Similarity judgments and visual working memory do not share the same cognitive representation

William X. Q. Ngiam and Michael D. Lee

School of Psychology, Adelaide University

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The representation in classic cognitive models

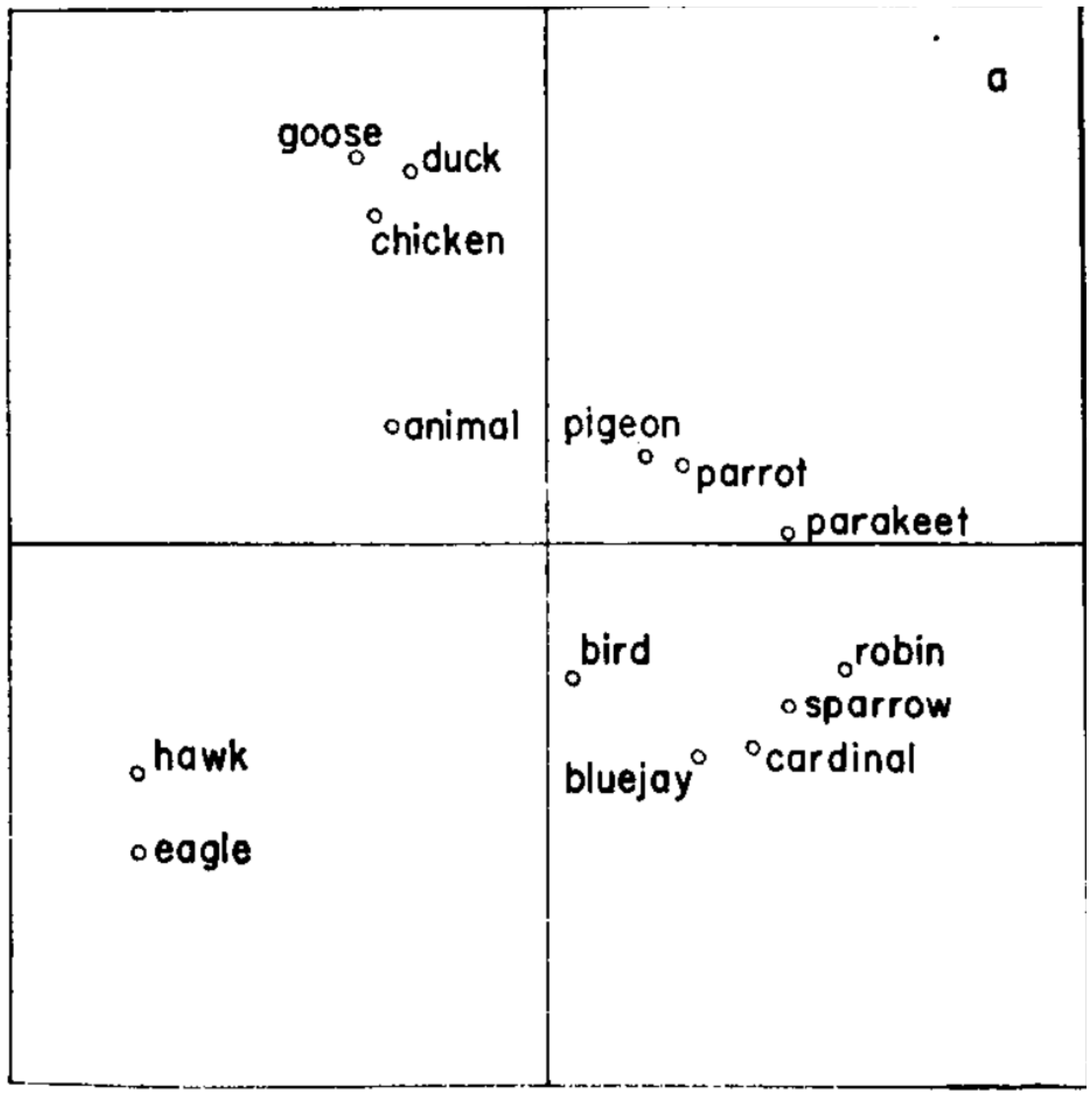
Classic formal models of cognition would derive the **psychological representation** using multidimensional scaling (MDS) of similarity judgments.

- Collect similarity ratings for pairs of items in the stimulus set
- Reduce those ratings into a representation that best preserves the distance between the items; the closer the items, the more similar.

The representation in classic cognitive models

This is the MDS representation for **birds**.

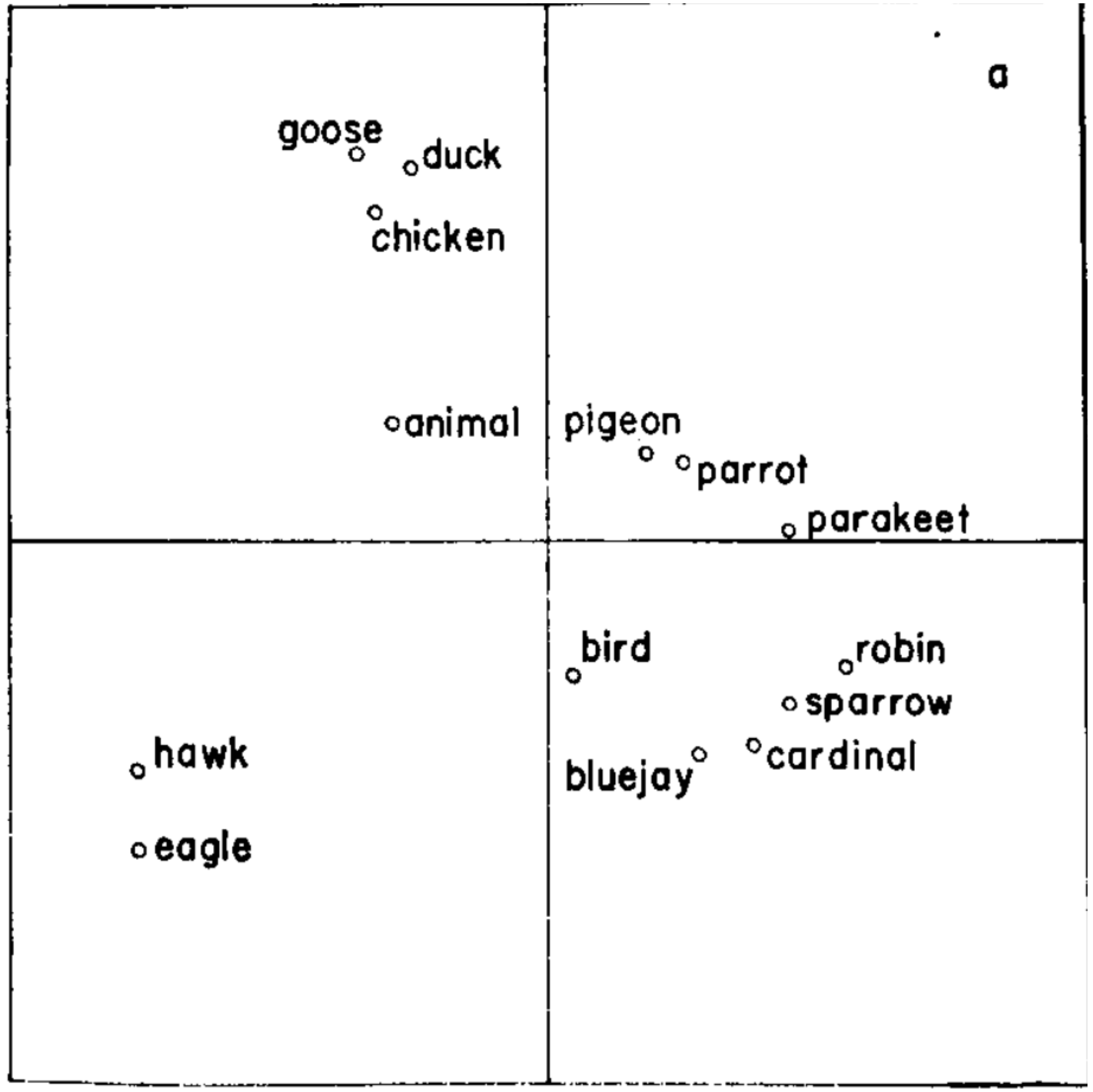
The distances between the birds reflect their psychological similarity; the closer, the more similar.



Rips, L. J., Shoben, E. J., & Smith, E. E. (1973). Semantic distance and the verification of semantic relations. *Journal of verbal learning and verbal behavior*, *12*(1), 1-20.

The representation in classic cognitive models

Formal models use these distances to predict behaviour (such as induction and generalisation).



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For example, say **ducks** are susceptible to Reinholf disease… do you think **geese** are also susceptible?

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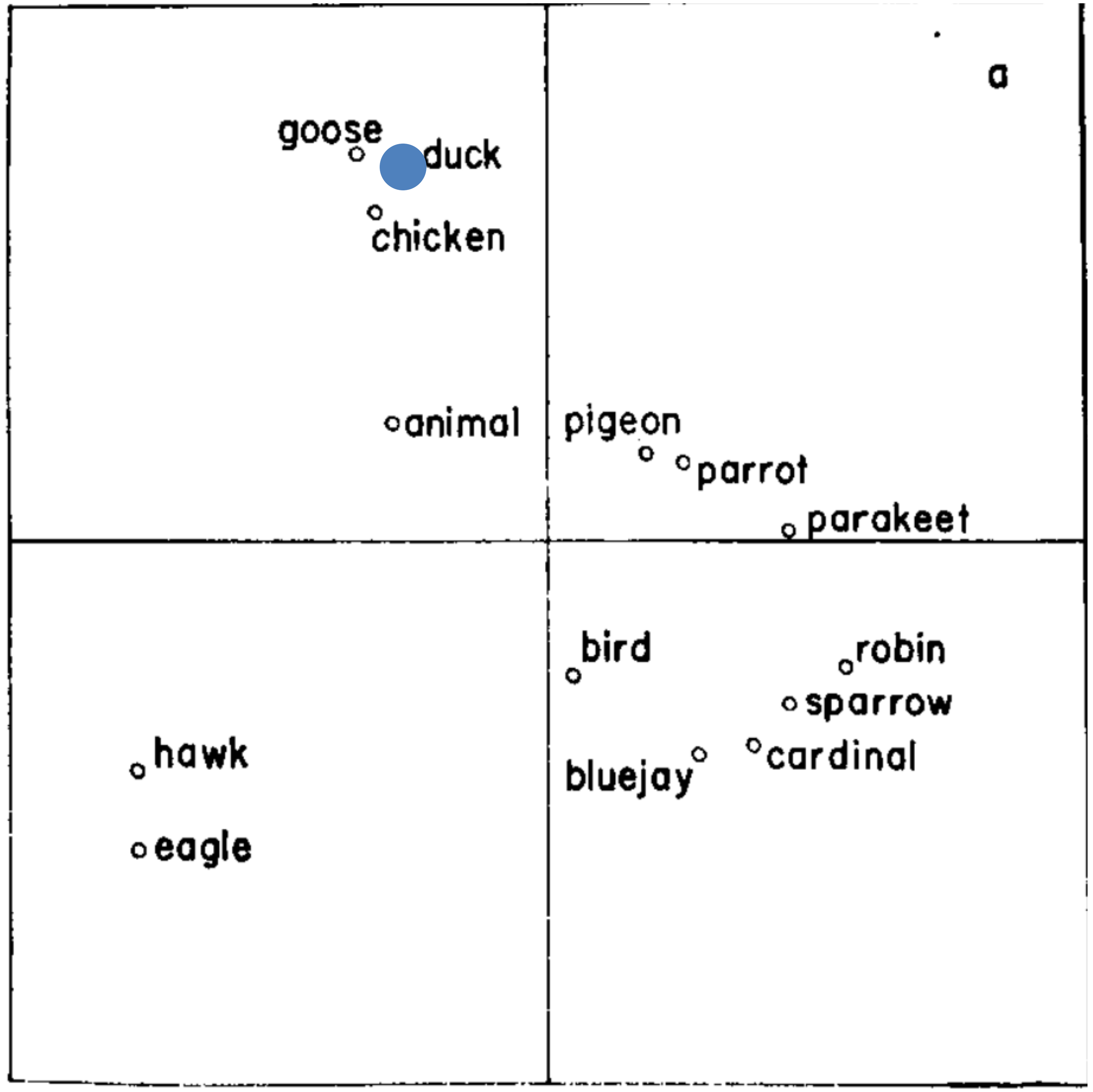

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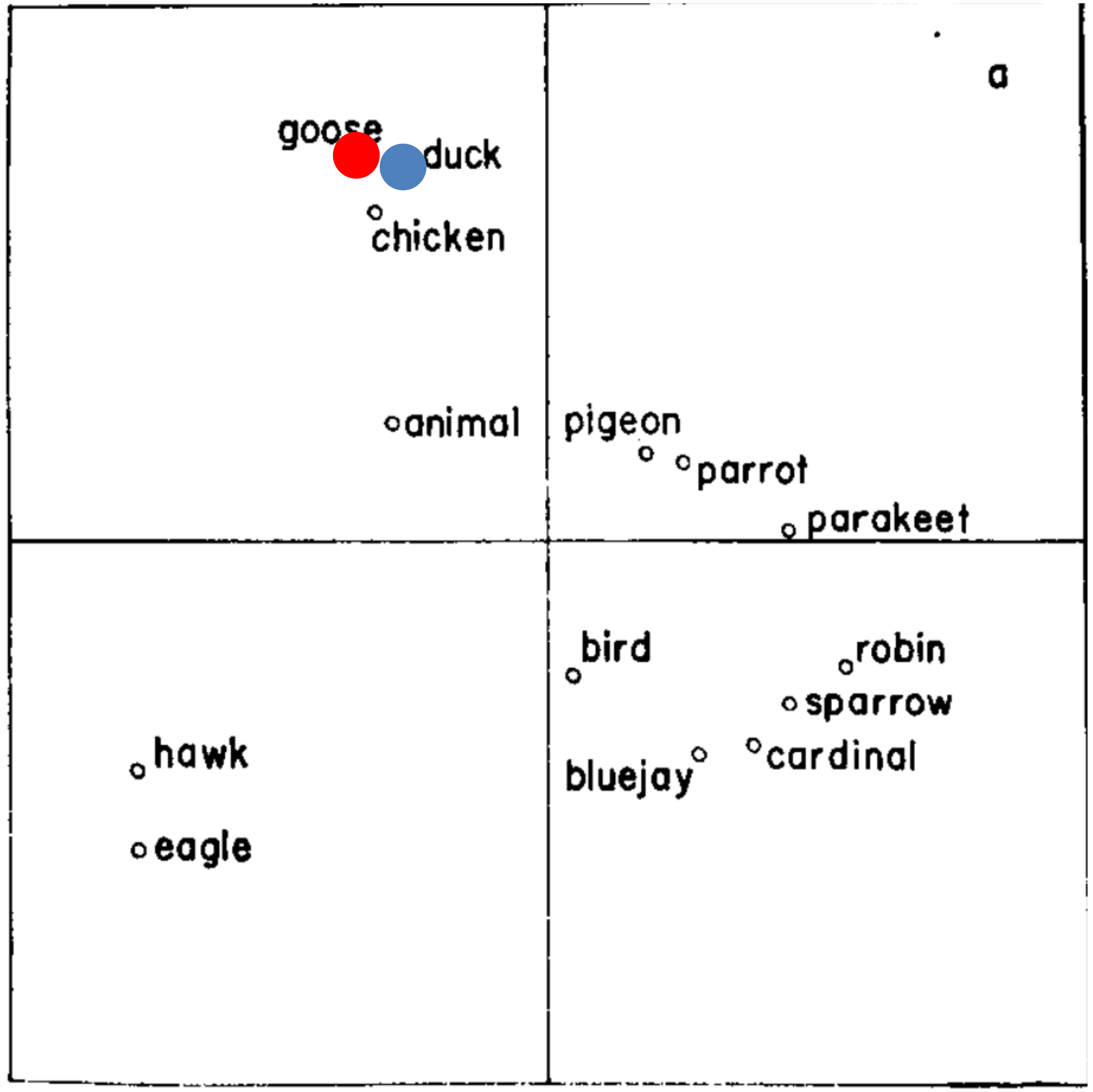
The representation in classic cognitive models

Formal models use these distances to predict behaviour (such as induction and generalisation).

