

Pattern Separation and Completion in the Hippocampus

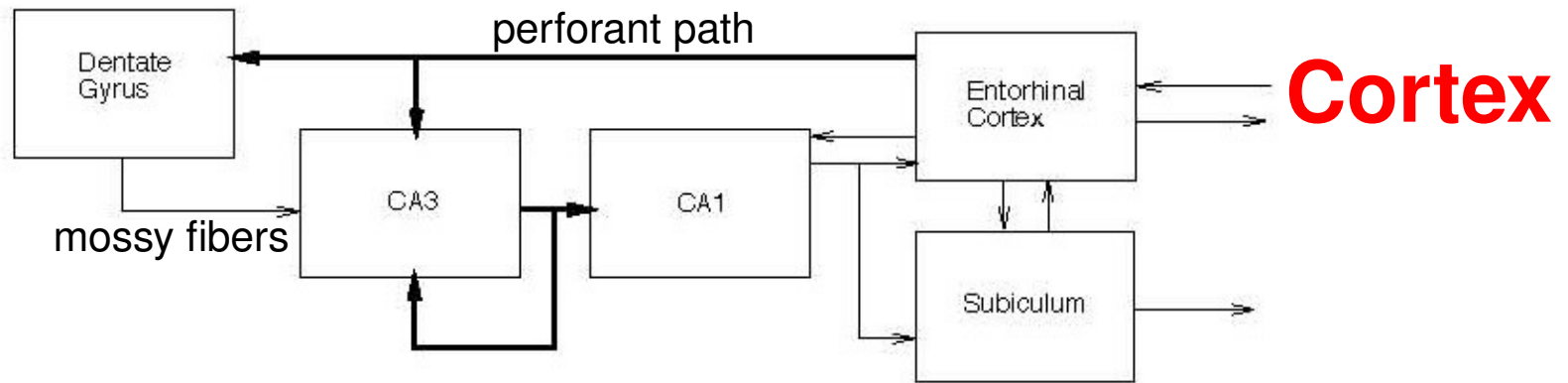
Computational Models of Neural Systems
Lecture 3.4

David S. Touretzky
October, 2025

Overview

- Pattern separation
 - Pulling similar patterns apart reduces memory interference.
- Pattern Completion
 - Noisy or incomplete patterns should be mapped to more correct or complete versions.
- How can both functions be accomplished in the same architecture?
 - Use conjunction (codon units; DG) for pattern separation.
 - Learned weights plus thresholding gives pattern completion.
 - Recurrent connections (CA3) can help with completion as in Marr's model, but aren't used in the model described here.

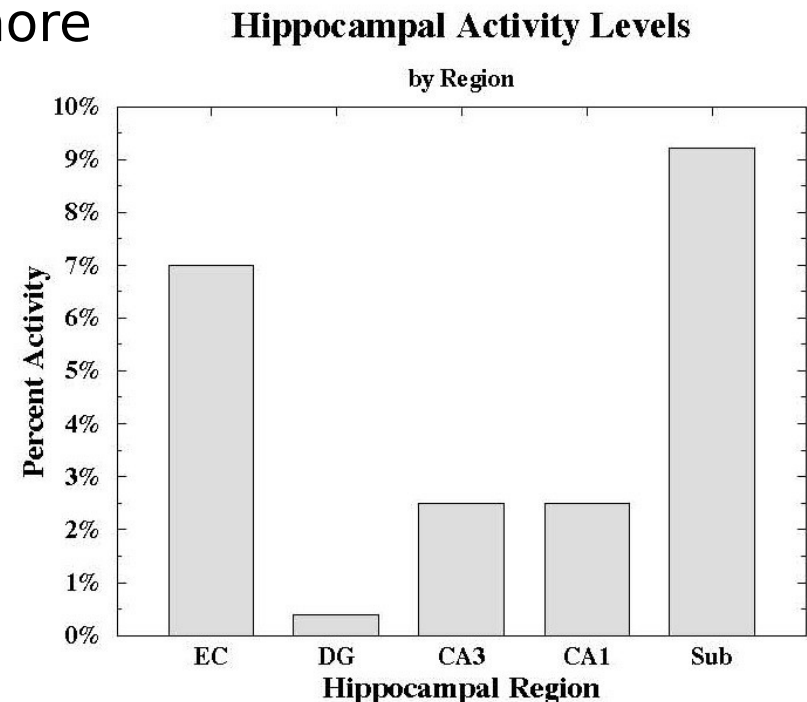
Information Flow



- Cortical projections from many areas form an EC representation of an event.
- EC layer II projects to CA3 (both directly and via DG), forming a new representation better suited to storage and retrieval.
- EC layer III projects to CA1, forming an invertible representation that can reconstitute the EC pattern.
- Learning occurs in all these connections.

Features of Hippocampal Organization

- Local inhibitory interneurons in each region.
 - May regulate overall activity levels, as in a kWTA network.
- CA3 and CA1 have less activity than EC and subiculum. DG has less activity than CA3/CA1.
 - Less activity means representation is more sparse, hence can be more highly orthogonal.

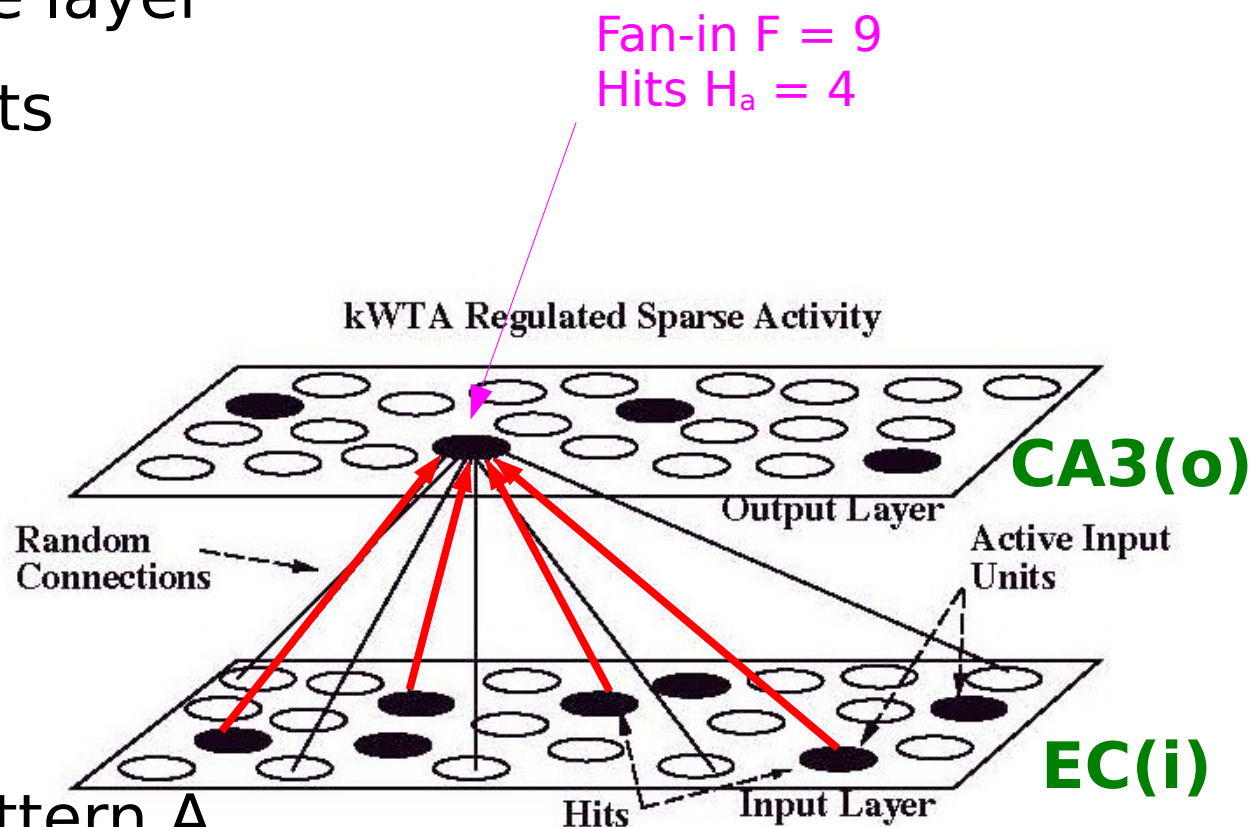


Connections in the Rat

- EC layer II (perf. path) projects diffusely to DG and CA3.
 - Each DG granule cell receives 5,000 inputs from EC.
 - Each CA3 pyramidal cell receives 3750-4500 inputs from EC. This is about 2% of the rat's 200,000 EC layer II neurons.
- DG has roughly 1 million granule cells. CA3 has 160,000 pyramidal cells; CA1 has 250,000.
- DG to CA3 projection (mossy fibers) is sparse and topographic. CA3 cells receive 52-87 mossy fiber synapses.
- NMDA-dependent LTP has been demonstrated in perforant path and Schaffer collaterals. LTP also demonstrated in mossy fiber pathway (non-NMDA).
- LTD may also be present in these pathways.

Model Parameters

- O'Reilly & McClelland investigated several models, starting with a simple two-layer k-WTA model (like Marr).
- $N_i, N_o = \#$ units in the layer
- $k_i, k_o = \#$ active inputs in one pattern
- $\alpha_i, \alpha_o =$ fractional activity in the layer; $\alpha_o = k_o/N_o$
- $F =$ fan-in of units in the output layer (must be $< N_i$)
- $H_a = \#$ of hits for pattern A



Measuring the Hits a Unit Receives

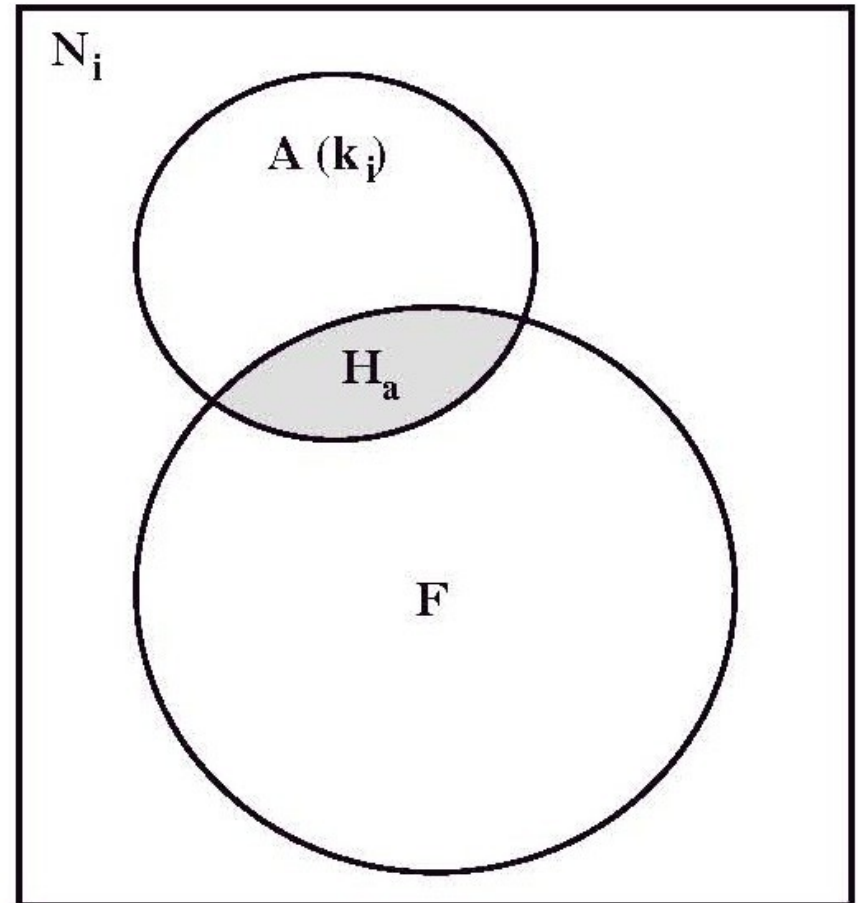
- How many input patterns?

$$\binom{N_i}{k_i}$$

- What is the expected number of hits H_a for an output unit?

$$\langle H_a \rangle = \frac{k_i}{N_i} F = \alpha_i F$$

- What is the distribution of hits, $P(H_a)$?



