Effects of rhythm on memory for spoken sequences: A model and tests of its stimulus-driven mechanism

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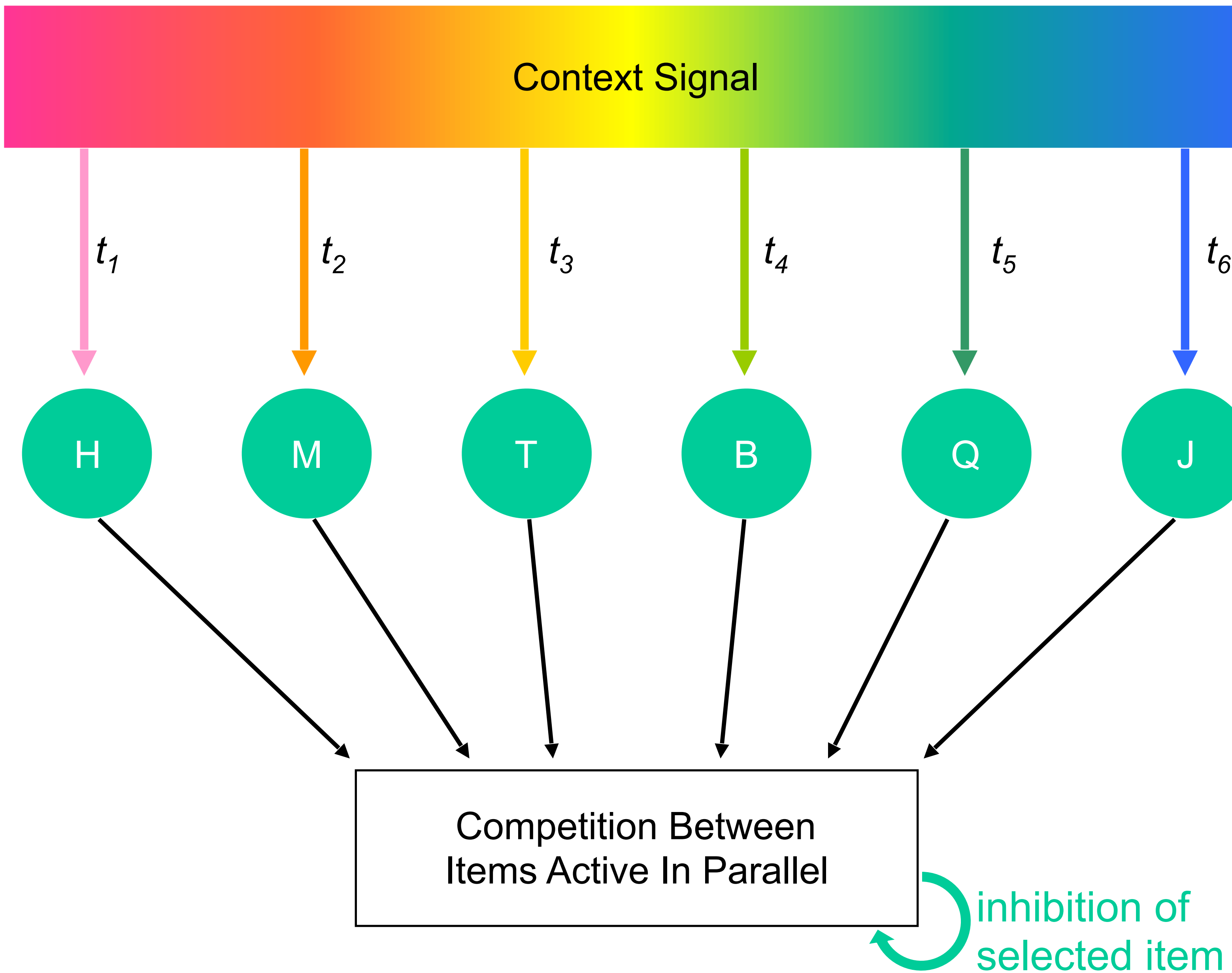
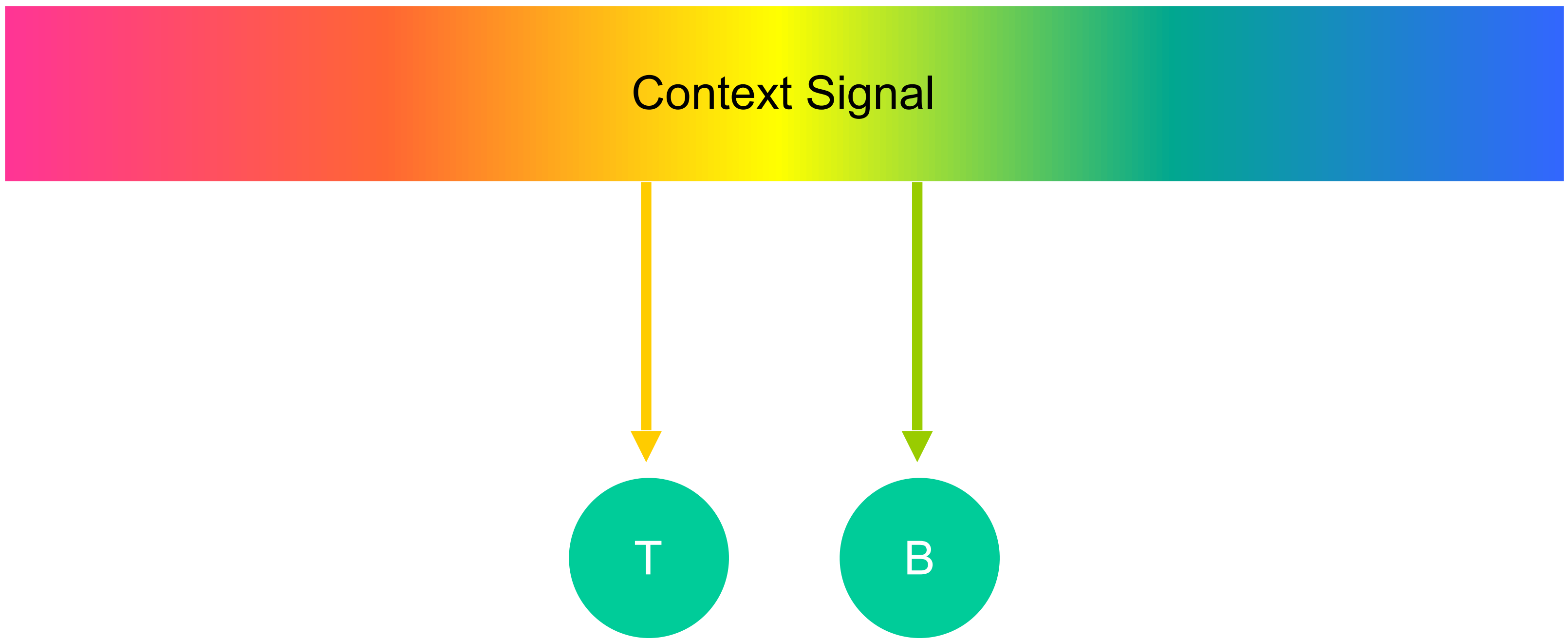


