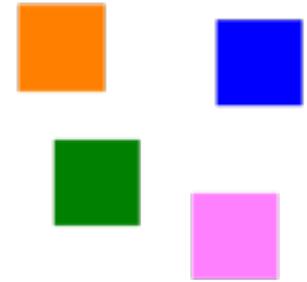


# *The whole report on visual working memory capacity*

*Dr William Xiang Quan Ngiam (he/him)  
for the UNSW Psychology Colloquium*



# Acknowledgement of Land and Country

- I want to recognize that at the University of Chicago, we inhabit, study, and work in the land of the Potawatomi, Miami, Peoria, and Kickapoo People.
- I want to pay respect to the Bedegal and Gadigal people of the Eora nation who are the Custodians of the lands on which the University of New South Wales is built.

# Thank you to my collaborators



Joshua Foster



Kirsten Adam



Krystian Loetscher



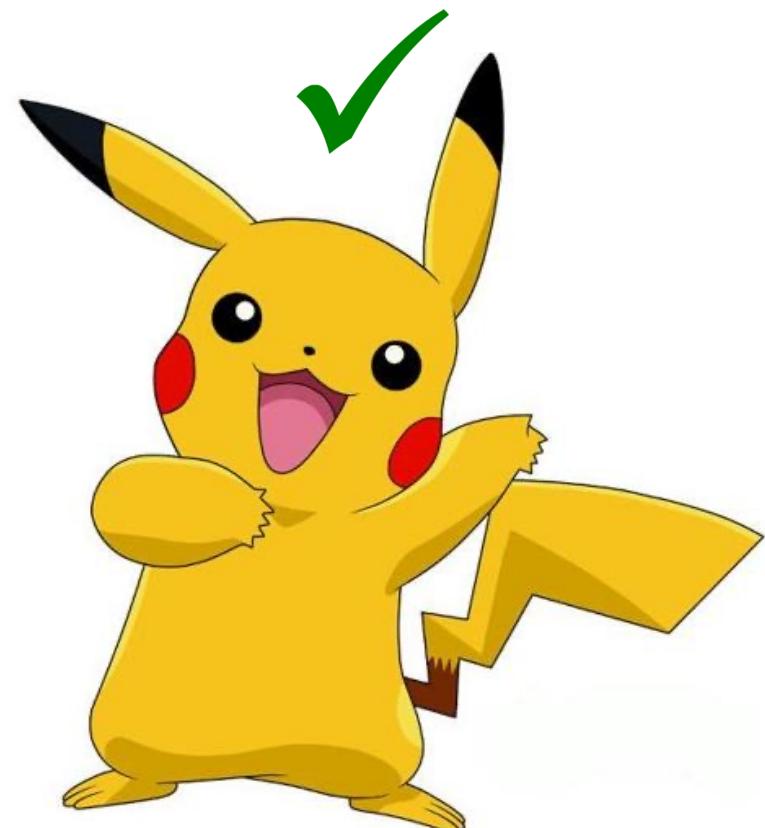
Ed Awh

# Memory is fascinating

- Our capacity for remembering information is **incredible**
- Some current memory world records:
  - **70,000** decimal places of Pi memorized by Rajveer Meena
  - **48** simultaneous blindfolded chess games by Timur Gareyev
  - **410** random words in sequence memorized in 15 minutes by Emma Alam

# Memory is fascinating

- Our capacity for remembering information is **fallible**



# Memory is fascinating

- Our capacity for remembering information is **fallible**



# What is visual working memory?

- The store for visual information that is actively being retained for ongoing cognition and perception
  - What you might be keeping '*in your mind's eye*'

# Can you find what is changing?



Genetic Science Learning Center, University of Utah. (2016, January 4) Memory demos. Retrieved January 30, 2022, from <https://learn.genetics.utah.edu/content/memory/demos/>

# Can you find what is changing?

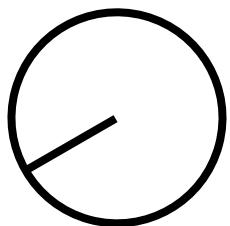
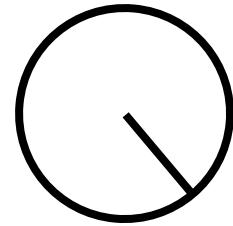
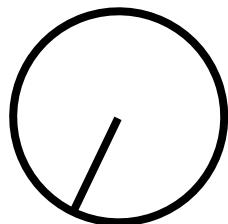
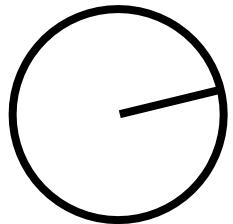
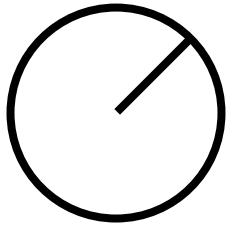
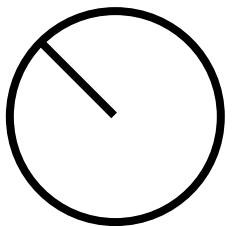


# What is visual working memory?

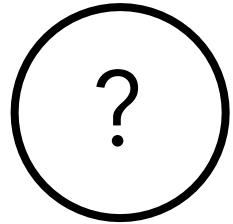
- The store for visual information that is **actively** being retained for ongoing cognition and perception
  - What you might be keeping '*in your mind's eye*'
- Despite our perceptual experience **feeling** full of detail, our online memory for visual information is **limited**
- While researchers agree it is limited, what gives rise to this sharp limit has been debated for decades

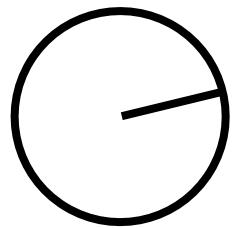
# Visual working memory capacity is item-based

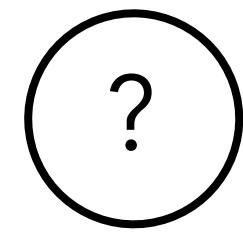
1. Because we **guess** beyond this item limit
2. Because there is an **object-based benefit of storage**

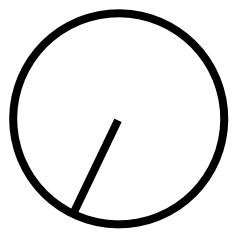


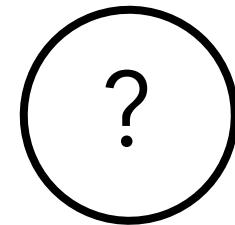


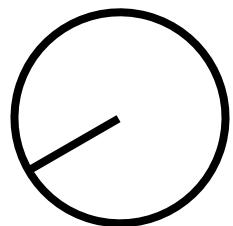
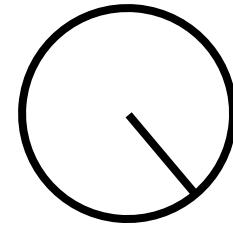
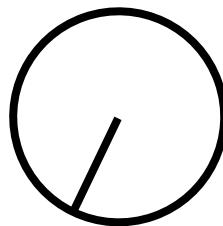
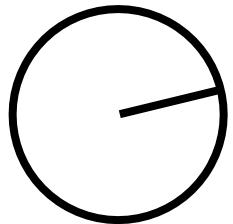
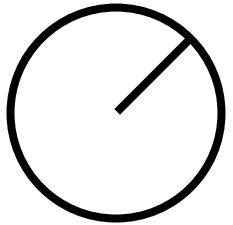
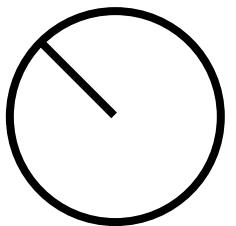






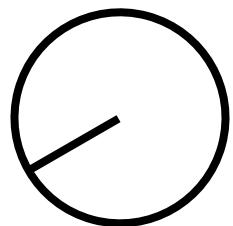
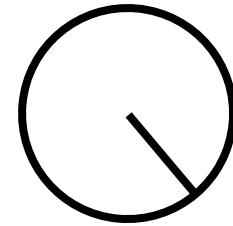
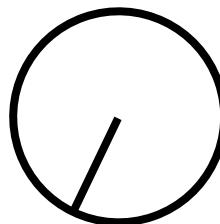
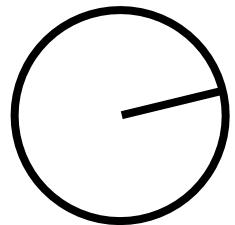
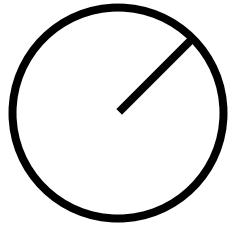
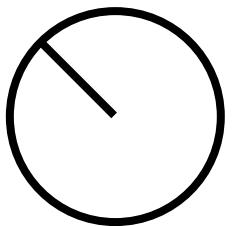




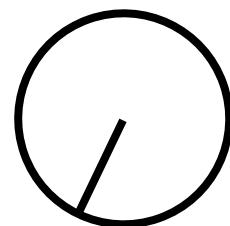
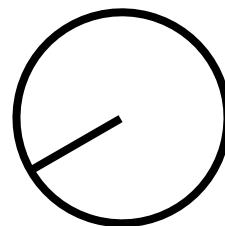
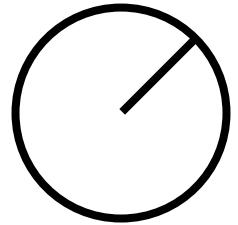


# The competing models

- Item-limit models (previously *slot models*)
  - Memory is contained to a few objects
  - There is no memory for objects beyond this capacity limit
- Variable precision models (previously *flexible resource models*)
  - Memory is distributed across all items
  - There is flexible allocation of mnemonic resources to all items
    - More allocation of resources leads to a higher fidelity memory representation



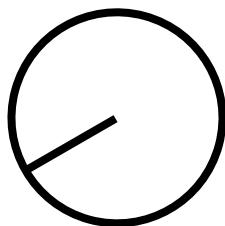
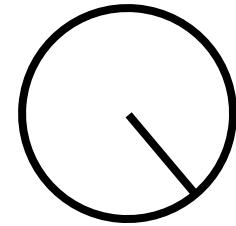
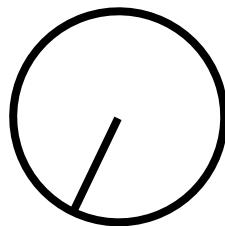
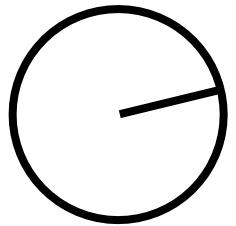
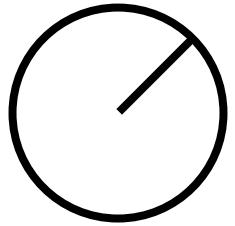
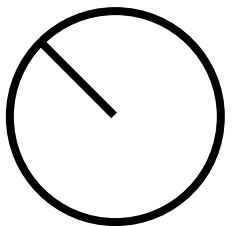




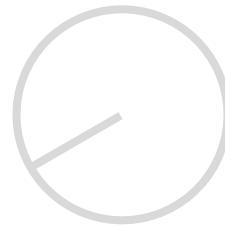
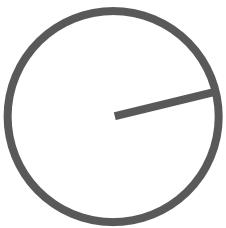
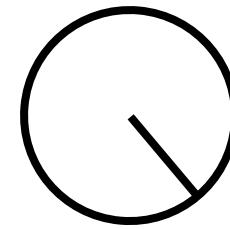
# The competing models

- Item-limit models (previously *slot models*)
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  - Memory is **distributed across all items**
  - There is **flexible allocation** of mnemonic resources to all items
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NB. An item limit is not mutually exclusive with a variable precision process (more on this later).

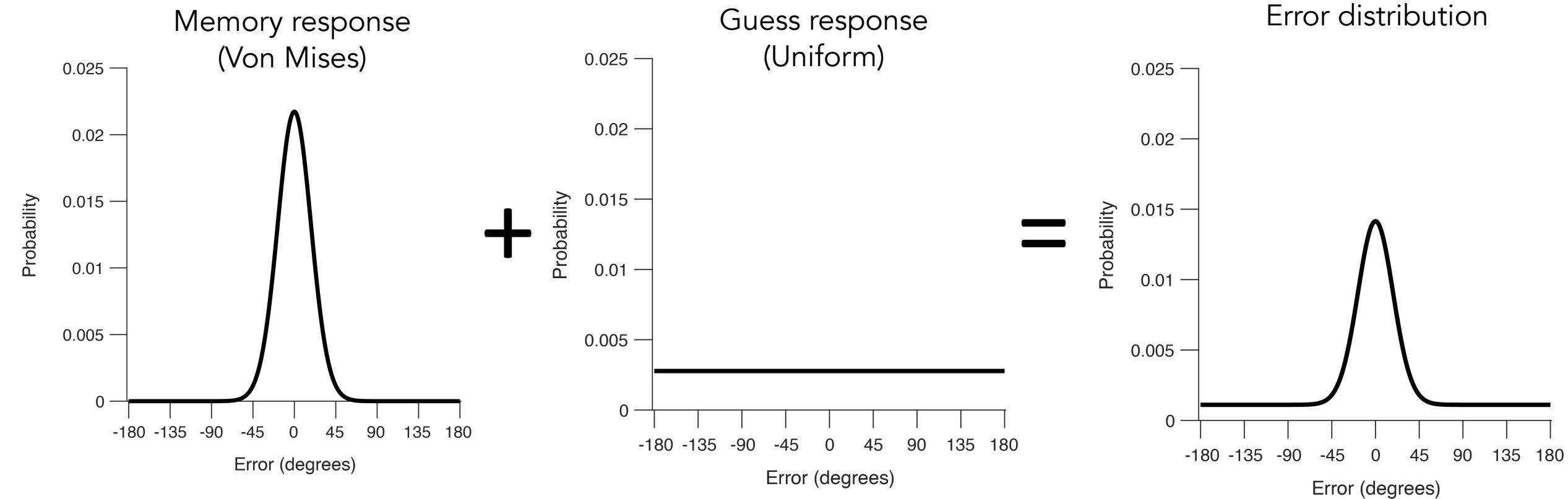






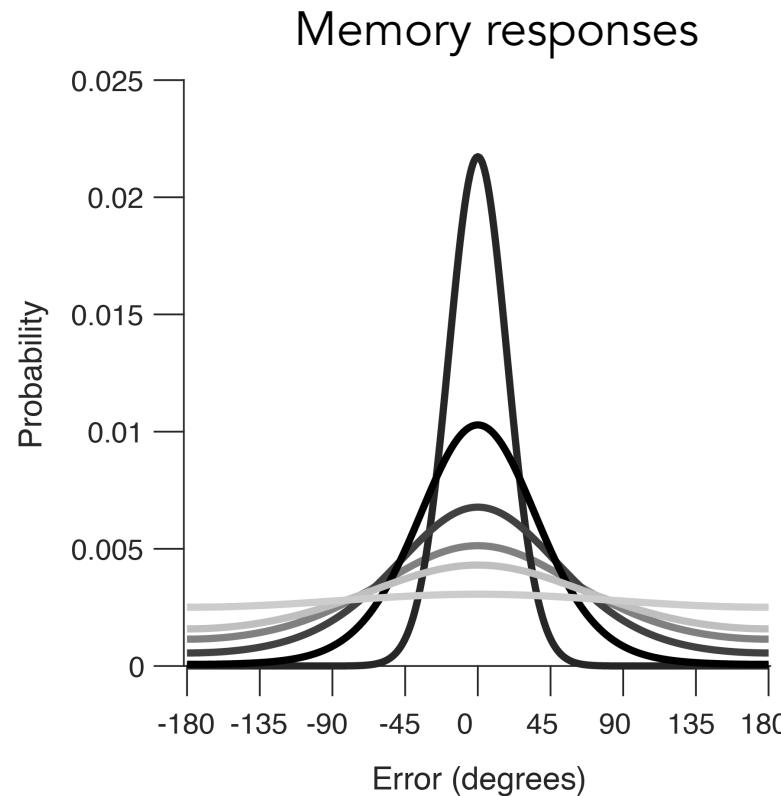
# Formal models

- Item-limit models (Zhang and Luck, 2008)

