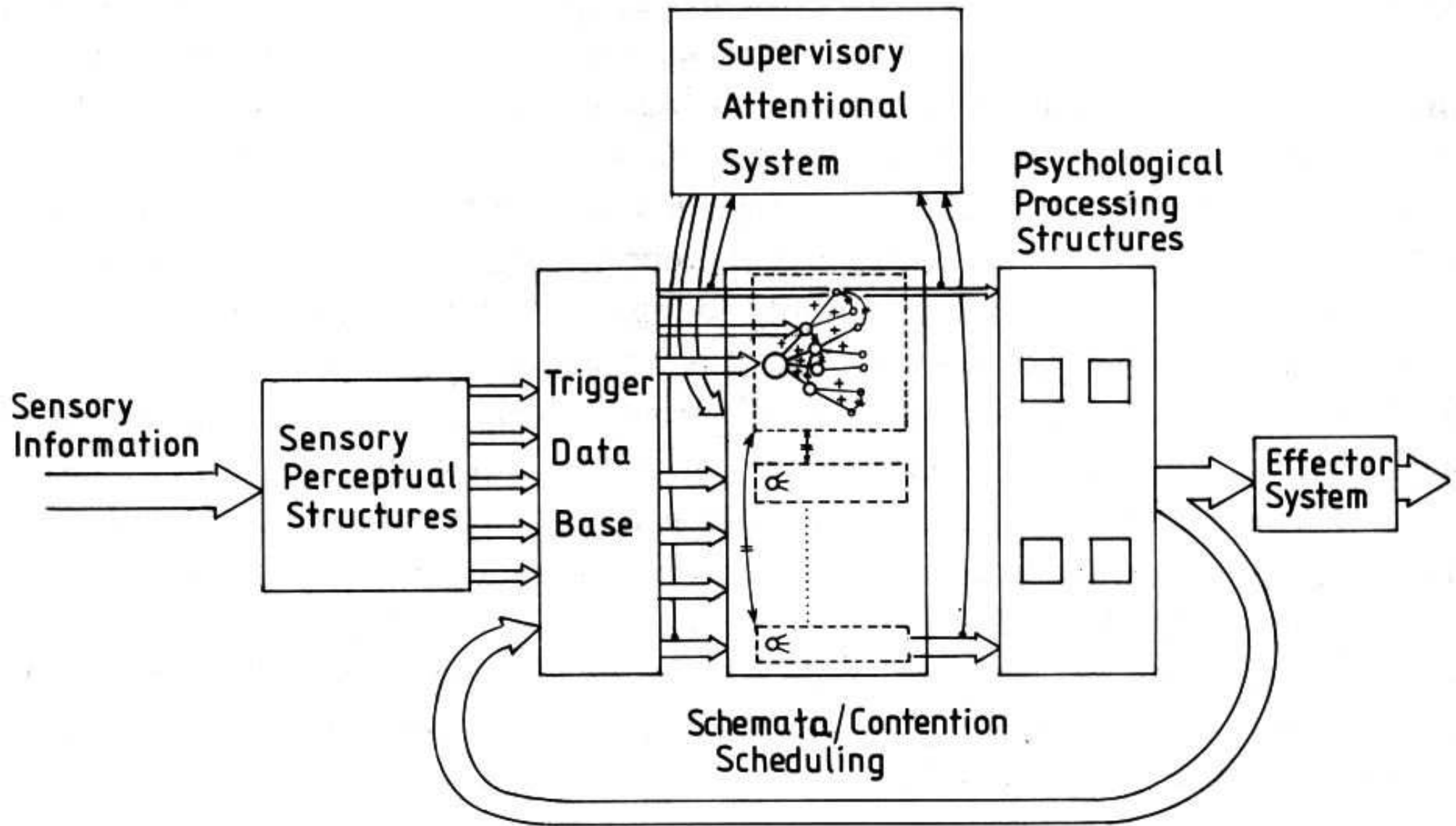


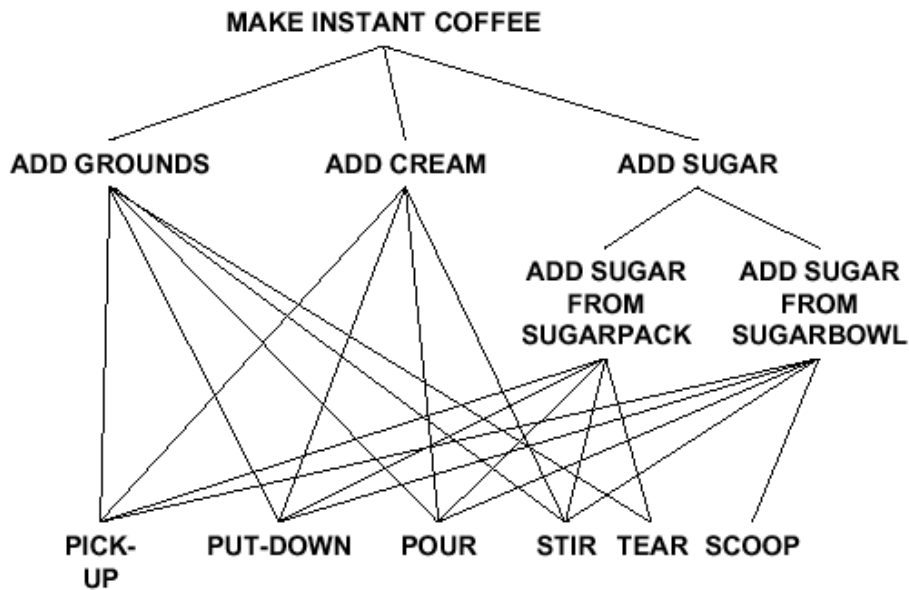
Norman and Shallice (1986)



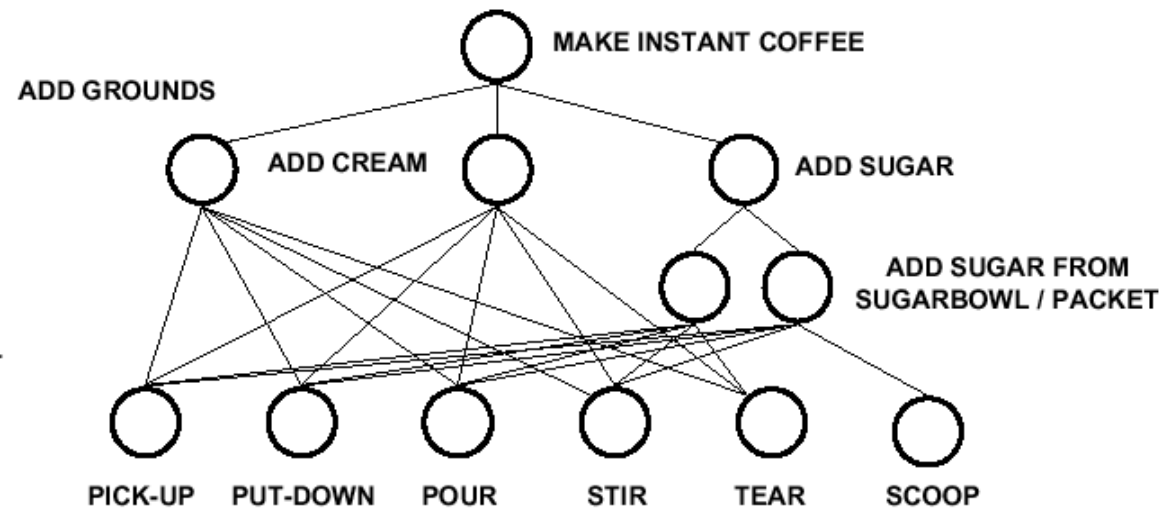
Hierarchical structure in routine sequential action

Miller, Gelanter and Pribram (1960), Estes (1972), Rumelhart and Norman (1982)
Shank and Abelson (1977), MacKay (1985, 1987), Fuster (1989), Grafman (1995)
Forde and Humphreys (1998), **Cooper and Shallice (2000)**

Knowledge



Representations/Processes?



Problems

- Weak learning theory for when (and how) to elaborate vs. add schemas
- No intrinsic sequencing mechanism

Hierarchical structure in conceptual knowledge

Quillian (1967)

Collins and Quillian (1969)

Anderson (1983, 1990);

Anderson and Lebiere (1998)

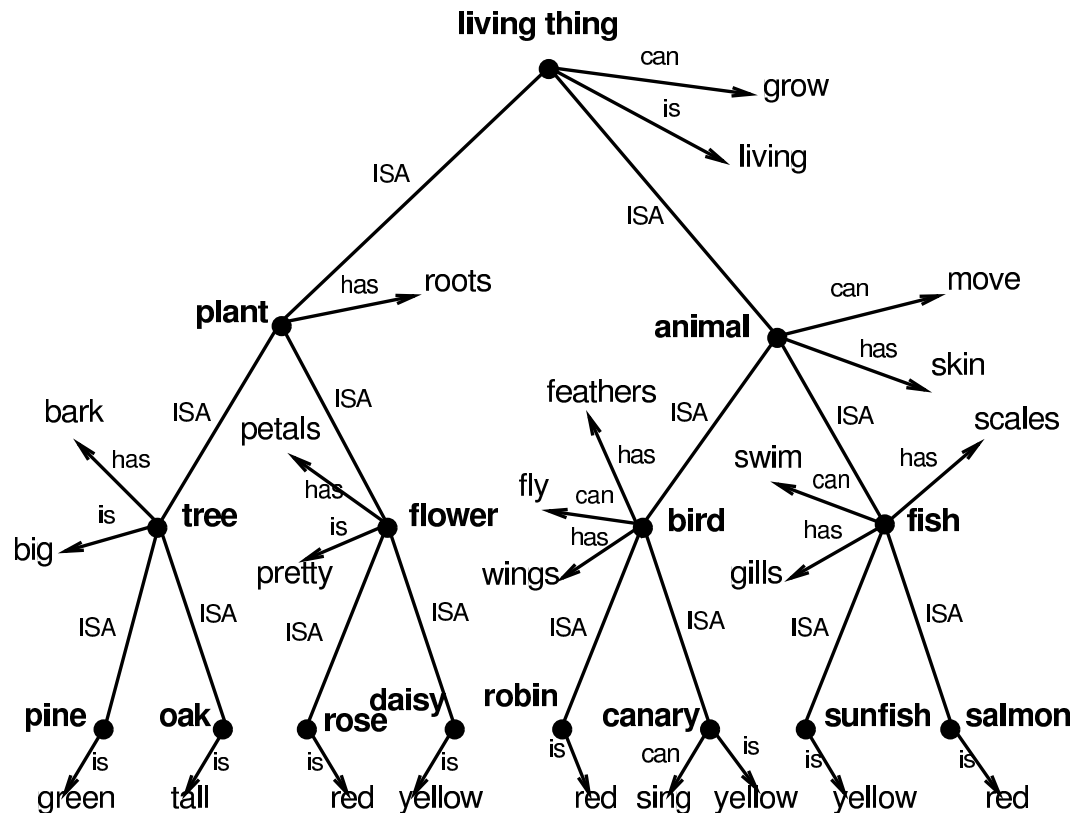
Hinton (1981)

Rumelhart and Todd (1993)

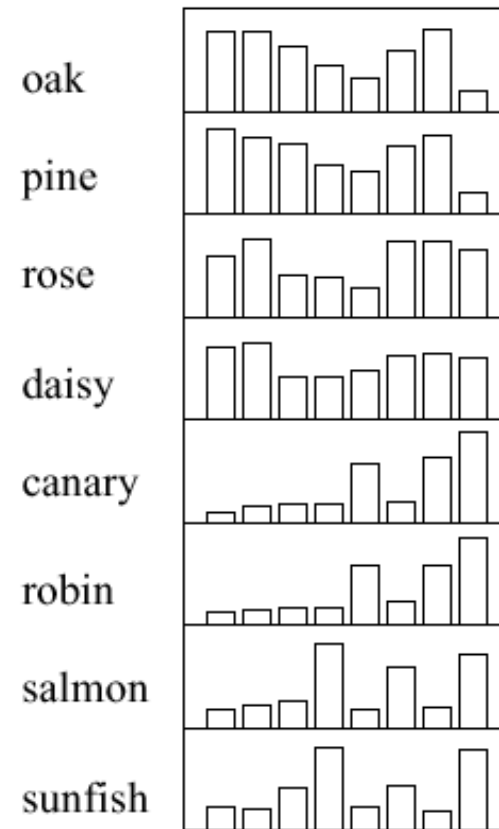
McClelland, McNaughton and O'Reilly (1995)

Rogers and McClelland (2004)

Knowledge

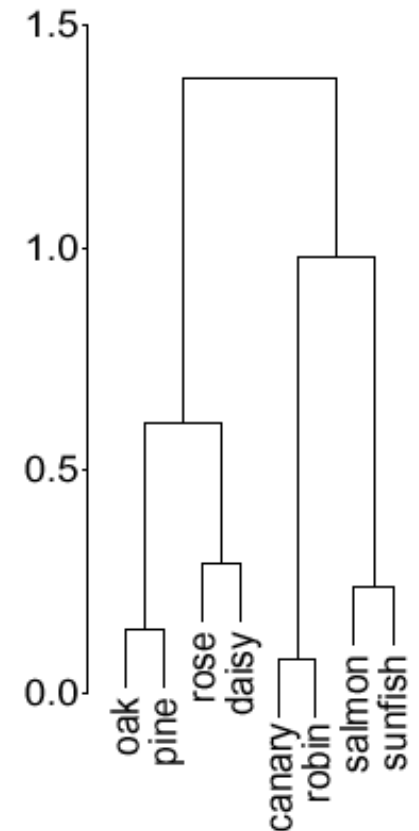


Representations



Epoch 500

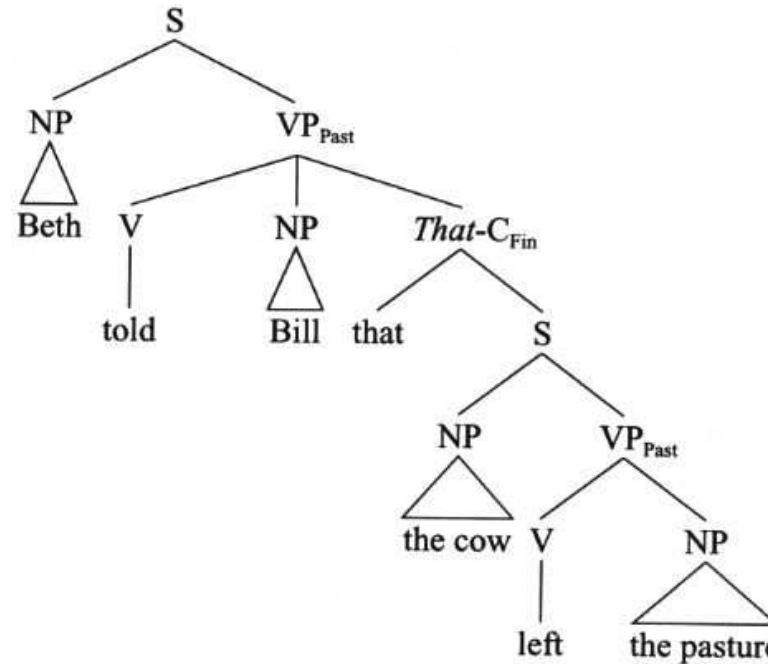
Similarities



Epoch 500

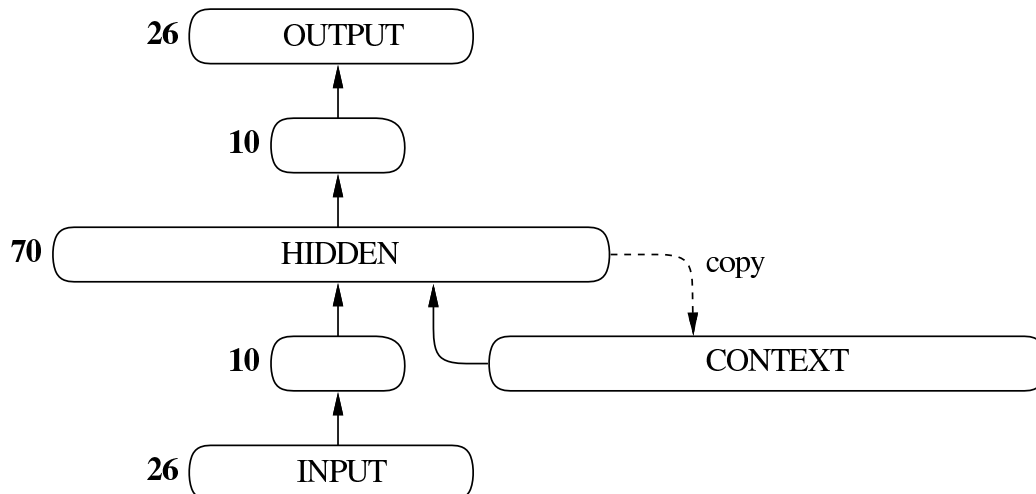
Hierarchical structure in sentence processing

“Beth told Bill that the cow left the pasture.”



