

Associative learning changes multivariate neural signatures of visual working memory

William XQ Ngiam

Awh / Vogel Lab, University of Chicago



Will Epstein



Henry Jones



Darius Suplica



William Thyer

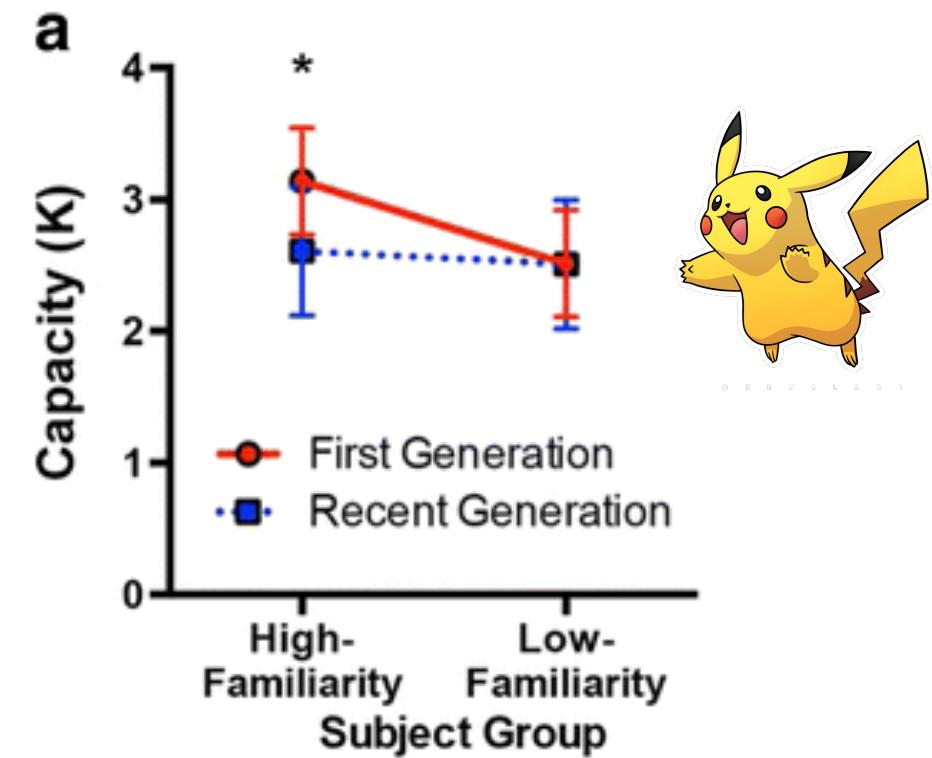
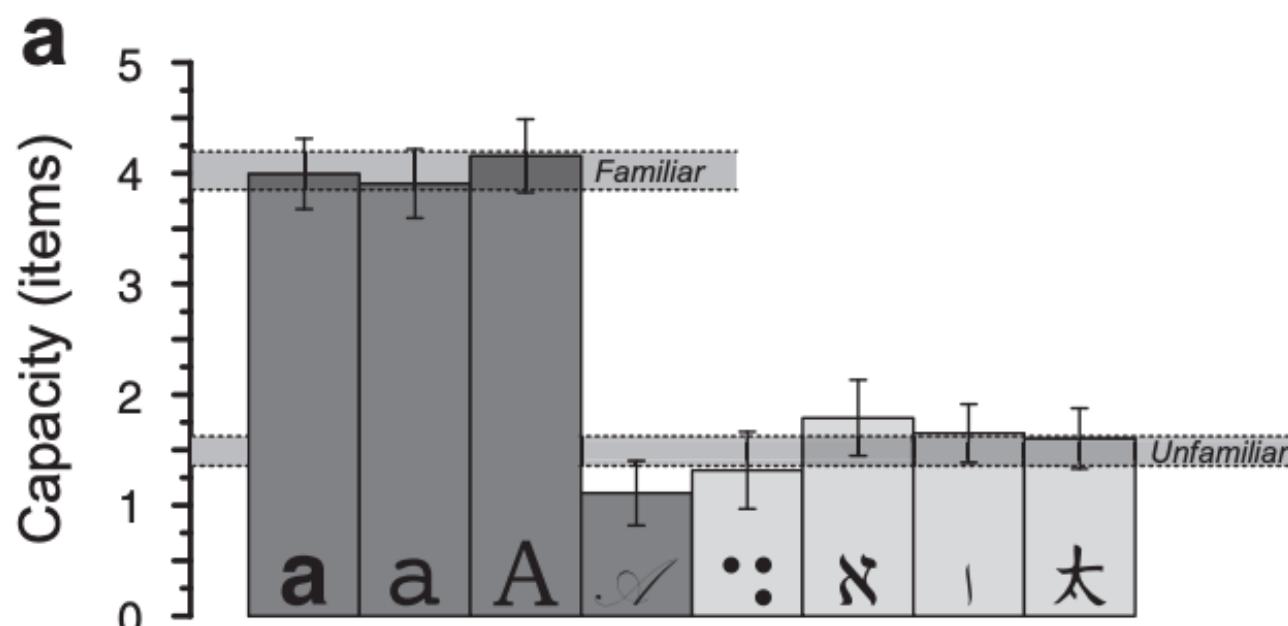


Edward Awh

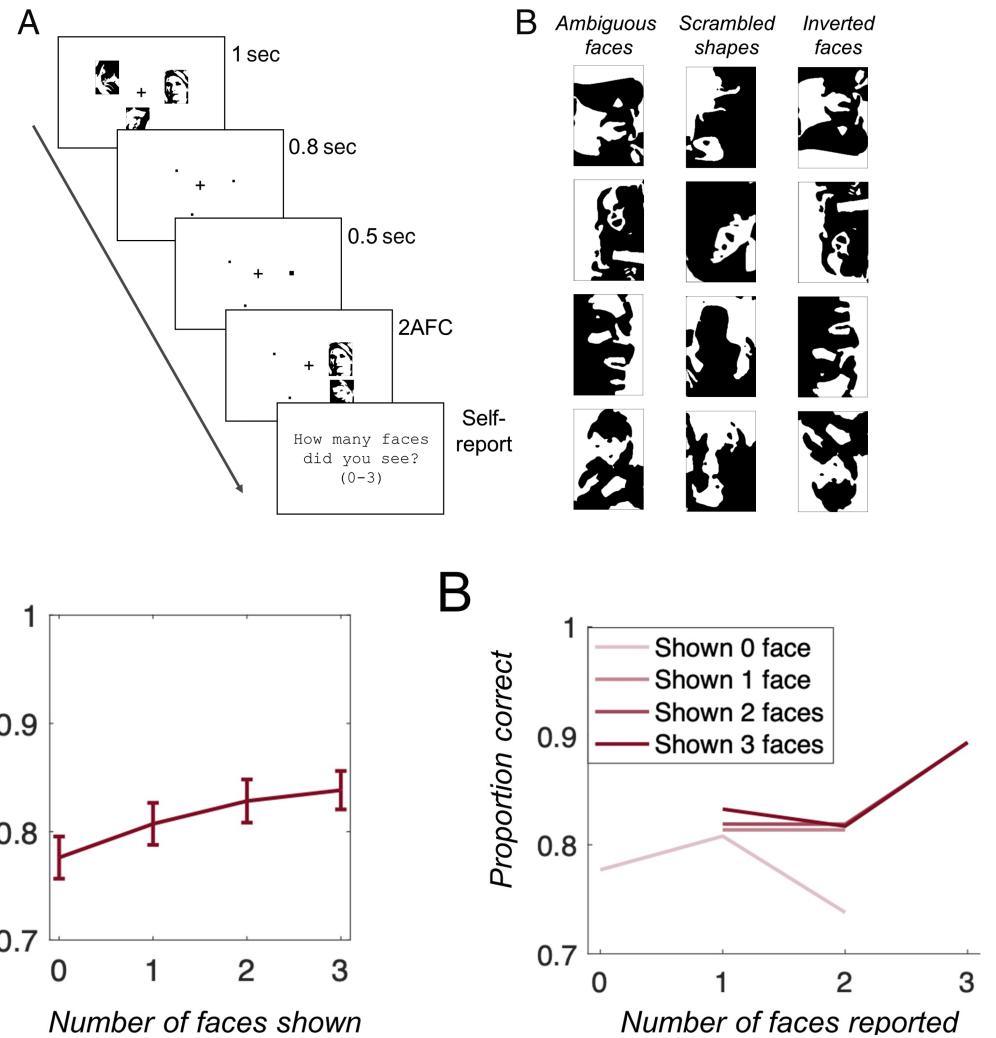
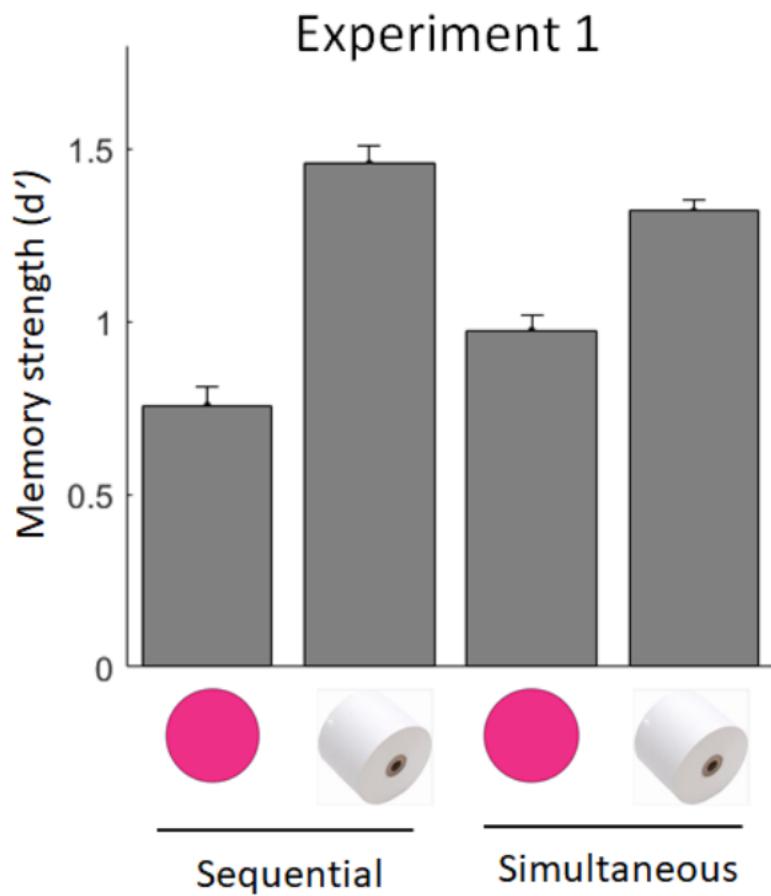


Working memory is aided by long-term memory

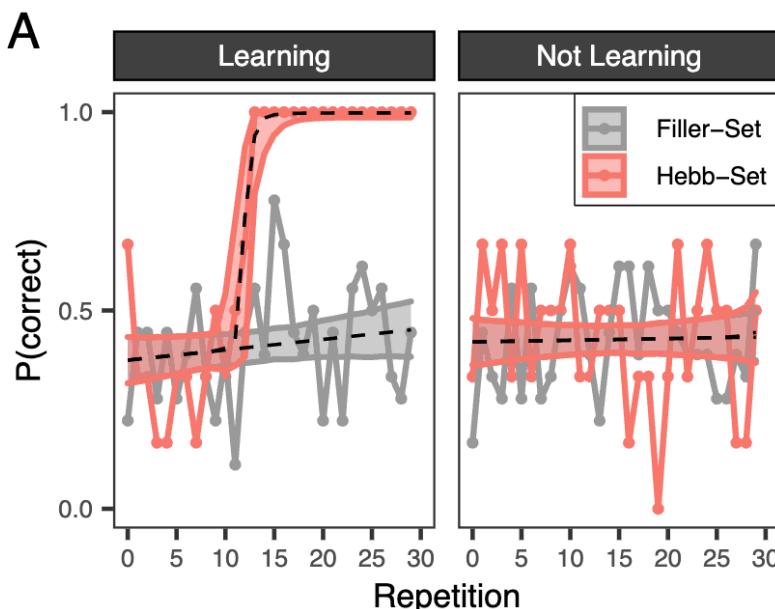
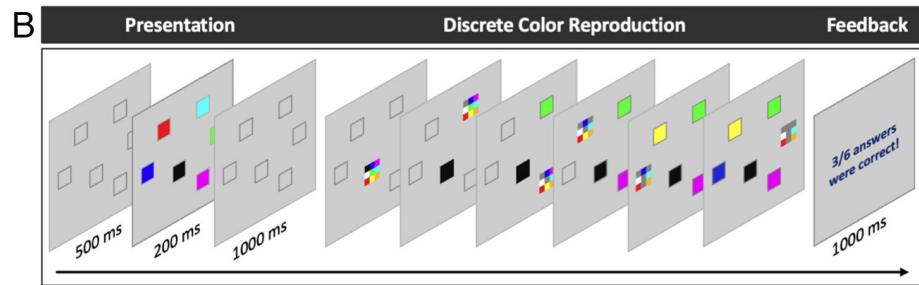
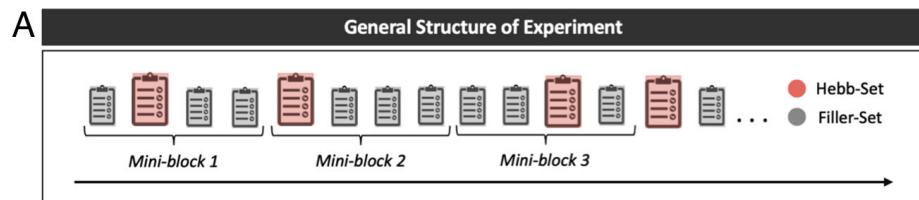
- A hallmark of our visual working memory system is its sharp capacity limit
- But this capacity limit can be overcome with **familiarity**:



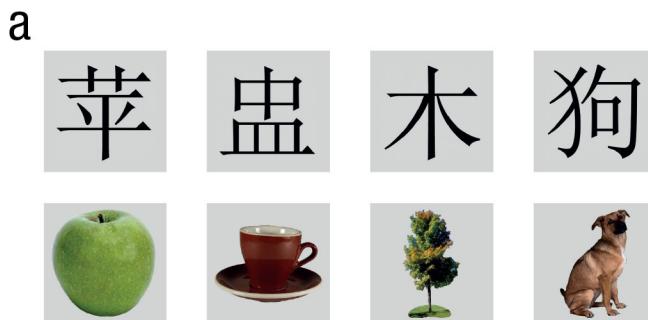
- Meaningfulness // real-world objects:



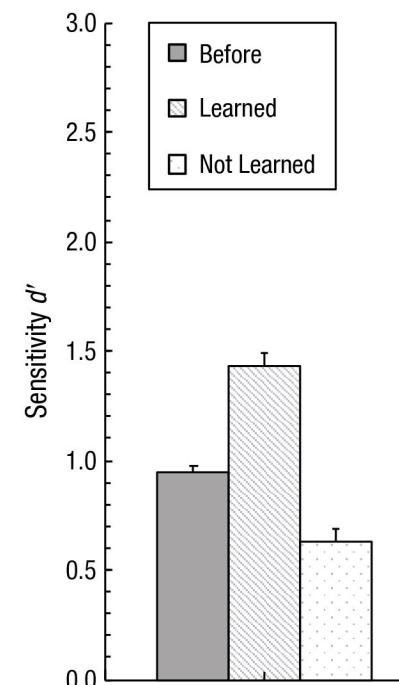
• Repetition learning // associative learning:



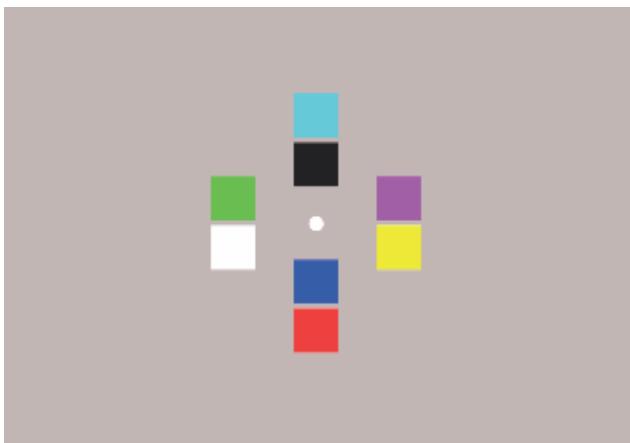
Musfeld et al. (2023) PNAS



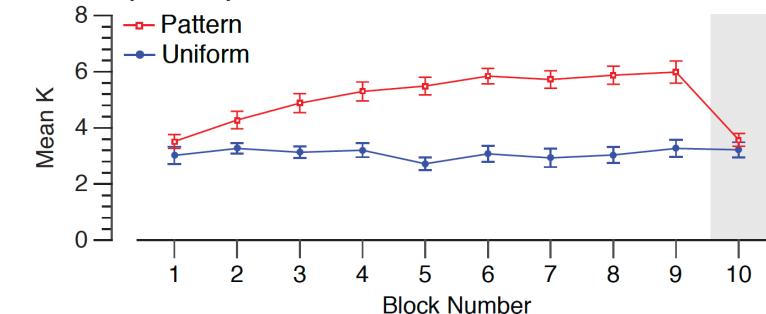
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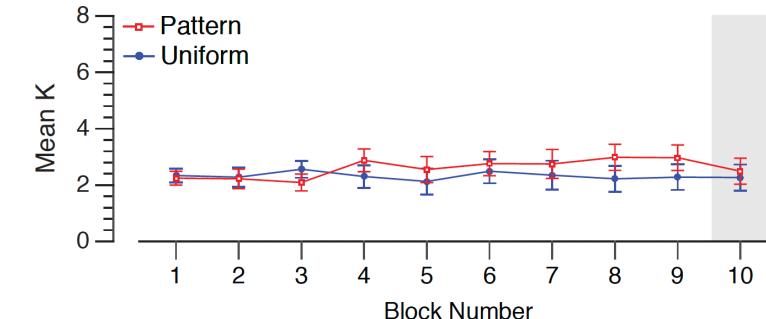
Conci et al. (2023) Psych Sci



Aware (n = 19)



Unaware (n = 13)



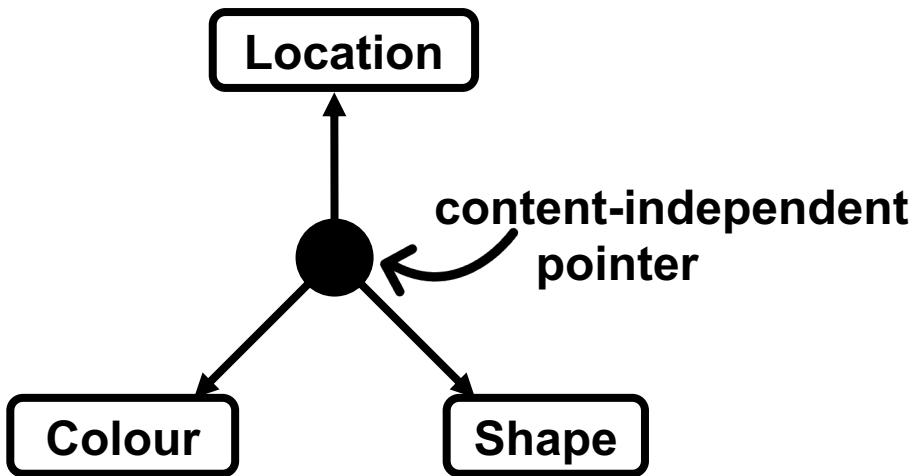
Ngiam et al. (2019) JEP:G

How is working memory performance improved?

