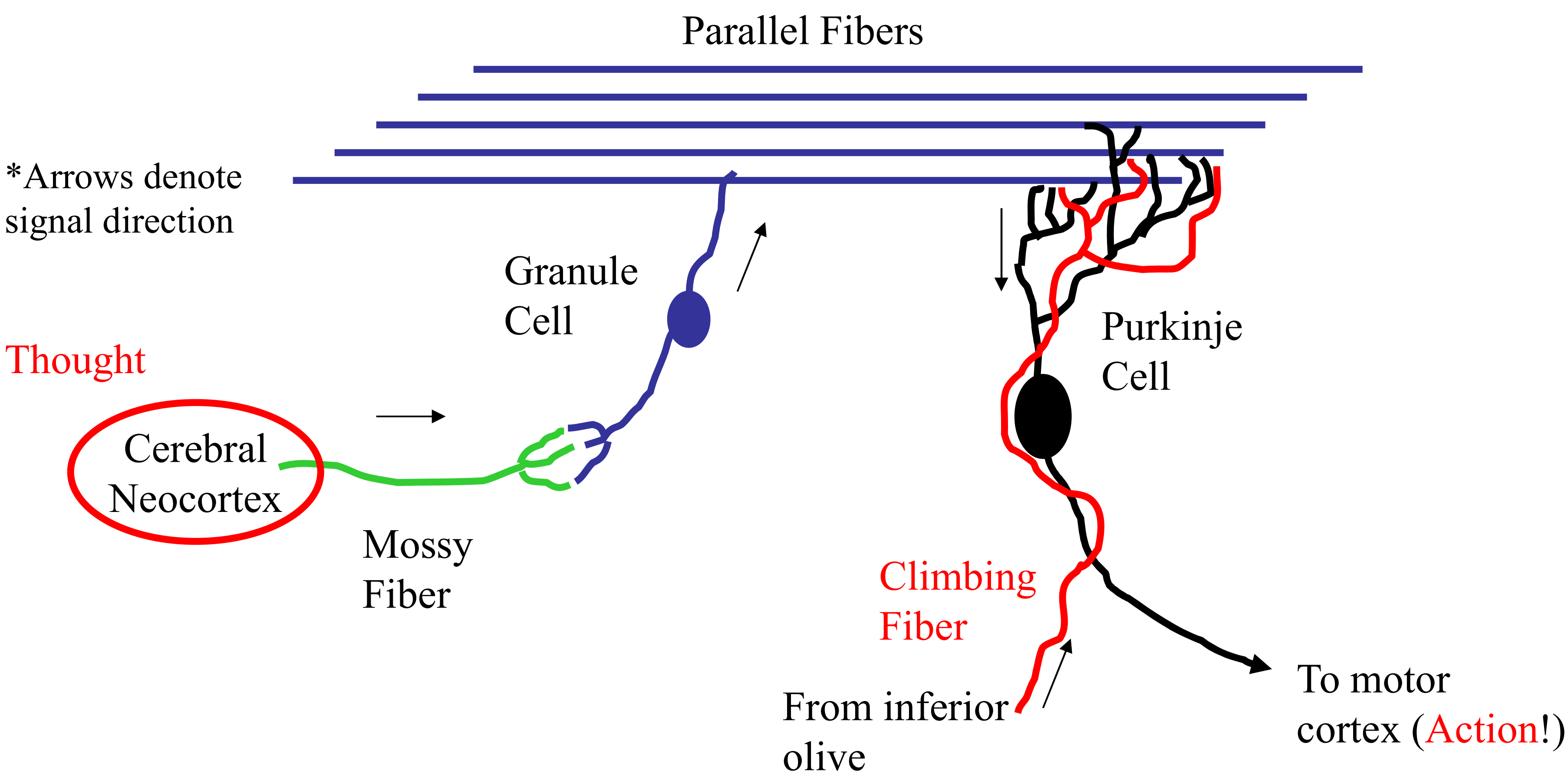


- Intelligent Physical Behavior: Performance of the proper motor movements in response to the current sensory stimuli.
  - *A large and well-defined brain is just evolution's latest and highest achievement in sensorimotor coordination, not its earliest or only example…*Churchland, pg. 95-6
- Vector processing: Transformation of sensory input vectors into motor output vectors
- Coordinated Behavior: Proper sequence of muscle-activations = proper trajectory in output-vector space.



