

LING5702: Lecture Notes 3

A Model of Neural Activation

Previous lectures described formal models of complex ideas.

The next few lectures will discuss how these can be represented as cued associations in the brain.

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Many psycholinguistic models are defined in terms of neural networks:

- language happens in the brain (brain damage → language damage)
- the brain is composed of neurons
- activation among neurons is associated with linguistic behavior (ERP, FMRI)

3.1 Biology of neural activation

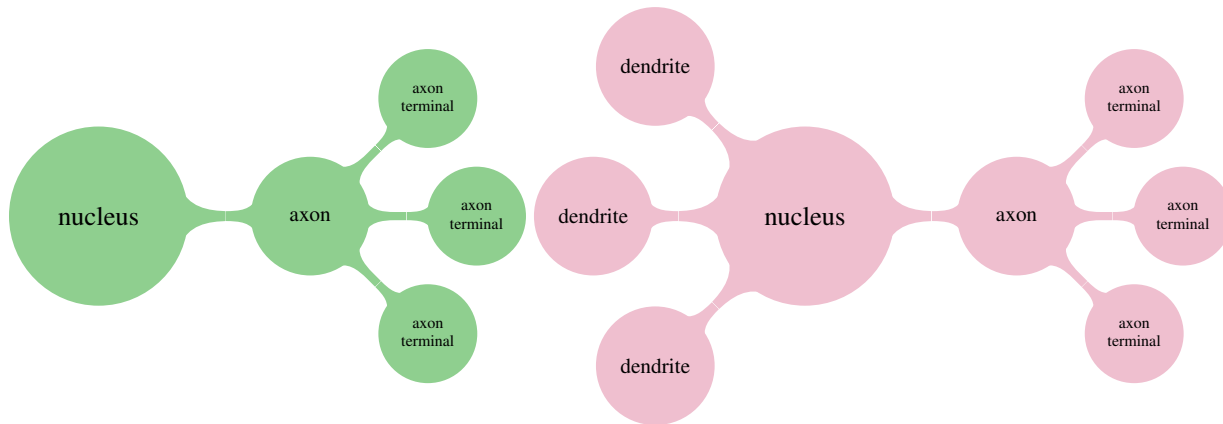
Neurons look like trees, with roots, trunks, and branches. A neuron has:

- **dendrites:** ‘roots’ near other neurons to receive chemical signals
- an **axon:** a ‘trunk’ along which the neuron propagates electric potential
- **axon terminals:** ‘branches’ near other neurons to send chemical signals

It also has:

- **synapses:** gaps betw. terminals and dendrites that permit thresholding
- **neurotransmitters:** chemicals that carry signals across synapses

- **vesicles:** bubbles in axon terminals that contain neurotransmitters
- **receptors:** attachment sites for neurotransmitters on dendrites



Neurons transmit signals or ‘fire’ by suddenly changing electric potential:

1. start with more K^+ but much fewer Na^+ ions than outside, creating **membrane potential**;
2. (**dendrites**) receptors receive neurotransmitters, open **ligand-gated** channels;
3. (**dendrites**) ligand-gated channels let Ca^{++}/Cl^- in or K^+ out, changing potential
(this is a **linear** function on the sum of pos/neg ions in the neuron);
4. (**axon**) if potential changes enough, **voltage-gated** channels come open;
5. (**axon**) voltage-gated channels let in many Na^+/Ca^{++} ions; neuron **depolarizes**
(this is a non-linear **threshold** function on the sum of positive/negative ions in the neuron);
6. (**axon terminals**) depolarization allows **vesicles** to meet surface, release neurotransmitters;
7. depolarization makes voltage-gated channels let out K^+ , **repolarize** cell;
8. ion pumps on surface put back Ca^{++}, Cl^-, Na^+, K^+ , neurotransmitters.