- Working memory load may be ***expanded*** for familiar // meaningful // learned stimuli
 - Additional resources are recruited allowing a greater amount of items to be held within working memory
- Working memory load is reduced via ***chunking***
 - Load is reduced by requiring fewer “chunks” to be held in working memory
 - Recall is improved by relying on recruitment of long-term memory

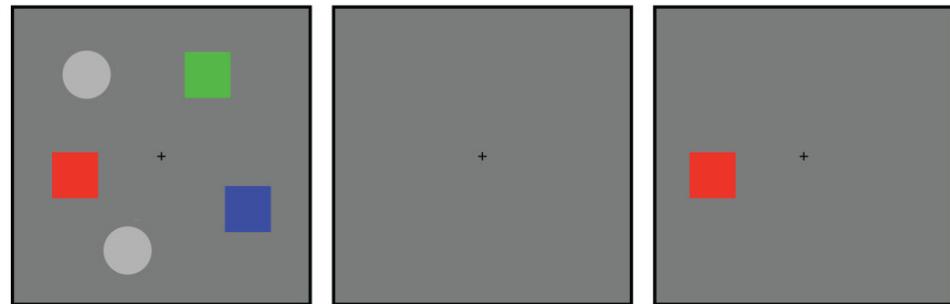
Pointers in working memory

- Pylyshyn (2009) proposed the visual system has an indexing mechanism that keeps track of an individual object through its changes
 - This index is **abstracted** from the contents of the object
- We propose that **items** in working memory are assigned to a **content-independent pointer**

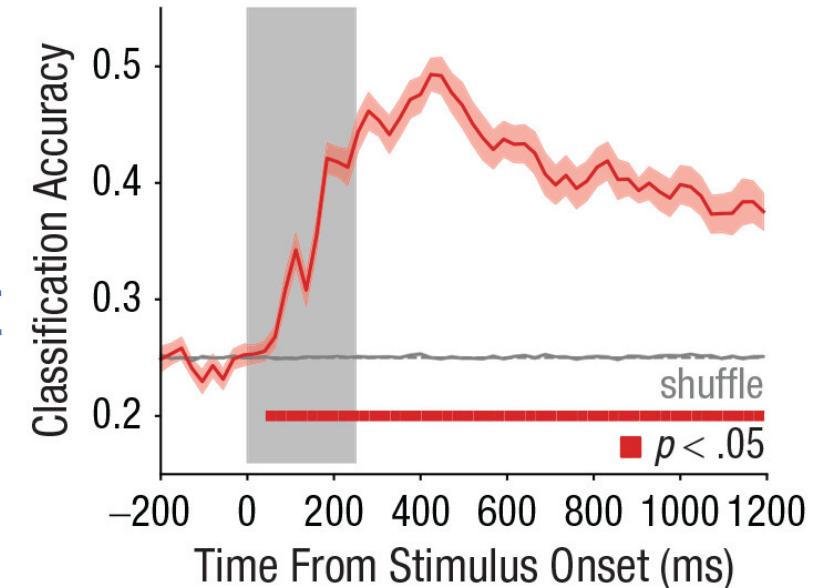


Multivariate neural signature of WM pointers

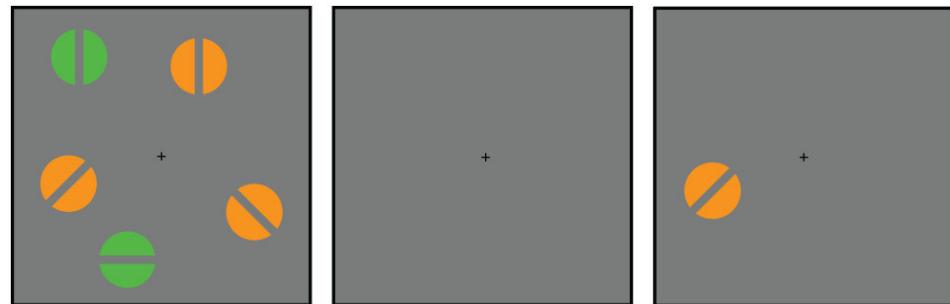
Experiment 1: Color



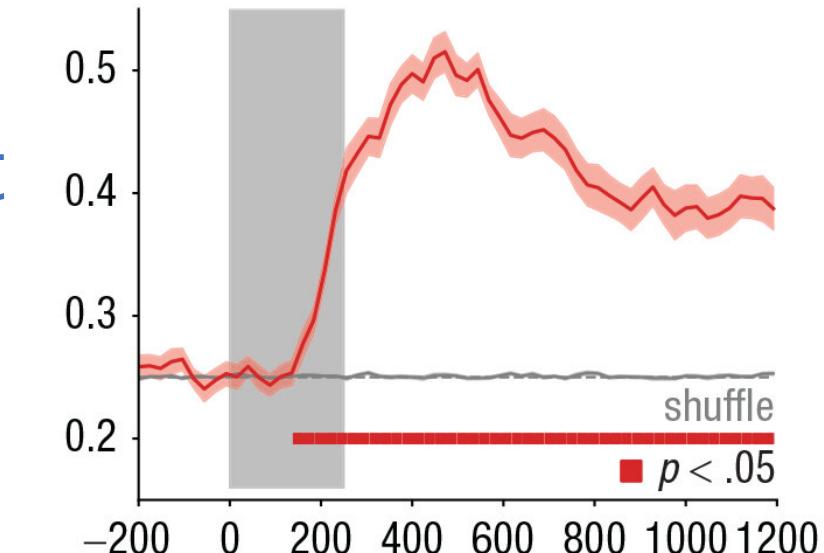
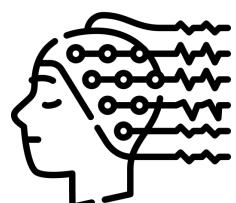
Train and test



Experiment 2: Orientation

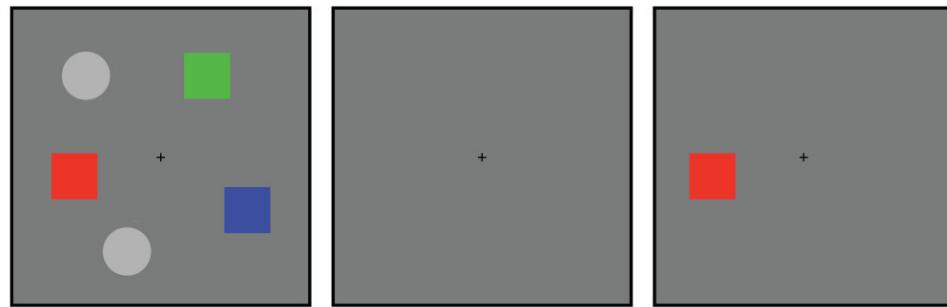


Train and test



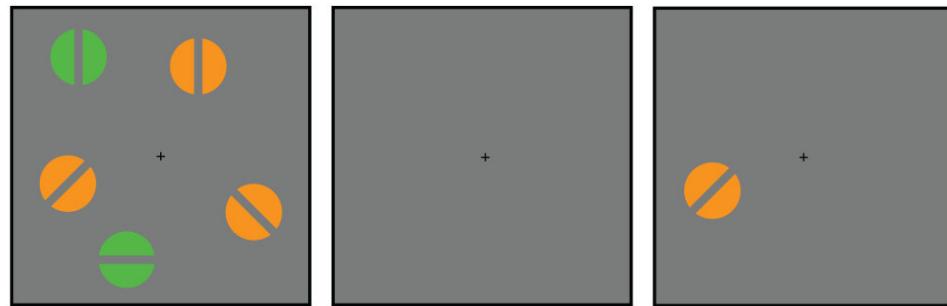
Multivariate neural signature of WM pointers

Experiment 1: Color



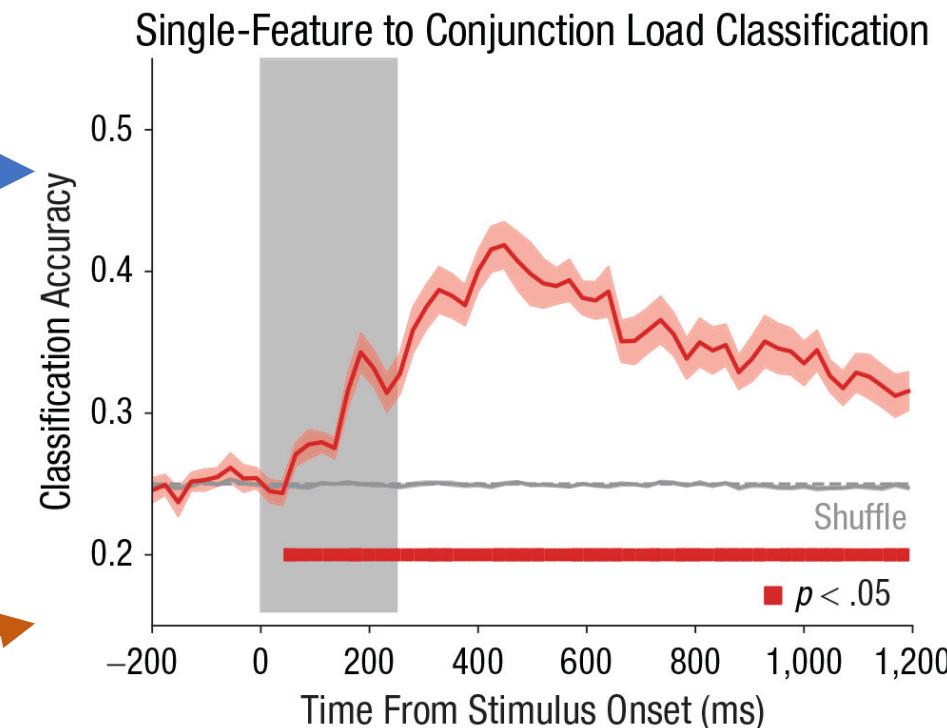
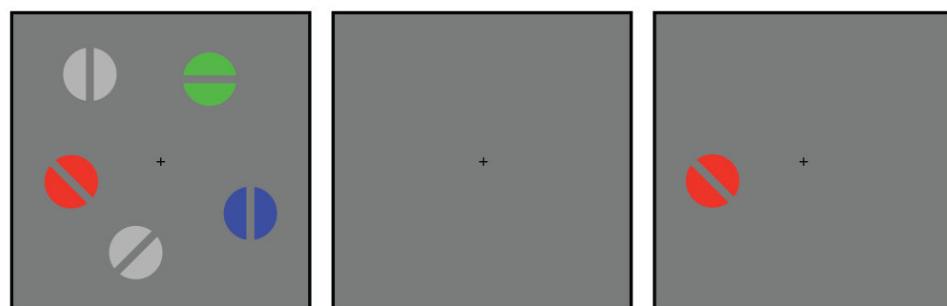
Train

Experiment 2: Orientation

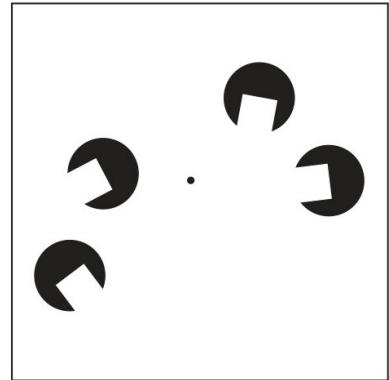


Test

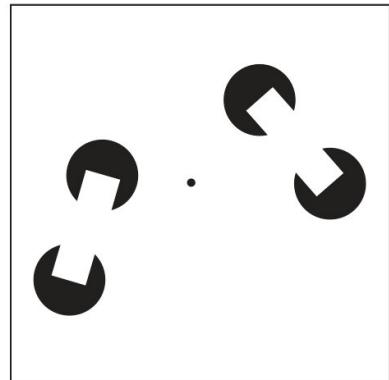
Experiment 3: Conjunction



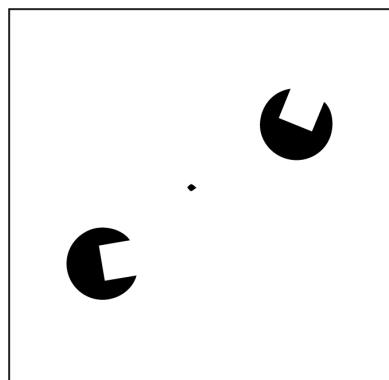
Multivariate neural signature of WM pointers



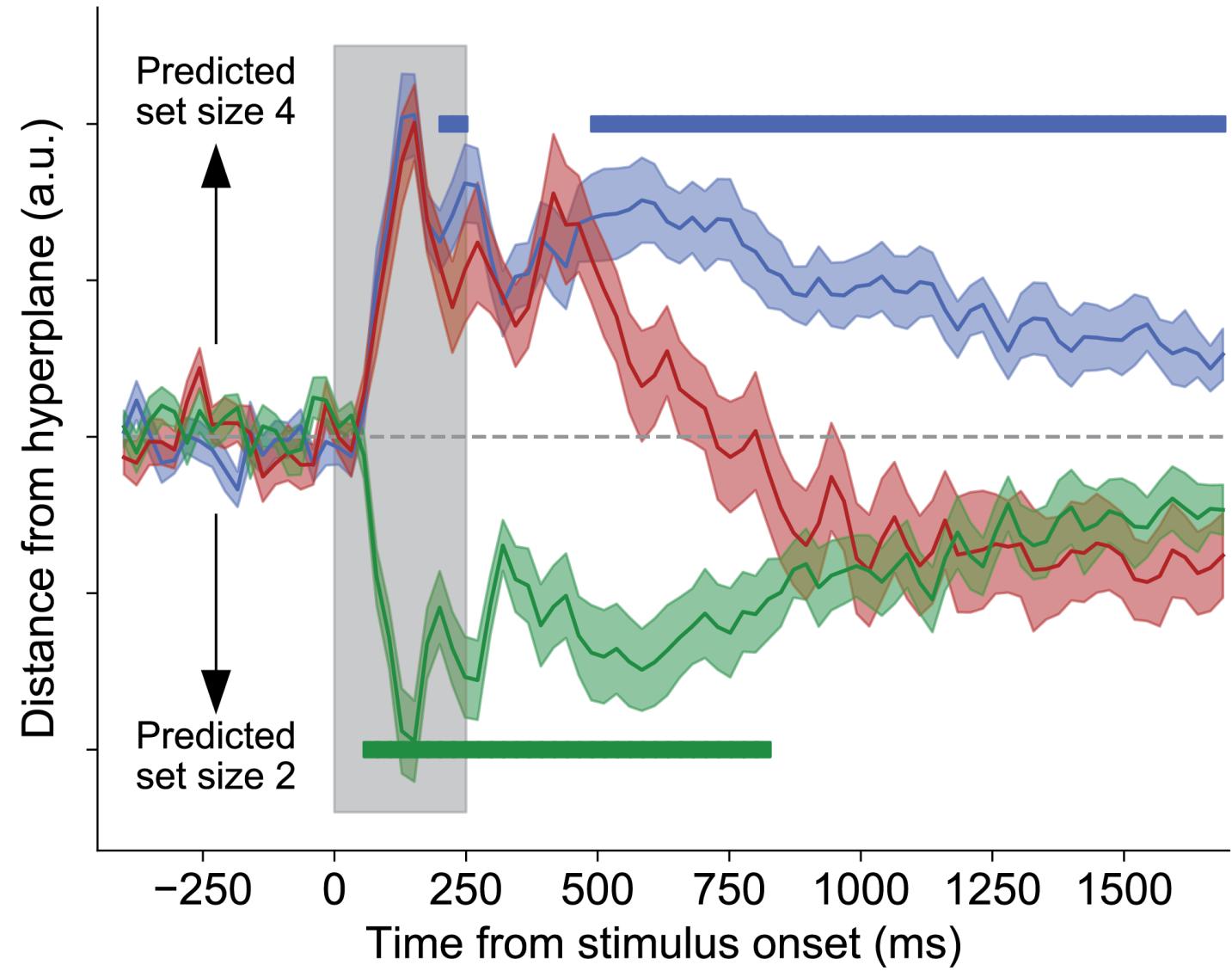
4 Ungrouped



4 Grouped



2 Ungrouped



Multivariate neural signature of WM pointers



Henry Jones



Darius Suplica

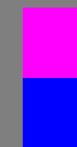
- The multivariate load signal for pointers is dissociated from spatial attention
Jones et al. (accepted), *Psychological Science*
- The load signal generalizes from color to motion coherence of random dot kinematograms
Henry's VSS talk this year

- The multivariate load signal is shared for audio and visual stimuli
in prep

Do working memory pointers connect to long-term memory?