Hypergeometric (not binomial; we're drawing without replacement)

Hypergeometric Distribution

- What is the probability of getting exactly H_a hits from an input pattern with k_i active units, given that the fan-in is F and the total input size is N_i ?
 - $C(k_i, H_a)$ ways of choosing active units to be hits
 - $C(N_i - k_i, F - H_a)$ ways of choosing inactive units for the remaining ones sampled by the fan-in
 - $C(N_i, F)$ ways of sampling F inputs from a population of size N_i

$$P(H_a \mid k_i, N_i, F) = \frac{\binom{k_i}{H_a} \binom{N_i - k_i}{F - H_a}}{\binom{N_i}{F}}$$

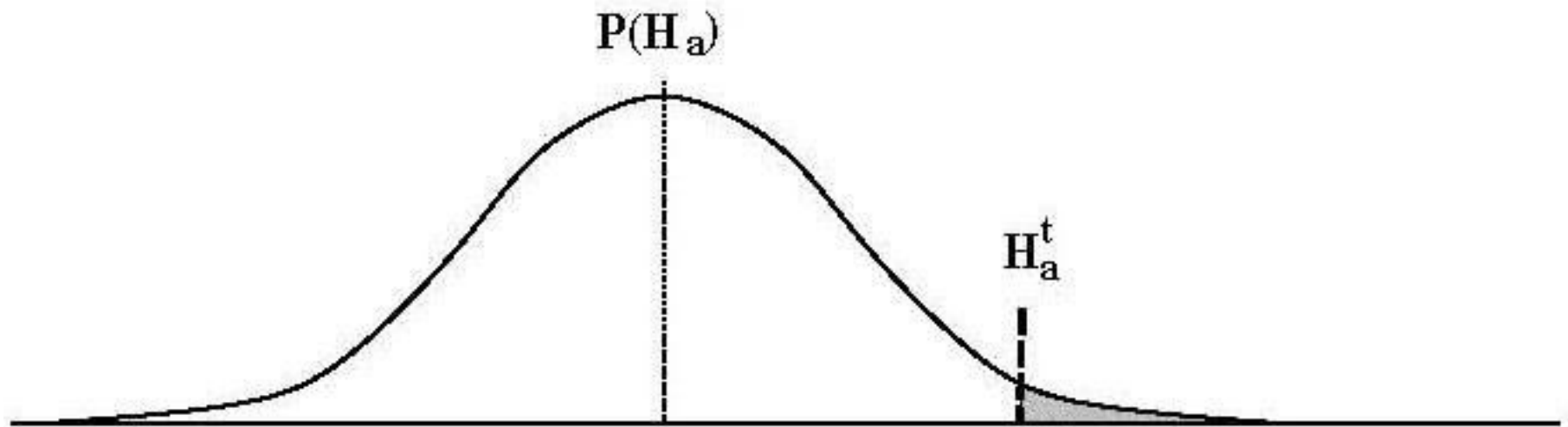
of ways to wire an output cell with H_a hits

of ways to wire an output cell

Determining the kWTA Threshold

- Assume we want the output layer to have an expected activity level of α_o .
- Must set the threshold for output units to select the tail of the hit distribution. Call this H_a^t .
- Use the summation to choose H_a^t to produce the desired value of α_o .

$$\alpha_o = \sum_{H_a = H_a^t}^{\min(k_i, F)} P(H_a)$$

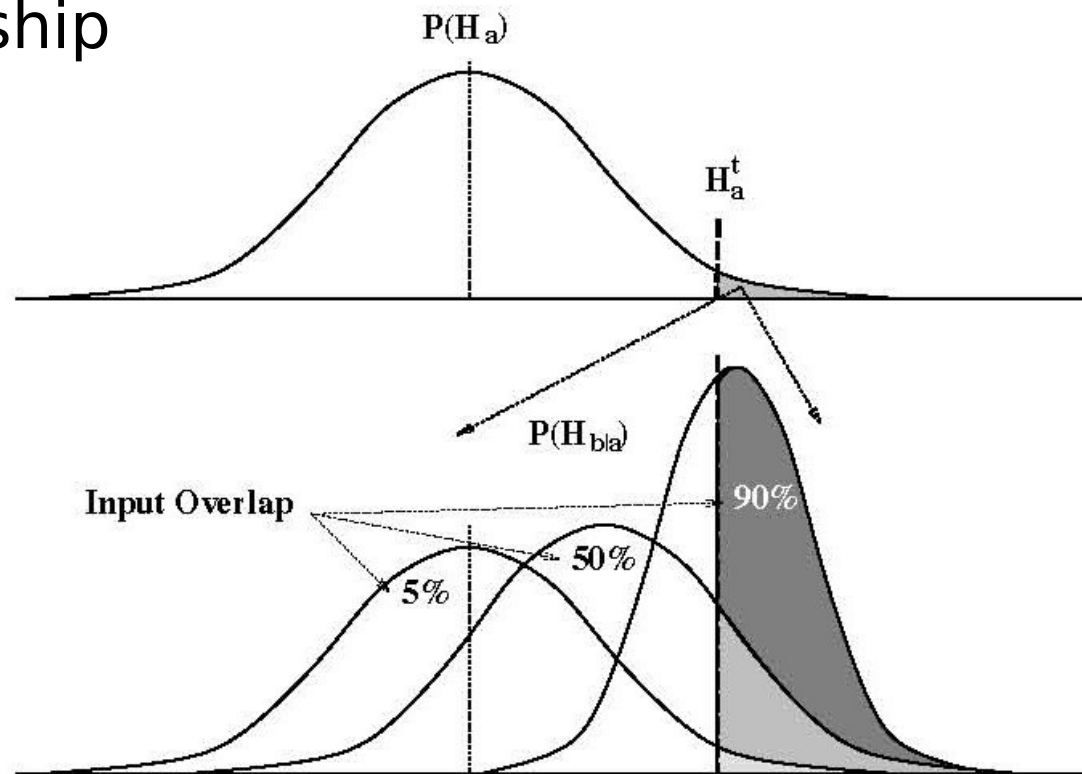


Pattern Overlap

- In order to measure pattern separation properties of the two-layer model, consider two patterns A and B.
 - Measure the input overlap Ω_i = number of units in common.
 - Compute the expected output overlap Ω_o as a function of Ω_i .
- If $\Omega_o < \Omega_i$ the model is doing pattern separation.
- To calculate output overlap we need to know H_{ab} , the number of hits an output unit receives for pattern B given that it is already known to be part of the representation for pattern A.

Distribution of H_{ab}

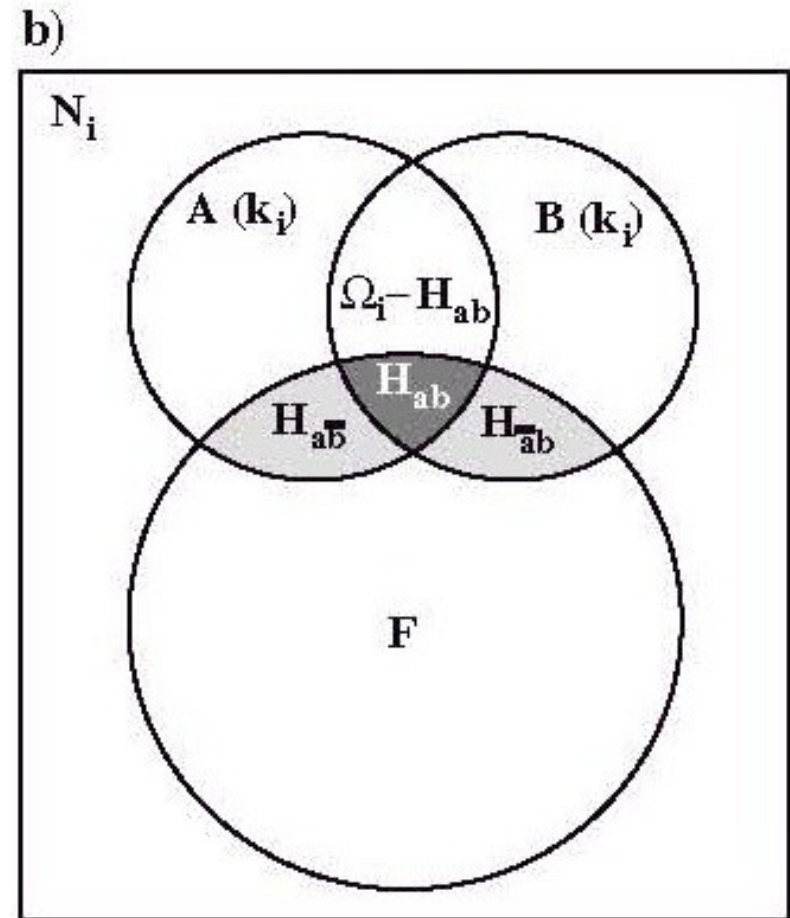
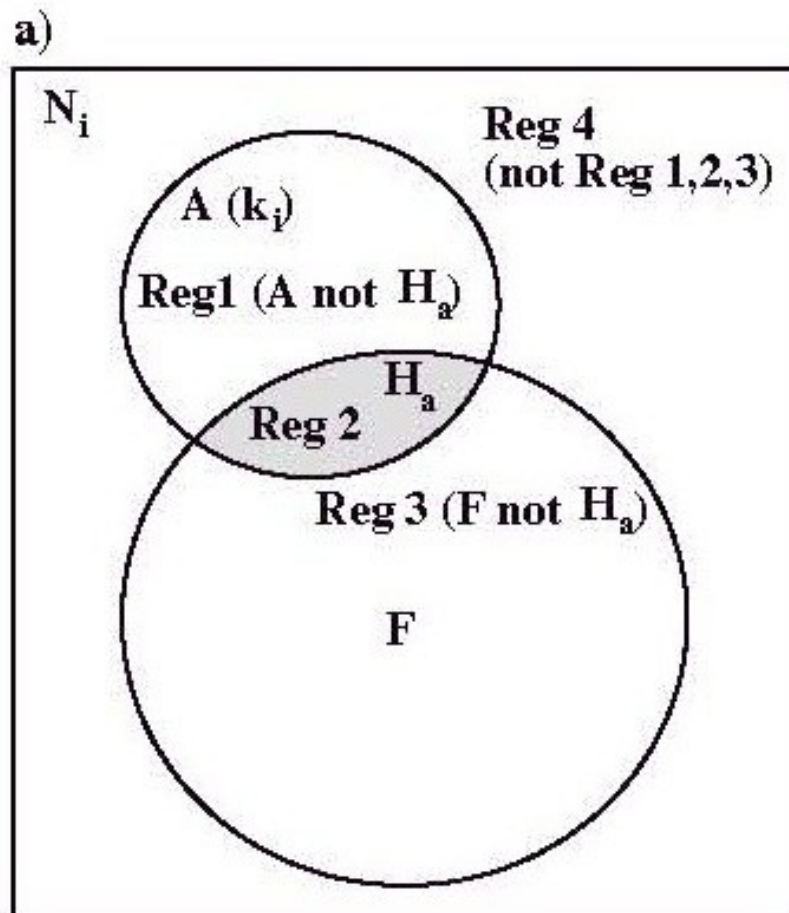
- For small input overlap, the patterns are virtually independent, and H_{ab} is distributed like H_a .
- As input overlap increases, H_{ab} moves rightward (more hits expected), and narrows: output overlap increases.
- But the relationship is nonlinear.