Context Signal
t1
t2
t3
t4
t5
t6
H
M
T
B
Q
J
Competition Between Items Active In Parallel
inhibition of selected item

Explaining Typical Errors

HM**TB**QJ → HM**BT**QJ

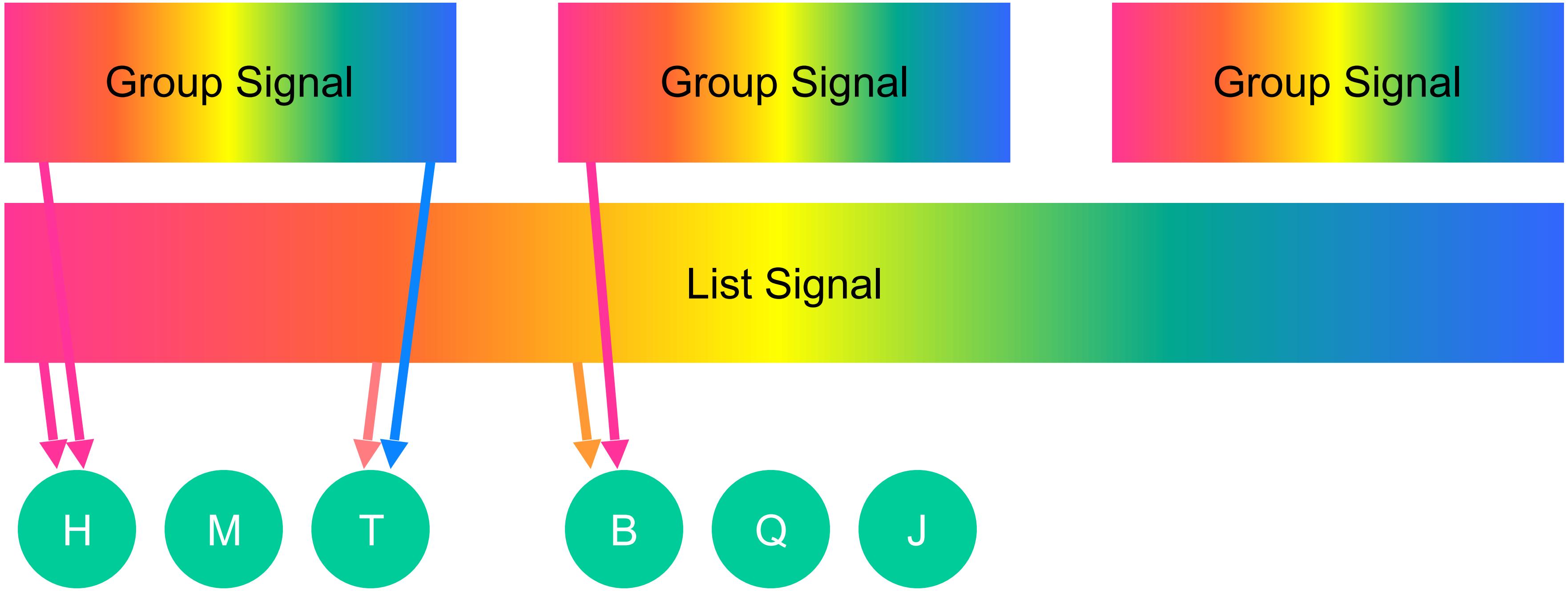


“Interposition” Errors

- In temporally grouped lists, there is a tendency for items to maintain their within-group position in errors, while for regular groupings overall error rates are reduced. (e.g., Ryan, 1969)
- H,M,T,…B,Q,J,…R,Y,Z
  - Here H might swap with B
  - T and B are unlikely to exchange

Non-Monotonic, Hierarchical Context Signal

Grouping helps to disambiguate adjacent serial positions at the cost of introducing longer range ambiguities



Context Signal: Unknown Properties

- General vs. Domain-Specific
  - same context signal in different domains (e.g., verbal, nonverbal) OR
  - different context signals in different domains
- Event-based vs. Time-based
  - state advances in steps corresponding to each item OR
  - state changes smoothly over time
- Top-down vs. Bottom-Up
  - state changes anticipated/imposed by executive system OR
  - stimulus properties drive state changes

Limitations of Existing Context Models

- Most models (e.g., Burgess & Hitch, 1999; Henson, 1998; Lewandowsky & Farrell, 2008) fail to specify the genesis of the context signal
  - the mechanism by which groups are detected and the grouping dimension of the signal is reset is not specified
  - unclear how the context signal would be generated online for irregular or unpredictable groupings
- Oscillator models provide such a mechanism (e.g., Brown et al., 2000; Henson & Burgess, 1997)
  - but, existing models use free-running oscillators that are not influenced by events in the world, but by their own interconnectivity
  - the bottom-up entrainment of oscillators is not implemented in these accounts

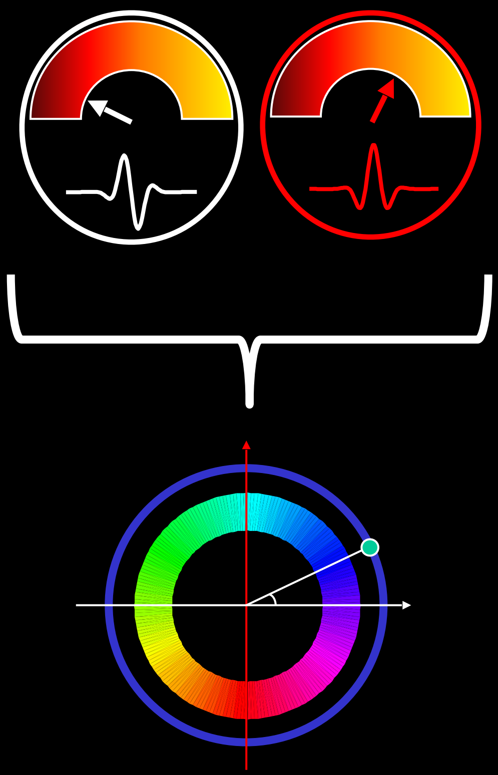
Bottom-Up Multi-scale Population (BUMP) Oscillator Model