Experiment 1: Training

- Subjects completed 600 trials to learn four color pairs:



Experiment 1: Training



Experiment 1: Training

- Two alternative-forced choice – which color was in the bolded location?

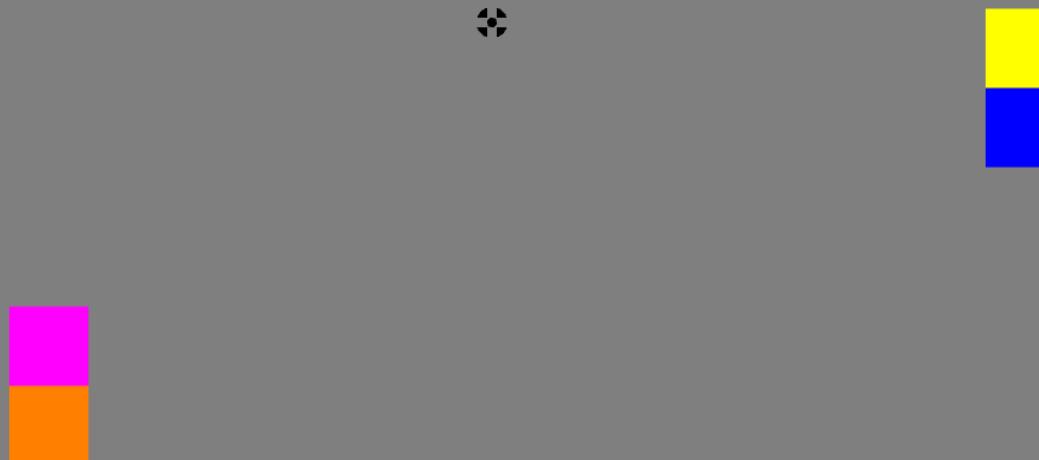


■ . ■



Experiment 1: Pre-training and post-training

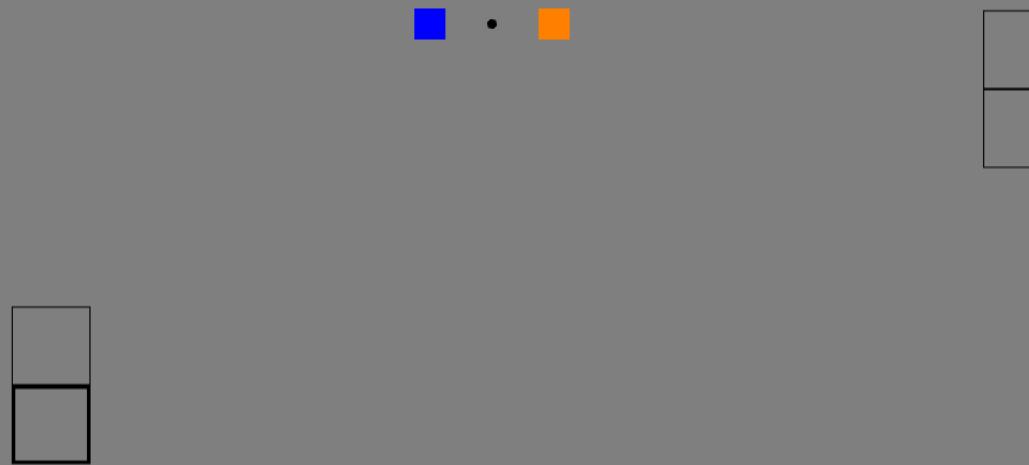
- Before training – 4 random colors
- After training – 4 paired colors (two learned pairs)



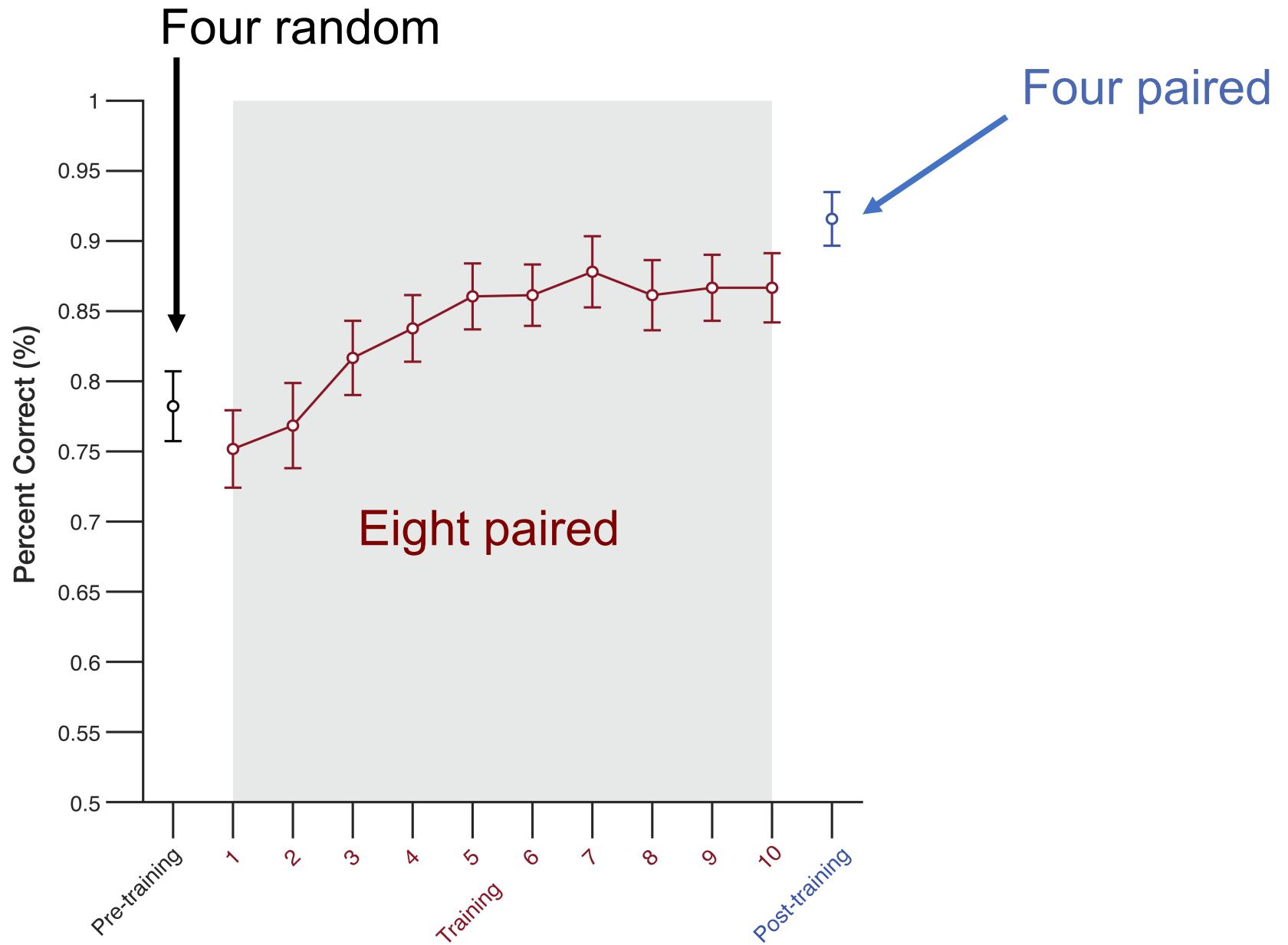
Experiment 1: Pre-training and post-training



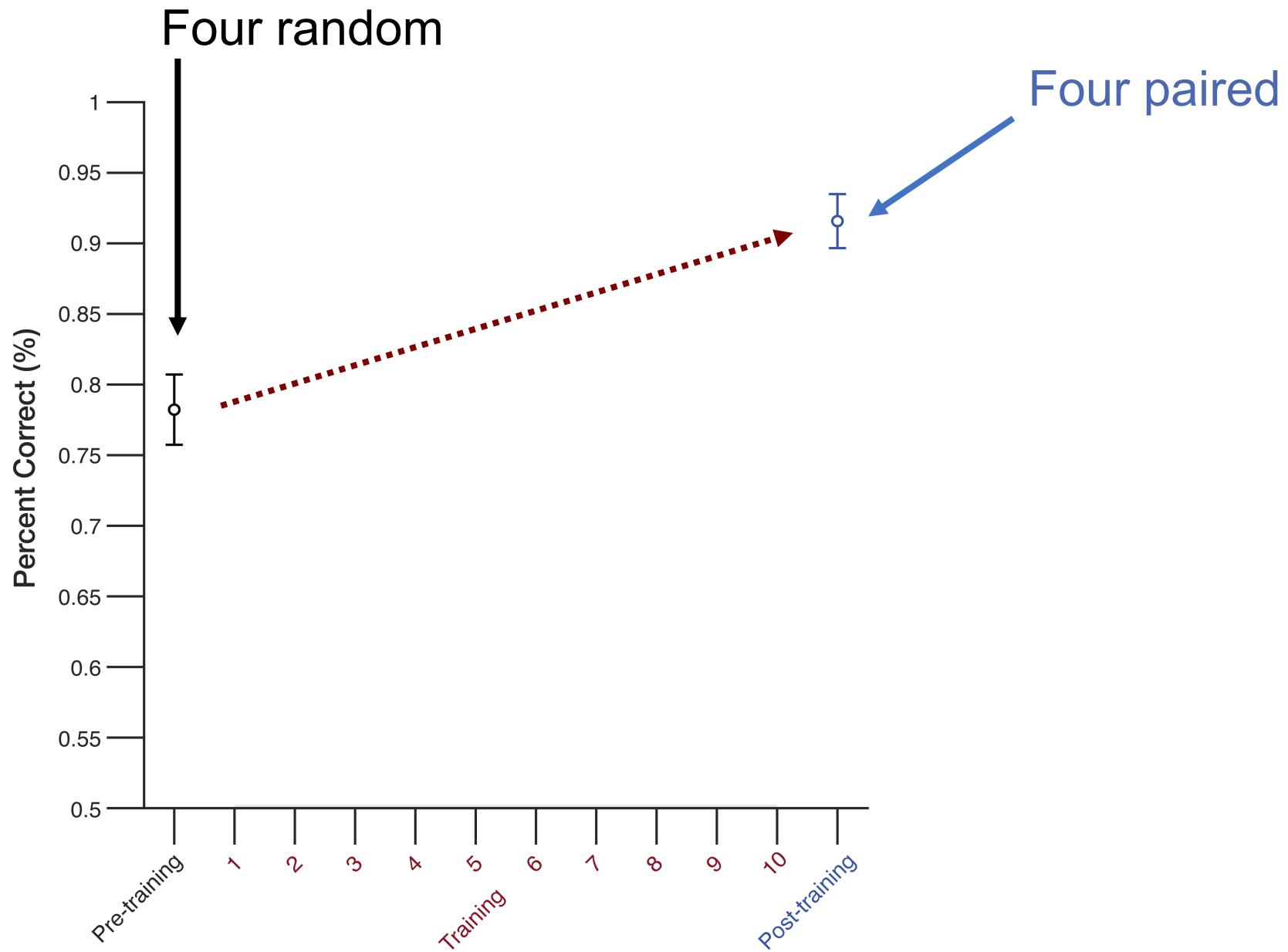
Experiment 1: Pre-training and post-training



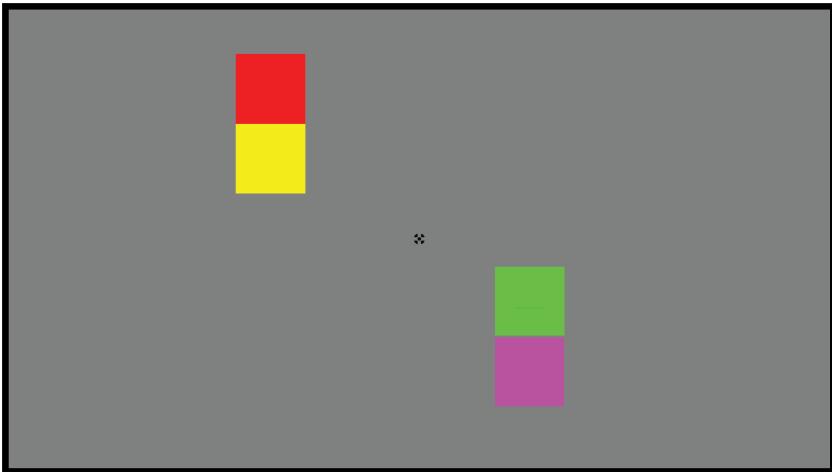
E1: training session – average performance



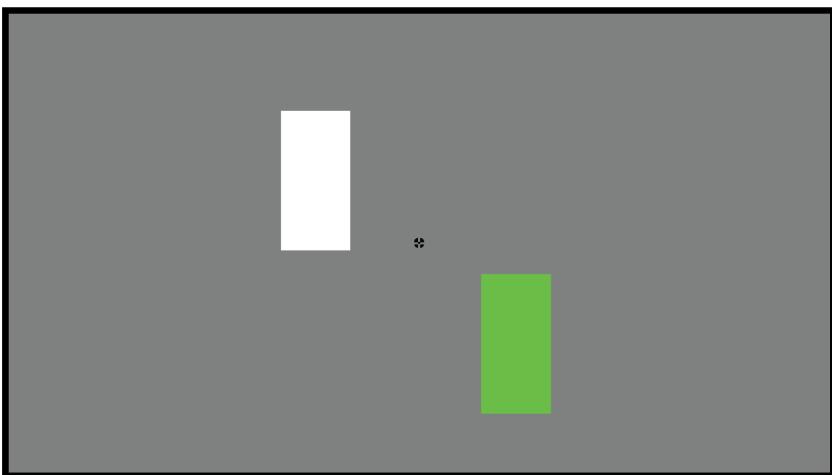
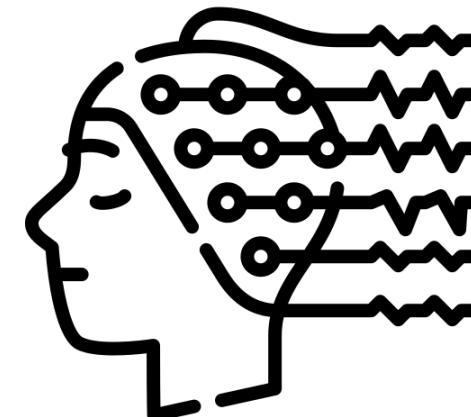
E1: training session – average performance



