Human Categorization

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"Classical" View (e.g., Aristotle)

Concepts are combinations of features, or "definitions".

Features are **necessary** and **sufficient**

- Necessary: if category, then features
- Sufficient: if features, then category

e.g.,

- *If car, then steering wheel, seats and an engine*
- *If X has a steering wheel, seats, and an engine, it is a car*

Classical View: Limitations (1)

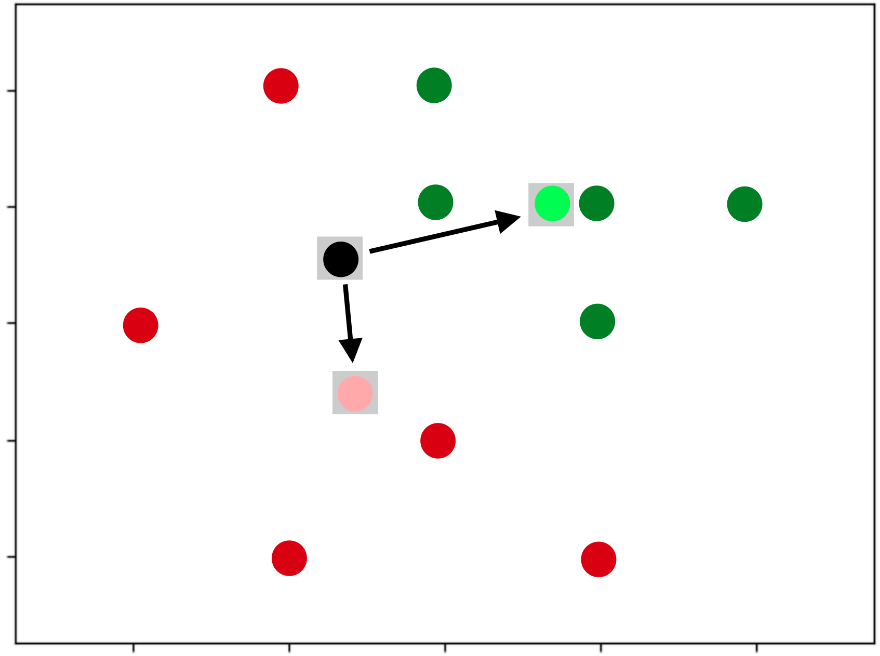
- Graded typicality (Rosch & Mervis, 1975).

e.g.,  vs. 

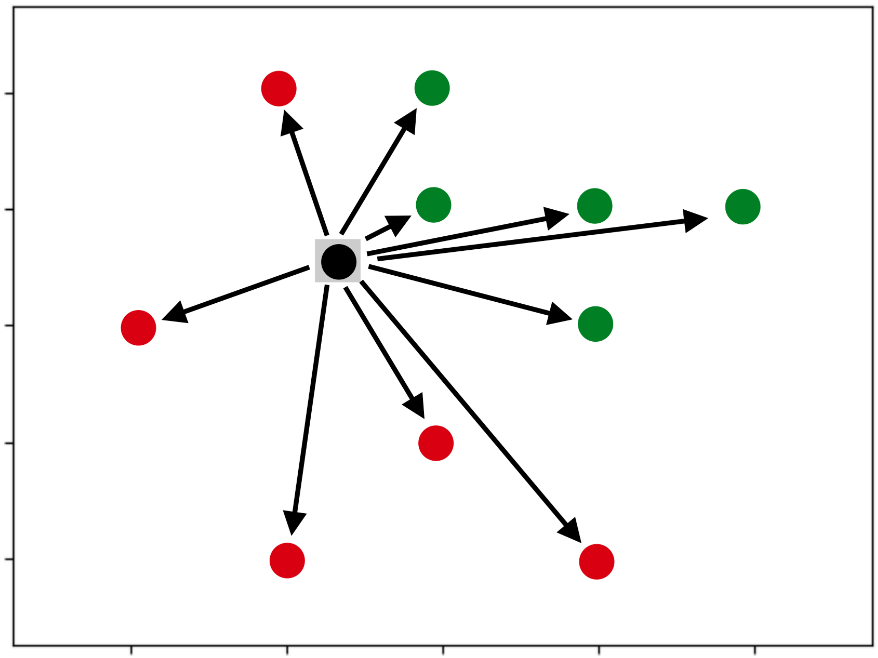
Classical View: Limitations (2)

- McCloskey & Glucksberg, 1978: Many categories change across time, and differ between participants
- Uncertainty. e.g., 
- Some concepts/categories don't have clear features or definitions
    - e.g, "just" vs. "unjust"

Prototype Theory (e.g., Reed, 1972)



Exemplar Theory (e.g., Nosofsky, 1986)



Psychological Distance

During object **identification**, individual objects must be differentiated, and all features are relevant.

- **Exemplar**: The distance, d, between object i and j:

$$d_{ij} = \sum_{k} |x_{ik} - x_{jk}|$$

- **Prototype***: The distance, d, between object i and prototype A:

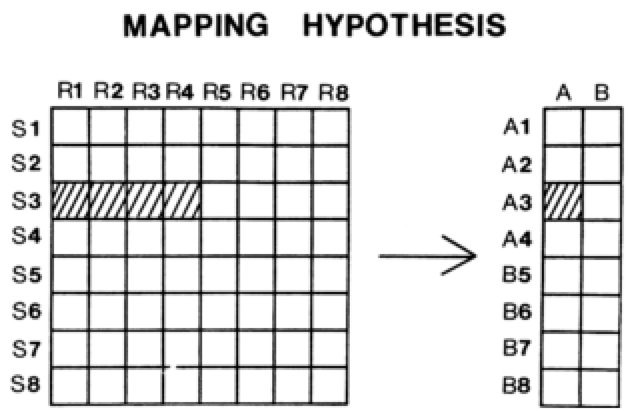
$$d_{iA} = \sum_{k} |x_{ik} - x_{Ak}|,$$

where k : dimension

* For comparison, throughout, we assume Multipicative Prototype Model...

The "Mapping" Hypothesis

Human categorization is closely related to identification. It should be possible to predict categorization accuracy from identification confusions.