(Hartley, Hurlstone, & Hitch, 2016; *Cog. Psychol.*)

- Time-based model of auditory-verbal STM for order
- During presentation, items are associated with the different states of a bottom-up driven timing signal
- At recall, the timing signal is replayed and the associations developed during learning re-activate items
- Items compete for selection on the basis of their activation (+ moderate random noise) and are then suppressed

Population Coding

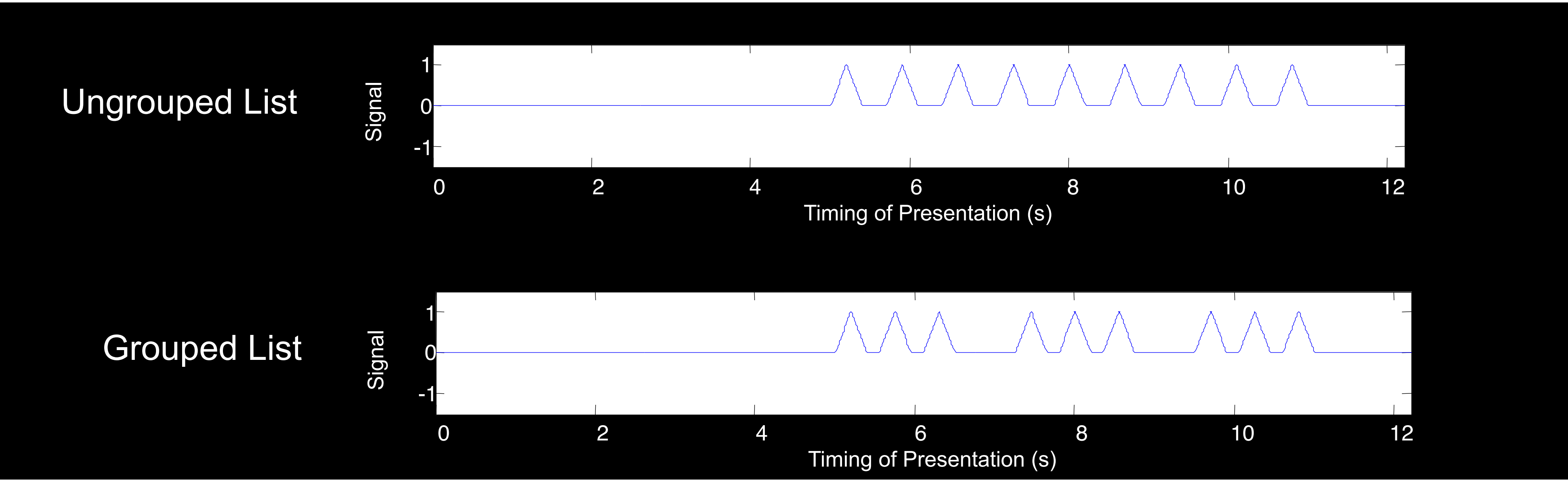
- Timing signal is based on the activity of a population of hypothetical neurons acting as temporal filters
- Neurons are sensitive to the envelope of incoming speech (Amplitude Modulation; AM), which we model explicitly
- Each neuron has an intrinsic tuning—a tendency for its activity to oscillate at a specific rate and phase
- Frequency tunings of the oscillators are chosen to span the range of presentations rates encountered in the task being modelled



Phase Offset Oscillators

- We use phase offset pairs of oscillators, each a phase quadrature filter
- For each frequency, one oscillator has a phase response aligned with peaks in the envelope (0° phase), whilst another has its phase offset by 90°
- The output of each pair is combined to given an overall amplitude and phase

Constructing The Input Signal



- We construct lists by creating an input signal based on AMs associated with the presentation of each item
- Each item is modelled as a ‘triangular pulse’ in amplitude
- Input signals for different grouping structures are modelled by varying the item onset times

Responses Of Oscillators

- Different oscillators are sensitive to AM on different scales
- For ungrouped lists:
  - oscillators with tunings close to the item presentation rate respond strongly and in phase with items (1 cycle per-item)
  - oscillators with tunings close to the list presentation rate respond to larger scale amplitude fluctuations (1 cycle per-list)
  - oscillators with intermediate tunings respond weakly to the beginning and end of a sequence
- For regularly grouped lists:
  - oscillators with tunings close to the group presentation rate are also recruited (1 cycle per-group)