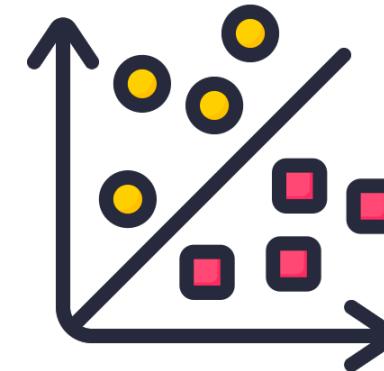
Experiment 1: EEG session



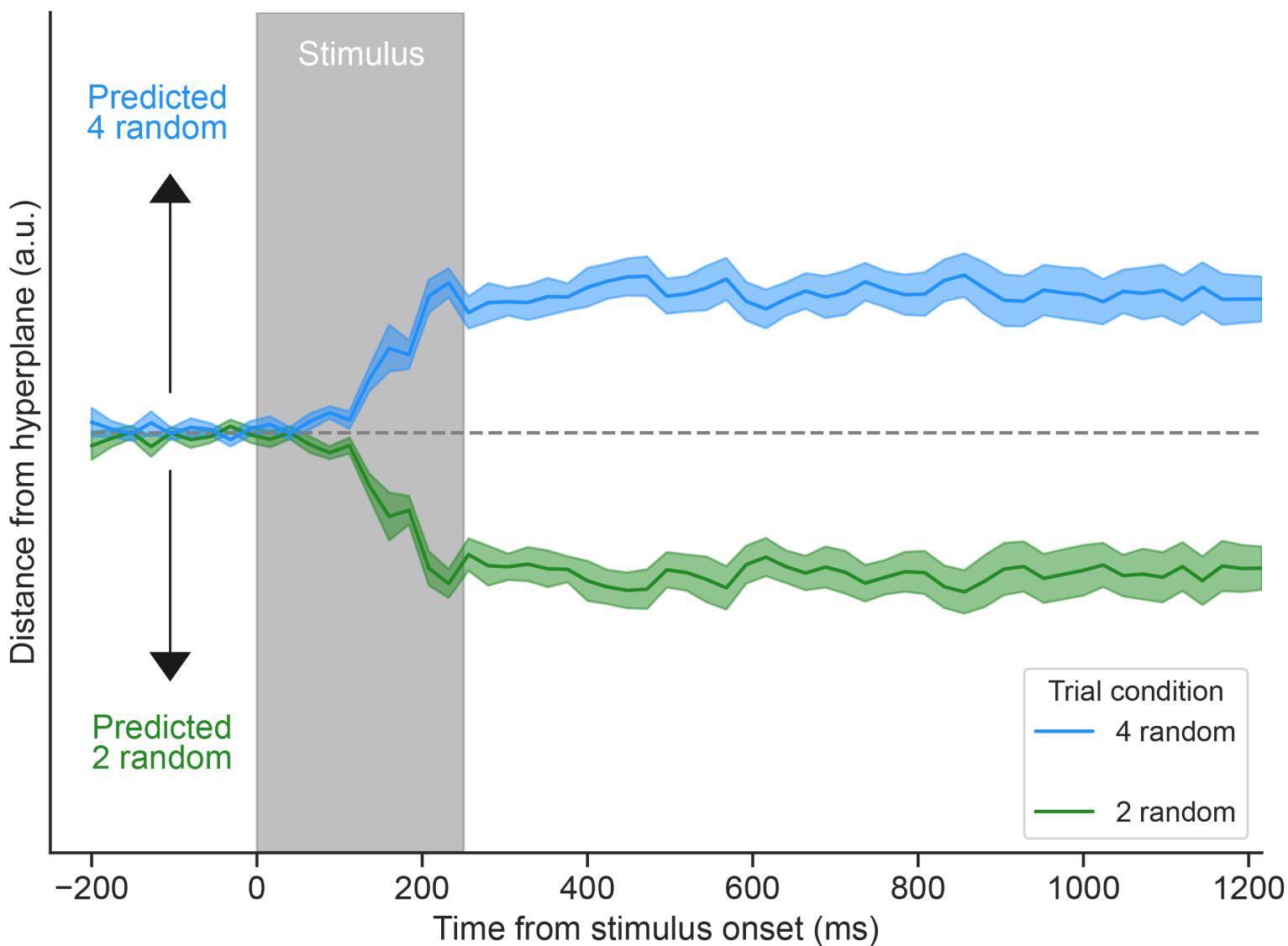
Four random
Four paired



Two random

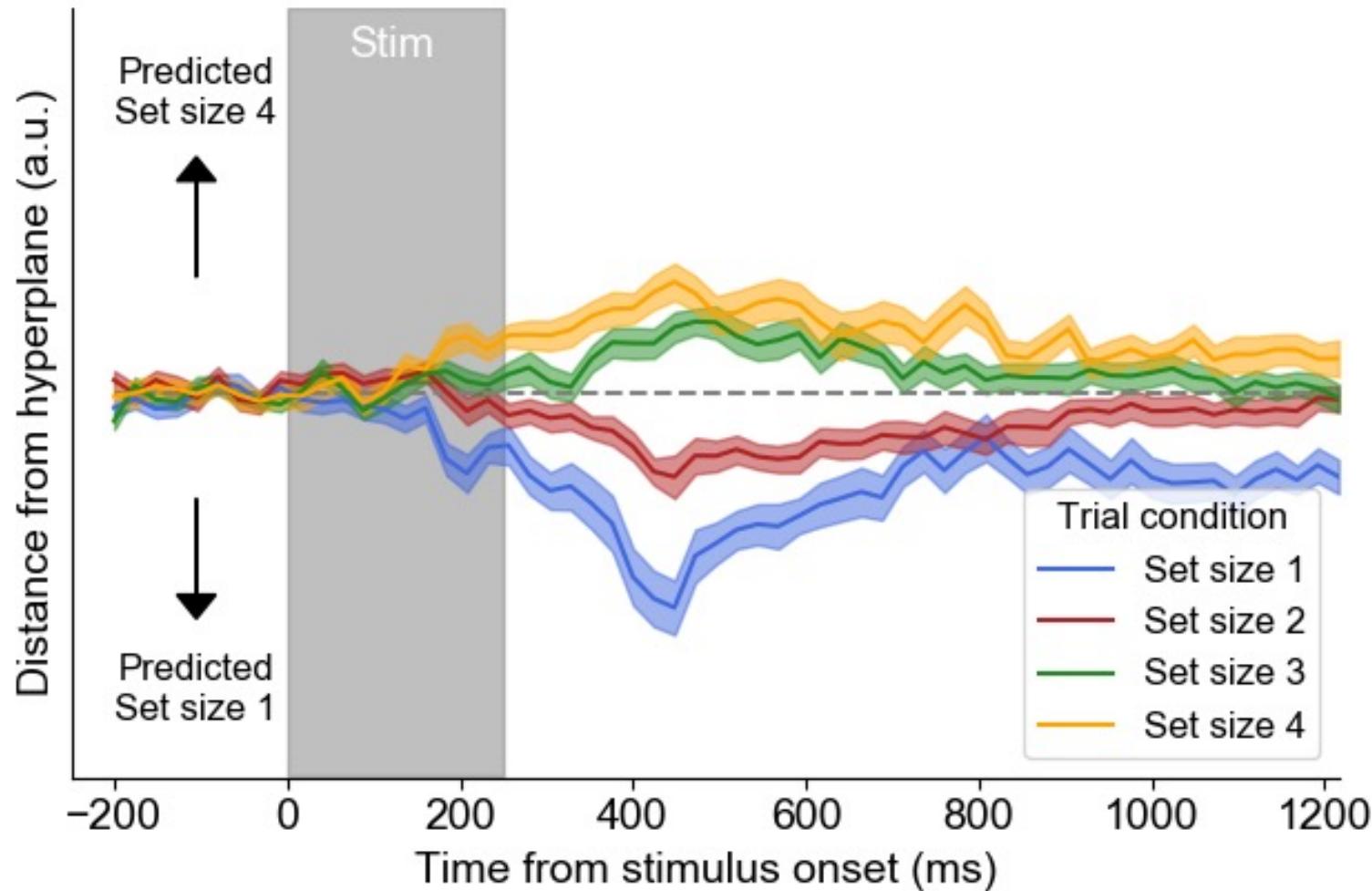


Train 2 random versus 4 random

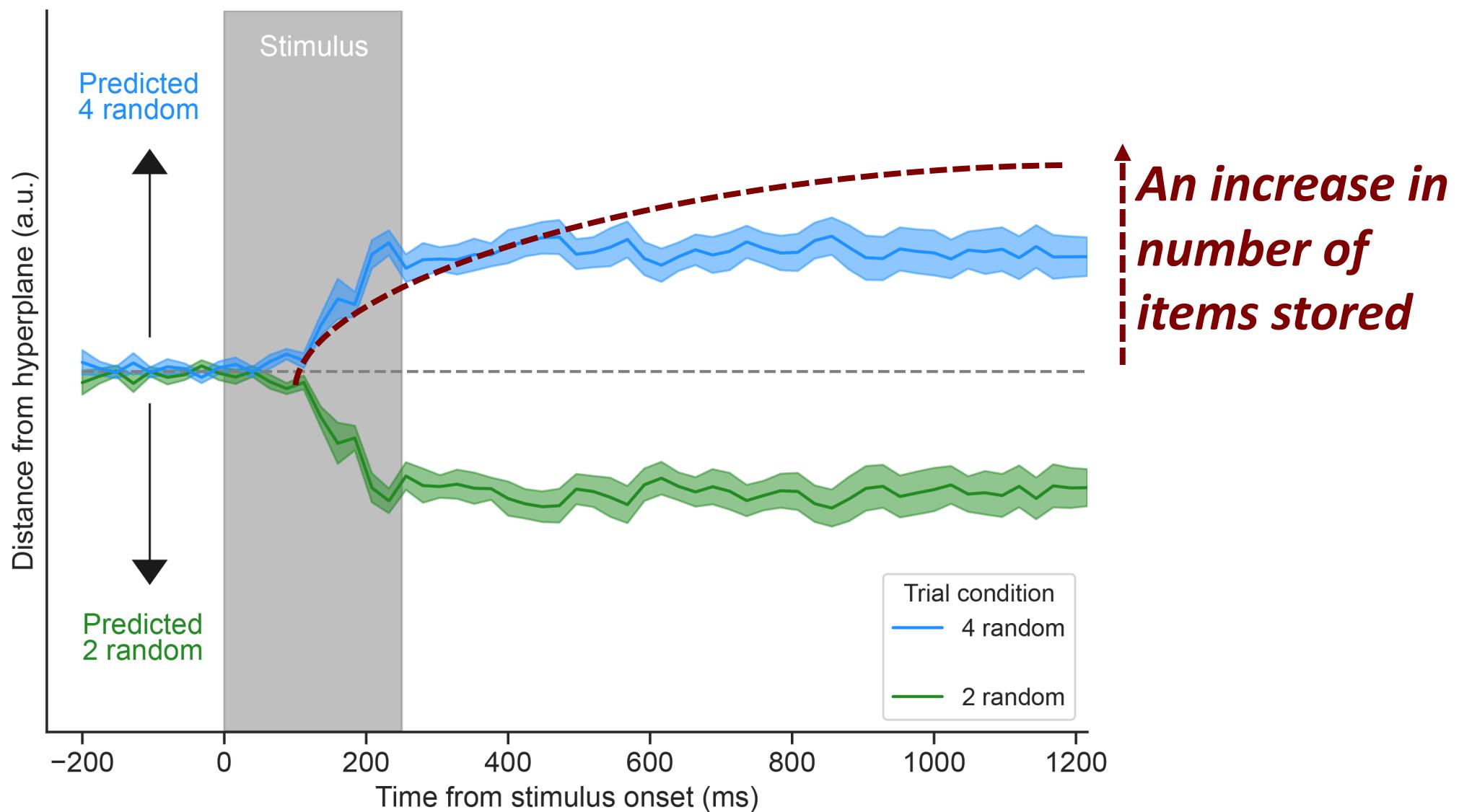


Different loads on the hyperplane

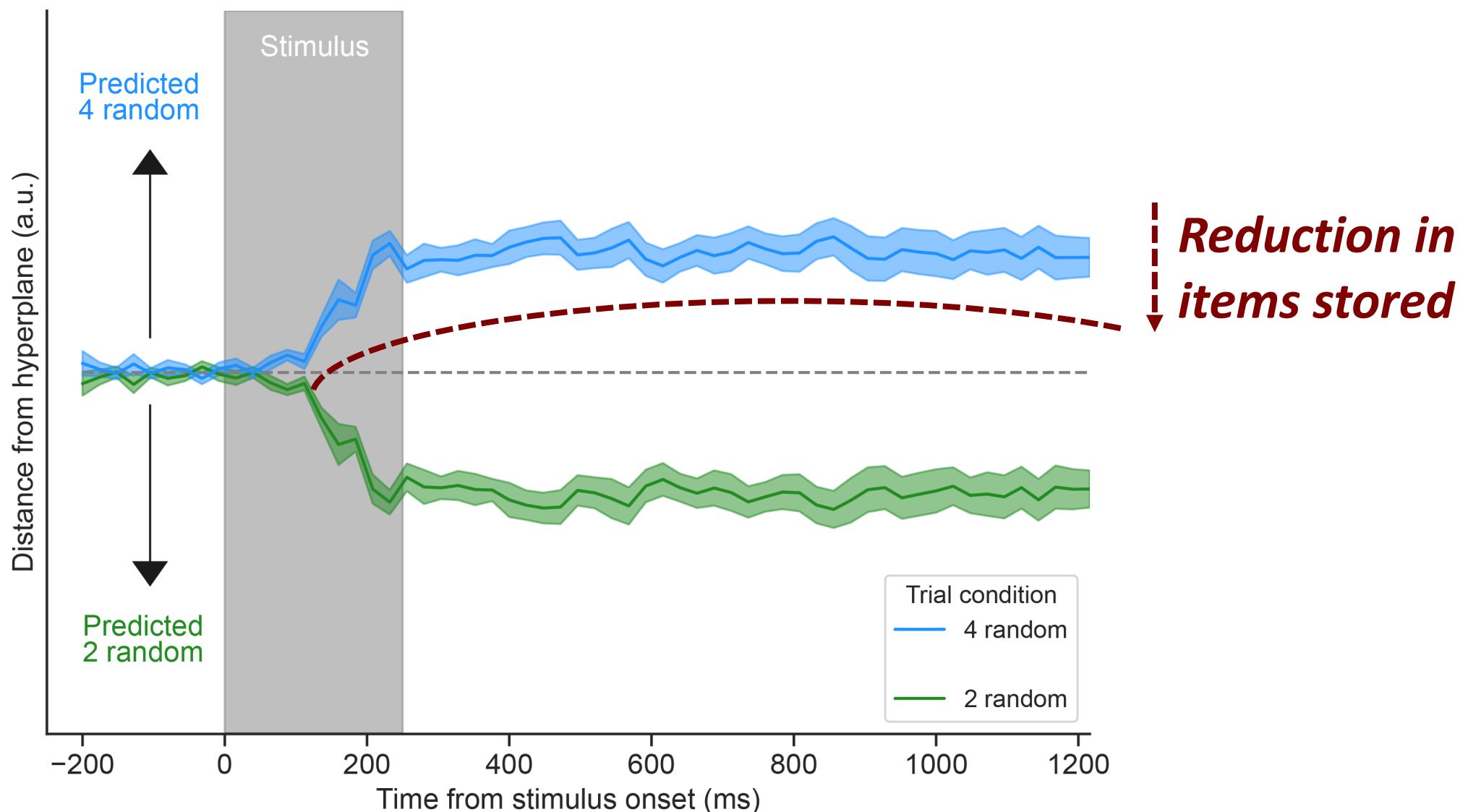
Train: Set size 2 and 3
Test: Set size 1 and 4



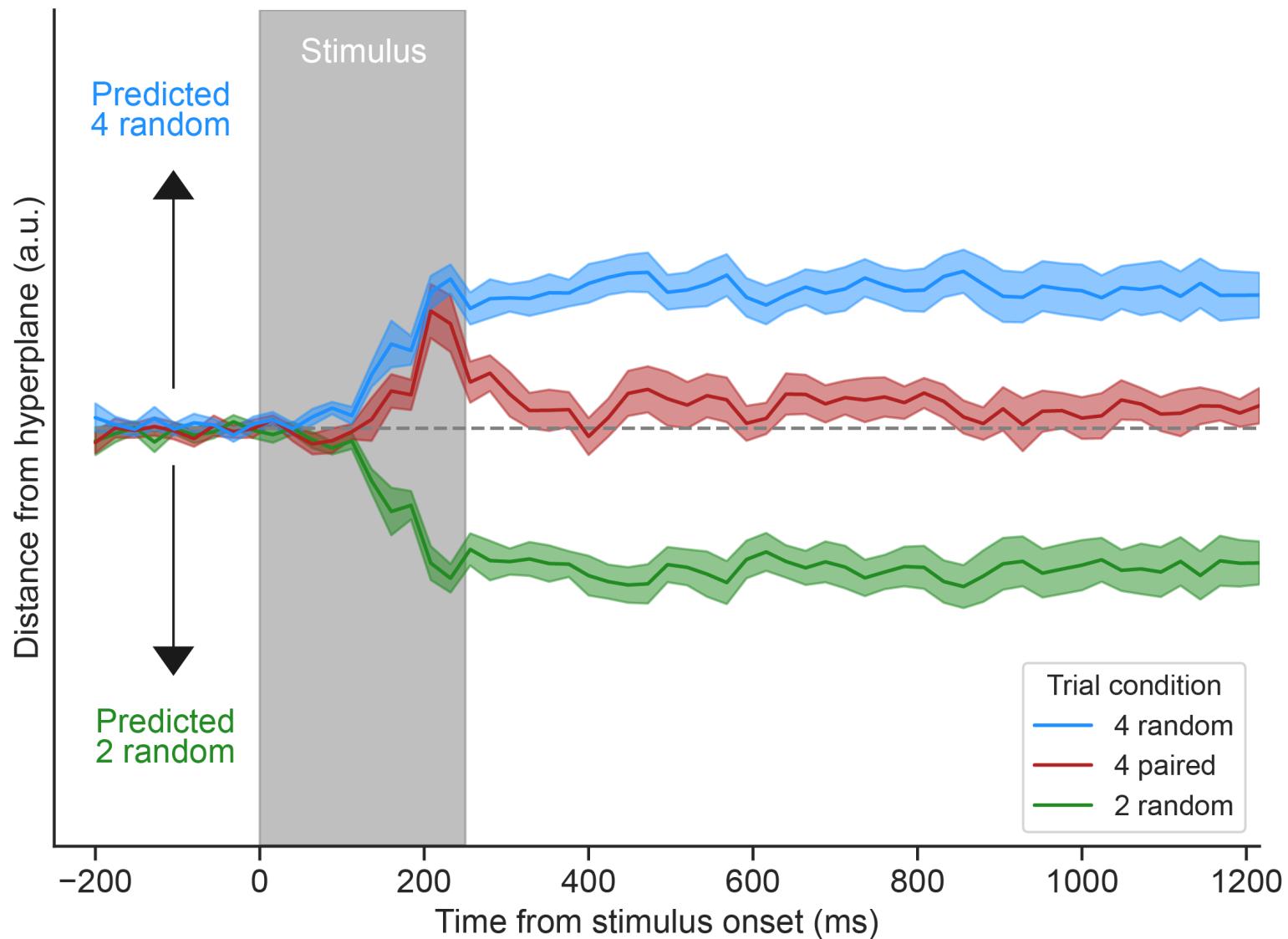
Train 2 random versus 4 random, where is 4 paired?



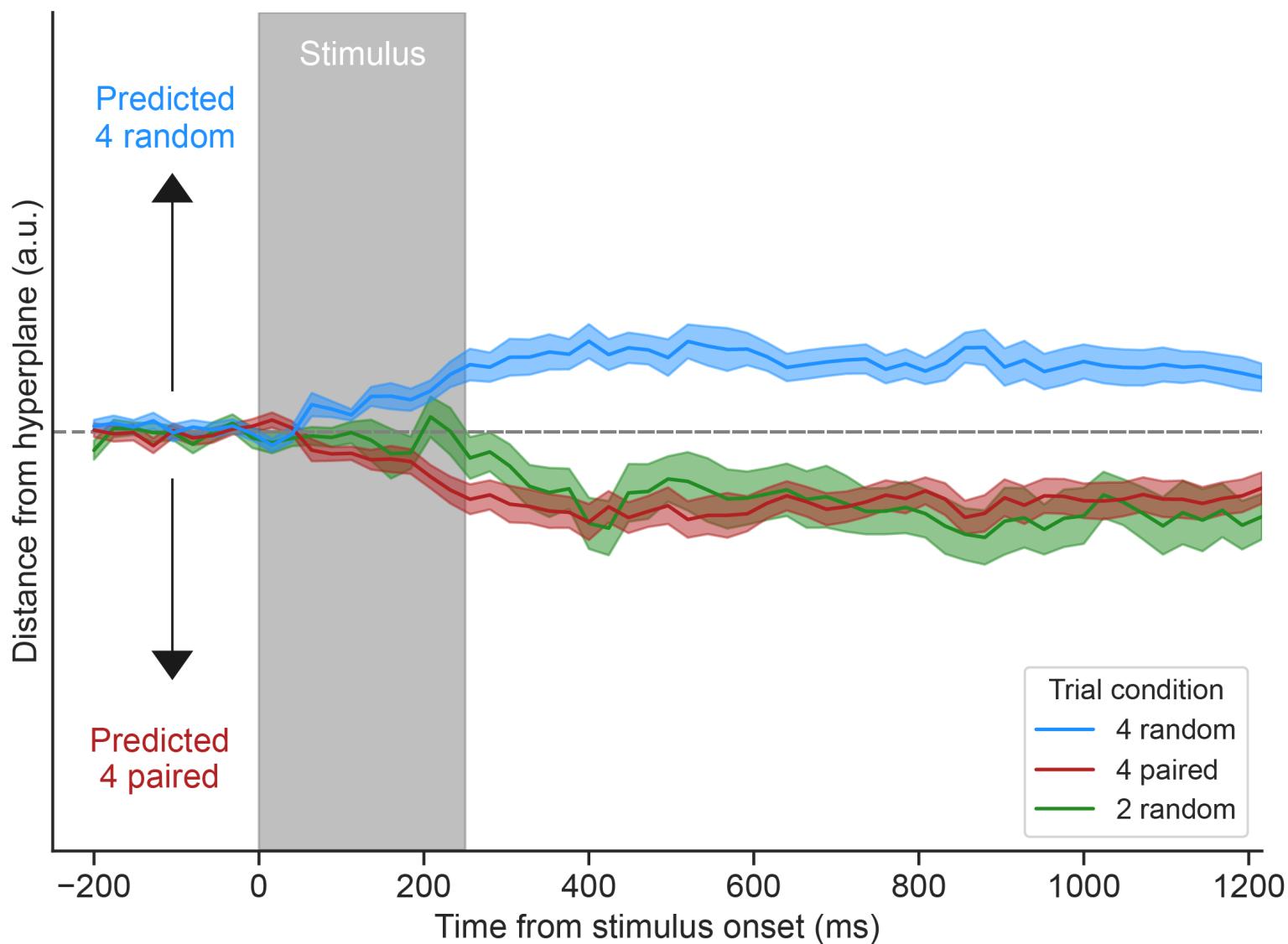
Train 2 random versus 4 random, where is 4 paired?