For example, say **ducks** are susceptible to Reinholf disease… one is likely to think **geese** are also susceptible.



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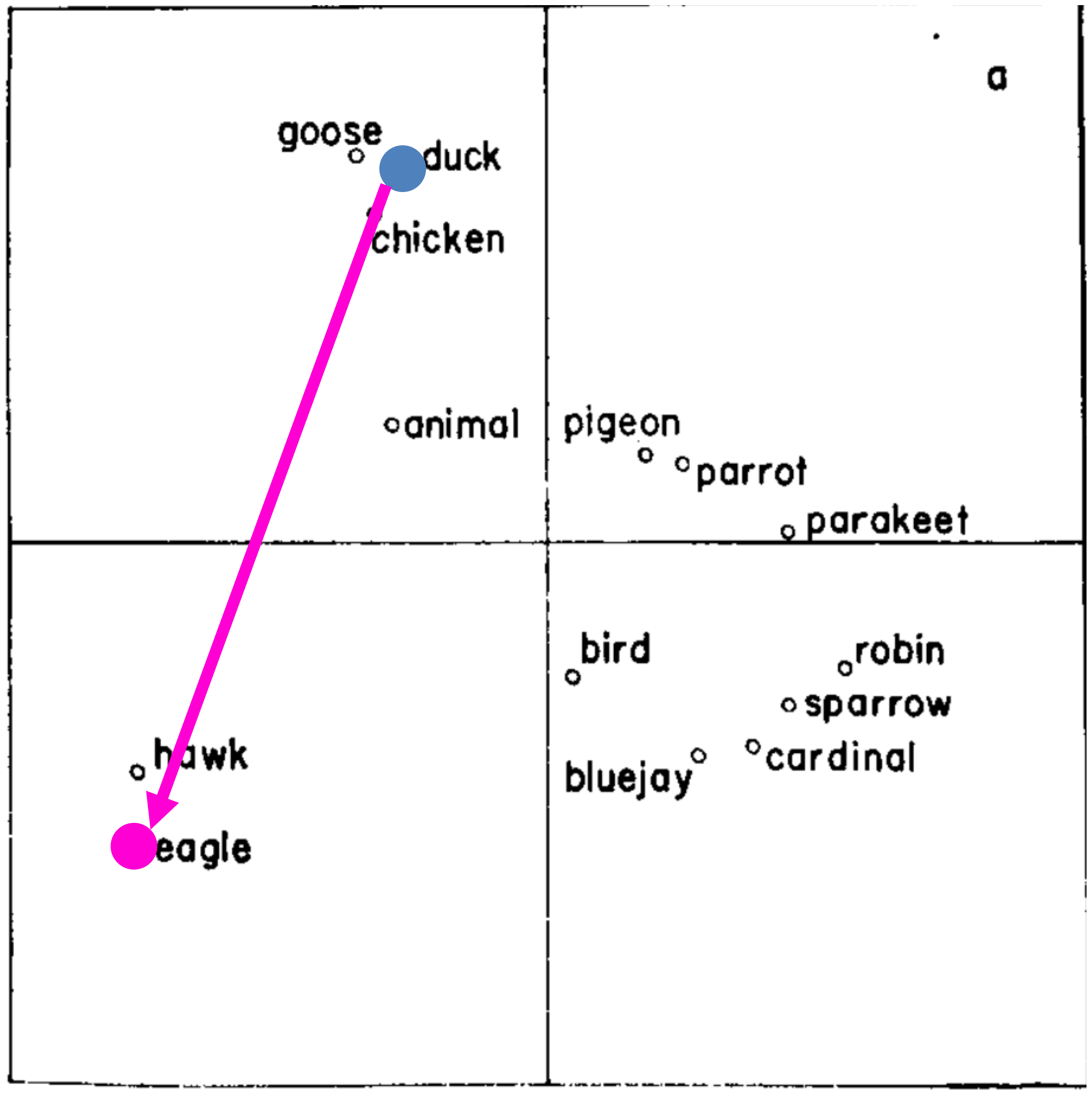
The representation in classic cognitive models

Formal models use these distances to predict behaviour (such as induction and generalisation).

For example, say **ducks** are susceptible to Reinholf disease… but less likely to think **eagles** are also susceptible.



Rips, L. J., Shoben, E. J., & Smith, E. E. (1973). Semantic distance and the verification of semantic relations. *Journal of verbal learning and verbal behavior*, *12*(1), 1-20.

The representation in classic cognitive models

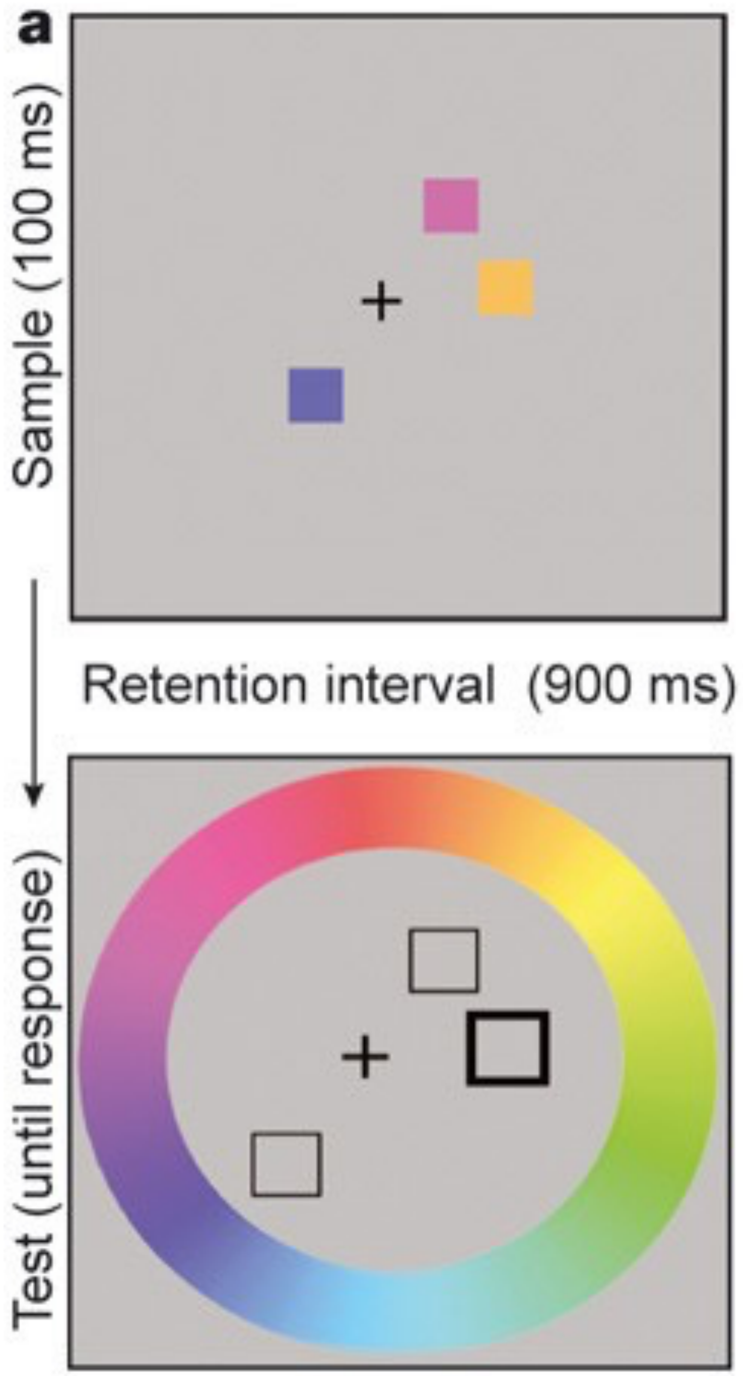
For historical reasons, the similarity-based MDS-representation has been considered **the psychological representation** underlying cognition.

Many cognitive modelers focus on the operations that occur on the representation, rather than explain the representation itself.

Nosofsky, R. M. (1992). Similarity scaling and cognitive process models. *Annual review of Psychology*, *43*(1), 25-53.
Shepard, R. N. (1987). Toward a universal law of generalization for psychological science. *Science*, *237*(4820), 1317-1323.

Two classes of visual working memory models

Most visual working memory models assume **the physical stimulus space** as the representation that cognitive mechanisms operate upon.



Models assume the physical space, such as this colour wheel

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), 233-235.

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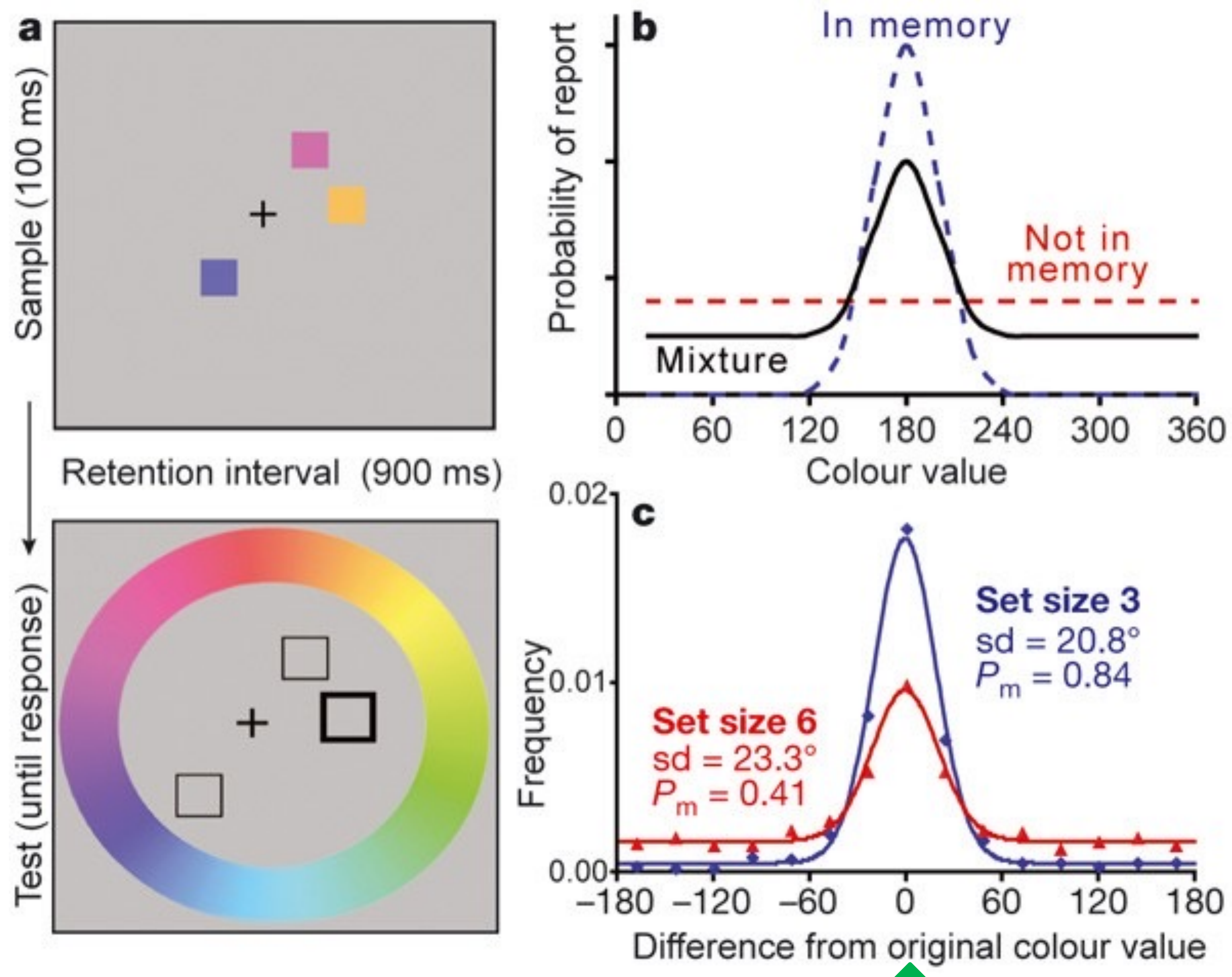


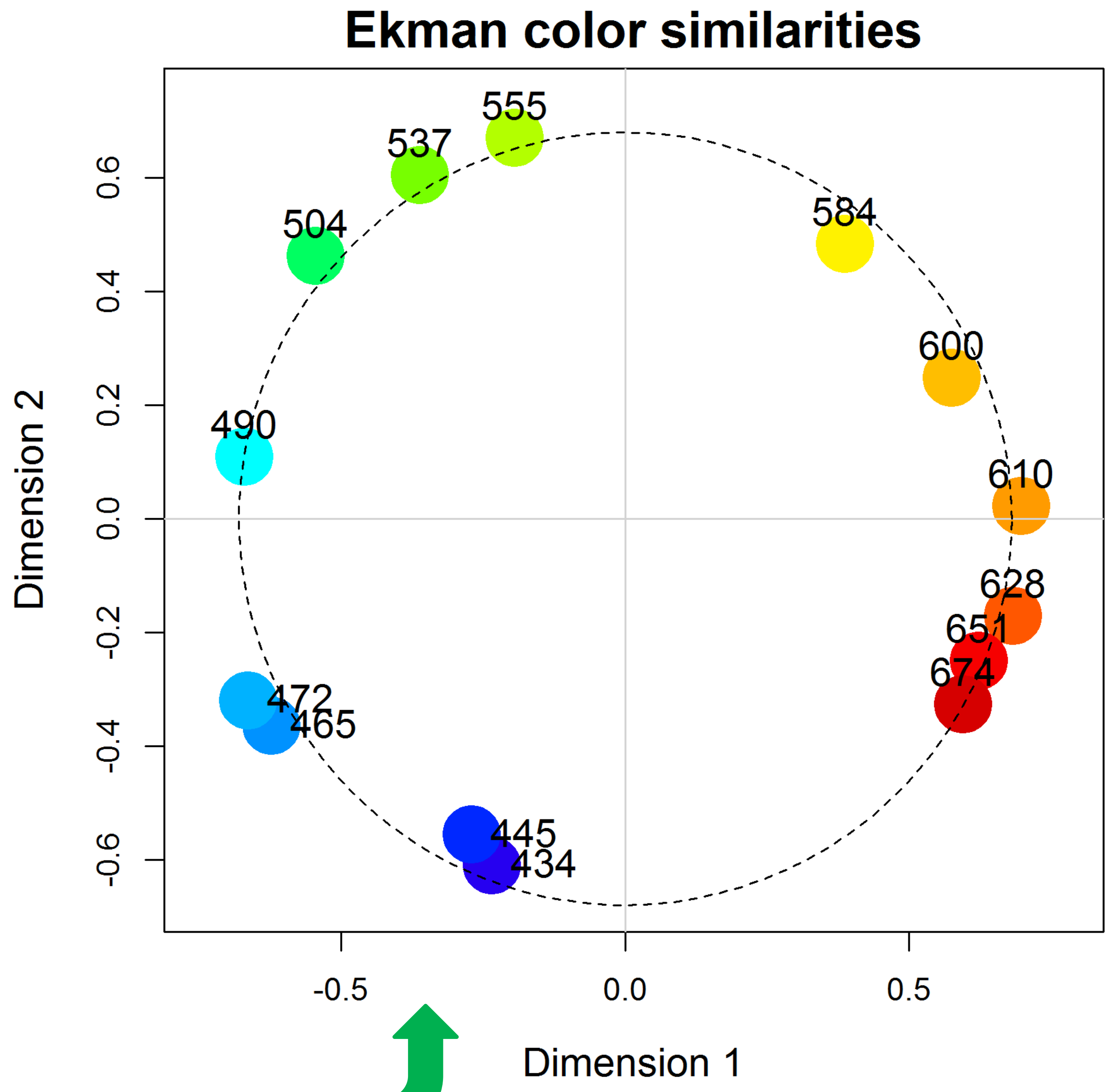
Memory operationalised in terms of absolute error on colour wheel

Zhang, W., & Luck, S. J. (2008). Discrete fixed-resolution representations in visual working memory. *Nature*, *453*(7192), 233-235.