Visualizing the Overlap

a) Hits from pattern A.

b) H_{ab} = overlap of A&B hits



Prob. of b Hits And Specific Values for $H_a, H_{ab}, H_{\bar{a}b}$ Given Overlap Ω_i

$$P_b(H_a, \Omega_i, H_{ab}, H_{\bar{a}b}) =$$

$$\frac{\binom{H_a}{H_{ab}} \binom{F - H_a}{H_{\bar{a}b}} \binom{k_i - H_a}{\Omega_i - H_{ab}} \binom{N_i - k_i - F + H_a}{k_i - \Omega_i - H_{\bar{a}b}}}{\binom{k_i}{\Omega_i} \binom{N_i - k_i}{k_i - \Omega_i}}$$

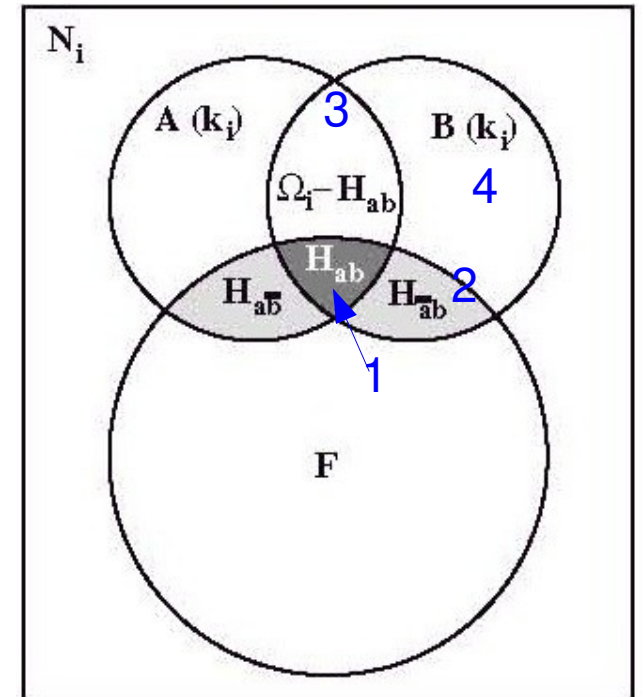
of ways of achieving H_b hits given overlap Ω_i (points to the numerator)

of ways of achieving $k_i - H_b$ non-hits given overlap Ω_i (points to the denominator)

of ways of achieving overlap Ω_i (points to the denominator)

$$\frac{\binom{k_i}{\Omega_i} \binom{N_i - k_i}{k_i - \Omega_i}}{\binom{k_i}{\Omega_i} \binom{N_i - k_i}{k_i - \Omega_i}}$$

1,3 2,4



Note: $H_b = H_{ab} + H_{\bar{a}b}$

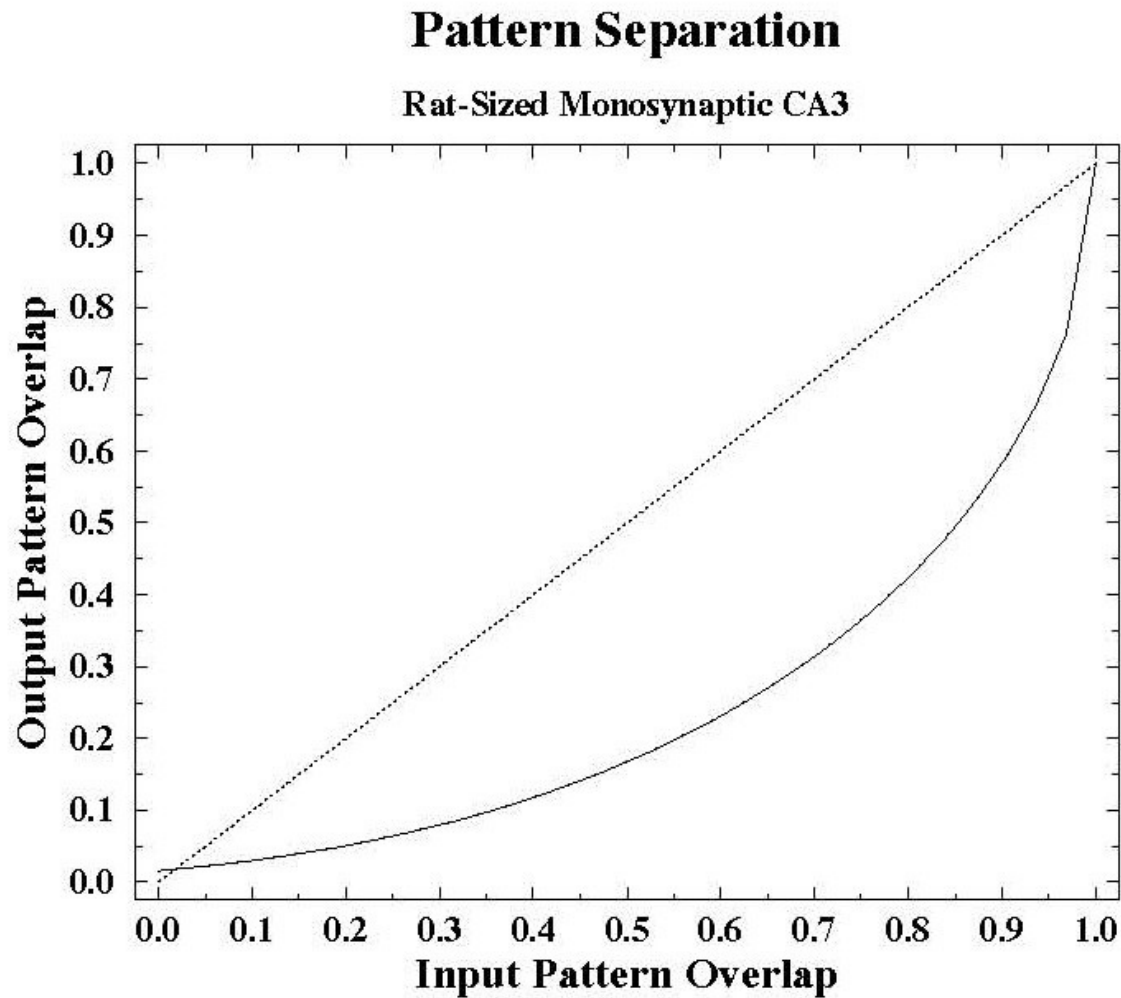
To calculate $P(H_b)$ we must sum P_b over all combinations of $H_a, H_{ab}, H_{\bar{a}b}$

Estimating Overlap for Rat Hippocampus

- We can use the formula for P_b to calculate expected output overlap as a function of input overlap.
- To do this for rodent hippocampus, O'Reilly & McClelland chose numbers close to the biology but tailored to avoid round-off problems in the overlap formula.

Area	α	N	F_{EC}	F_{DG}
EC	6.25%	200,000	—	—
DG	0.39%	850,000	4,006	—
CA3	2.42%	160,000	4,003	64