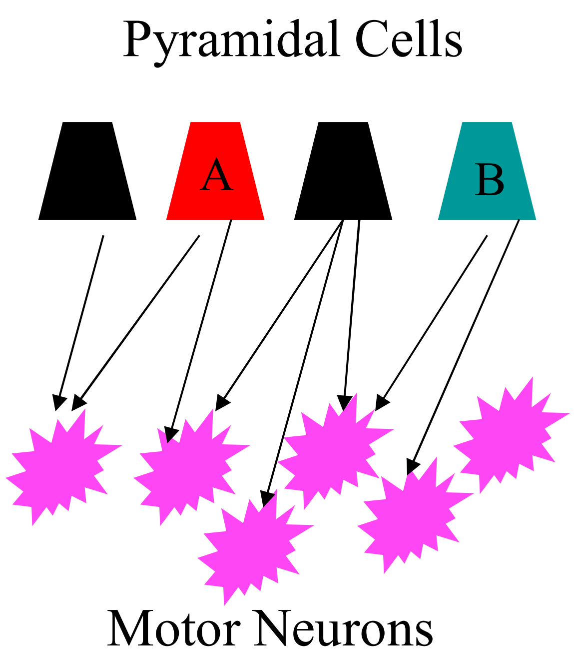
Mapping Thoughts to Actions in the Brain

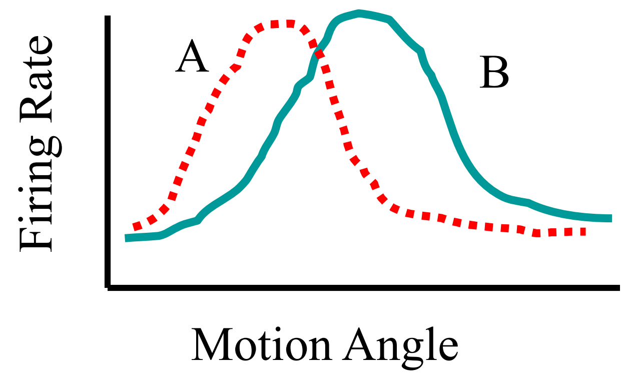
- The cerebellum, which controls a good deal of motor activity, has a feed-forward structure with few backward (i.e., recurrent) connections.
- The cerebrum sends commands to initiate action, which are fed forward from mossy to granule to parallel to Purkinje and out to motor neurons.



Distributed Coding in the Motor Cortex

- Cortical area # 4 = The Motor Cortex (M1)
- Pyramidal cells in M1 get inputs from the cortex & thalamus; they send outputs to motor neurons.
- But pyramidals => motor neurons is an N-N mapping.
- So during any movement, MANY pyramidal and motor neurons are firing. I.e. Movement coding is DISTRIBUTED across the pyramidal cells.