Elman (1991, 1993)

- Simple recurrent network trained to predict words in pseudo-English sentences



S → NP VI . | NP VT NP .

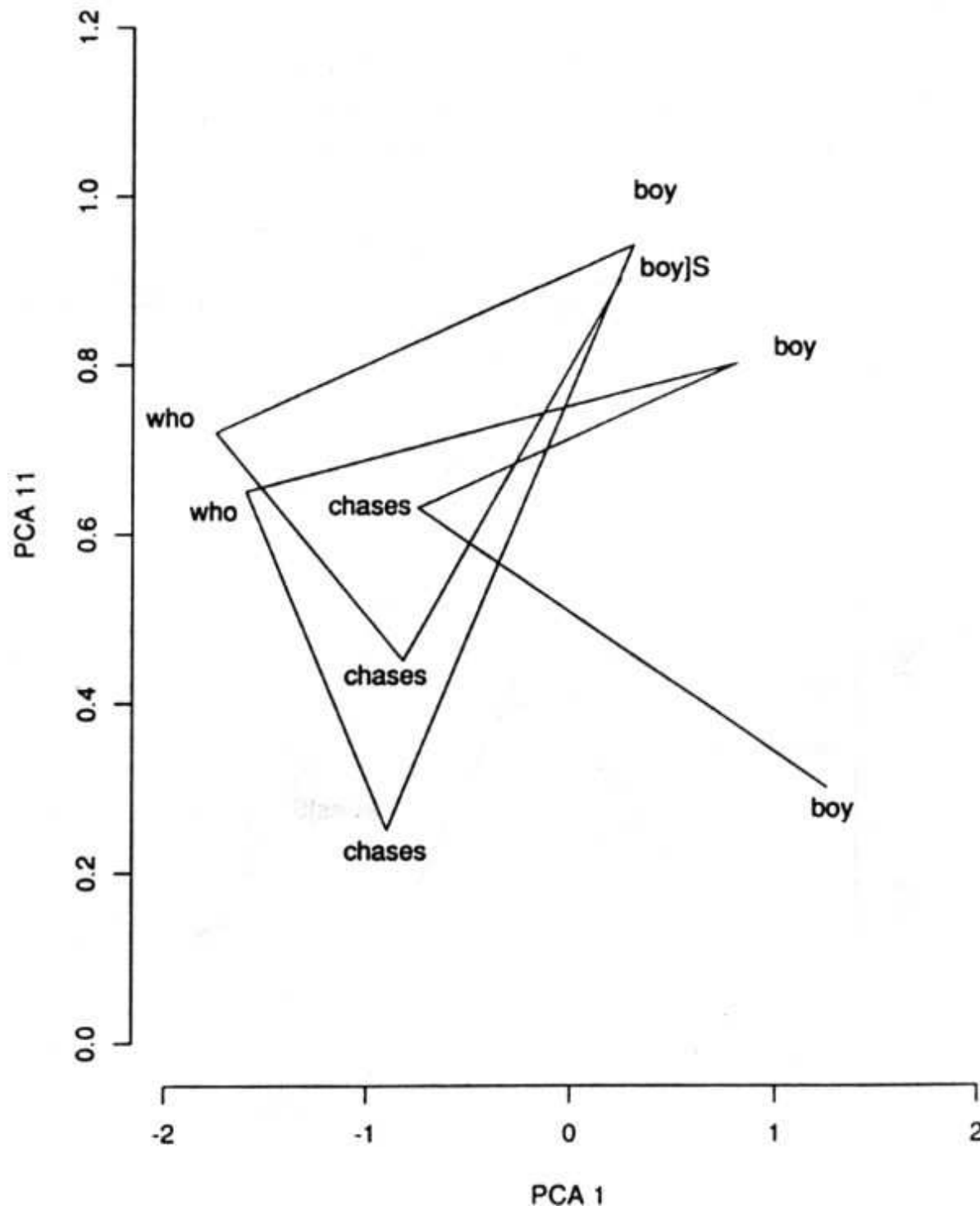
NP → N | N RC

RC → who VI | who VT NP | who NP VT

N → boy | girl | cat | dog | Mary | John |
boys | girls | cats | dogs

VI → barks | sings | walks | bites | eats |
bark | sing | walk | bite | eat

VT → chases | feeds | walks | bites | eats |
chase | feed | walk | bite | eat



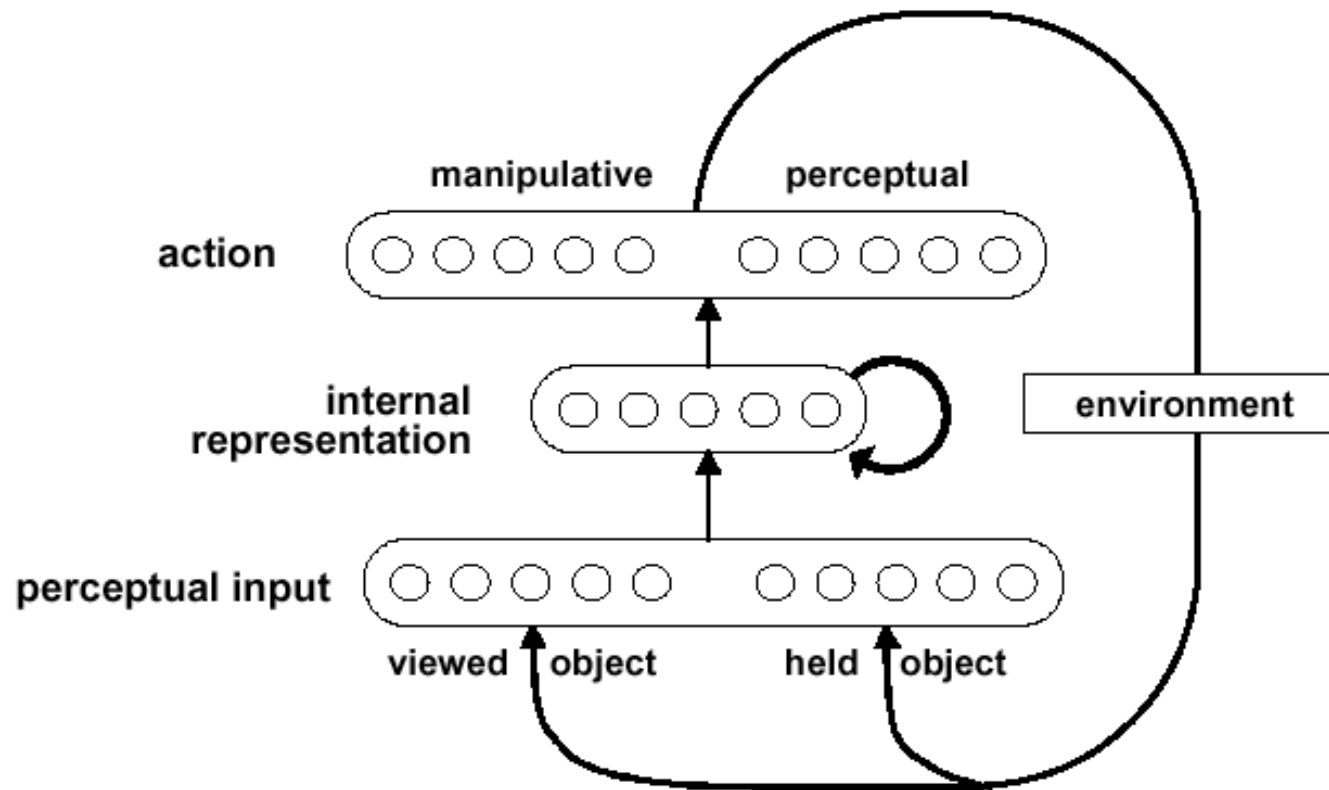
Boy chases boy who chases
boy who chases boy .

Principal Components Analysis (PCA) of network's internal representations

- Largest amount of variance (PC-1) reflects **word class** (noun, verb, function word)
- Separate dimension of variation (PC-11) encodes **syntactic role** (agent/patient) for nouns and **level of embedding** for verbs

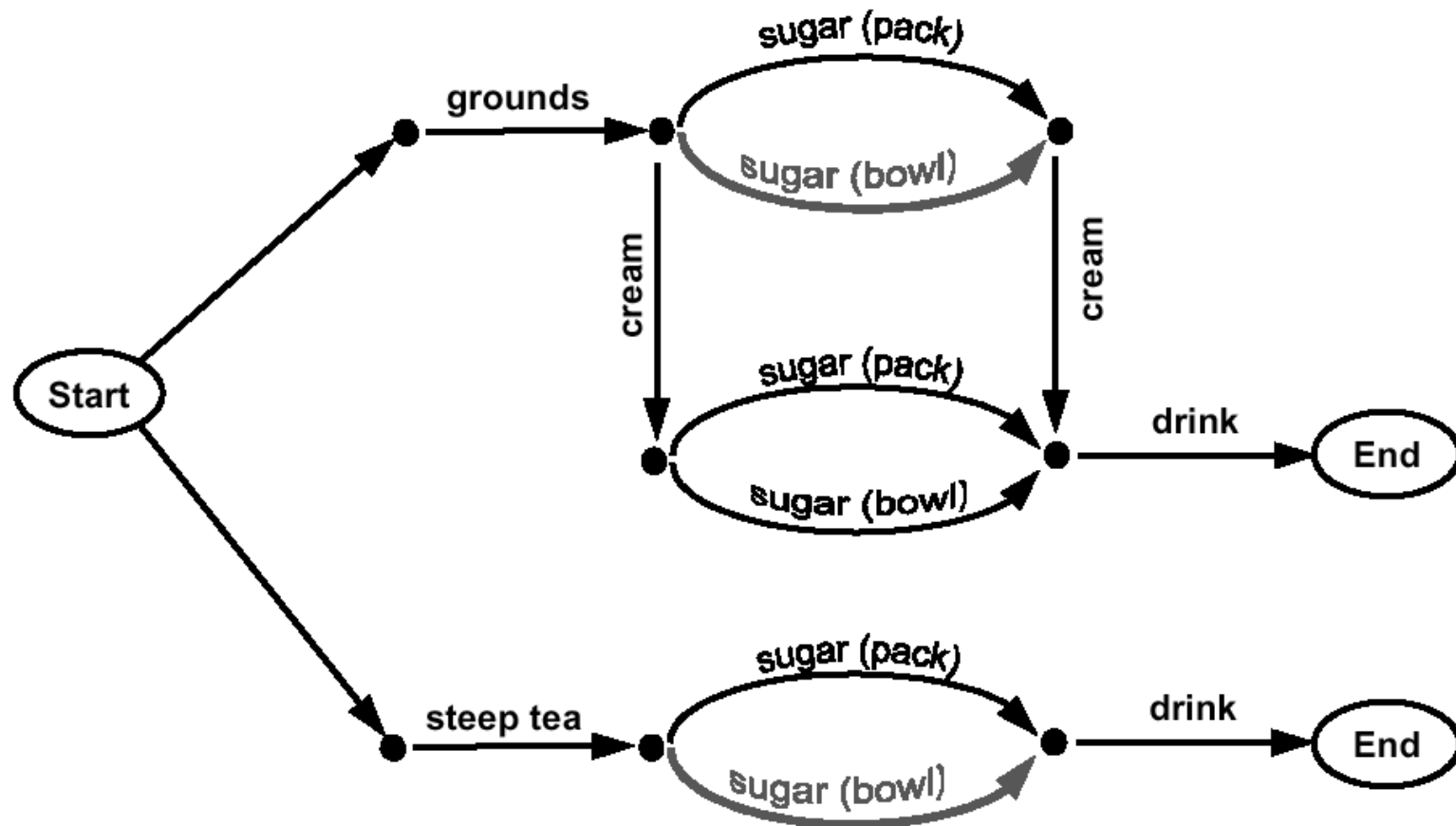
A distributed connectionist approach to sequential action

Botvinick and Plaut (2004, *Psych. Rev.*)



- Simple recurrent network that maps perceptual inputs *and internal representations of task context* onto actions
 - Input codes currently viewed/held objects; output is manipulative or perceptual action
 - Trained by observing skilled coffee- and tea-making, and on general *affordances*
 - Tested by applying most strongly activated action to environment and repeating

Task structure: Making instant coffee (and tea)



- Hierarchically structured
- Actions/subtasks may appear in multiple contexts
- Environmental cues alone sometimes insufficient to guide action selection
- Subtasks may be disjoint or executed in variable order

Grounds

Step	Fixated object	Held object	Action
1	cup, 1-handle, clear-liquid	nothing	fixate-coffee-pack
2	packet, foil, untorn	nothing	pick-up
3	packet, foil, untorn	packet, foil, untorn	pull-open
4	packet, foil, torn	packet, foil, torn	fixate-cup
5	cup, 1-handle, clear-liquid	packet, foil, torn	pour
6	cup, 1-handle, brown-liquid	packet-foil-torn	fixate-spoon
7	spoon	packet, foil, torn	put-down
8	spoon	nothing	pick-up
9	spoon	spoon	fixate-cup
10	cup, 1-handle, brown-liquid	spoon	stir

Sugar (bowl)

11	cup, 1-handle, brown-liquid	spoon	fixate-sugar
12	cup, 2-handles, lid	spoon	put-down
13	cup, 2-handles, lid	nothing	pull-off
14	cup, 2-handles, sugar	lid	fixate-spoon
15	spoon	lid	put-down
16	spoon	nothing	pick-up
17	spoon	spoon	fixate-sugarbowl
18	cup, 2-handles, sugar	spoon	scoop
19	cup, 2-handles, sugar	spoon-sugar	fixate-cup
20	cup, 1-handle, brown-liquid	spoon-sugar	pour
21	cup, 1-handle, brown-liquid	spoon	stir

Cream

22	cup, 1-handle, brown-liquid	spoon	fixate-carton
23	carton, closed	spoon	put-down
24	carton, closed	nothing	pick-up
25	carton, closed	carton, closed	peel-open
26	carton, open	carton, open	fixate-cup
27	cup, 1-handle, brown-liquid	carton-open	pour
28	cup, 1-handle, light-, brown-liquid	carton-open	fixate-spoon
29	spoon	carton-open	put-down
30	spoon	nothing	pick-up
31	spoon	spoon	fixate-cup
32	cup, 1-handle, light-, brown-liquid	spoon	stir

Drink

33	cup, 1-handle, light-, brown-liquid	spoon	put-down
34	cup, 1-handle, light-, brown-liquid	nothing	pick-up
35	cup, 1-handle, light-, brown-liquid	cup, 1-handle, light-, brown-liquid	sip
36	cup, 1-handle, light-, brown-liquid	cup, 1-handle, light-, brown-liquid	sip
37	cup, 1-handle, empty	cup, 1-handle, empty	say-done

Adding coffee grounds: Detail

Step	Fixated object	Held object	Action
1	cup, 1-handle, clear-liquid	nothing	fixate-coffee-pack
2	packet, foil, untorn	nothing	pick-up
3	packet, foil, untorn	packet, foil, untorn	pull-open
4	packet, foil, torn	packet, foil, torn	fixate-cup
5	cup, 1-handle, clear-liquid	packet, foil, torn	pour
6	cup, 1-handle, brown-liquid	packet-foil-torn	fixate-spoon
7	spoon	packet, foil, torn	put-down
8	spoon	nothing	pick-up
9	spoon	spoon	fixate-cup
10	cup, 1-handle, brown-liquid	spoon	stir
	●		
	●		
	●		
	●		

Neural network models of serial order. . . [retain] a dynamics dependent on chaining. . . . They also seem to us unlikely to be prone to the kinds of serial order errors discussed below [omissions, transpositions].