Synaptic connections may be **positive or negative**, e.g.:

1. **pyramidal neurons** may emit neurotransmitters that gate positive ions
2. **interneurons** may emit neurotransmitters that gate negative ions

Synaptic connections also have **weights**:

1. repeated firing removes Mg blockers, so the ‘rest state’ depolarizes a bit
2. fewer Mg blockers increases phosphate, makes receptors more efficient
3. fewer Mg blockers triggers construction of more receptors (to let in more ions)

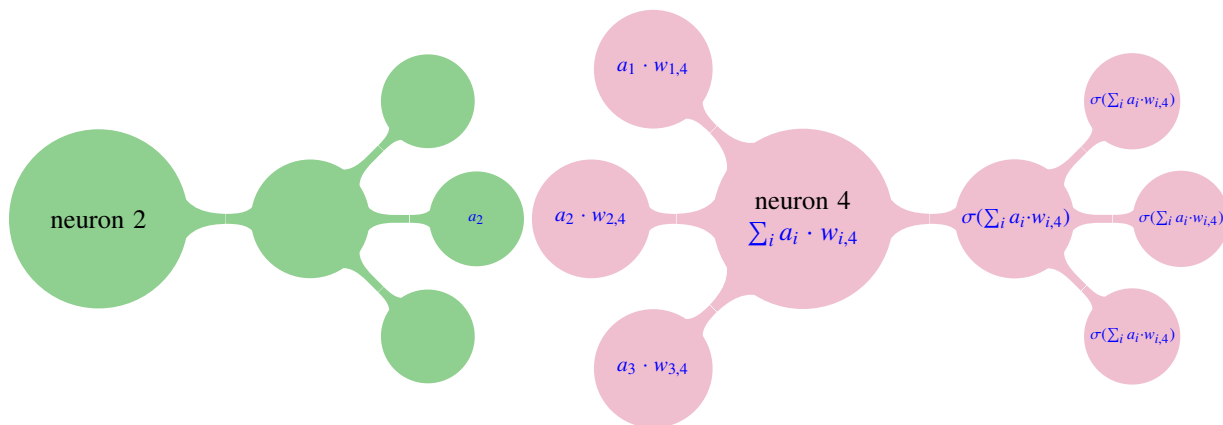
3.2 A simple model of neural activation [Mcculloch & Pitts, 1943]

The **linear function** and **threshold function** can modeled mathematically:

1. a_i, a_j : real-valued activation of artificial neural units i and j
2. $w_{i,j}$: real-valued weight (pos/neg) of connection from unit i to unit j
3. $\sum_i a_i \cdot w_{i,j}$: connection-weighted (**linear**) sum of impinging neural units
4. σ : sigmoid (S-shaped) **threshold** function, e.g. logistic: $\sigma(x) = \frac{1}{1+e^{-x}}$

$$a_j = \sigma \left(\sum_i a_i \cdot w_{i,j} \right)$$

For example, if **neuron 2** impinges on **neuron 4** (neurons 1 and 3 not shown):



Individual neurons don't have real-valued activation; they fire all-or-none if they reach threshold.

Neural models like this may therefore be more similar to **clusters** of neurons.

Neurons in the cortex seem to be organized into columnar clusters:

- neurons in the same cluster seem to fire together
- clusters may have real-valued (or at least graded) activation

3.3 Distributed representation of concepts/referents [Horton & Adams, 2005]

Do individual clusters correspond to concepts/referents ('localist' model)? Inconsistent w. plasticity.

Activation for concepts/referents may be instead **distributed** over clusters

- **mental states** for concepts or referents are characterized by patterns of activation, e.g.:

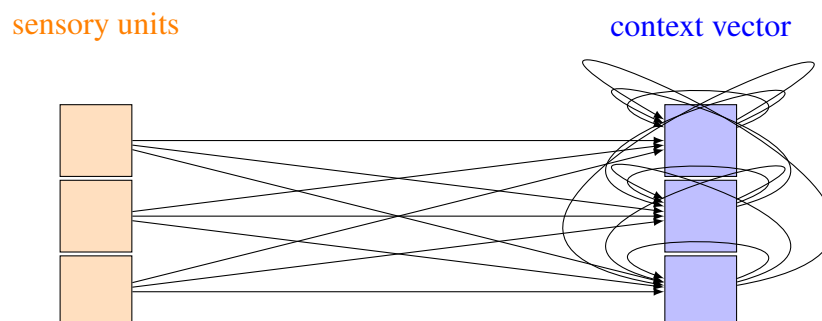
'airplane'	'celery'	'my house'	
.0	.0	.58	← neuron/cluster closest to center of motor cortex
.58	.50	.0	← neuron/cluster second closest to center of motor cortex
.0	.50	.58	← neuron/cluster third closest to center of motor cortex
.58	.0	.0	⋮
.0	.50	.0	← neuron/cluster closest to center of auditory cortex
.58	.0	.58	← neuron/cluster second closest to center of auditory cortex
.0	.50	.0	⋮

