Probabilistic palimpsest memory: multiplicity, binding and coverage in visual short-term memory

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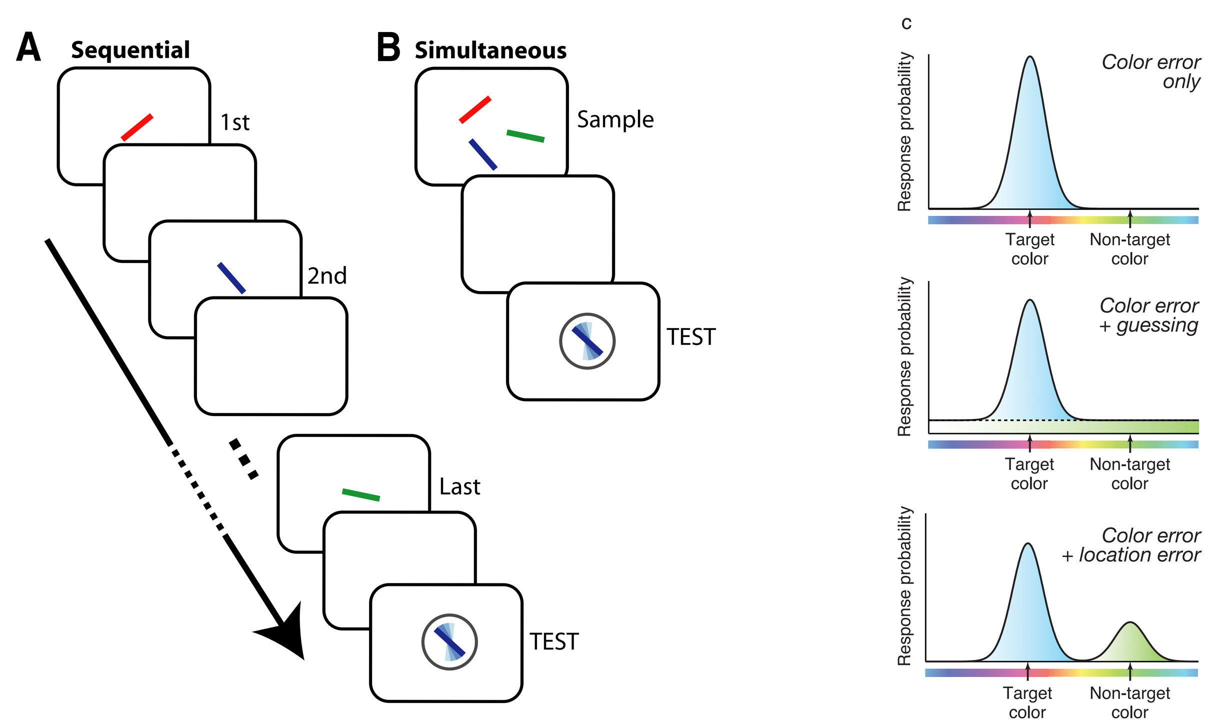
Introduction

- Recent results in visual short-term memory support a unified shared memory resource.
- We propose a probabilistic model of a finite capacity memory network, capable of reproducing experimental psychophysical human data.
- We assess how different population code representations are able to cope with the multiplicity and multidimensional binding requirements of this task.

Visual Short-term memory

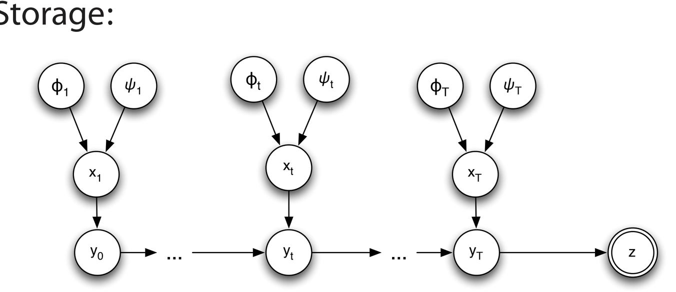
- Task [1]: remember colored oriented bars. Cue one bar with correct color, should recall its orientation.
- Sequential and simultaneous version of the task.
- Obtain smooth decay of precision of recall as the number of items to remember increases, incompatible with a slot model.