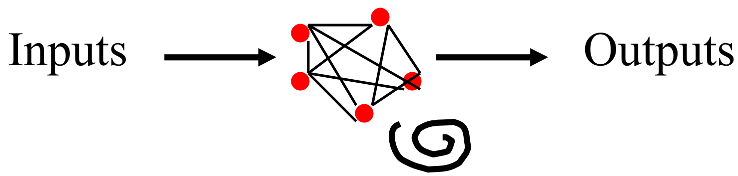
Associative-Memory Networks

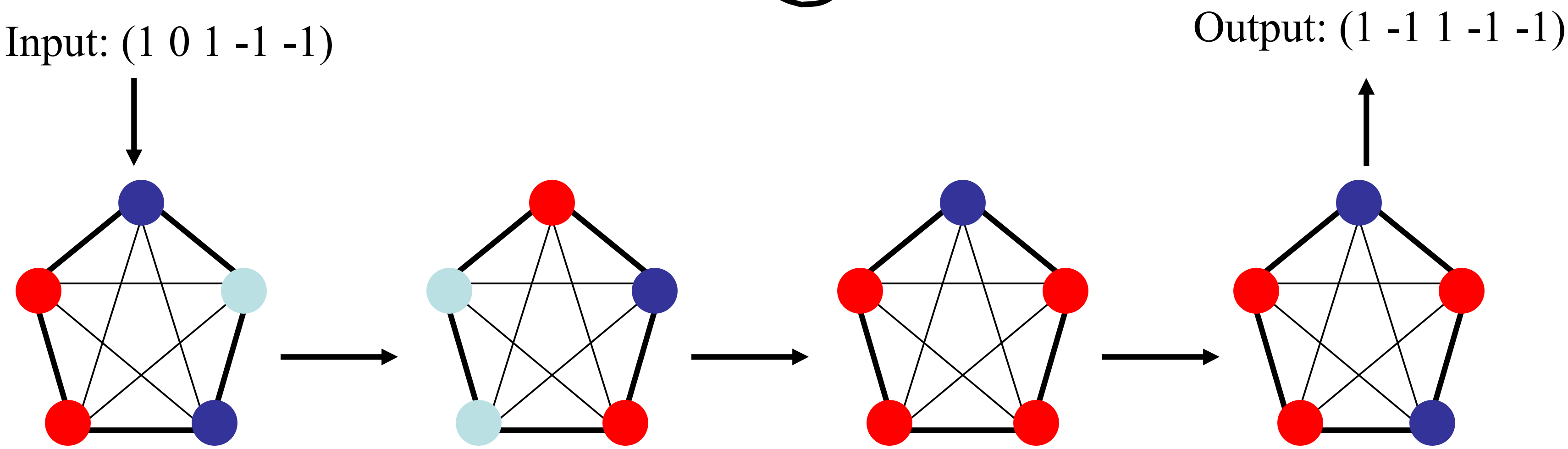
Input: Pattern (often noisy/corrupted)

Output: Corresponding pattern (complete / relatively noise-free)

