A Cognitively Plausible Visual Working Memory Model

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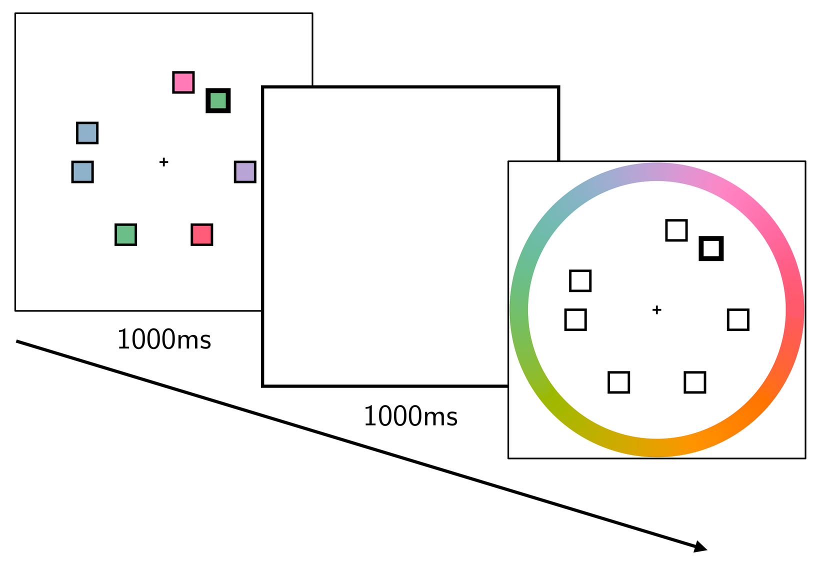
Introduction

TLDR: We propose a novel visual working memory (VWM) model based on a probabilistic interpretation of the Semantic Pointer Architecture [SPA; Eliasmith, 2013, Furlong and Eliasmith, 2023]. Our model only requires three interpretable hyper-parameters: **spatial capacity** λ_g, **feature certainty** λ_c, and **memory decay** γ and replicates behavioural data.

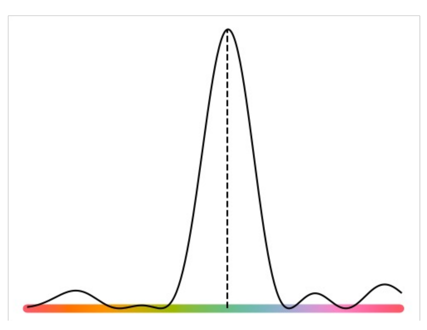
Colour Reproduction Task: Participants memorise up to eight coloured squares. After a 1s delay, a probe screen indicates the target location and participants select the remembered colour from a colour wheel. Oberauer and Lin [2017] reported
(1) **set size effect** – reproduction error increases with more items,
(2) **non-target bias** – errors are more likely to reflect colours of nearby non-targets than random ones,
(3) **pre-cues** improve accuracy for the probed item, while **post-cues** do not.

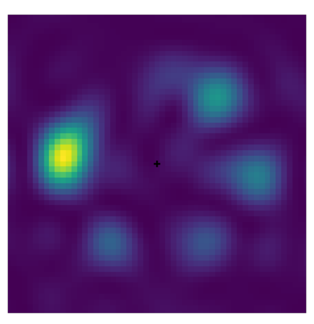


Method

Our models are based on **Spatial Semantic Pointers (SSPs)** [Komer et al., 2019], where $\phi_\lambda(\mathbf{x})$ defines a mapping between feature space and a distributed representation via a spatial phase code. We encode our SSP-VWM with:

$$M = \sum_i \overset{\text{memory decay}}{\delta(i)} \cdot \left[\underbrace{\phi_{\lambda_c}(c_i)}_{\text{feature embedding}} \overset{\text{binding}}{\circledast} \underbrace{\phi_{\lambda_g}(x_i, y_i)}_{\text{spatial embedding}} \right]$$

