A two-state detect-or-guess model of visual perception and memory: human visual decisions rely on fixed resolution system

Hee Yeon Im
Johns Hopkins University

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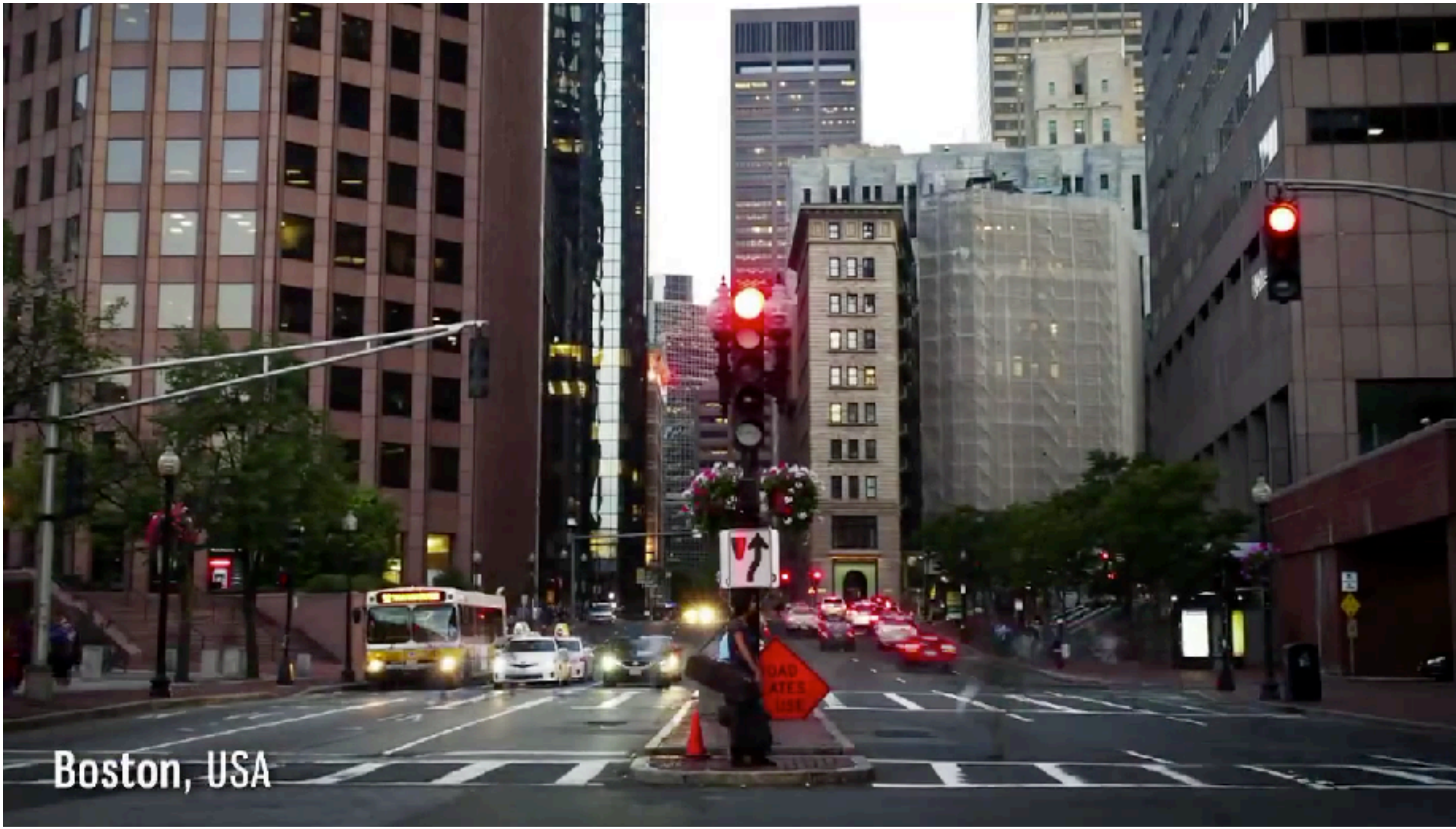
Visual environment are dynamic and overflowing with information