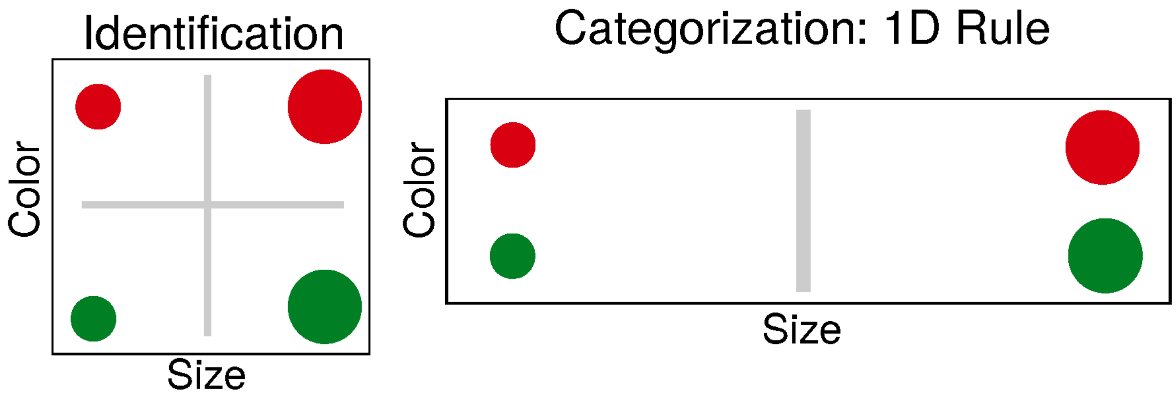


Shepard (1961): mapping does not explain categorization.

- Categorization involves abstraction and/or attention

fig: Nosofsky, 1986.

Attention "Warps" Psychological Space



... increasing the ratio of within- to between-category similarity.

Psychological Distance: Categorization

Much flexibility in human categorization can be modeled by including attentional parameters, w:

e.g., in the Generalized Context Model (an exemplar model; Nosofsky, 1986):

$$d_{ij} = \sum_k w_k |x_{ik} - x_{jk}|,$$

Integral vs. Separable Dimensions

Garner (1976): Can dimensions be ignored?

- **Separable**: reaction time same for 2D stimuli with 1D rule, and 1D stim with 1D rule. E.g., [red square and red circle vs. green square and green circle] vs. [red square vs. green square]
- **Integral**: Dimensions interact. E.g., when categorizing 2D auditory stim based on 1D "frequency" rule:
  - Faster RT* when intensity is positively correlated with frequency
  - Slower RT* when intensity is orthogonal to frequency

* relative to a 1D rule with 1D stimuli (e.g., intensity held constant).

The Minkowski r Metric

Using the Minkowski distance metric, the r parameter allows us to use **Euclidean** (r=2) or **City Block** (r=1) distance measures, which are appropriate for **integral** vs. **separable** dimension stimuli:

$$d_{ij} = \left(\sum_k w_k |x_{ik} - x_{jk}|^r \right)^{1/r}$$

Similarity

Similarity is an exponential function of distance, and is influenced by the sensitivity parameter, c.

$$s_{ij} = d^{-cd_{ij}}$$

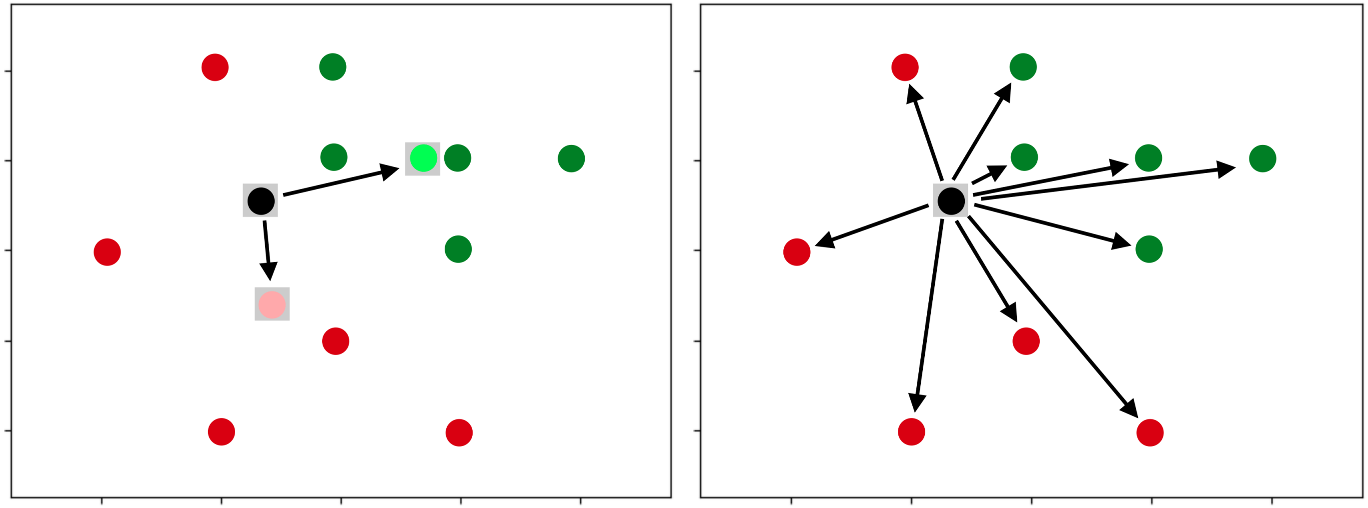
- when c is high, insensitive to w
- when c is low, w more influential

Choice (Luce, 1963; Shepard, 1957)

The probability of choosing category A, given stimulus, i, is given by the choice rule :

$$P(A|i) = \frac{\sum_{a \in A} s_{ia}}{\sum_{a \in A} s_{ia} + \sum_{b \in B} s_{ib}}$$

Prototypes vs. Exemplars



The 5/4 Category Structure

The 5–4 Category Structure

Stimulus	Dimension diagnosticity: High 1	Low	High 2	Medium
Category A items				
A1	1	1	1	0
A2	1	0	1	0
A3	1	0	1	1
A4	1	1	0	1
A5	0	1	1	1
Category B items				
B1	1	1	0	0
B2	0	1	1	0
B3	0	0	0	1
B4	0	0	0	0