The representation in visual working memory

A recent model (the TCC model; Schurgin et al., 2020) argued that working memory is best modelled in terms of **psychological similarity.**

Similarity-based MDS-representation of colours



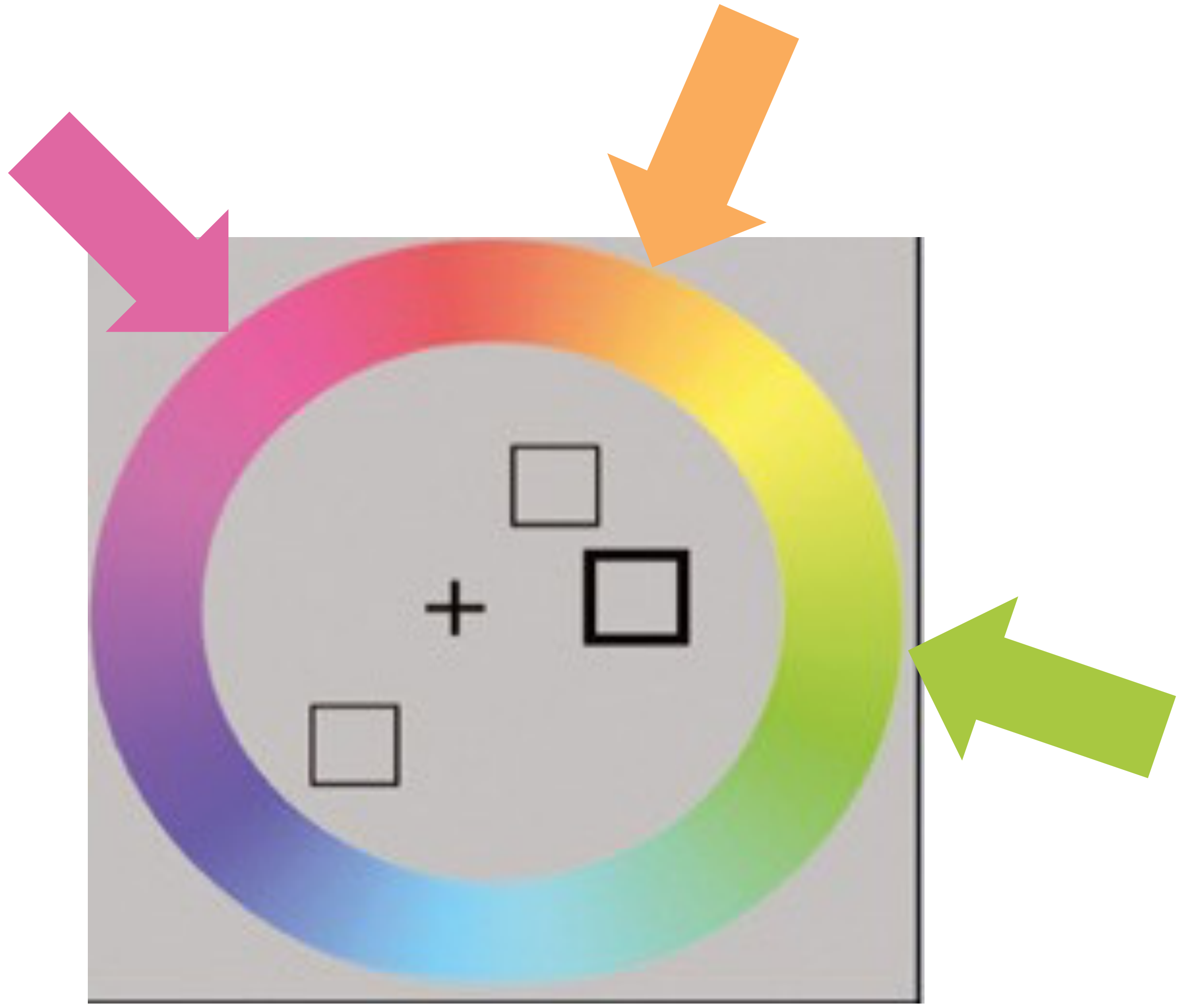
Ekman, G. (1954). Dimensions of color vision. *The Journal of Psychology*, *38*(2), 467-474.

Schurgin, M. W., Wixted, J. T., & Brady, T. F. (2020). Psychophysical scaling reveals a unified theory of visual memory strength. *Nature human behaviour*, 4(11), 1156-1172.

The representation in visual working memory

They made the point that confusability would not be captured on the physical stimulus space.

For example, **orange** is more similar to **pink** than **green**, despite being the same distance in absolute degrees.



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The representation in visual working memory

Recent work has found that adjustments for psychological similarity do not improve model fits for visual working memory performance.

But there remain issues with assuming the physical stimulus space or the similarity-based space to build cognitive models.

Thus, the question remains – **what is the representation underlying visual working memory?**

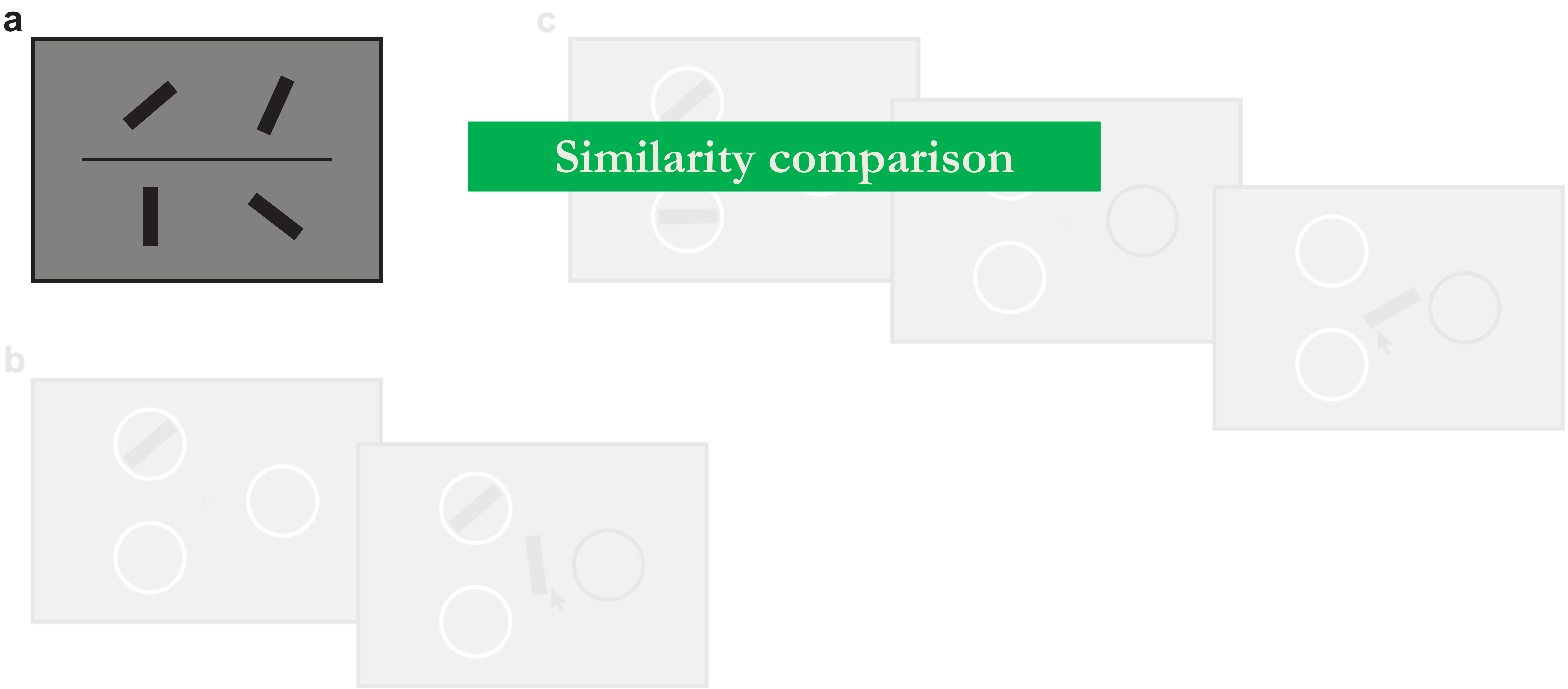
Oberauer, K. (2023). Measurement models for visual working memory—A factorial model comparison. *Psychological review*, *130*(3), 841.
Tomić, I., & Bays, P. M. (2024). Perceptual similarity judgments do not predict the distribution of errors in working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 50(4), 535.

Our modeling approach

In brief, we used Bayesian MCMC methods to recover the **latent representation** underlying three cognitive tasks using oriented lines. The data comes from an open dataset (Tomic and Bays, 2024).

Tomić, I., & Bays, P. M. (2024). Perceptual similarity judgments do not predict the distribution of errors in working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *50*(4), 535.

The cognitive tasks



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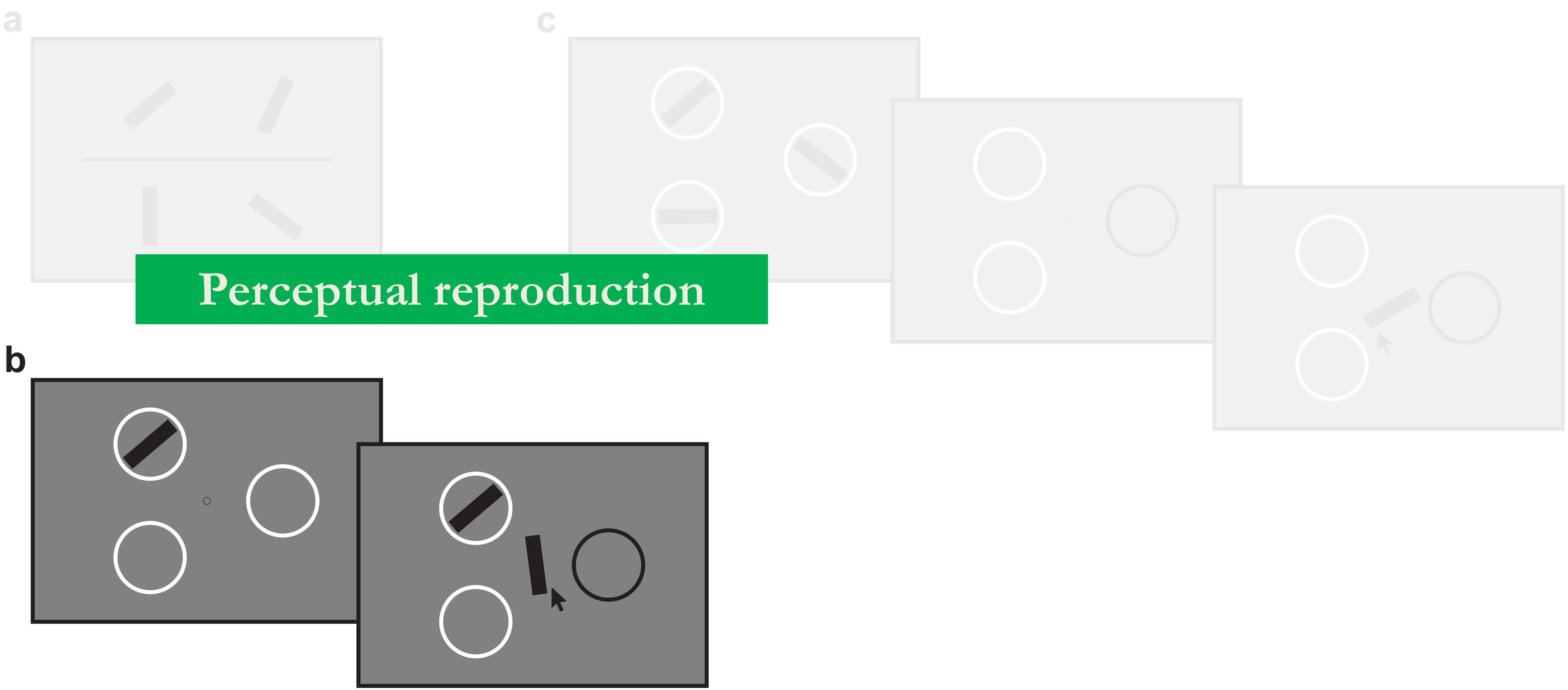

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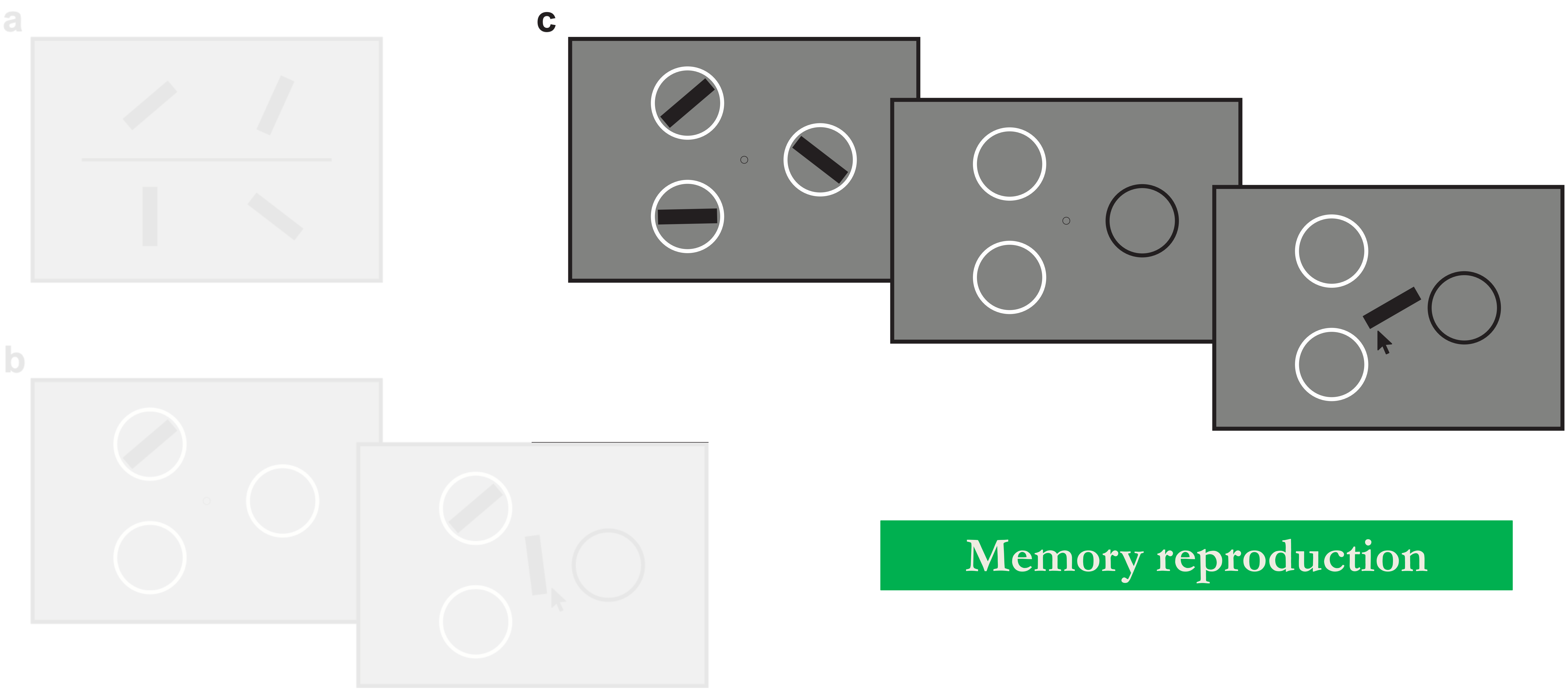


Memory reproduction

Tomić, I., & Bays, P. M. (2024). Perceptual similarity judgments do not predict the distribution of errors in working memory. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 50(4), 535.