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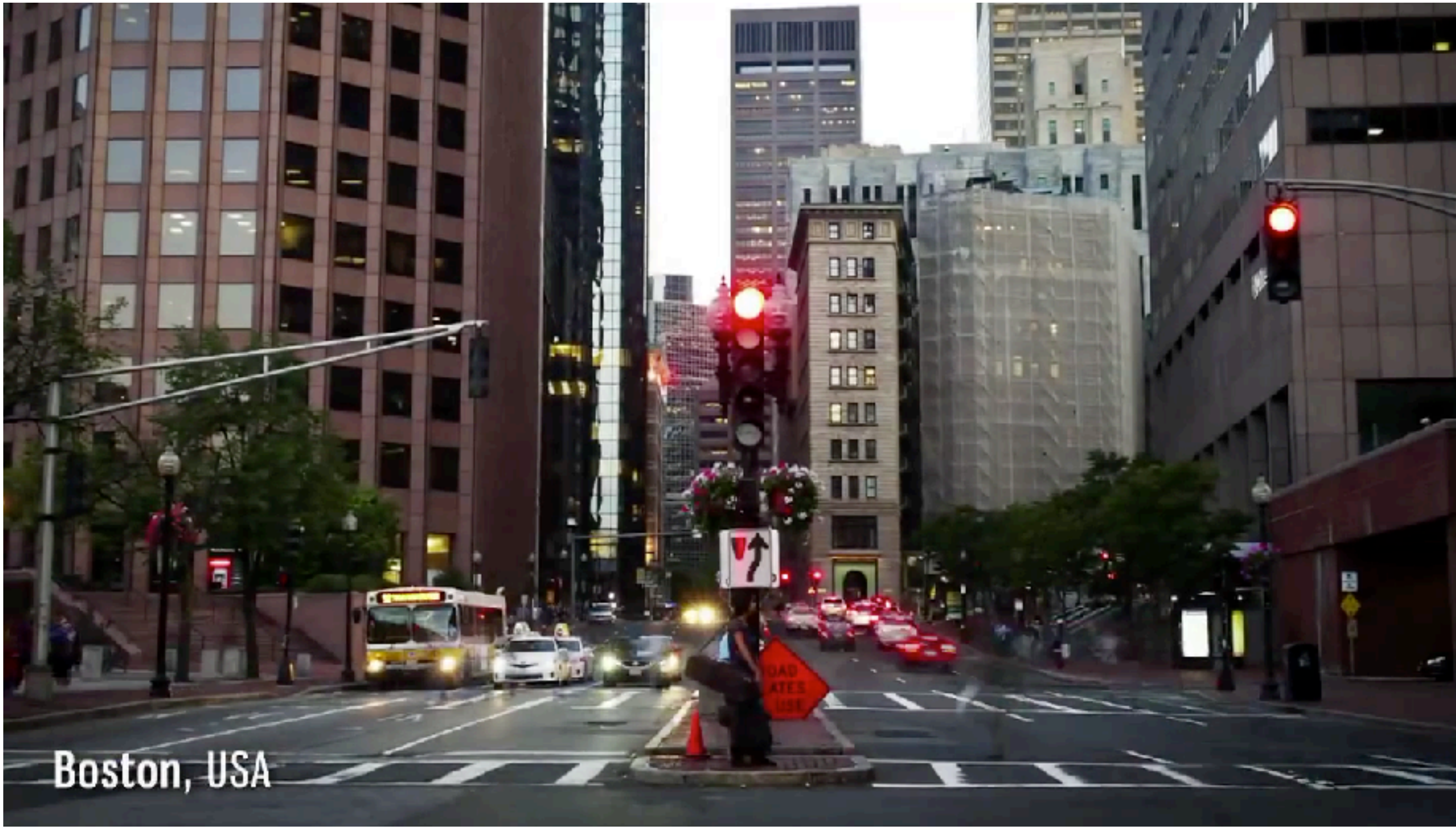

We always make visual decisions to adaptively guide actions

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Rules of thumb for better outcomes

(1) Spending more time makes a difference

Rules of thumb for better outcomes

(2) Only focus one thing at a time

In order to make better visual decisions

Longer processing time

In order to make better visual decisions

Longer processing time

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<u>Longer processing time</u>

In order to make better visual decisions

Longer processing time

Fewer information load

In order to make better visual decisions

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Fewer information load

Two major factors that improve human visual decisions

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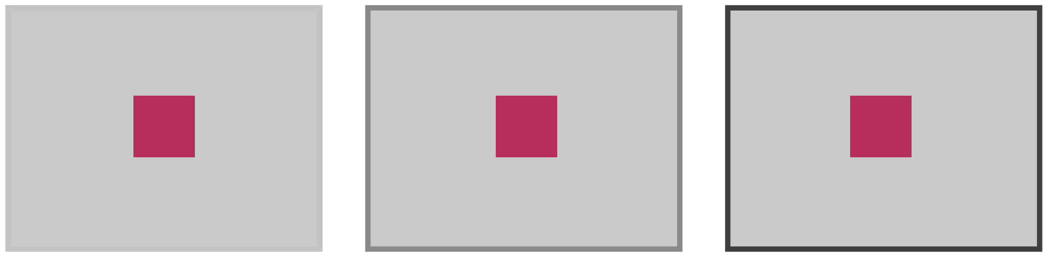