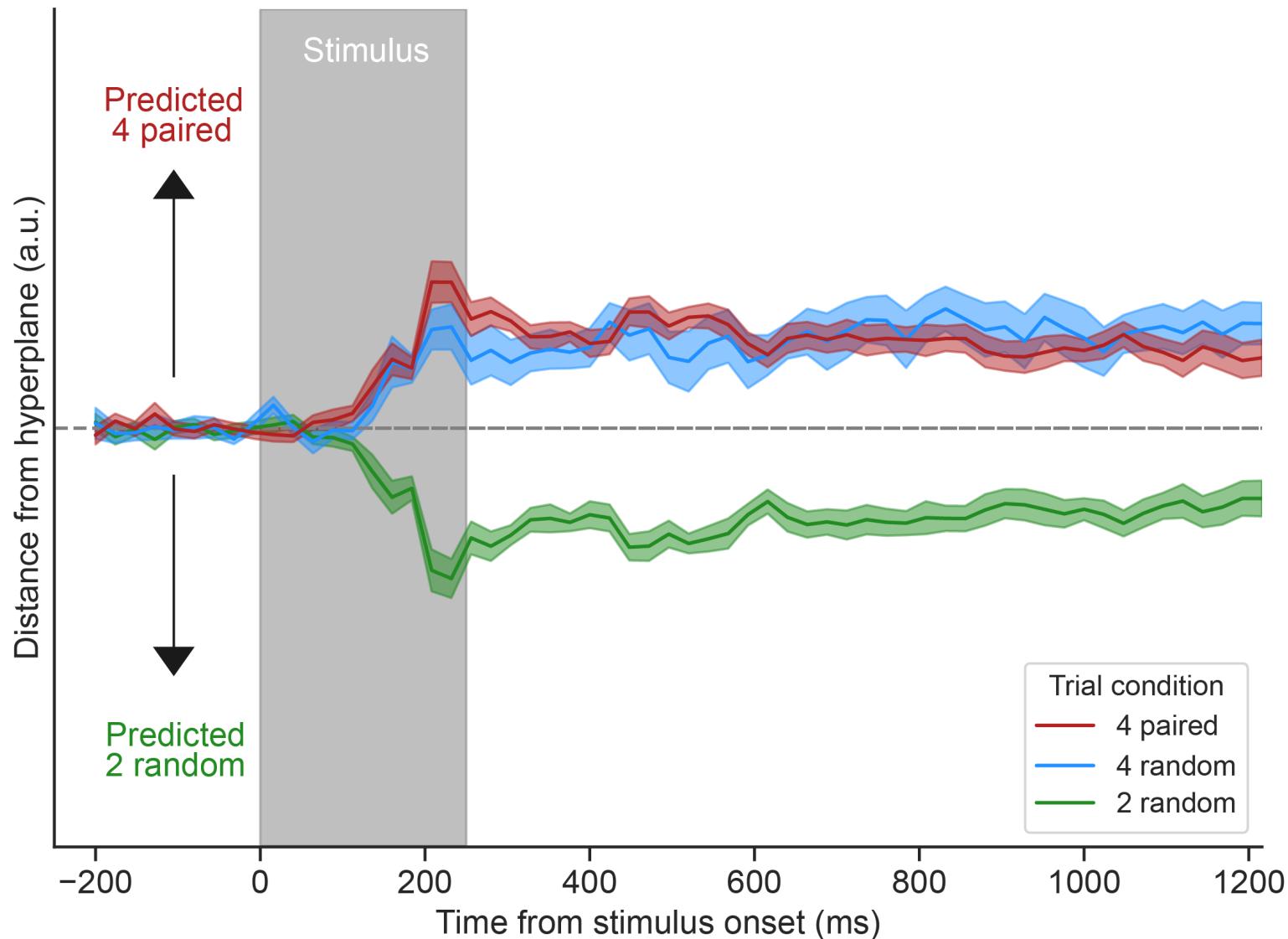
Train 2 random versus 4 random, test 4 paired



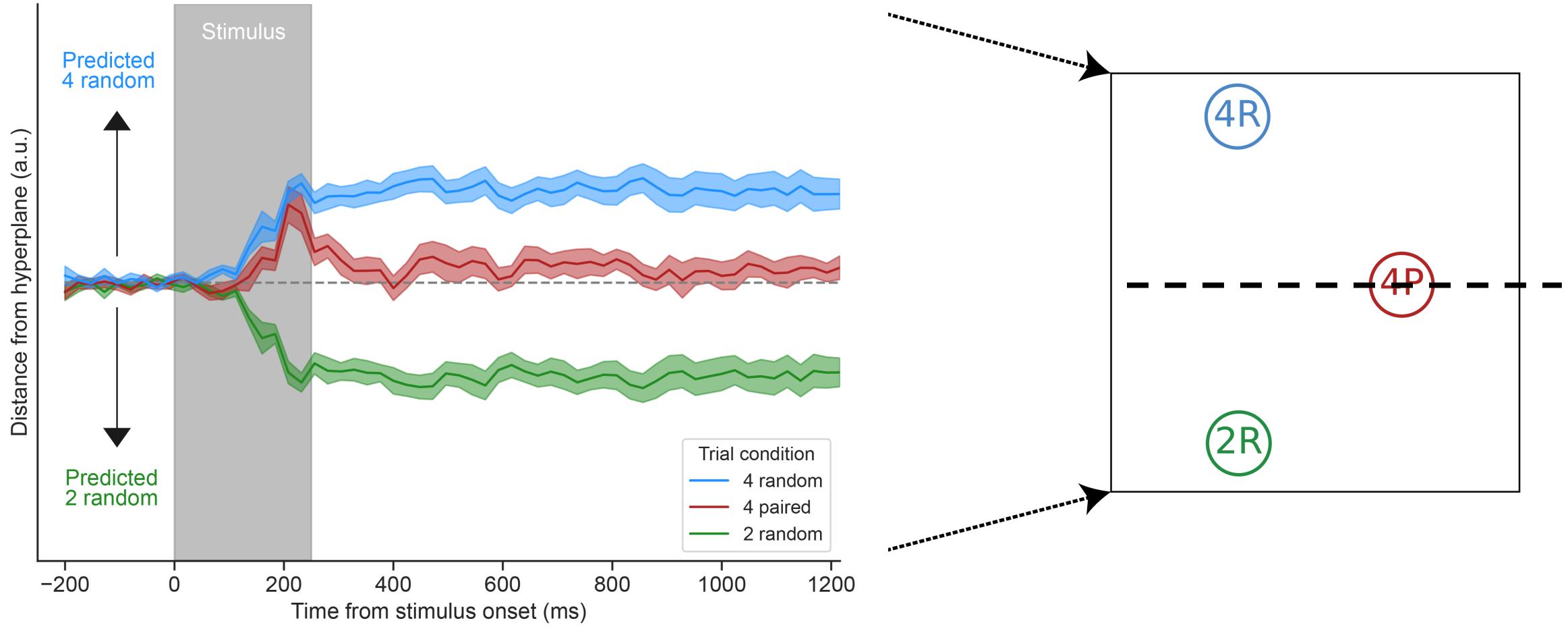
Train 4 random versus 4 paired, test 2 random



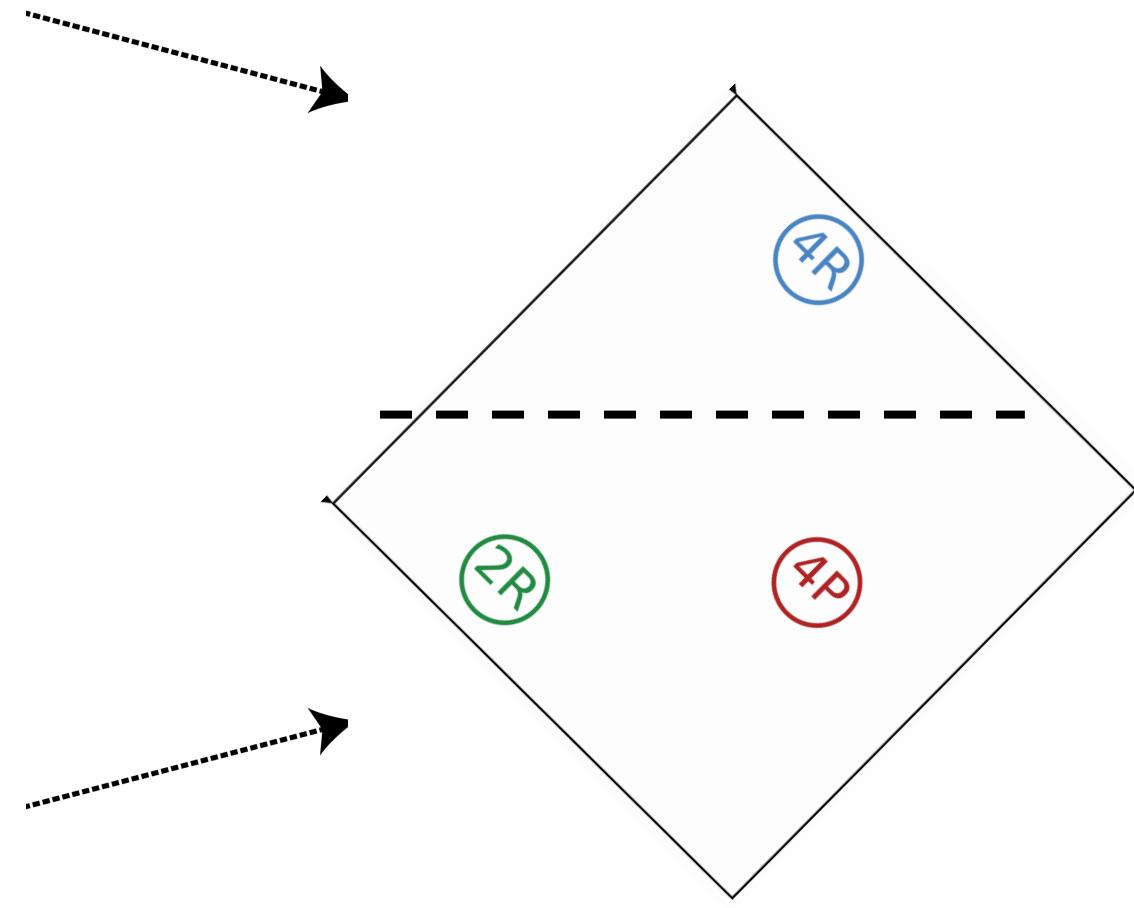
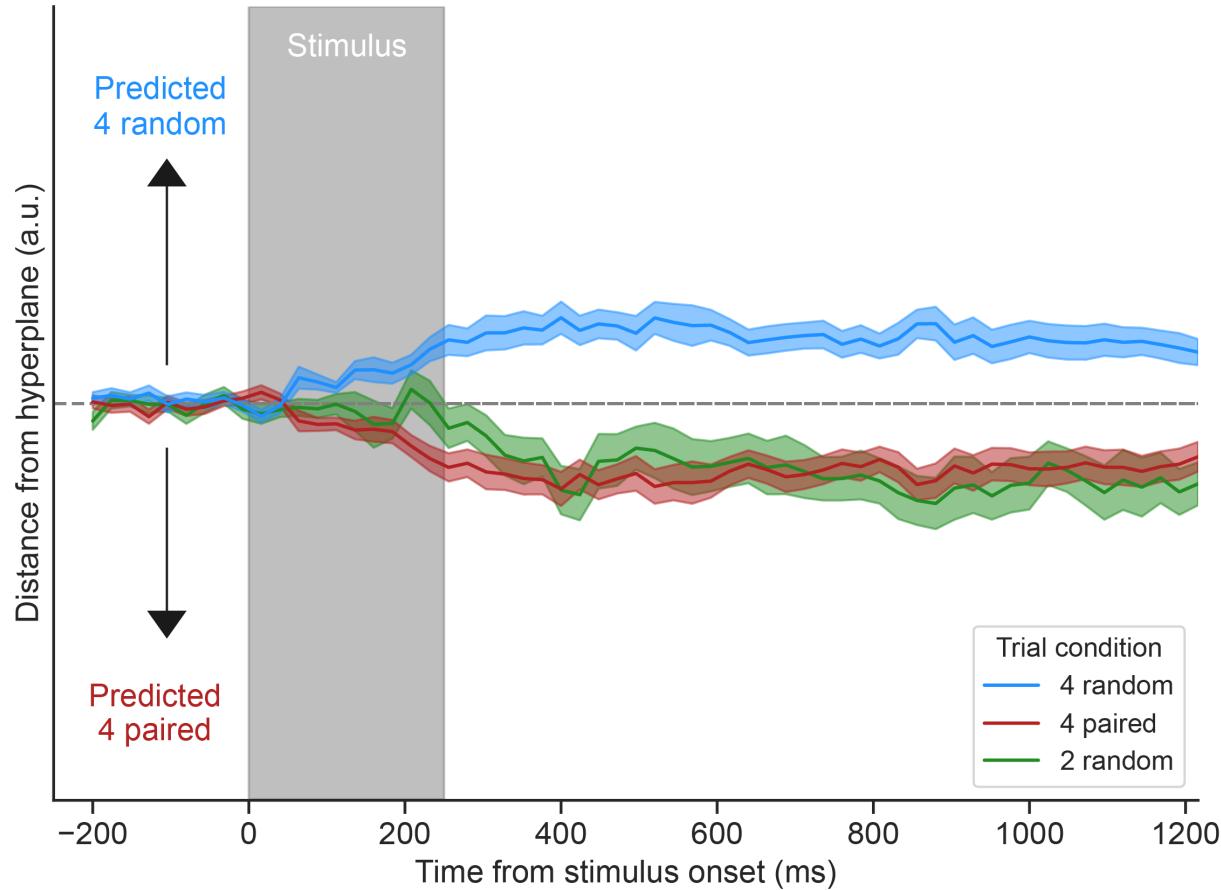
Train 2 random versus 4 paired, test 4 random