—Houghton and Hartley (1995, *Psyche*, p. 5)

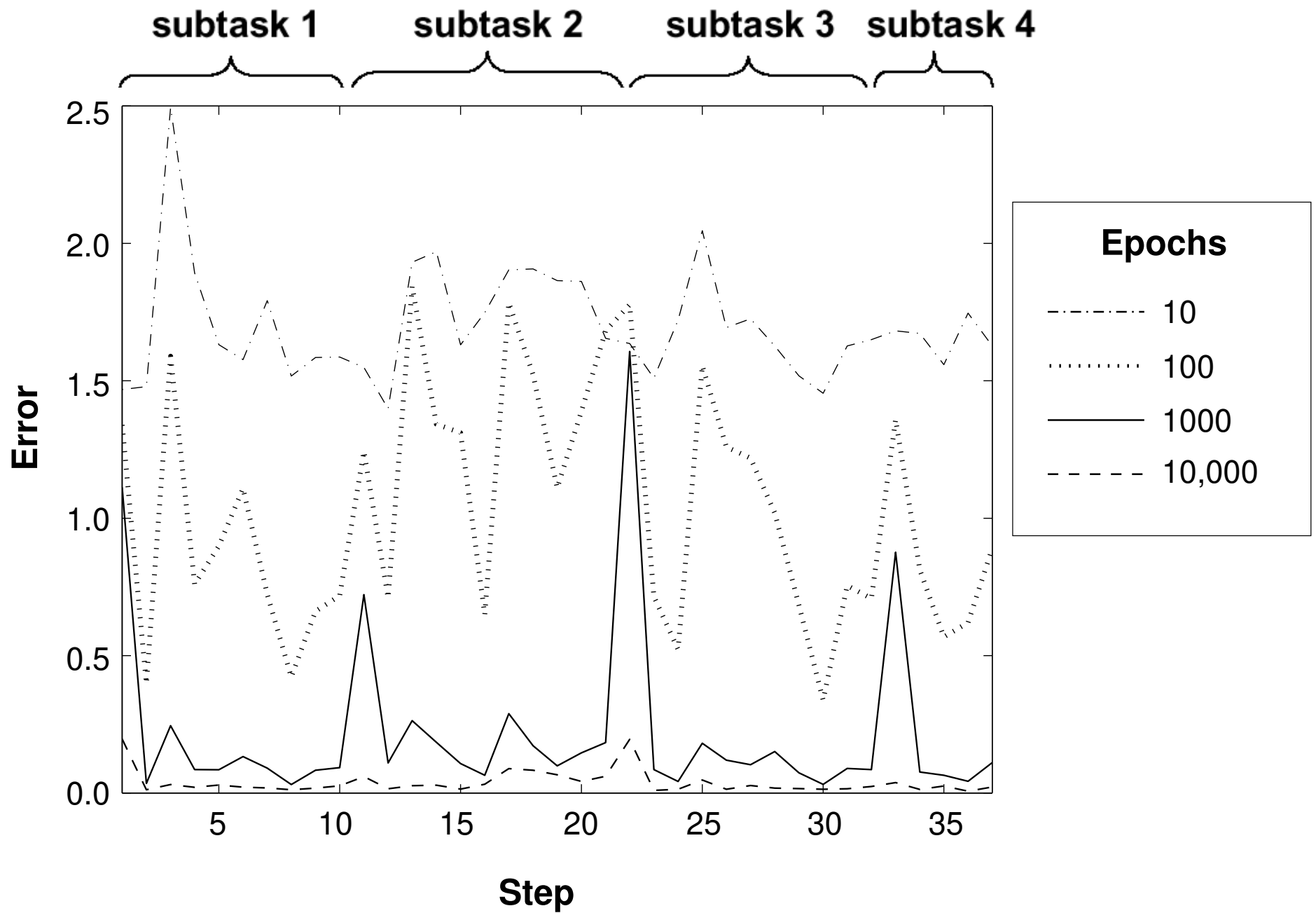
Recurrent networks lack “temporal competence. . . the intrinsic dynamics that would enable them to progress autonomously through a sequence.”

—Brown, Preece and Hulme (2000, *Psych. Review*, p. 133)

The principal difficulty in obtaining [omission and other sequence errors] within recurrent networks appears to arise from the lack of any separate representation of hierarchical relations (i.e., source/component schema relationships) and order information (i.e., the relative ordering of component schemas within a single source schema). It is thus difficult for order information to be disrupted without disruption to hierarchical relations.

—Cooper and Shallice (2000, *Cog. Neuropsych.*, p. 329)

Acquisition



Normal performance

Proportions of testing trials

With coffee instruction

GROUND S → SUGAR (PACK) → CREAM → DRINK	0.35
GROUND S → SUGAR (BOWL) → CREAM → DRINK	0.37
GROUND S → CREAM → SUGAR (PACK) → DRINK	0.14
GROUND S → CREAM → SUGAR (BOWL) → DRINK	0.14

With tea instruction

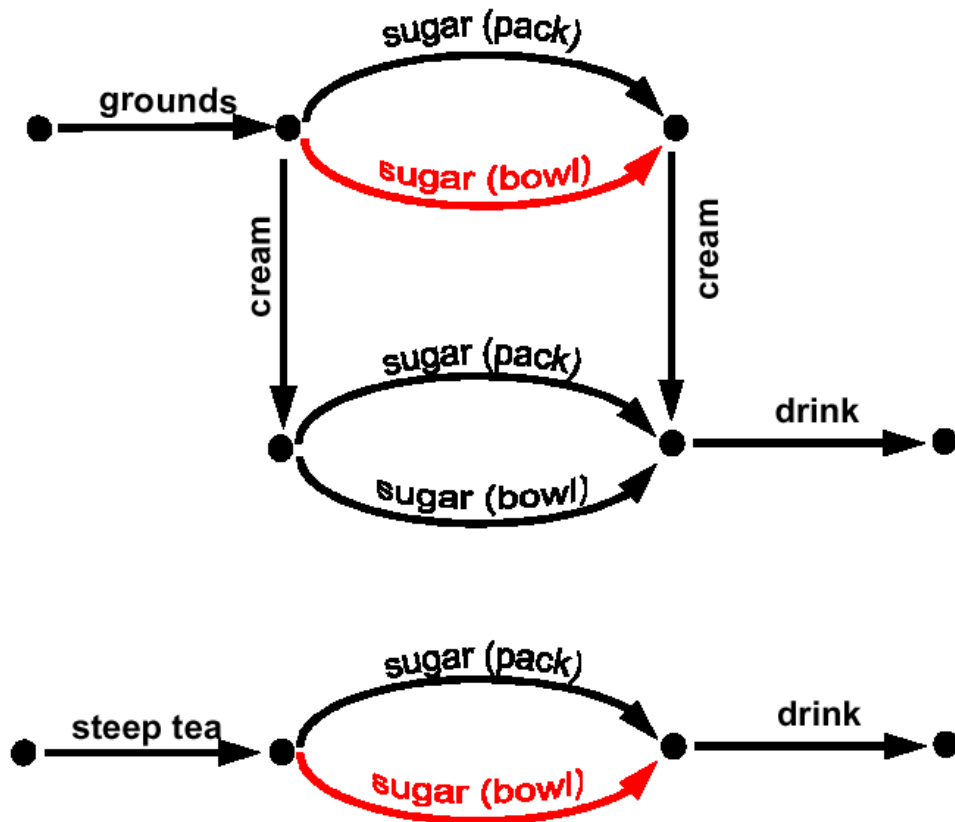
TEABAG → SUGAR (PACK) → DRINK	0.46
TEABAG → SUGAR (BOWL) → DRINK	0.54

With no instruction

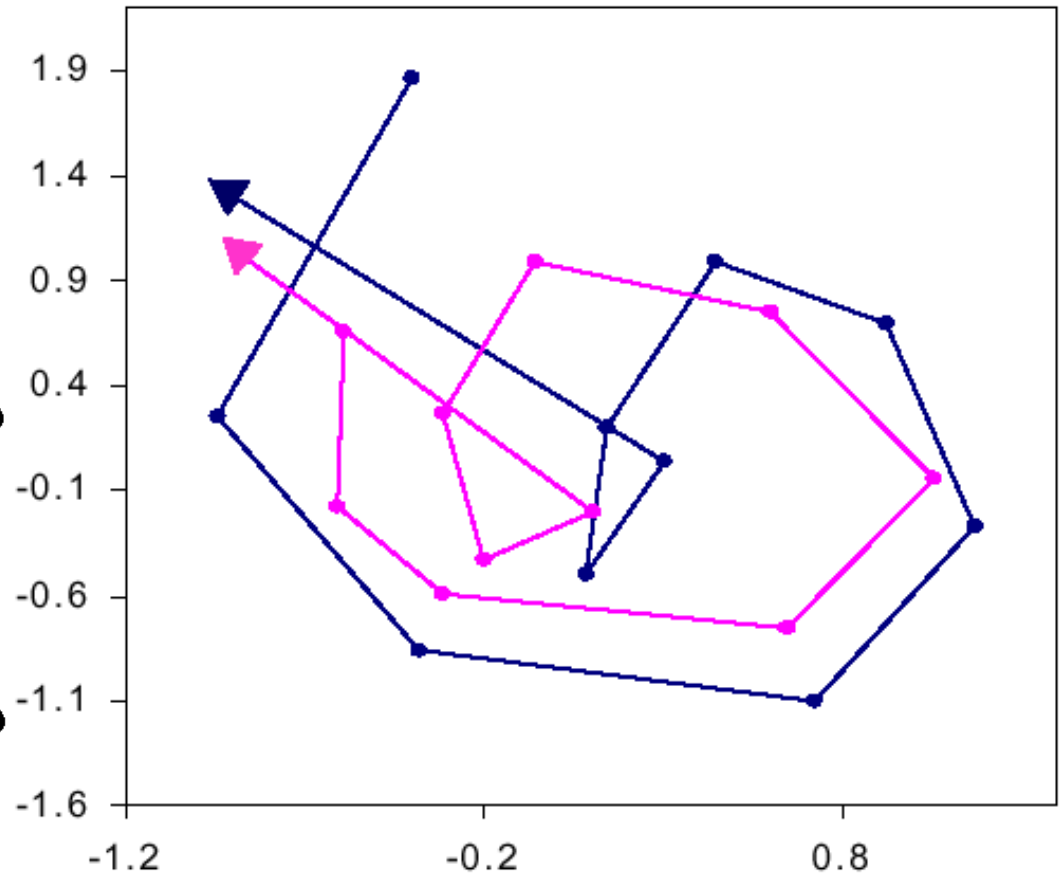
GROUND S → SUGAR (PACK) → CREAM → DRINK	0.15
GROUND S → SUGAR (BOWL) → CREAM → DRINK	0.18
GROUND S → CREAM → SUGAR (PACK) → DRINK	0.12
GROUND S → CREAM → SUGAR (BOWL) → DRINK	0.10
TEABAG → SUGAR (PACK) → DRINK	0.20
TEABAG → SUGAR (BOWL) → DRINK	0.25

Normal performance: Task context

How are different task contexts maintained across identical subtasks?



Multi-Dimensional Scaling



Slips of action (Reason, 1990)

Distraction: Distort context activations with **mild-to-moderate** noise

Sample of behavior:

cream omitted



pick-up coffee-pack
pull-open coffee-pack
pour coffee-pack into cup
put-down coffee-pack
pick-up spoon
stir cup
put-down spoon
pick-up sugar-pack
tear-open sugar-pack
pour sugar-pack into cup
put-down sugar-pack
pick-up spoon
stir cup
put-down spoon
pick-up cup*
sip cup
sip cup
say-done

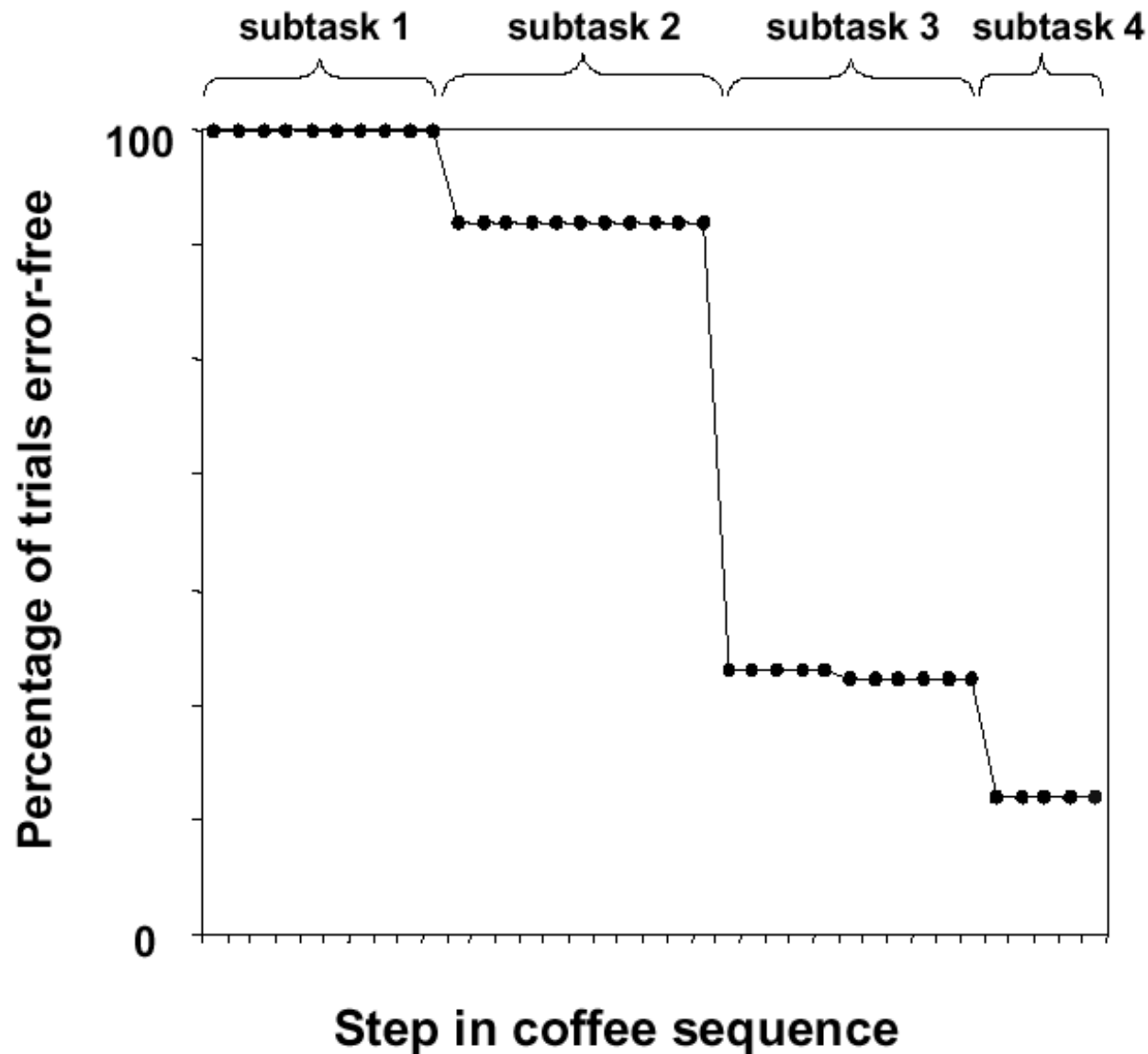
grounds

sugar (pack)

drink

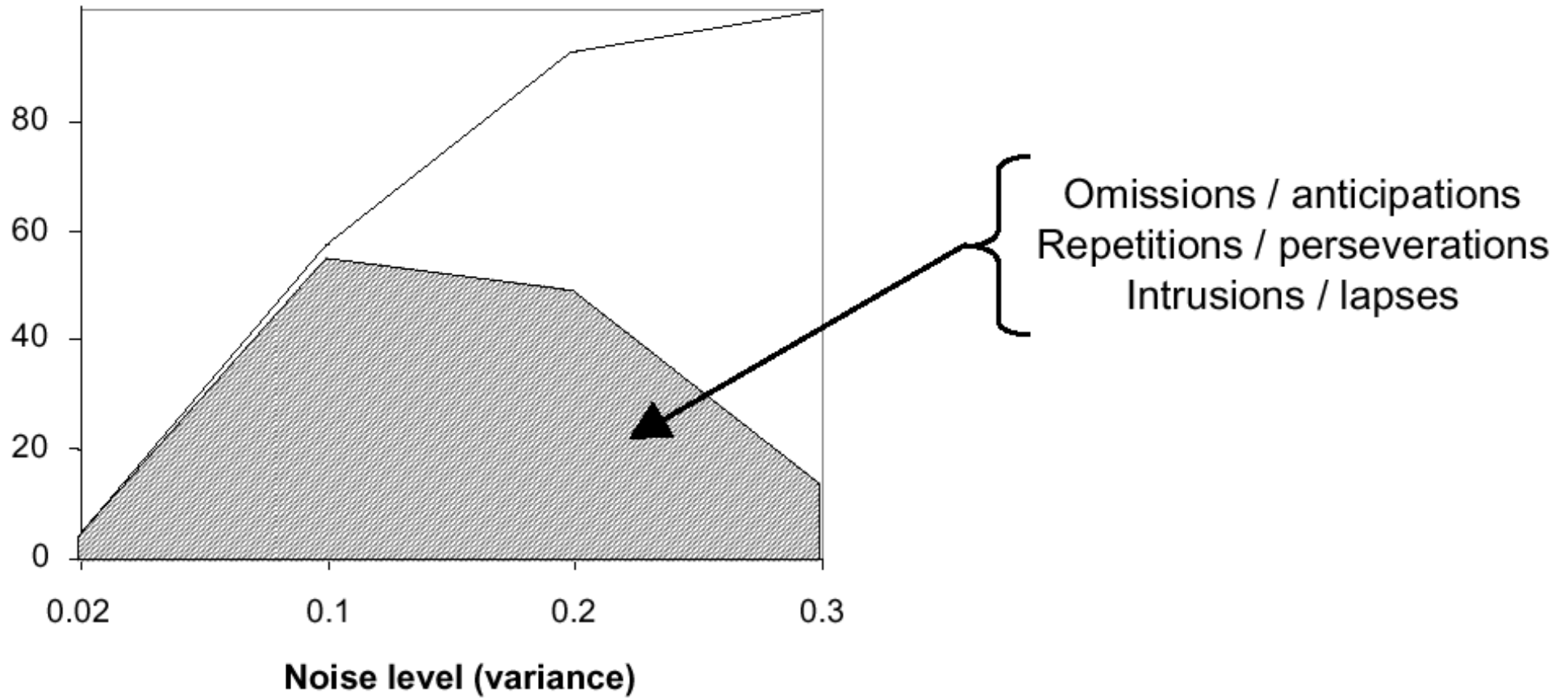
Slips of action

Errors occur at **decision points** (boundaries between subtasks)