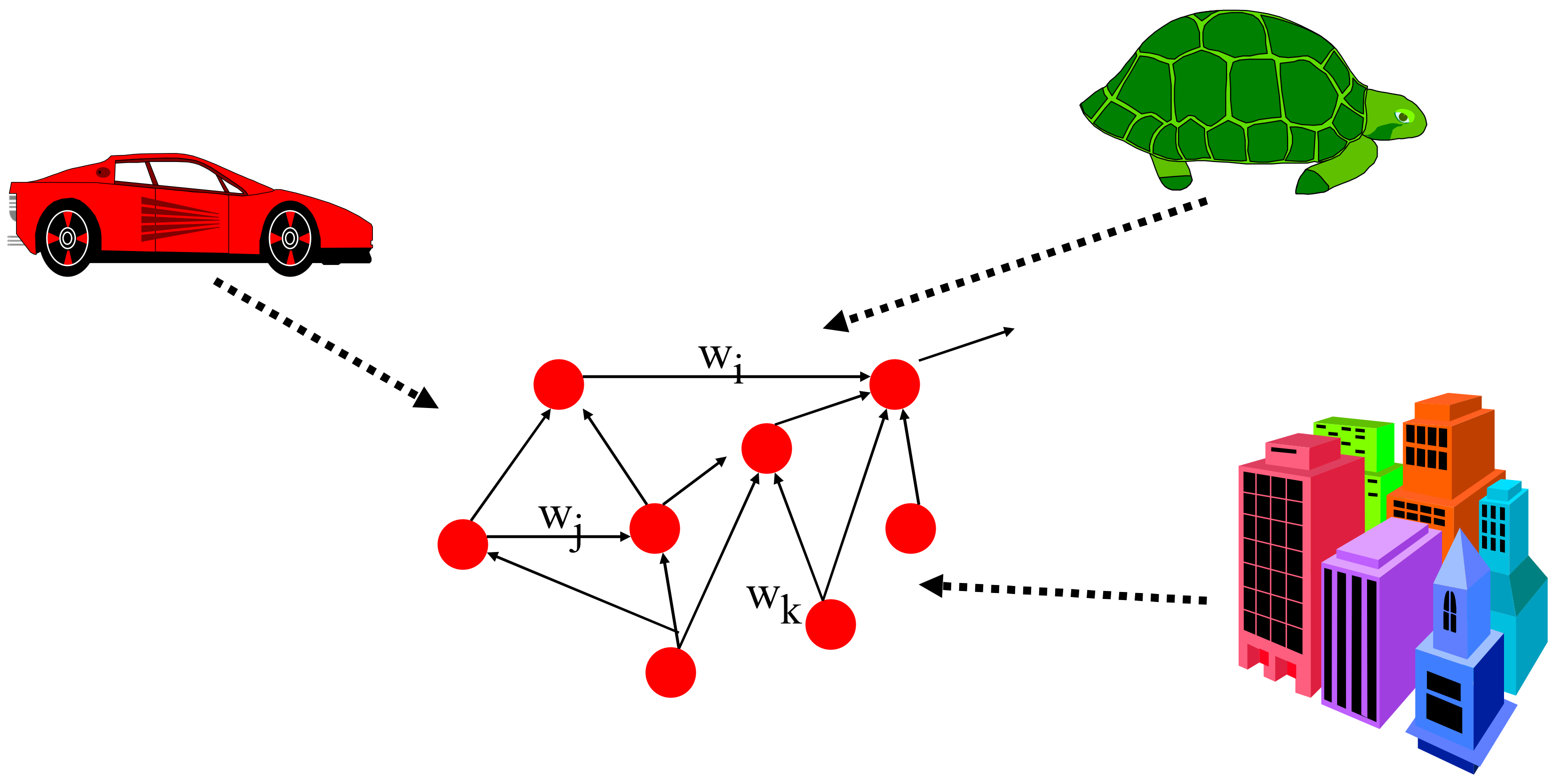
Process

1. Load input pattern onto core group of highly-interconnected neurons.
2. Run core neurons until they reach a steady state.
3. Read output off of the states of the core neurons.





Distributed Information Storage & Processing



Information is stored in the weights with:

- Concepts/Patterns spread over many weights, and nodes.
- Individual weights can hold info for many different concepts

Hebb's Rule

Connection Weights ~ Correlations

``When one cell repeatedly assists in firing another, the axon of the first cell develops synaptic knobs (or enlarges them if they already exist) in contact with the soma of the second cell." (Hebb, 1949)

↓

In an associative neural net, if we compare two pattern components (e.g. pixels) within many patterns and find that they are frequently in:

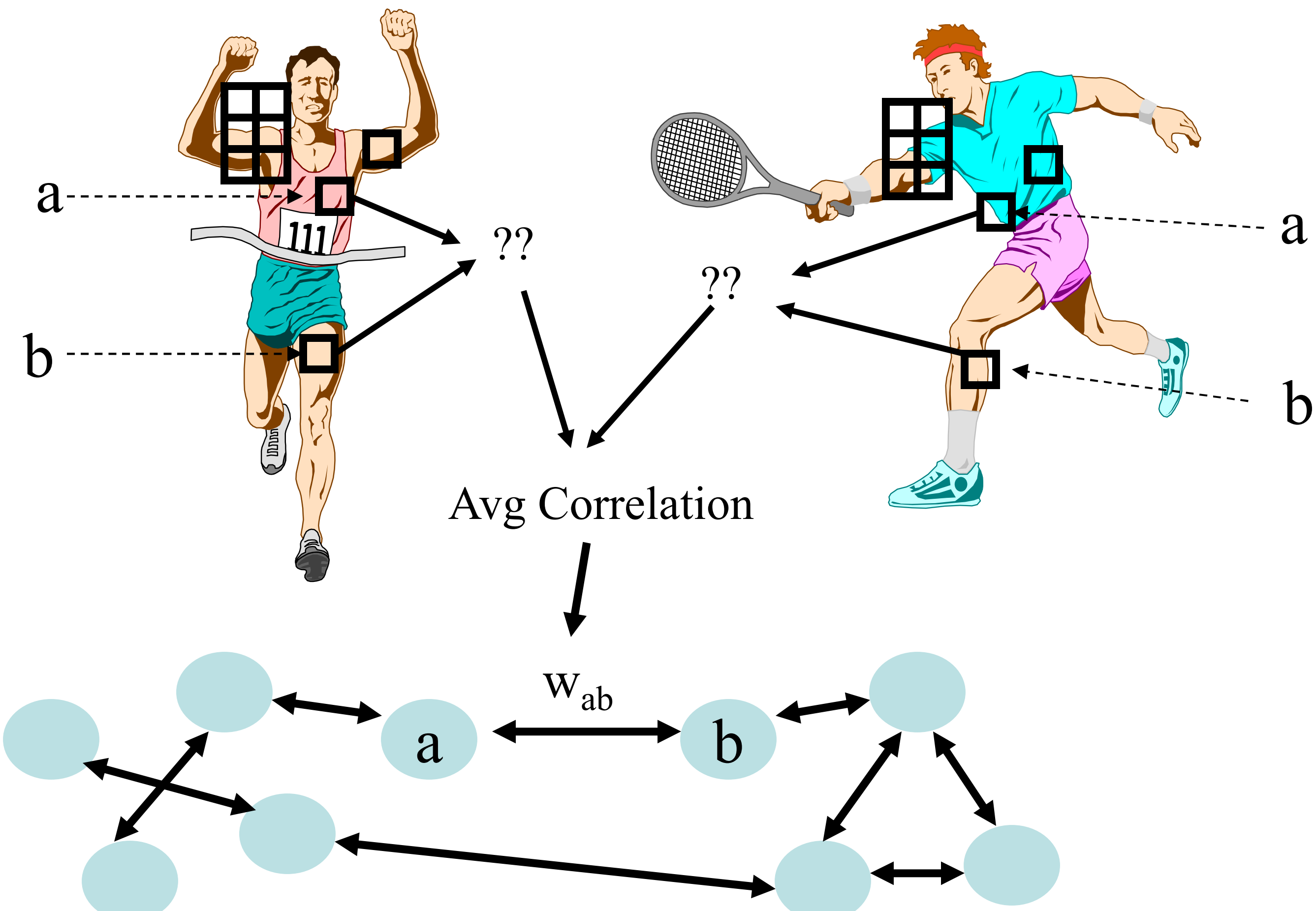
a) the same state, then the arc weight between their NN nodes should be positive
b) different states, then arc weight between their NN nodes should be negative

<u>Matrix Memory:</u>

The weights must store the average correlations between all pattern components across all patterns. A net presented with a partial pattern can then use the correlations to recreate the entire pattern.