- maybe 20,000 clusters in human cortex: 20,000-dimensional space; room for many ideas!
(in contrast, physical space has only 3 dimensions: $L \times W \times H$, color space has 3: $R \times G \times B$)
- mental states for concepts are locations/regions/coordinates in this space ('vector-space')
- there's no actual limit on the number of states/concepts/referents, just potential for confusability
- if sparsely encoded (many units inactive), we can have mixture states of several referents at once!

3.4 Models of activation over time [Elman, 1991]

Over time (e.g. during sentence processing), the activation of neurons/clusters changes.

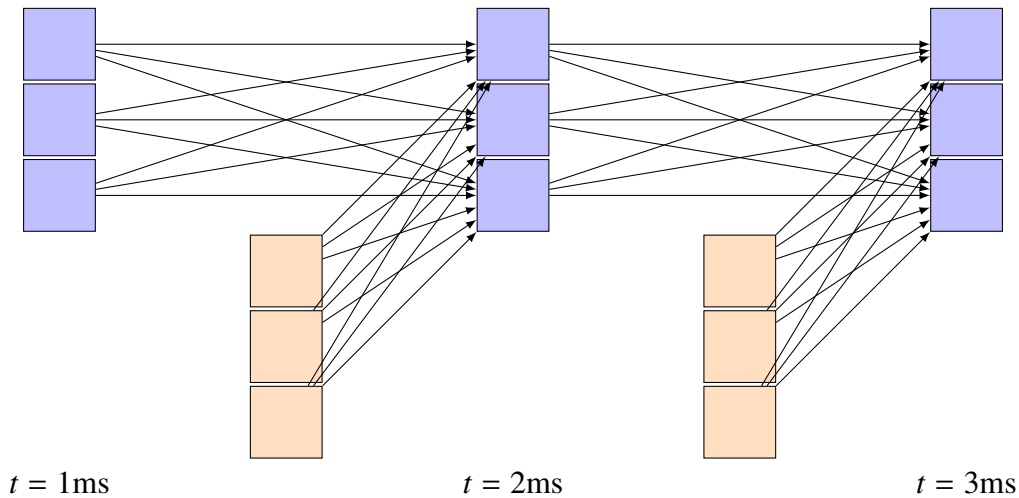
These changes can be modeled with **Recurrent Neural Networks**:



- the model is defined in terms of a 'context' vector of neural units, as shown above;
- activation of the context vector defines a mental state, as noted above;
- the context vector is connected to sensory units (observations);

- the **context vector** is also connected to *itself* at previous time step, forming a **circuit**;
- the model learns to **transition** between states by associating each previous and current state (these associations are determined by synaptic weights, as we'll see later);
- the learned transitions define a sequence of mental states for any sequence of observations.

Here's what it looks like unrolled through time:



We will assume this kind of transition model, with transitions defined by synaptic weights.

Experiments with these models have shown learning of syntax:

- word order predictions
- number agreement

3.5 Mental states composed of features [Howard & Kahana, 2002]

Mental states for concepts are distributed over the cortex in different brain areas:

- visual cortex (posterior)
- auditory cortex (medial, bilateral)
- motor cortex (medial, dorsal)

Mental states therefore have various **features**: visual, auditory, proprioceptive, ...

- features may be encoded by several neuron or cluster units (boxes in the vectors)

Working memory may be modeled with **temporal features**:

- temporal feature values change over time
- recurrent learning builds associations between present and past contexts

- recent past events easily cued from current temporal features (STM)
- distant past events cued not so easily, need other features (LTM)

References

- [Elman, 1991] Elman, J. L. (1991). Distributed representations, simple recurrent networks, and grammatical structure. *Machine Learning*, 7, 195–225.
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