Slips of action

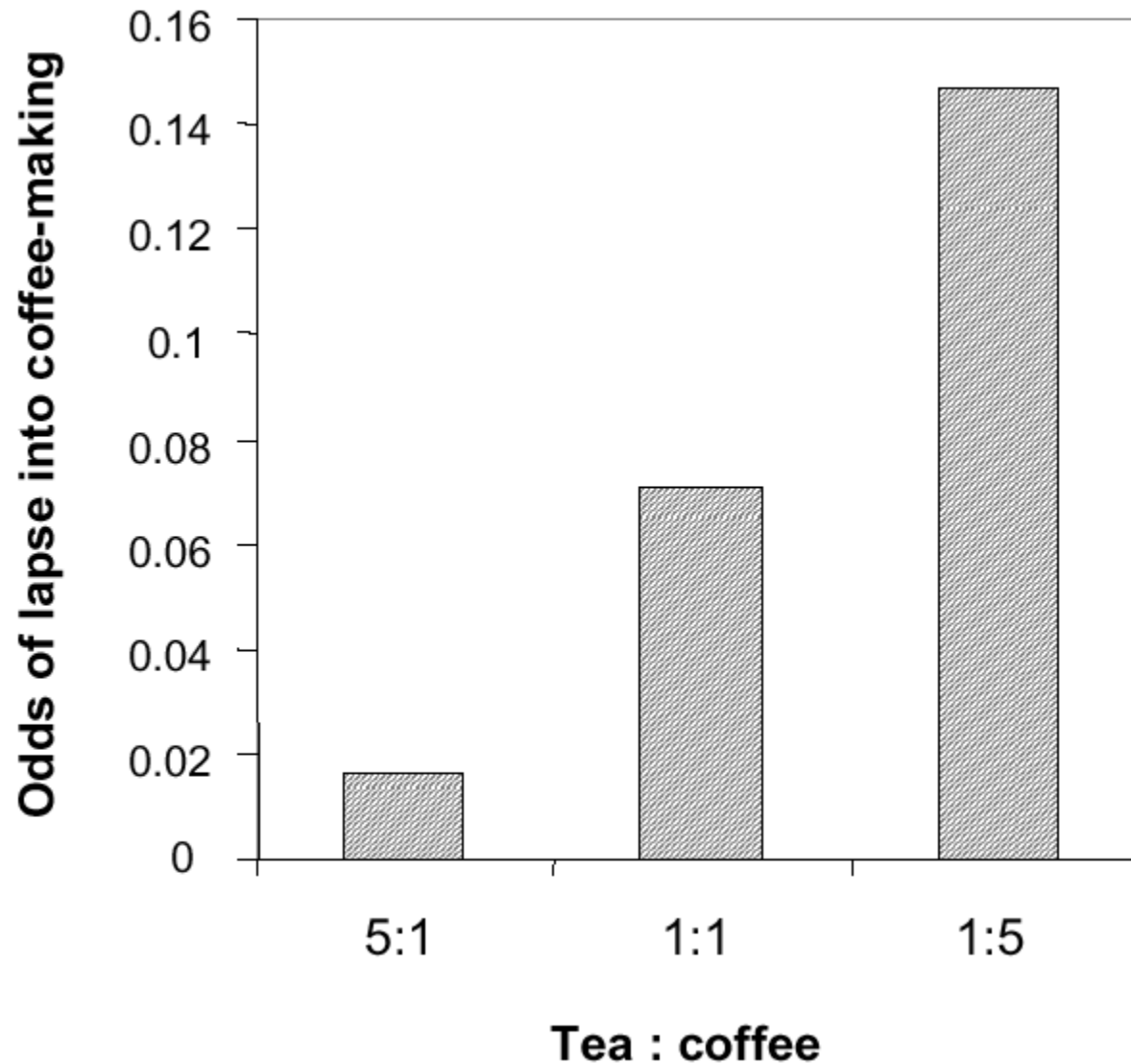
Errors take the form of **displaced but intact subtask sequences**



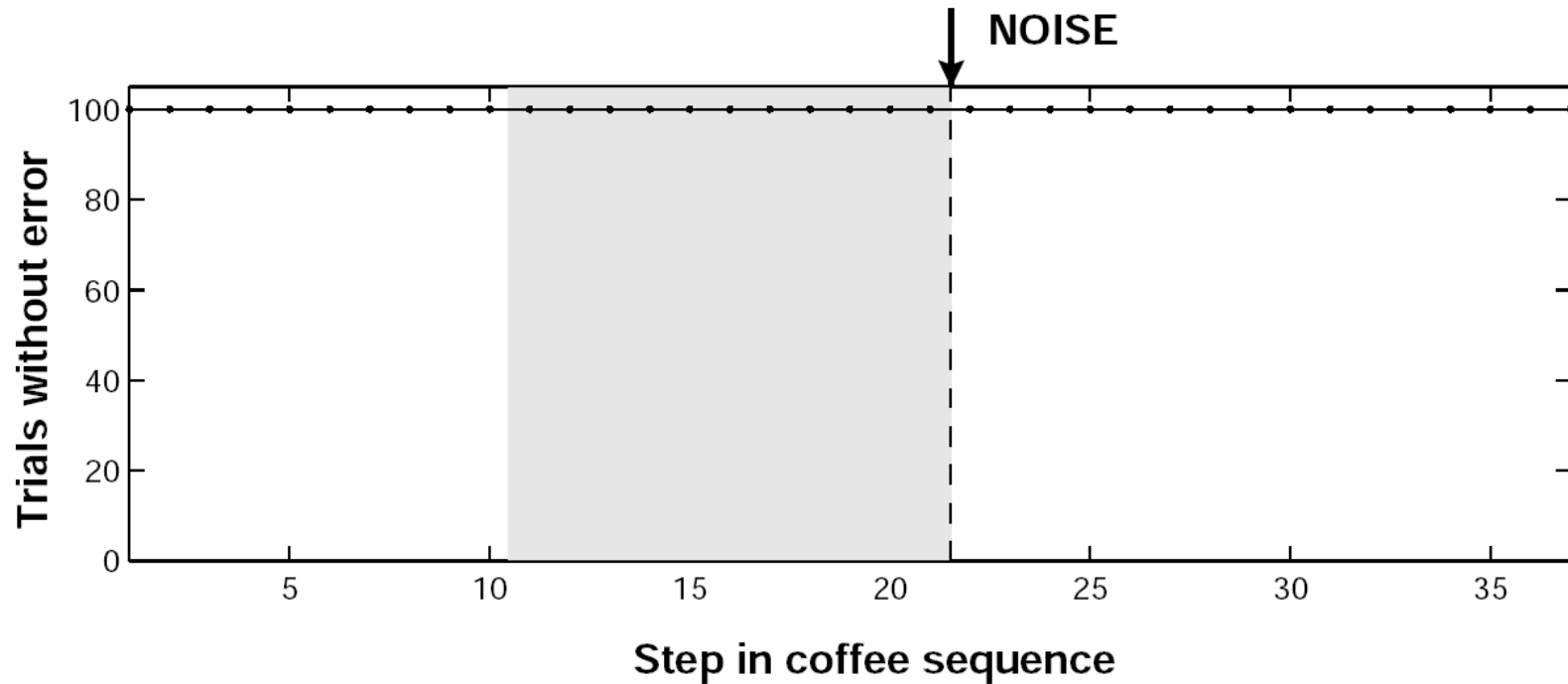
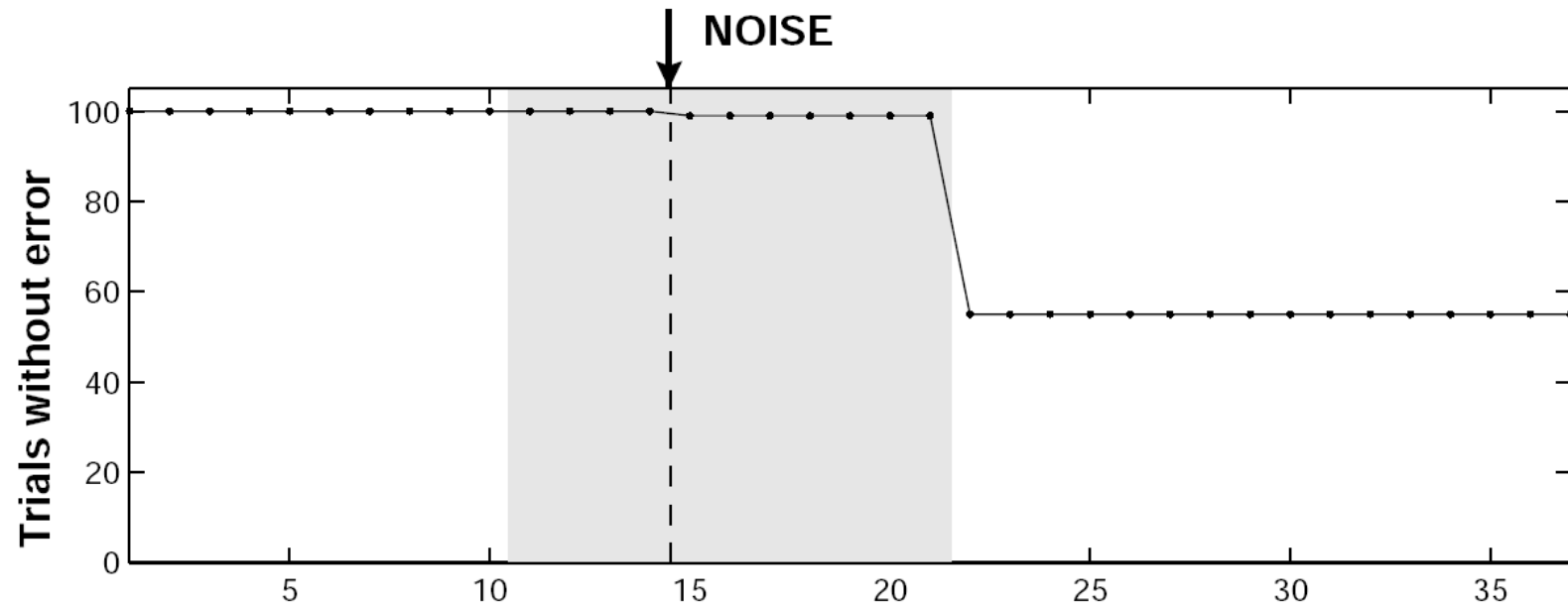
Slips of action

Lapses typically involve shift **from less frequent to more frequent task**

STEEP-TEA $\Rightarrow$ ADD-SUGAR $\Rightarrow$ **ADD-CREAM***

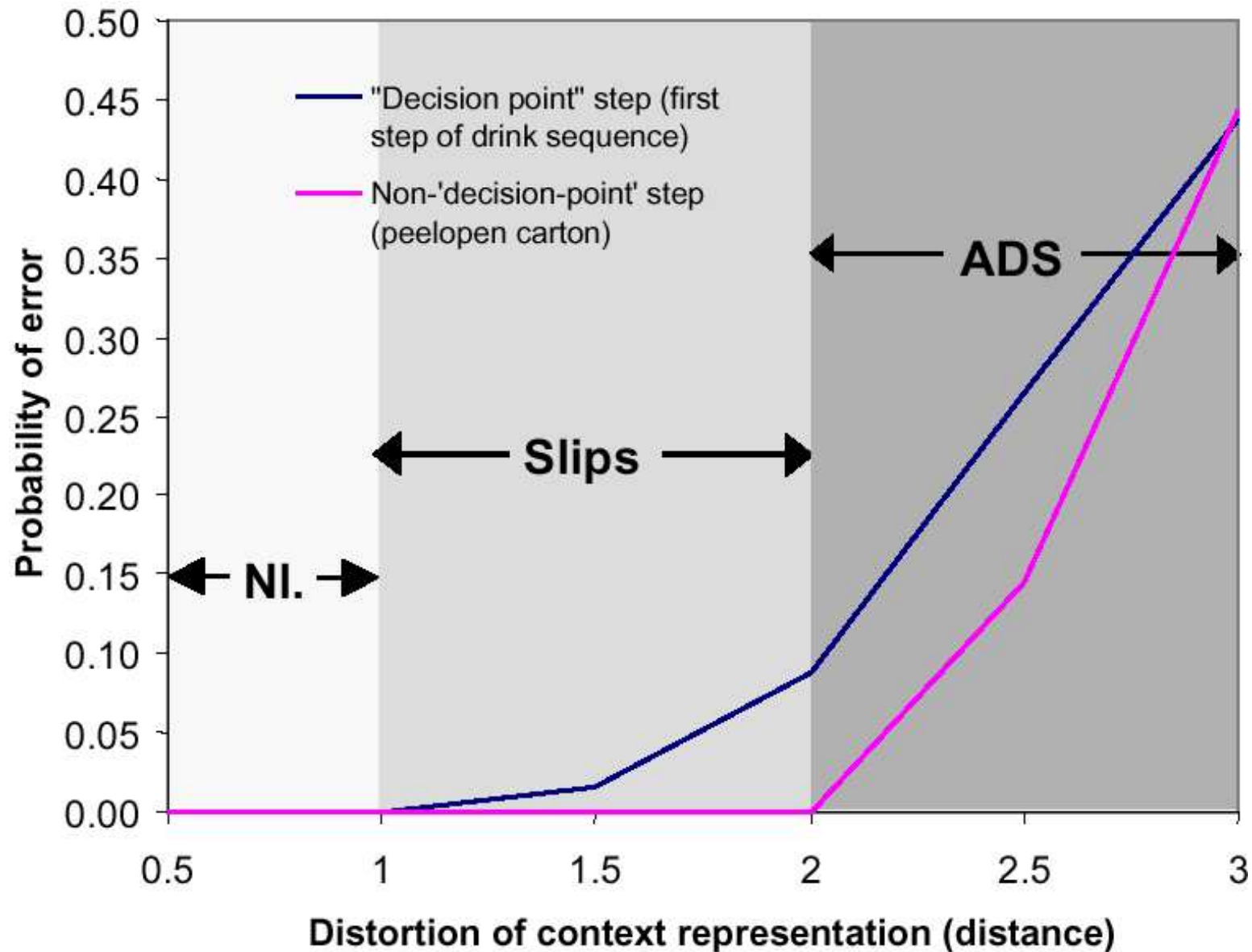


Prediction: Timing of distraction



Action Disorganization Syndrome (Schwartz et al., 1991)

Neural damage: Distort context activations with **severe noise**



Action Disorganization Syndrome

Sample of behavior:

pick-up coffee-pack
pull-open coffee-pack
put-down coffee-pack*
pick-up coffee-pack
pour coffee-pack into cup
put-down coffee-pack
pick-up spoon

} **disrupted subtask**

stir cup
put-down spoon
pick-up sugar-pack
tear-open sugar-pack
pour sugar-pack into cup
put-down sugar-pack

} **subtask fragment**

sugar repeated →

pick-up cup*
put-down cup
pull-off sugarbowl lid
put-down lid
pick-up spoon
scoop sugarbowl with spoon
put-down spoon*
pick-up cup*