Our modeling goal

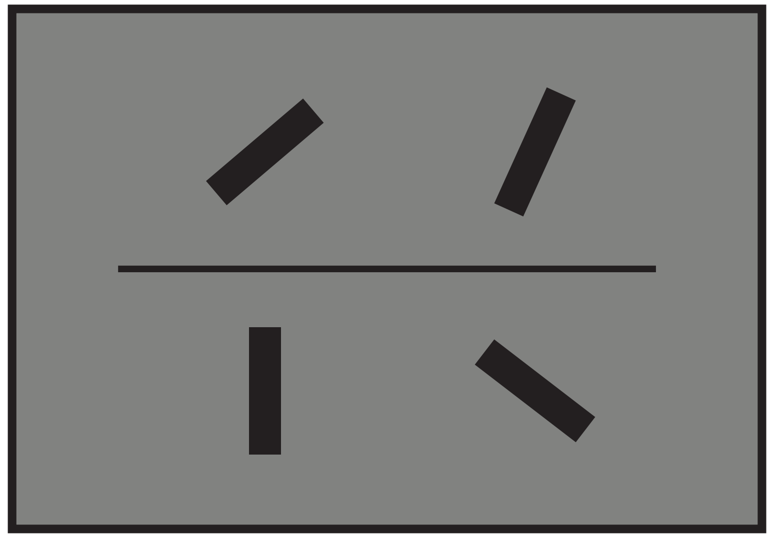
Our goal was to recover the latent representations of the orientation stimuli in the three cognitive tasks.

Note that the latent representation is modelled using the task data itself, not outsourced to MDS with similarity judgments.

Our modeling approach

We took a Bayesian generative modeling approach – we built a **Thurstonian model** that fits for the underlying representation.

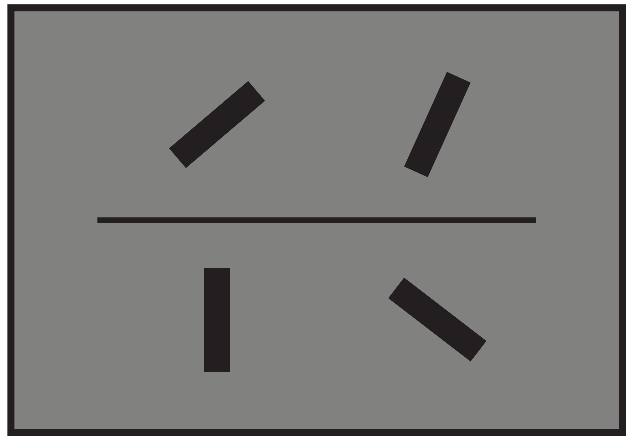
a

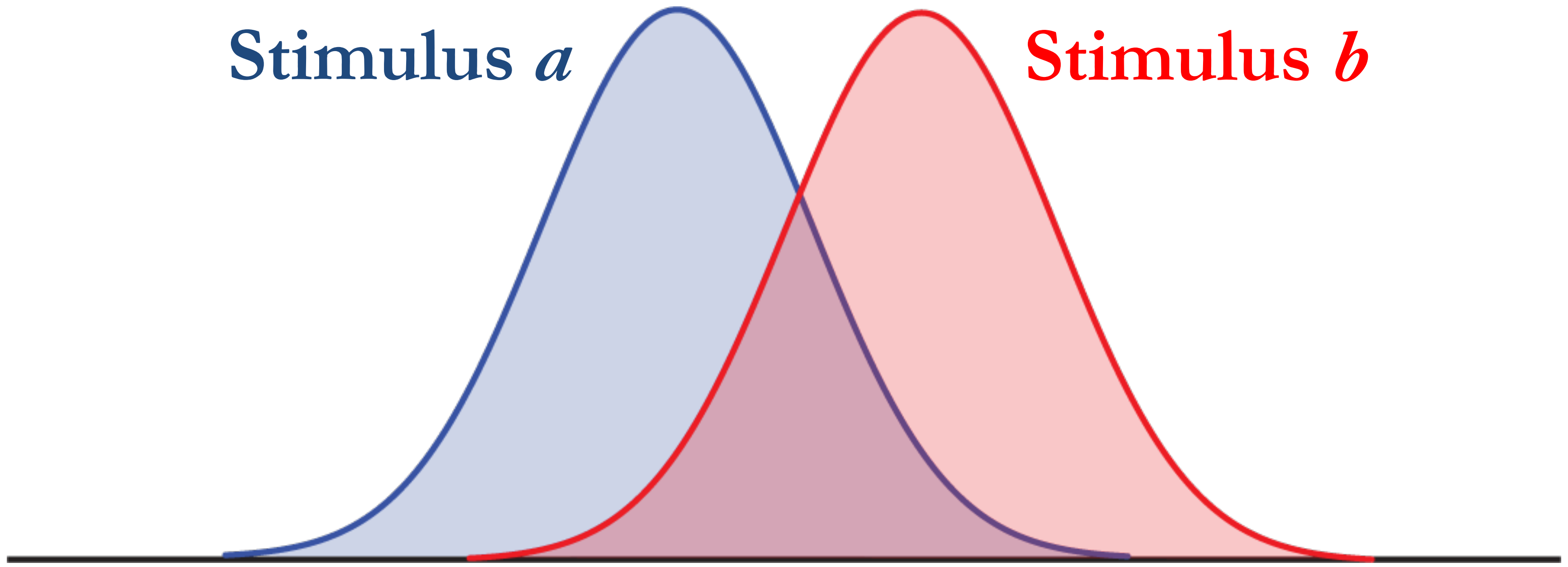


Similarity comparison

Our modeling approach

a



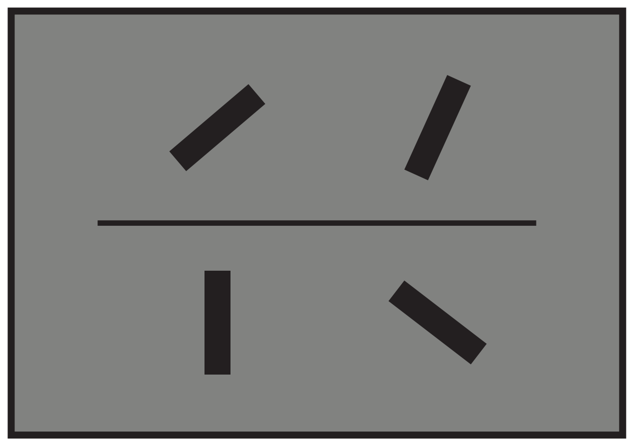


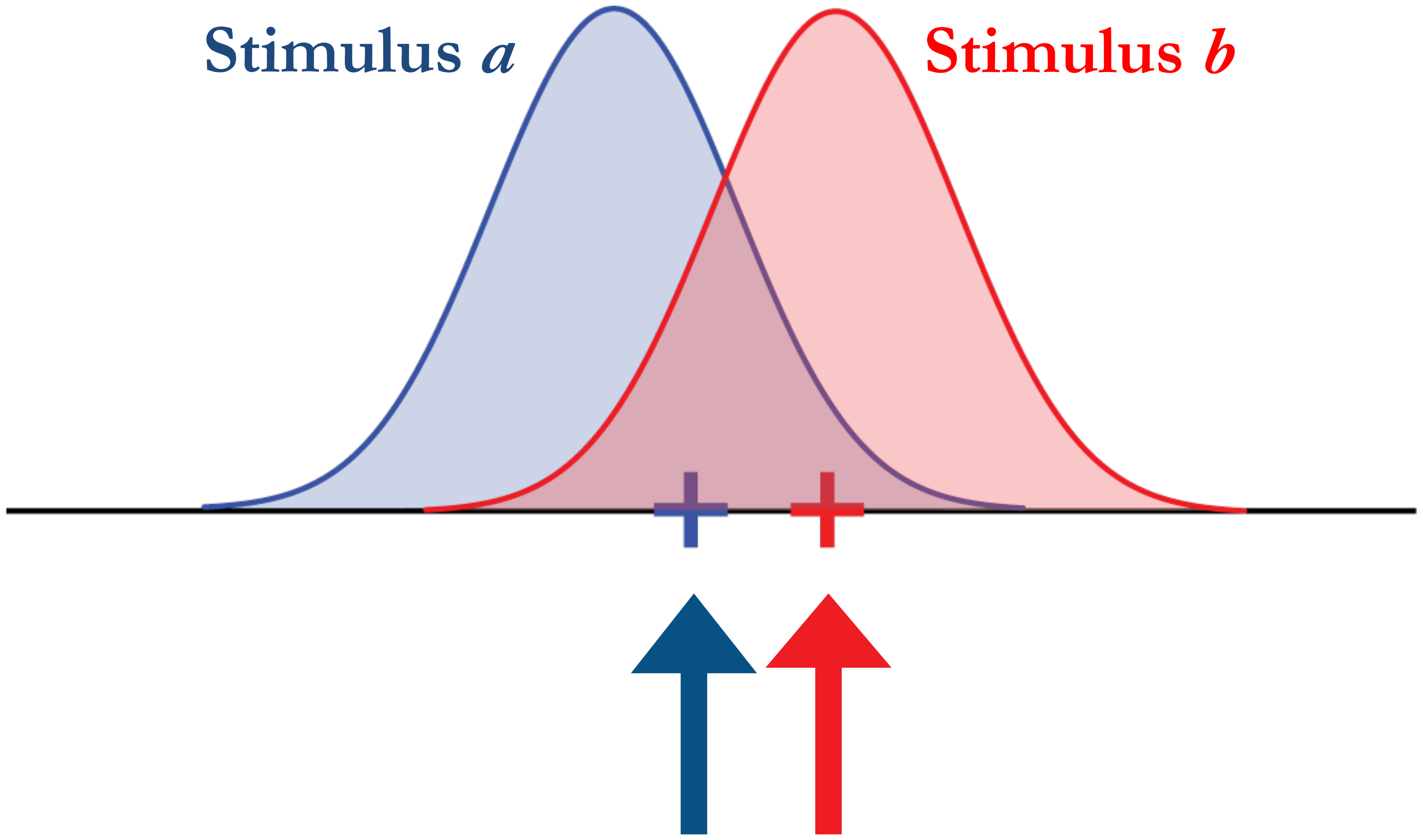
We model the latent representation of each orientation stimulus as a circular Gaussian distribution, centred on a value (μ_n) and with a common width (σ).

For model identifiability
$$\begin{cases} \mu_1 = 0 \\ \mu_2 \sim \text{uniform}(0\,, \frac{\pi}{2}) \end{cases}$$

Uninformed priors
$$\begin{cases} \mu_3, \ldots \mu_n \sim \text{uniform}(0\,, \pi) \\ \sigma \sim \text{uniform}(0\,, \pi) \end{cases}$$

Our modeling approach



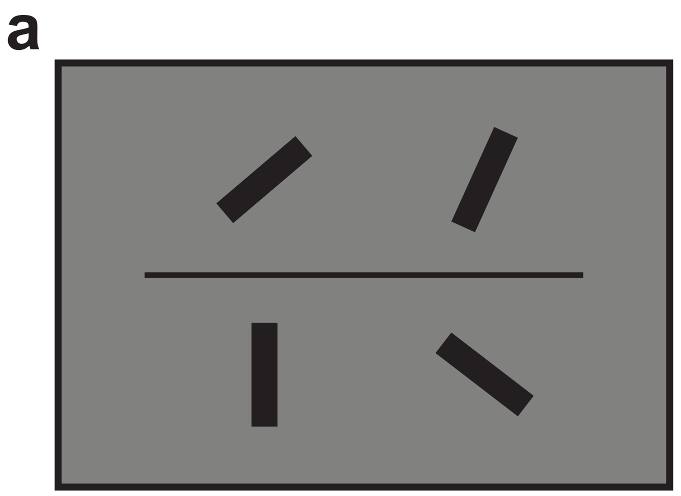


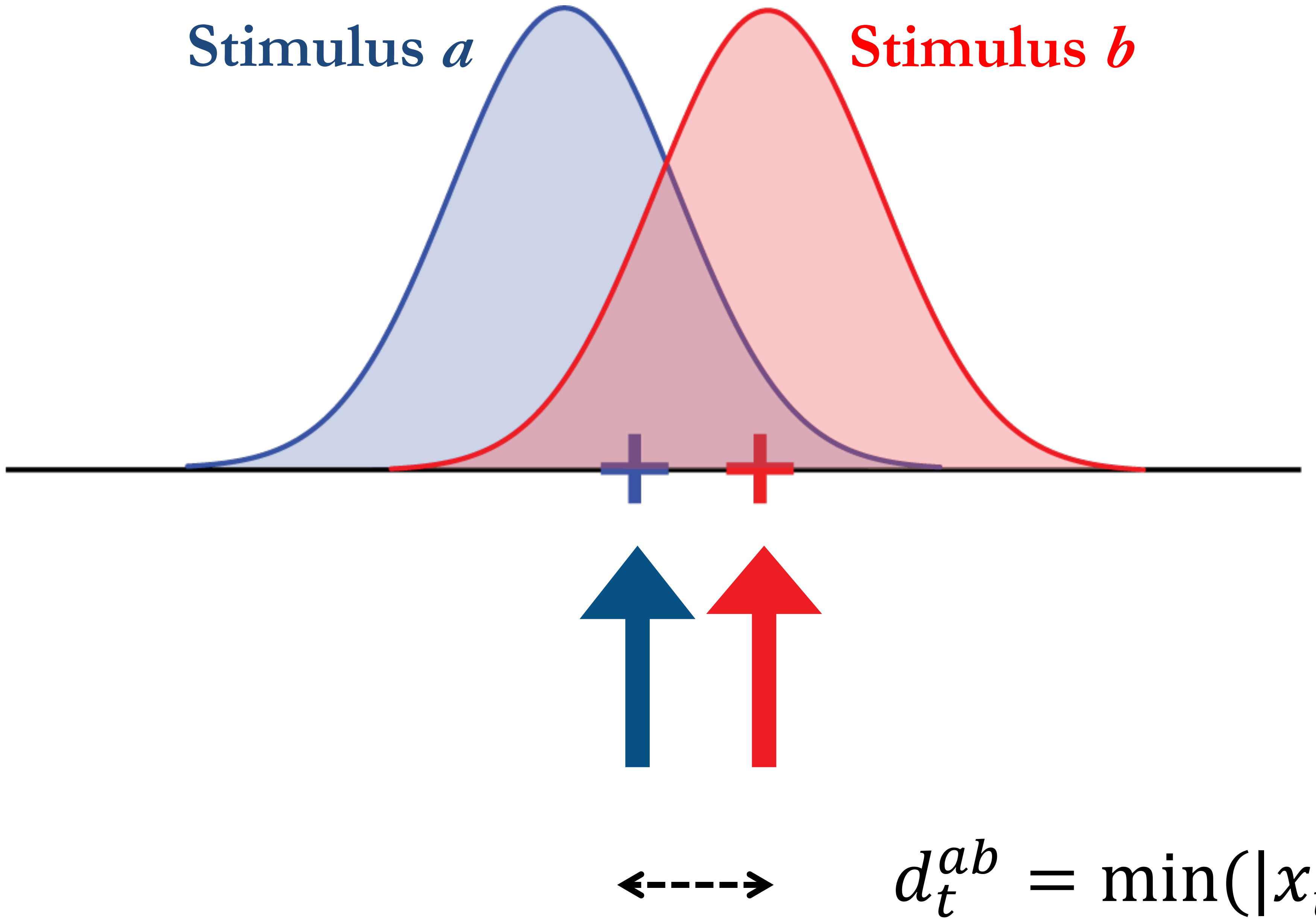
The participant takes one sample from each latent representation of the pair.

