1

Memory

Memory is not unitary.

1. Weights versus activations.
2. Specialized neural systems: computational tradeoffs.

2

Weights vs Activations

Weights:

- Long-lasting.
- Requires re-activation.

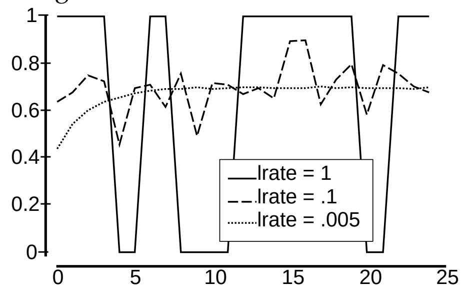
Activations:

- Short-term.
- Already active, can influence processing.

3

Weight-based Memories

Rapid weight changes causes interference:



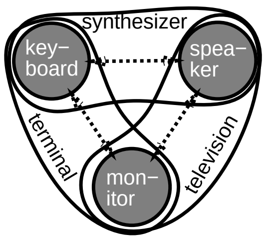
Two systems needed:

- Slow learning cortex.
- Rapid learning hippocampus (pattern sep avoids interference).

4

Activation-based Memories

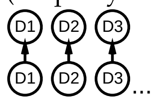
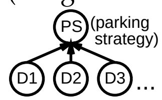
Spreading activation causes interference.



Two systems needed:

- Interconnected posterior cortex.
- Isolated prefrontal cortex.

5 Complementary Learning Systems

Goals:	Remember Specifics	Extract Generalities
Example:	Where is car parked?	Best parking strategy?
Need to:	Avoid interference	Accumulate experience
	Solution:	
1.	Separate reps (keep days separate) 	Overlapping reps (integrate over days) 
2.	Fast learning (encode immediately)	Slow learning (integrate over days)
3.	Learn automatically (encode everything)	Task-driven learning (extract relevant stuff)
	These are incompatible, need two different systems:	
System:	Hippocampus	Neocortex

6 Cortical Priming

Even slow cortical weight changes yield one-trial learning effects..

win____

handle
winter
shower...
win____

Spell $/r\bar{e}d/$.
Name a musical instrument that uses a reed.
Spell $/r\bar{e}d/$.

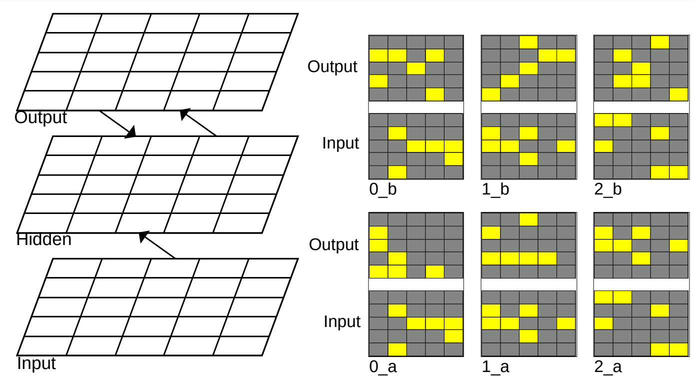
7 Cortical Priming

Residual activation can also result in priming.

Three factors:

- Duration (short-term activations vs long-term weights).
- Content (visual, semantic, etc.)
- Similarity (repetition, semantic relation, etc).

8 Weight-based Priming Model



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Priming Data

trial	Event	sum_se	Outp_dist	ev_nm	sm_nm	both_err
0	0_a	5.22935	0	0_b	1	0
1	1_a	6.48608	0	1_b	1	0
2	2_a	7.77501	0.273233	2_b	1	0
3	3_a	7.64788	0	3_b	1	0
4	4_a	5.41569	0.551383	4_b	1	0
5	5_a	0	0	5_a	0	0
6	6_a	10.2454	0	6_b	1	0
7	7_a	8.33851	0	7_b	1	0
8	8_a	5.64973	2.61438	8_b	1	0
9	9_a	10.2408	0	9_b	1	0
10	10_a	3.21385	1.06278	10_b	1	0
11	11_a	2.82117	2.42077	11_b	1	0
12	12_a	4.69916	0.253711	12_b	1	0
13	0_b	6.68981	0	0_a	1	0
14	1_b	5.40769	0.330821	1_a	1	0
15	2_b	7.51547	0	2_a	1	0
16	3_b	7.73557	0	3_a	1	0
17	4_b	1.94789	1.94789	4_b	0	0
18	5_b	0.414954	0.414954	5_b	0	0
19	6_b	10.5514	0	6_a	1	0
20	7_b	8.79166	0	7_a	1	0
21	8_b	9.64561	0	8_a	1	0
22	9_b	10.2245	0	9_a	1	0
23	10_b	3.53423	0.766472	10_a	1	0
24	11_b	7.46935	0	11_a	1	0
25	12_b	5.72054	0	12_a	1	0

10

AB-AC List Learning

Humans can rapidly learn overlapping associations without too much interference.

Example: learn AB paired associates:
window-reason
bicycle-garbage
...

Then AC paired associaties:
window-locomotive
bicycle-dishtowel

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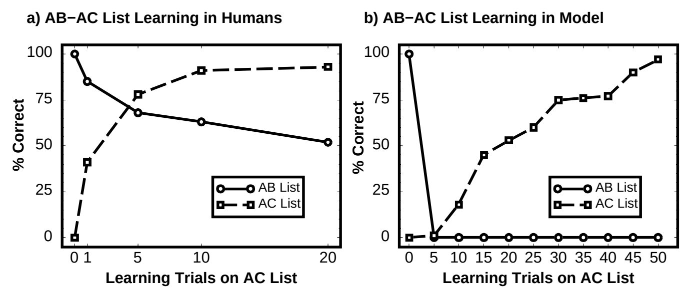
AB-AC List Learning

Then test on AB list:
window- ?
bicycle- ?

and on AC list:
window- ?
bicycle- ?

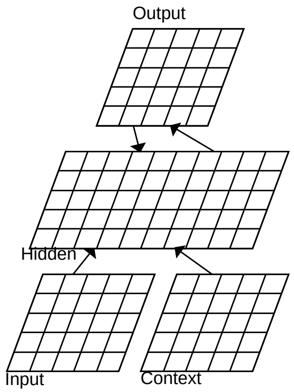
12

AB-AC List Learning



Standard network has *catastrophic* interference (McCloskey & Cohen, 1989).

13 AB-AC Exploration



Input = A, Output = B,C

Context identifies list (random distortions).

14 Memory

Memory is not unitary.

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