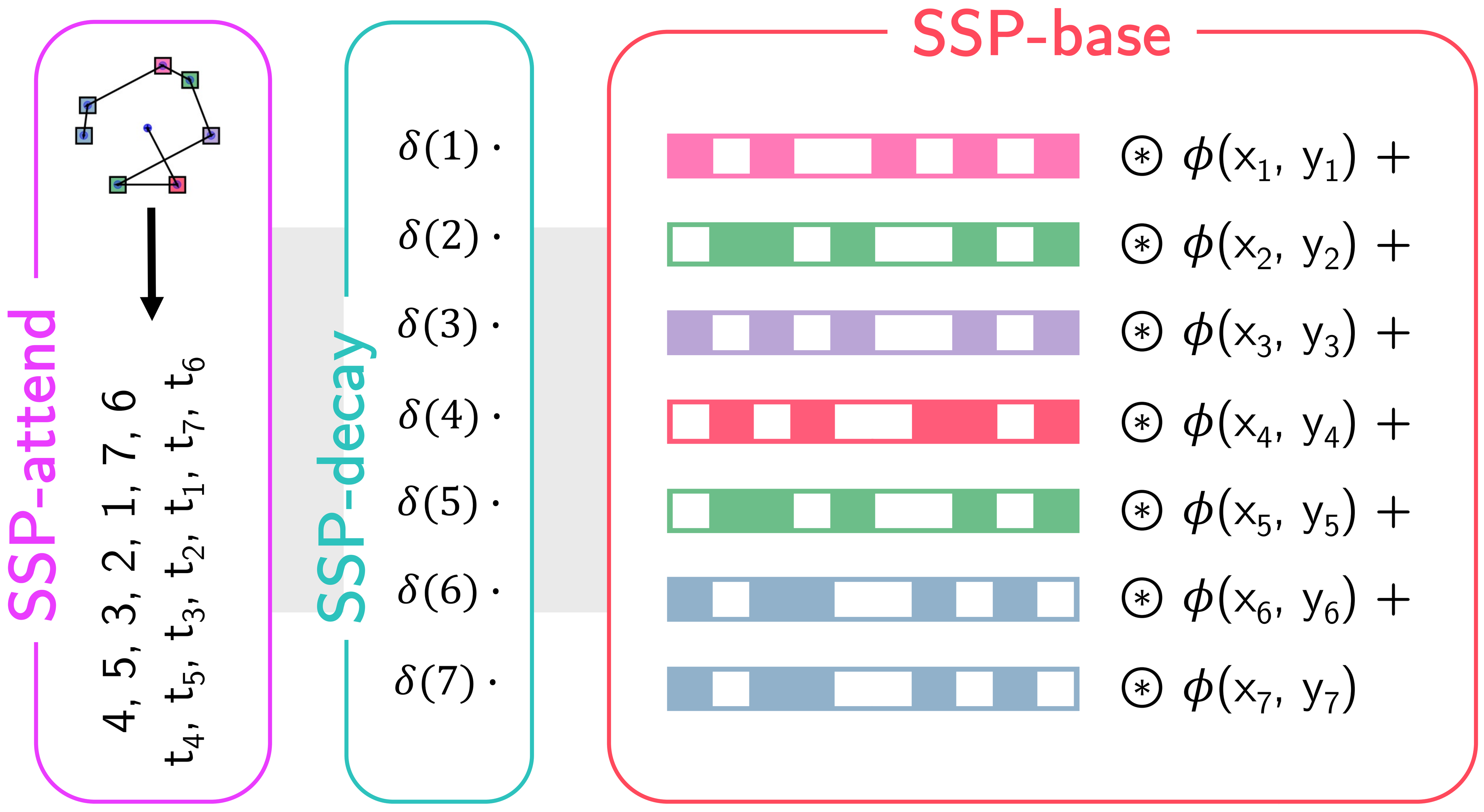




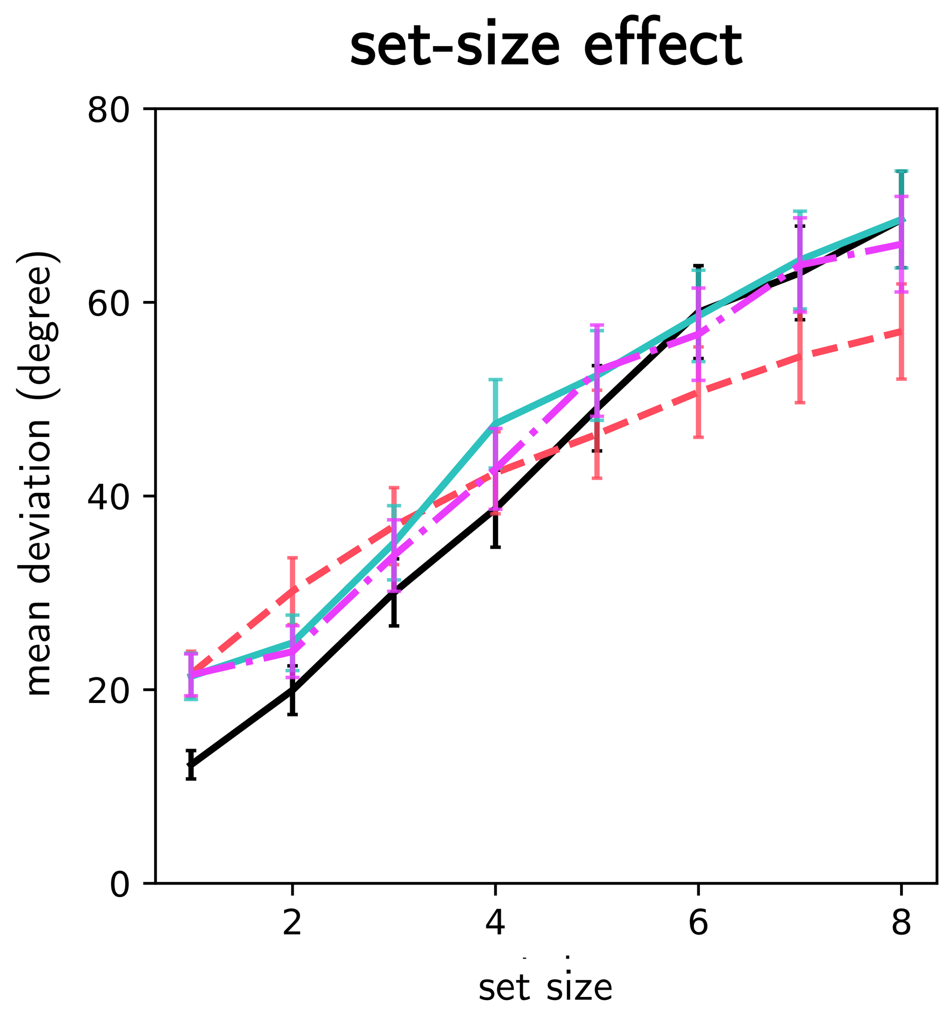
SSP-base: Encodes all colours and their spatial location with memory decay disabled ($\gamma = 1$)