Prototype predicts A1 easier to learn

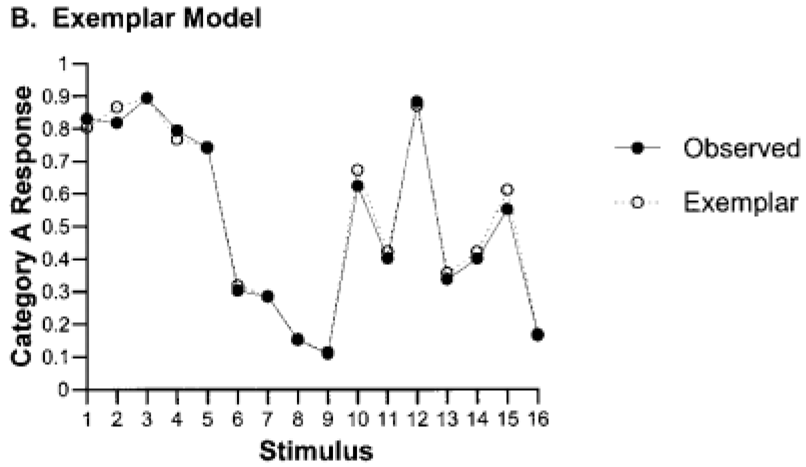
- A1 shares 3 features with the A prototype (0000 is most common on each D) but only one with the B prototype (1111)

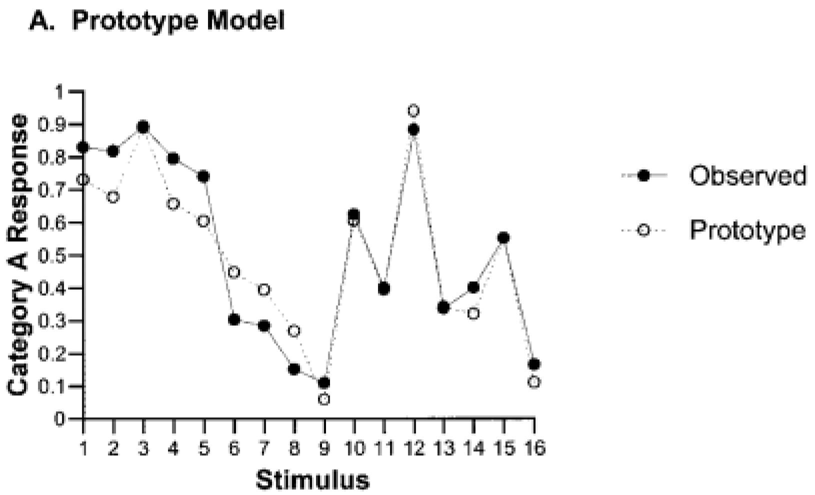
Exemplar predicts A2 easier to learn

-A2 shares 3 features with 2 A members (A1 and A3) and less than or equal to 2 with any B member.

-Inconsistent experimental results...

Model Comparison

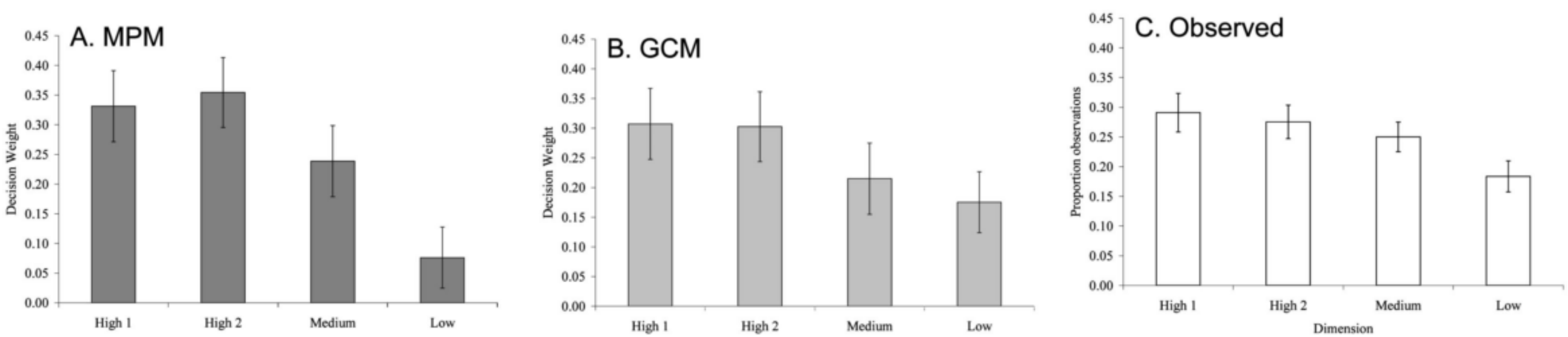




Smith & Minda (2000): Exemplar models typically provide a better fit to choice data than prototype models, particularly on trained items (stim 1-9)

Eye Tracking

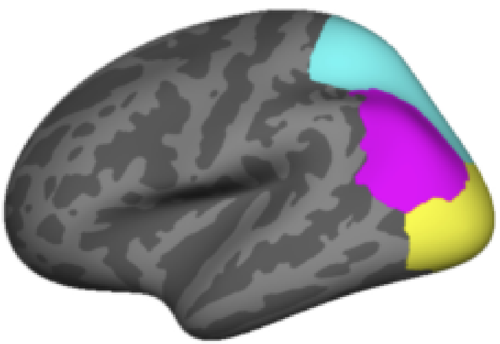
Smith Minda (2000): GCM posits suboptimal attention weights (i.e., attention to uninformative dimensions)

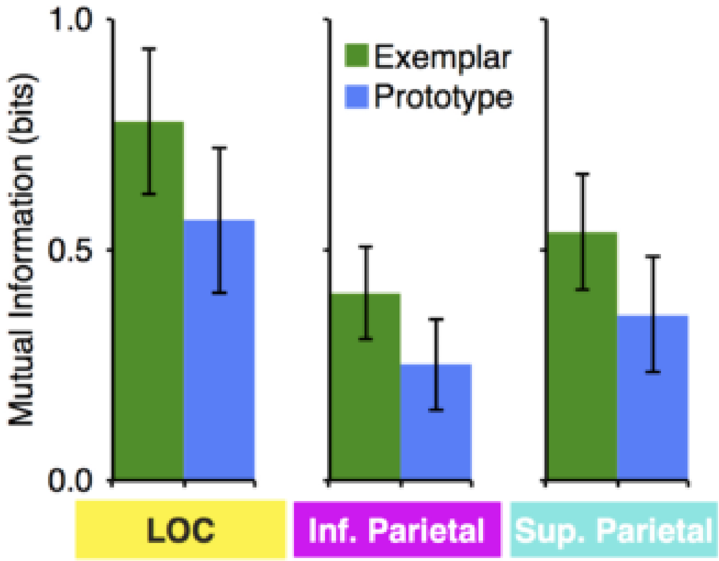


Rehder & Hoffman, (2005): Eye fixation data more closely matched predictions of GCM