Correlated Field Components

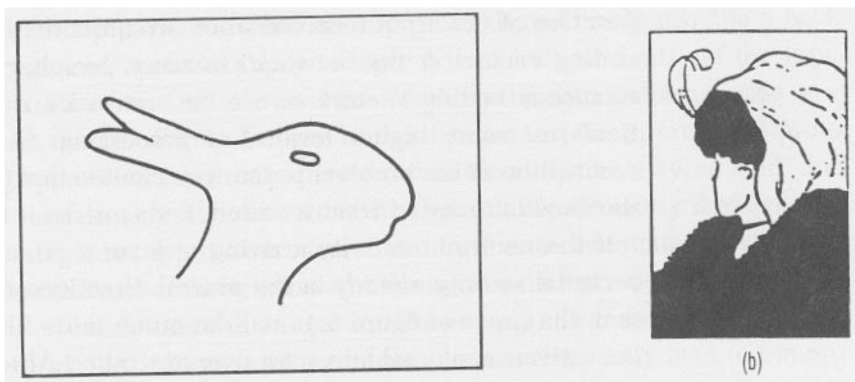
- Each component is a small portion of the pattern field (e.g. a pixel).
- In the associative neural network, each node represents one field component.
- For every pair of components, their values are compared in each of several patterns.
- Set weight on arc between the NN nodes for the 2 components ~ avg correlation.



Hopfield Nets in the Brain

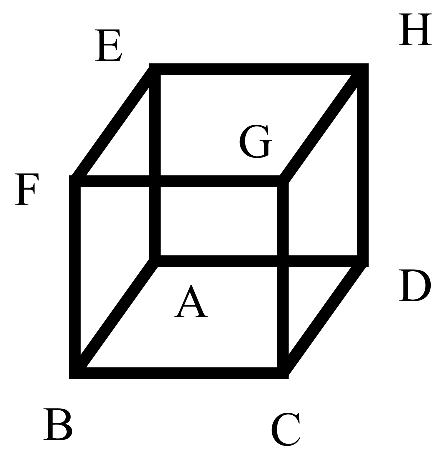
- The cerebral cortex is full of recurrent connections, and there is solid evidence for Hebbian synapse modification there. Hence, the cerebrum is believed to function as an associative memory.

- Flip-flop figures indicate distributed hopfield-type coding, since we cannot hold both perceptions simultaneously (binding problem)