Model

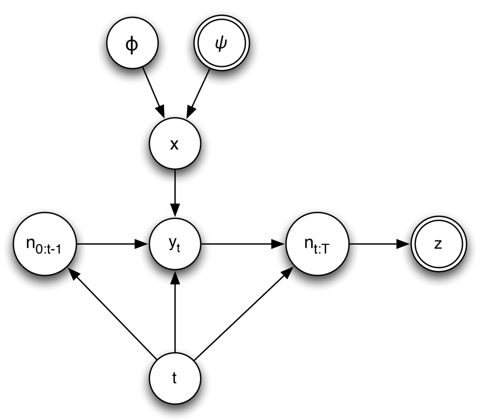
- Assume simple storage and recall processes, with different candidate population codes for items representation.
- Storage process as palimpsest: additive through time, decay and noise.
- Recall process: infer correct item, given cued colour and memory state. Strategy: recall correct item, amidst noise created by all other items (similar to [2]).
- Implemented through Gibbs sampling, using a Slice sampler with MCMC jumps.
- Marginalize over time/item identity, not a full recall paradigm.

Storage:



$$
\begin{aligned}
\phi_t &\sim VonMises(\nu_o, \kappa_o)\\
\psi_t &\sim VonMises(\nu_c, \kappa_c)\\
\mathbf{x_t} \mid \phi_t, \psi_t &\sim N(\boldsymbol{\mu}(\phi_t, \psi_t), \sigma_x^2 \mathbf{I})\\
\mathbf{y_t} \mid \mathbf{y_{t-1}}, \mathbf{x_t} &\sim N(\mathbf{A_t y_{t-1}} + \mathbf{B_t x_t}, \sigma_y^2 \mathbf{I})\\
\mathbf{z} \mid \mathbf{y_T} &\sim \delta(\mathbf{z} - \mathbf{y_T})
\end{aligned}
$$

Recall:

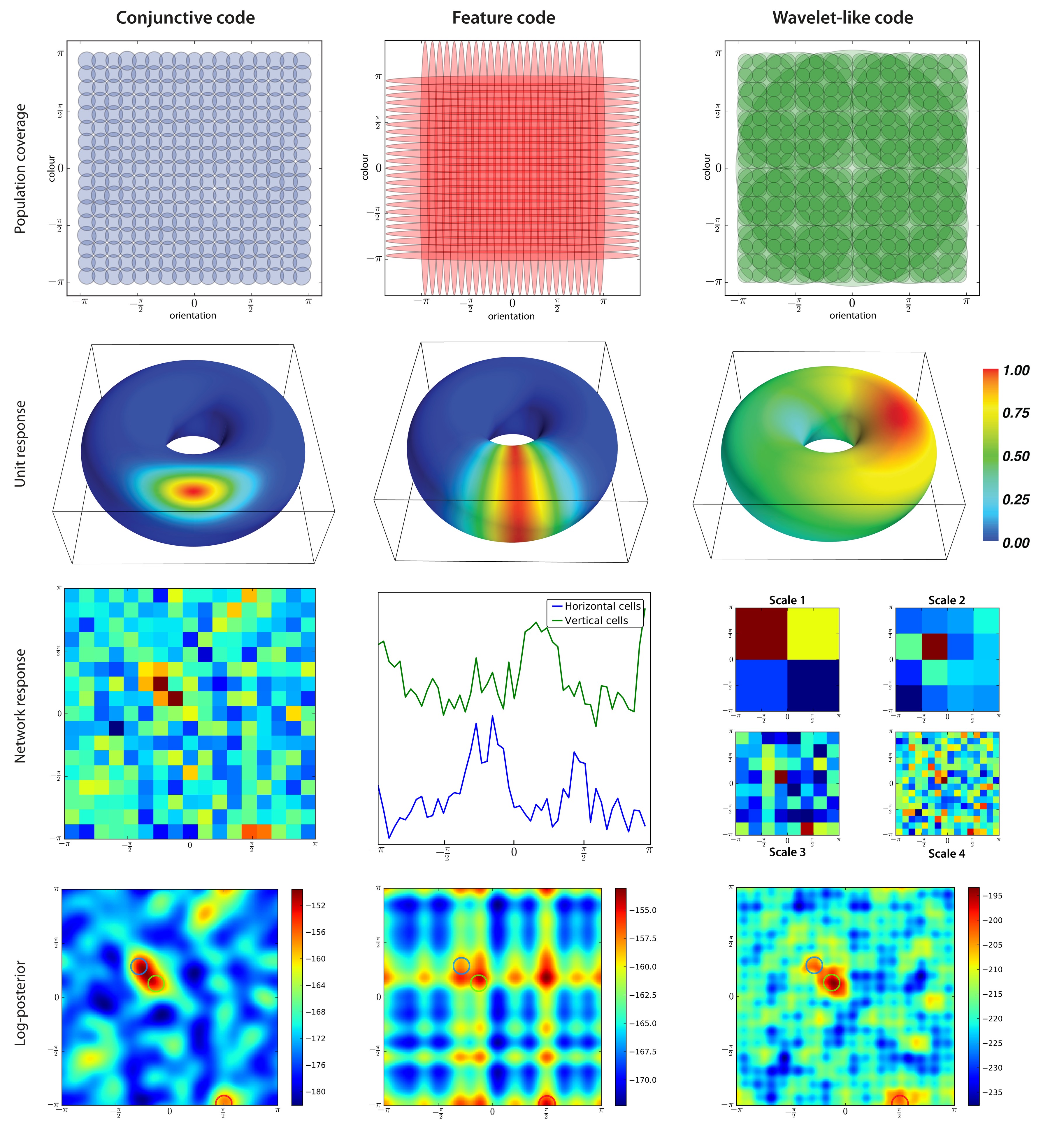


$$
\begin{aligned}
\phi &\sim VonMises(\nu_o, \kappa_o)\\
\psi &\sim VonMises(\nu_c, \kappa_c)\\
\mathbf{z} \mid \phi, \psi &\sim N\Big(\mathbf{m_t^+} + \mathbf{A^{T-t+1}} \mathbf{m_{t_c}^-} + \\
&\qquad \mathbf{A^{T-t}} \mathbf{B}_t \boldsymbol{\mu}(\phi, \psi) \,,\; \boldsymbol{\Sigma}_{\mathbf{t^+}} + \\
&\qquad \mathbf{A^{T-t}} \left(\sigma_{\mathbf{y}}^{\mathbf{2}} \mathbf{I} + \mathbf{A} \boldsymbol{\Sigma}_{\mathbf{t}}^- \mathbf{A^T} + \sigma_x^2 \mathbf{B}_t \mathbf{B}_t^T\right) (\mathbf{A^{T-t}})^T \Big)
\end{aligned}
$$

Population code mean response

$$
\mu_{i,j}(\phi, \psi) = C \ \exp\left(\kappa_1 \cos(\phi - \theta_i) + \kappa_2 \cos(\psi - \gamma_j) - \kappa_3 \cos(\phi - \theta_i - \psi + \gamma_j)\right)
$$

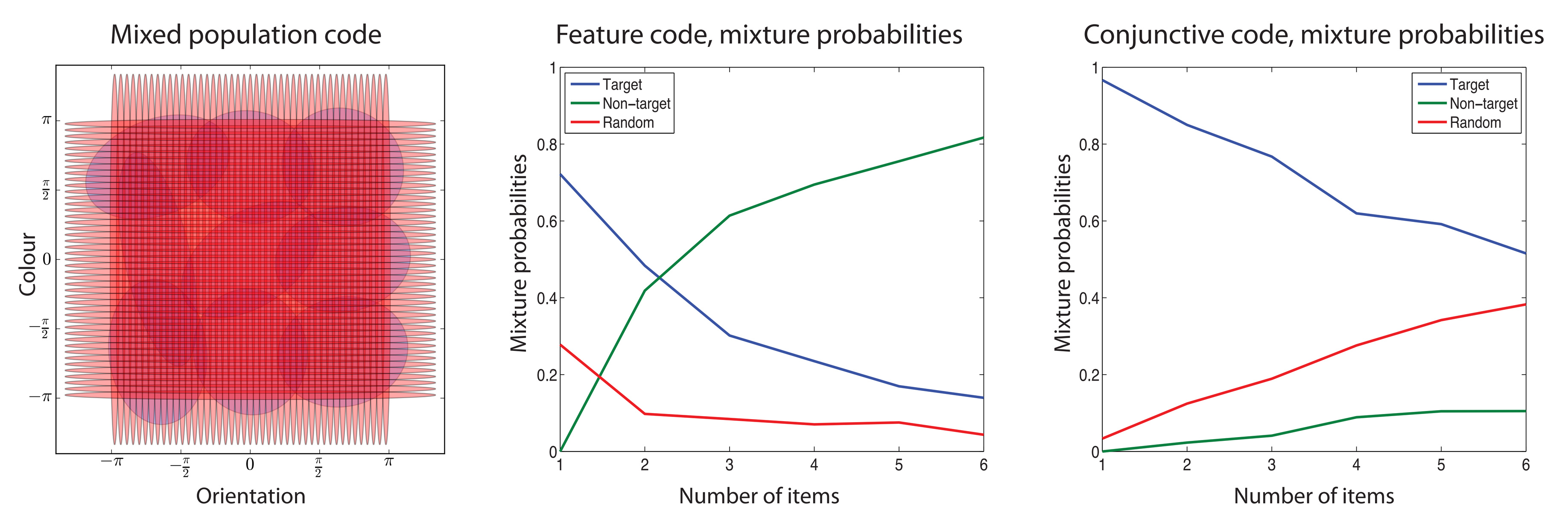
Characteristics of representations



- Trade-offs: coverage, scaling, correlation and feature binding.