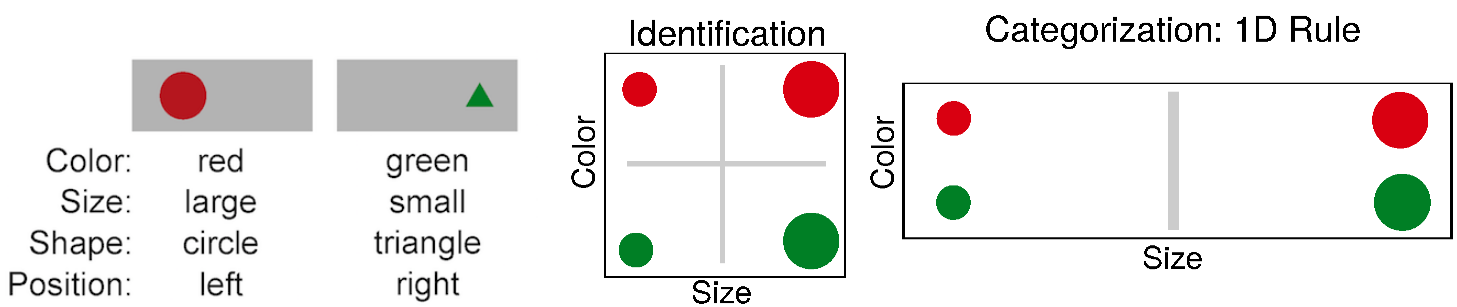
FMRI

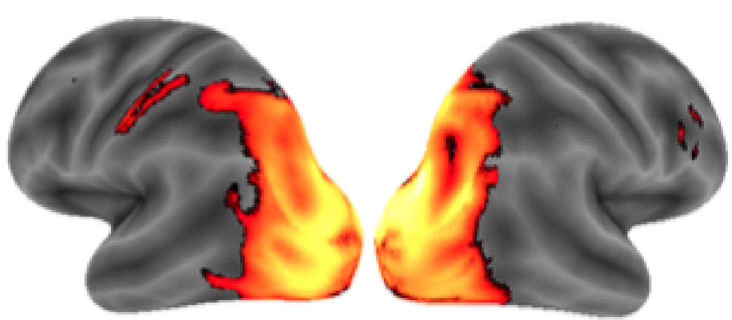
Mack et al. (2013): Neural stimulus representations were more consistent with exemplar model than prototype model.

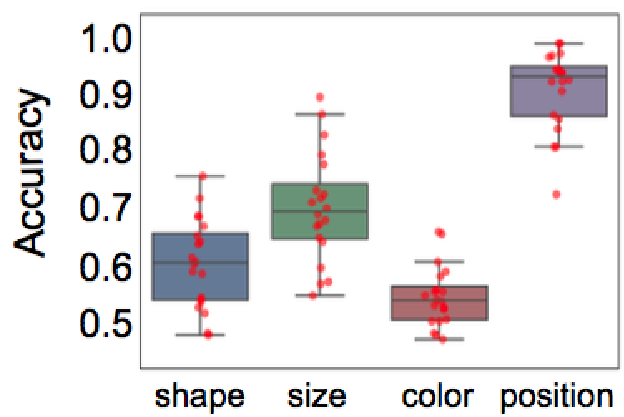




Braunlich & Love, (in prep.): Discriminablity of neural feature representations covary with individual differences in attentional parameters. Better match for GCM than MPM.







Flexible Clustering

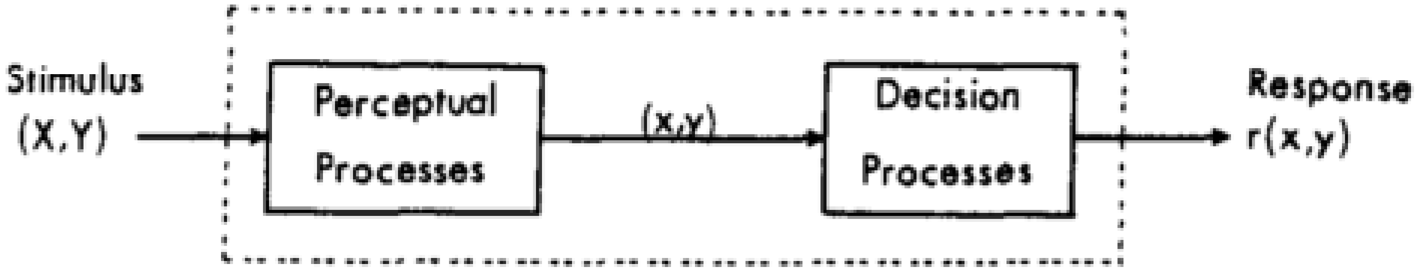
Anderson (1991: Rational Model of Categorization

Love & Gureckis (2004): SUSTAIN

- Based on structure in external world, and our experiences with it, we can flexibly learn intermediate category representations.

Rules

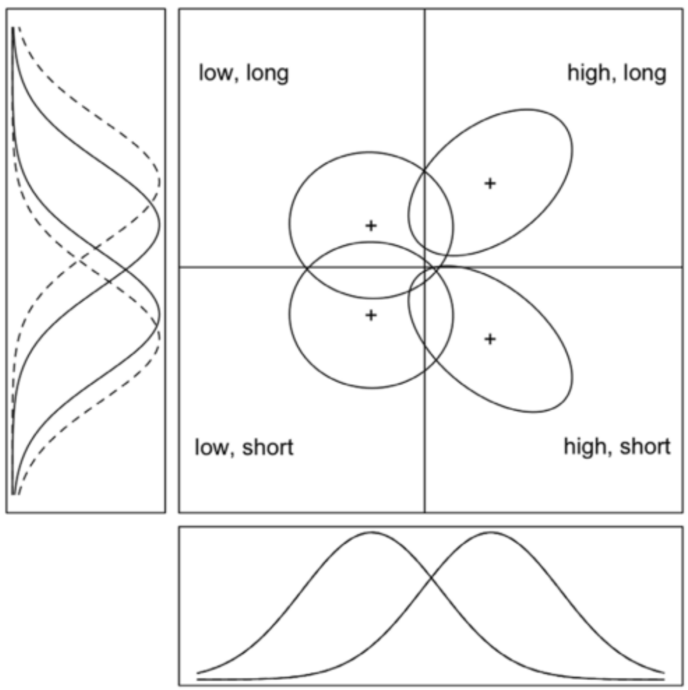
Ashby & Townsend (1986): General Recognition Theory