$$x_t^{a} \sim \text{Gaussian}(\mu_{a_t}, \frac{1}{\sigma^2})$$

$$x_t^{b} \sim \text{Gaussian}(\mu_{b_t}, \frac{1}{\sigma^2})$$

Our modeling approach



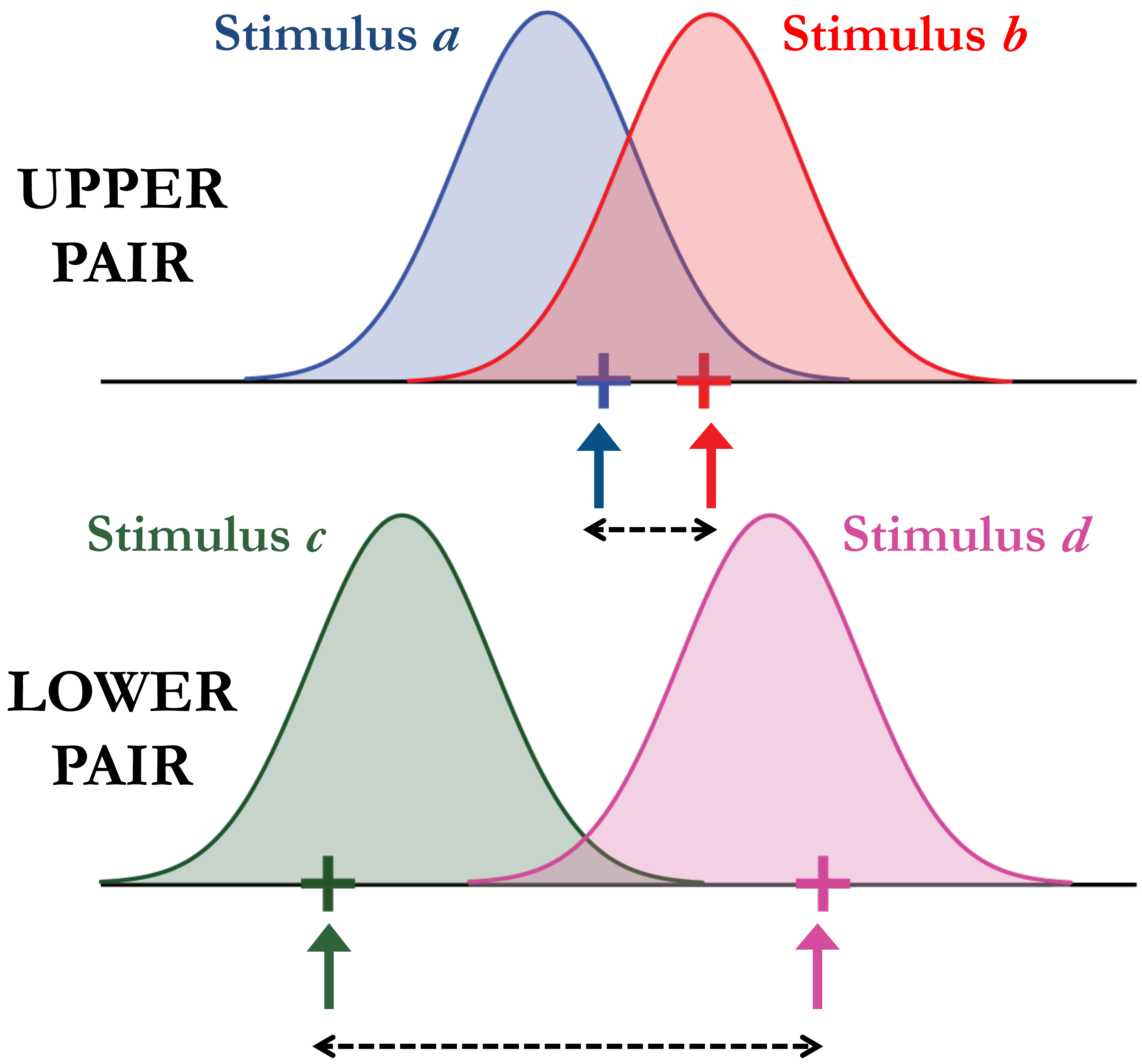


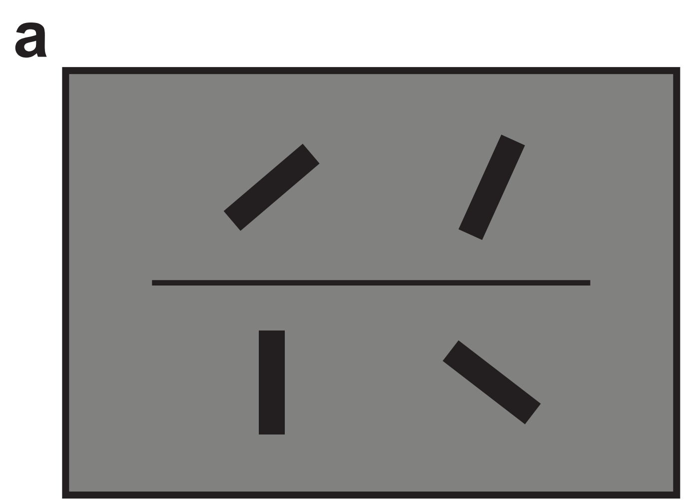
The psychological distance between the pair of stimuli is the distance between the samples

$$d_t^{ab} = \min(|x_t^a - x_t^b|, \pi - |x_t^a - x_t^b|)$$

Accounts for semi-circular nature of angles

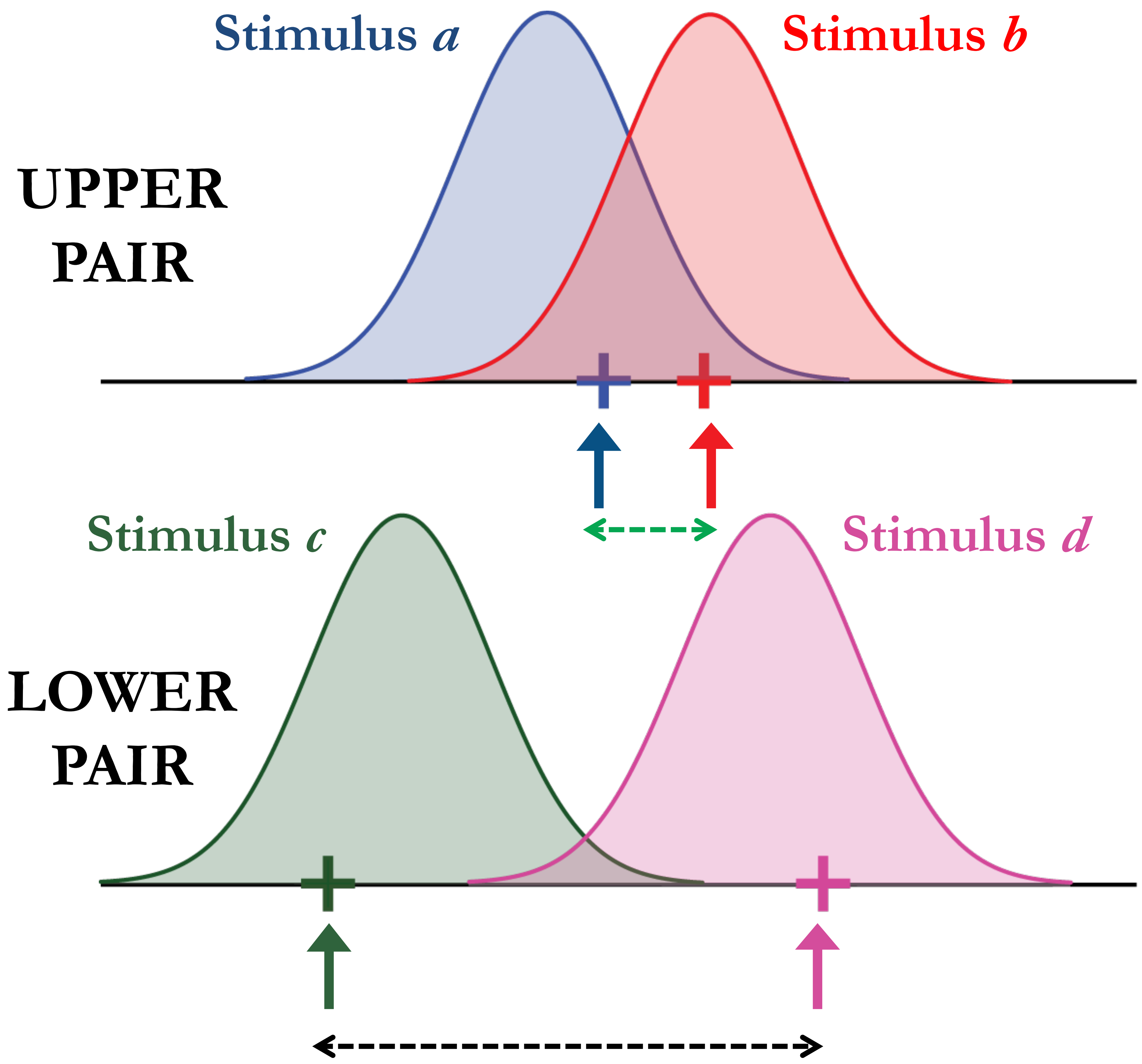
Our modeling approach

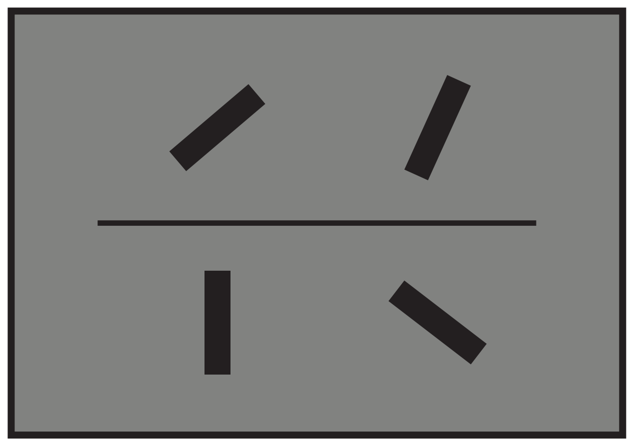




Repeat to calculate the psychological distance for the orientation stimuli in the second pair.

Our modeling approach

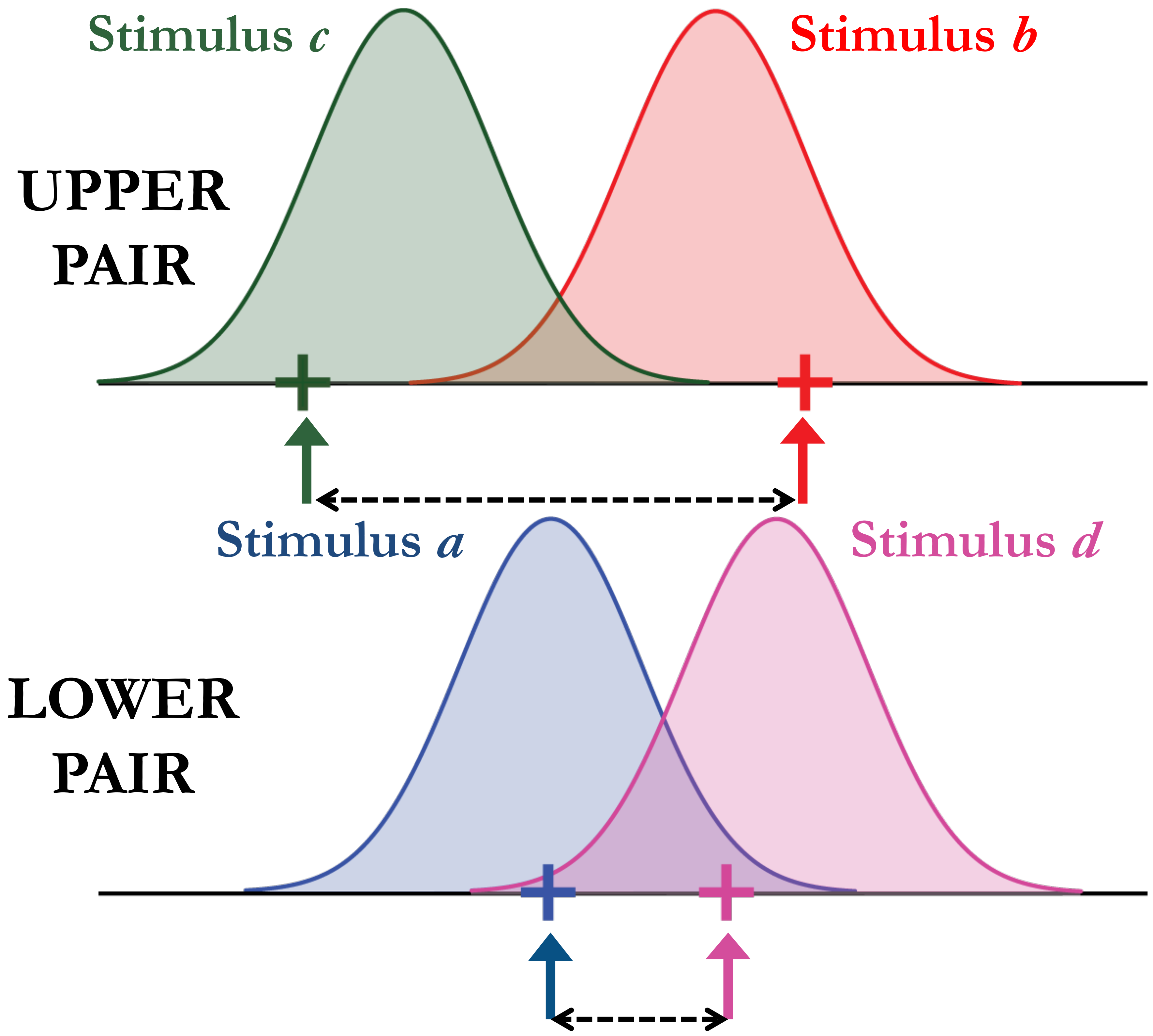


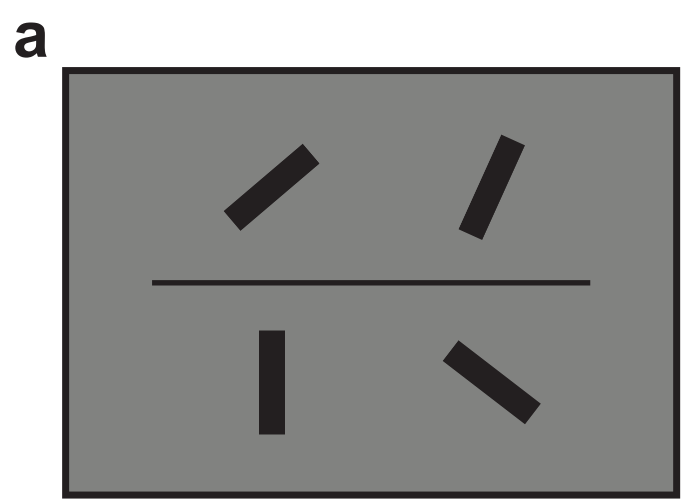


Repeat to calculate the psychological distance for the orientation stimuli in the second pair.