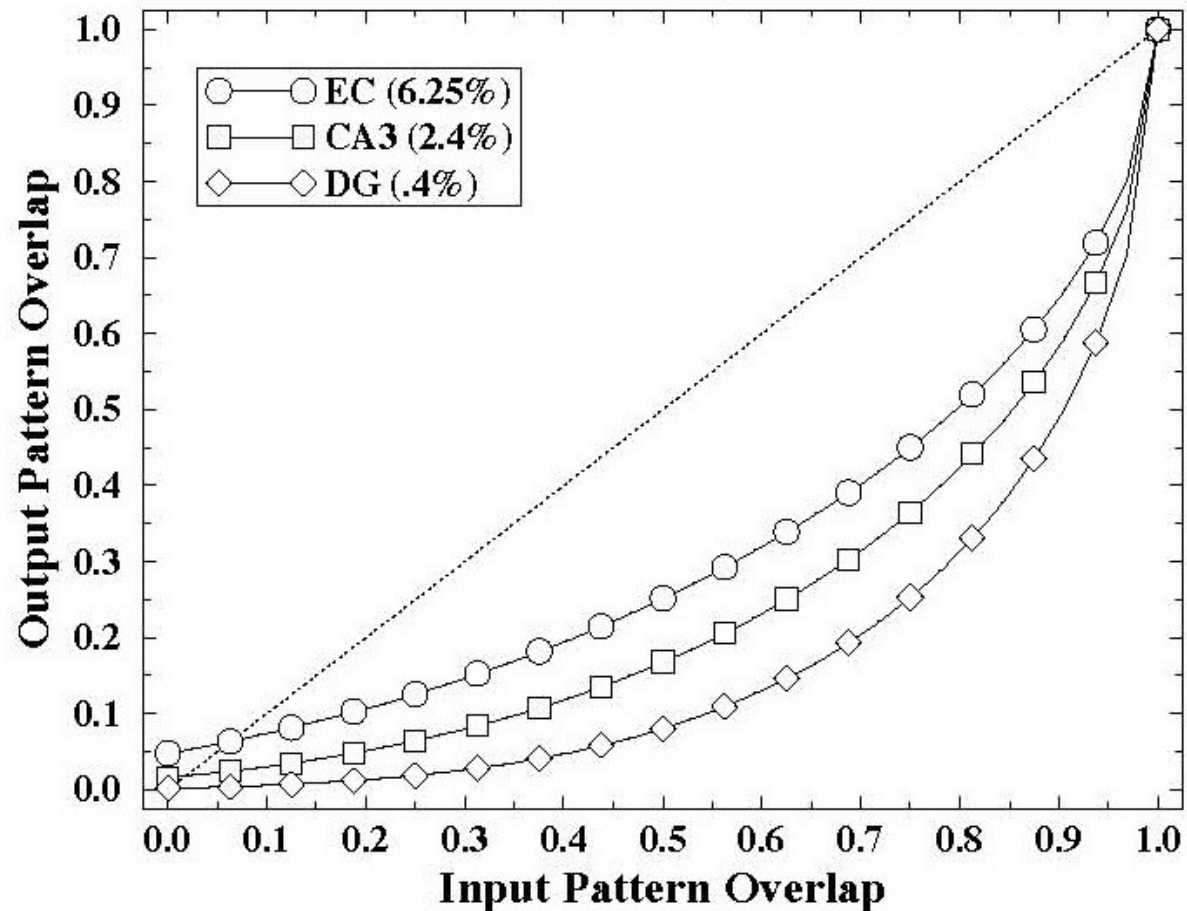
Estimated Pattern Separation in CA3



Sparsity Increases Pattern Separation

Activity Levels and Pattern Separation

Rat-Sized DG, Monosynaptic CA3, and EC

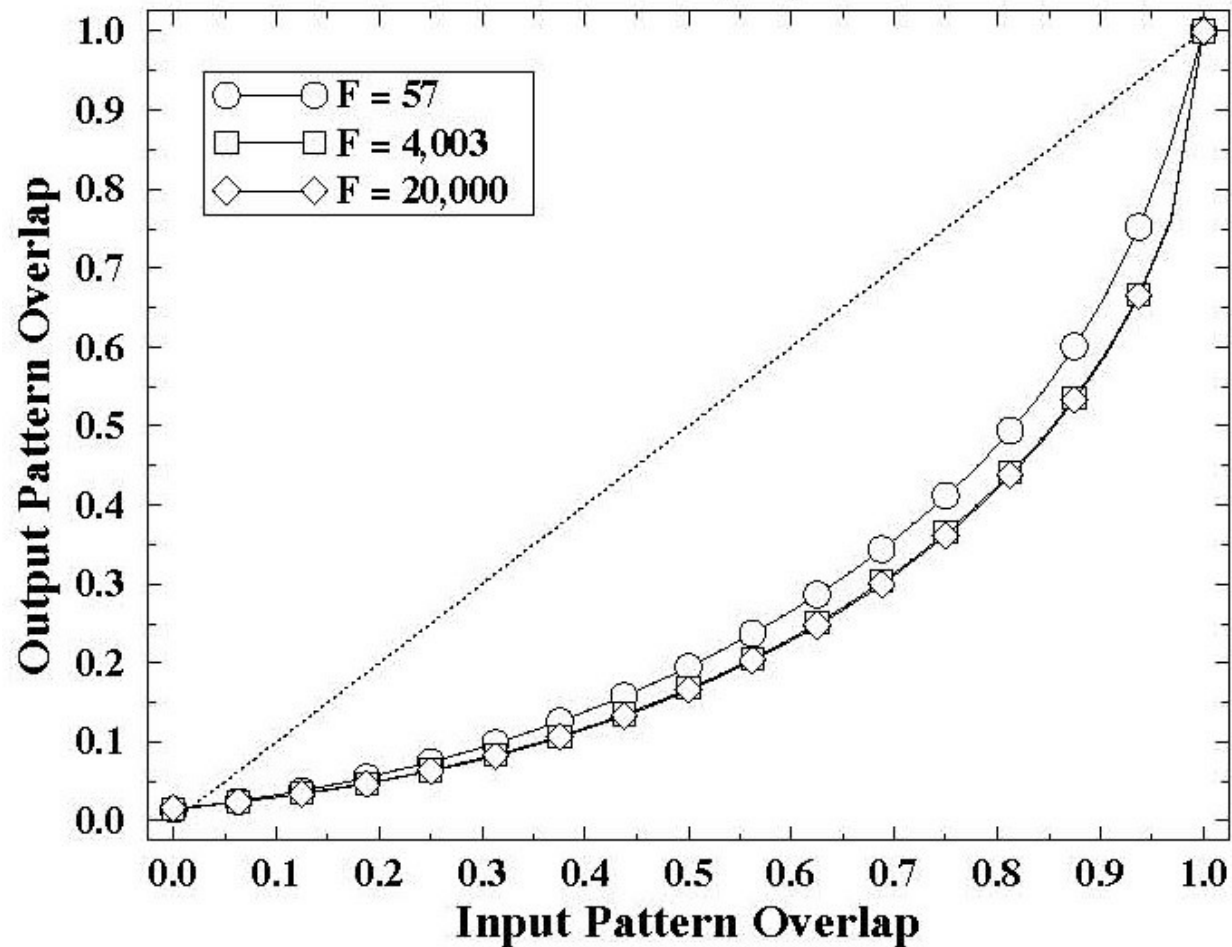


Pattern separation performance of a generic network with activity levels comparable to EC, CA3, or DG. Sparse patterns yield greater separation.

Fan-In Size Has Little Effect

Fan-in Size and Pattern Separation

Rat-Sized Monosynaptic CA3

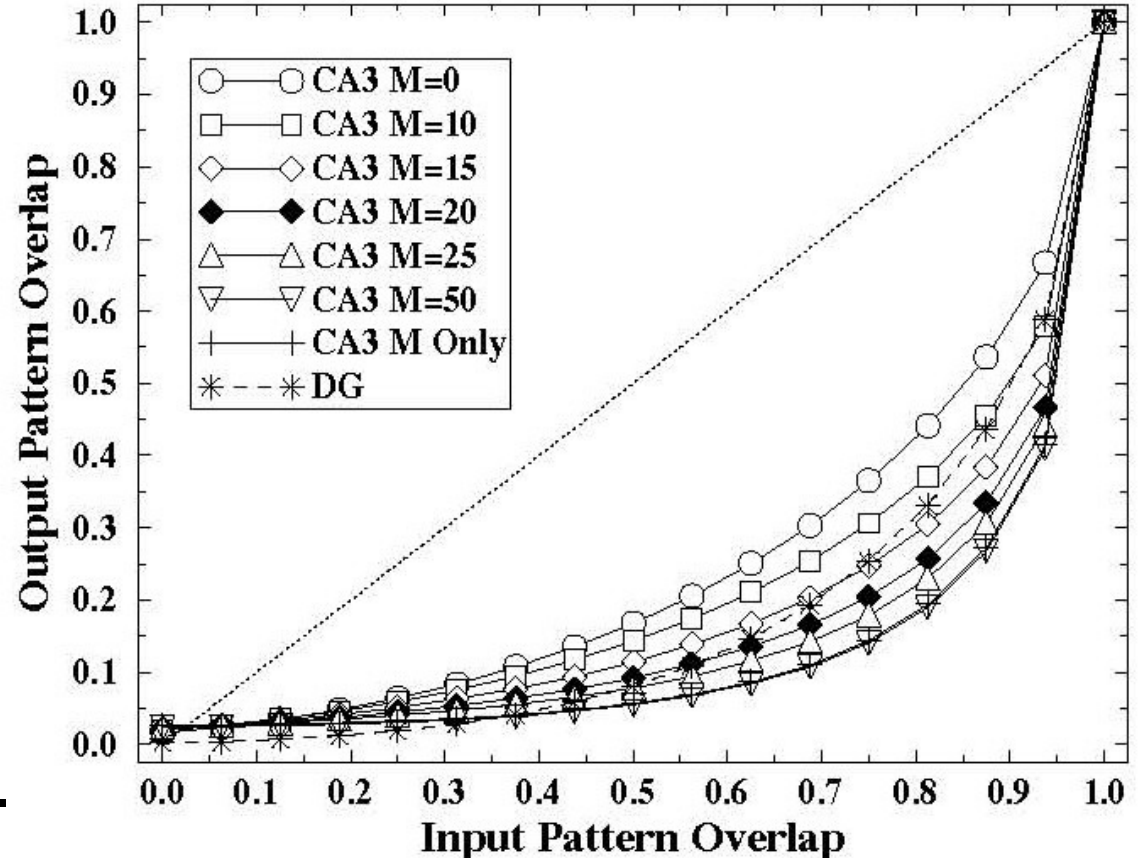


Adding Input from DG

- DG makes far fewer connections (64 vs. 4003), but they may have higher strength. Let M = mossy fiber strength.

Mossy Fiber Strength and Pattern Separation

Rat-Sized CA3 w/Mossy and Perforant Path Inputs



- Separation in DG (*) is better than in CA3 without DG (○).
- DG connections help for $M \geq 15$.
- With $M=50$, DG projection alone (+) is as good as DG+EC (▽).