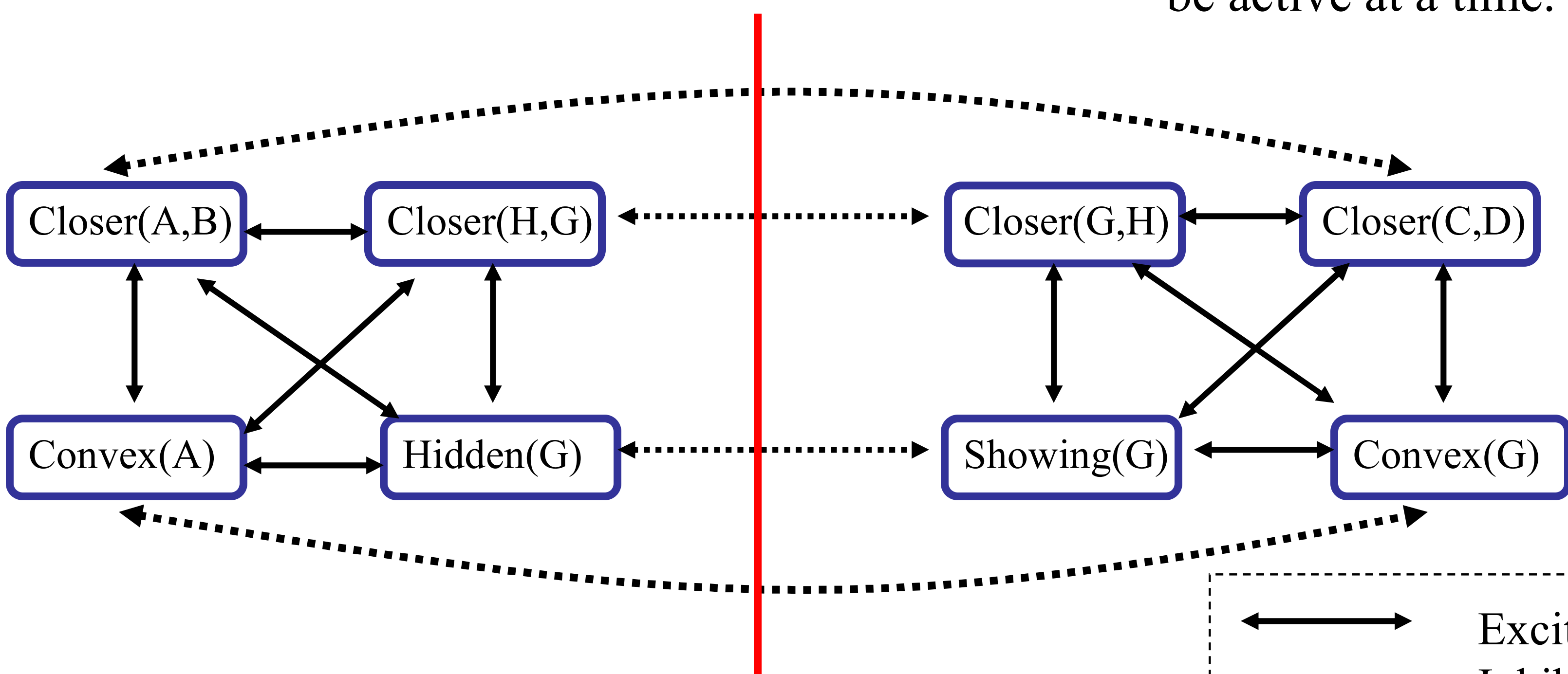


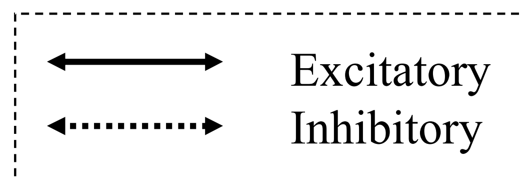
The Necker Cube

Which face is
closer to the viewer?
BCGF or ADHE?



Only one side of the
(neural) network can
be active at a time.

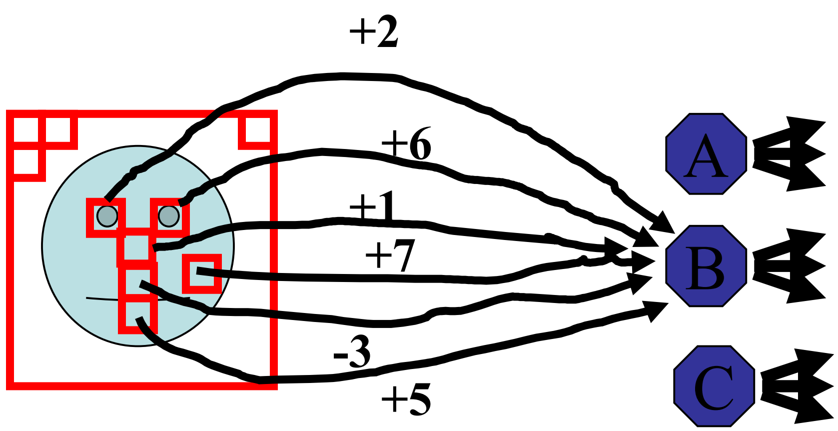


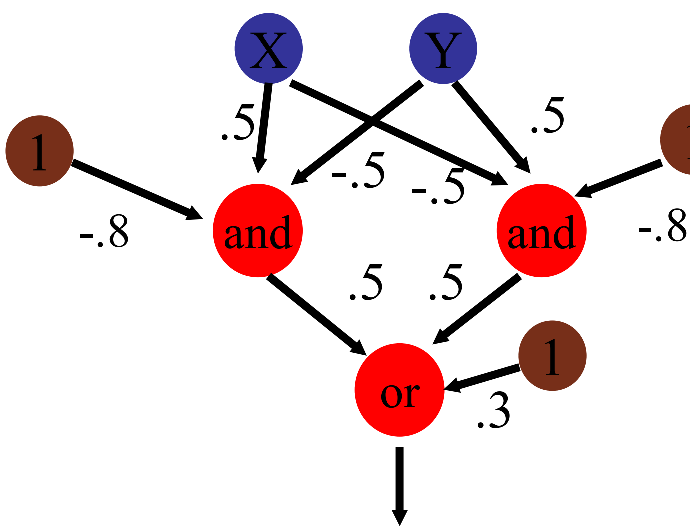


Steven Pinker (1997) “How the Mind Works”, pg. 107.