The shorter distance determines which pair is selected as being **more similar.**

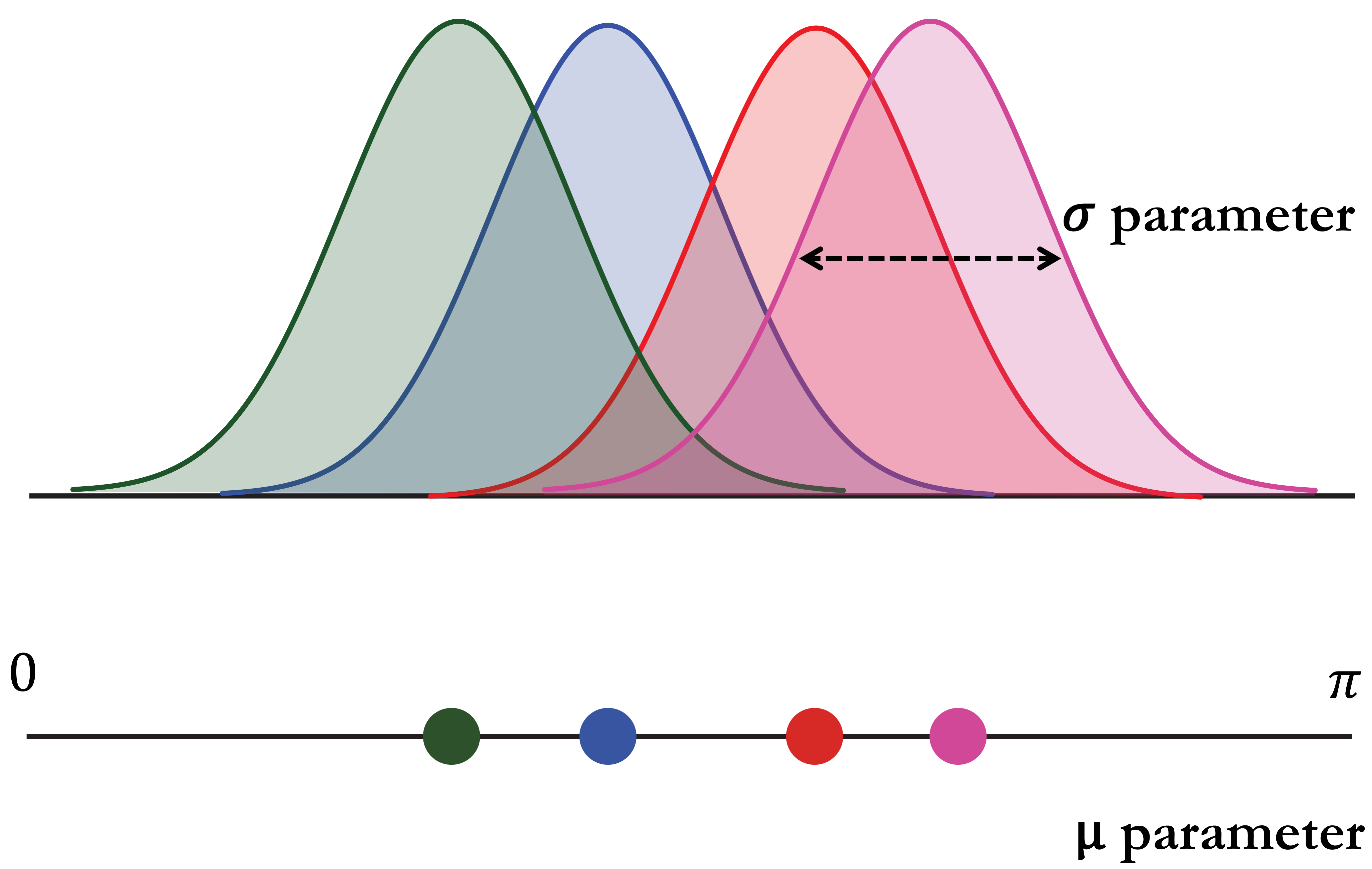
Our modeling approach





Repeat over a number of trials.

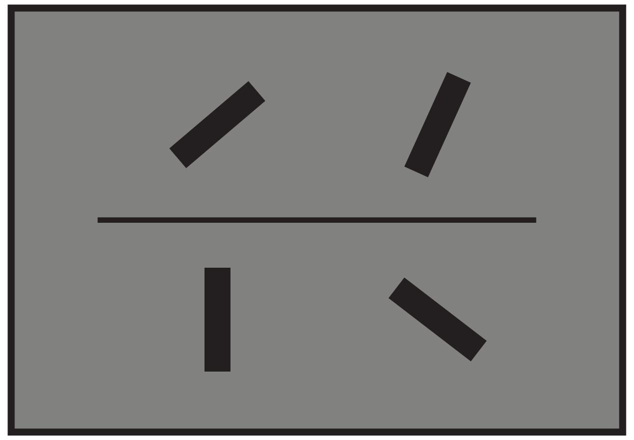
Our modeling approach



The model fits for the latent representations – the center of the distribution, and their common width – based on the response data.

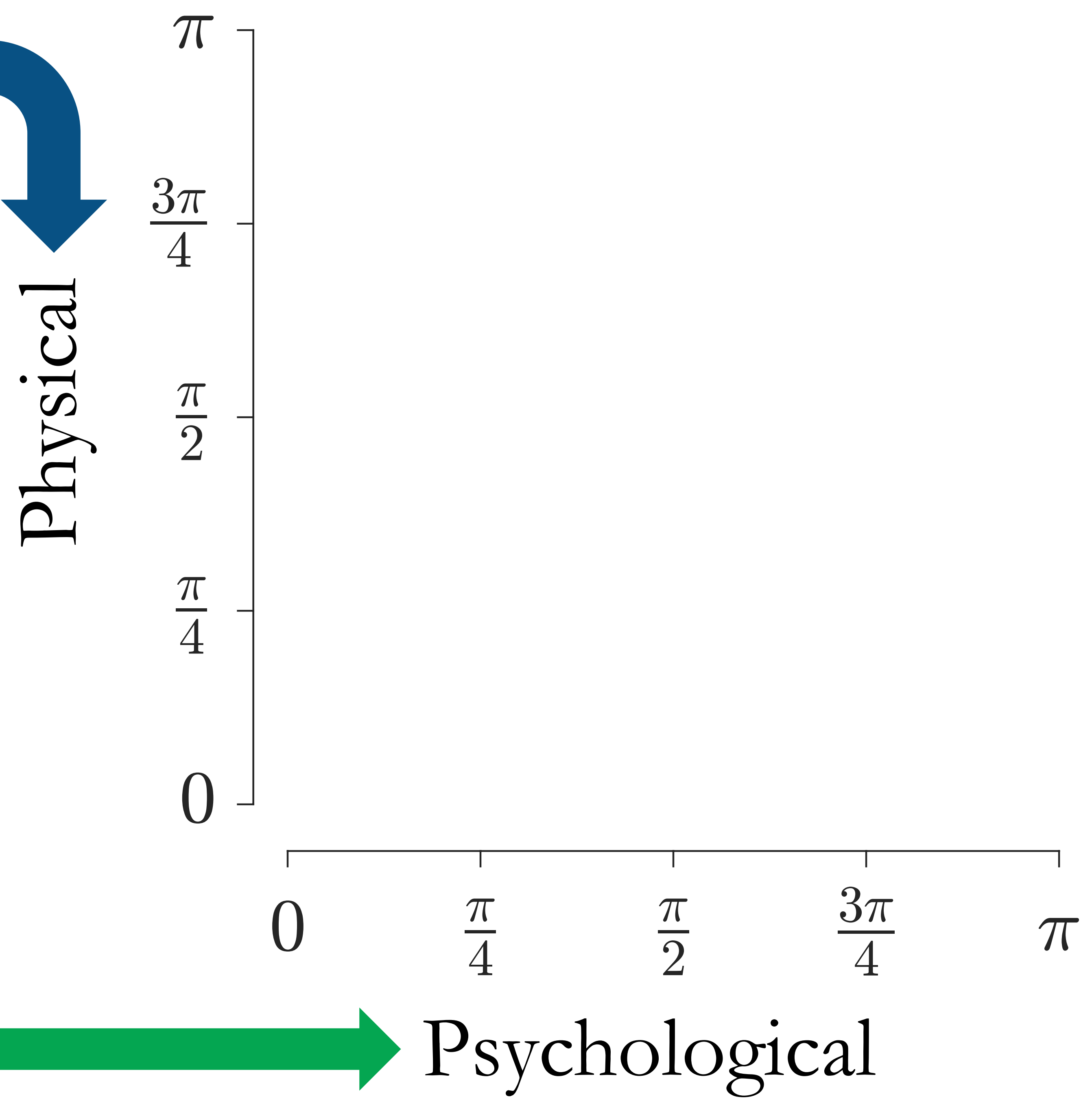
Similarity comparison

a



A

The orientation angle of the line stimulus



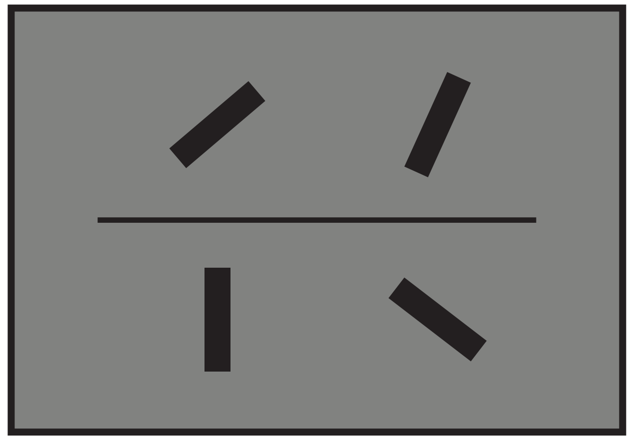
The mental representation of the line orientation

Similarity comparison

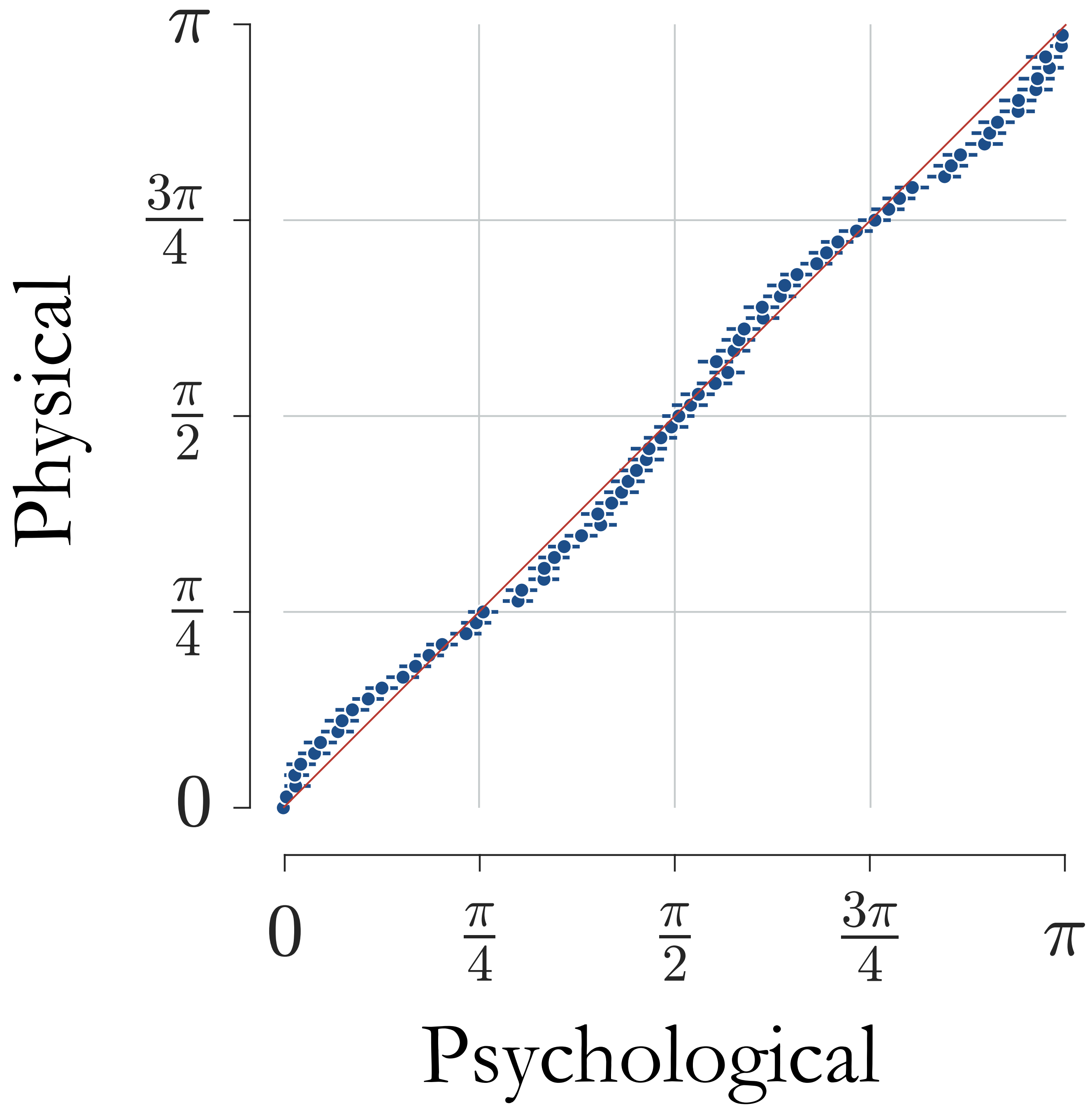
The representation does not match the physical stimulus space – it is not exactly a diagonal line.