- Noise in percesption/identification: stimuli are represented as multivariate distributions. If multivariate normal, then GRT is a multivariate extension of Signal Detection Theory.
- Noise in decision-boundary: "criterial noise"

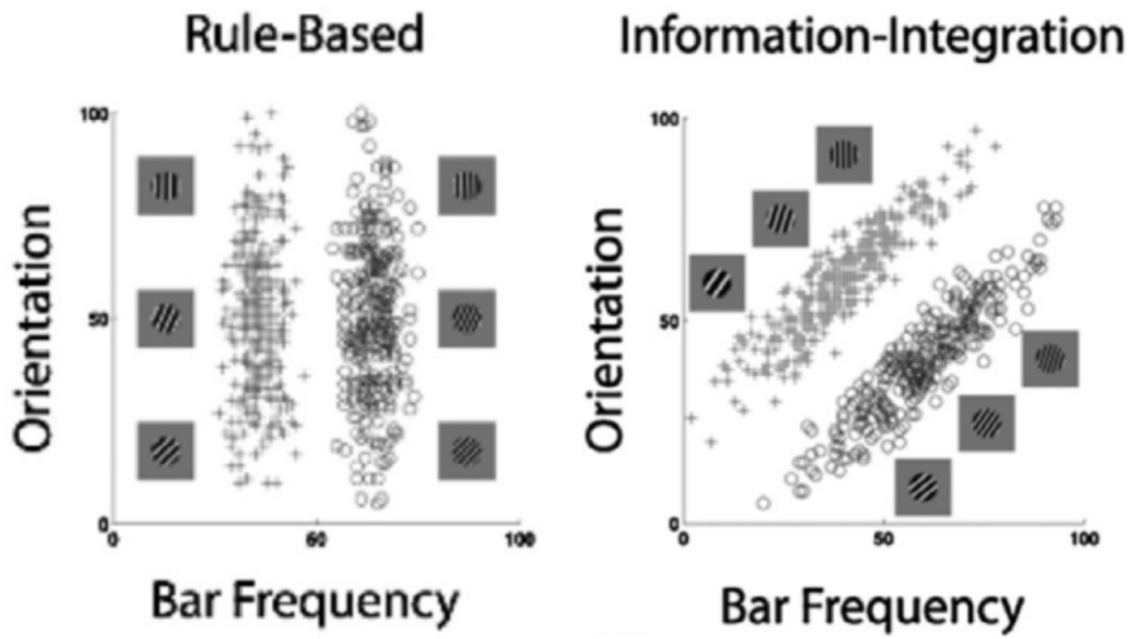
Ashby & Townsend (1986): General Recognition Theory

Decision bounds (straight lines) parcellate perceptual space into response regions:



Multiple-Process Models (1)

Ashby et al. (1998): COVIS (Competition between verbal and implicit systems



RB: fast learning, strong generalization

II: slow, reward-dependent learning, poor generalization

Multiple-Process Models (2)

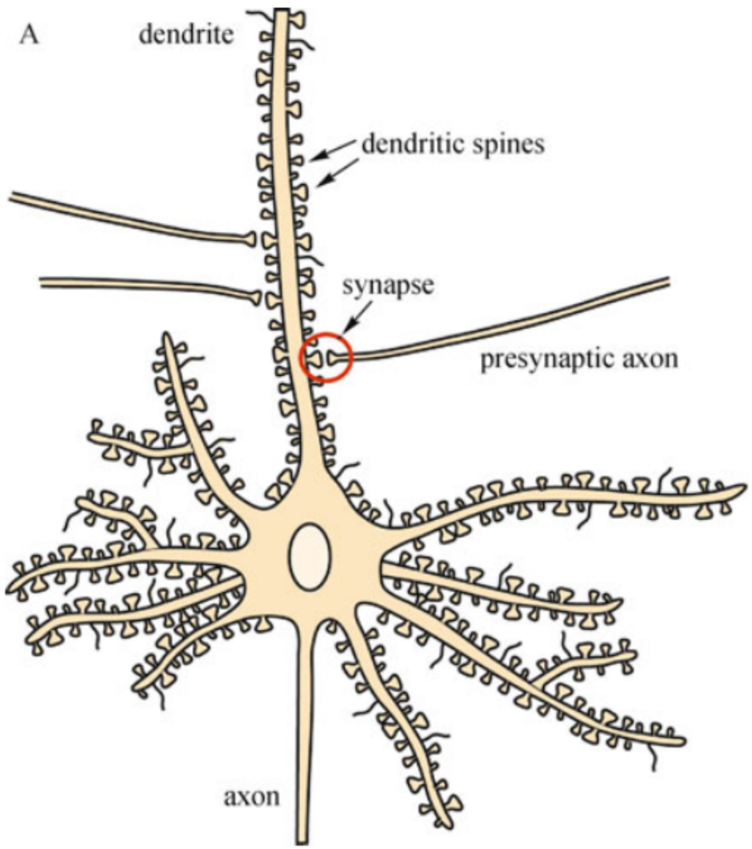
Nosofsky et. al. (1994): RULEX: Rule + Exception

- People learn simple rules and specific exceptions.
- Very good fits to learning data

Summary

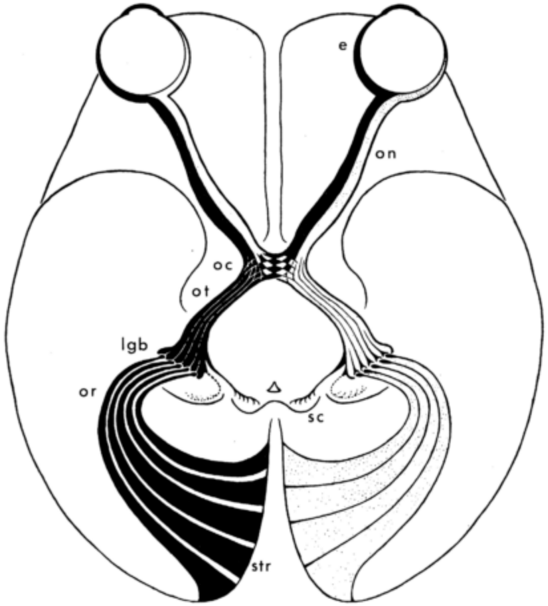
- Low number of stimuli, high reps favor exemplars
- Initial learning characterized by hypothesis testing over simple rules
- High number of reps/ high number of stimuli, might facilitate direct stimulus ➡️ response associations (e.g., Information-Integration Structure)