} **subtask fragment**

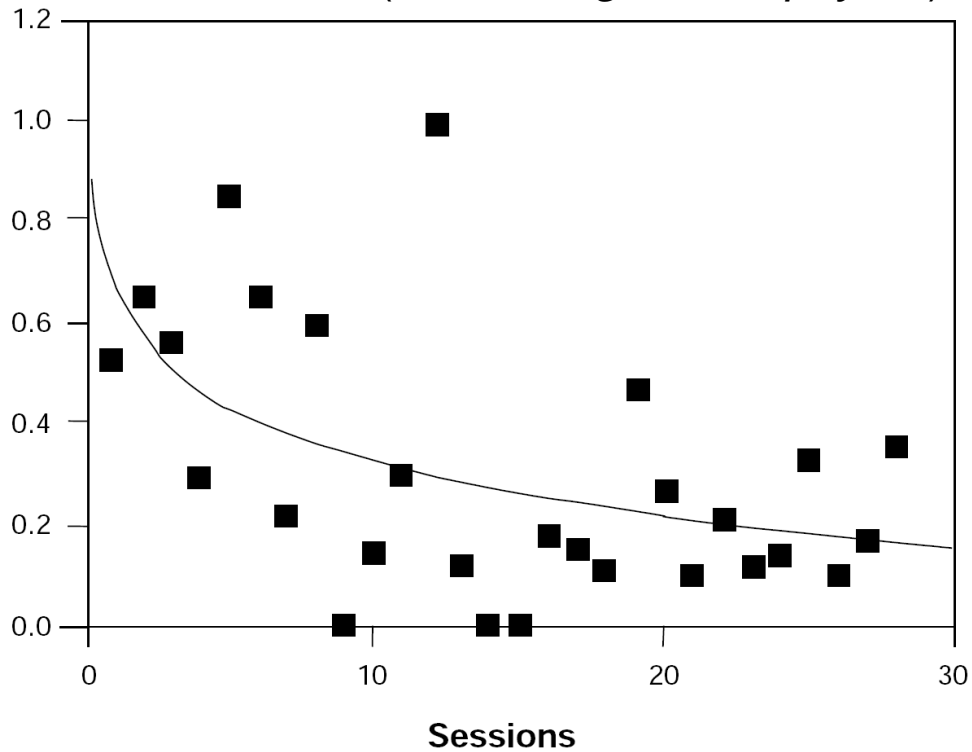
cream omitted →

sip cup
sip cup
say-done

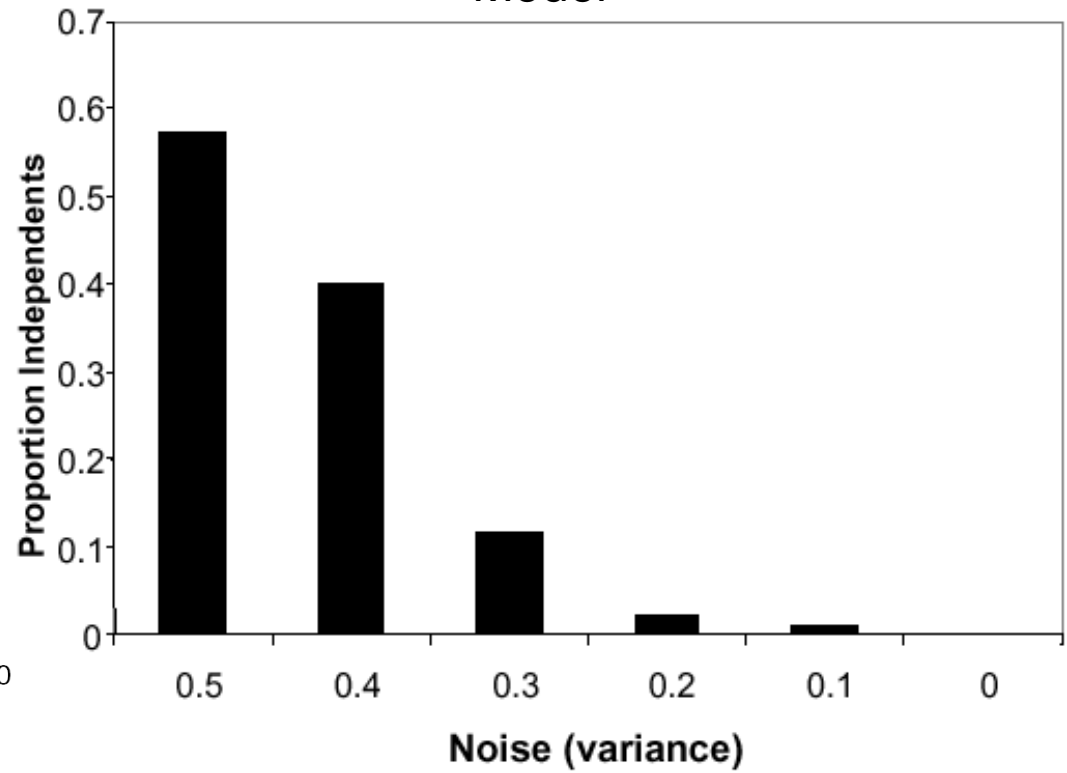
Action Disorganization Syndrome

Decrease in **independent actions** with decreasing ADS severity

Schwartz et al. (1991, *Cog. Neuropsych.*)



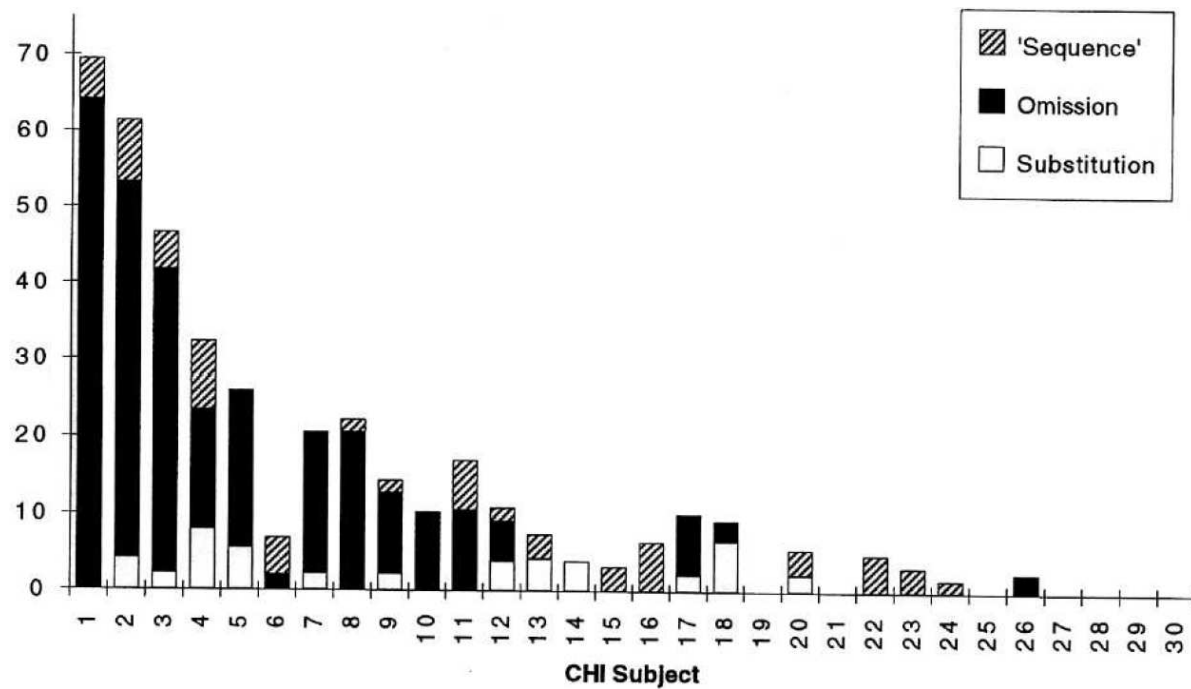
Model



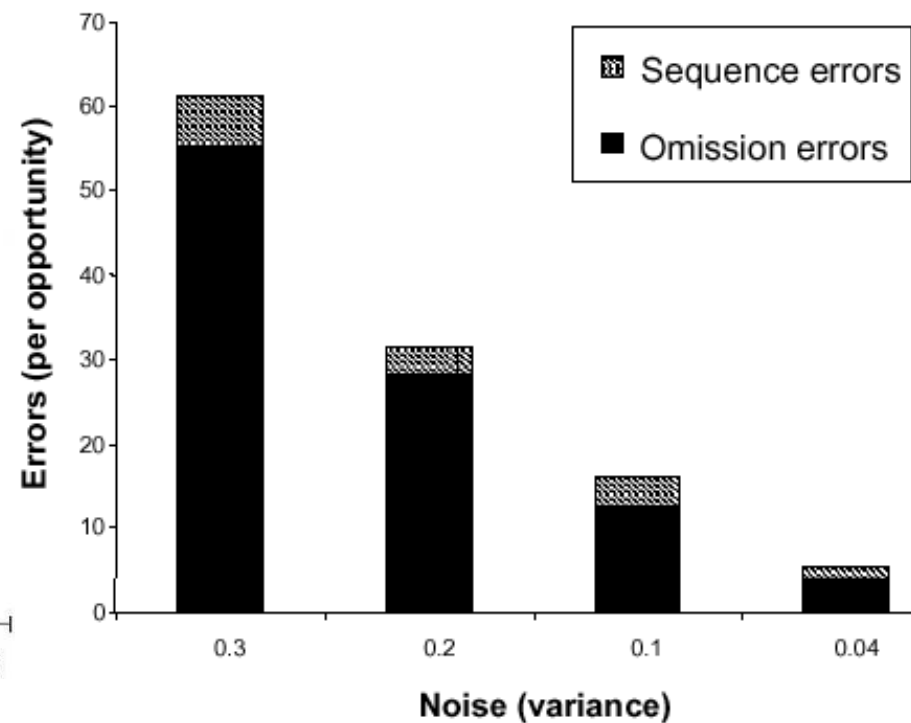
Action Disorganization Syndrome

Patients who make more errors commit a higher proportion of **omission errors**

Schwartz et al. (1998, *Neuropsych.*)

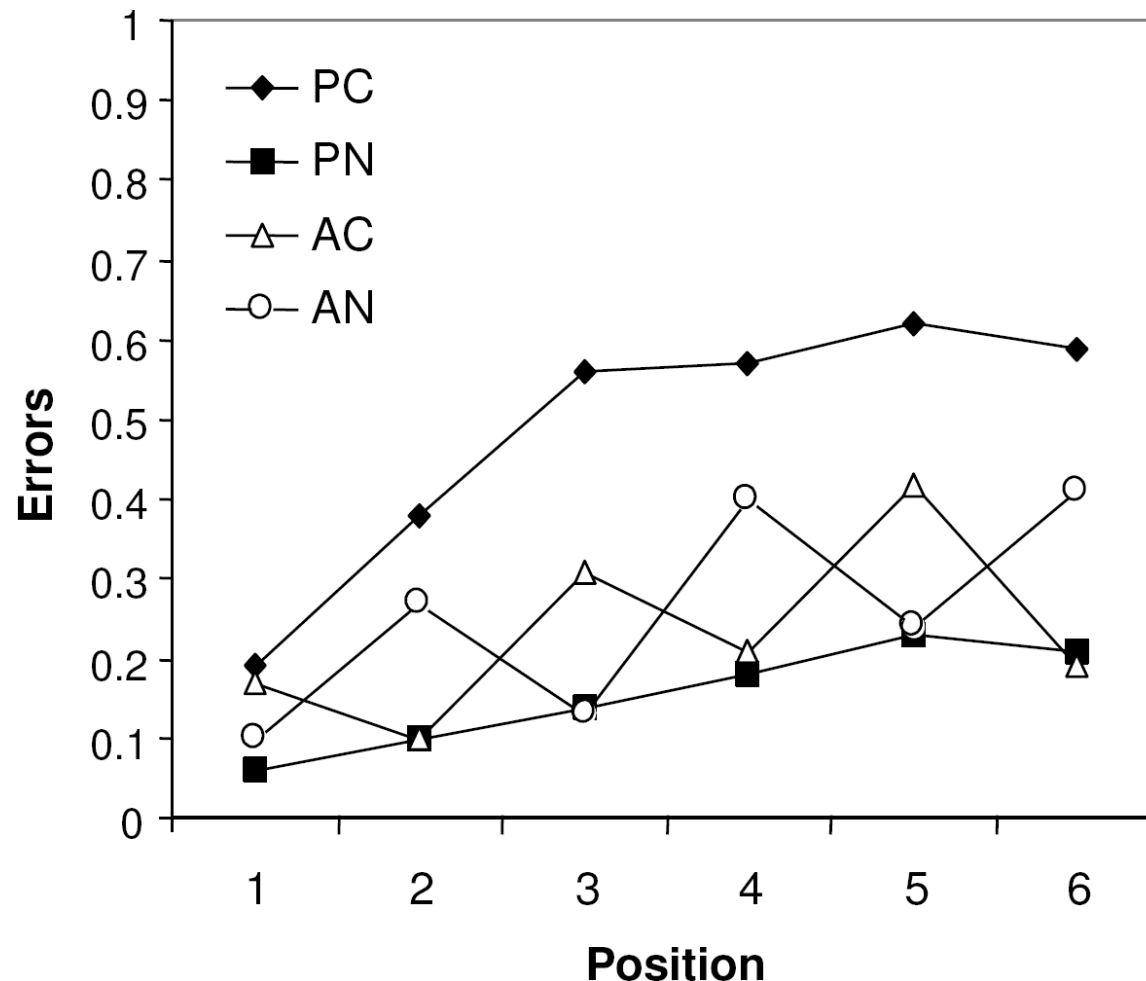


Model



Recurrent networks and “chaining”

- Recurrent networks thought to depend on item-item associations (chaining)
- Incompatible with findings from **immediate serial recall**



Pure/Alternating
Confusable/Nonconfusable

Example AC list:

B R D Q P L

Baddeley (1968, *QJEP*); Henson, Norris, Page, & Baddeley (1996, *QJEP*)

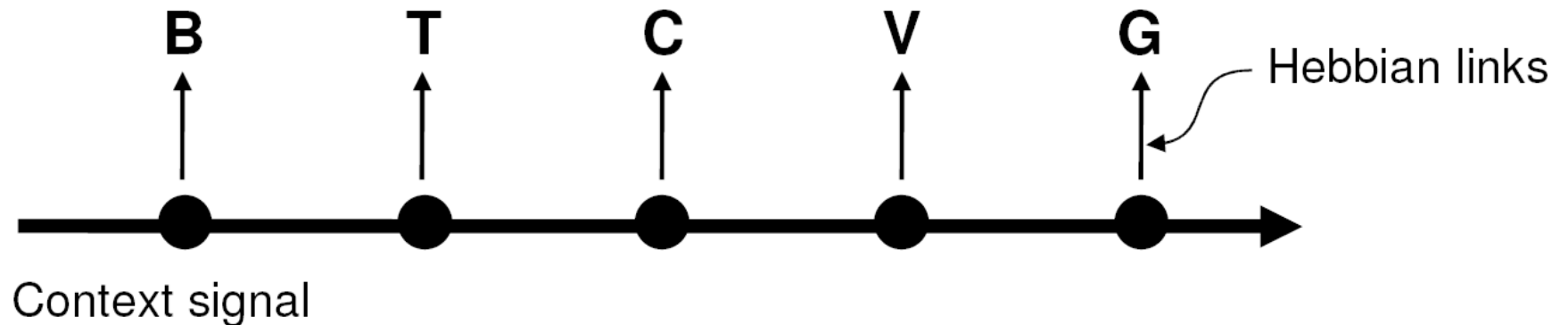
Context-association models of serial recall

Burgess and Hitch (1992)

Henson (1996, 1998)

Houghton (1990)

Brown, Preece, and Hulme (2000)

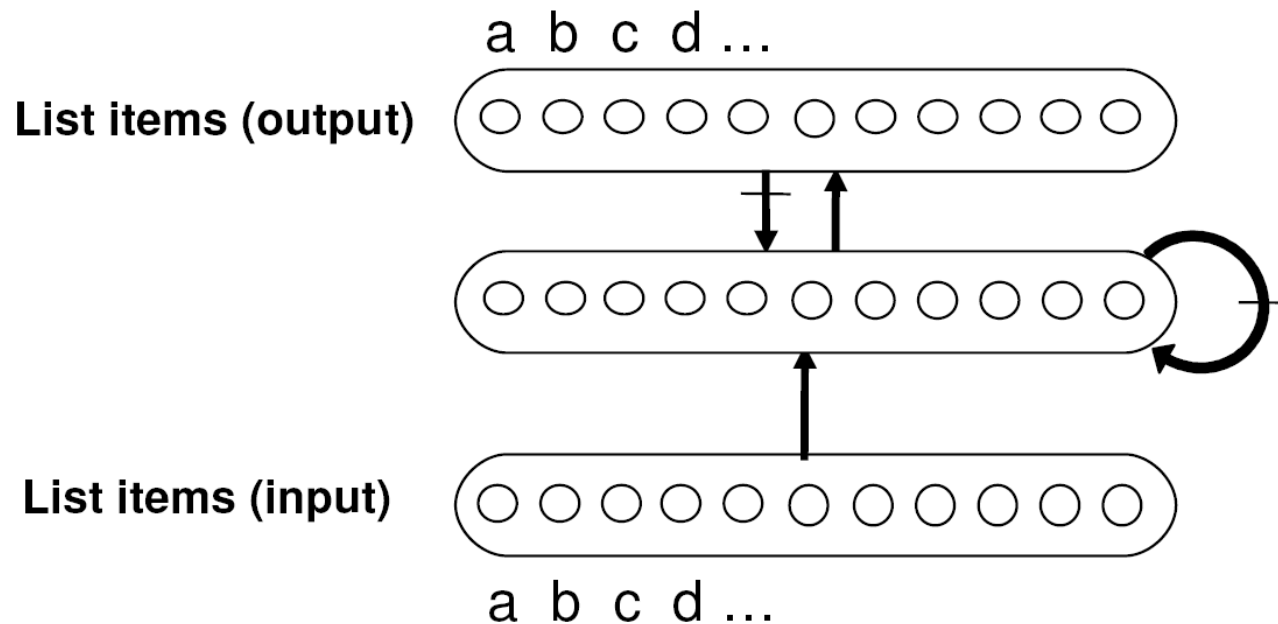


“Interactions between short- and long-term memory pose problems for most models of serial recall.”