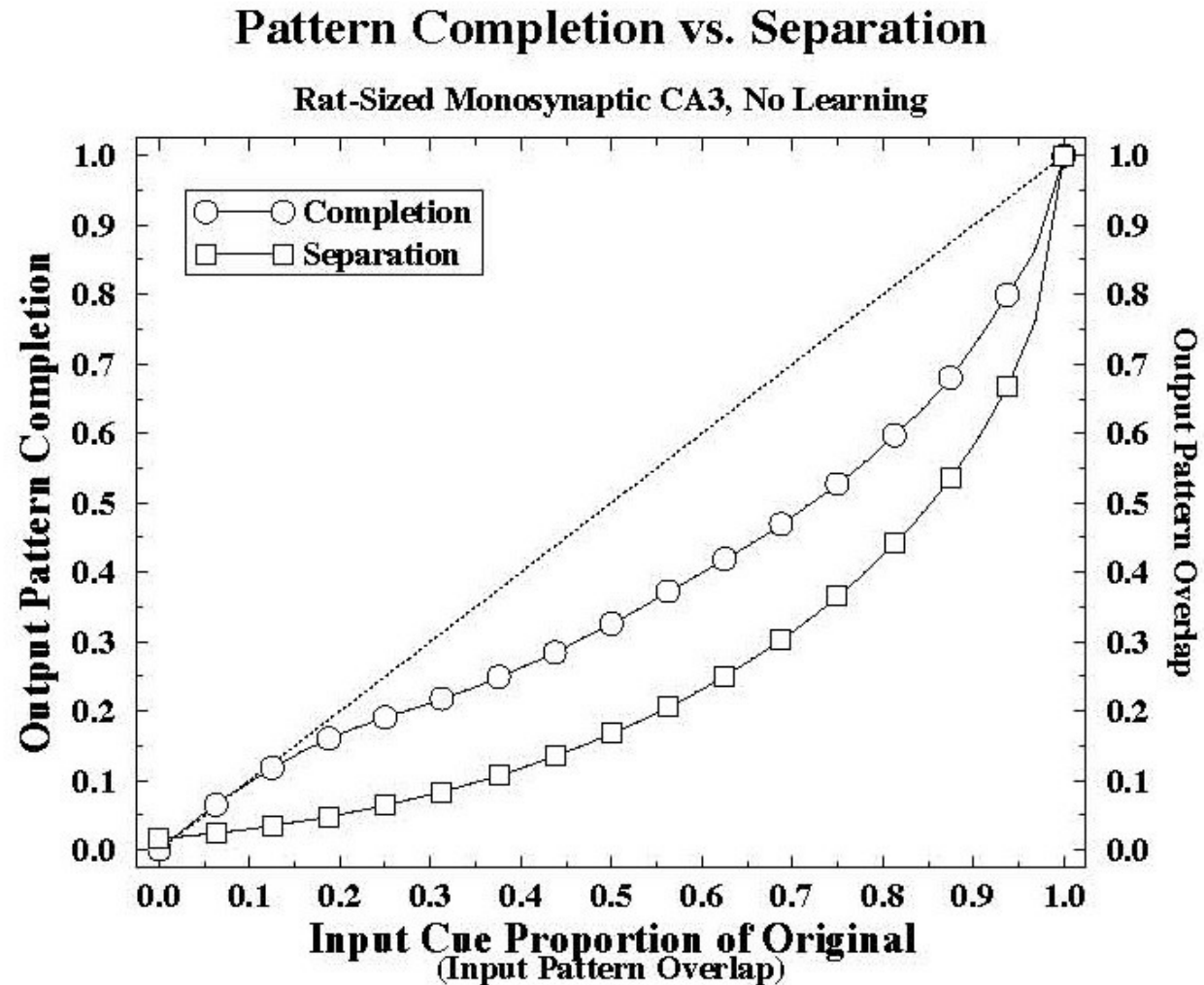
Combining Two Distributions

- CA3 has far fewer inputs from DG than from EC.
- But the DG input has greater variance in hit distribution.
- When combining two equally-weighted distributions, the one with the greater variance has the most effect on the tail.
- For 0.25 input overlap:
 - DG hit distribution has std. dev. of 0.76
 - EC hit distribution has std. dev. of 15.
 - Setting $M=20$ would balance the effects of the two projections.
- In the preceding plot, the $M=20$ line appears in between the $M=0$ line (EC only) and the “M only” line.

Without Learning, Partial Inputs Are Separated, Not Completed

Less separation between A and subset(A) than between patterns A and B, because there are no noise inputs.

But Ω_o is still less than Ω_i

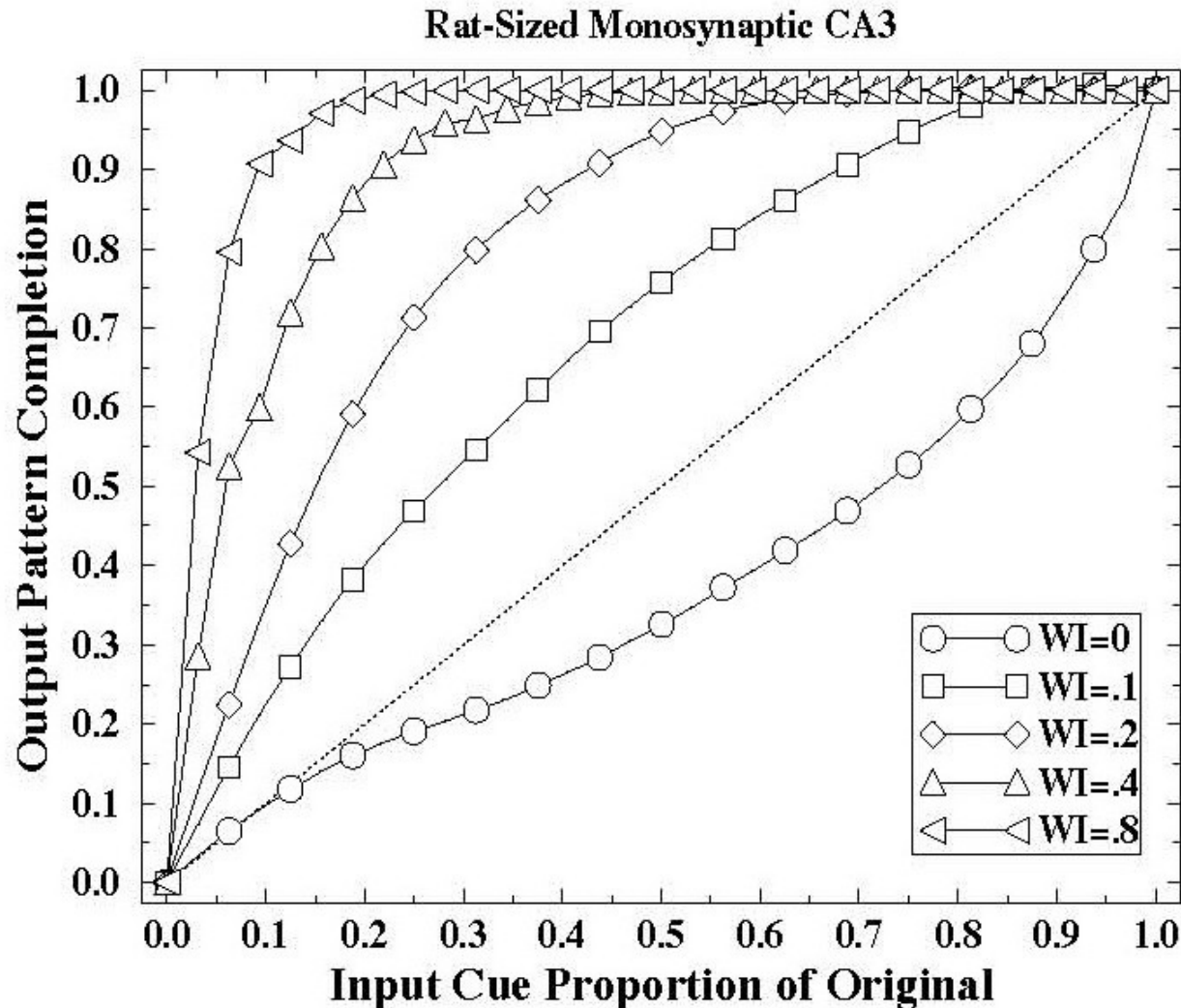


Pattern Completion

- Without learning, completion cannot happen.
- Two learning rules were tried:
 - WI: Weight Increase (like Marr)
 - WID: Weight Increase/Decrease
- WI learning multiplies weights in H_{ab} by $(1+L_{rate})$.
- WID learning increases weights as per WI, but also exponentially decreases weights to units in $F-H_a$ by multiplying by $(1-L_{rate})$.
- Result: WID learning improves both separation and completion.