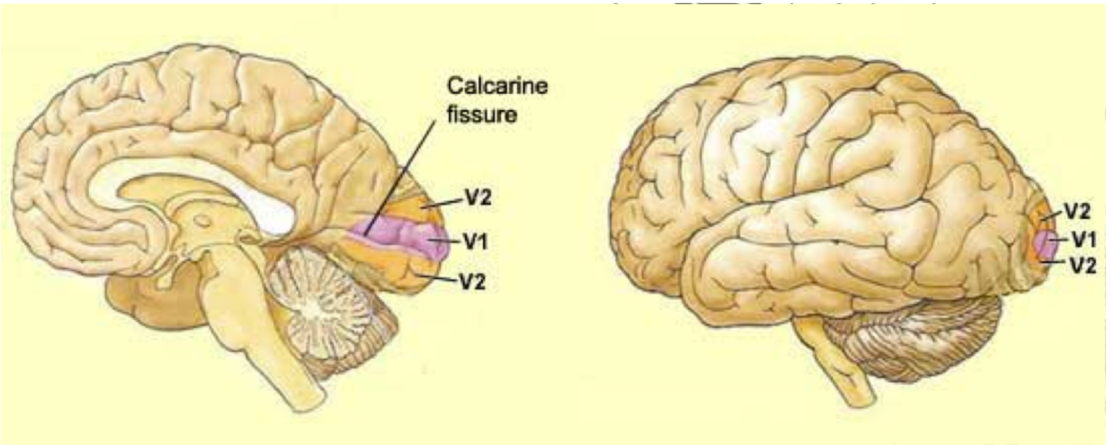
The Neuron



Smrt, R. D., & Zhao, X. (2010). Epigenetic regulation of neuronal dendrite and dendritic spine development. Frontiers of Biology in China, 5(4), 304–323.

From Eyes to Cortex:





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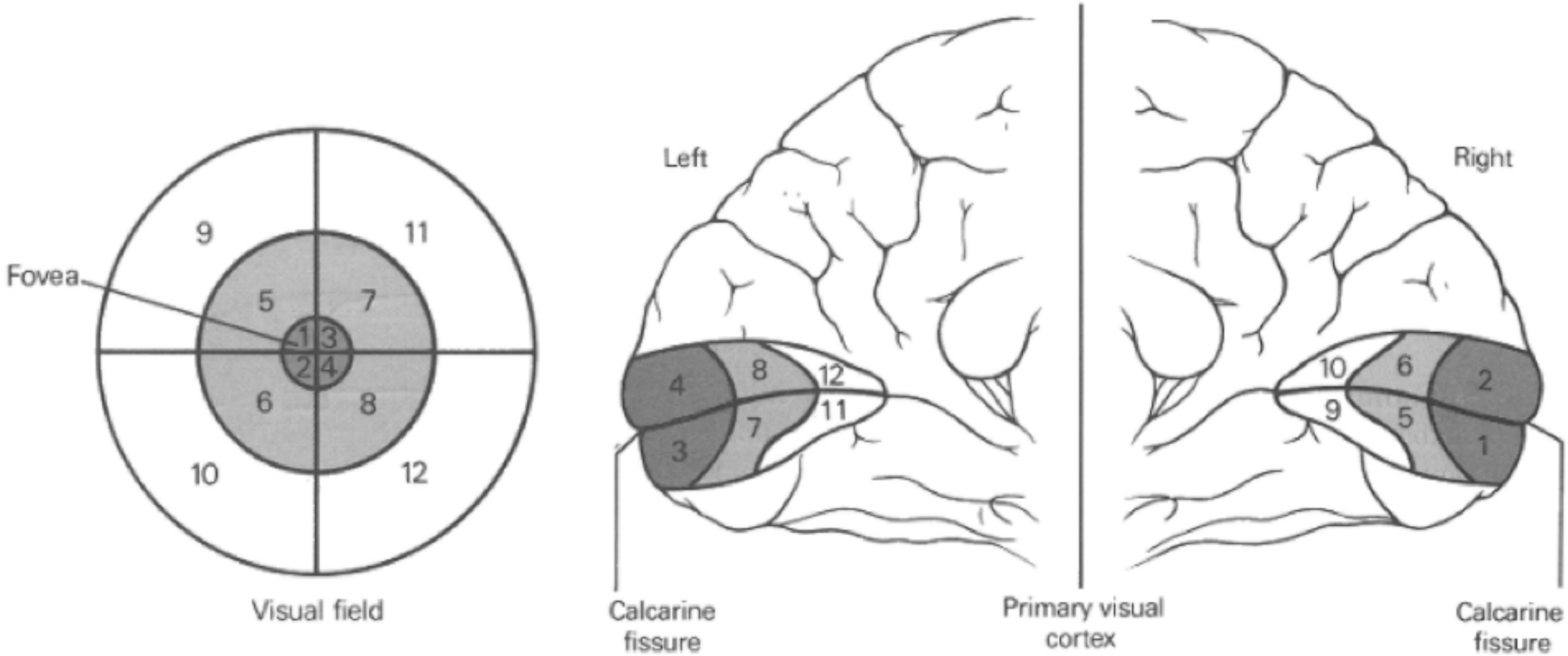
Retinotopic Mapping in V1