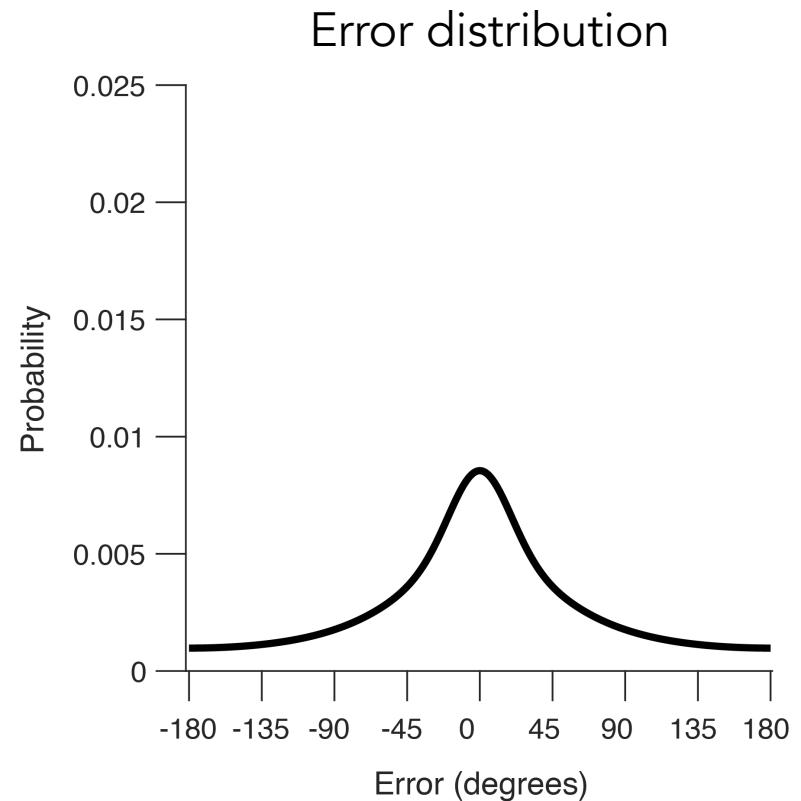


# Formal models

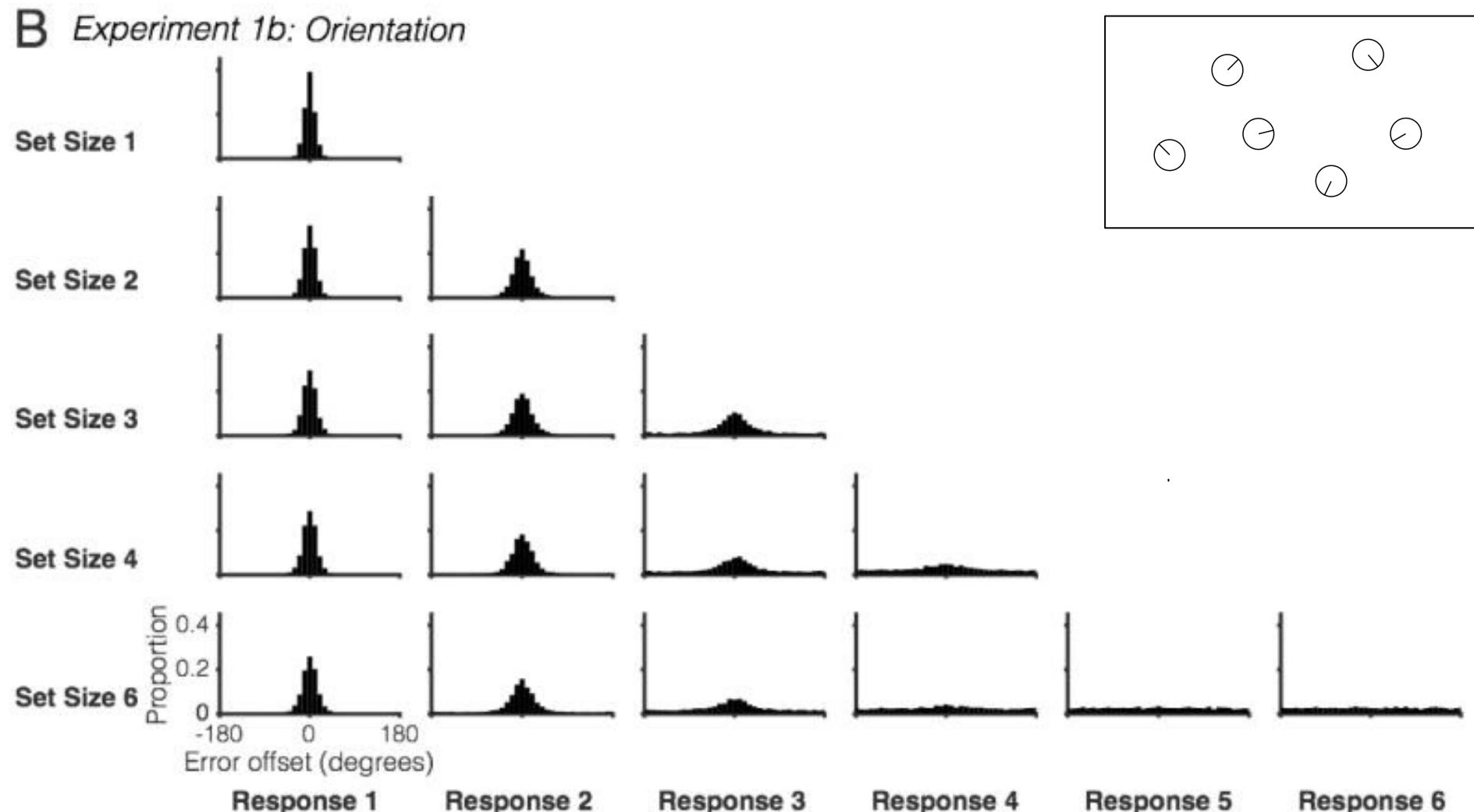
- Variable precision models (van den Berg et al., 2012)



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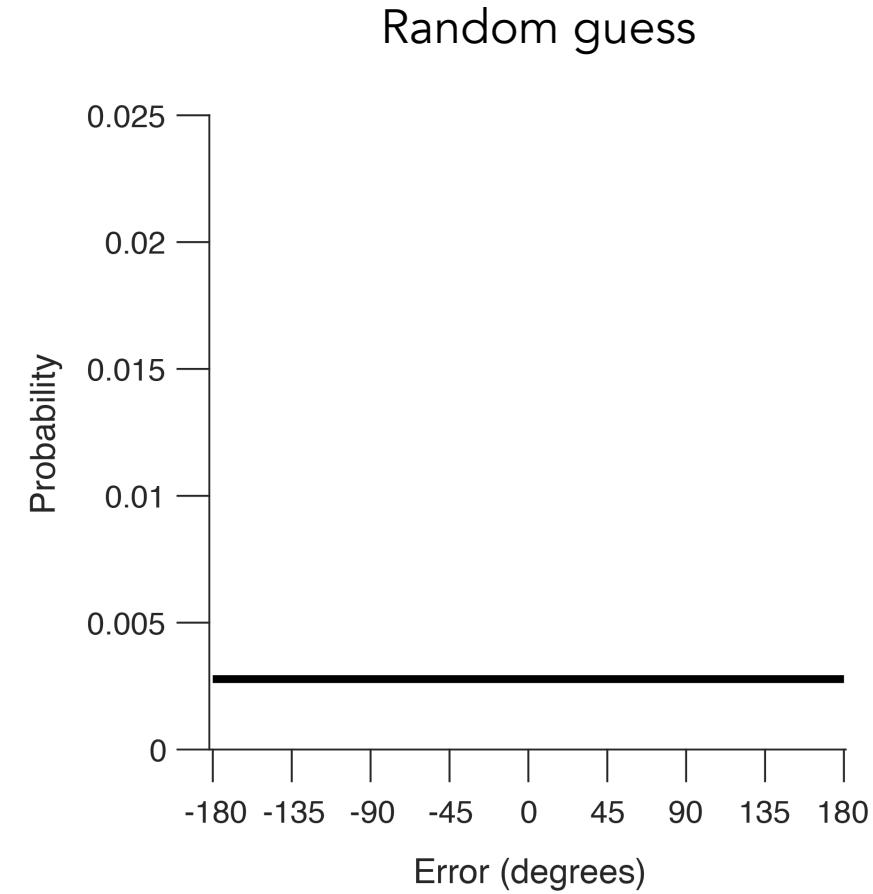
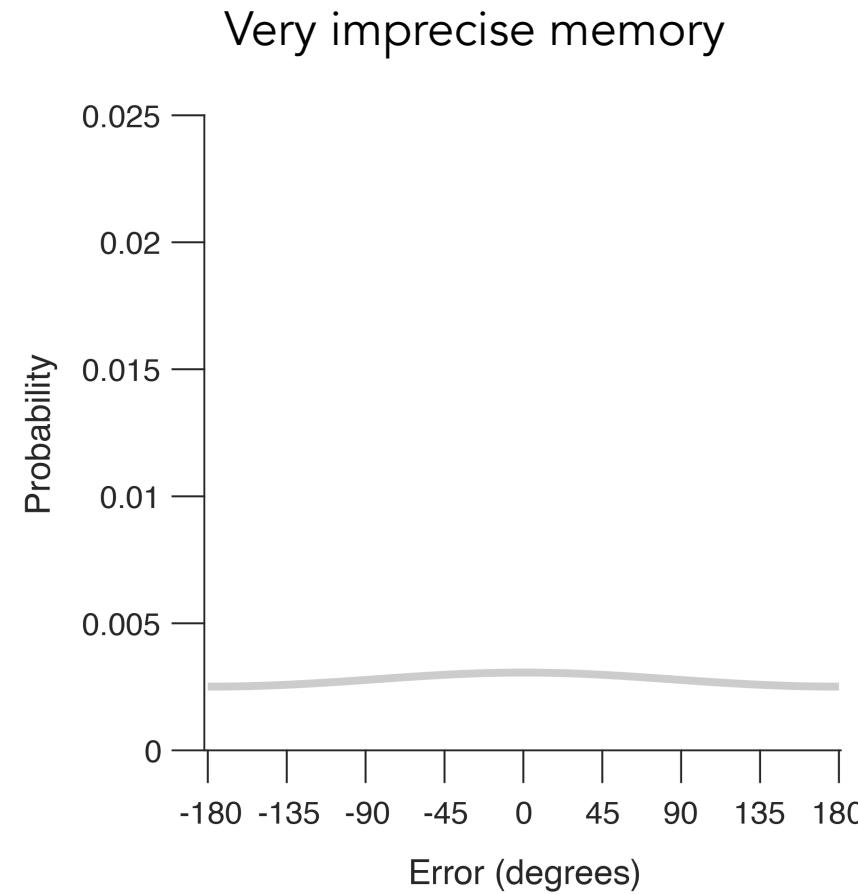


# Whole-report recall task

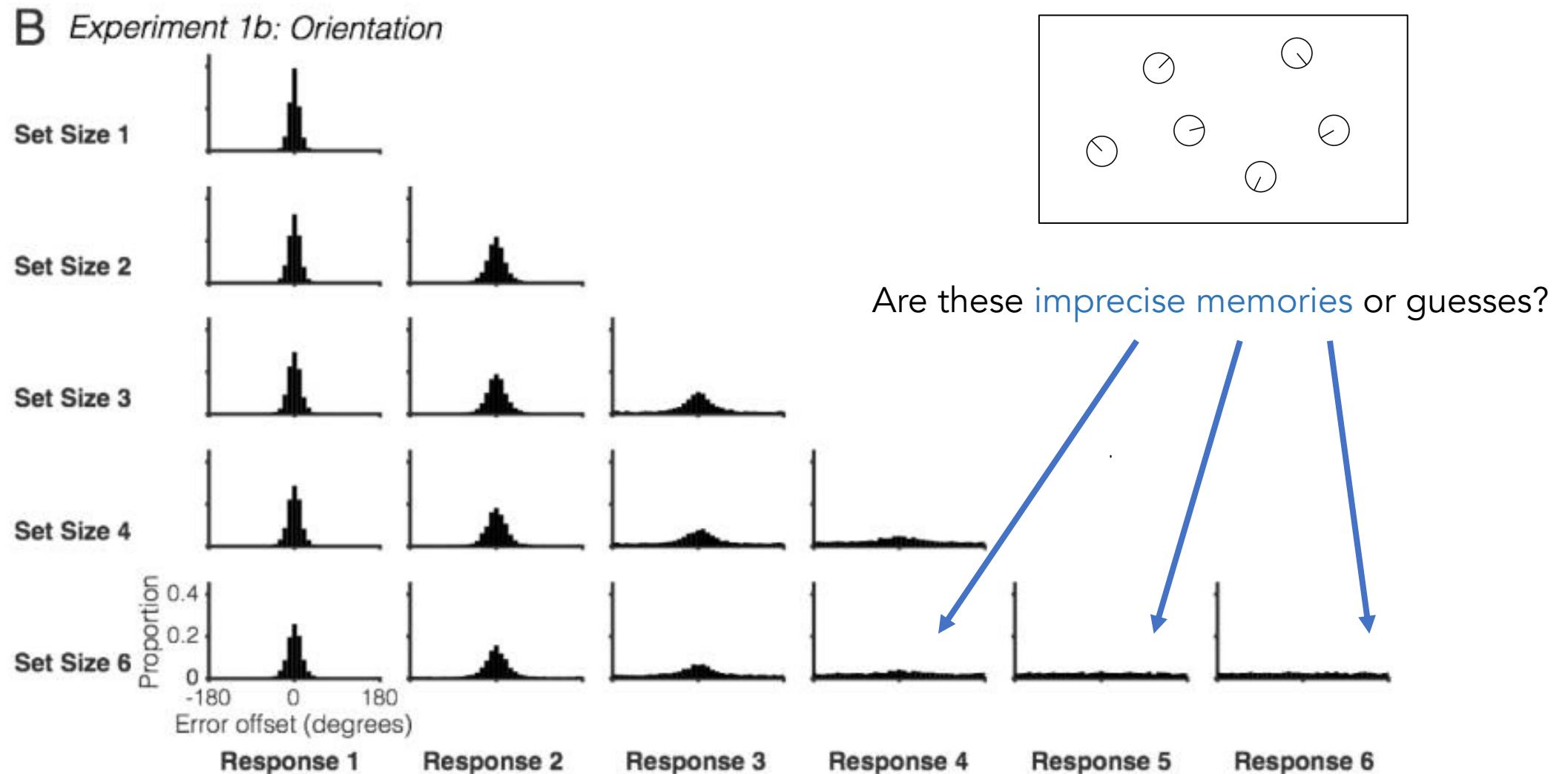


# The issue

- A very imprecise memory response can **mimic** a random guess



# The issue

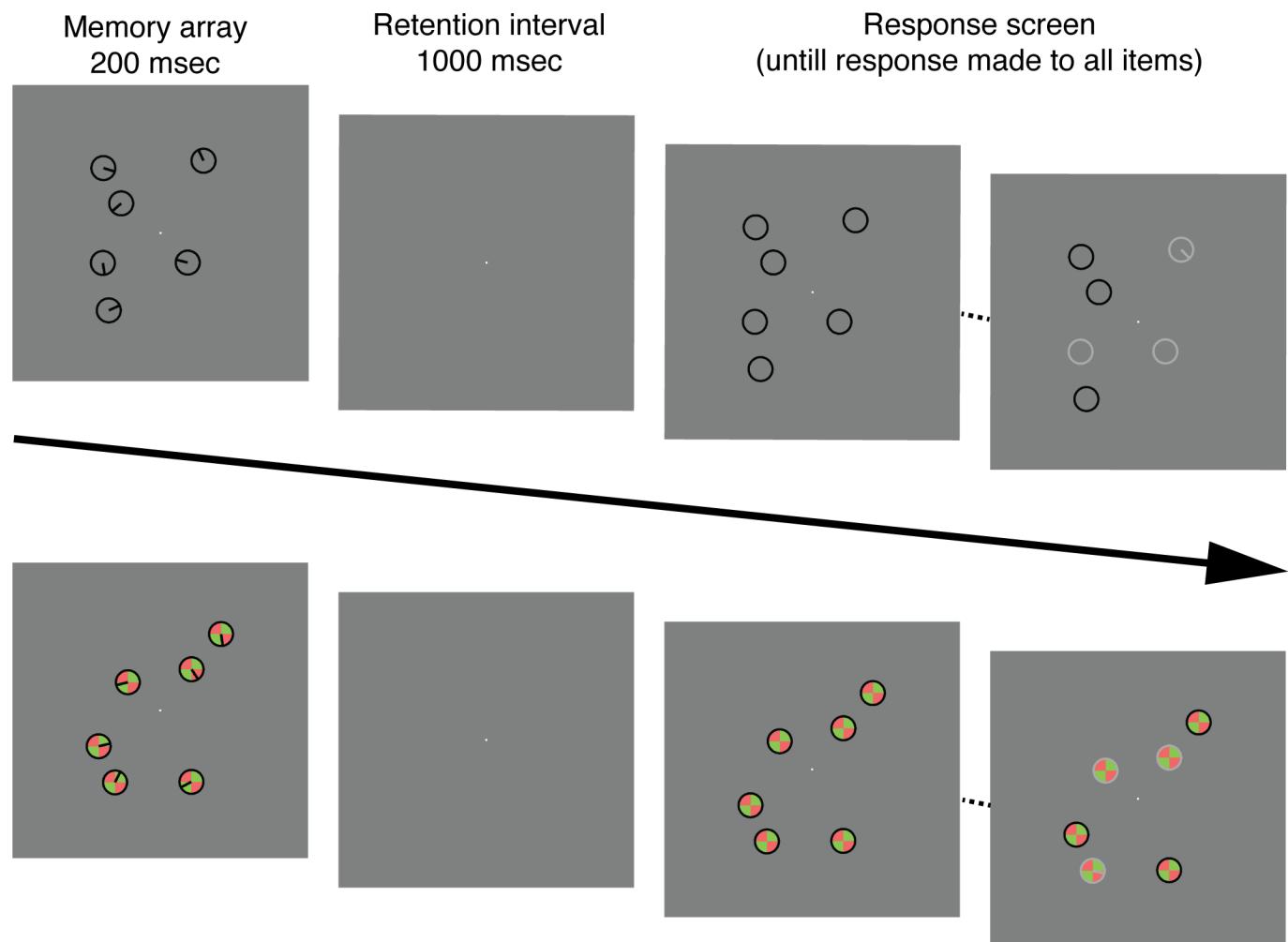


# Our solution

- Create an experimental paradigm where guesses are **distinct** from imprecise memories
  - Have guesses produce a **different distribution** to a uniform distribution