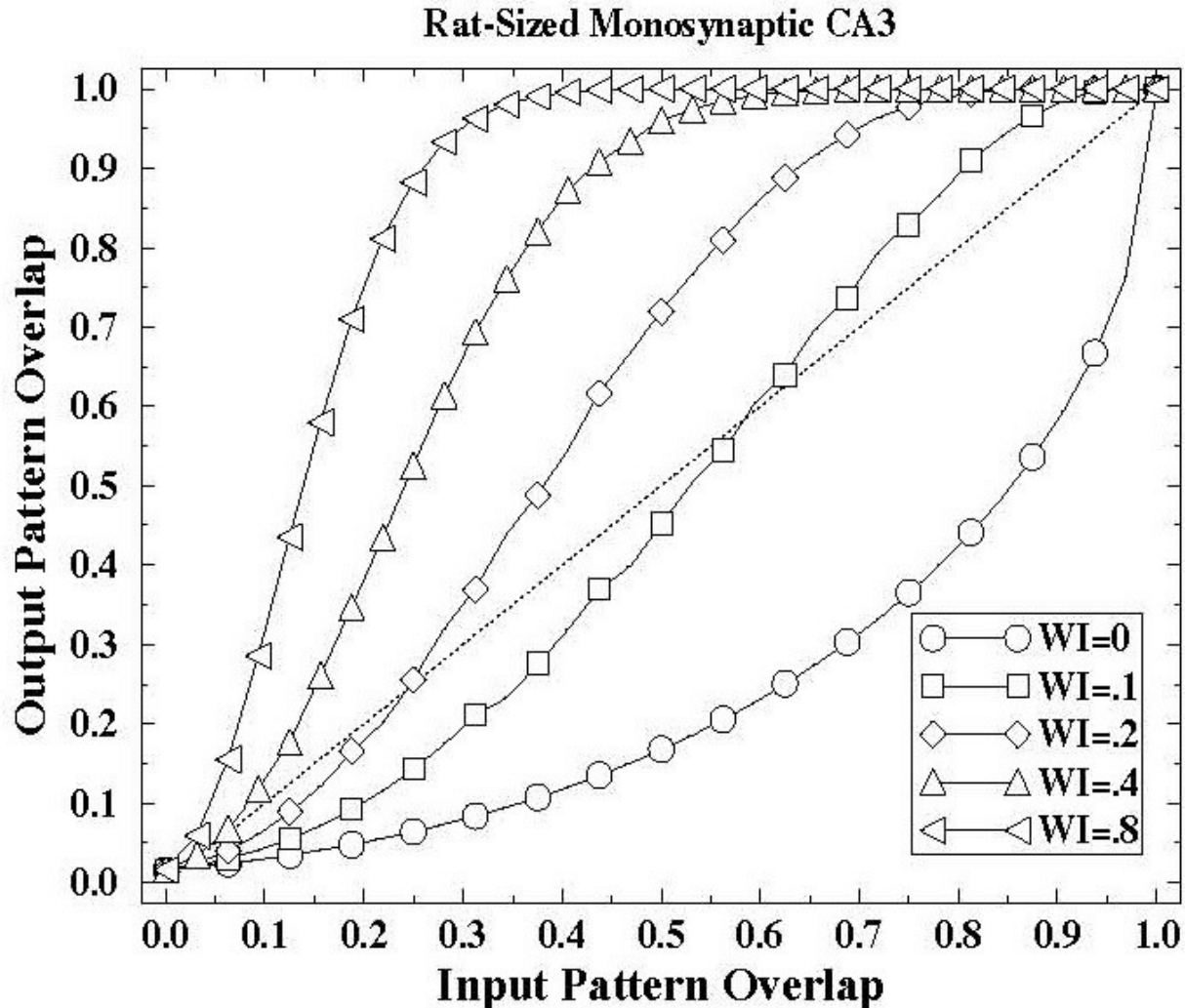
WI Learning and Pattern Completion

a) WI Learning and Pattern Completion



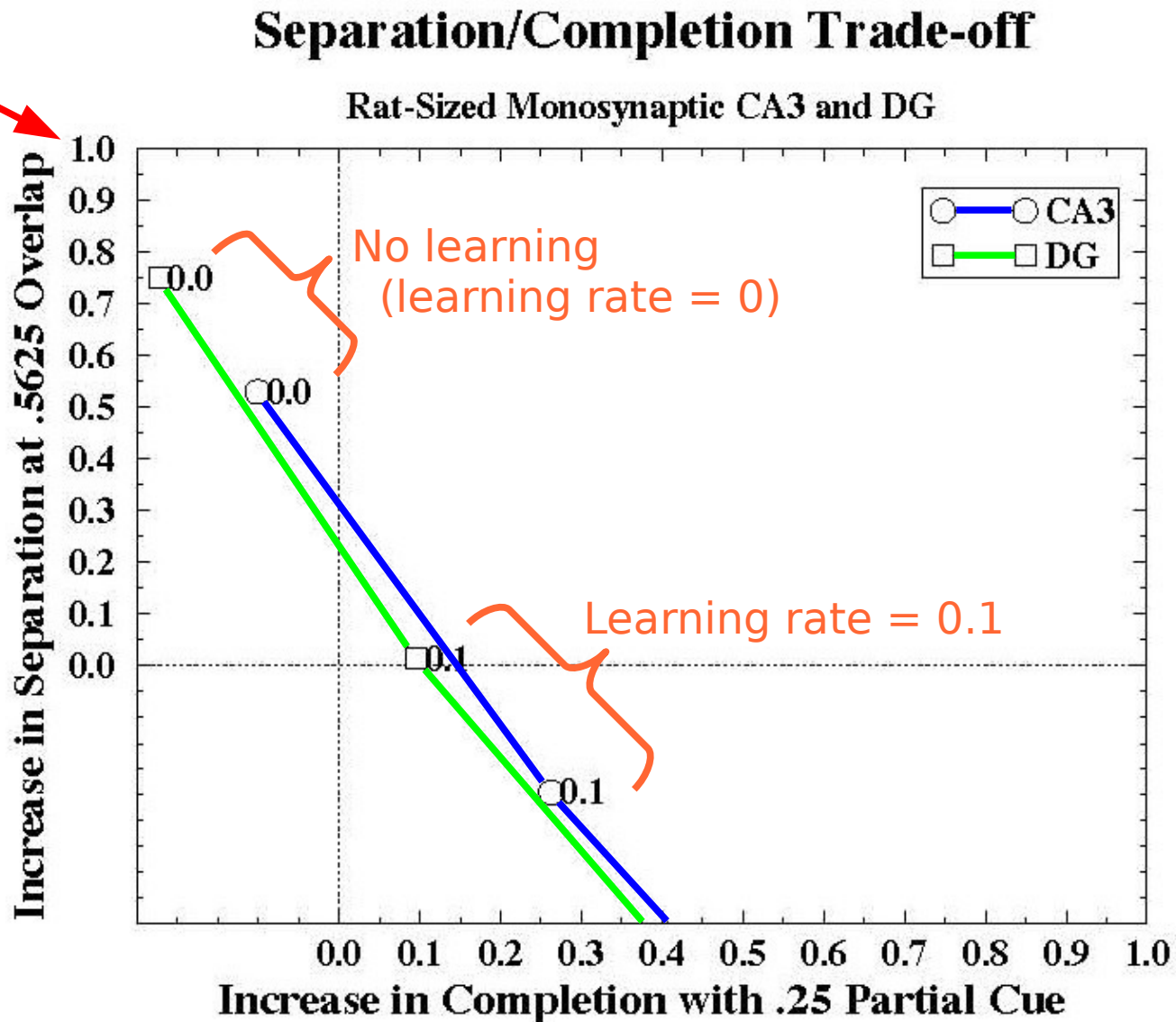
WI Learning Reduces Pattern Separation

b) WI Learning and Pattern Separation



WI Learning Hurts Separation

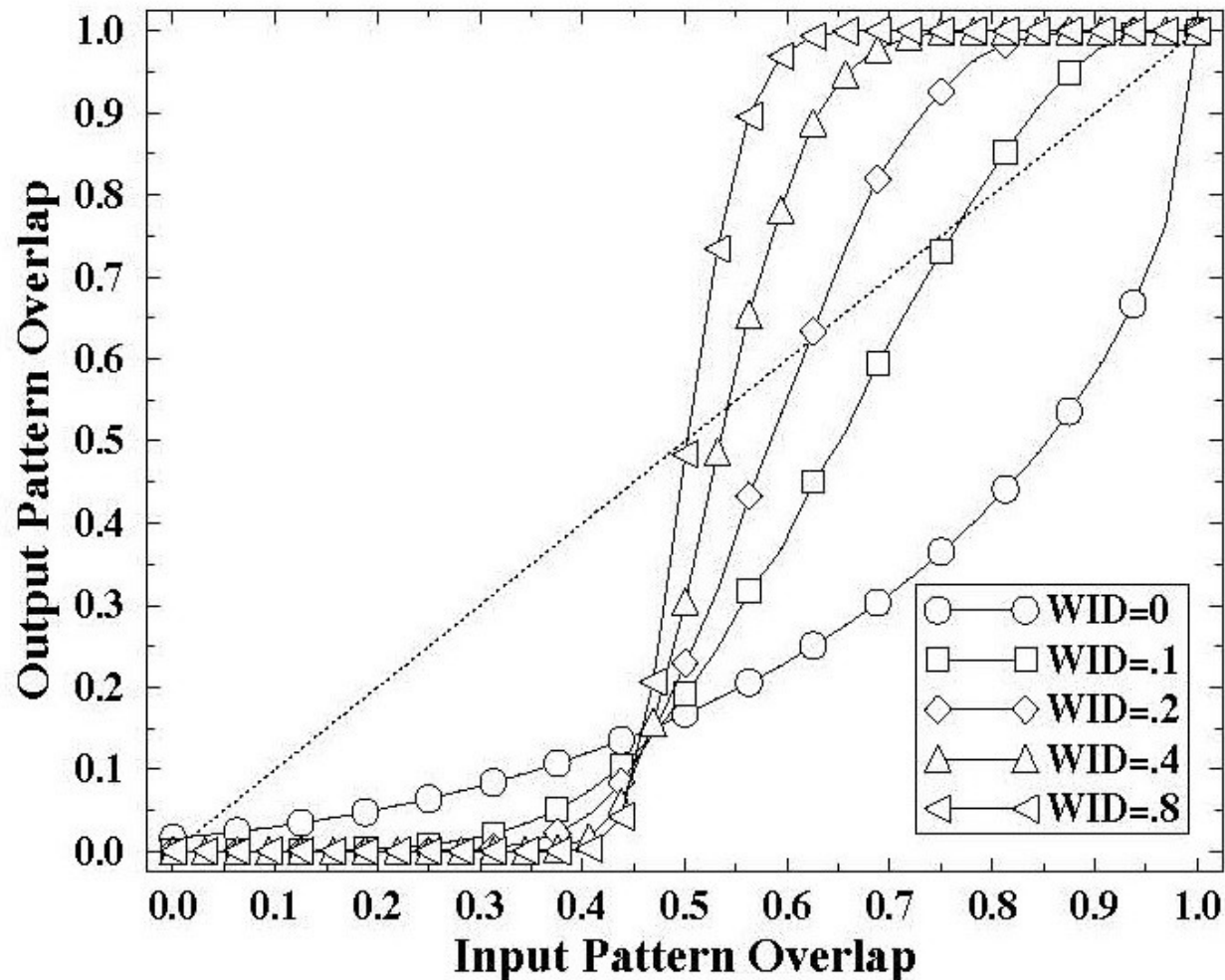
Percent of possible improvement



WID Learning Has A Good Tradeoff

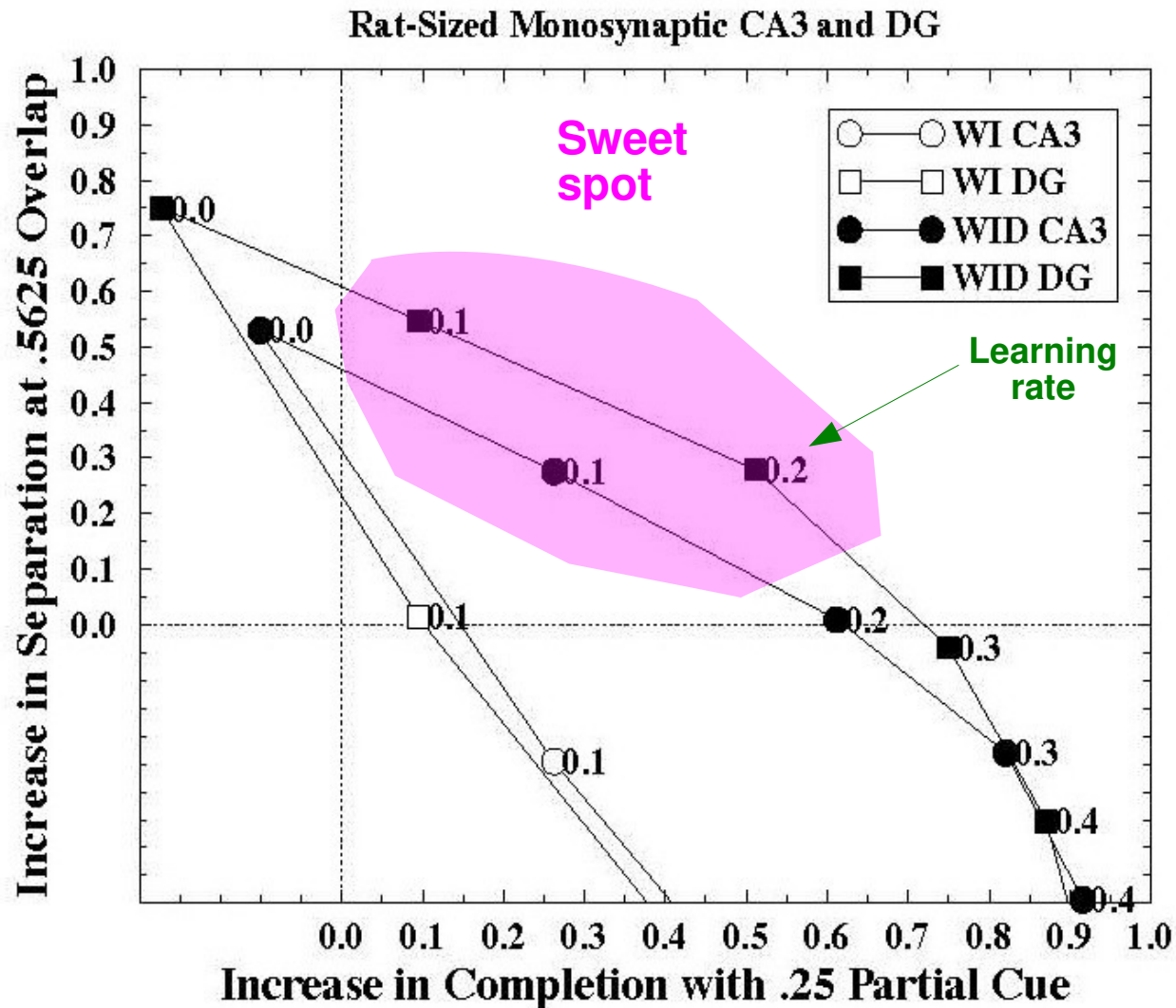
a) WID Learning and Pattern Separation

Rat-Sized Monosynaptic CA3



WI vs. WID Learning

b) Separation/Completion Trade-off: WI vs. WID



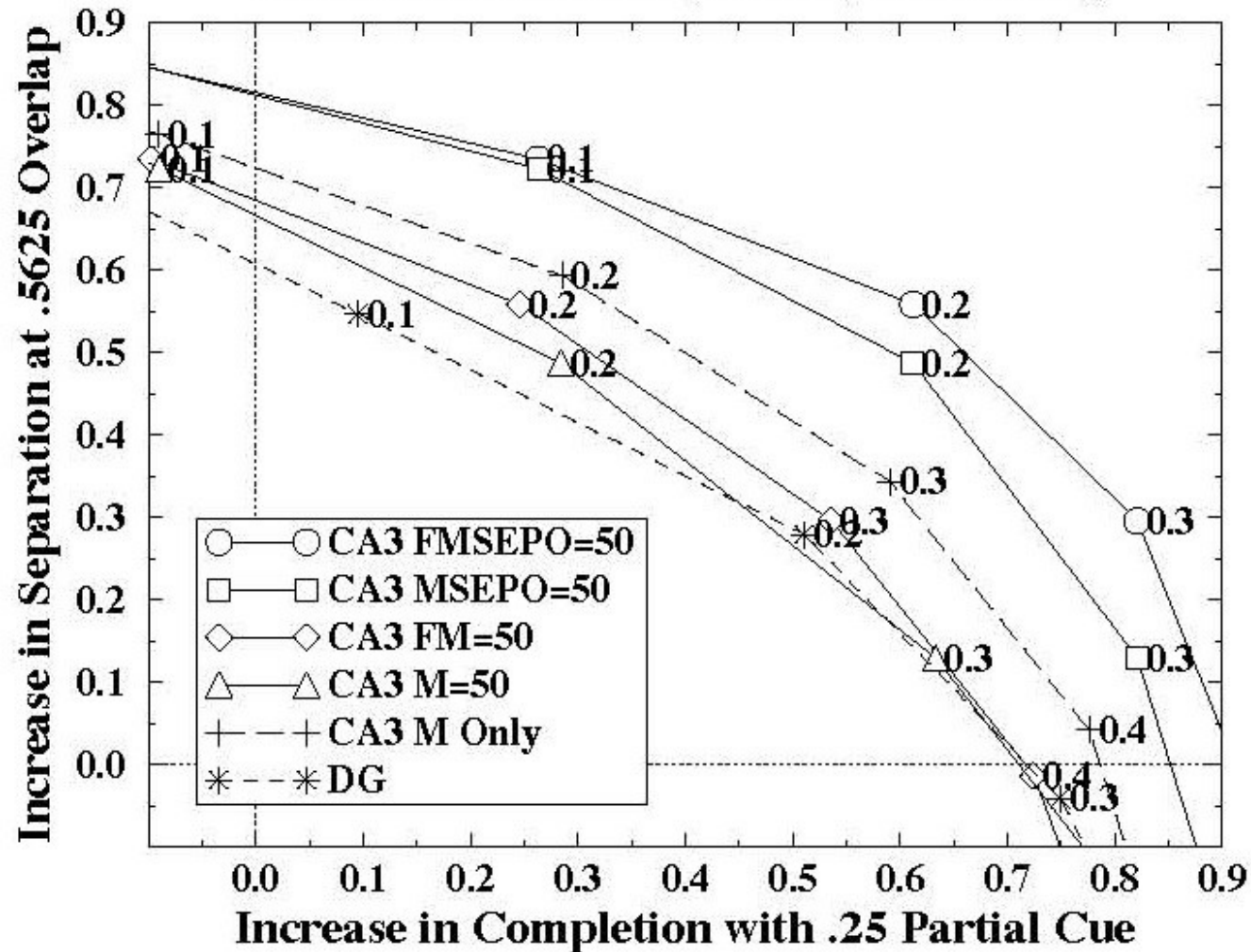
Hybrid Systems

- Multiple completion stages don't help (cf. Willshaw & Buckingham's comparison of Marr models.)
 - With noisy cues, completion produces a somewhat noisy result which would lead to further separation at the next stage.
- MSEPO — mossy fibers only for separation (learning).
 - Perhaps partial EC inputs aren't strong enough to drive DG.
- FM —fixed mossy system: no learning on these fibers.
 - Learning reduces pattern separation. Real mossy fibers undergo LTP, but it's not NMDA-dependent (so non-Hebbian).
- FMSEPO — combination of FM + SEPO.
 - Optimal tradeoff between separation and completion.

Performance of Hybrid Models

Separation/Completion Trade-off: Hybrids