—Henson (1998, *Cog. Psych.*)

A recurrent network model of immediate serial recall

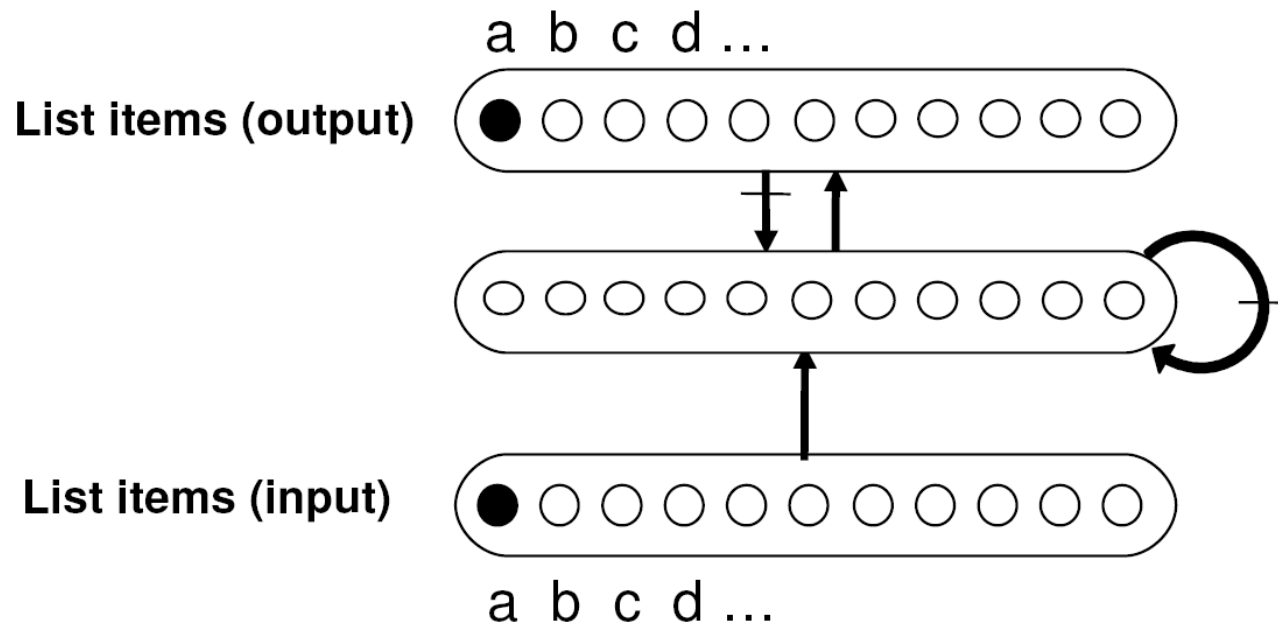
Botvinick and Plaut (2006, *Psych. Rev.*)



- Trained and tested on ISR (list lengths 1-9); proxy for *language* learning
- Weights not allowed to change during testing
- Three versions: localist inputs; inputs with similarities; bigram frequencies

A recurrent network model of immediate serial recall

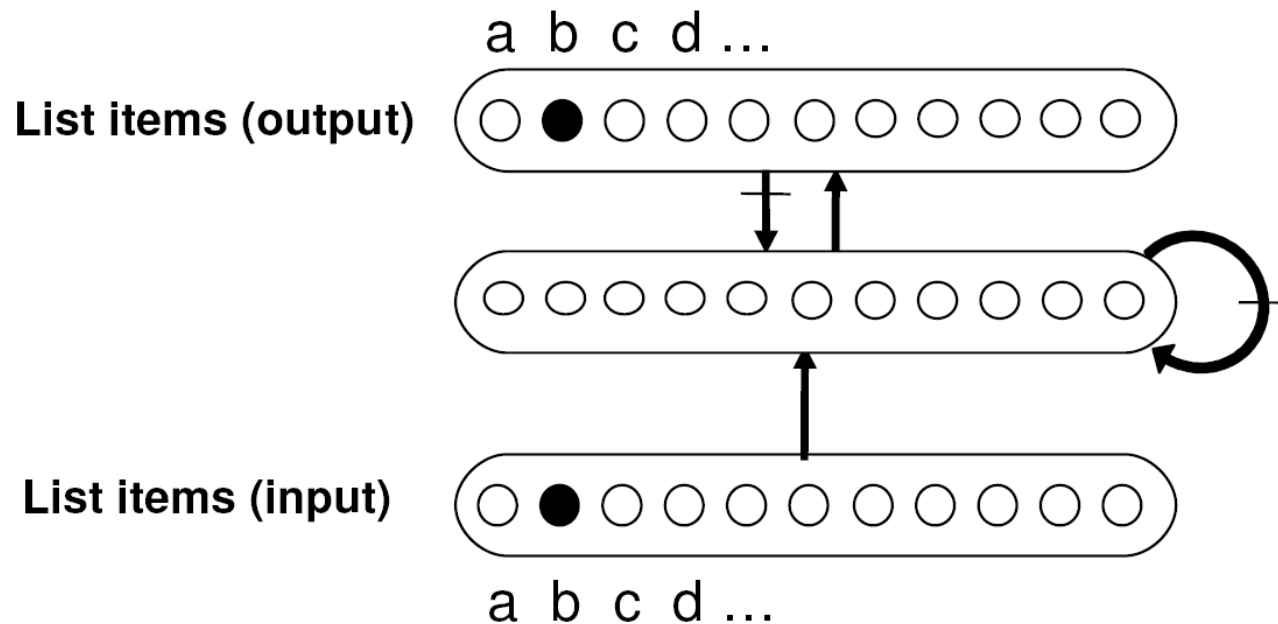
Botvinick and Plaut (2006, *Psych. Rev.*)



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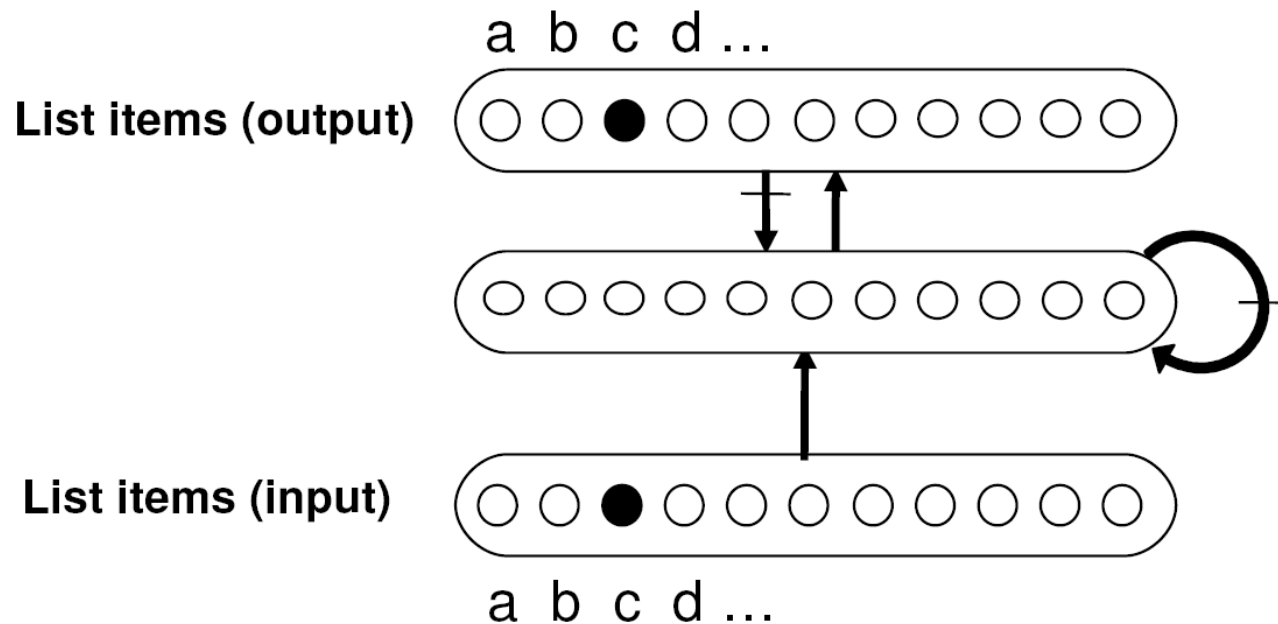
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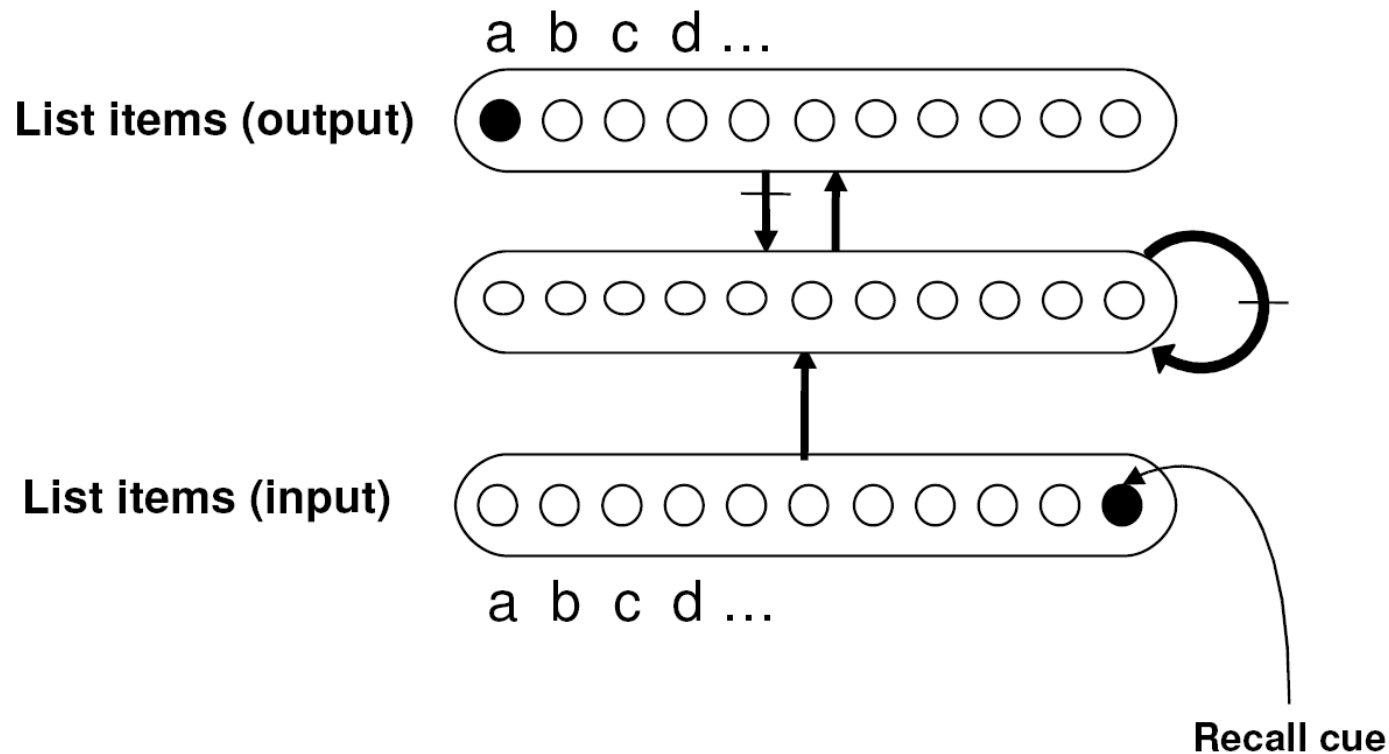
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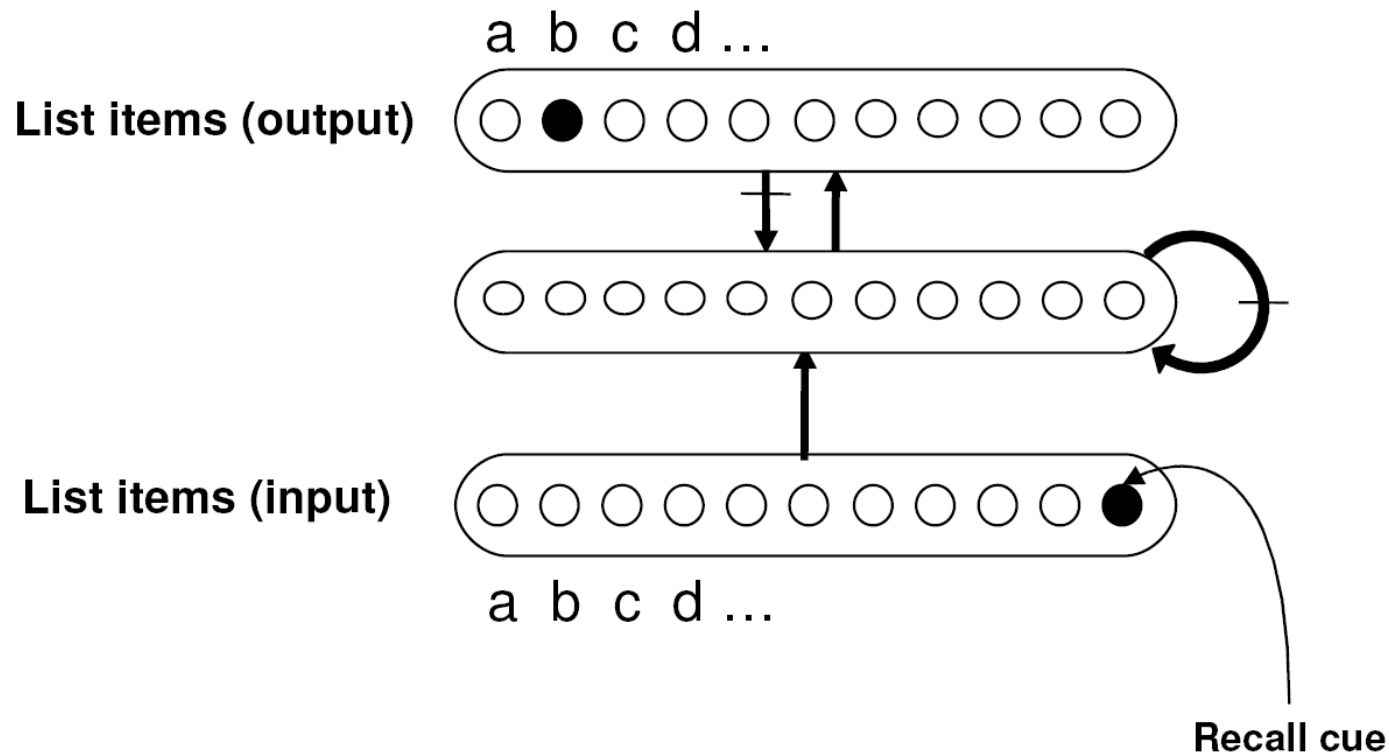
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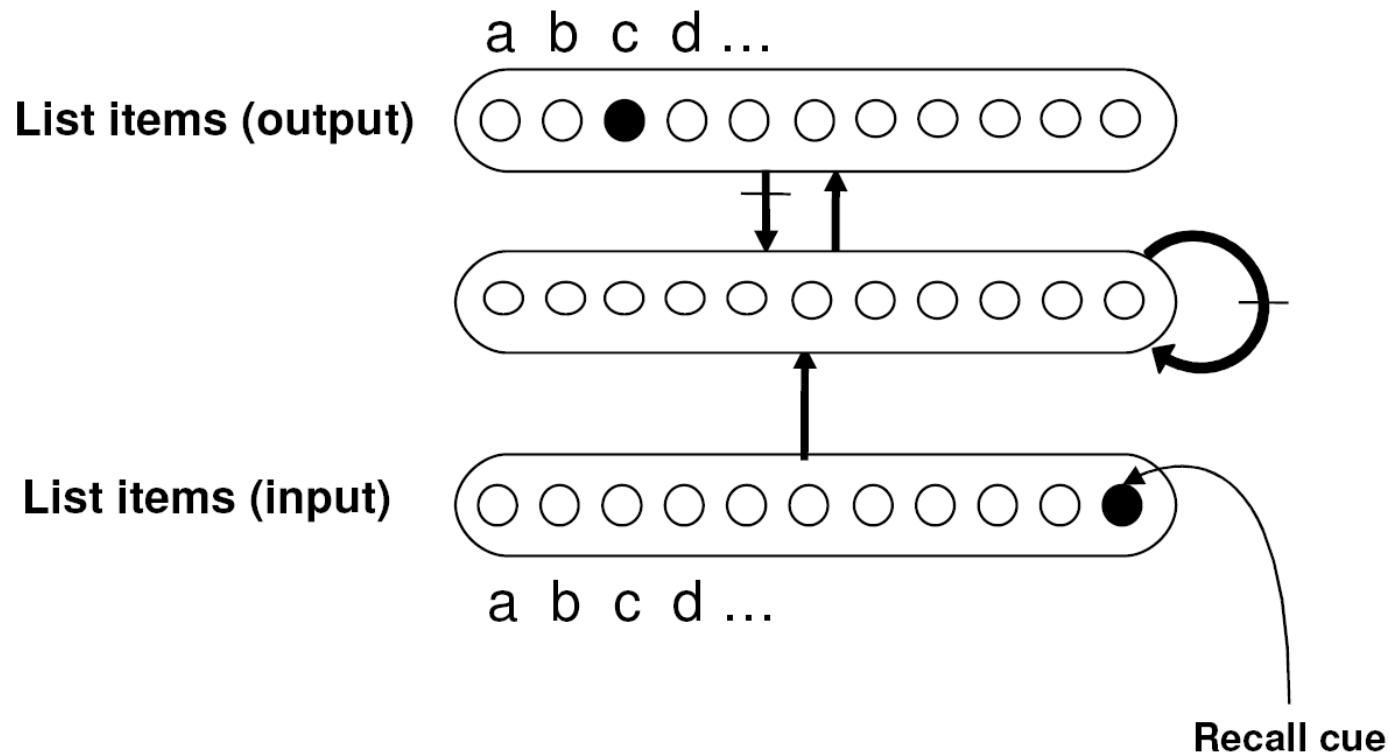
Botvinick and Plaut (2006, *Psych. Rev.*)