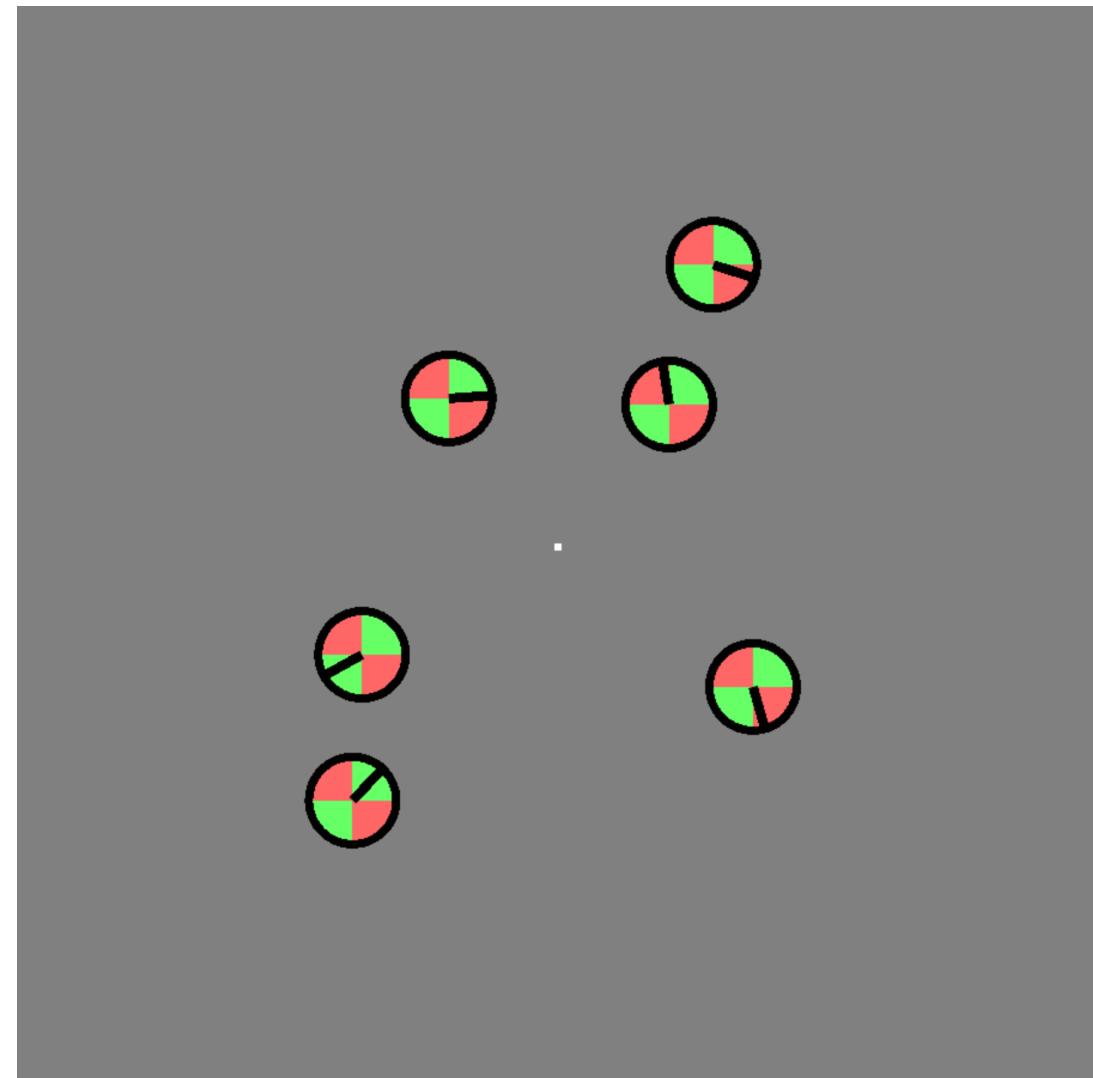
# Experiment design

- Whole-report of six orientations
  - Experiment 1 ( $n = 40$ )
    - 120 trials with coloured quadrant backgrounds
    - 80 trials with no background
  - Experiment 2 ( $n = 30$ )
    - 160 trials with the coloured quadrant background rotated 45 degrees



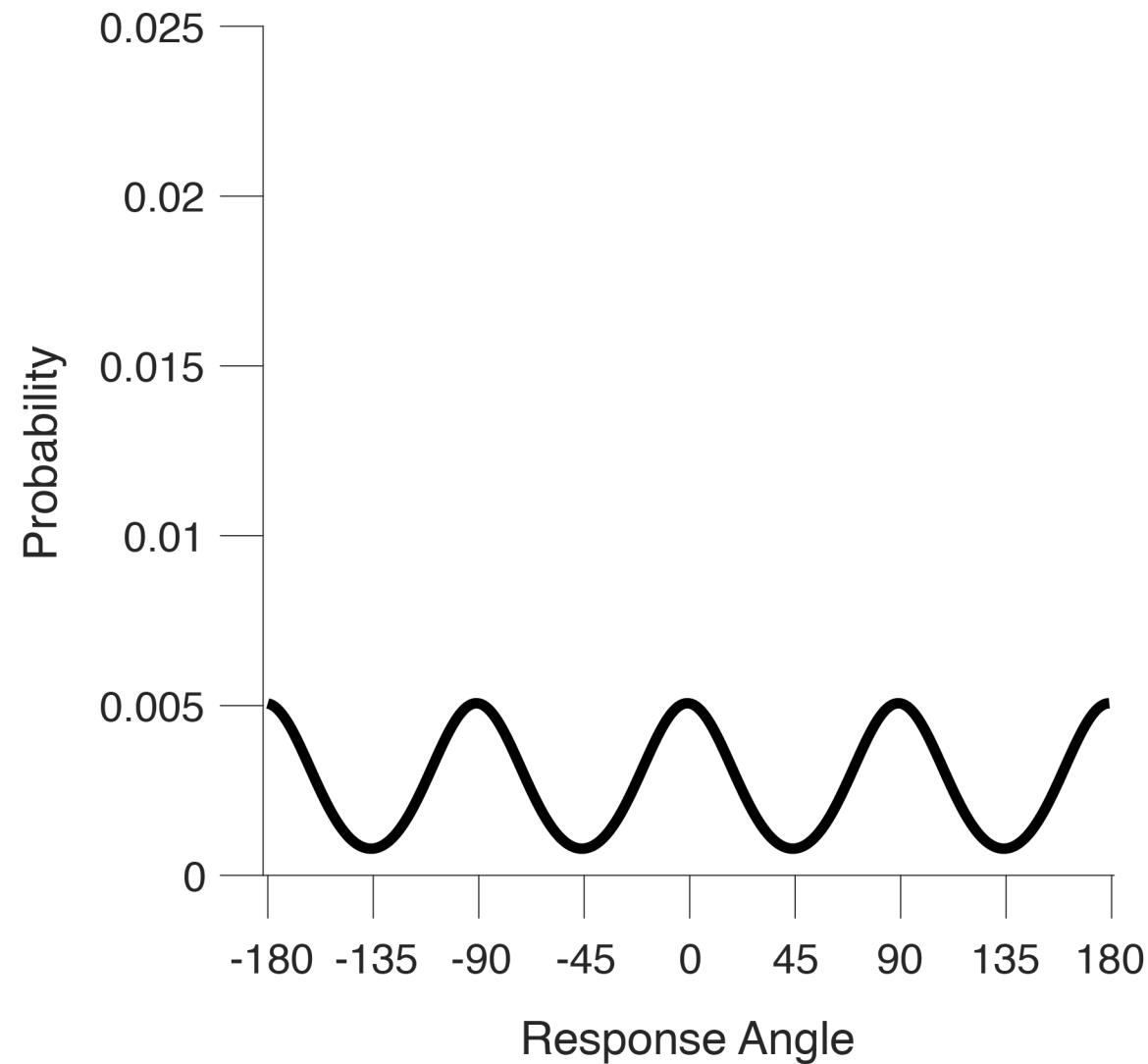
# What will **guesses** look like?

- We expect participants to respond towards **the middle of the colored quadrants**
- A response that is **independent** to the presented angle

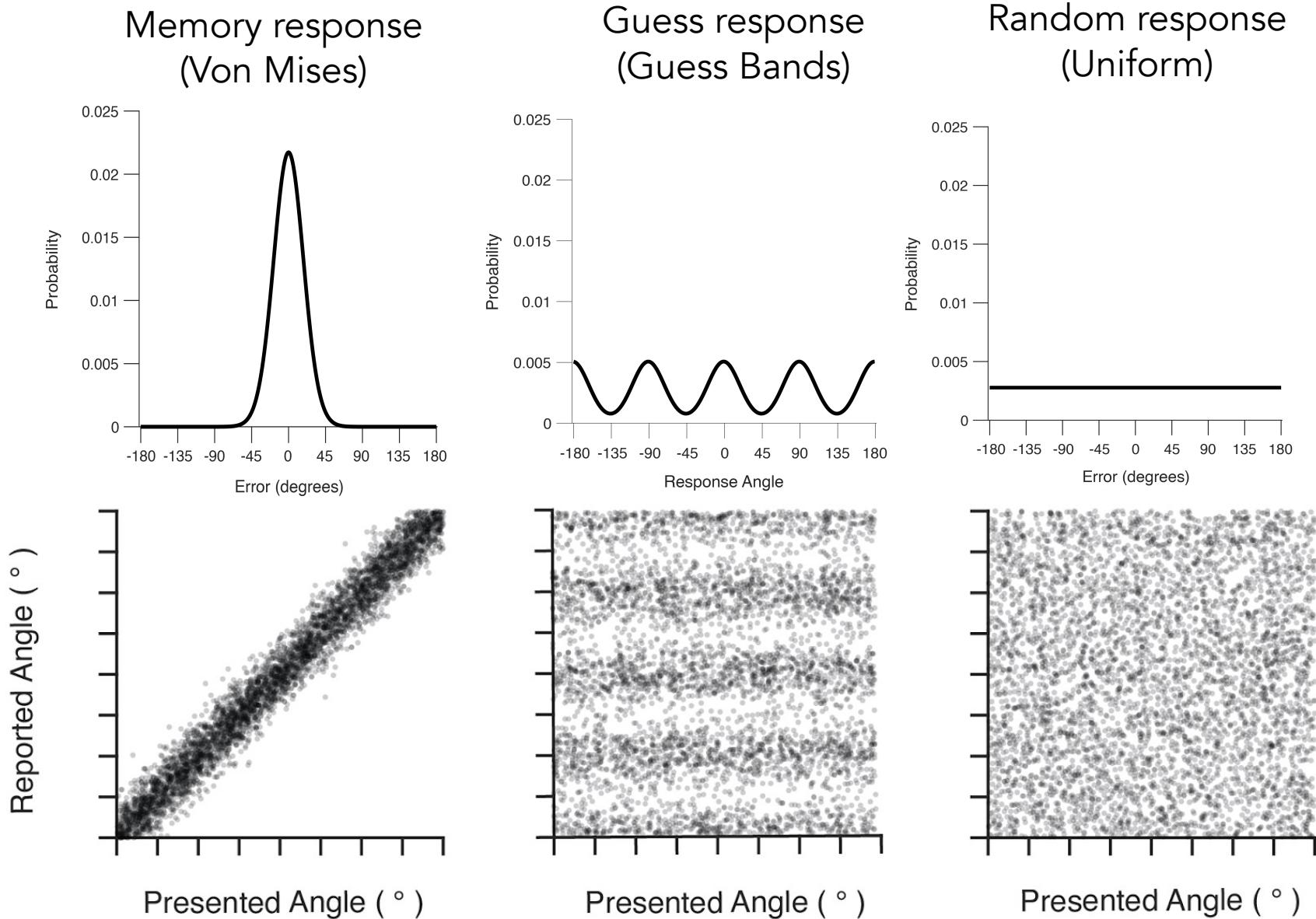


# What should guesses look like?

- We expect participants to respond towards **the middle of the colored quadrants**
- Probability distribution is **clearly distinguishable** from a wide Von Mises distribution
- A response that cannot be explained by an **imprecise memory**

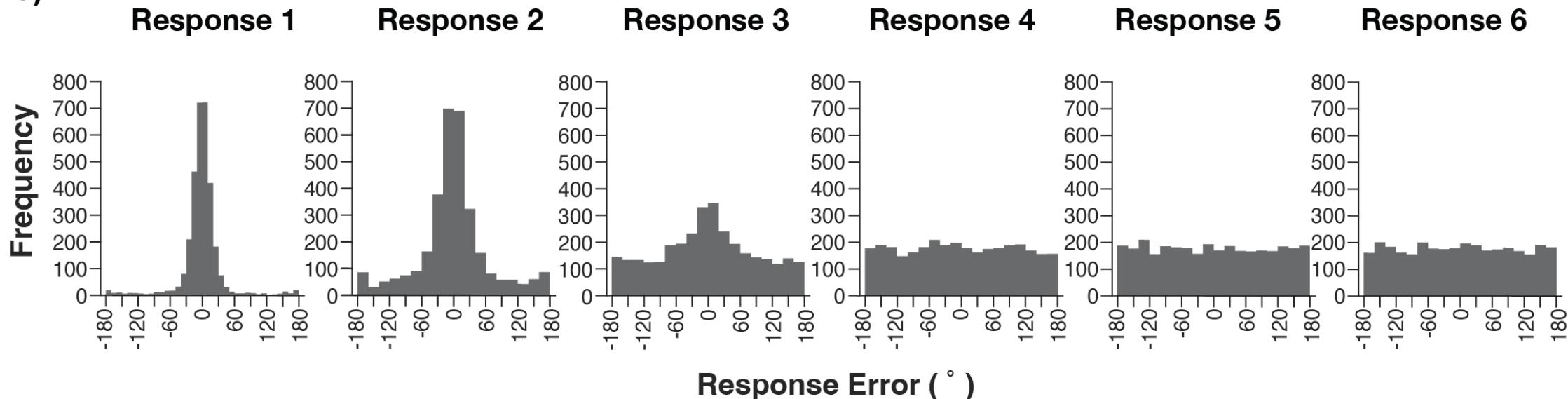


# What we predict we will observe

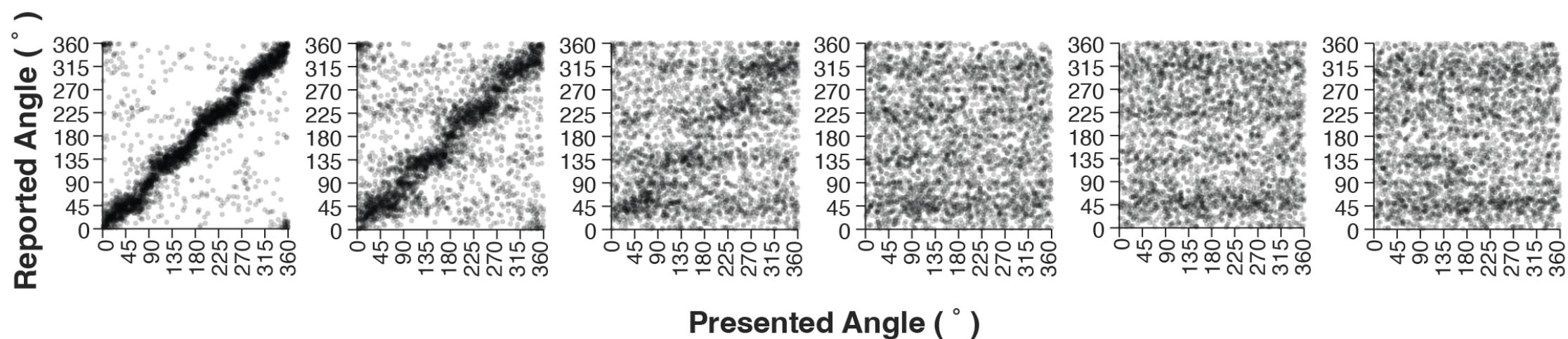


# Experiment 1 Results – Standard condition

a)

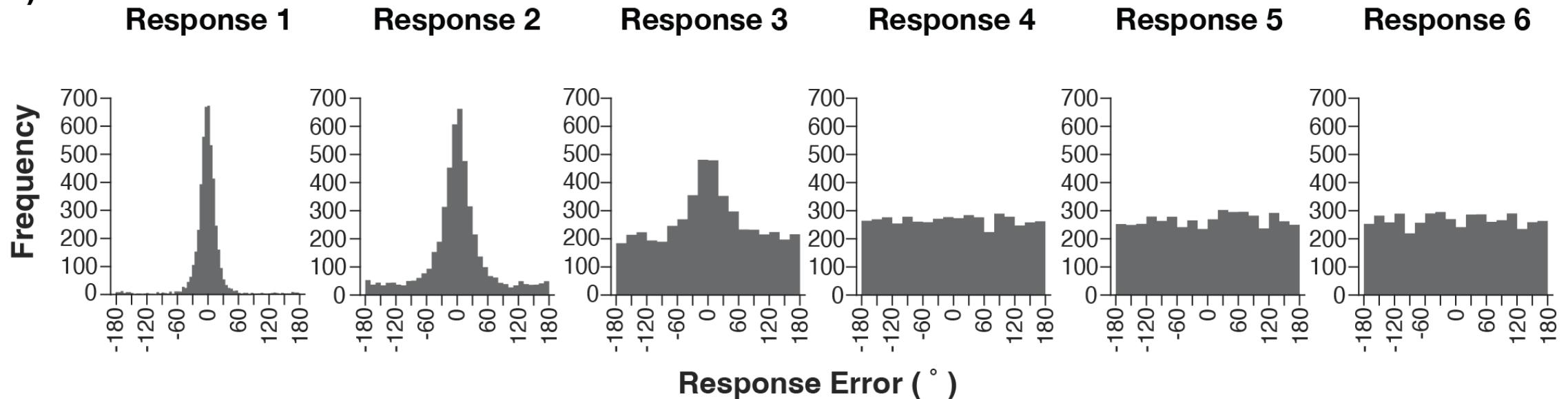


b)

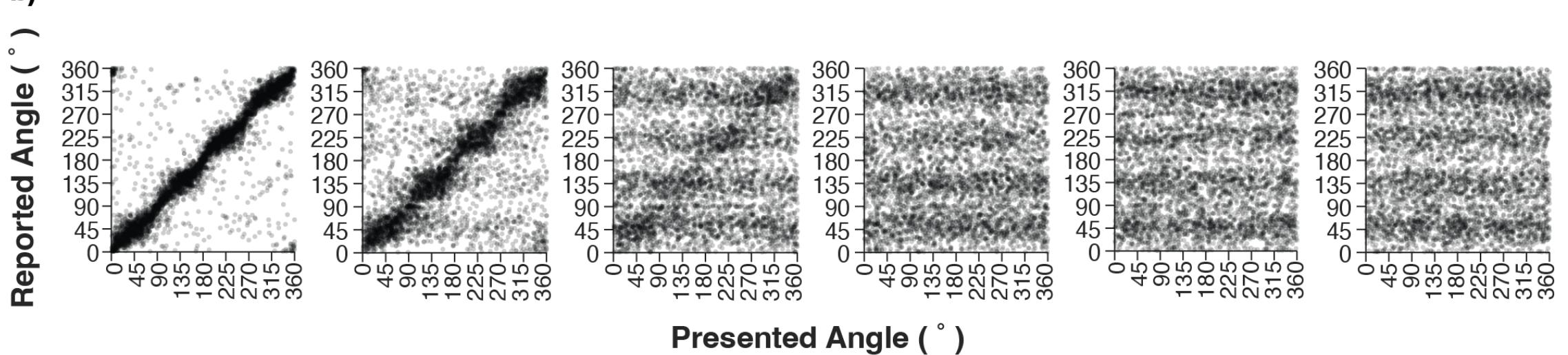


# Experiment 1 Results – Background condition

a)