Clear deviations where close to vertical lines appear more vertical, and close to horizontal lines appear more horizontal.

a



A

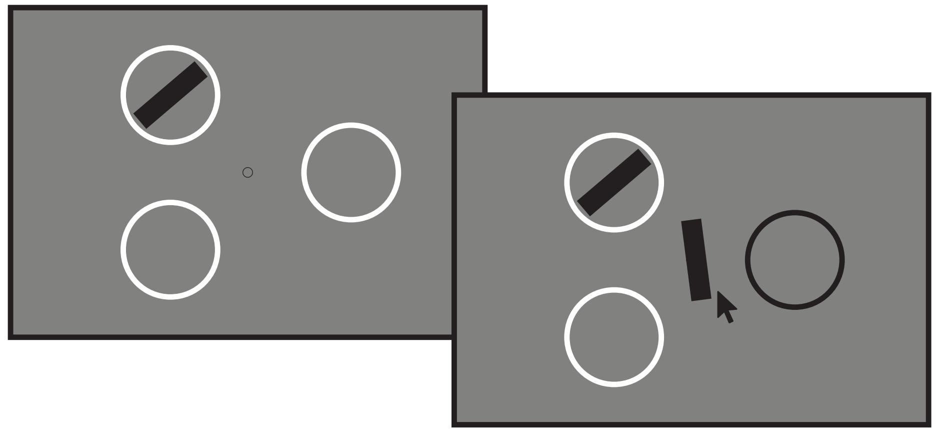


Perceptual reproduction

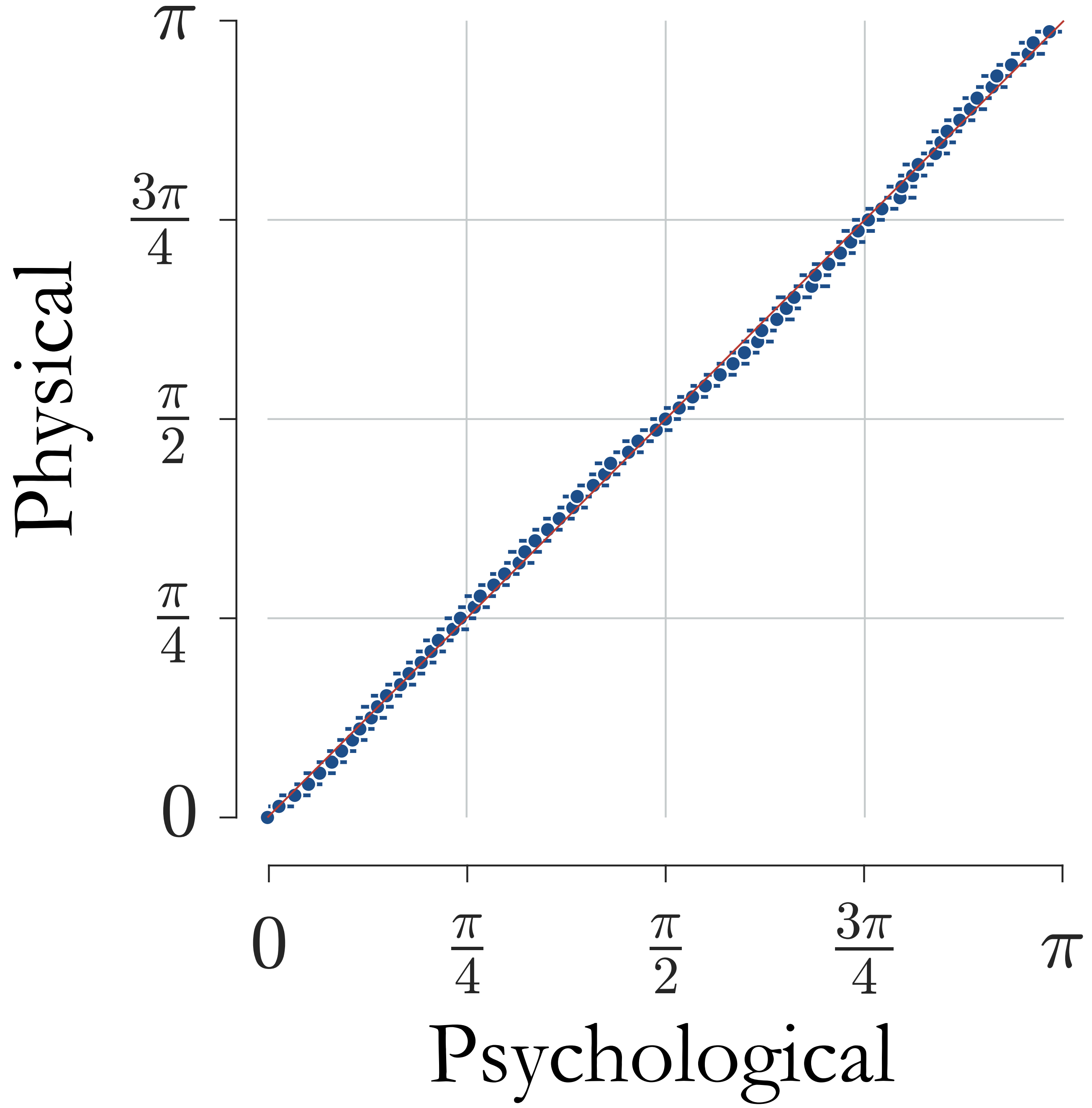
The representation is very close to the physical stimulus space, but there are noticeable deviations.

Lines that are not quite horizontal or not quite vertical are slightly biased away from the cardinal directions. This is the opposite to the similarity comparison.

b



B

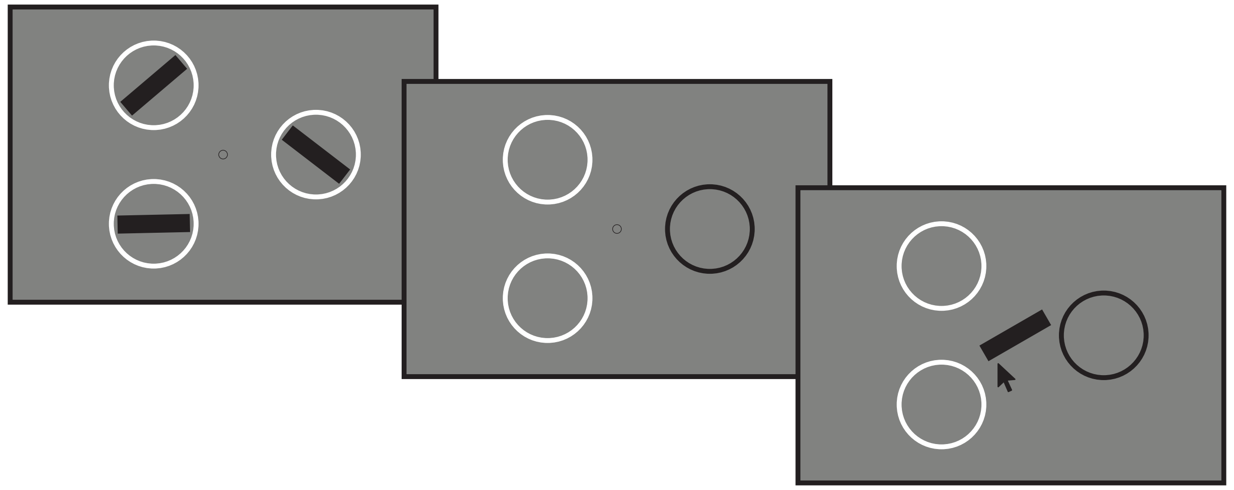


Memory reproduction

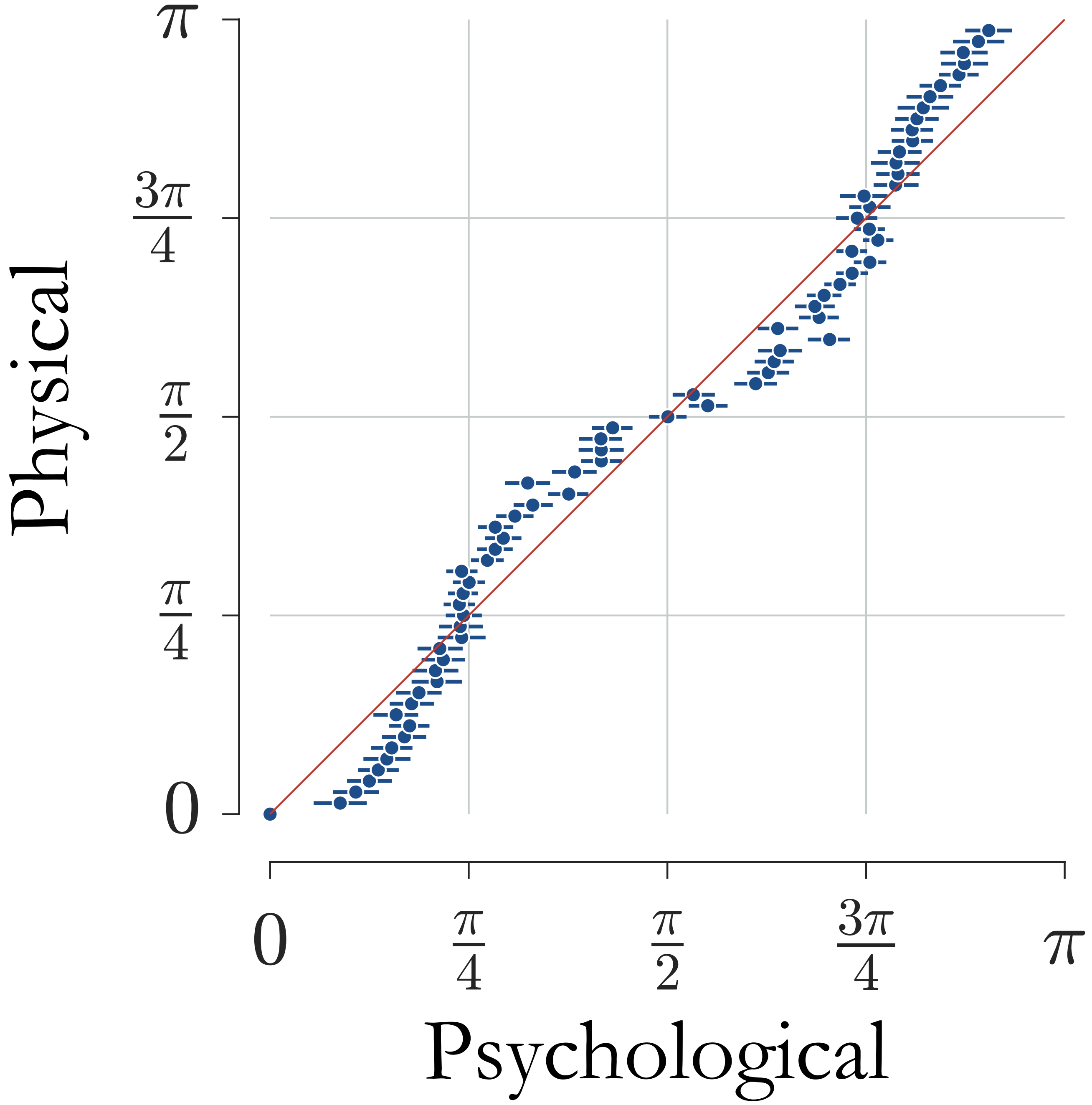
The representation is similar to the perceptual reproduction task but with larger deviations.

Lines are represented more towards the oblique directions than they actually are.