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A recurrent network model of immediate serial recall

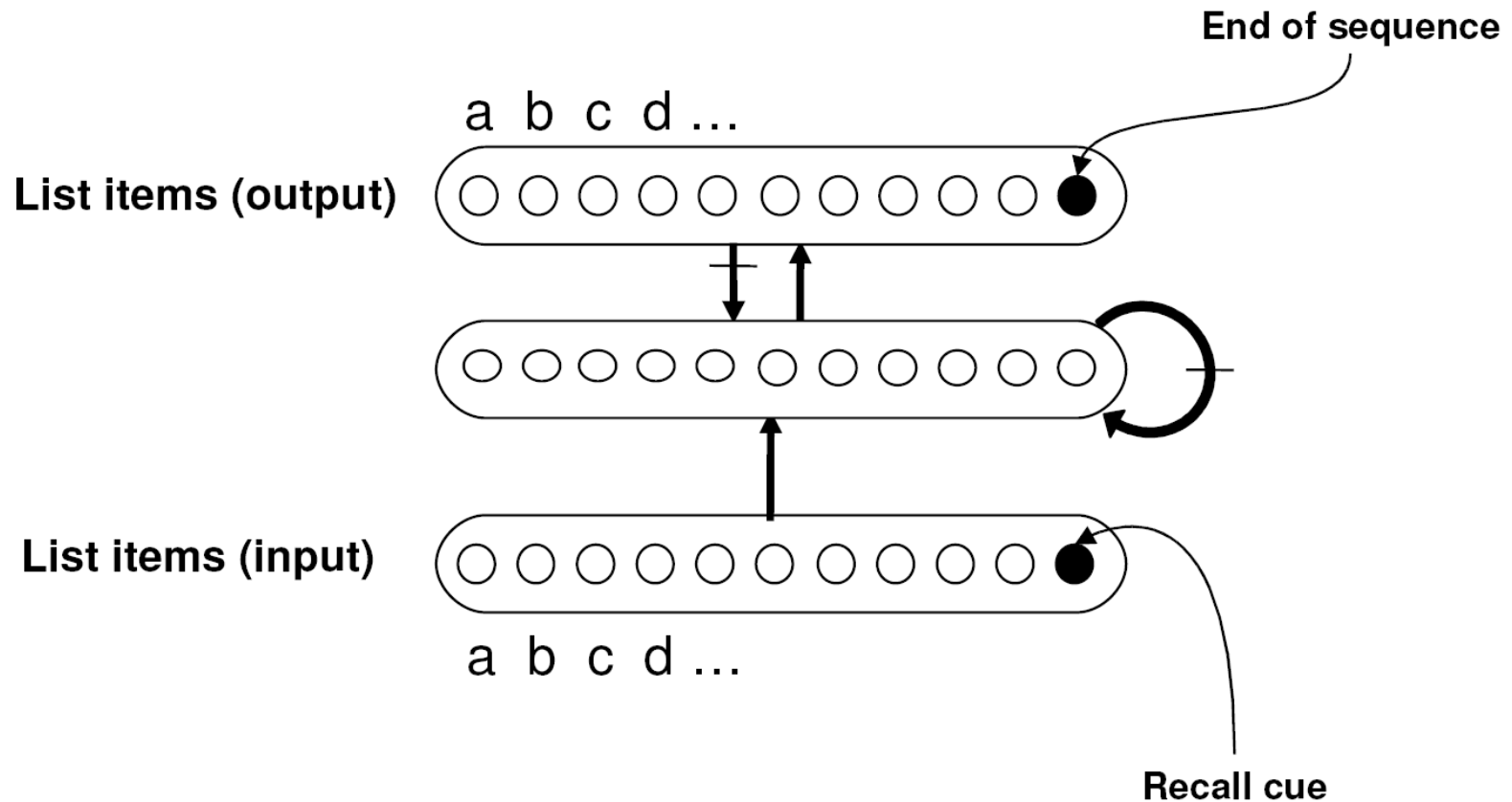
Botvinick and Plaut (2006, *Psych. Rev.*)



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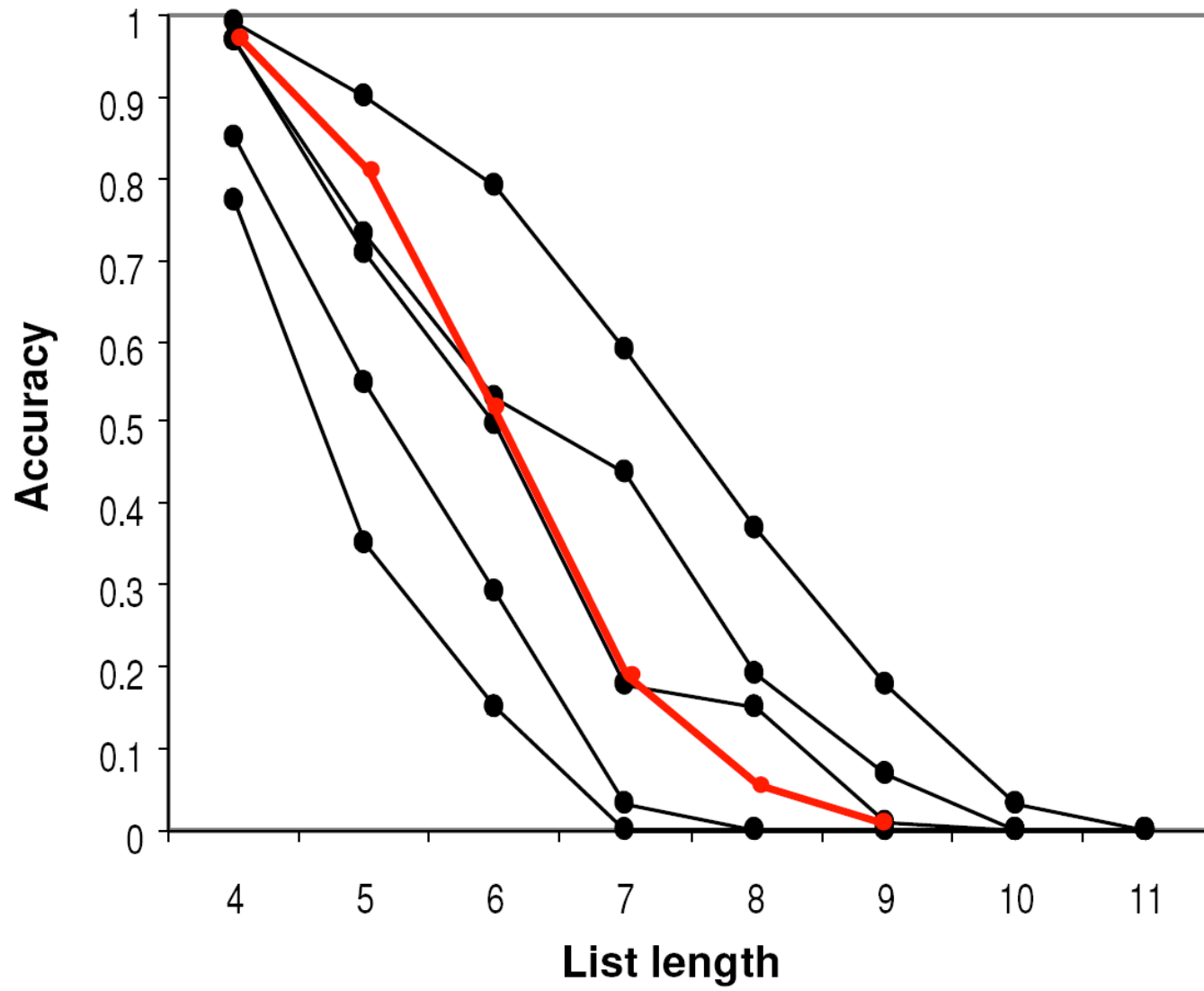
A recurrent network model of immediate serial recall

Botvinick and Plaut (2006, *Psych. Rev.*)



- Trained and tested on ISR (list lengths 1-9); proxy for *language* learning
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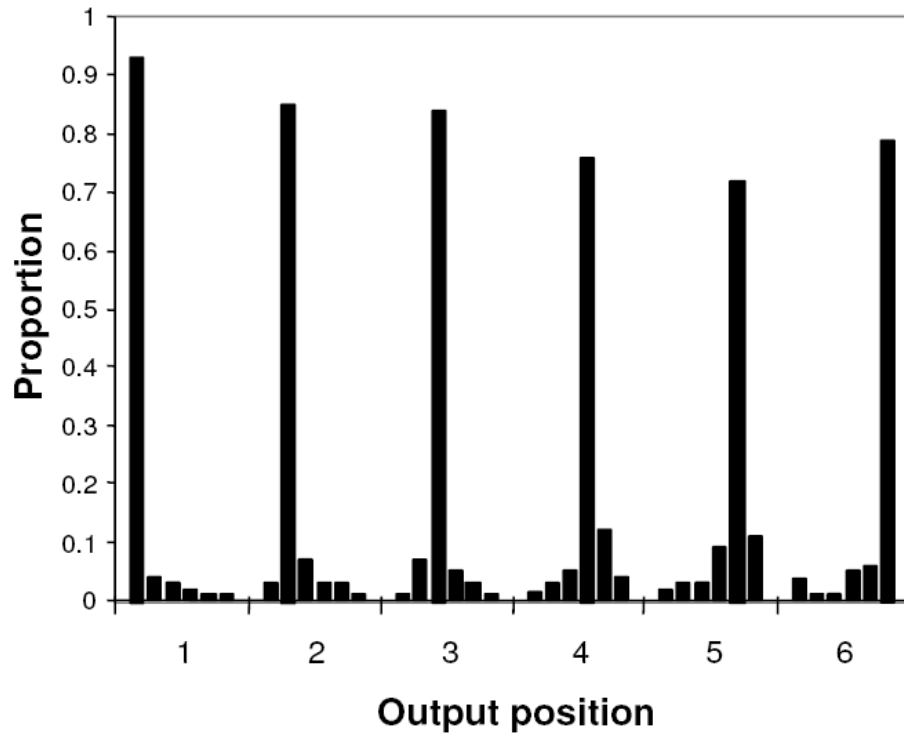
Results: List length



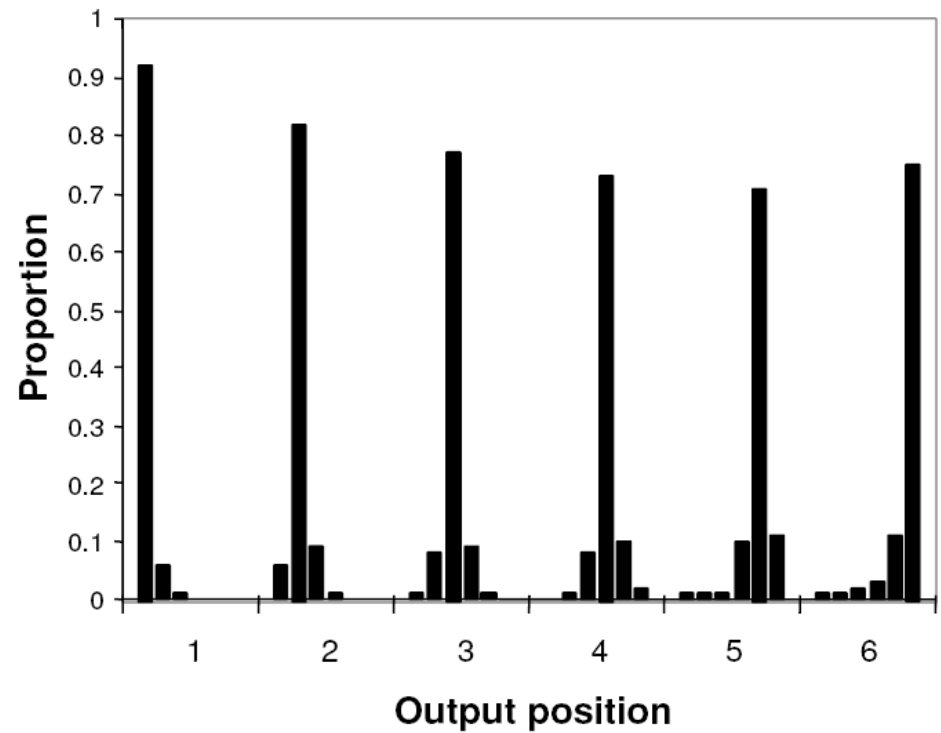
Crannel and Parrish (1957, J. Psychol.)