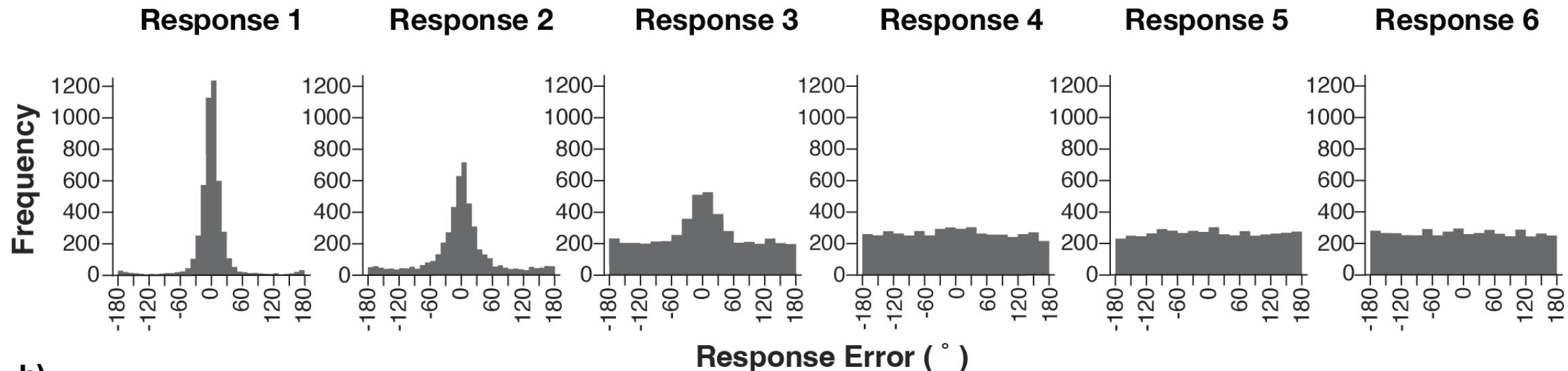


b)

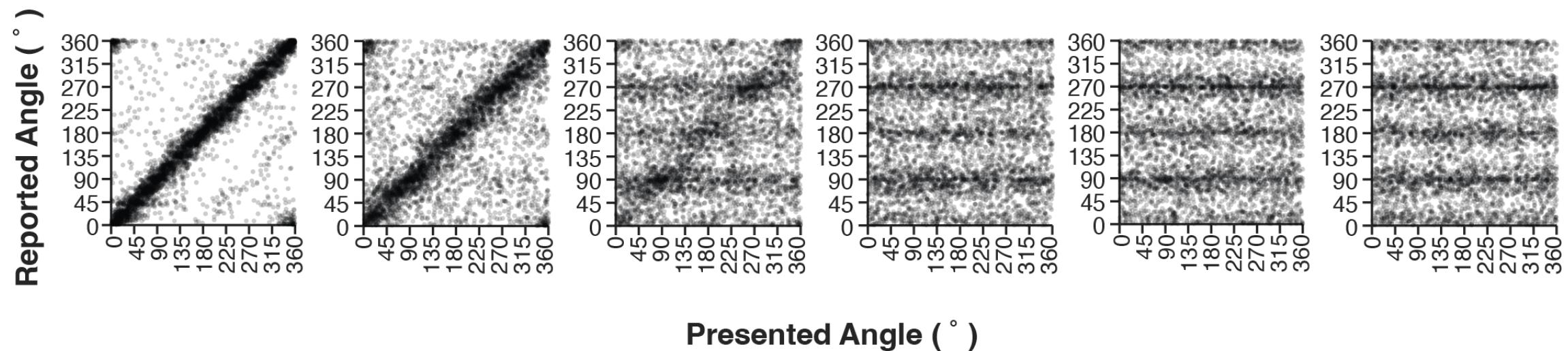


# Experiment 2 Results

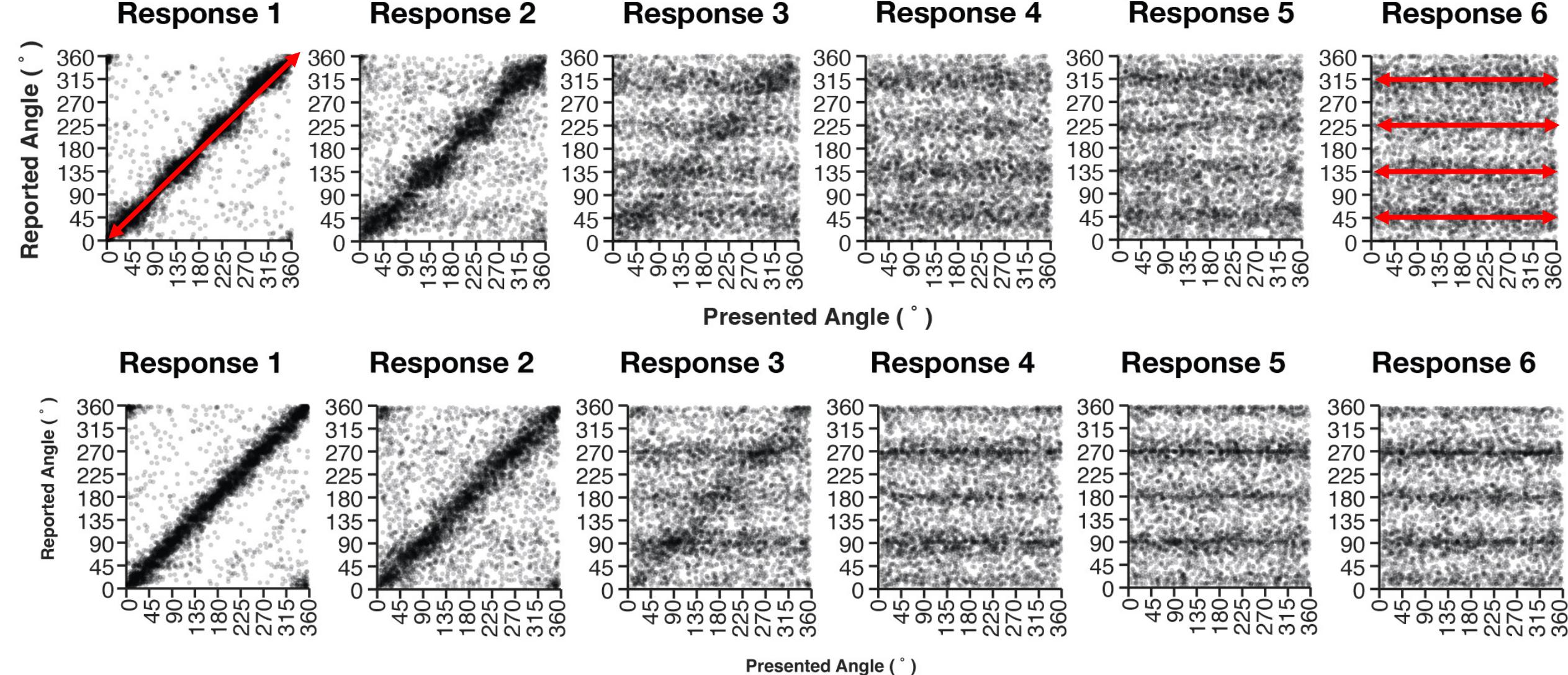
a)



b)

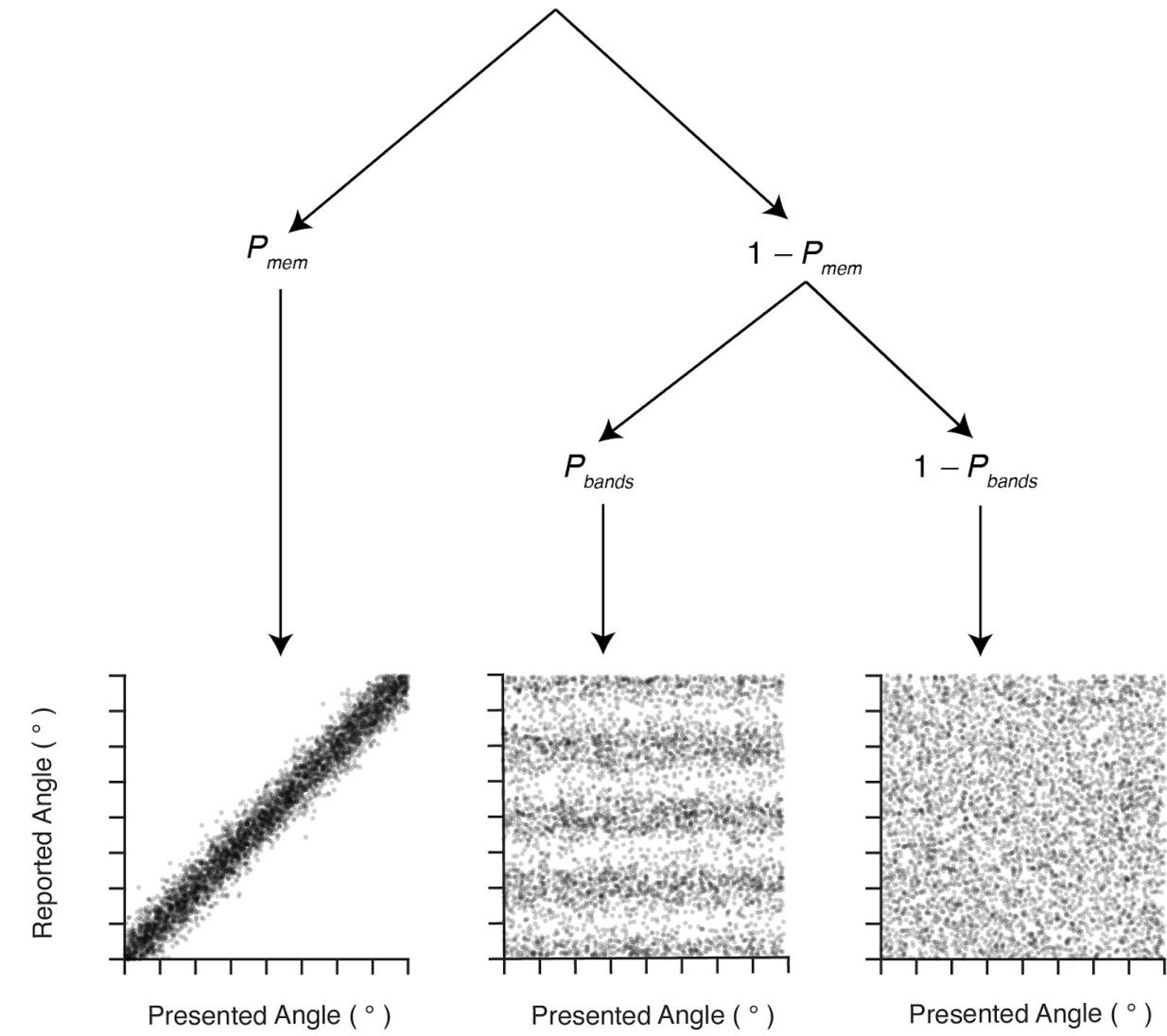


# Clear visual evidence for 'guess bands'



# Maximum likelihood estimation

- Assume a probability of every possible response with given parameter estimates (**a probability distribution**)
- Calculate the “summed probability” for the observed pattern of data
- Find the parameter estimates that give the highest total probability (**maximum likelihood**)
- That’s your best-fitting model!

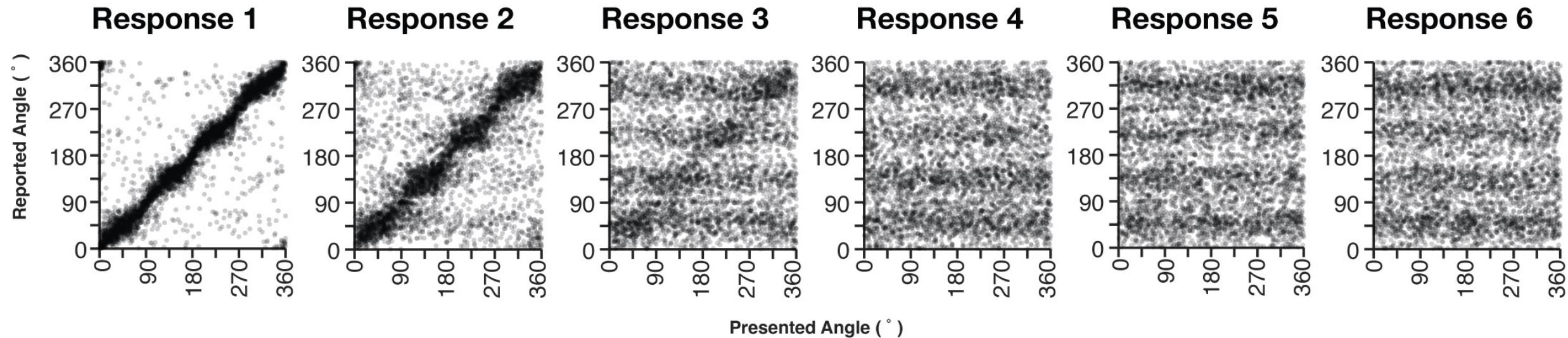


# Model comparison

- Maximum likelihood estimation of the parameters for models with each possible permutation of the components:
  - Von Mises (a memory response)
    - Width of the Von Mises was a free parameter
  - Bands (a guess response)
    - Width of the bands was a free parameter
  - Uniform (a random response)
- 100 replicates with a maximum of 10000 iterations
  - Compared on the Bayesian Information Criterion (BIC)

# Experiment 1 model comparison

- At the aggregate level:
  - For the first three responses, Von Mises + Guess Bands was the best-fitting model ( $\Delta\text{BIC} < 9$ ).
  - For the last three responses, Von Mises + Guess Bands + Uniform was the best-fitting model ( $\Delta\text{BIC} > 57$ )



# Estimated prevalence of responses

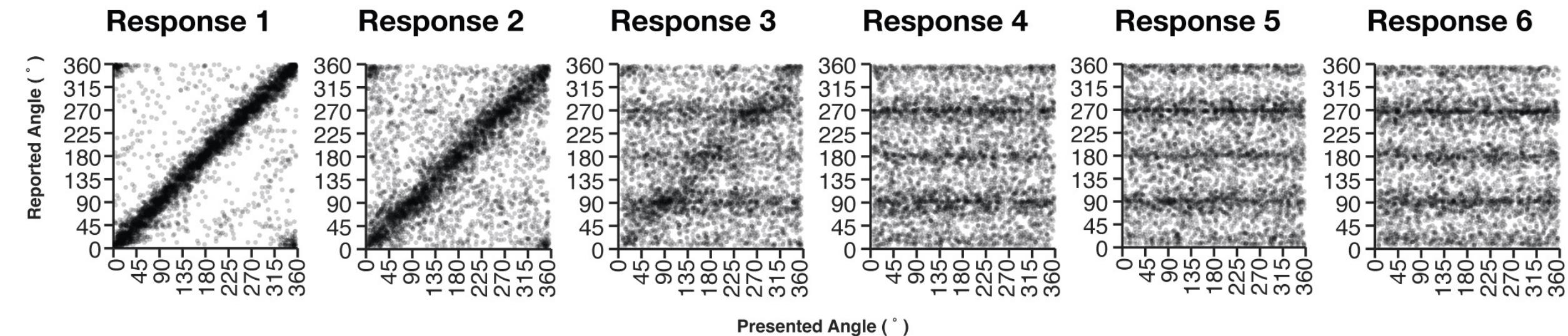
- Parameter estimates from Von Mises + Guess Bands + Uniform model

Response	Memory	Guess Bands	Uniform
1st	$90.59\% \pm 0.57\%$	$9.41\% \pm 1.15\%$	$0\% \pm 0.58\%$
2nd	$66.03\% \pm 1.68\%$	$33.97\% \pm 2.20\%$	$0\% \pm 0.52\%$
3rd	$20.37\% \pm 0.63\%$	$46.64\% \pm 12.16\%$	$32.99\% \pm 11.53\%$
4th	$0.19\% \pm 0.09\%$	$41.96\% \pm 8.29\%$	$57.85\% \pm 8.20\%$
5th	$0.30\% \pm 0.12\%$	$35.78\% \pm 4.53\%$	$63.92\% \pm 4.41\%$
6th	$0.39\% \pm 0.12\%$	$39.12\% \pm 6.25\%$	$60.49\% \pm 6.13\%$

- Memory responses are constrained to the first three responses
- Substantial prevalence of 'guess band' responses in later responses

# Experiment 2 model comparison

- At the aggregate level:
  - For the **first response**, **Von Mises + Uniform** was the best-fitting model ( $\Delta\text{BIC} = 8$ ).
  - For the **last four responses**, **Von Mises + Guess Bands + Uniform** was the best-fitting model ( $\Delta\text{BIC} > 24$  from 3<sup>rd</sup> response onward)



# Estimated prevalence of responses

- Parameter estimates from Von Mises + Guess Bands + Uniform model

Response	Memory	Guess Bands	Uniform
1st	$87.84\% \pm 0.00\%$	$0.64\% \pm 0.00\%$	$11.52\% \pm 0.00\%$
2nd	$64.13\% \pm 1.18\%$	$2.08\% \pm 0.90\%$	$33.79\% \pm 2.08\%$
3rd	$21.07\% \pm 0.61\%$	$37.26\% \pm 6.25\%$	$41.67\% \pm 5.65\%$
4th	$0.31\% \pm 0.11\%$	$48.10\% \pm 6.02\%$	$51.59\% \pm 5.91\%$
5th	$0.21\% \pm 0.11\%$	$48.70\% \pm 4.70\%$	$51.09\% \pm 4.58\%$
6th	$0.25\% \pm 0.11\%$	$47.22\% \pm 4.35\%$	$52.53\% \pm 4.24\%$