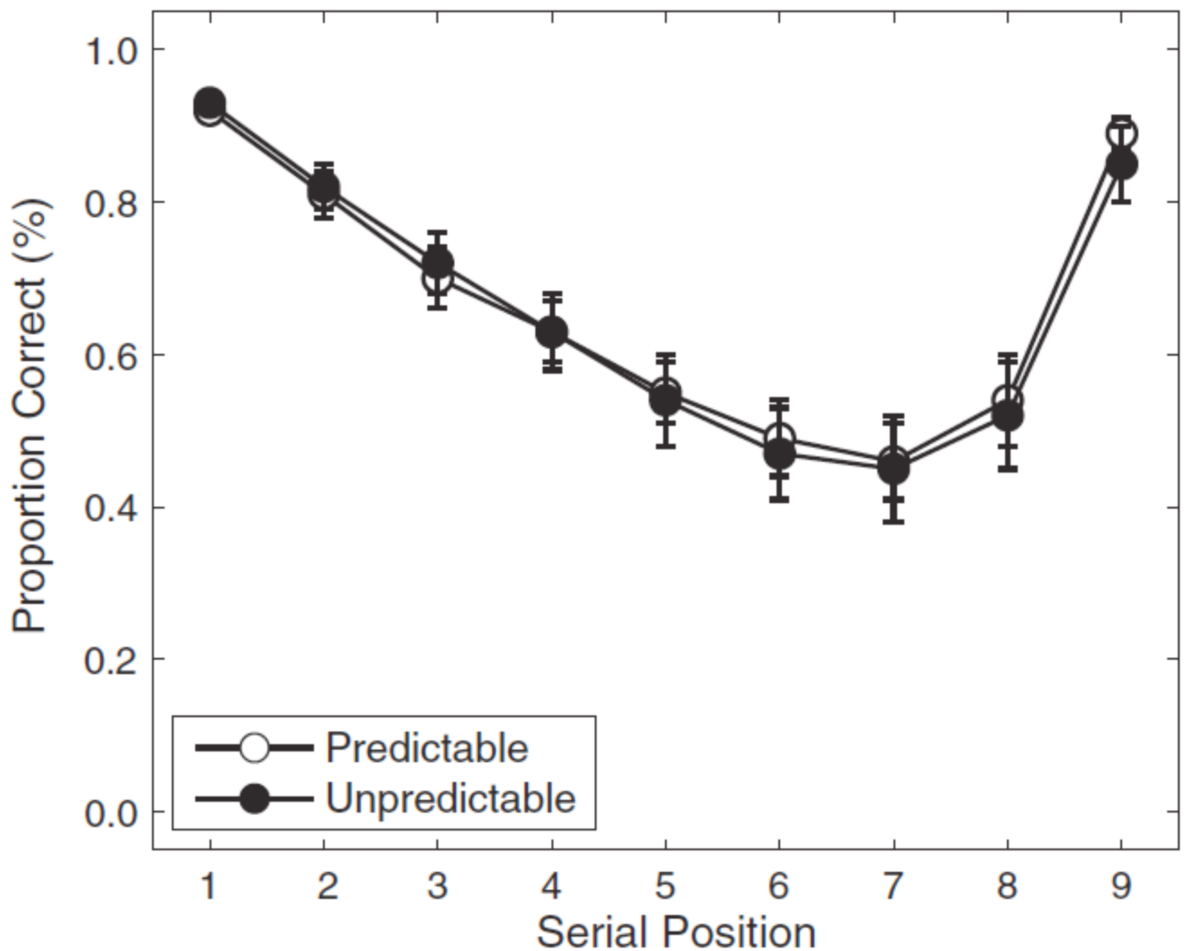
Tests of BUMP's Bottom-Up Mechanism

- Ryan (1969, Exp. 2) examined serial recall of spoken nine-item lists (digits *1-9*) organised into three temporal groups of varying size
- Employed 28 different patterns of temporal grouping:
  - viz. all permutations of the patterns 1-1-7; 1-6-2; 1-3-5; 2-2-5; 1-4-4; 2-3-4 plus a 3-3-3 pattern
- Participants received 2 trials for each pattern of grouping, with patterns presented in random order
  - participants unable to anticipate pattern of grouping on forthcoming trials

Tests of BUMP’s Bottom-Up Mechanism

- We replicated and extended Ryan’s (1969) experiment
- Compared recall performance for predictably and unpredictably grouped lists
    - unpredictable condition is same as Ryan’s (1969) experiment except we used 10—rather than 2—trials per grouping pattern
    - predictable condition—which Ryan did not include—was identical, but different patterns of grouping presented in blocks of 10 trials
- If grouping effects reflect the action of a bottom-up mechanism, recall performance for the different grouping patterns should be unaffected by predictability

Overall Accuracy



Accuracy By Grouping Patterns

	List-type			List-type	
Pattern	Predictably grouped	Unpredictably grouped	Pattern	Predictably grouped	Unpredictably grouped
117	.608	.611	324	.722	.683
126	.646	.649	333	.802	.790
135	.624	.681	342	.746	.717
144	.722	.678	351	.617	.648
153	.640	.641	414	.732	.659
162	.581	.562	423	.635	.732
171	.532	.514	432	.710	.719
216	.608	.630	441	.706	.683
225	.724	.644	513	.665	.632
234	.746	.671	522	.757	.659
243	.697	.675	531	.697	.686
252	.665	.657	612	.644	.665
261	.552	.579	621	.643	.710
315	.632	.675	711	.621	.559