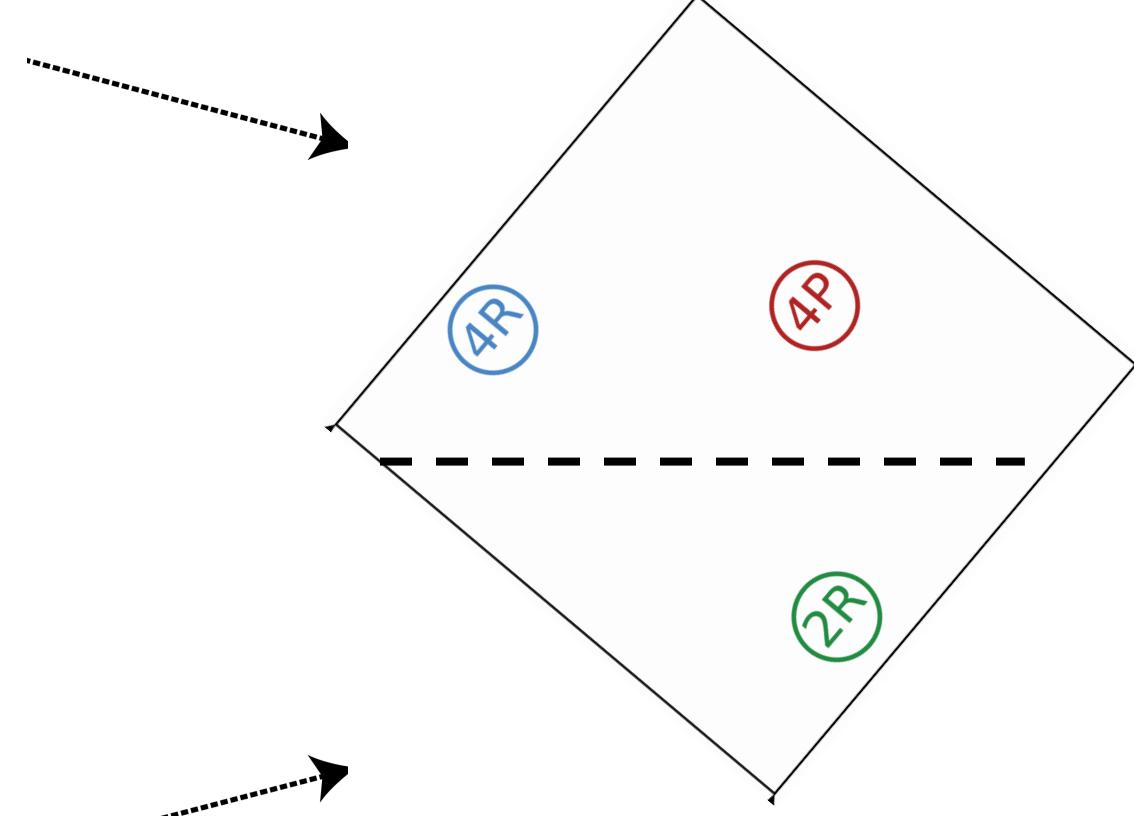
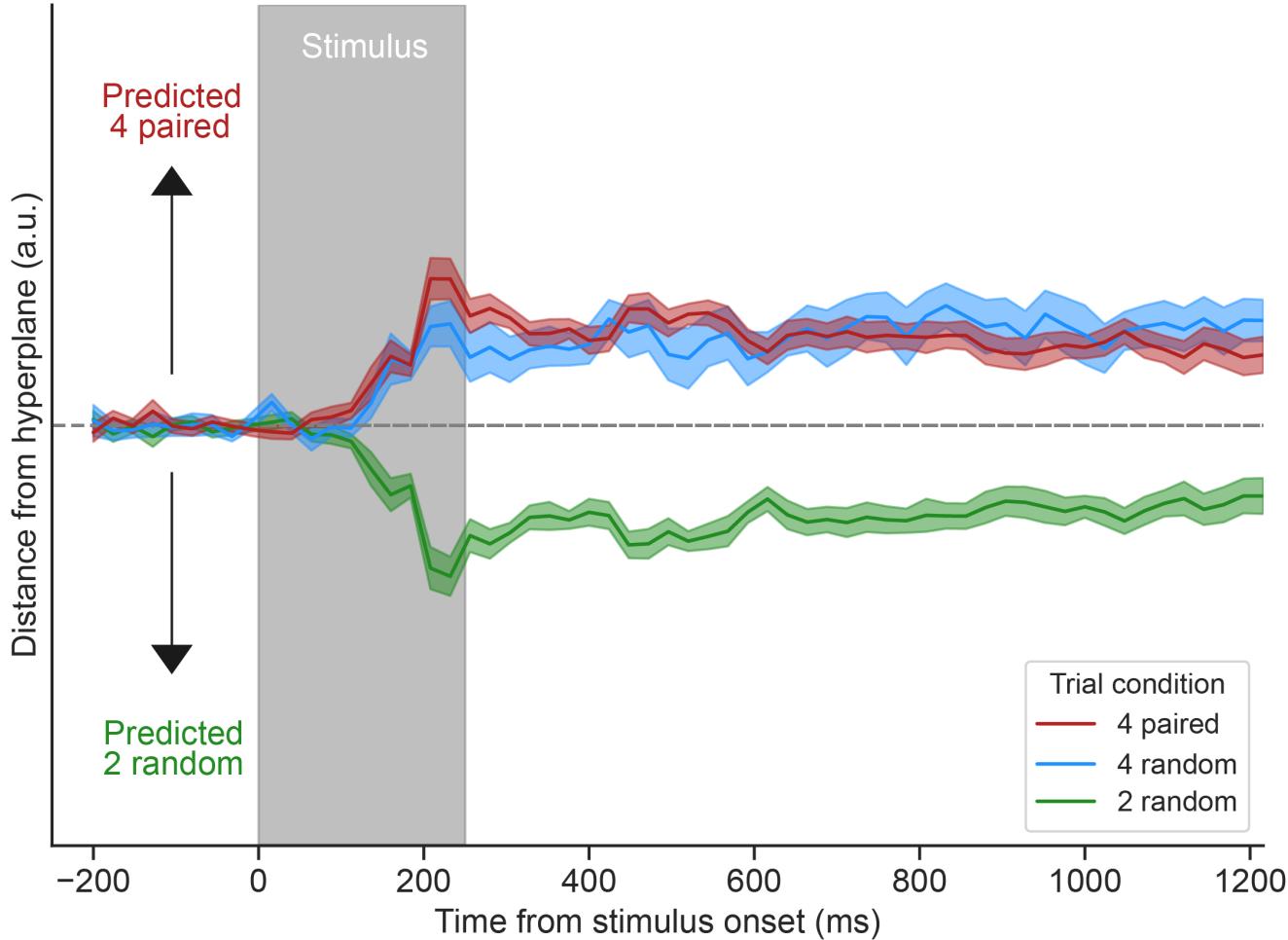
Multidimensional scaling



Multidimensional scaling

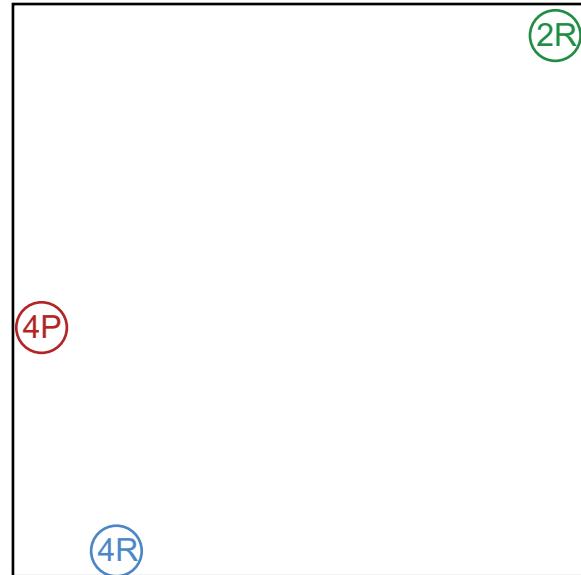
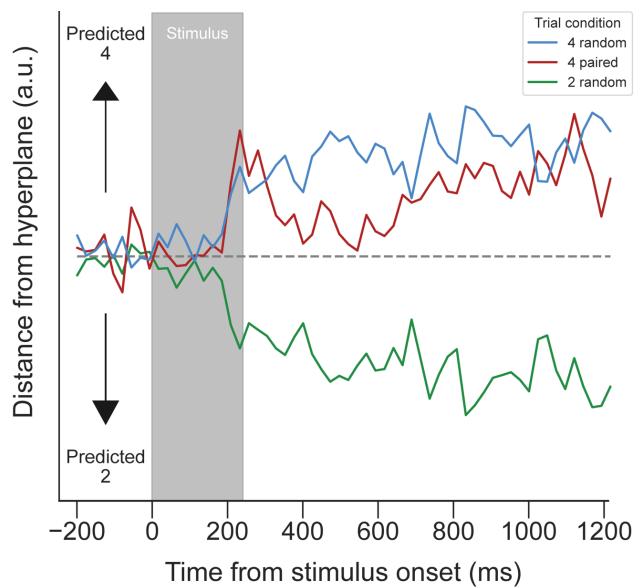


Multidimensional scaling

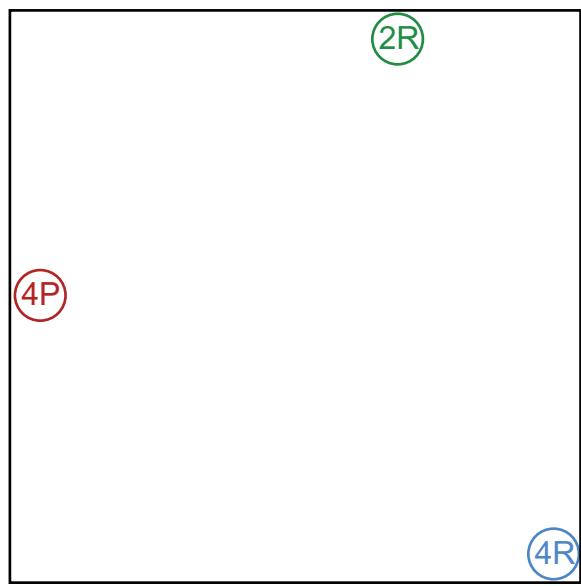
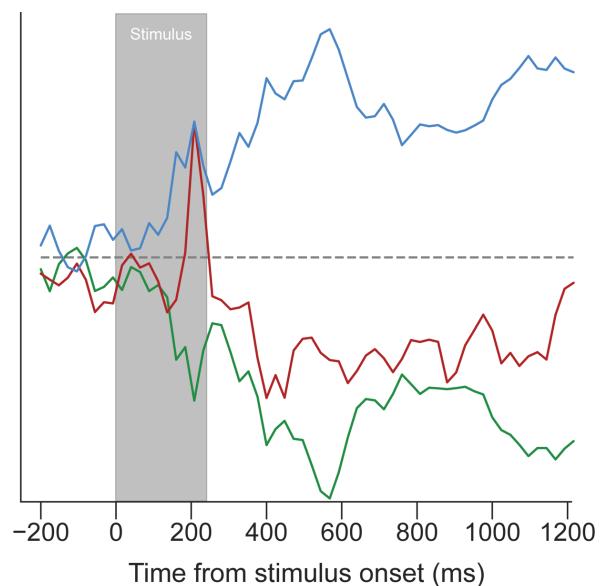


Individual differences

“Weak chunking”

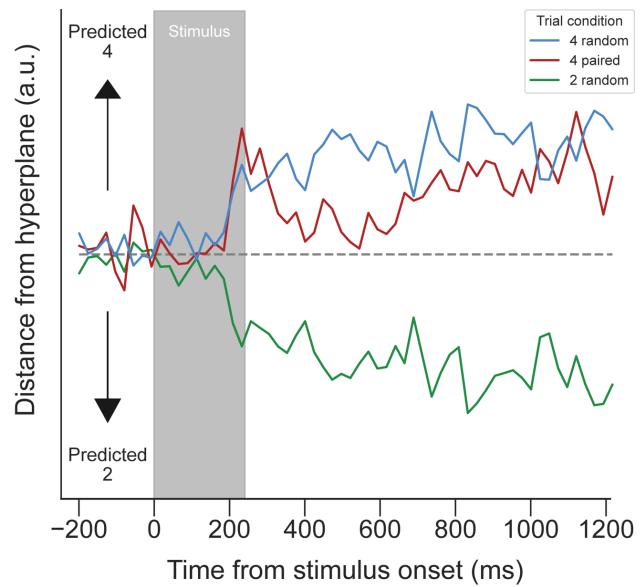


“Strong chunking”

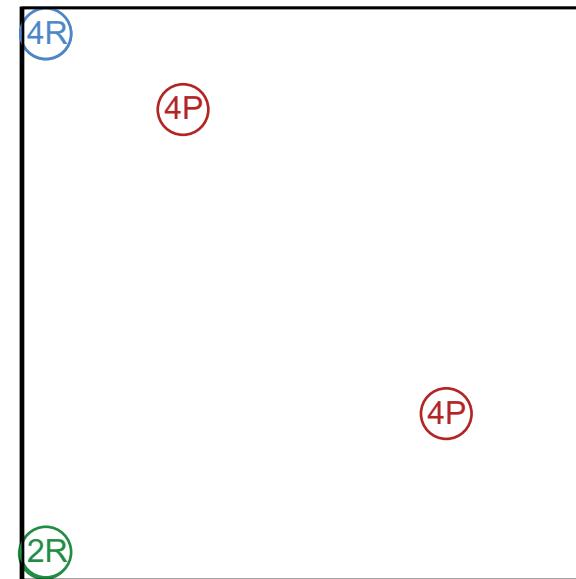
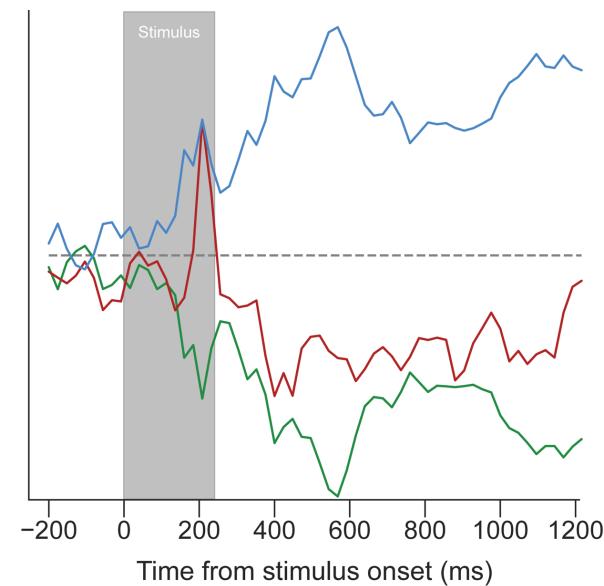


Individual differences

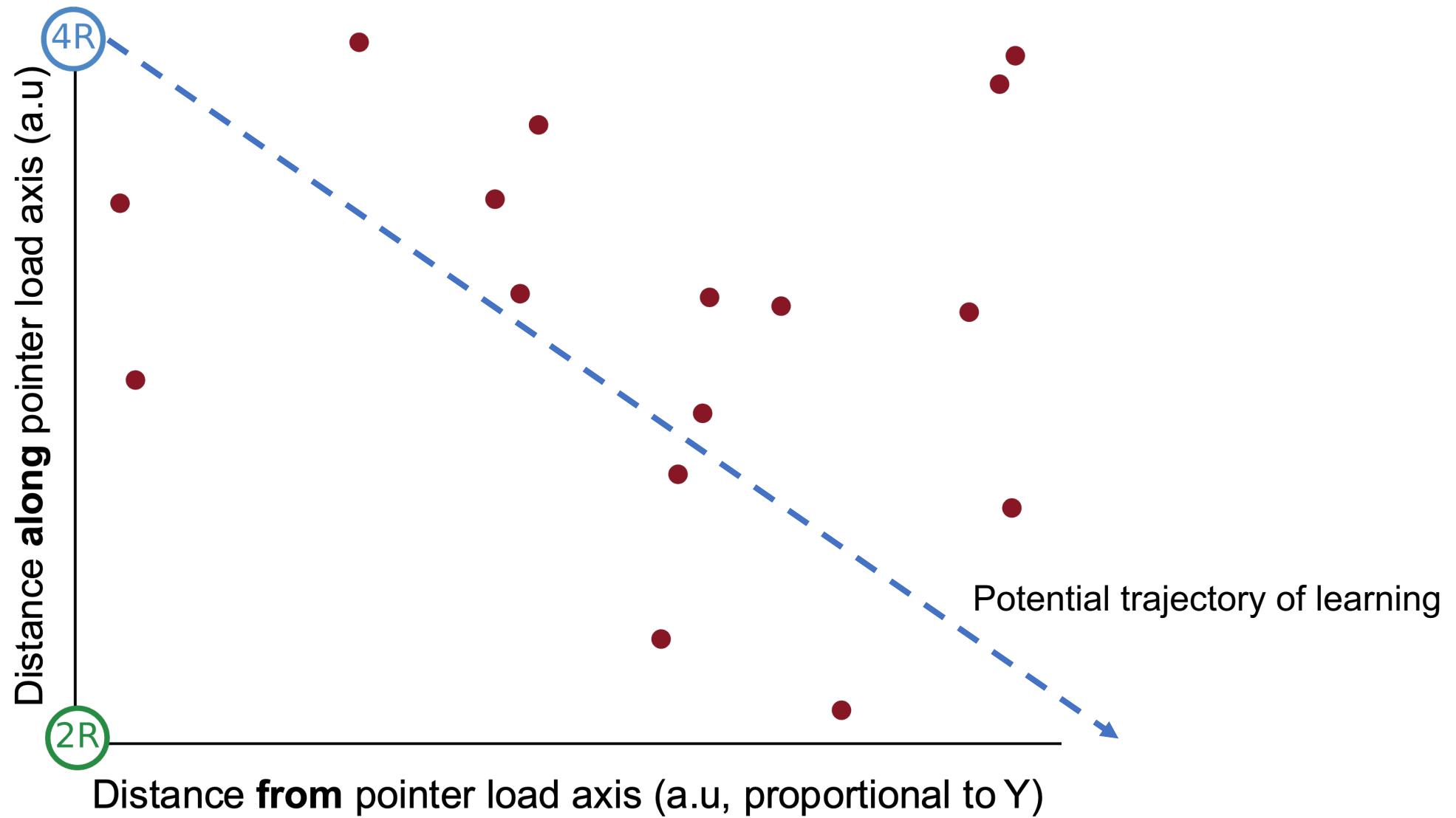
“Weak chunking”



“Strong chunking”



Individual differences



Experiment 2

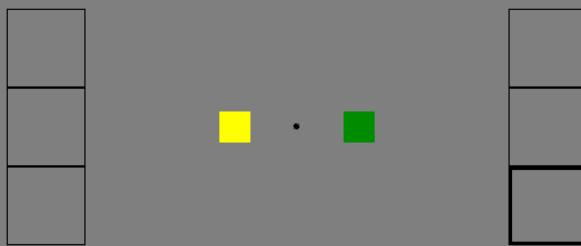
- Trained subjects to learn three color triplets



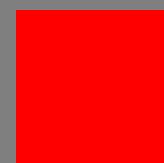
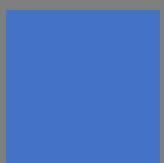
Experiment 2