- Memory responses are constrained to the first three responses
- Substantial prevalence of 'guess band' responses in later responses

# Formal model comparison on individual data

- Experiment 1
  - In early responses, the Von Mises + Uniform (M1) model best fits most participants' data
  - In later responses, the Guess Bands only (M4) model best fits most participants' data

	M1	M2	M3	M4	M5	M6
1st	28	-	-	-	10	2
2nd	19	-	1	2	18	-
3rd	14	-	1	2	13	-
4th	6	-	-	30	4	-
5th	5	2	2	25	6	-
6th	6	1	2	23	8	-

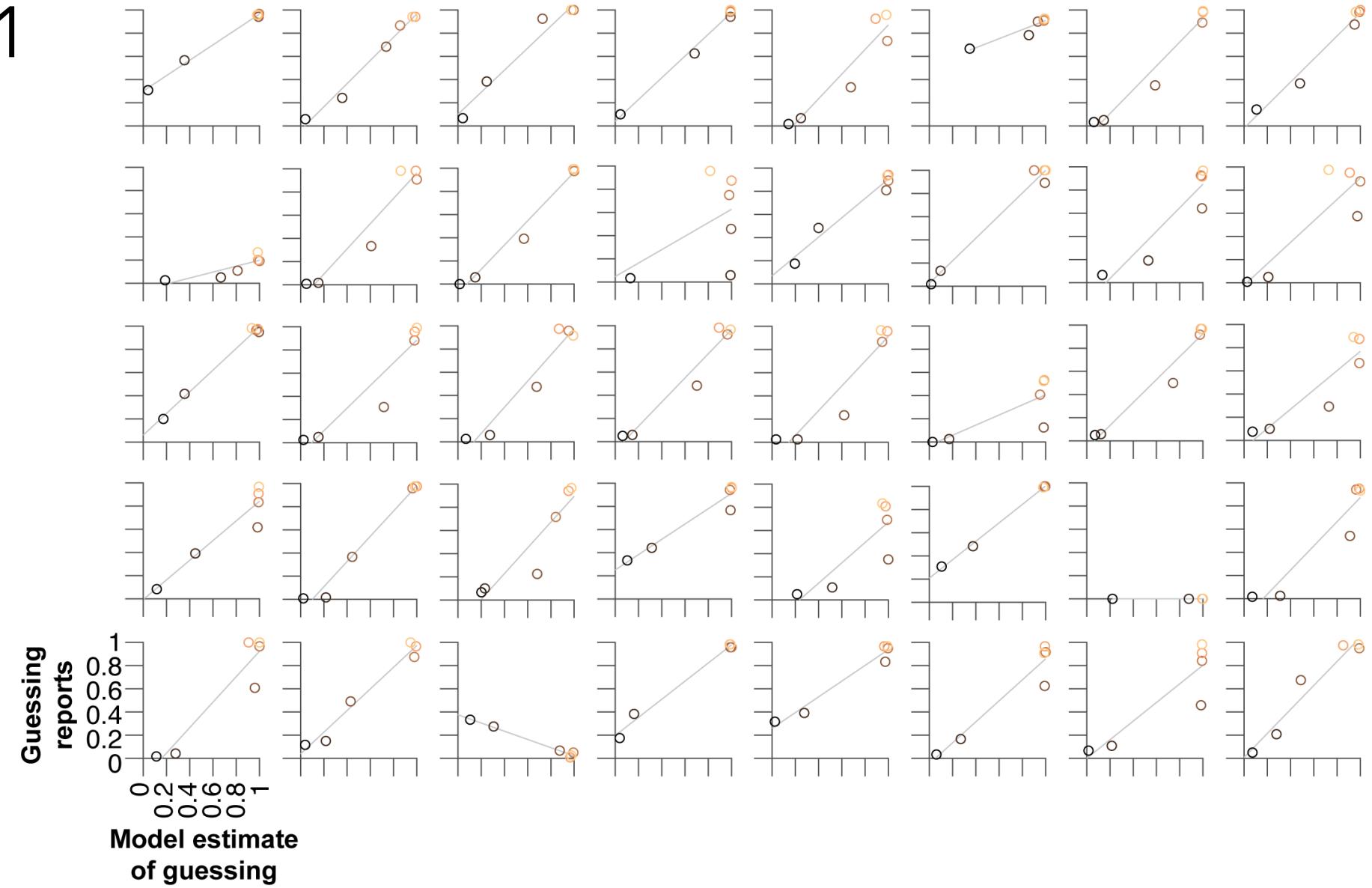
# Formal model comparison on individual data

- Experiment 2
  - In early responses, the Von Mises + Uniform (M1) model best fits most participants' data
  - In later responses, the Guess Bands only (M4) model best fits most participants' data

	M1	M2	M3	M4	M5	M6
1st	23	-	1	-	4	2
2nd	17	-	3	-	10	-
3rd	4	4	5	7	10	-
4th	4	7	5	9	5	-
5th	5	11	1	11	2	-
6th	1	5	3	16	5	-

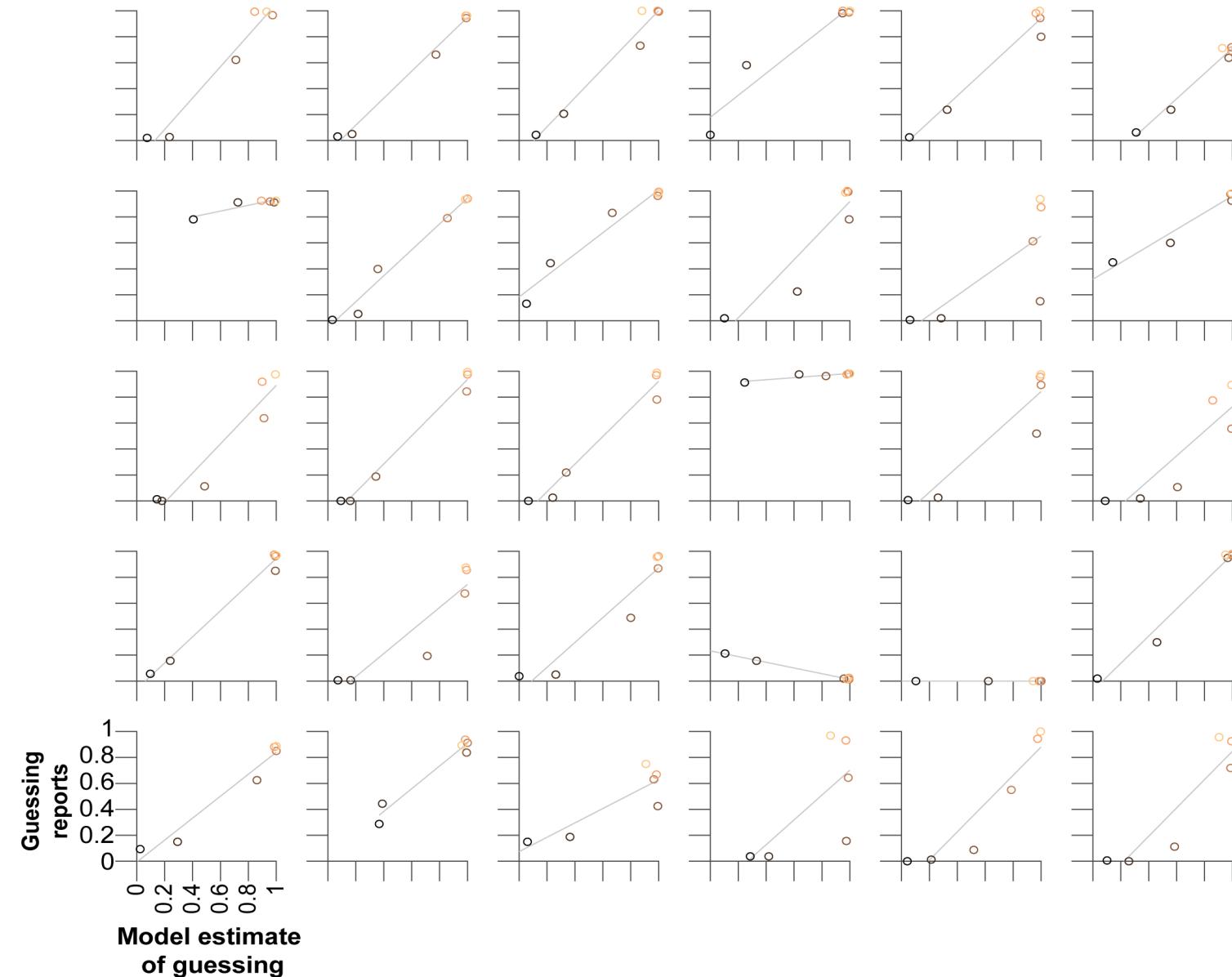
# Self-reports of guesses match model estimates

- Experiment 1  
(background condition)



# Self-reports of guesses match model estimates

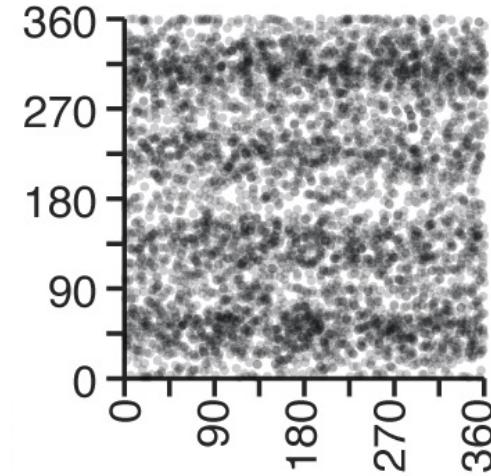
- Experiment 2



# Visual working memory capacity is item-based

1. Because we **guess** beyond this item limit

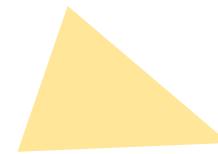
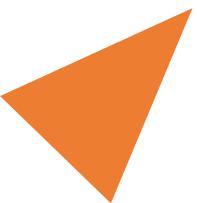
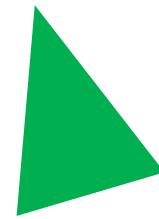
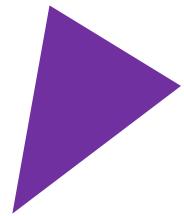
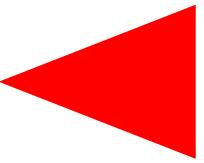
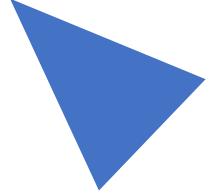
- Memory responses were constrained to the **first three responses**
- A substantial proportion of later responses produced '**guess bands**'
  - These responses cannot be attributed to imprecise memories



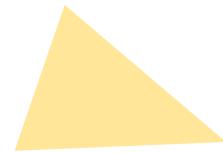
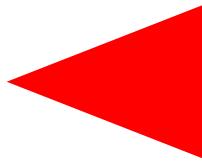
2. Because there is an object-based benefit of storage

But if there's an item-limit...

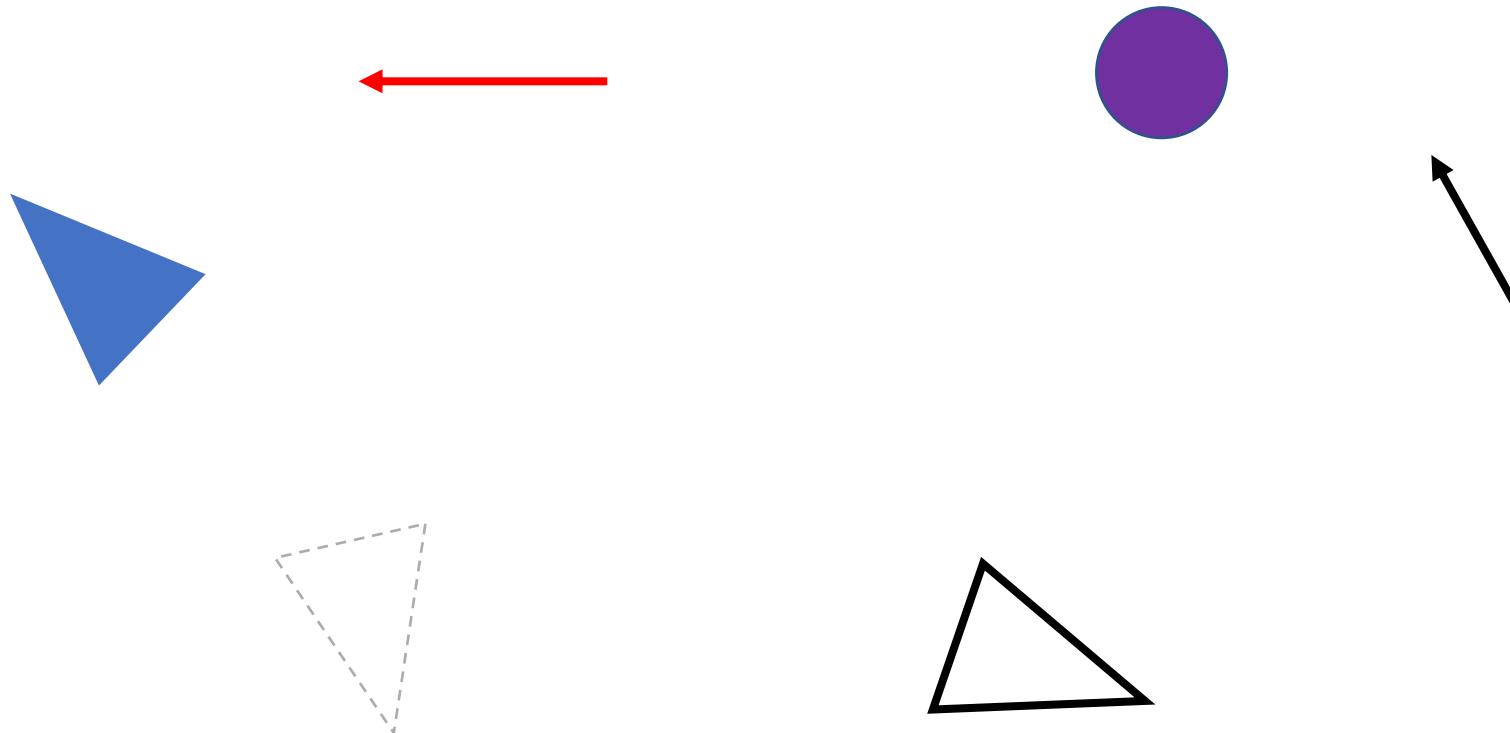
- Are there object-based representations?
  - Does the same observed item limit apply for objects with multiple features?
  - Or is there an additional cognitive resource devoted to feature bindings?