Rat-Sized CA3 with Mossy and DG, WID Learning



What Is the Mossy Fiber Pathway Doing?

- Adds a high variance signal to the CA3 input, which...
- Selects a random subset of CA3 cells that are already highly activated by EC input.
- This enhances separation when recruiting the representations of stored patterns.
- But it hurts retrieval with partial or noisy cues.
 - So don't use it. Use MSEPO or FMSEPO.

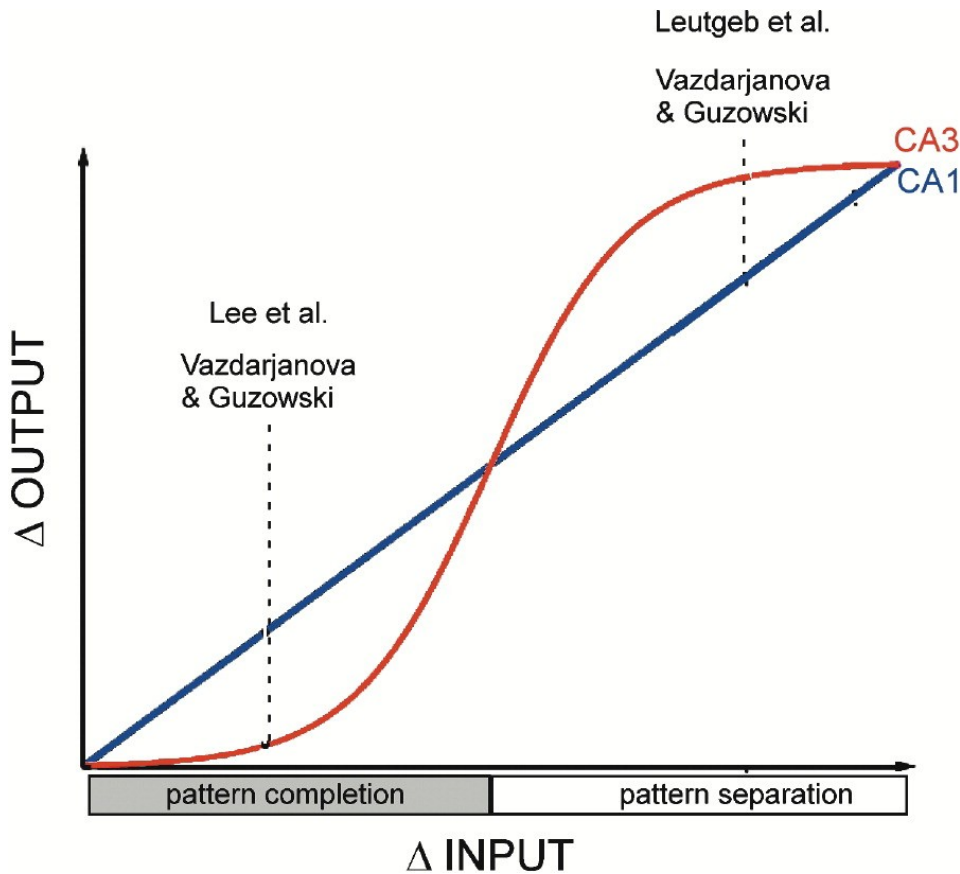
Conclusions

- The main contribution of this work is to show how separation and completion can be accomplished in the same architecture.
- The model uses realistic figures for numbers of units and connections.
- Fan-in size doesn't seem to matter.
- WID learning is necessary for a satisfactory tradeoff between separation and completion.
- DG contributes to separation but perhaps not to completion.

Limitations of the Model

- Simplified anatomy: the model only included EC→CA3 and EC→DG→CA3 connections.
- No CA3 recurrent connections.
- No CA1.
- Only a single pattern stored at a time:
 - Store A, measure overlap with B.
 - No attempt to measure memory capacity.
- A more realistic model would be too hard to analyze.

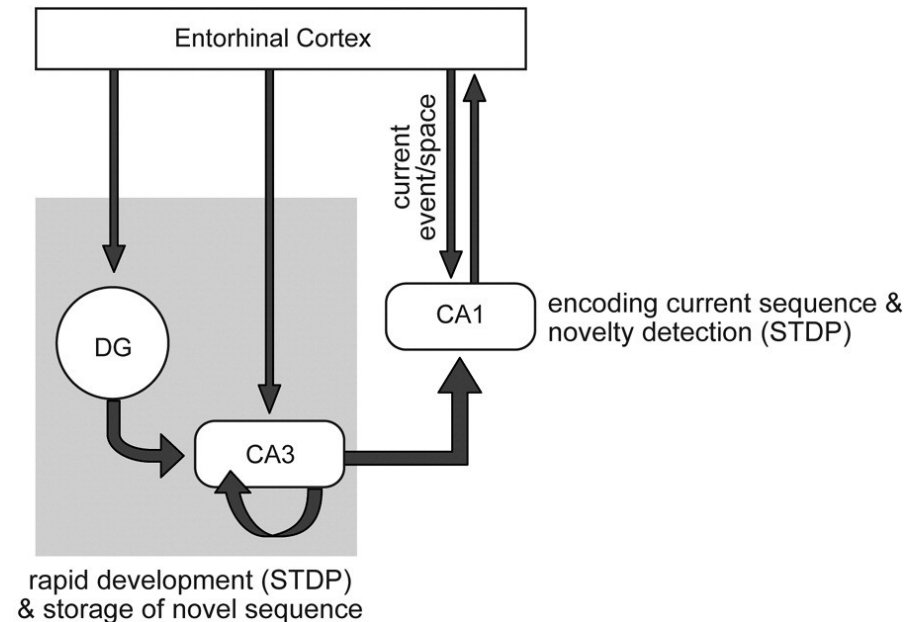
Possible Different Functions of CA3 and CA1