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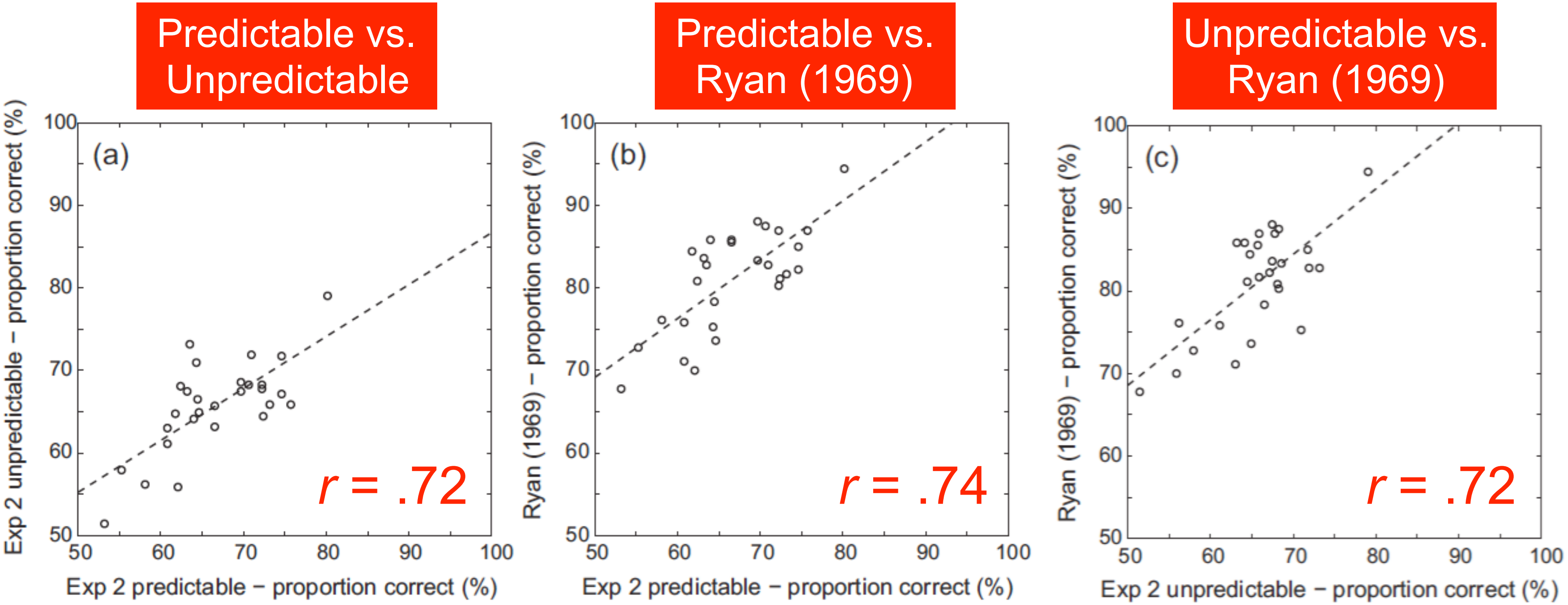
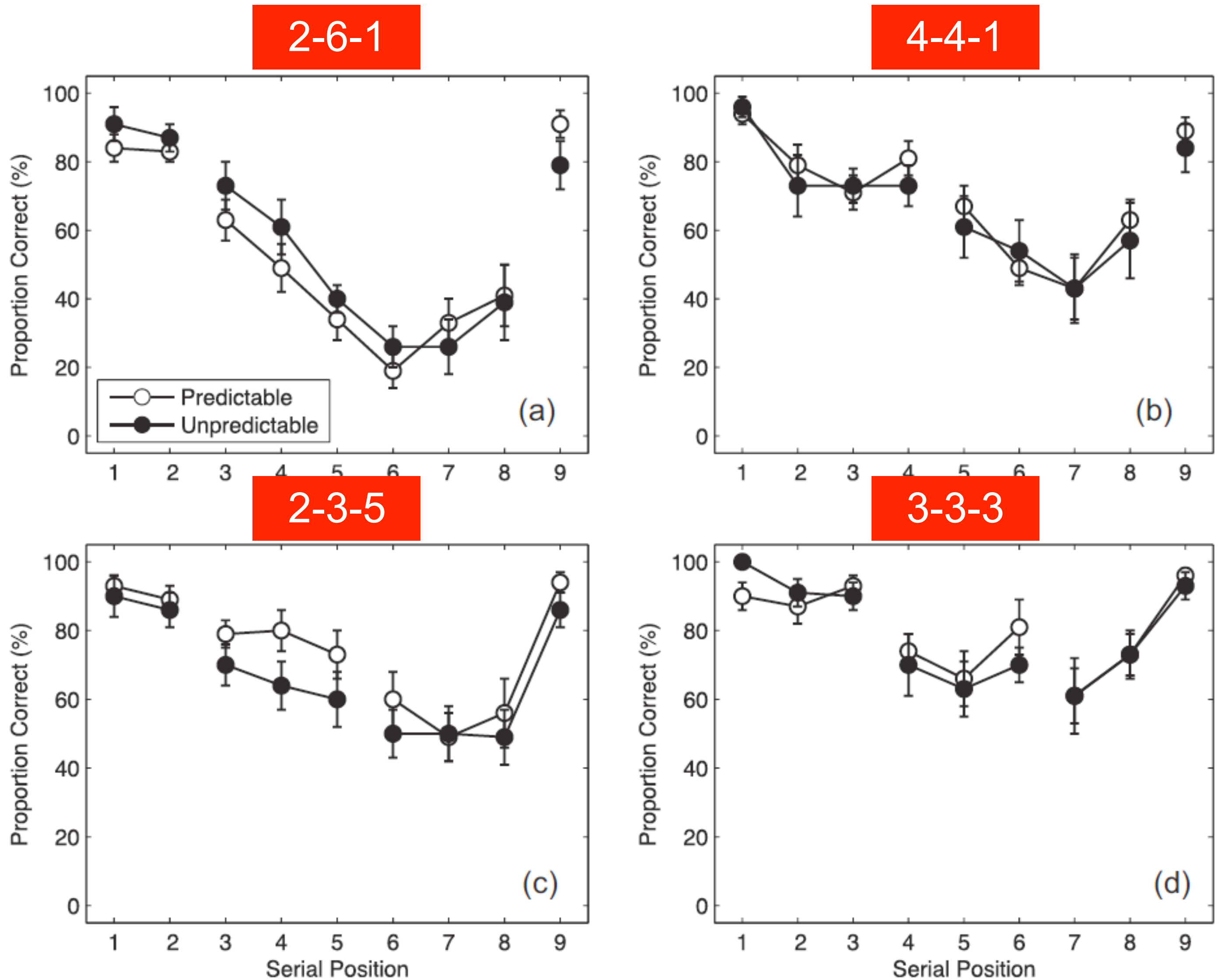
Scatterplots of Predictable, Unpredictable, & Ryan (1969)

