Behavioral Evidence that the Rapid Formation of Distributed Representations Benefits Inference

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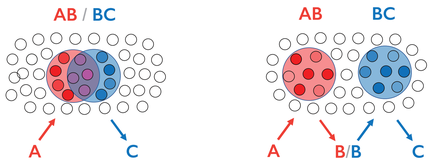
Inference over distributed vs. localist representations

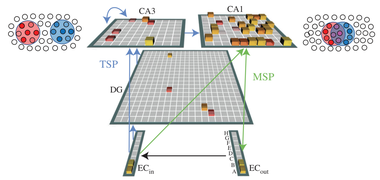


Distributed representations

fast & automatic association

Localist representations

requires additional processing time for spreading activation



A neural network model of the hippocampus

both codes reside in the hippocampus

(Schapiro et al., 2017)

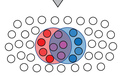
Under what conditions does the brain form distributed representations, and what do those representations allow you to do?

Predictions

In neural network models, interleaved exposure facilitates forming distributed representations

Interleaved learning

AB BC AB BC ··· AB BC AB BC

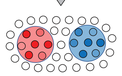


representations more distributed

support rapid AC association

Blocked learning

AB AB AB AB ··· BC BC BC BC



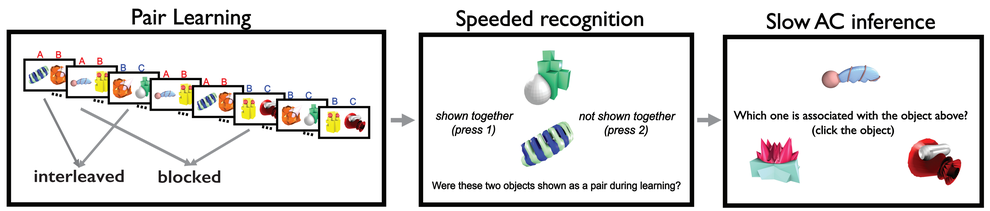
interference without orthogonalization

AC inference requires extra time

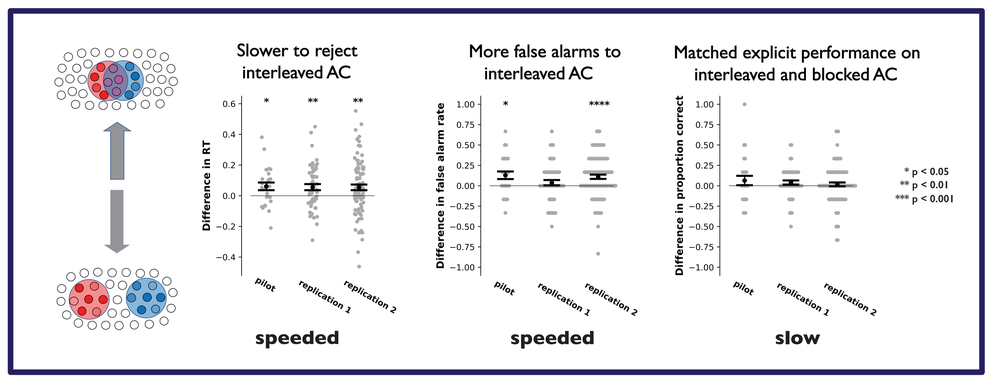
In an implicit speeded task, inference over interleaved pairs should be superior to inference over blocked pairs.

In an explicit slower task, associative inference can be solved with either strategy and should result in equivalent performance. (Schlichting et al., 2015)

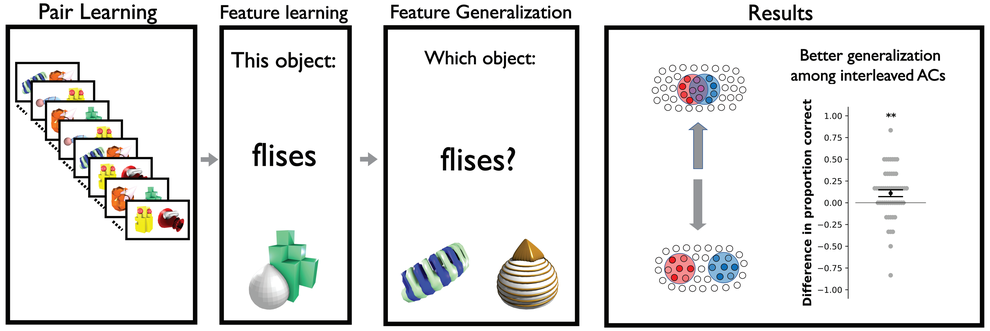
Exp 1: Interleaving facilitates rapid AC association



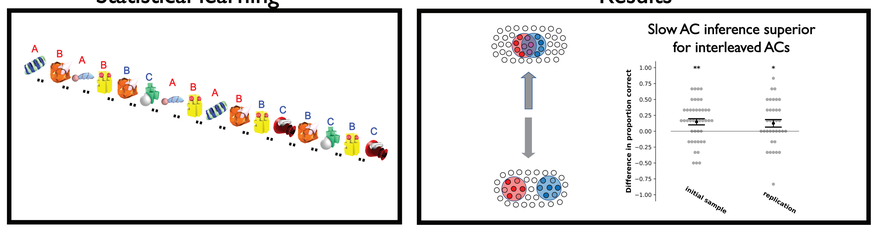
Results



Exp 2: Interleaving affords subsequent feature inference

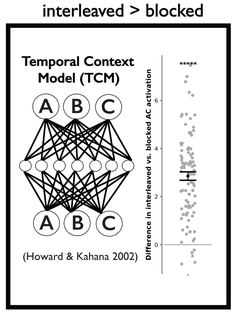


Exp 3: Only interleaving permits slow inference based on statistical regularities



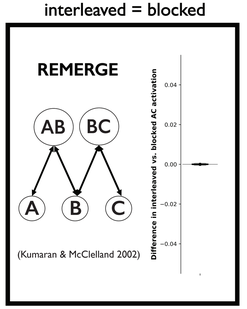
Models

Model using a **distributed** code: interleaved > blocked



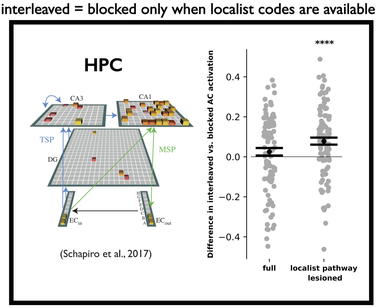
(Howard & Kahana 2002)

Model using a **localist** code: interleaved = blocked



(Kumaran & McClelland 2002)

Model using **both** codes: interleaved = blocked only when localist codes are available



(Schapiro et al., 2017)

Conclusions

We present evidence that, as in neural network models, interleaved exposure to information facilitates the formation of distributed representations in humans. Once formed, such representations support rapid, automatic inference across novel associations, and are especially critical for inference when learning requires statistical integration of information over time.

Together, these results demonstrate the power of interleaved learning and implicate the use of distributed representations in rapid learning of structured information in humans.

References

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