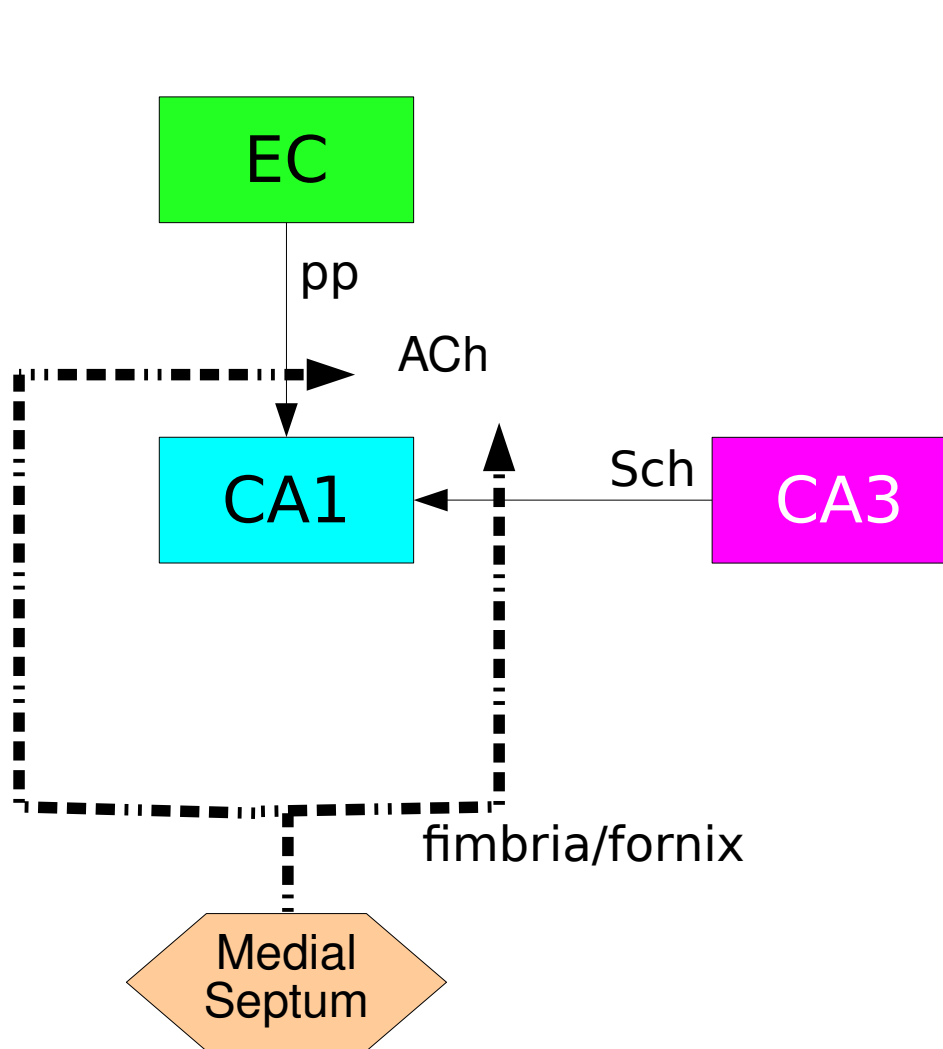
Measured by IEG (Immediate Early Genes):
Arc/H1a catFISH method

Guzowski, Knierim, and Moser (2004)

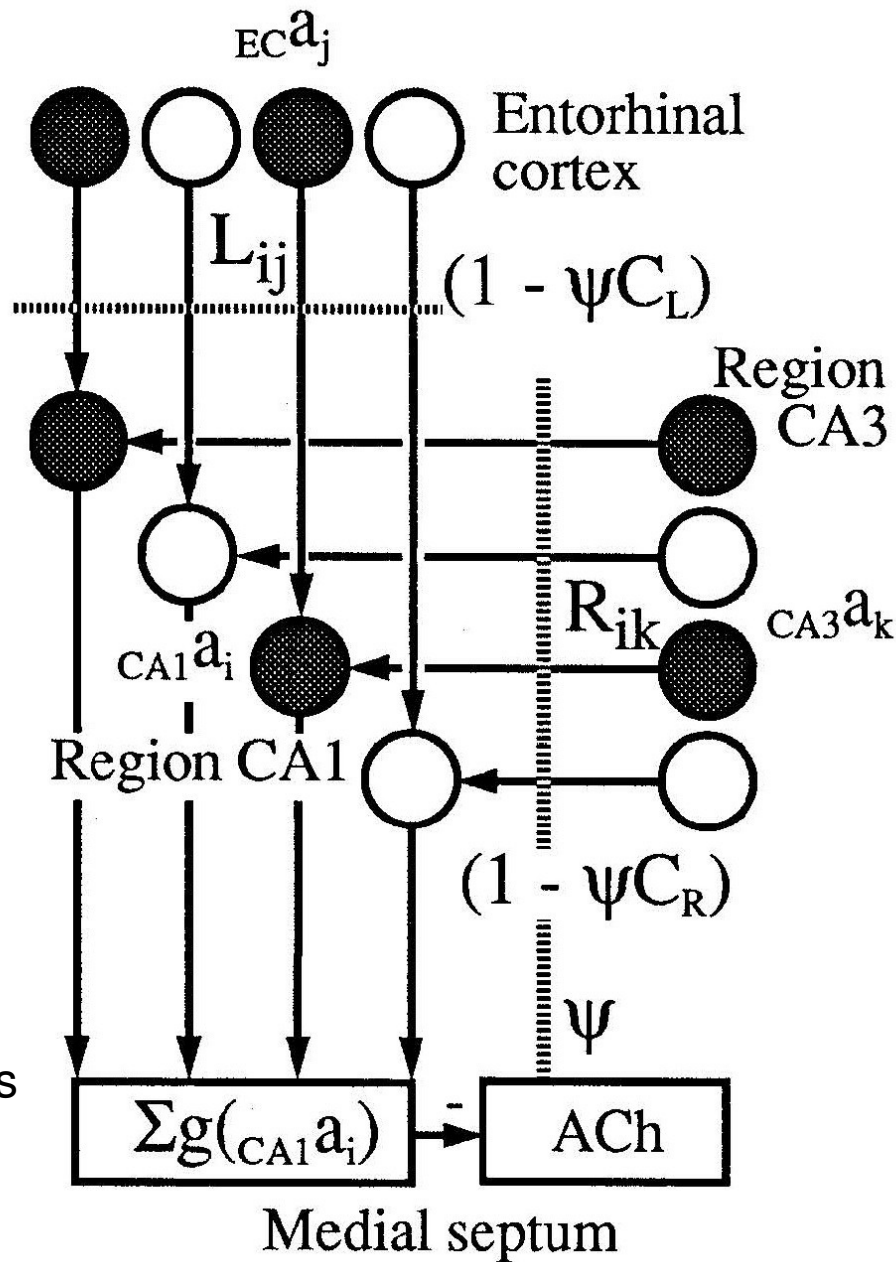
Expose rats to two environments 30 minutes apart. Environments can be (i) identical, (ii) similar but with changes to local or distal cues, or (iii) completely different.



Hasselmo's Model: Novelty Detection

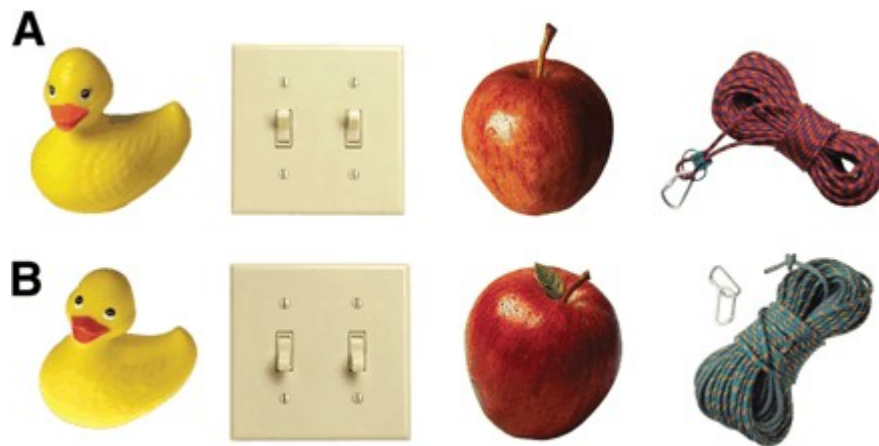


Acetylcholine reduces synaptic efficacy (prevents CA3 from altering CA1 pattern) and enhances synaptic plasticity.



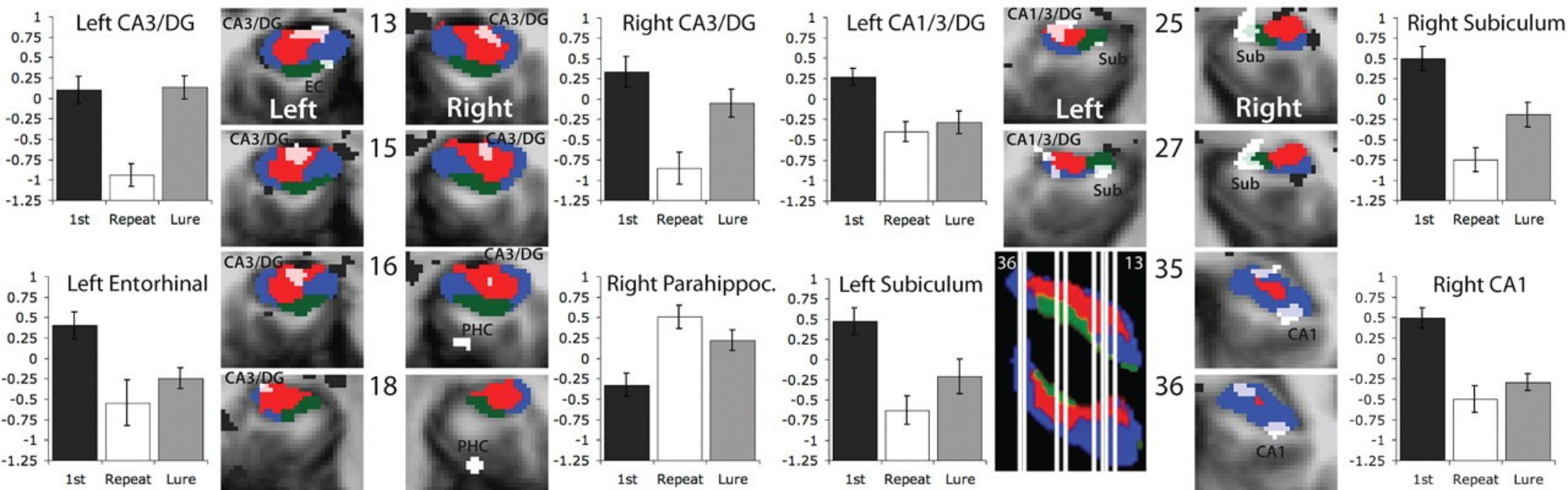
Pattern Separation in Human Hippocampus

- Bakker et al., *Science*, March 2008: fMRI study
- Subjects were shown 144 pairs of images that differed slightly, plus additional foils. Asked for an unrelated judgment about each image (indoor vs. outdoor object).



- Three types of trials: (i) new object, (ii) repetition of a previously seen object, (iii) slightly different version of a previously seen object: a *lure*.

Eight ROIs Found



- Couldn't resolve DG vs. CA3 so treated as one region.
- Regions outlined above: CA3/DG CA1 Subiculum
- Areas of significant activity within MTL shown in white.
- New objects, repetitions, and lures were reliably discriminable. Generally, repetitions → lower activity.

Bias Scores for ROIs

- $bias = (first - lure) / (first - repetition)$
- Scores close to 1 \rightarrow completion; 0 \rightarrow separation.
- CA3/DG shows more pattern separation than other areas.