c

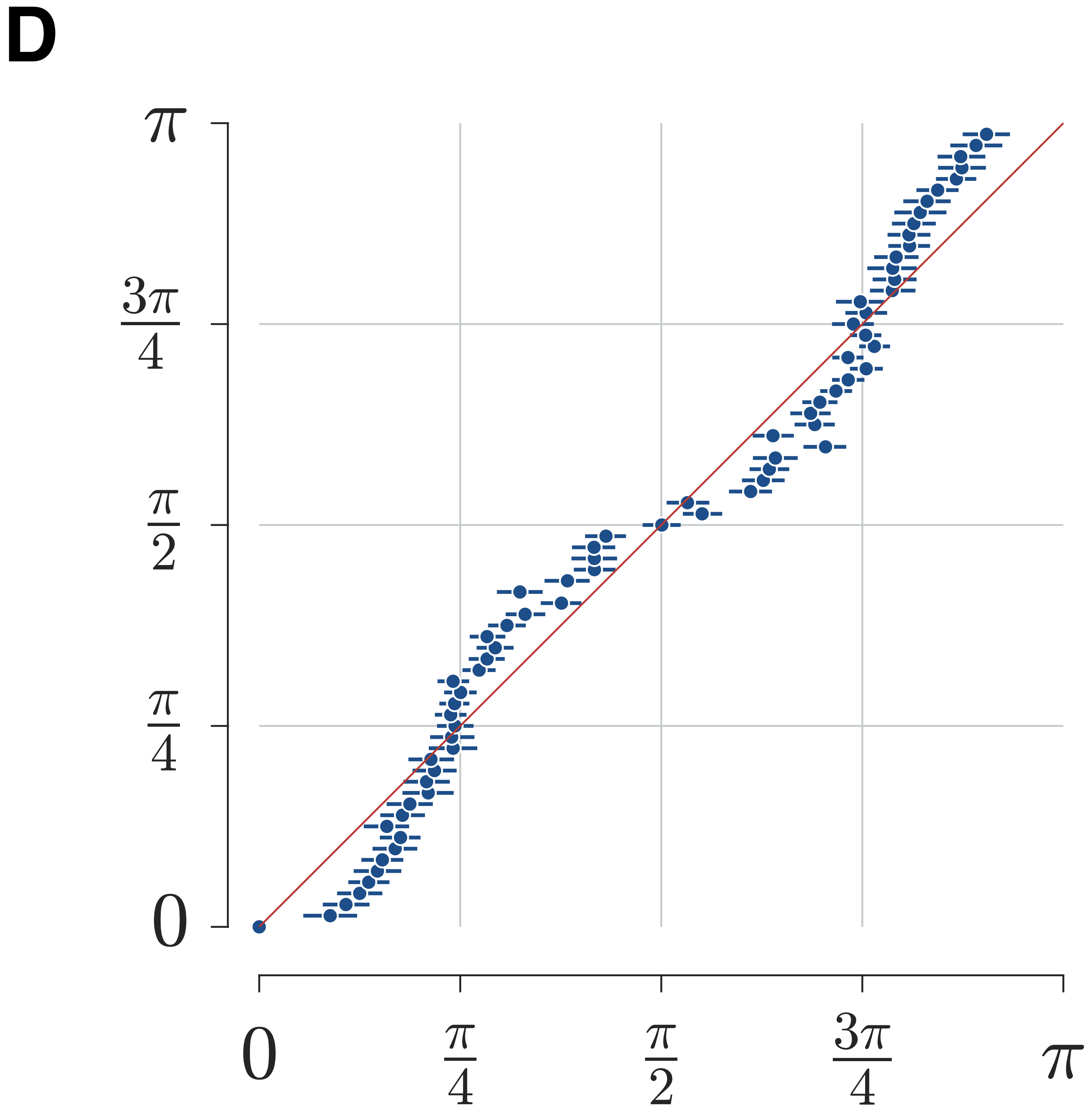


D



Conclusions

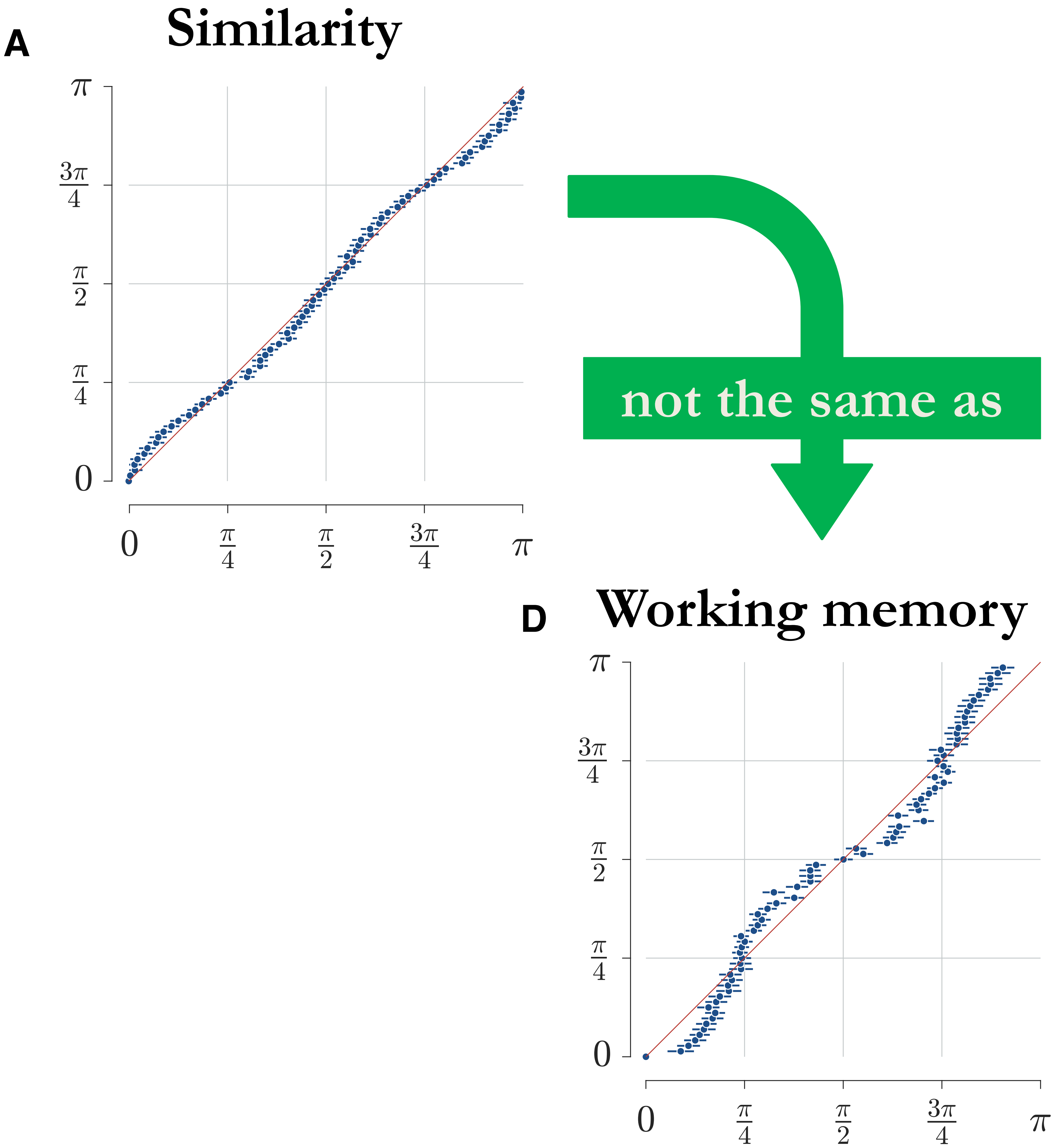
The cognitive representation for memory reproduction does not match the physical stimulus space. Therefore, models **should not assume the physical stimulus space** when modelling working memory performance.



Conclusions

Similarity comparisons and both reproduction tasks **do not share the same cognitive representation.**

Therefore, psychological similarity cannot be assumed to be the basis for working memory.



Conclusions

Cognitive researchers ought not to assume the cognitive representation can be recovered using MDS of similarity-based judgments.

We advocate for our modeling approach that fits the cognitive representation **jointly** with the theorised mechanisms underlying the tasks.

Thank you!

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william.ngiam@adelaide.edu.au

https://palm-lab.github.io

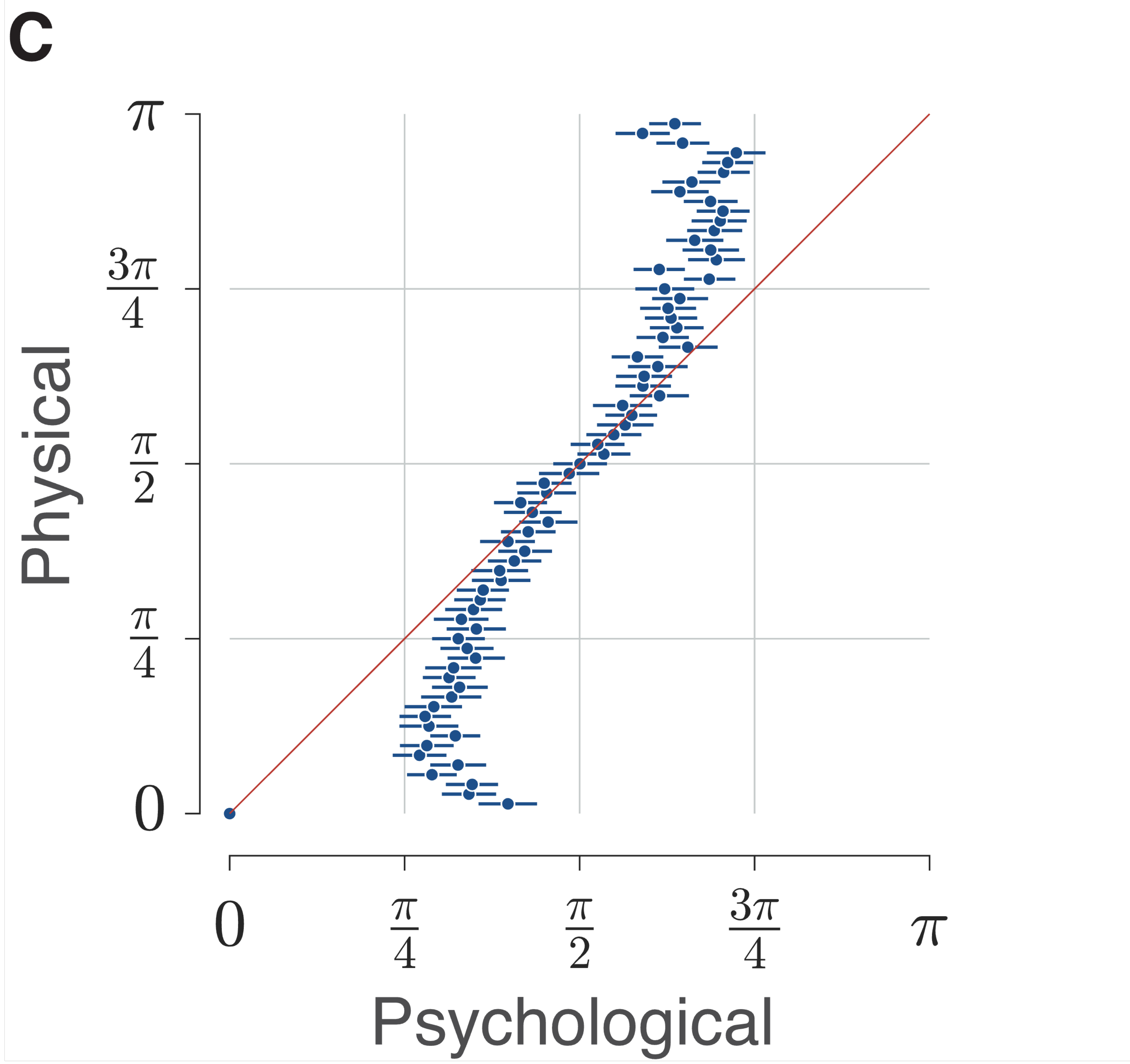
@williamngiam.github.io

Adelaide University

Bonus slide #1 – improve model, improve fit

Refining the cognitive model by adding reasonable mechanisms improves the fit (and the recovered representation).

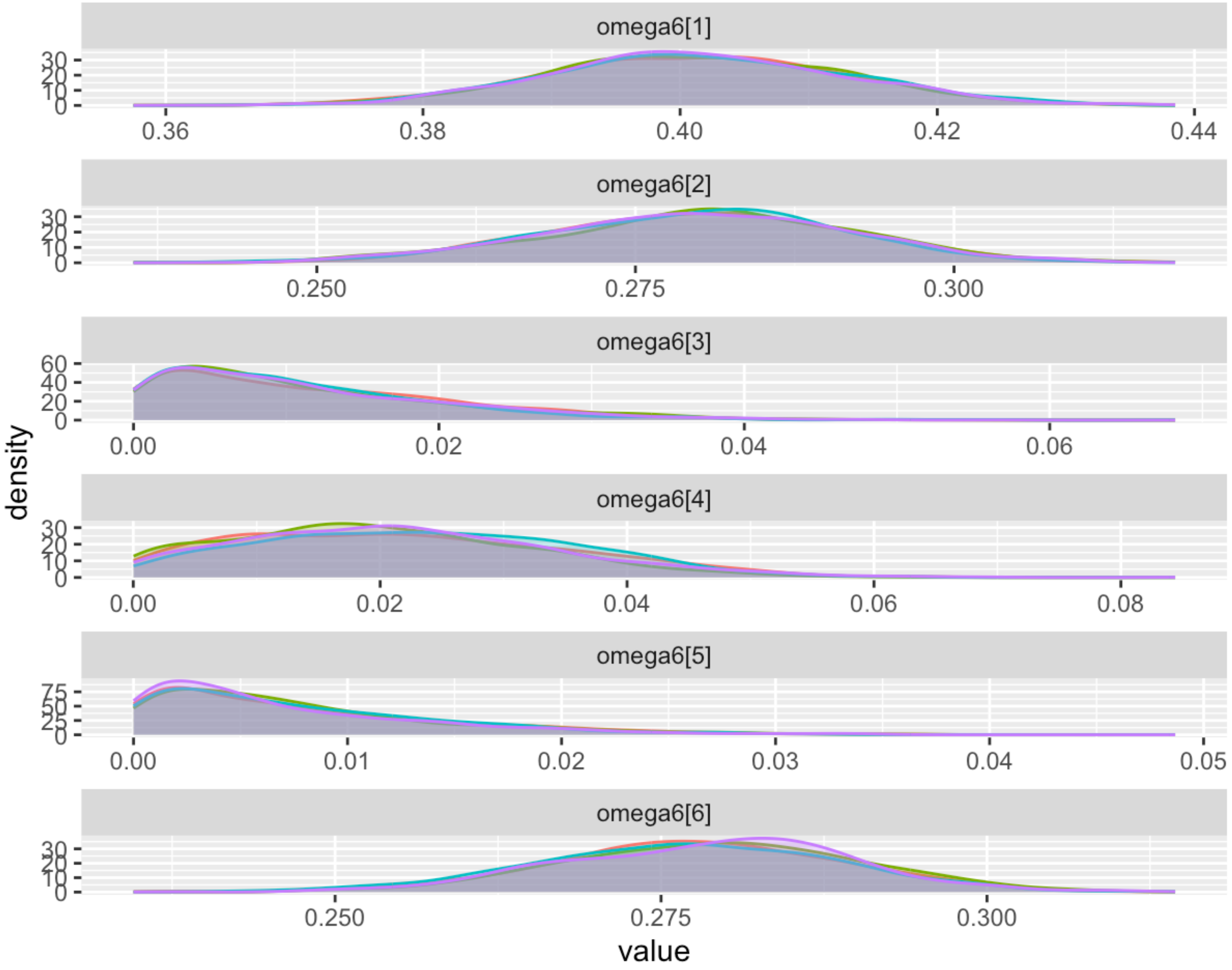
These are the results if **swap errors** are not included in the model.



Bonus slide #2 – swap error rate

The model includes the estimated standard deviation and swap error rate. The swap rates are shown in this figure.

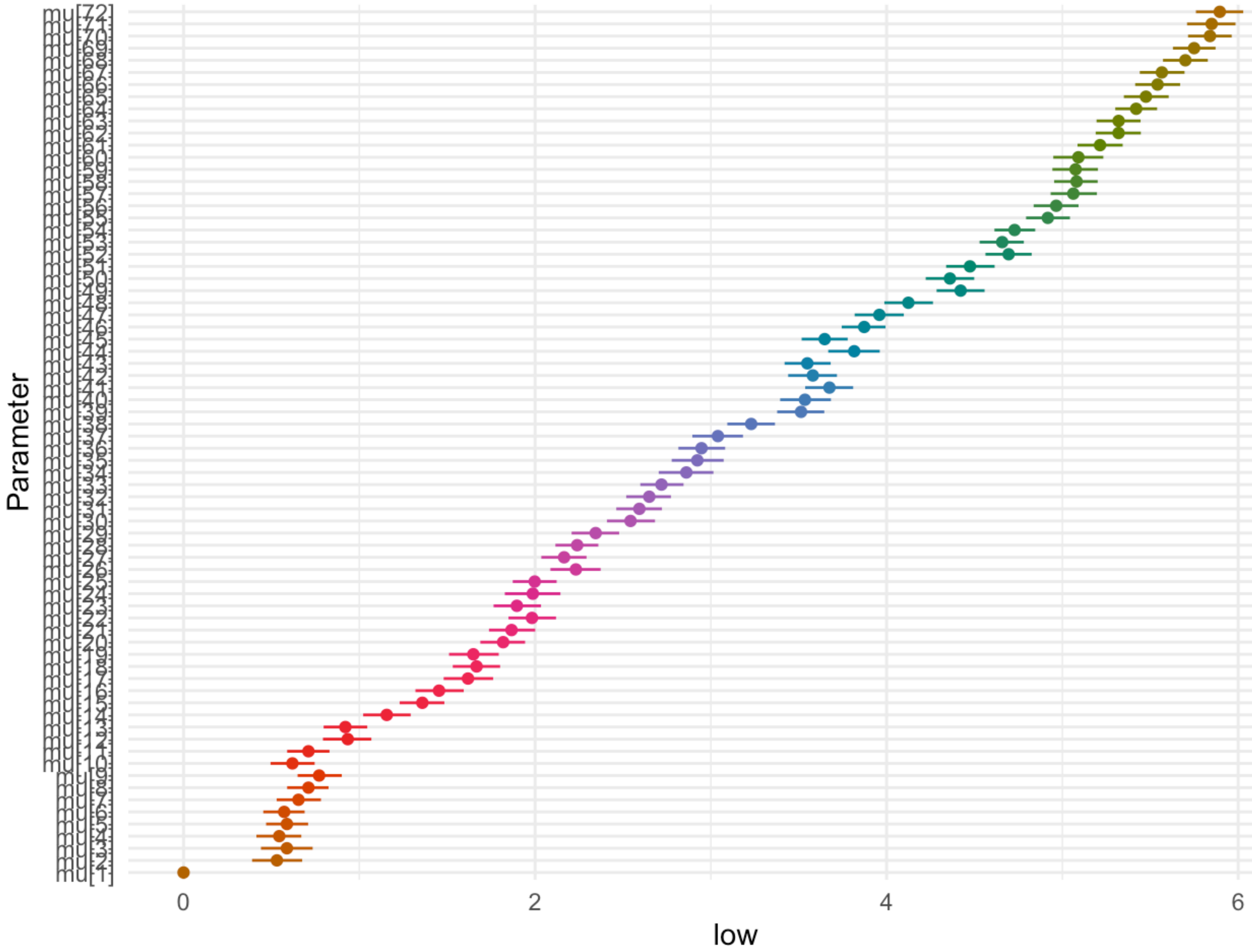
It appears swaps occur for the nearest neighbouring stimuli.



Bonus slide #3 – latent representation of colour

We applied the same model to the memory reproduction task that used **colour stimuli**.

Each colour in the plot is what was shown in the experiment.



Bonus slide #4 – model selection?

There are a few theorised working memory models – memory + guess, memory + swap, memory + swap + guess.

A current project is to figure out how to rigorously conduct model comparison and **select** the most likely model across various datasets.