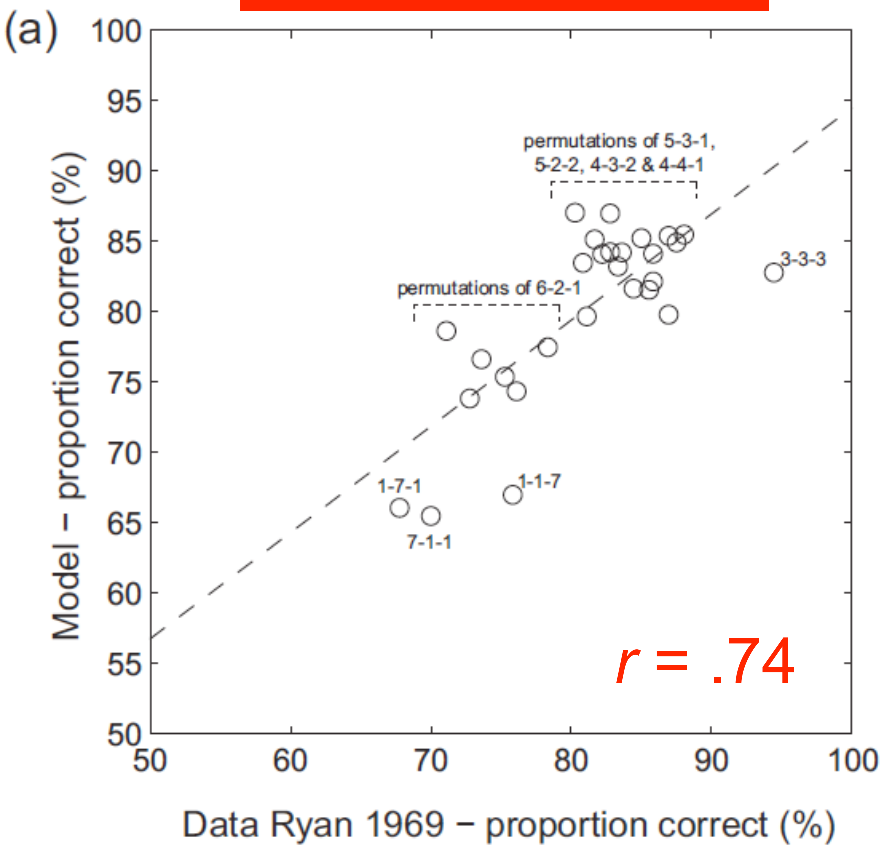


Sample Serial Position Curves

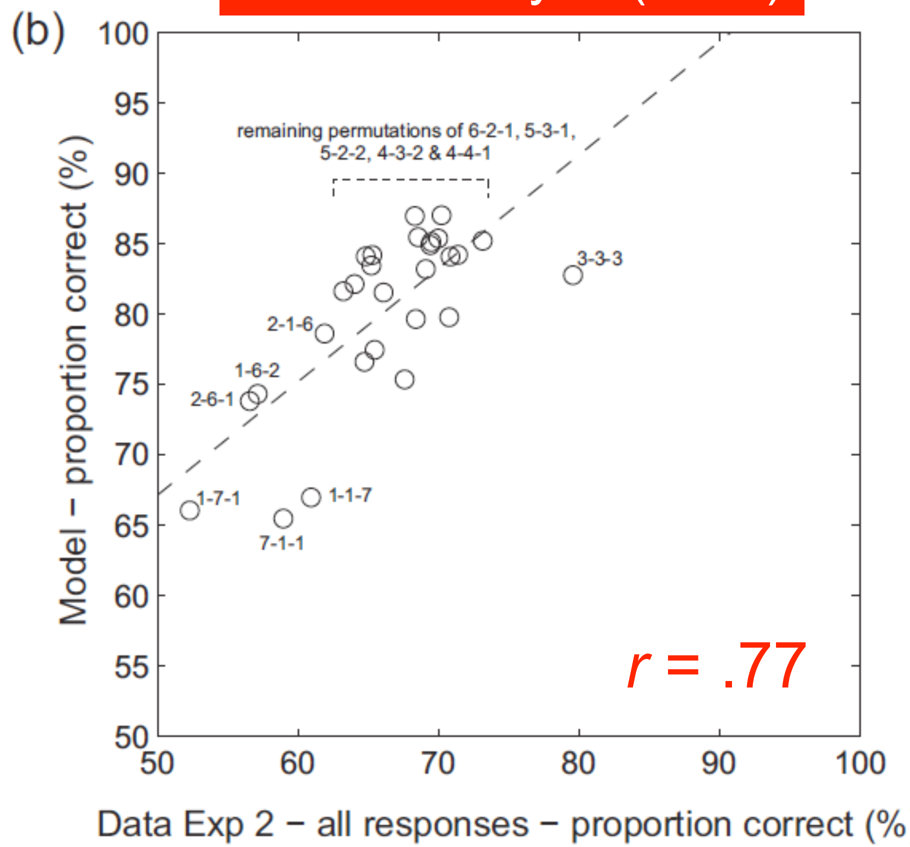


BUMP Simulations

BUMP vs. New data



BUMP vs. Ryan (1969)



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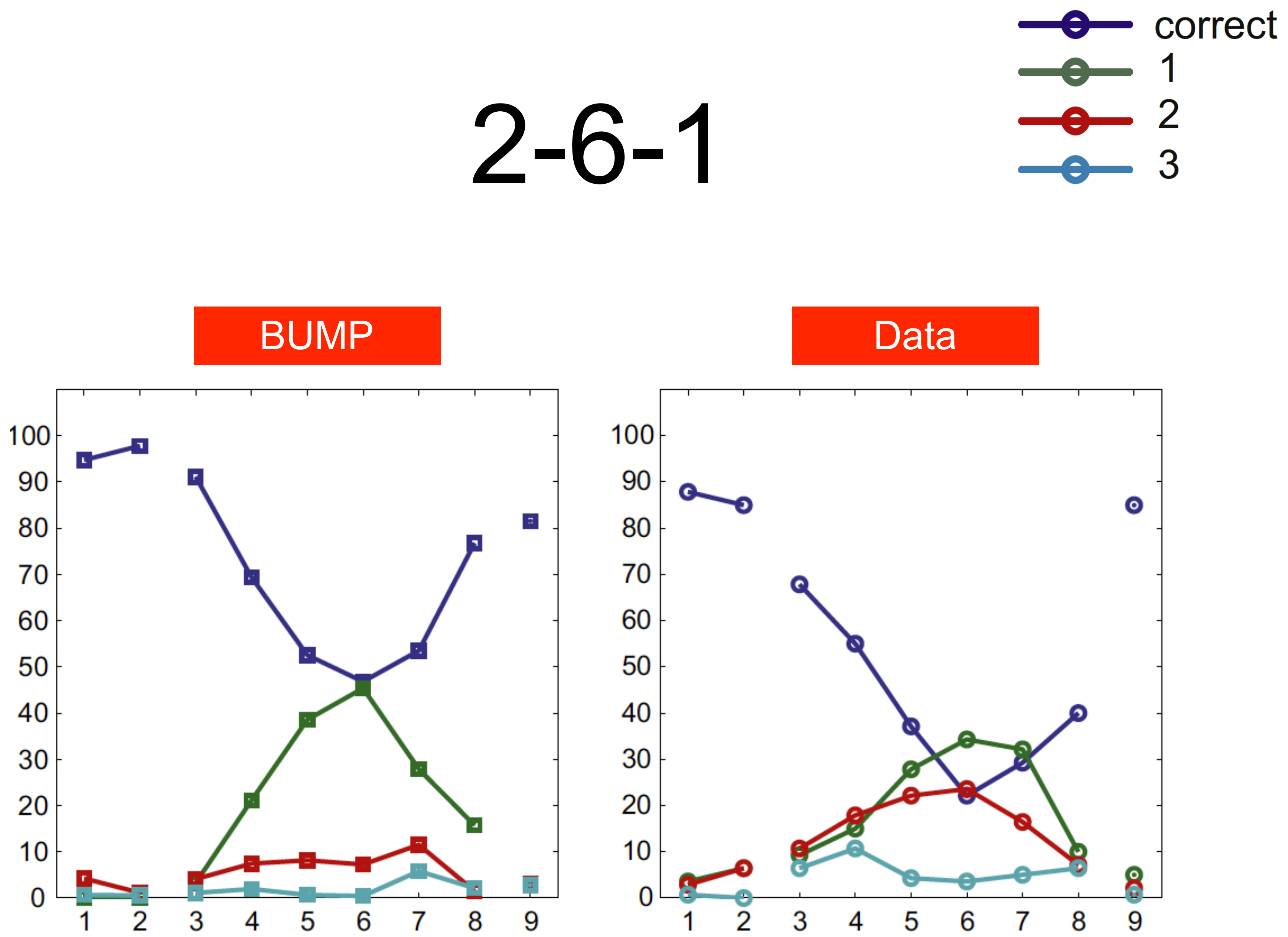