Results: Primacy, recency, transpositions

Data



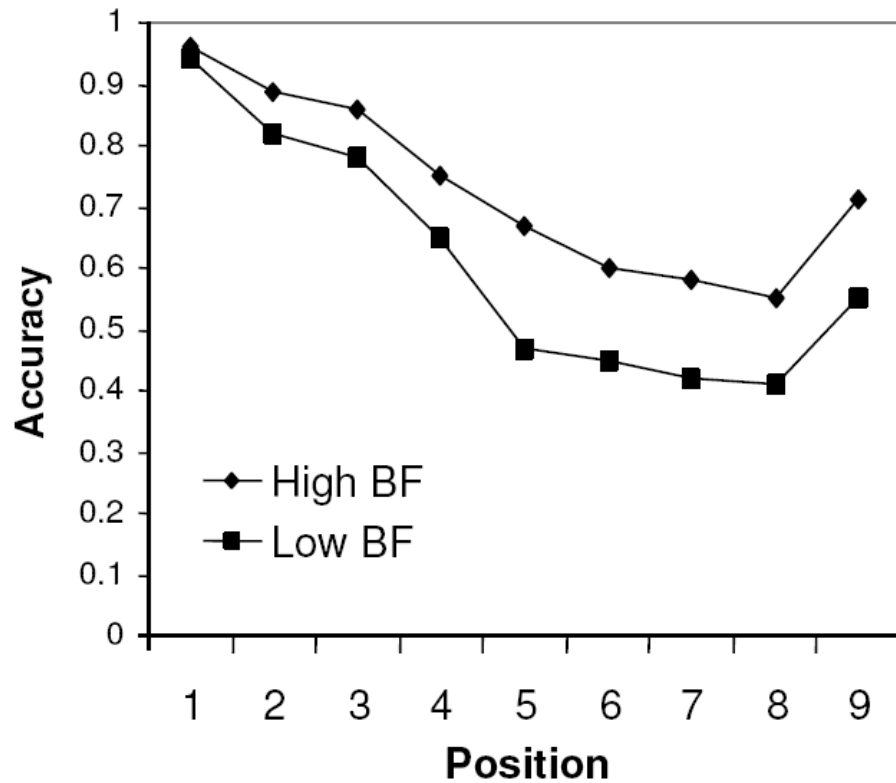
Simulation



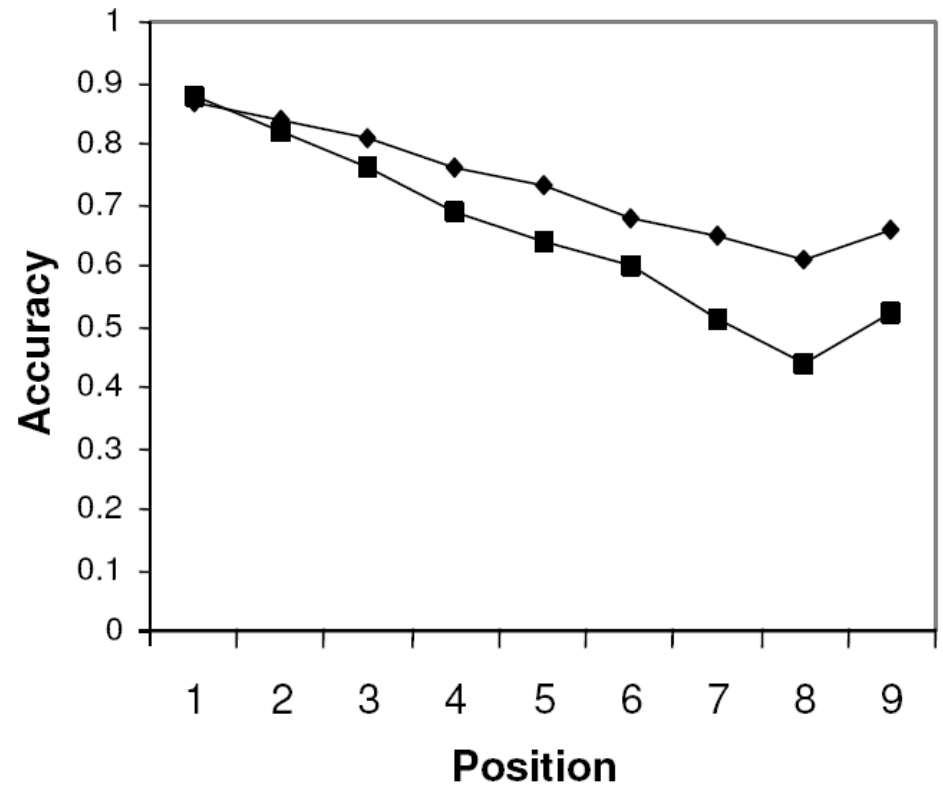
Henson, Norris, Page and Baddeley (1996, *QJEP*)

Results: Bigram frequencies

Data



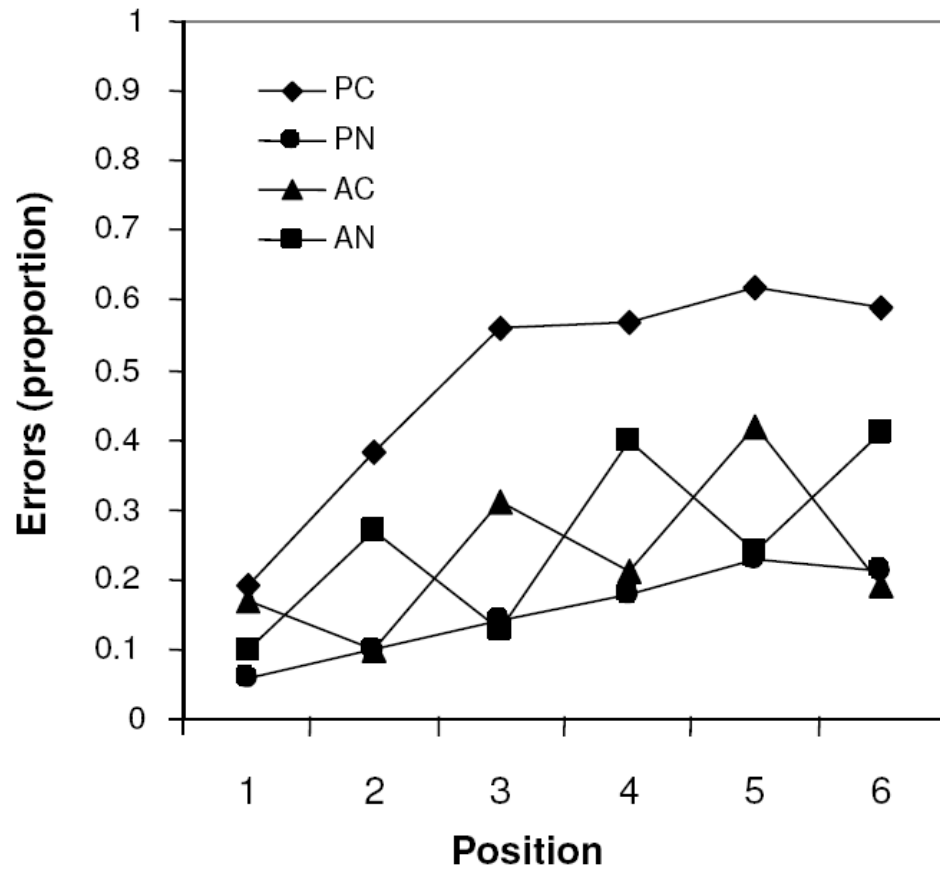
Simulation



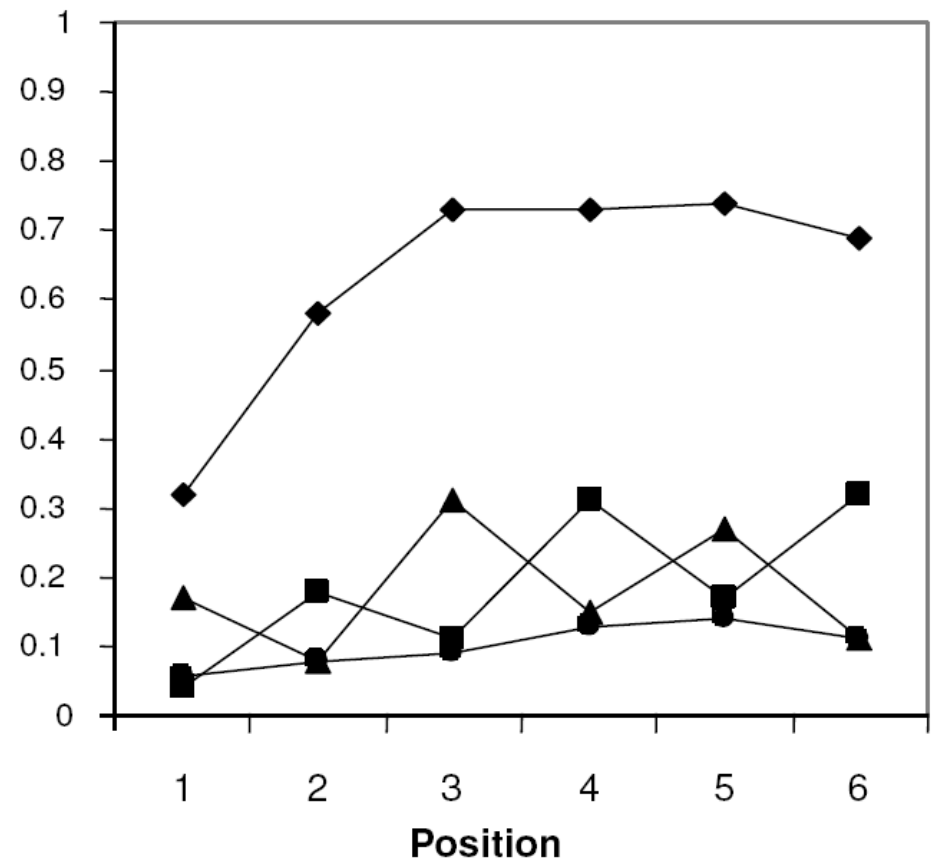
Kantowitz, Ornstein, and Schwartz (1972, J. Exp. Psych.)

Results: “Sawtooth” pattern

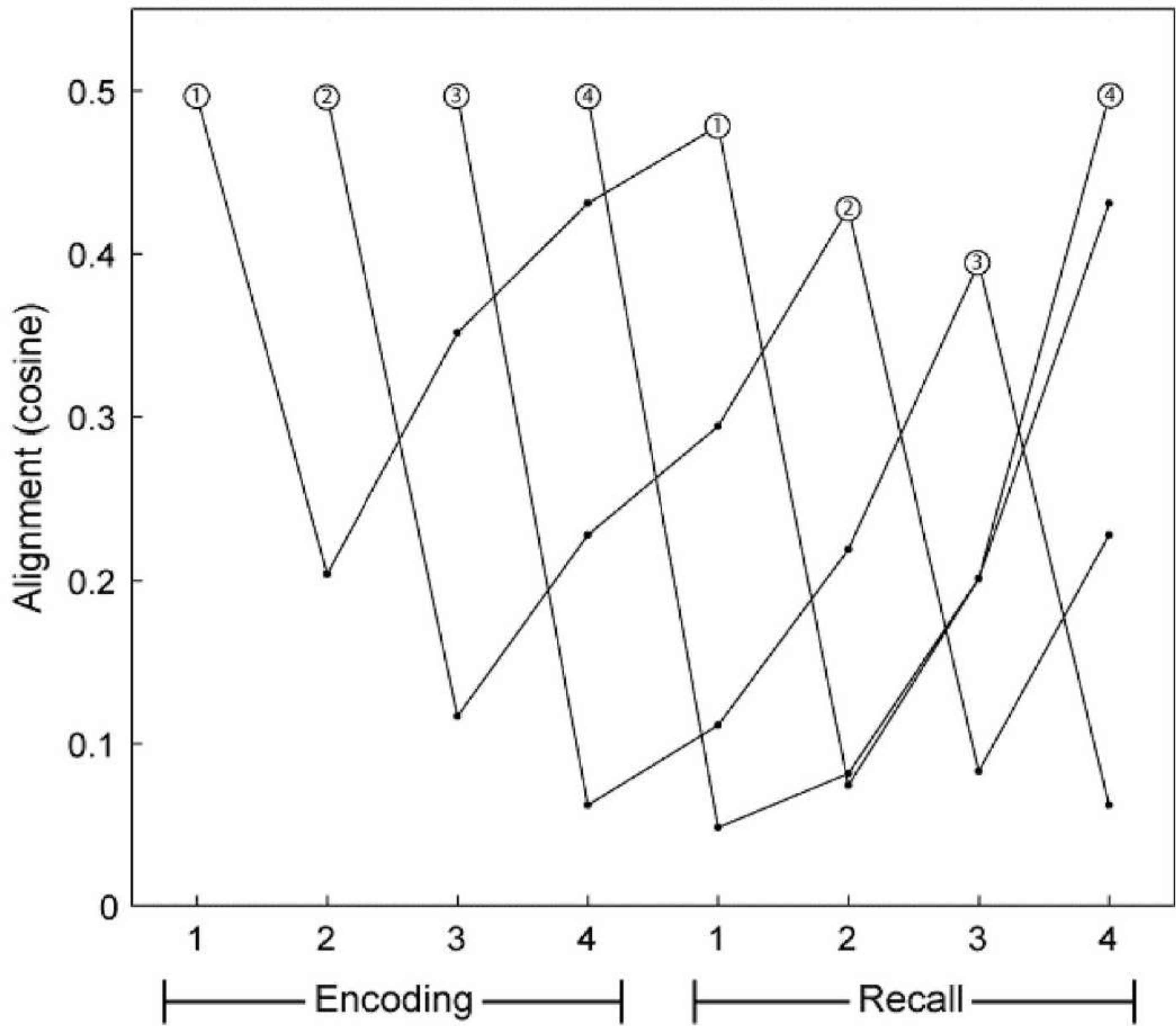
Data



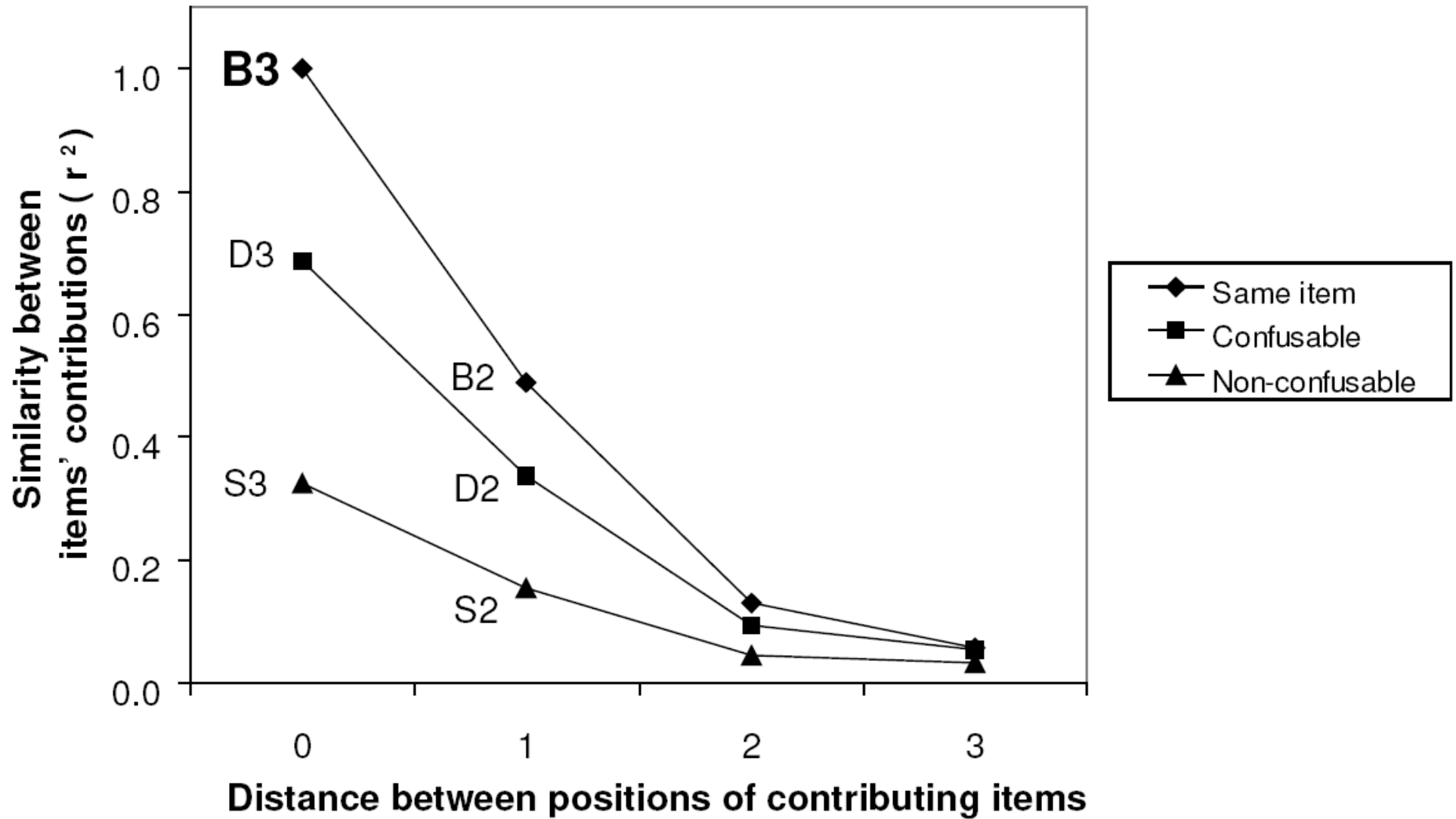
Simulation



Baddeley (1968, *QJEP*)



Analysis: Representational similarity



Conclusions

- Distributed recurrent networks can learn to exhibit hierarchically organized behavior without (structurally) hierarchically organized representations
 - Schemas are emergent functional properties of a system mapping perception to action
 - Sequential knowledge shaped by experience with task domains
- Sequential knowledge in recurrent networks need not *rely* on item-item associations (chaining)
 - Networks *are* sensitive to statistical structure of training environment (including item-item associations) when tested on this structure
- Explicit computational modeling can play a critical role in fully understanding the implications of theoretical claims
 - Intuitions about the computational properties of neural (and neural-like) systems can be misleading