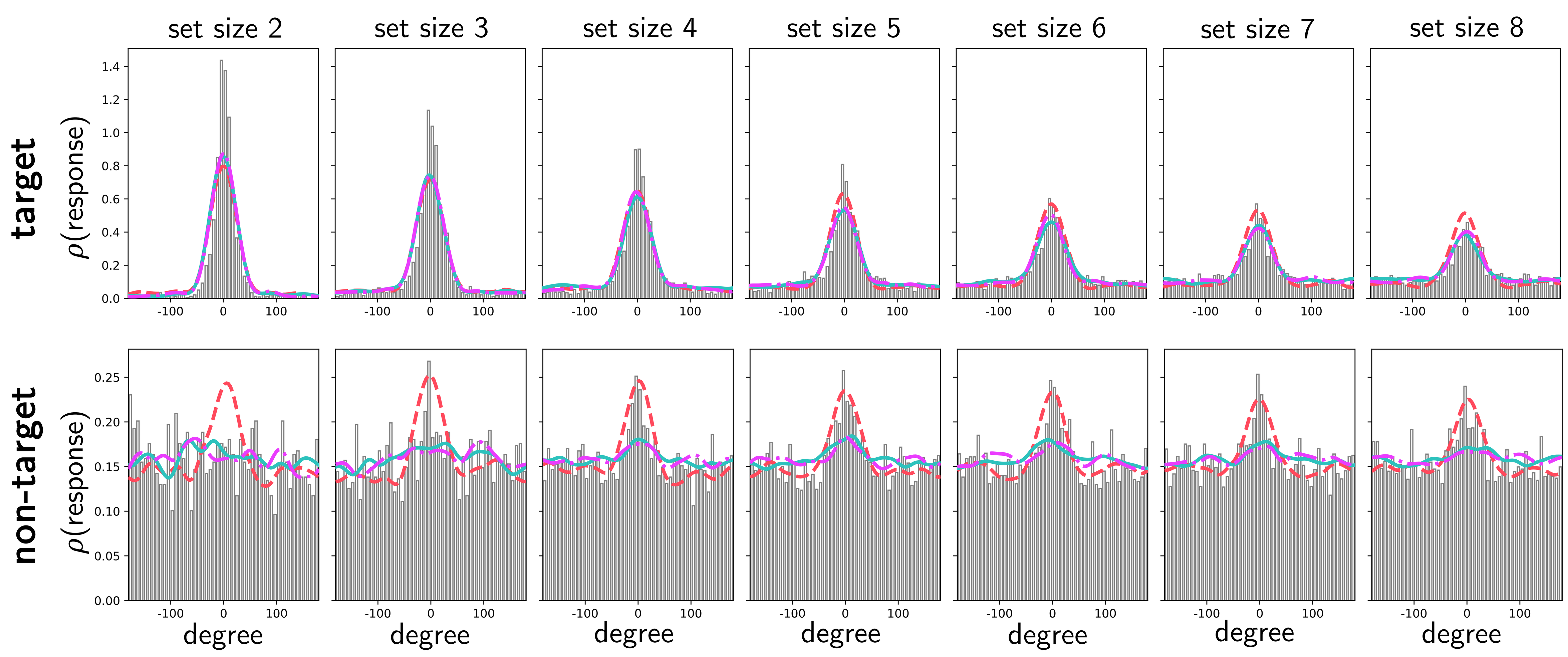
SSP-decay: Adds memory decay with $\delta(i) = \gamma^i$ and $\gamma < 1$

SSP-attend: Predicts scanpath with EMMA [Salvucci, 2001]



Results





Conclusion: All our models are capable of producing performance that is statistically equivalent to results observed by Oberauer and Lin [2017], while only requiring **three hyper-parameters** instead of six.
We replicate the (1) set-size effect, (2) non-target bias, and (3) pre-cue and post-cue effects.
Further, we find that including a memory decay (SSP-decay) results in a **statistically significant improvement** in model fit ($p \ll 0.001$).

	Experiment 1			Experiment 2	Experiment 3
Model	Target	Non-target	Average	Average	Average
SSP-base	0.064 (0.001)	0.015 (0.001)	0.040 (0.001)	0.035 (0.001)	0.032 (0.001)
SSP-decay	0.045 (0.002)	0.012 (0.001)	0.028 (0.001)	0.031 (0.002)	**0.021** (0.001)
SSP-attend	**0.044** (0.002)	**0.012** (0.001)	**0.028** (0.001)	**0.031** (0.002)	0.022 (0.001)

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