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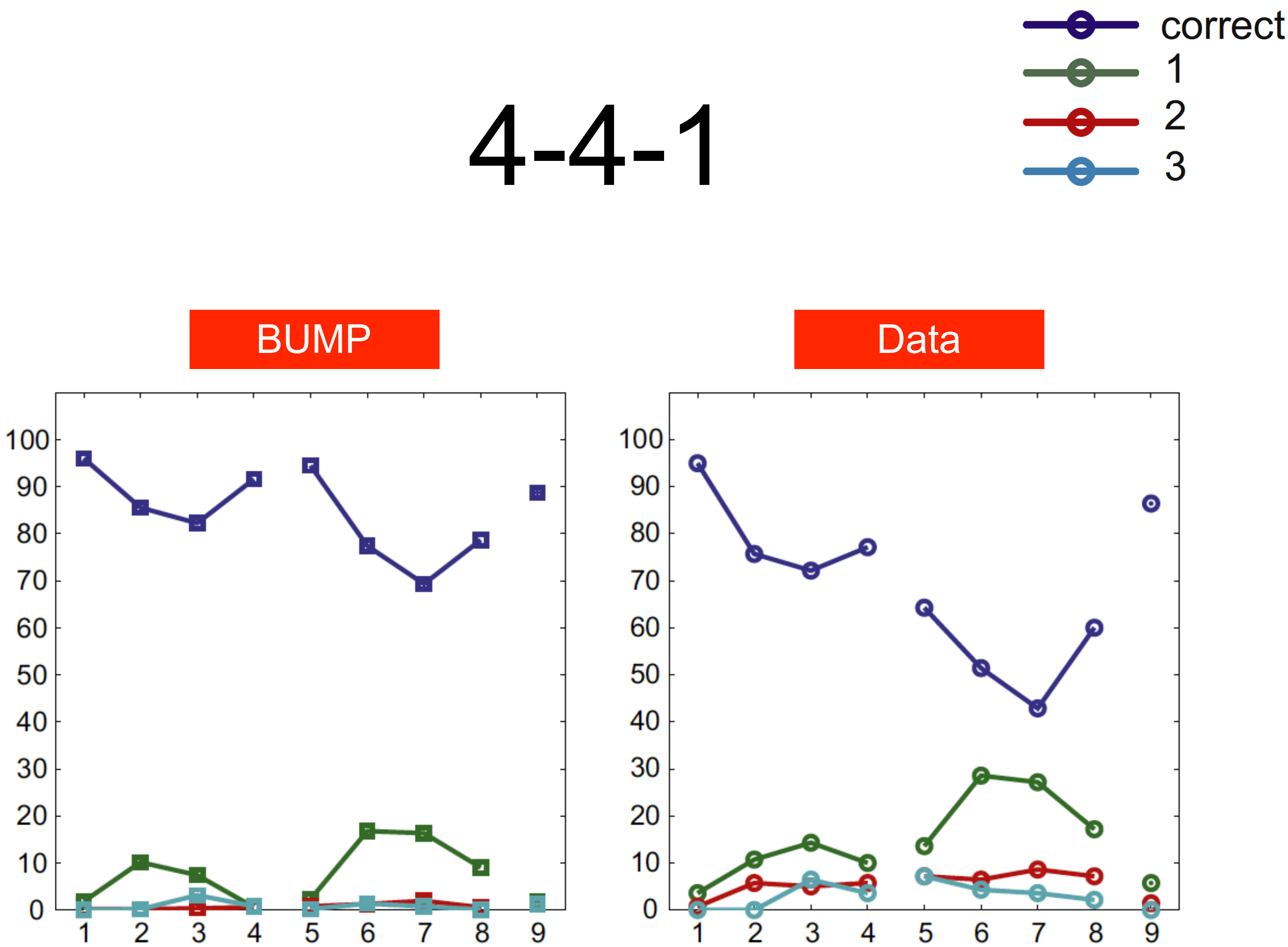