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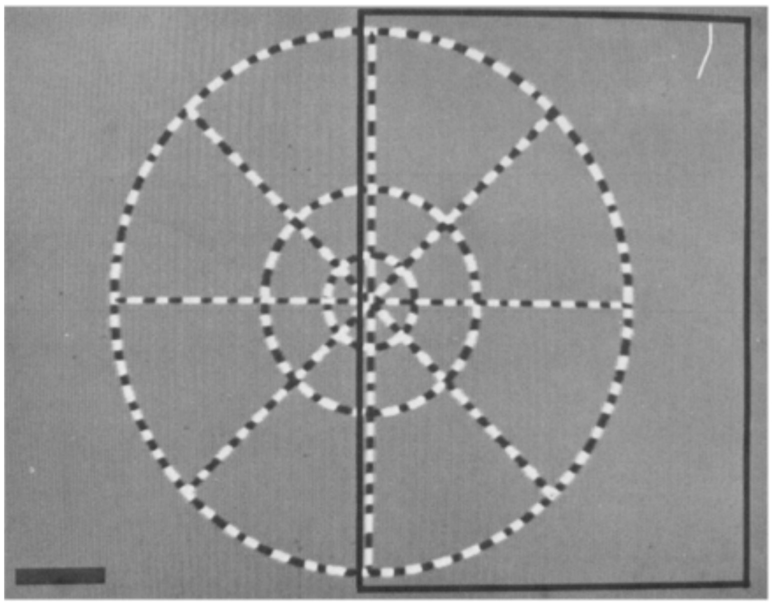
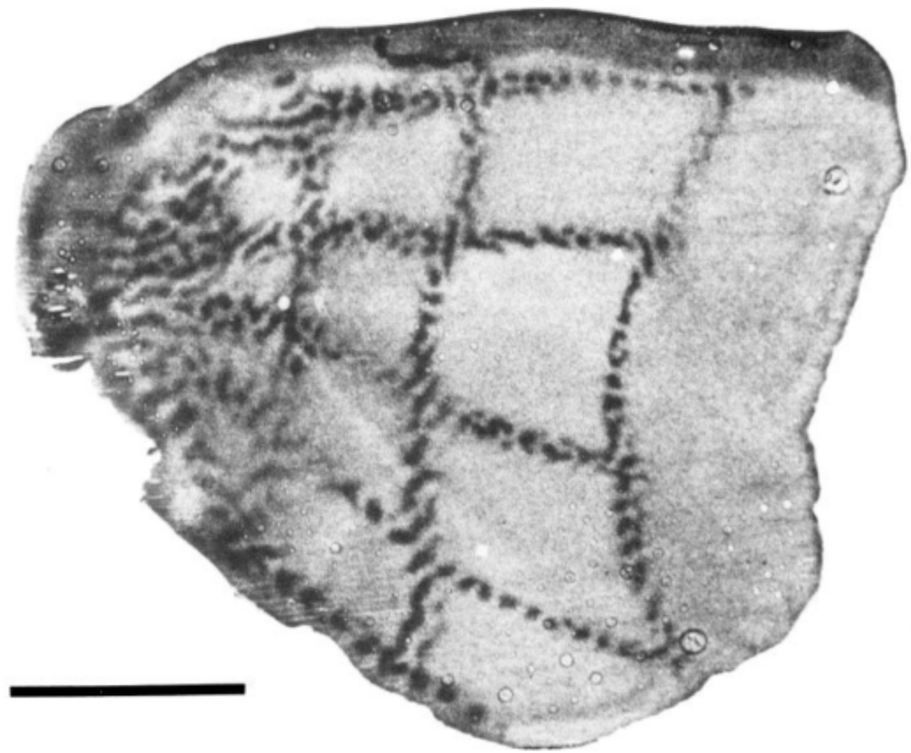
Retinotopic Mapping in V1





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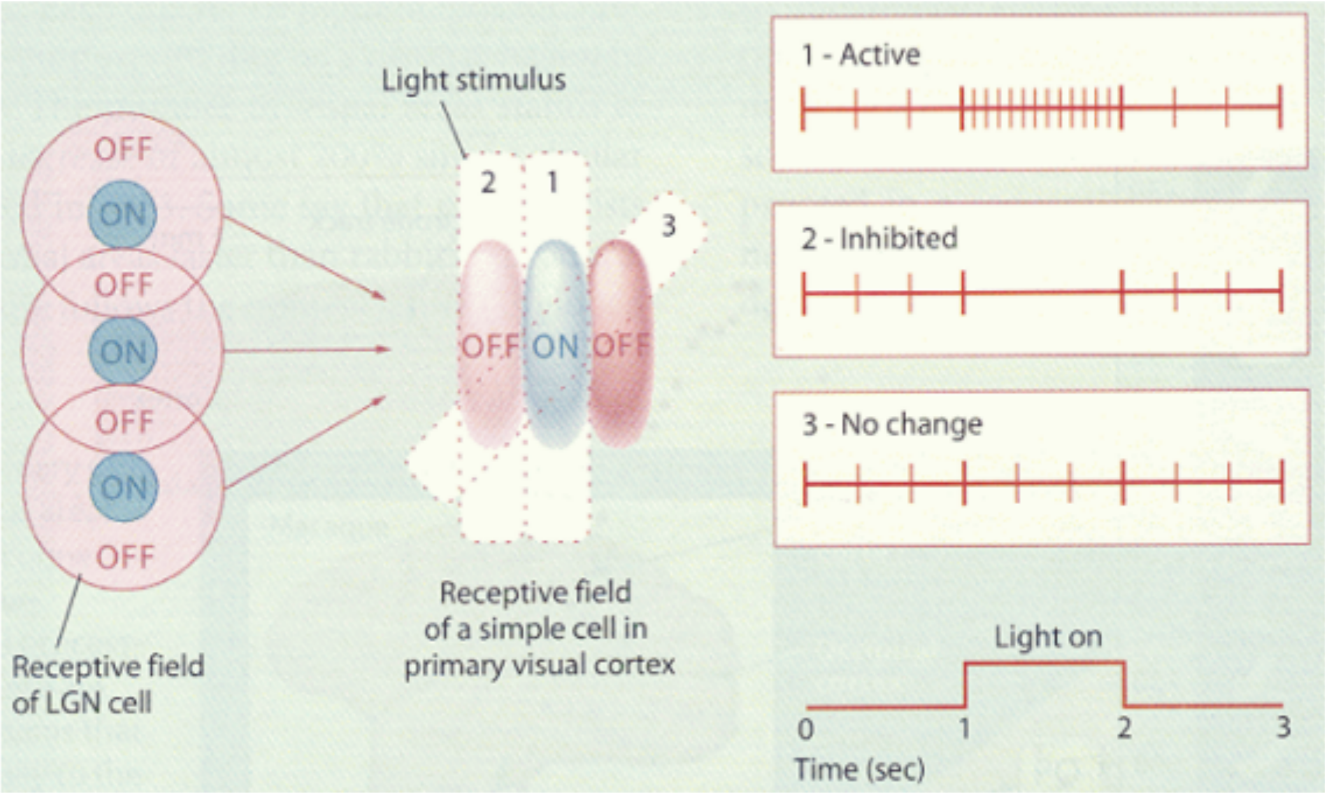
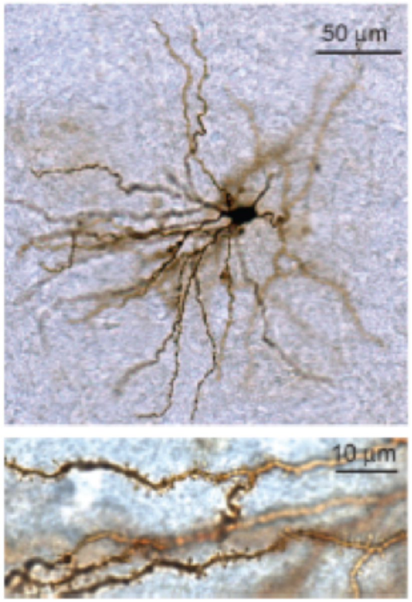
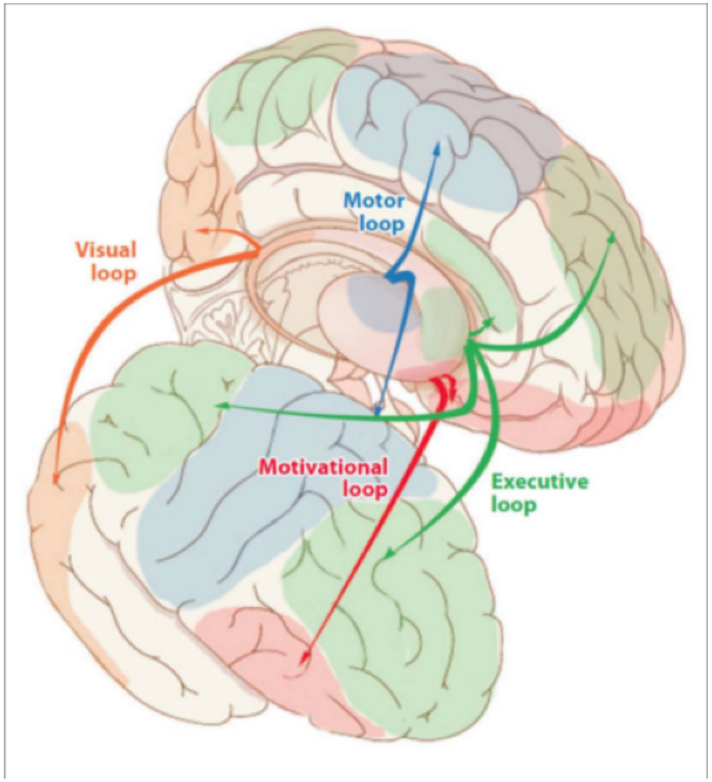
Hierarchical Structure