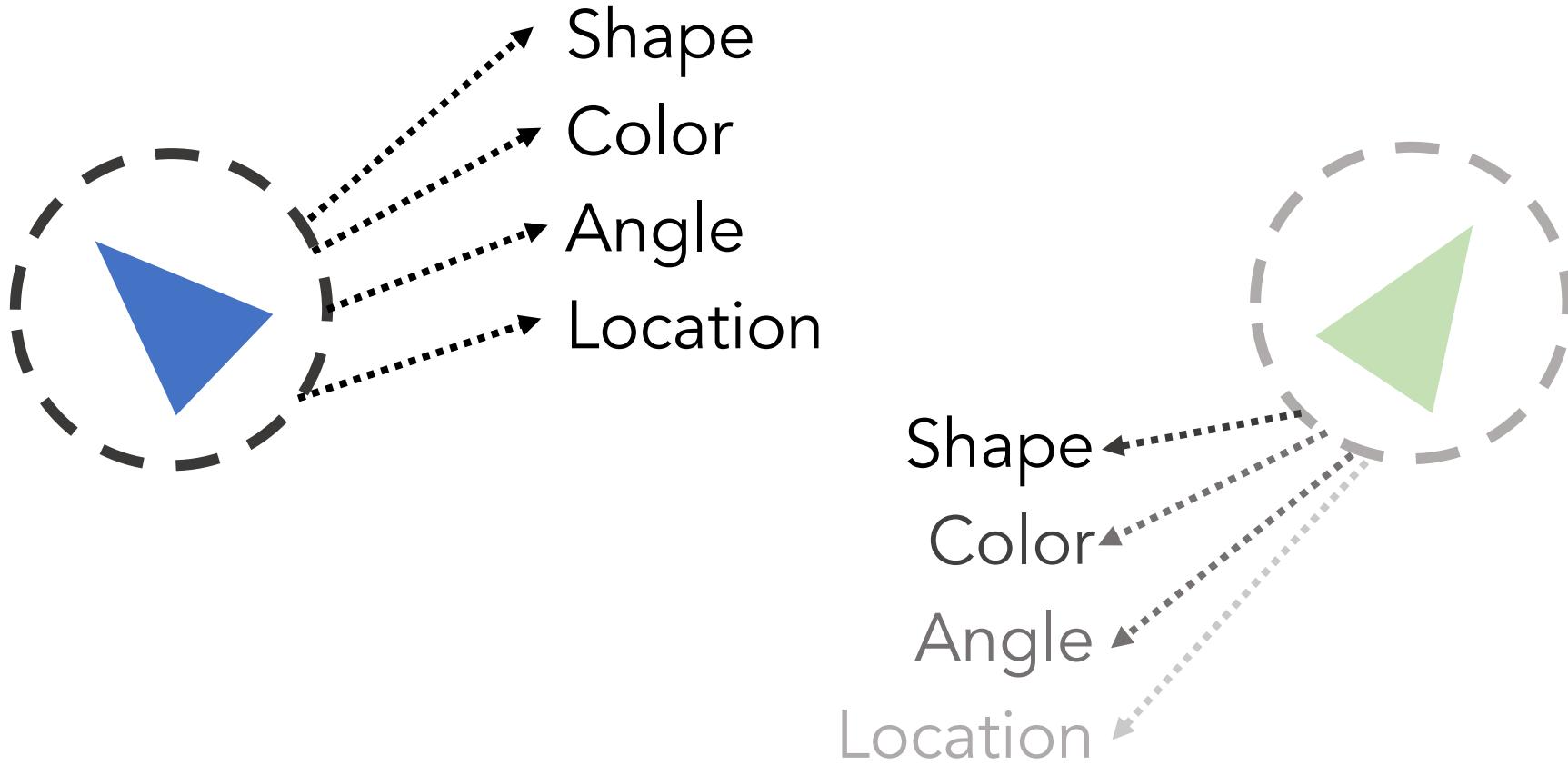
# The strong object model



# The independent features model

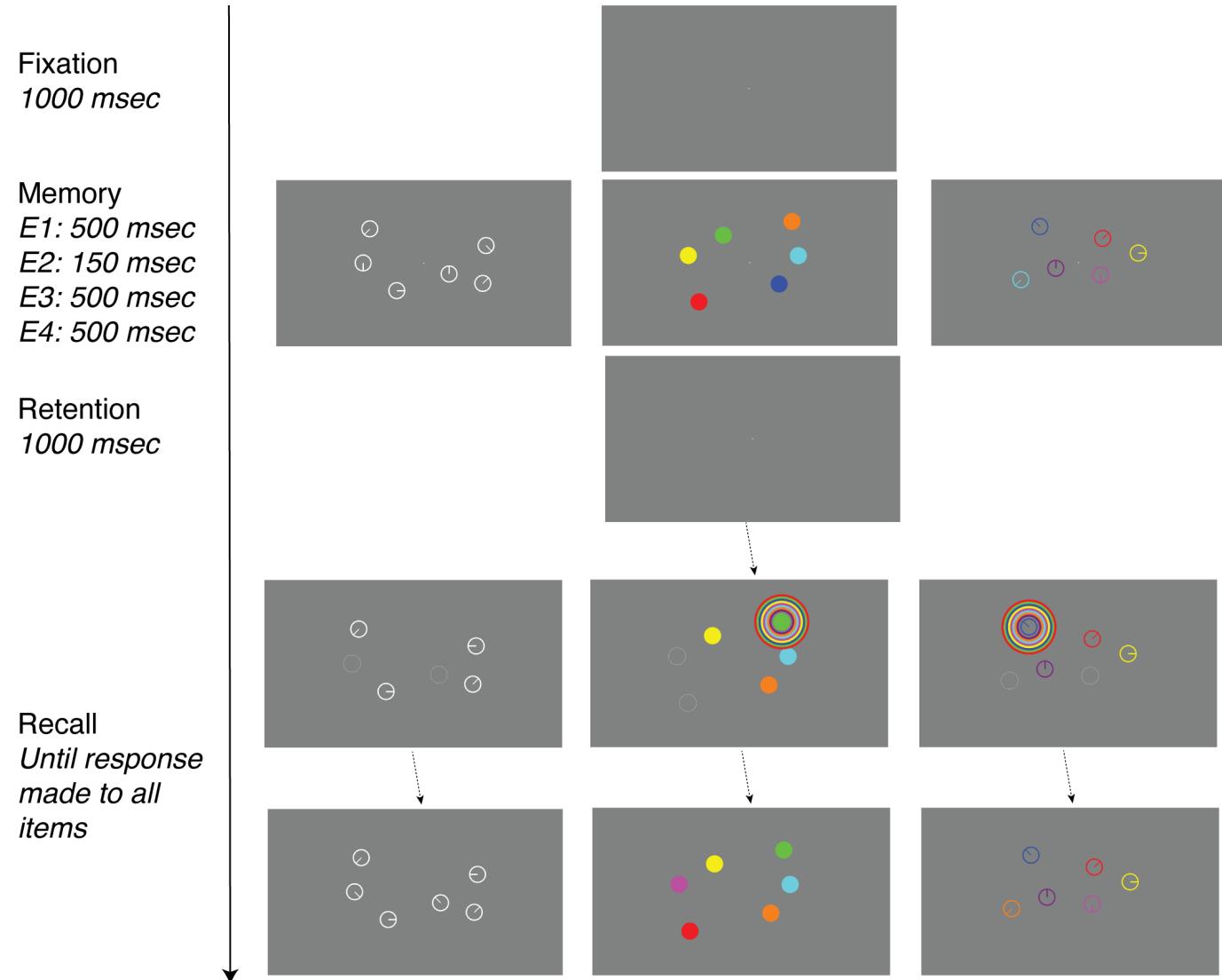


# A pointer model



# Whole-report with conjunctions

- Four experiments (all  $n = 30$ ):
  - E1 + E2: Coloured clocks
    - Angle only, colour only, and conjunction conditions
  - E3: Coloured triangles
    - Only the conjunction condition
  - E4: Coloured shapes
    - Shape only, colour only, and conjunction conditions
- Response interface that collects both features with one click



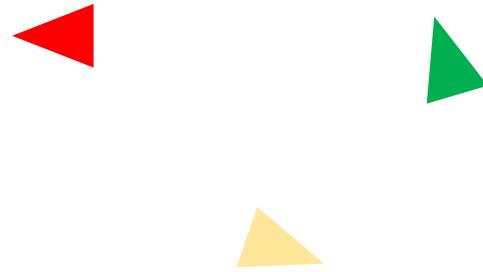




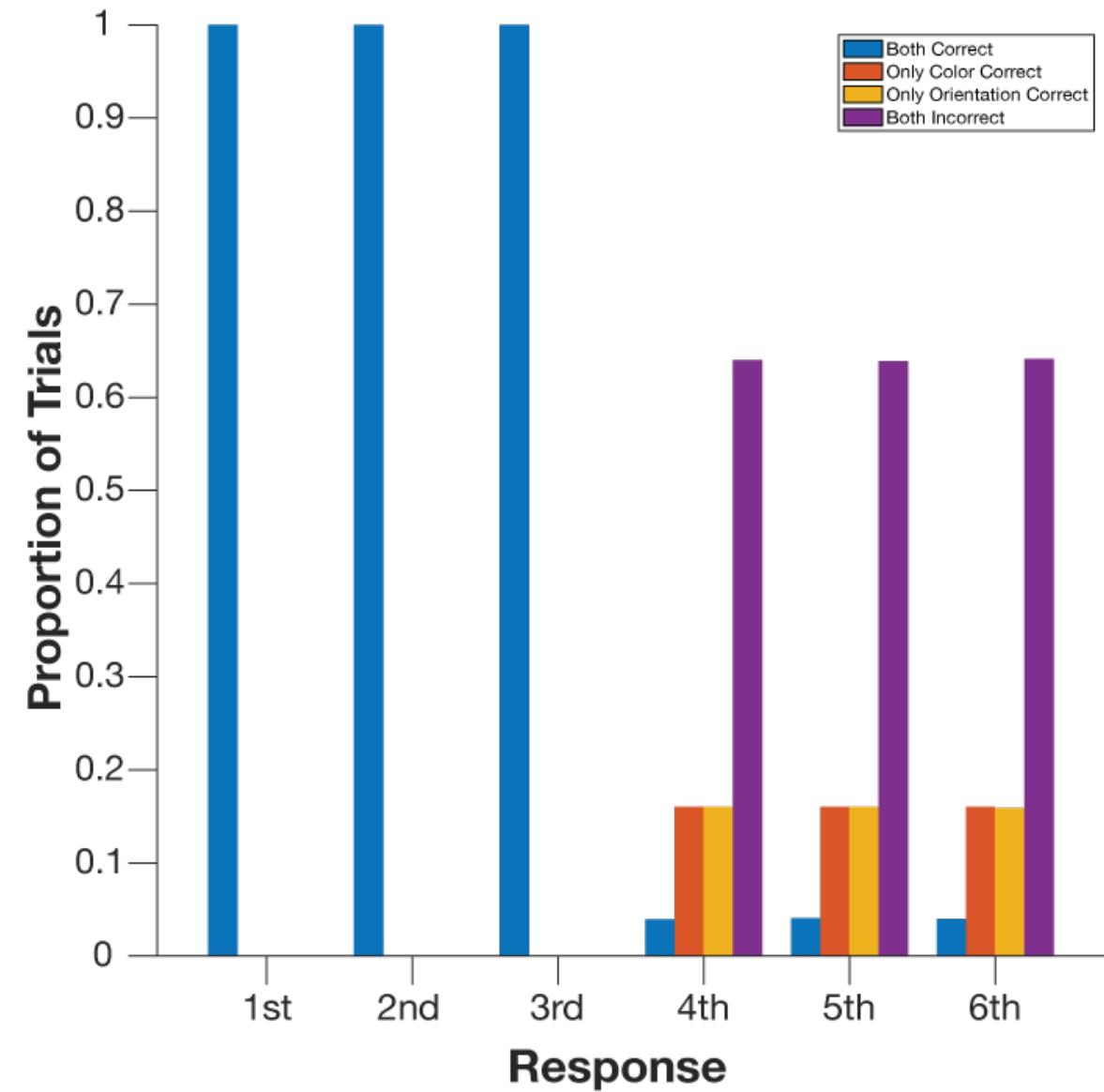


# Model predictions

Strong object model

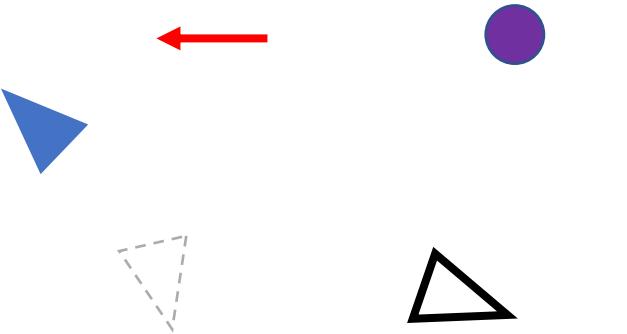


- Three objects are perfectly stored
- Pure guesses occur beyond those three objects

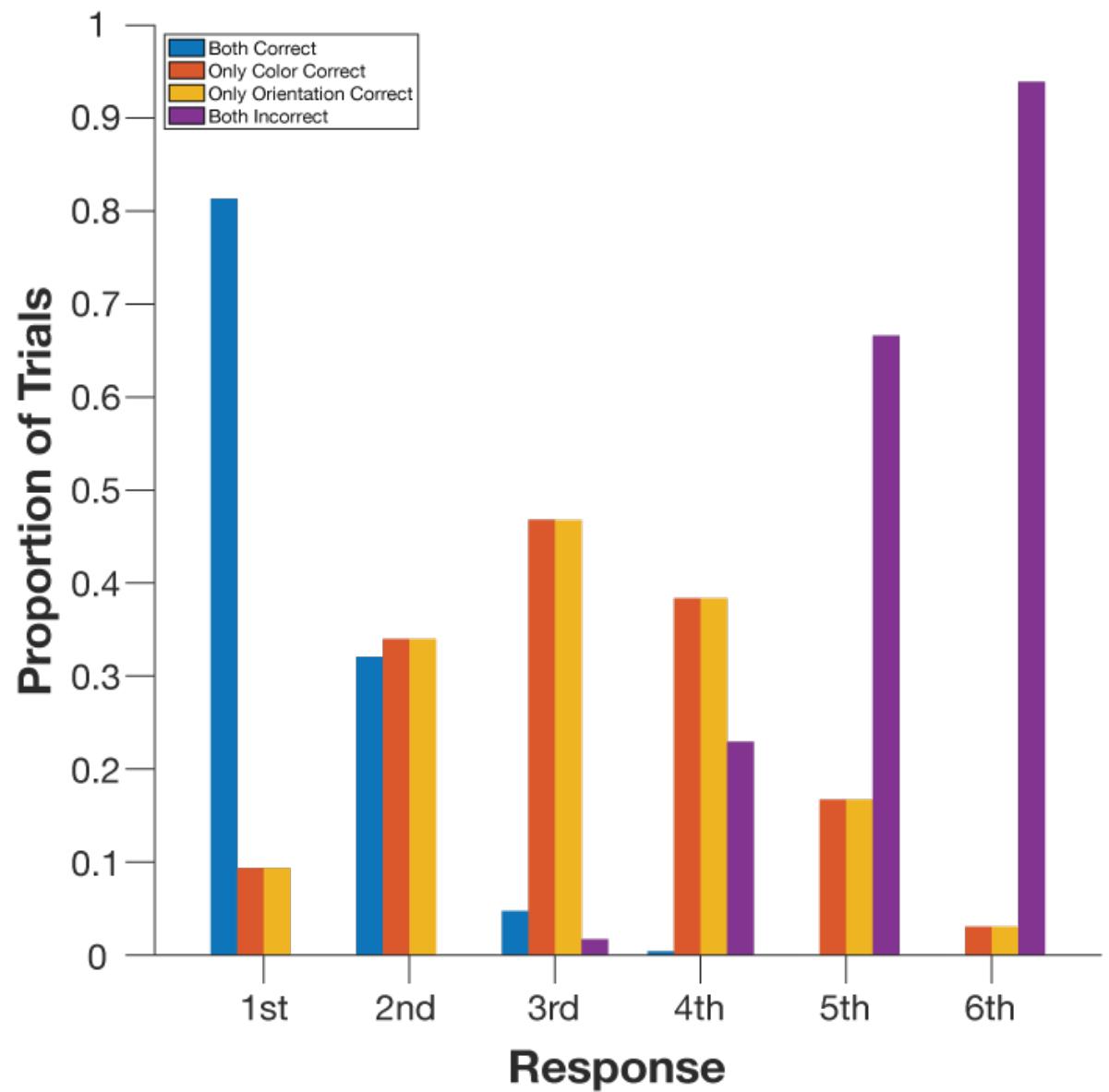


# Model predictions

## Independent feature model



- Memory is distributed to all features regardless of objecthood
- Every feature has an independent probability of storage

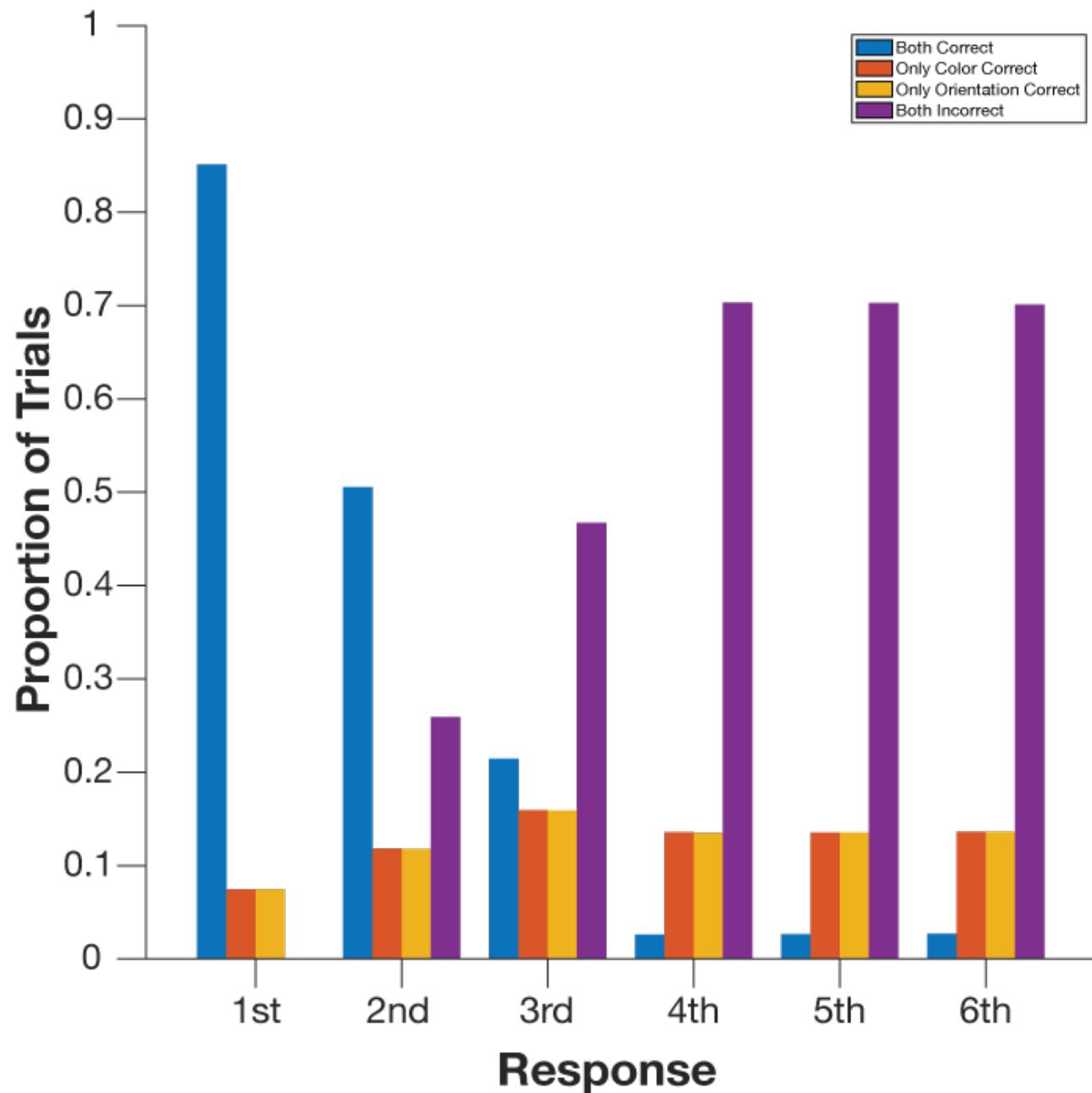


# Model predictions

## Pointer model



- Memory is constrained to three objects but features may be dropped independently
- Pure guesses occur beyond this item limit