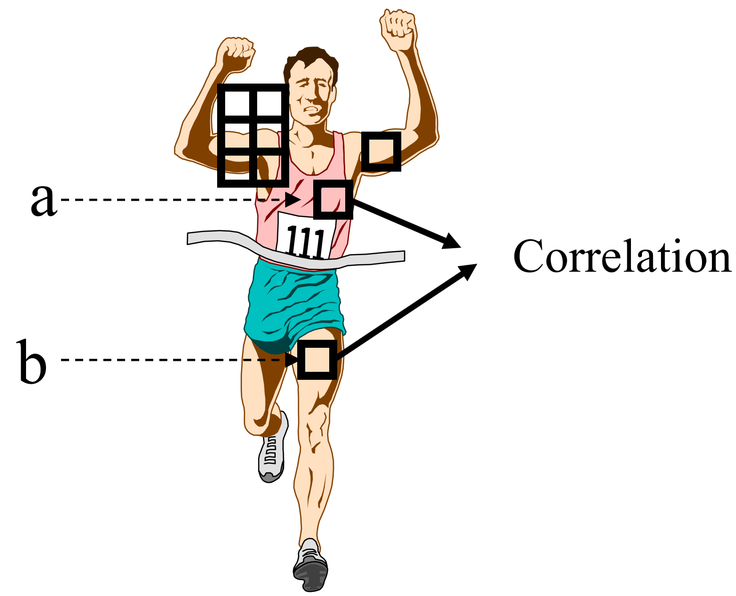
What's in a Link?

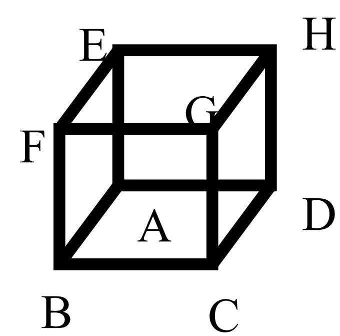
An implicit coding of the preferences that a node has for upstream values.





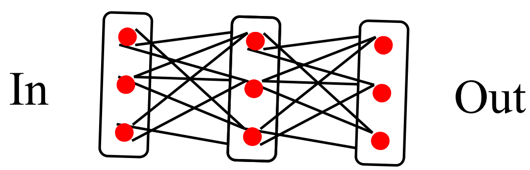
An implicit coding of the correlation between the data elements represented by the two nodes.

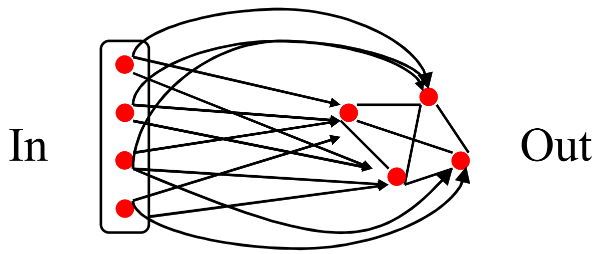




Architectures & Node/Link Semantics

- Feedforward Networks & Competitive Networks
  - Nodes = Semi-local or local coding of low-level and high-level **concepts**
  - Arcs = Preferred upstream values; I.e. preconditions for concept membership. (The inter-layer inhibitory arcs in competitive networks embody the **control** information that only one node can win/fire)





- Hopfield Networks
  - Nodes = Semi-local or distributed coding for elements of the input pattern
  - Arcs = Average correlations (across many patterns) between the input elements represented by the arc's 2 nodes. The inter-layer nodes are just for transferring the inputs to the clique.