Experiment 2



Awareness Test



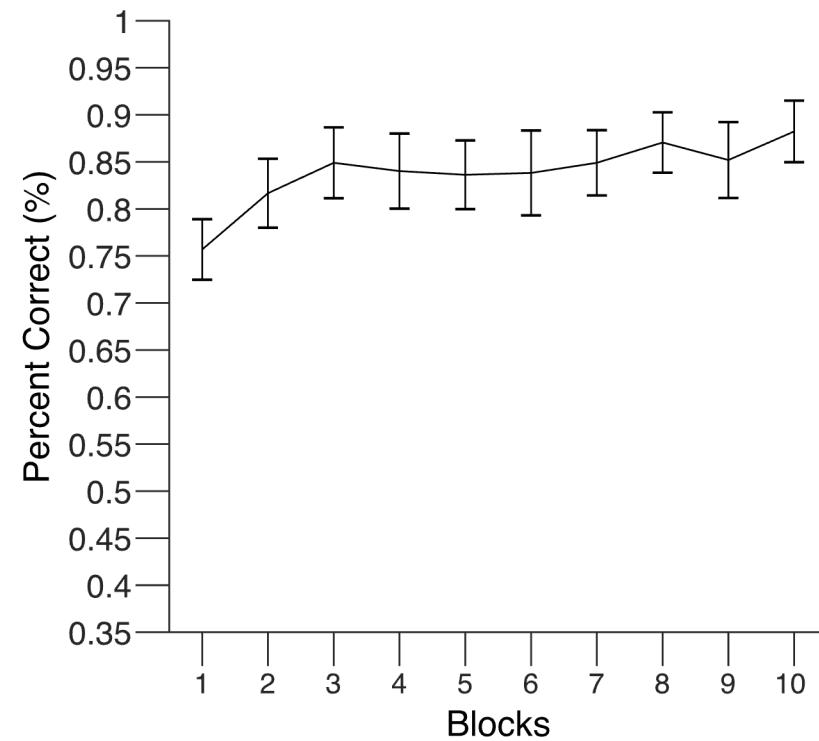
Awareness Test



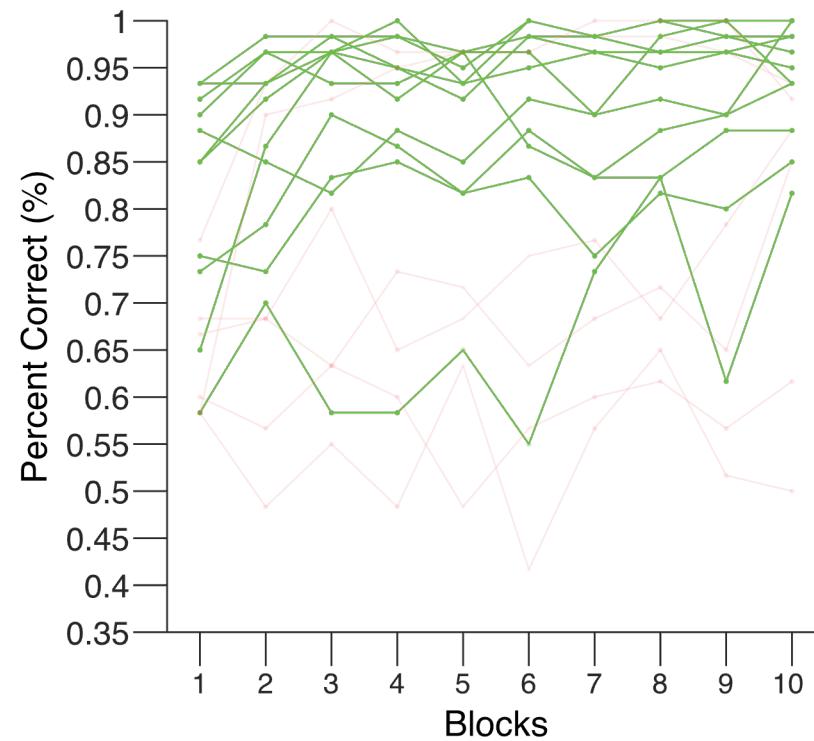
- Only subjects who correctly produced all triplets were considered “learners”

Experiment 2 Training

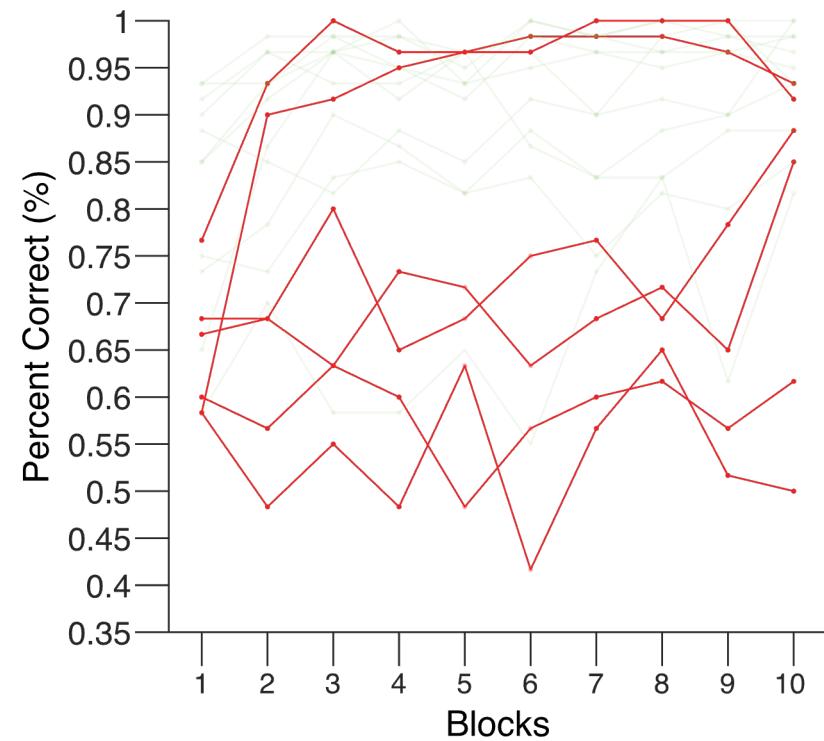
Aggregate



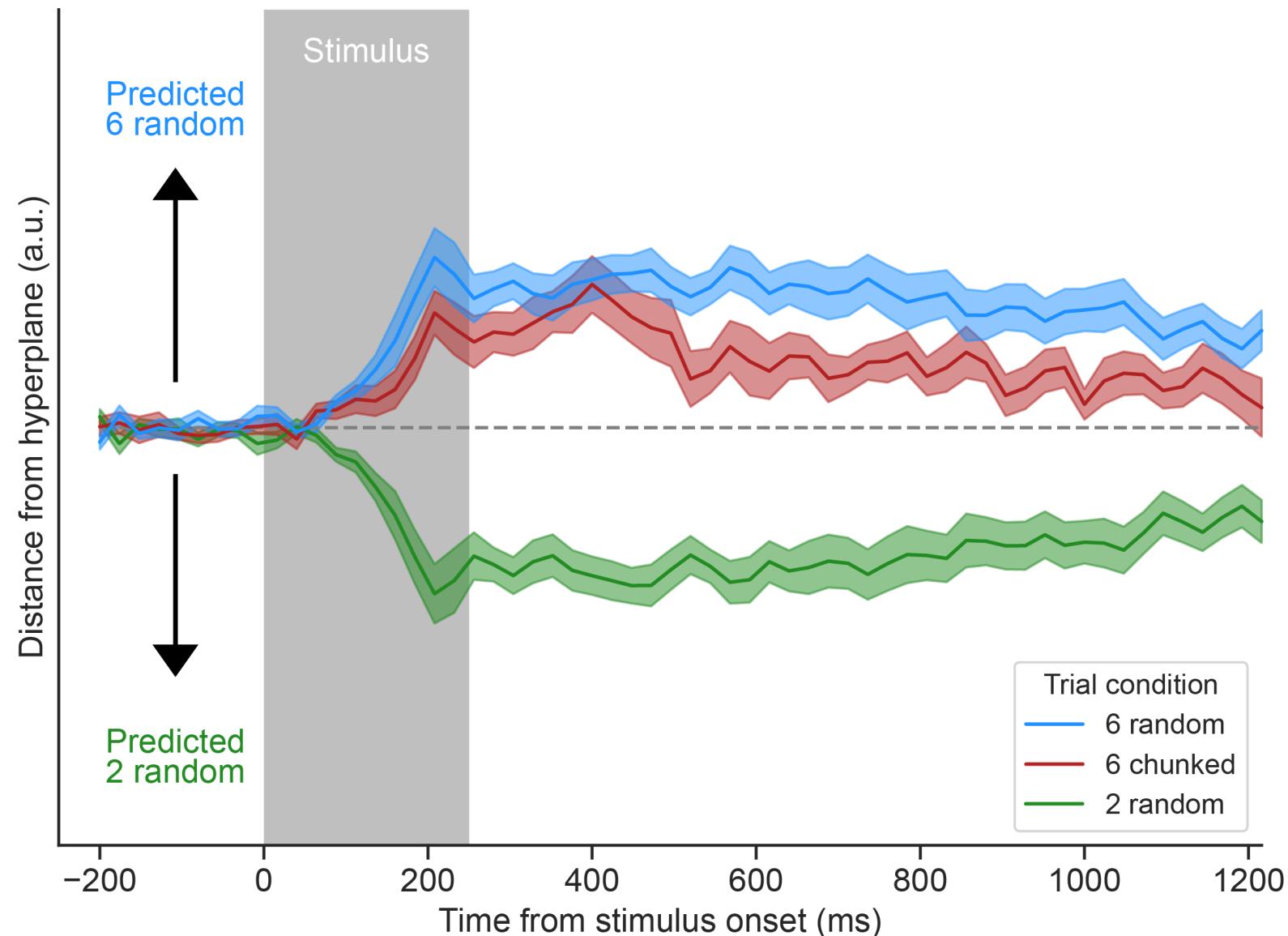
Learners



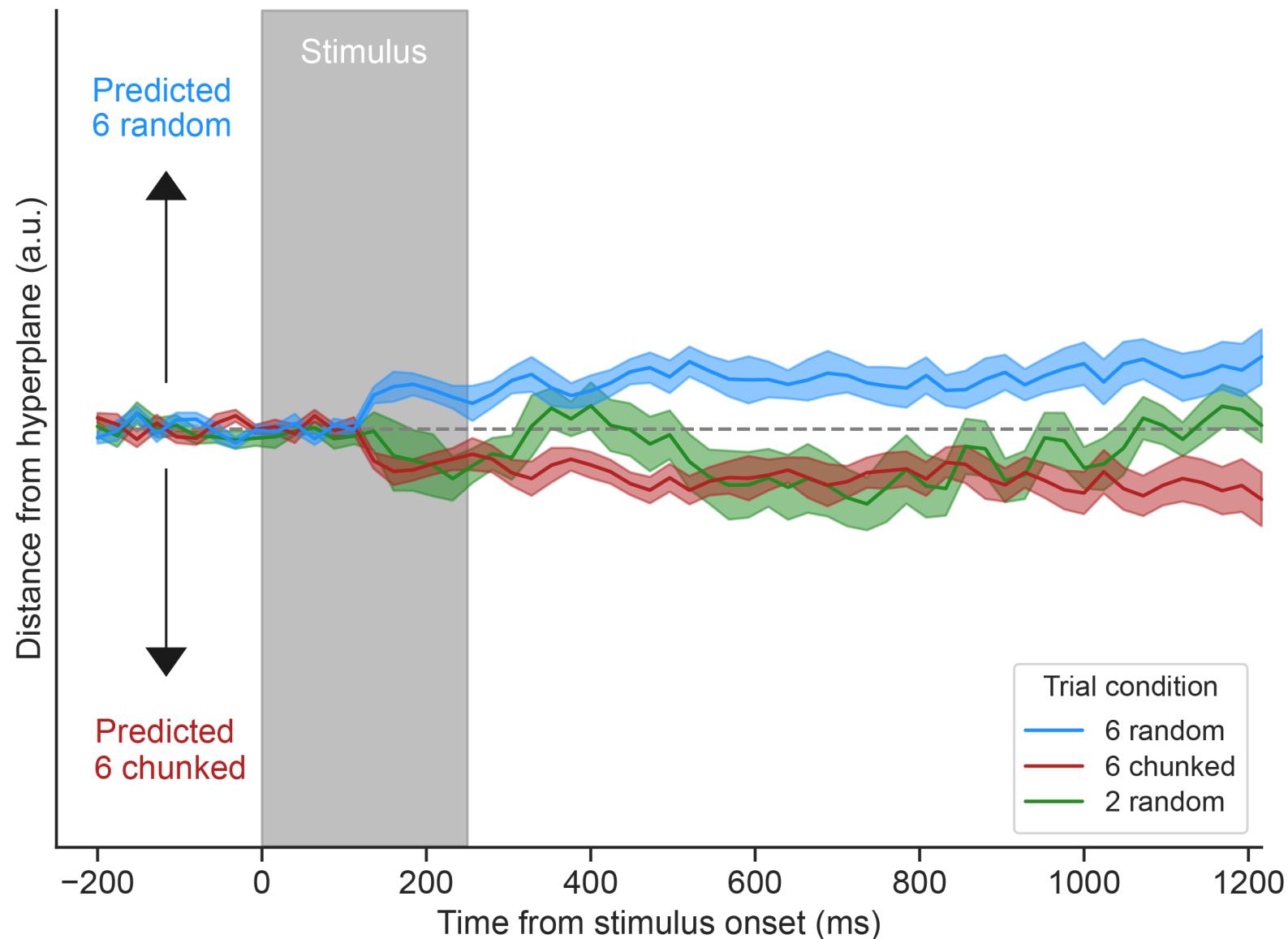
Non-learners



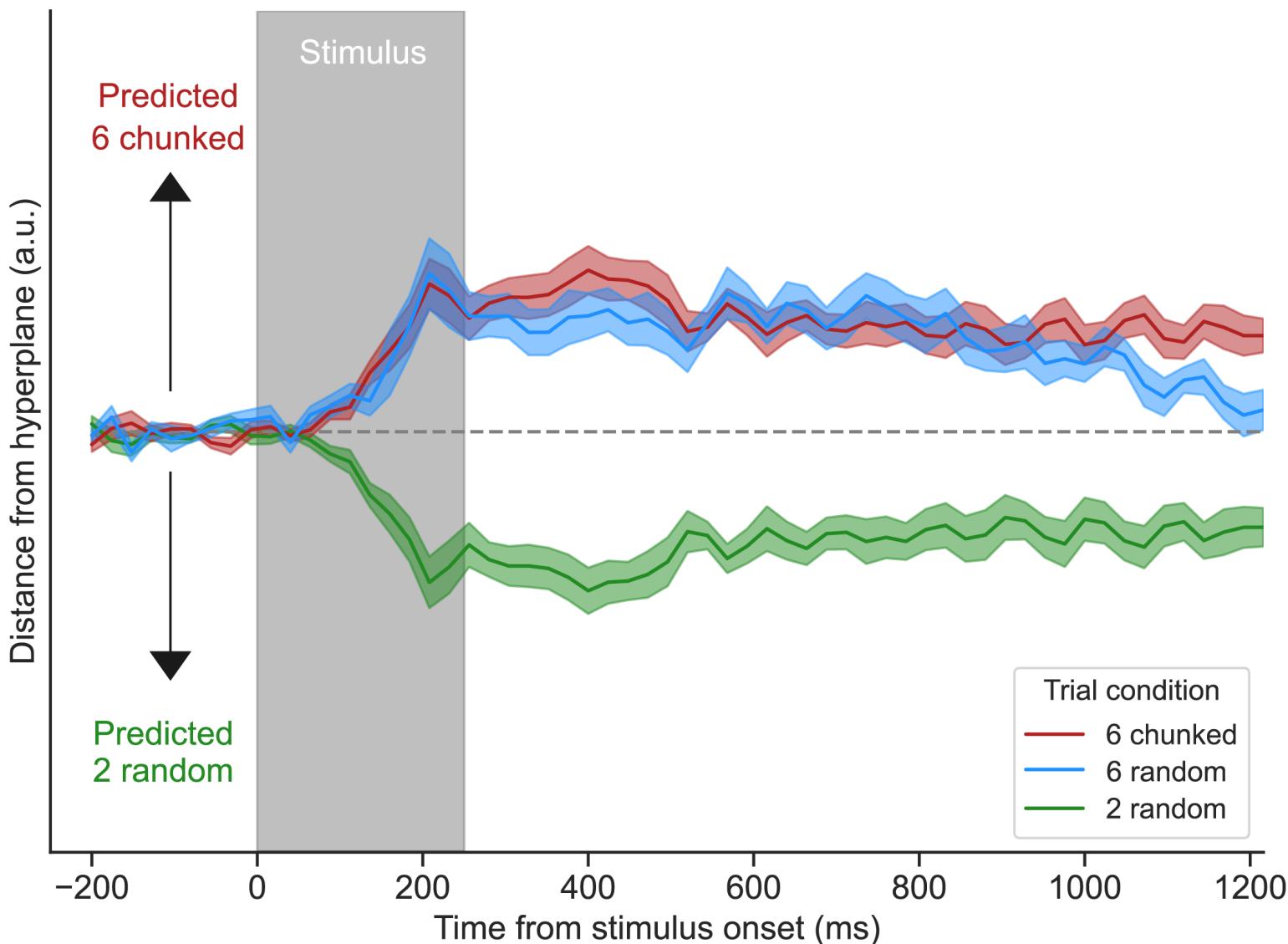
Train 6 random versus 2 random, test 6 chunked