Multiplicity can be resolved by mixed population

- Feature-based population codes fail under multiplicity.
- Conjunctive and wavelet codes do not reproduce experimental misbinding errors.
- Simple solution: add conjunctive neurons to feature code, providing binding information.

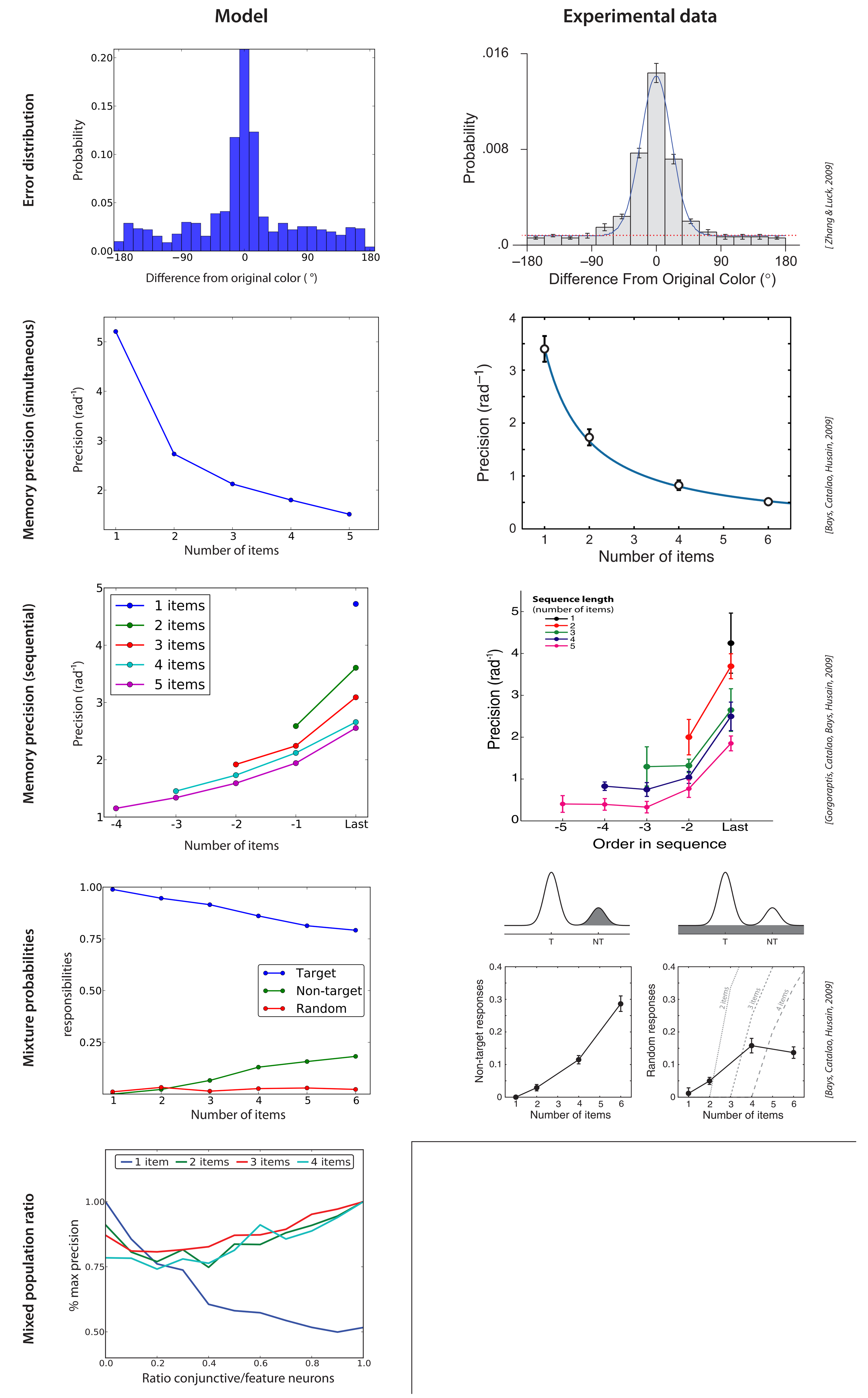


References

[1] N. Gorgoraptis, R.F. Catalao, P. Bays, M. Husain, *J. Neuroscience*, 2011

[2] C. Savin, P. Dayan, M. Lengyel, *NIPS*, 2011

Experimental fits



Conclusions

- Proposed a probabilistic model of finite capacity memory network. Very simple storage process, normative recall procedure.
- Yet able to reproduce experimental statistics: experimental problem is highly underconstrained.
- The interaction between items in the representation is key; these constrain error types and biases.

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