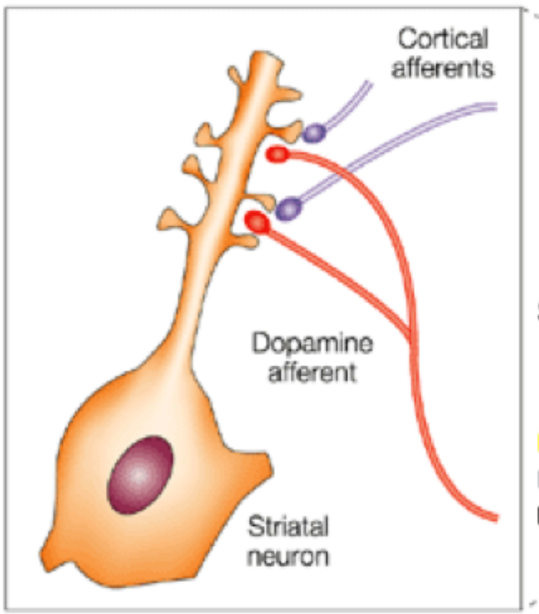


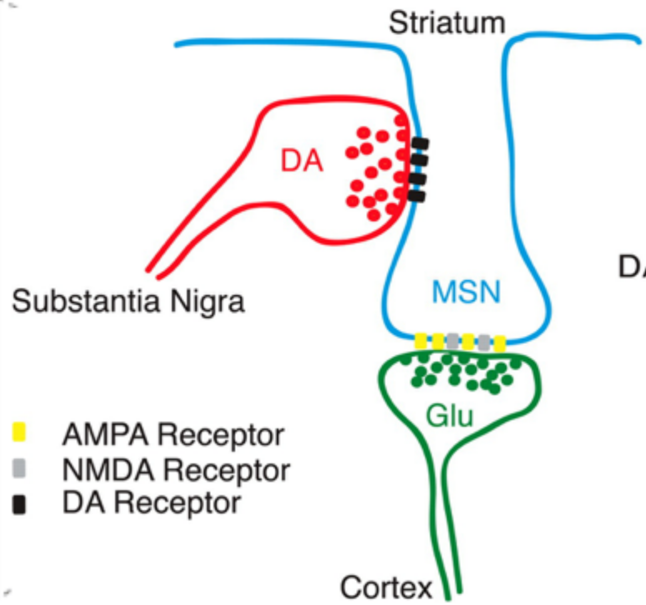
Corticostriatal Loops

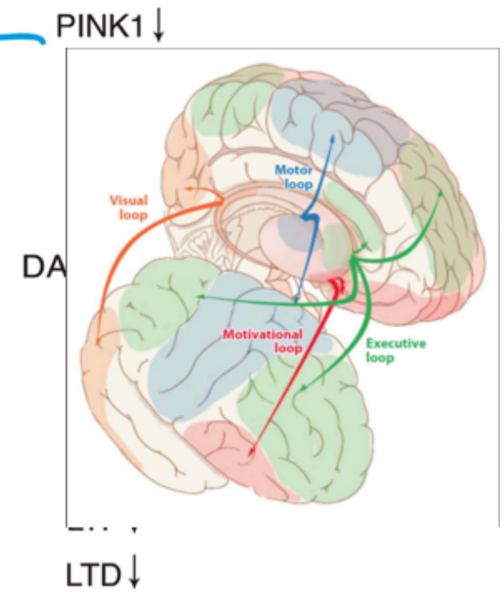




3-Factor Hebbian Learning







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