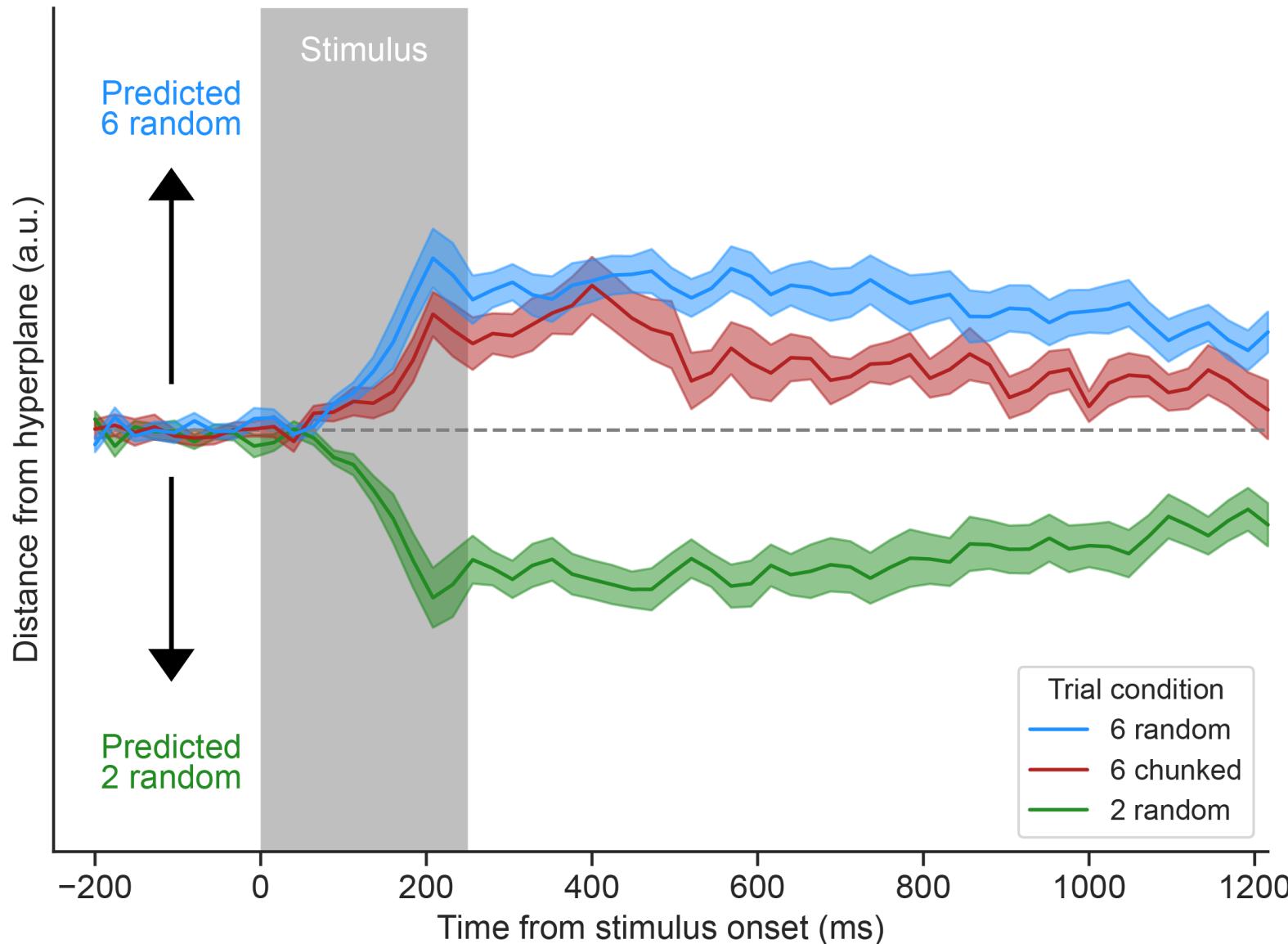
Train 6 random versus 6 chunked, test 2 random



Train 2 random versus 6 chunked, test 6 random



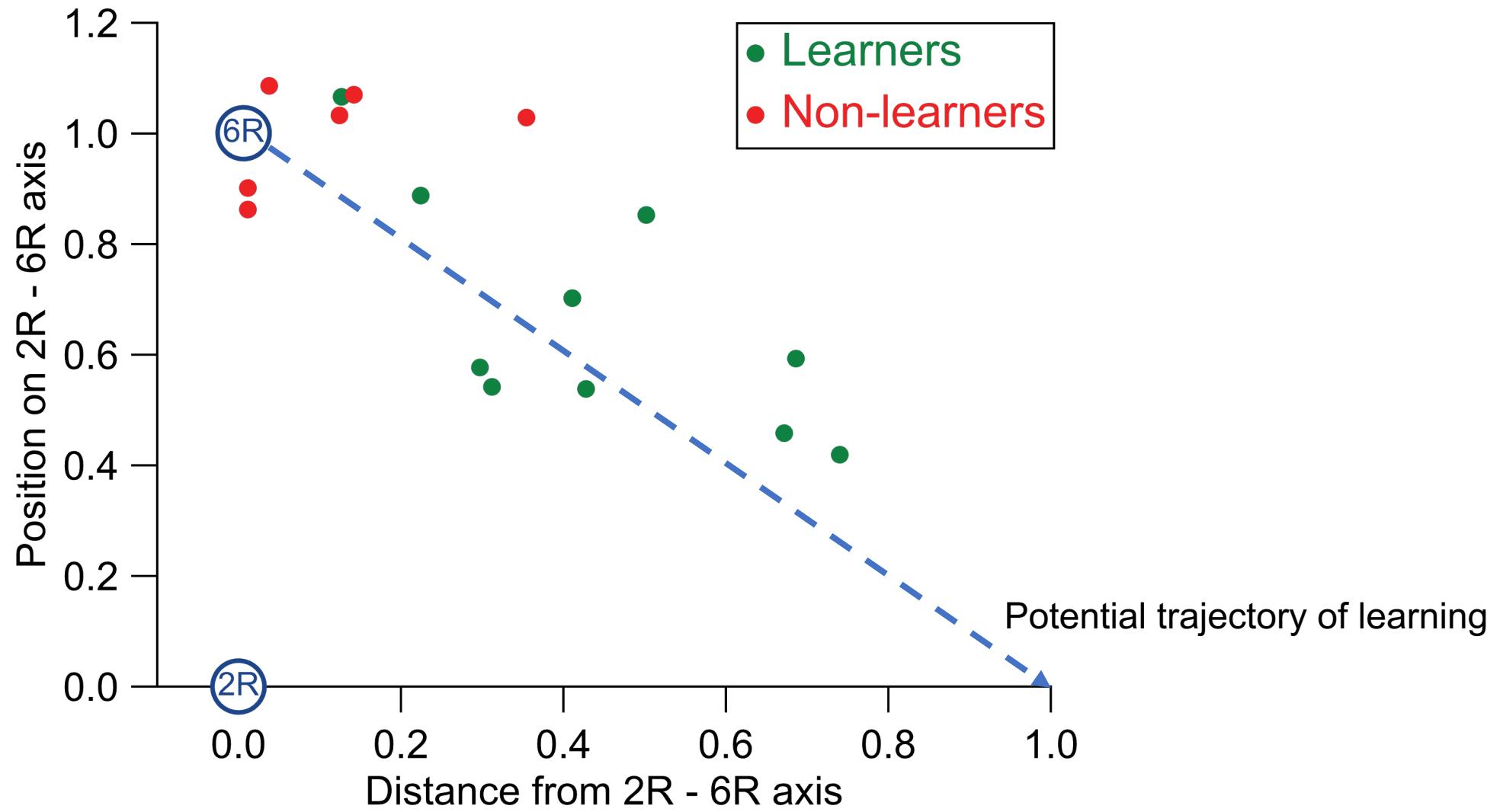
Train 6 random versus 2 random, test 6 chunked



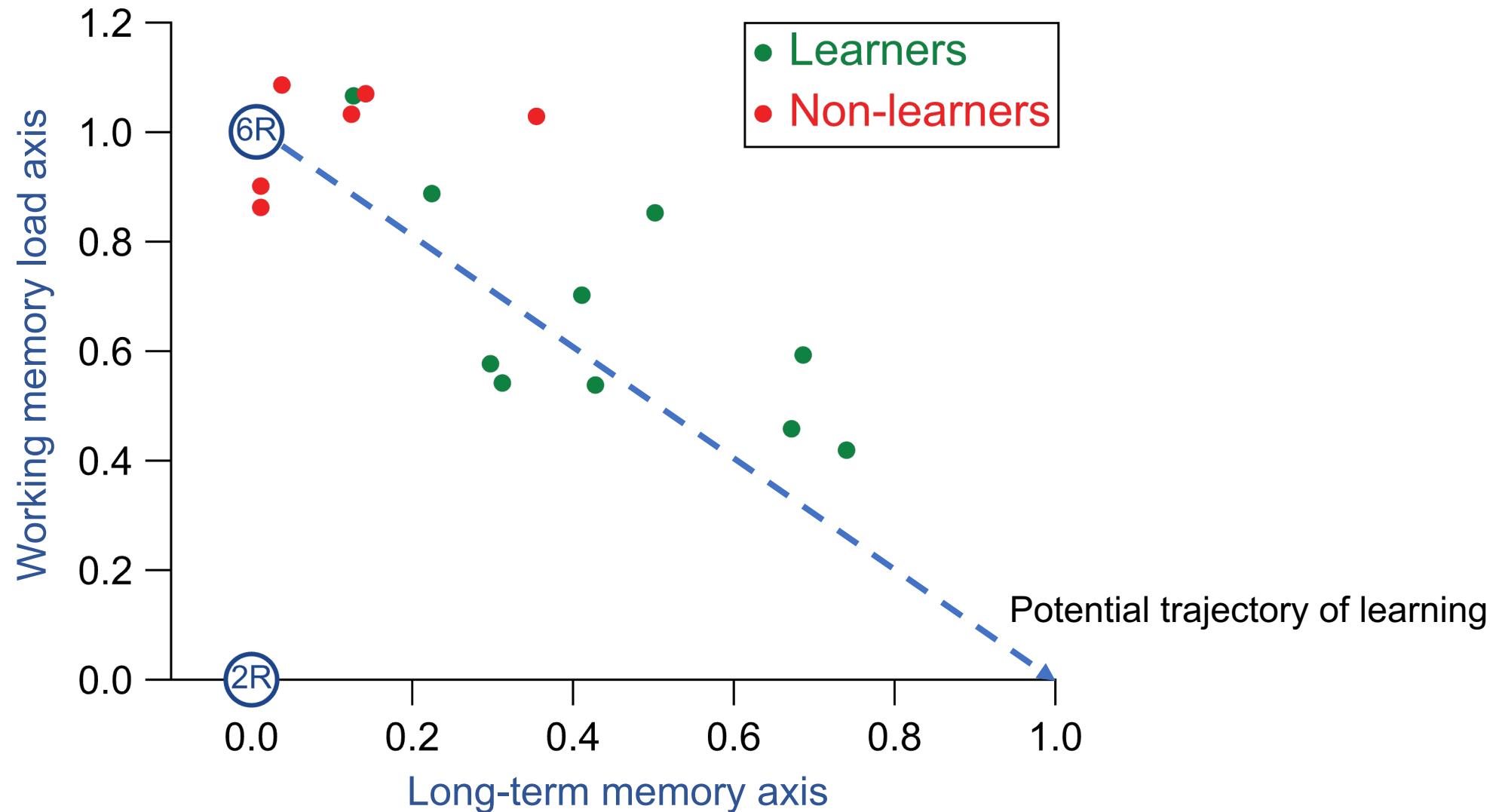
Multidimensional scaling



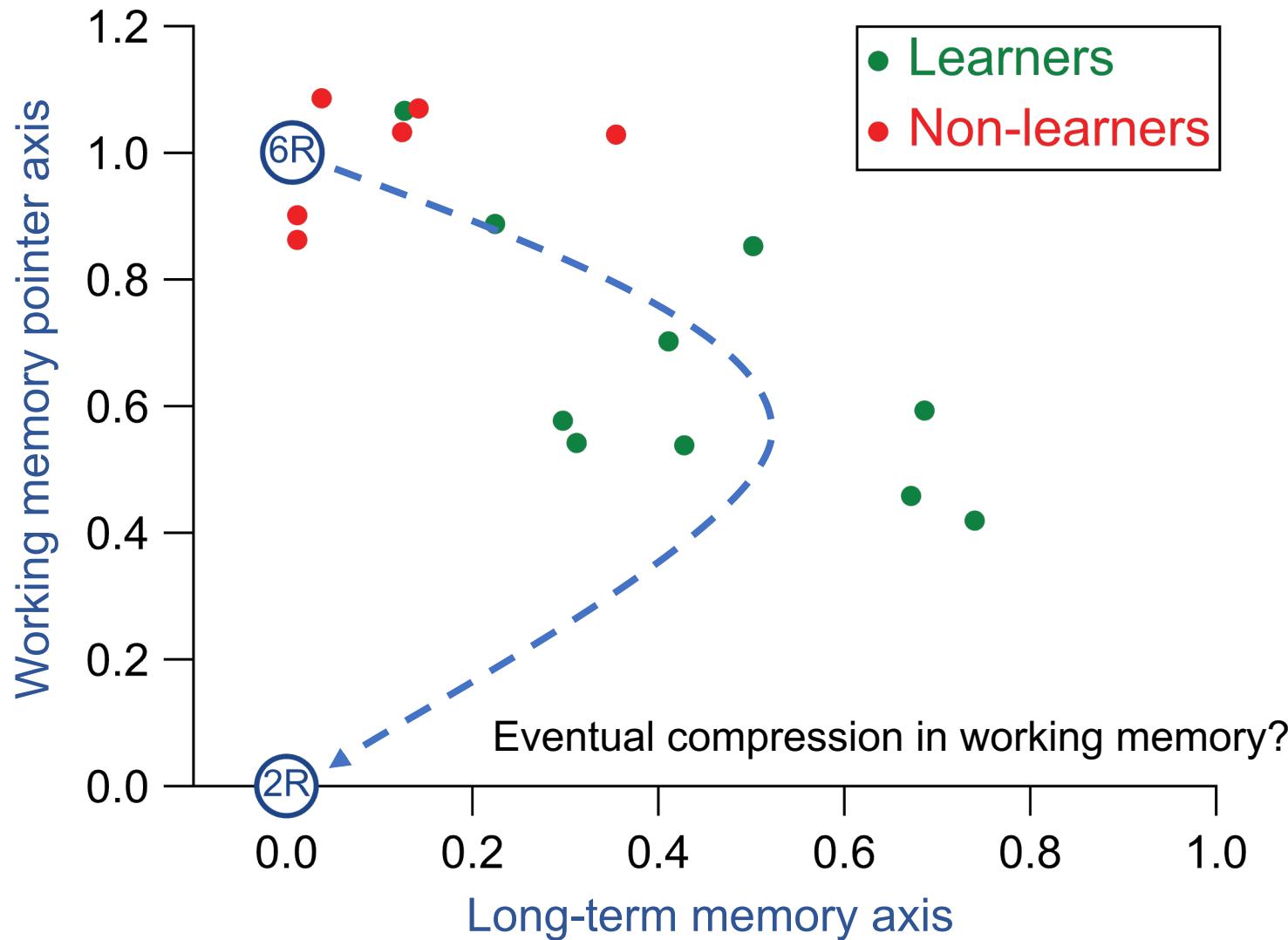
Multidimensional scaling on each subject



Multidimensional scaling on each subject



Multidimensional scaling on each subject



Conclusions

- We asked whether associative learning:
 - Increases the number of individuated representations in working memory (memory compression)
 - Or enables items to be chunked reducing the number of items stored in working memory
- A multivariate neural signal for items in working memory shows associative learning **reduces** the number of items stored in working memory
- Furthermore, neural signatures of associative learning showed the reduction only in those that successfully learnt the association
- This falls in line with a **chunking** account – associative learning does not allow one to circumvent item limits



William Thyer



Henry Jones



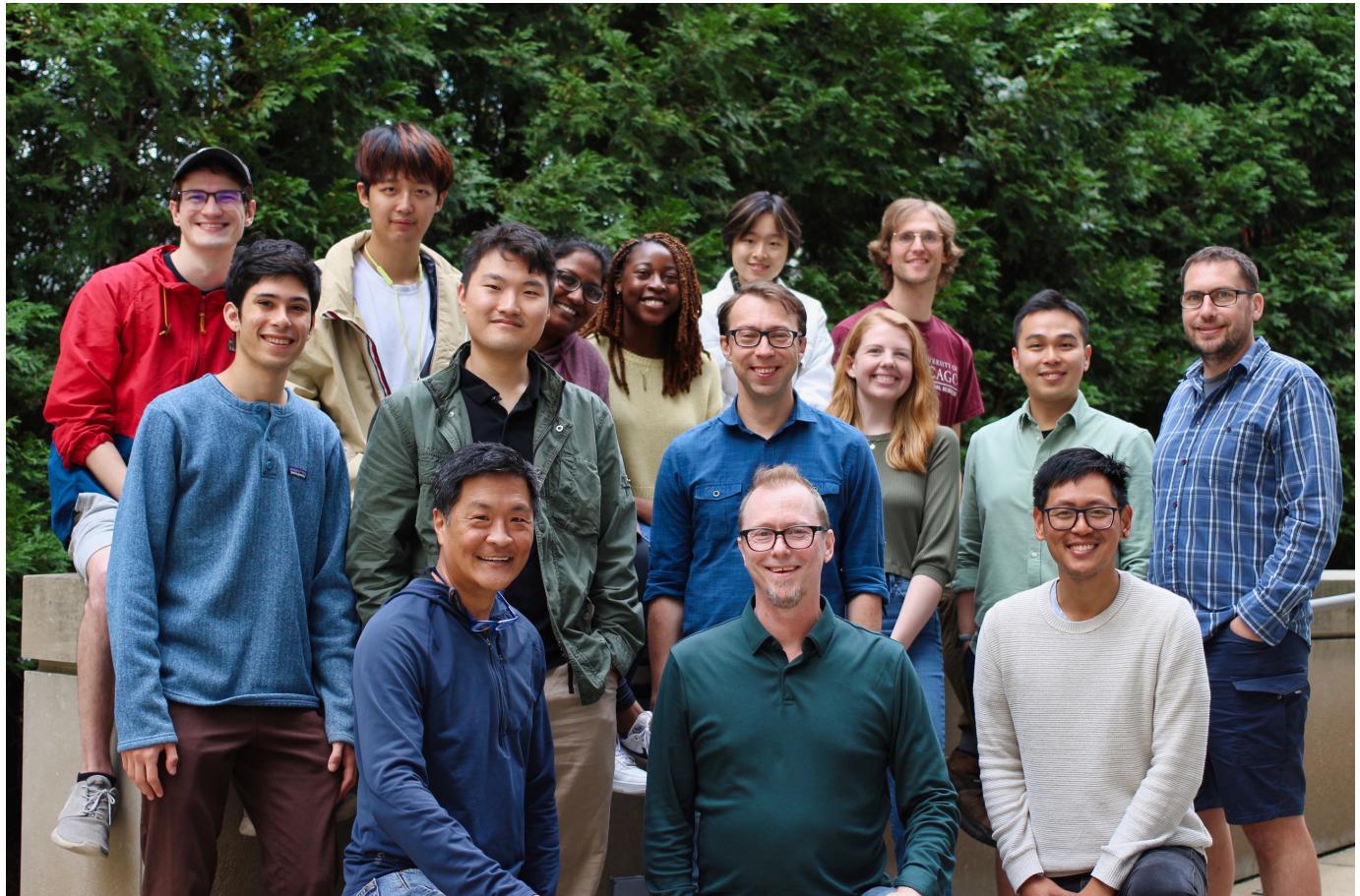
Darius Suplica



Will Epstein



Edward Awh



Awh/Vogel Lab

NIH



william.ngiam@adelaide.edu.au



@willngiam.bsky.social