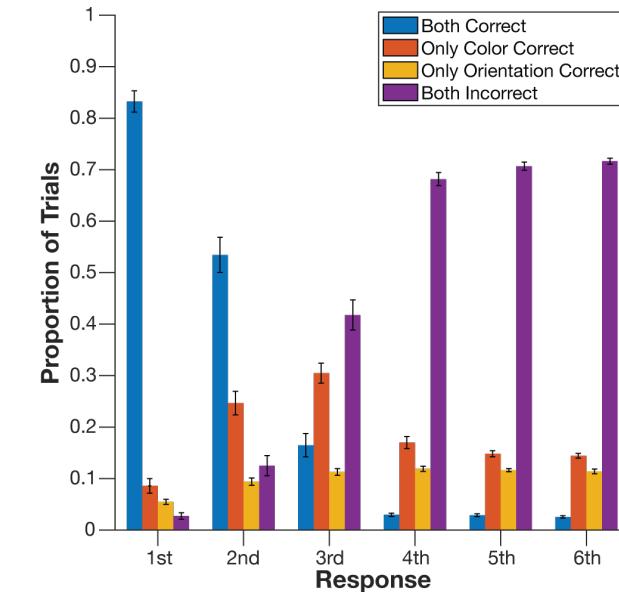
# Recall accuracy

Mean Recall	Experiment 1	Experiment 2	Experiment 3	Experiment 4
Colors	$3.21 \pm 0.74$	$2.94 \pm 0.64$		$3.61 \pm 0.75$
Orientations/Shapes	$2.79 \pm 0.44$	$2.45 \pm 0.45$		$3.39 \pm 0.64$
Conjunctions	$1.62 \pm 0.38$	$1.38 \pm 0.42$	$1.47 \pm 0.44$	$1.92 \pm 0.43$
Features in the conjunctions	$4.94 \pm 0.68$	$4.52 \pm 0.83$	$5.11 \pm 0.65$	$5.34 \pm 0.85$

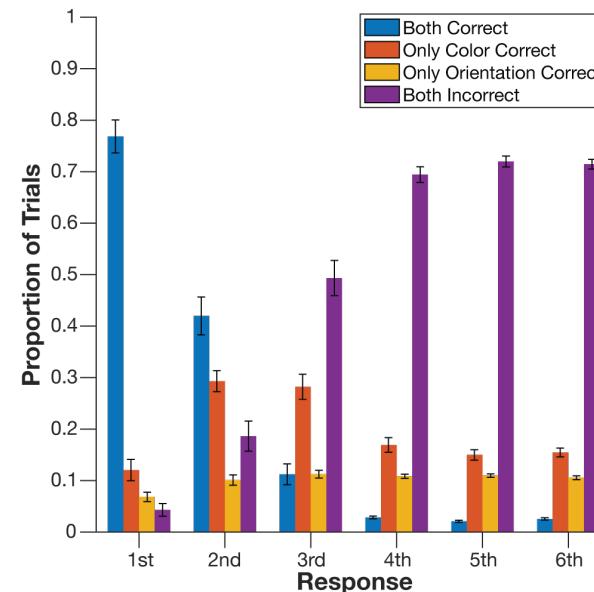
- There is a **drop in recall performance** when storing conjunction stimuli
- There is an **object-based benefit**
  - More features are recalled overall in the conjunction condition compared to the single-feature conditions (~5 features versus ~3 features)

# Accuracy across responses

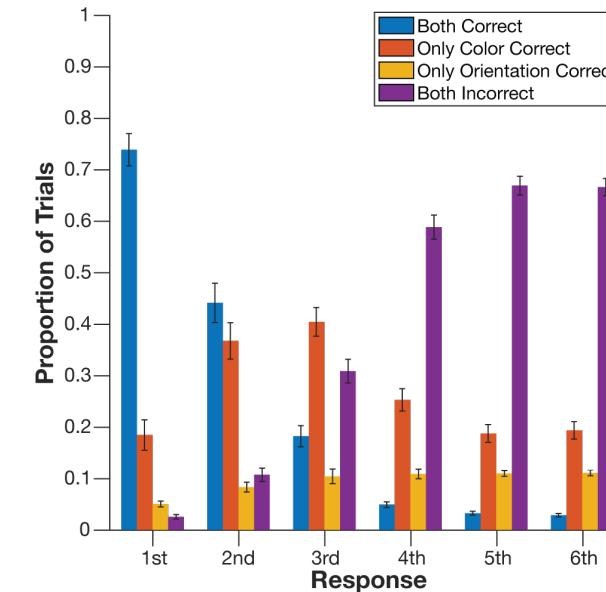
Experiment 1



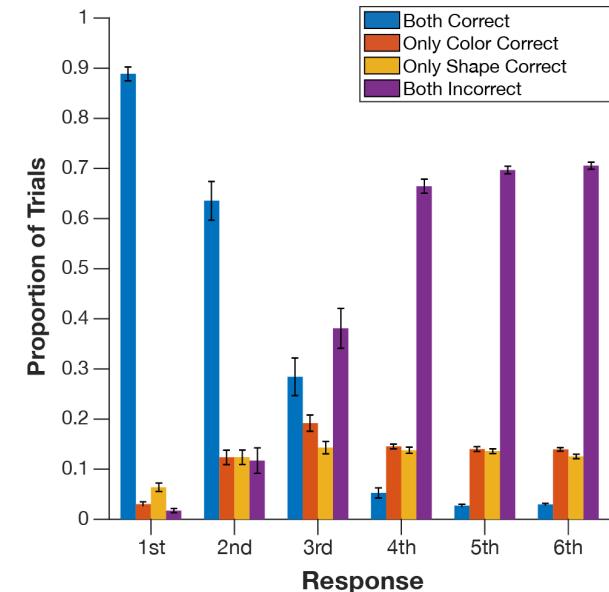
Experiment 2



Experiment 3



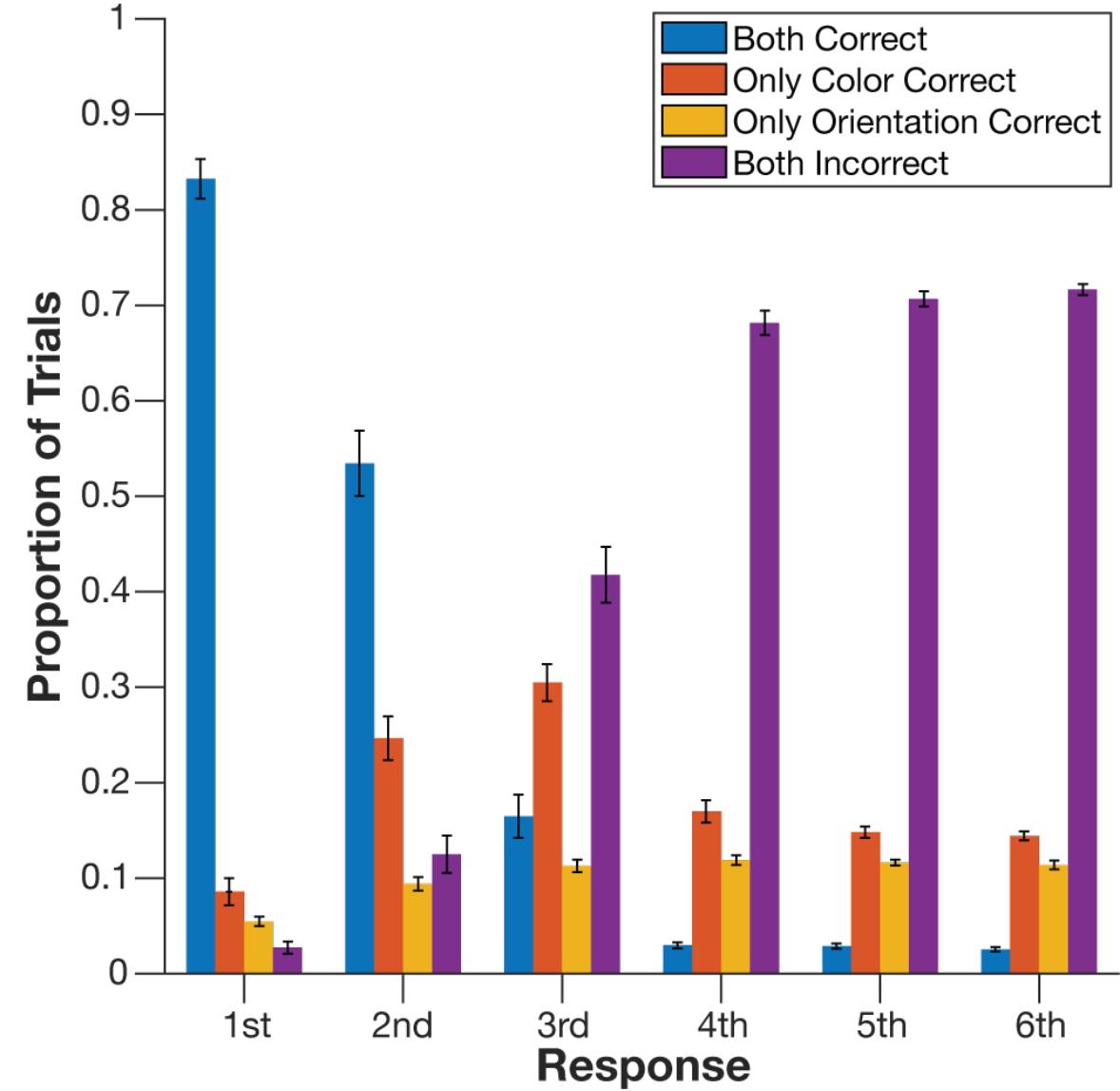
Experiment 4



- The same empirical pattern was replicated across four experiments

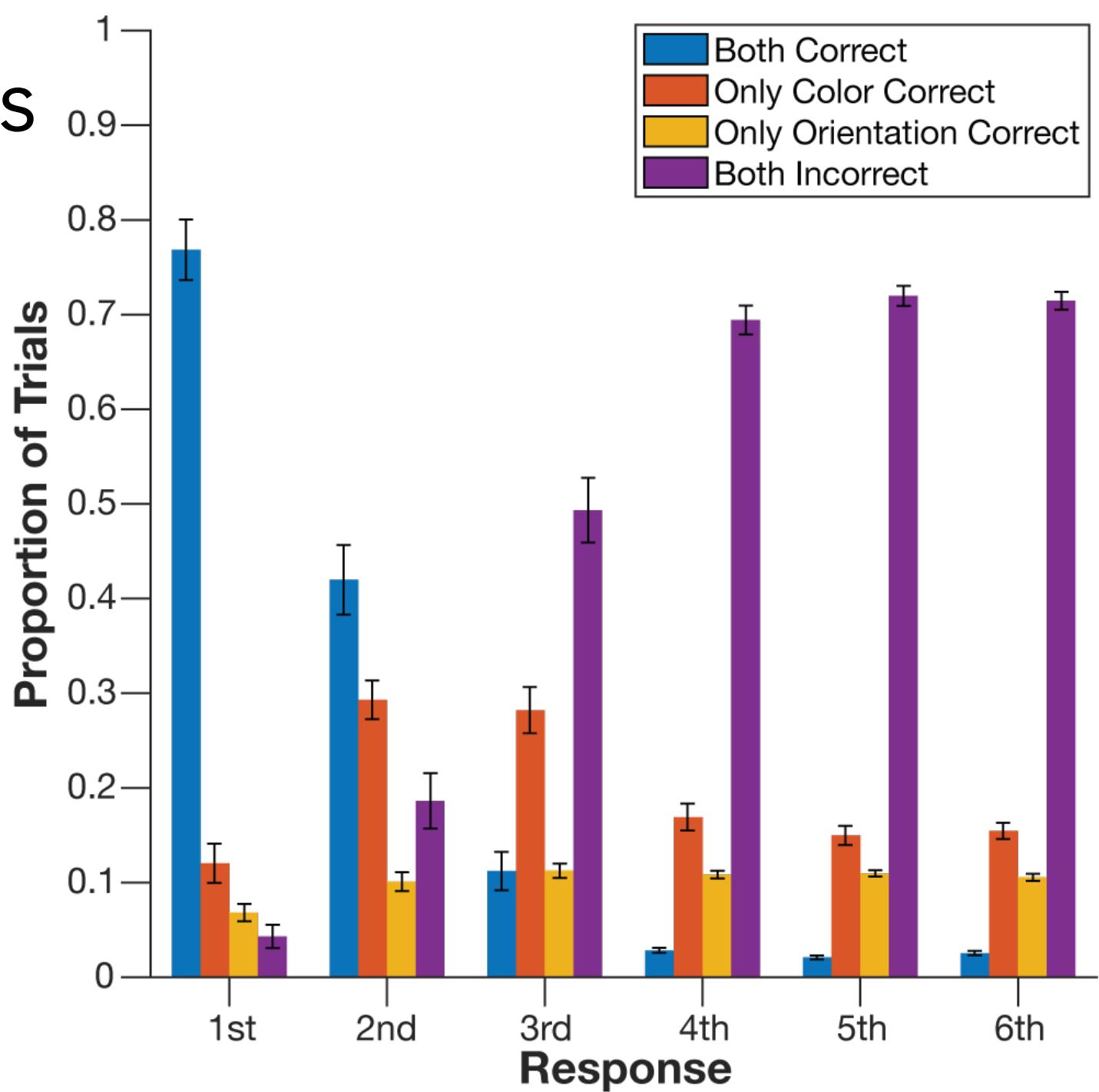
# Experiment 1 Results

- Accurate recall was concentrated to the **first three responses**
- The last three responses are pure guesses