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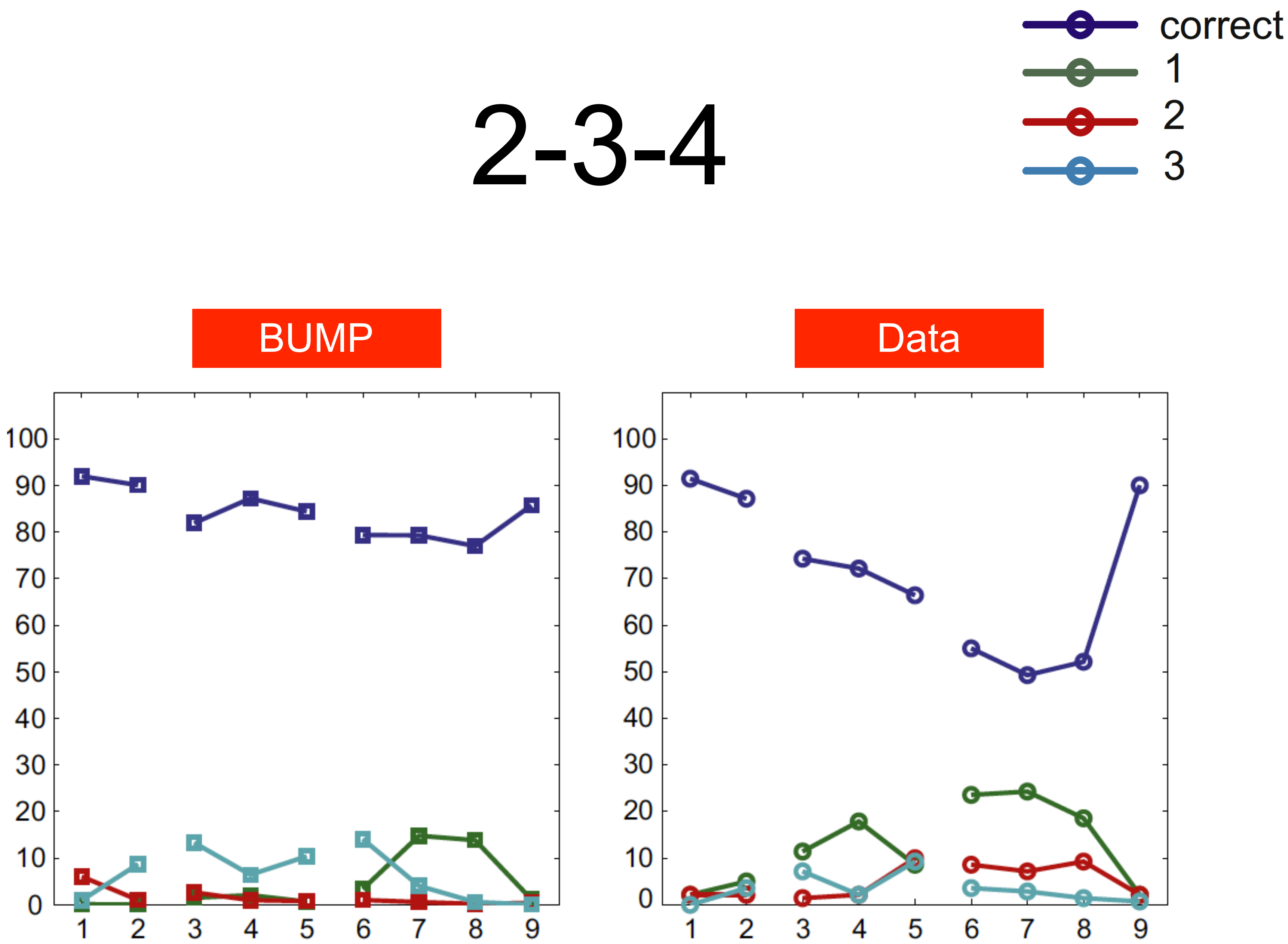

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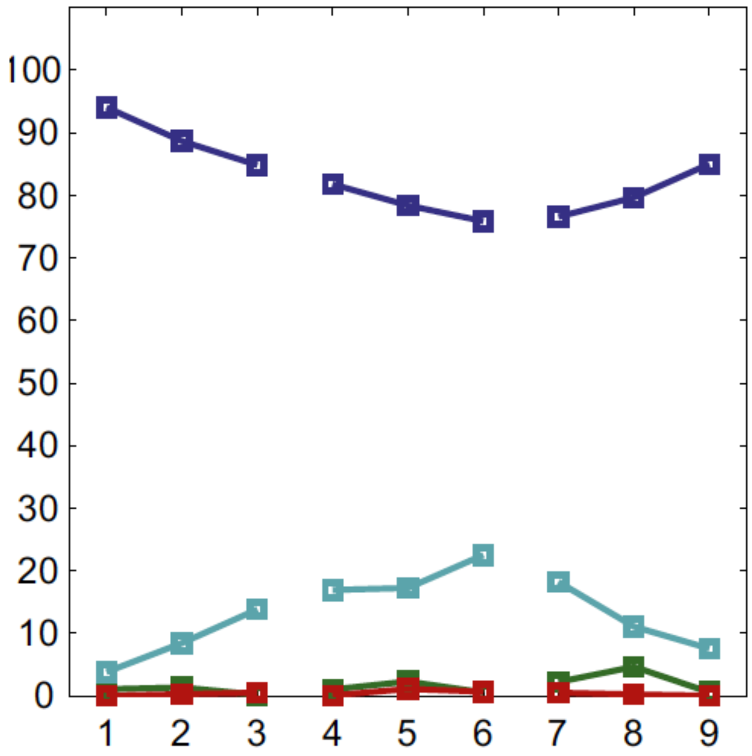
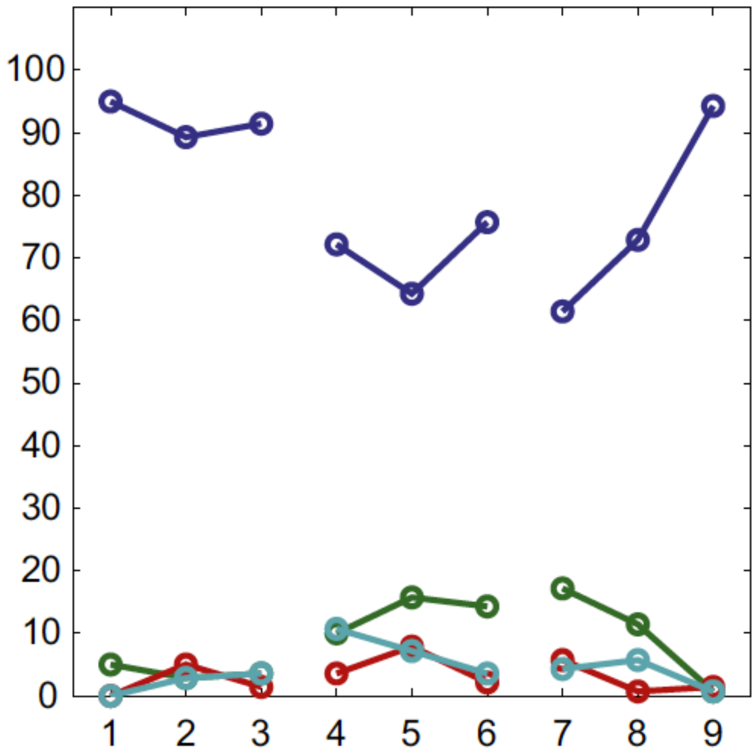
BUMP



Data



Conclusions: Bottom-Up Oscillator Population

- Bottom-Up: addresses theoretical issues with top-down models
  - data from temporal grouping experiment suggest that representation of serial position influenced by bottom-up process
  - mechanism solves problem of choosing appropriate rate of change for a given task and detecting/anticipating start and end of sequence
- Accounts for grouping effects in STM:
  - explains interposition errors, grouping advantage, detailed pattern of error data with different groupings
- Time-based & Event-based:
  - changes smoothly over time but driven by events