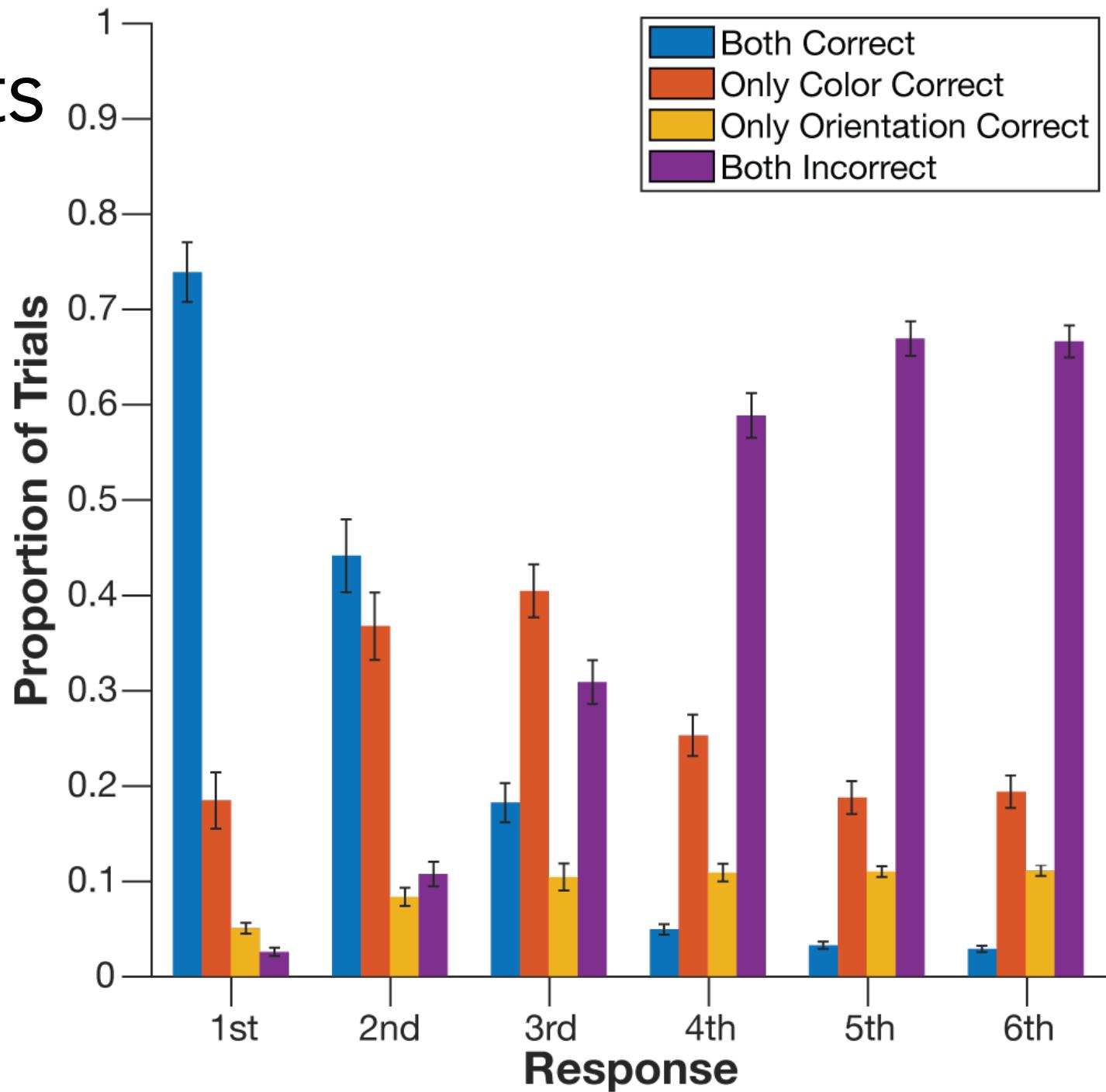
# Experiment 2 Results

- Shorter encoding time



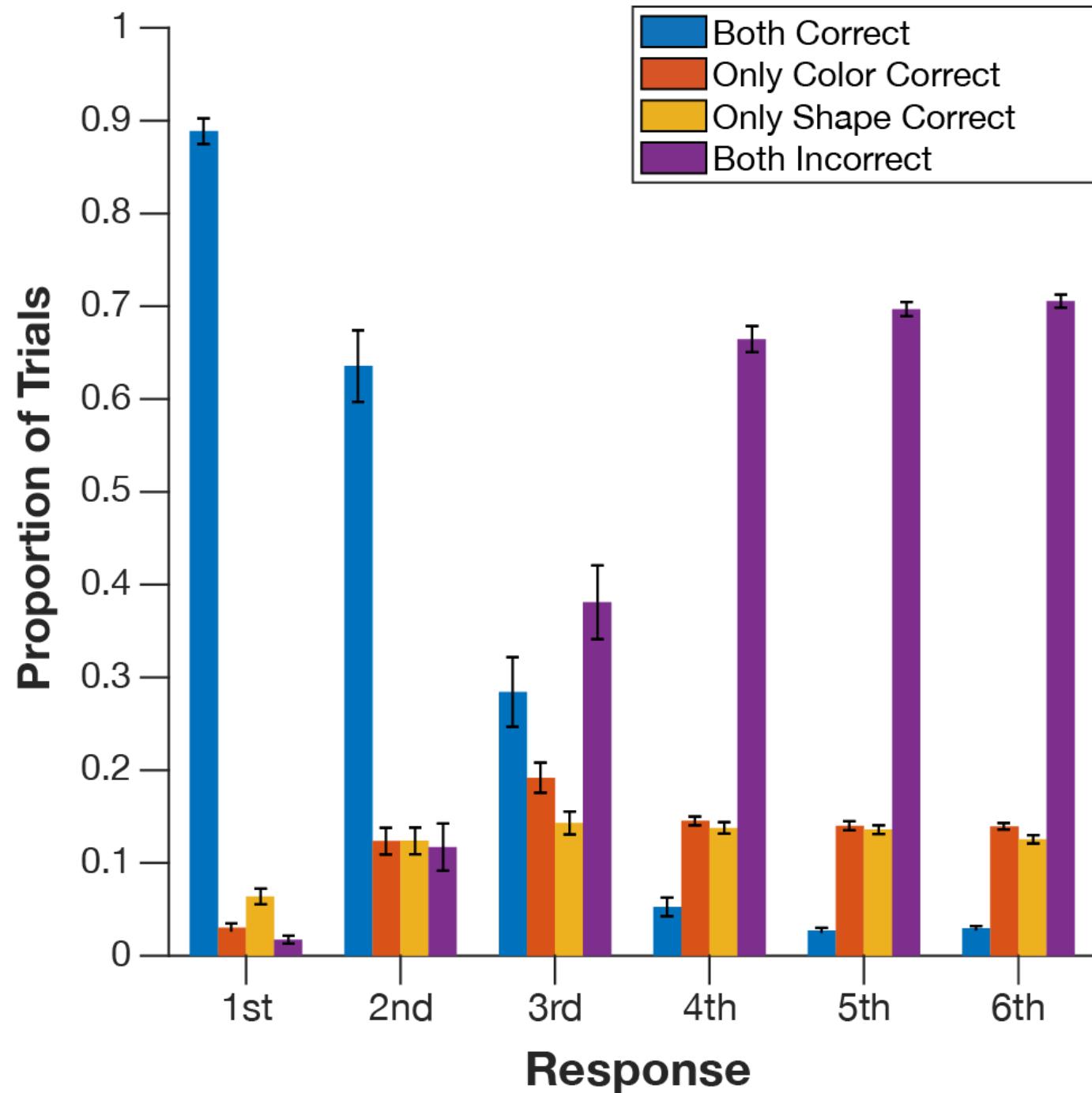
# Experiment 3 Results

- Coloured triangles



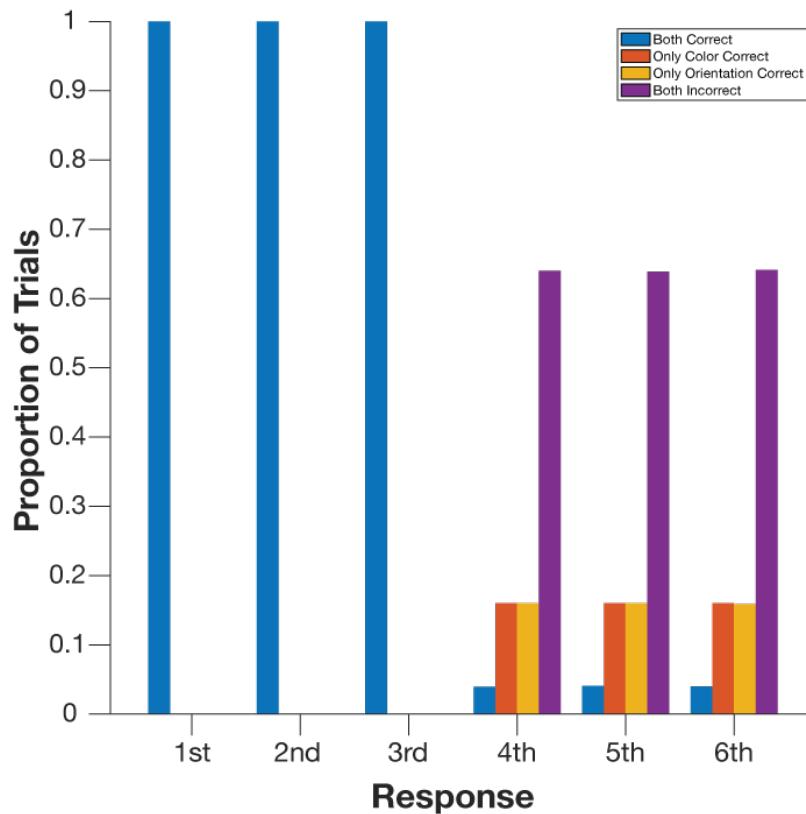
# Experiment 4 Results

- Colour and shape conjunctions

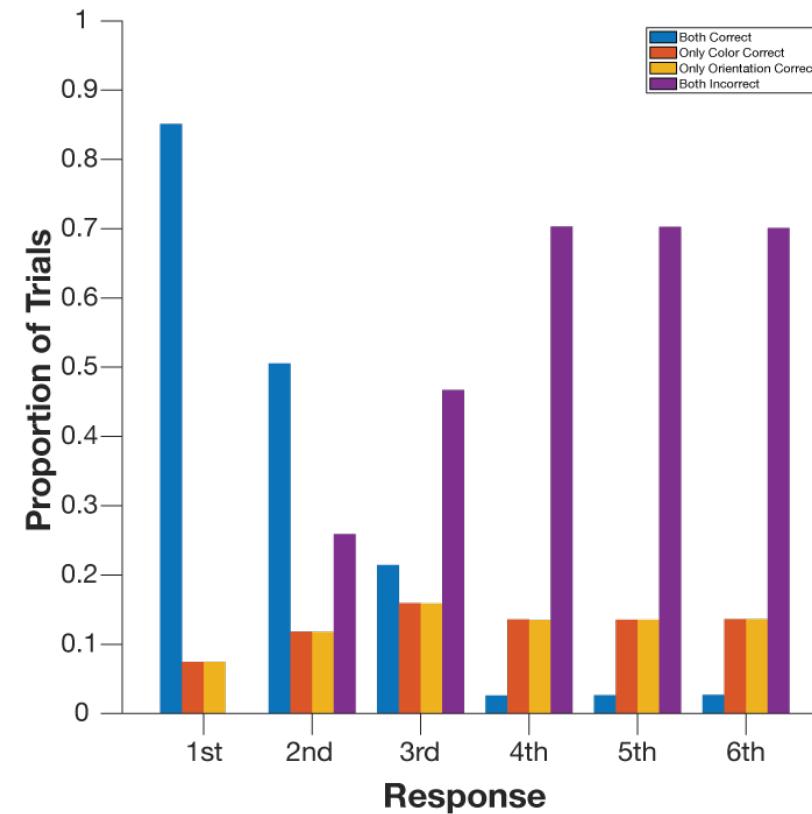


# Formal model comparison

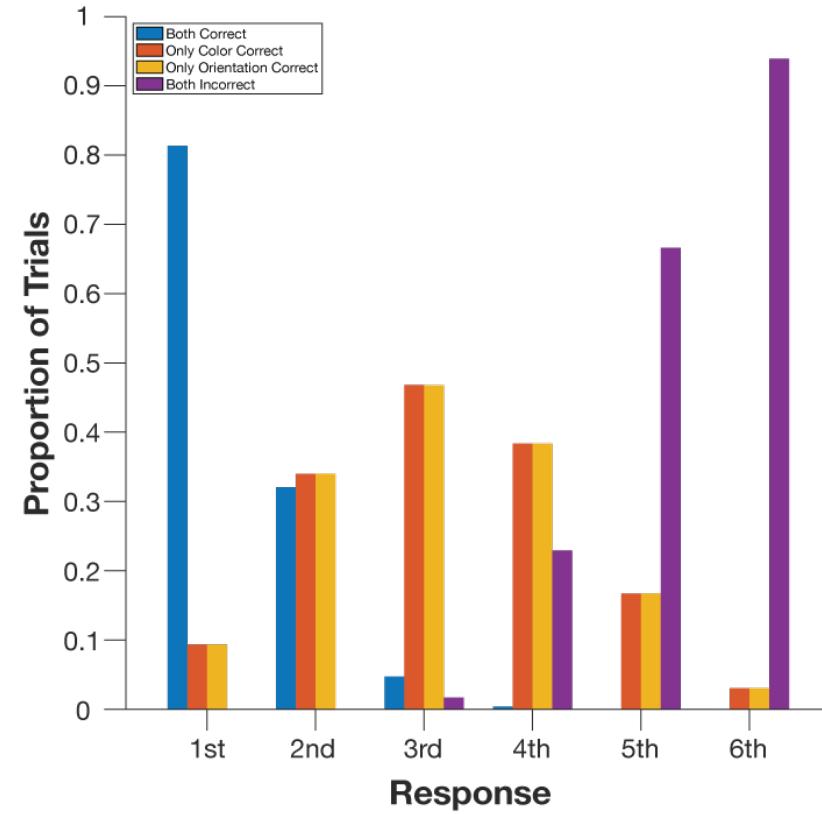
Strong object model



Pointer model



Independent feature model



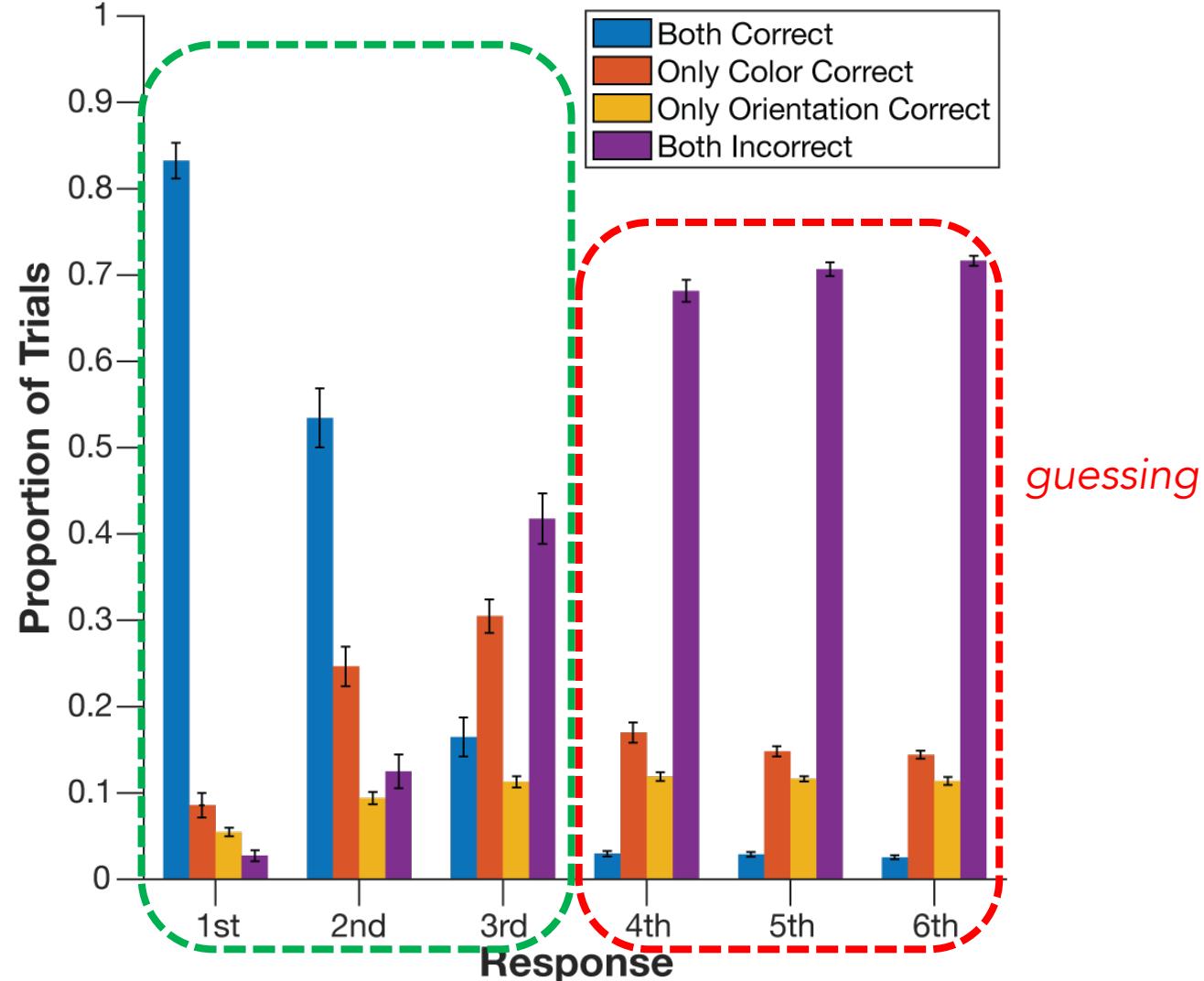
# Formal model comparison

- For all experiments, the AIC and BIC is lowest for the pointer model for all 30 participants

Model	Strong Object Model	Pointer Model	Independent Feature Model
E1 AIC ( $\times 10^3$ )	4.9788	3.3262	4.8337
E1 BIC ( $\times 10^3$ )	4.9843	3.3372	4.8392
E2 AIC ( $\times 10^3$ )	4.9073	3.3102	4.7006
E2 BIC ( $\times 10^3$ )	4.9128	3.3212	4.7061
E3 AIC ( $\times 10^3$ )	5.6572	3.4974	4.8706
E3 BIC ( $\times 10^3$ )	5.6627	3.5084	4.8761
E4 AIC ( $\times 10^3$ )	4.7300	3.2115	4.8776
E4 BIC ( $\times 10^3$ )	4.7355	3.2225	4.8831

# Accuracy across responses

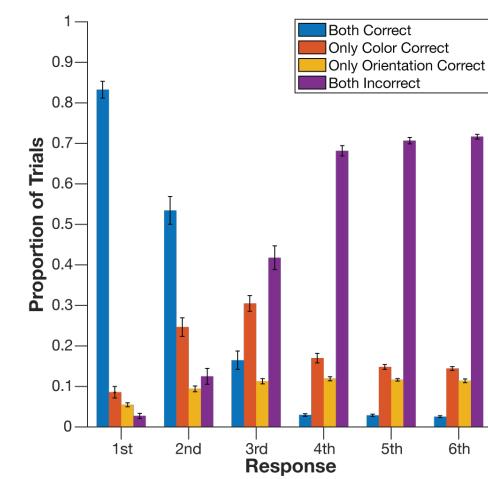
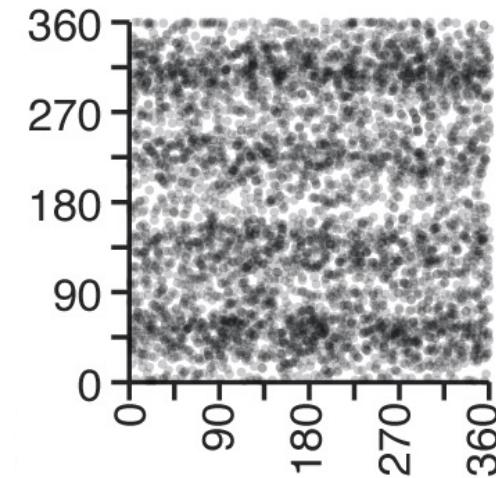
*pointers with  
probabilistic feature  
loss*



*guessing*

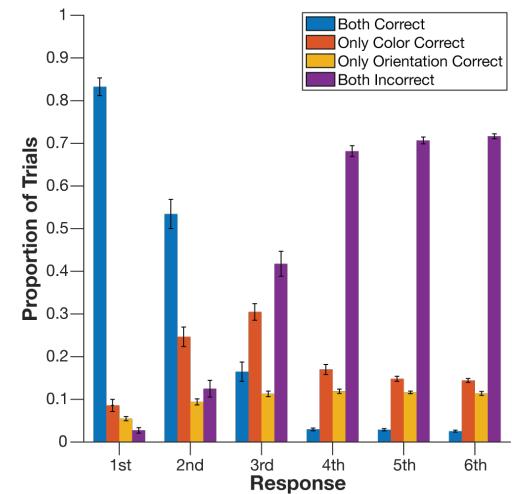
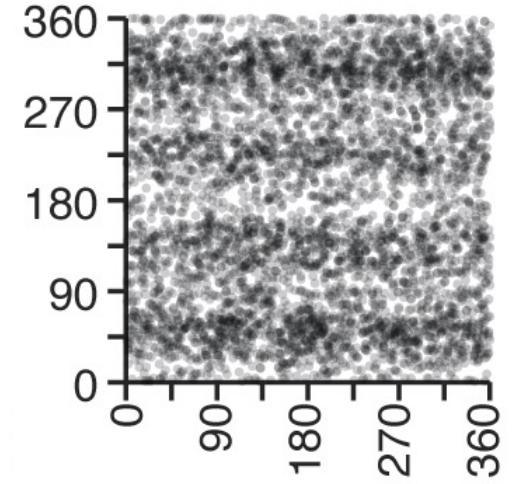
# Visual working memory capacity is item-based

1. Because we guess beyond this item limit
  - Memory responses were constrained to the first three responses
  - A substantial proportion of later responses produced 'guess bands'
    - These responses cannot be attributed to imprecise memories
2. Because there is an **object-based benefit of storage**
  - But this storage is **not lossless** as features are dropped
  - Accurate recall is concentrated to the **first three responses**



# Summary

- We observed '*guess bands*', a signature of guessing
  - These responses are not imprecise memories
- Visual working memory is *object-based*
  - More features are recalled when organized by objects, but this storage is not lossless
- Visual working memory is constrained to the *first three responses*
  - There is an item limit in visual working memory capacity



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