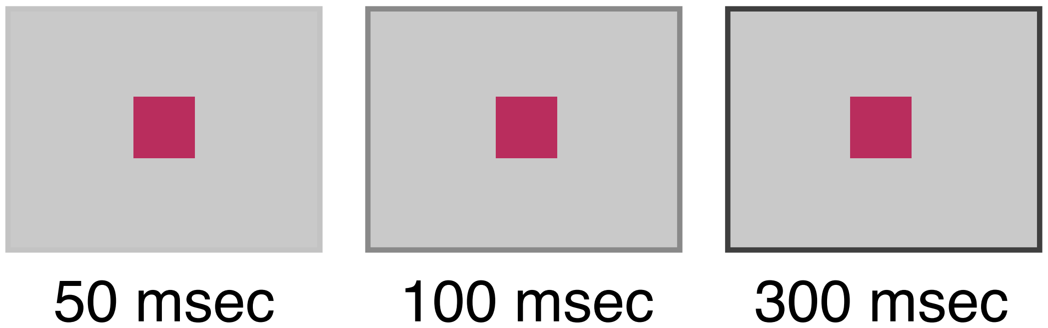
50 msec 100 msec 300 msec

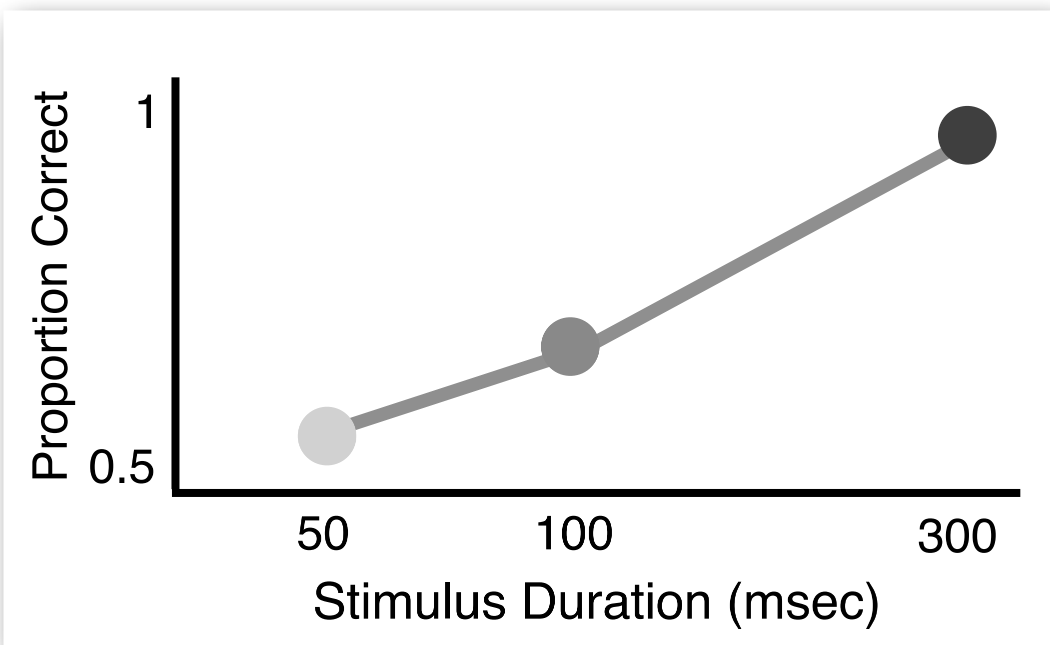
Fewer information load

Two major factors that improve human visual decisions

Longer processing time

Fewer information load

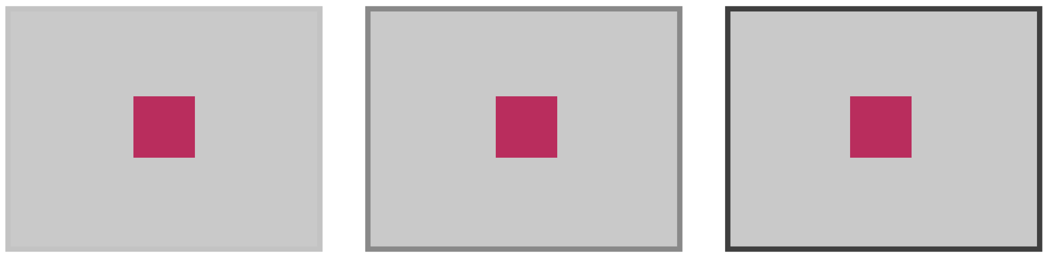




(e.g., Carrasco & McElree, 2001; Gegenfurtner & Sperling, 1993; Ratcliff, 2006; Vogel, Woodman, & Luck, 2006)

Two major factors that improve human visual decisions

Longer processing time



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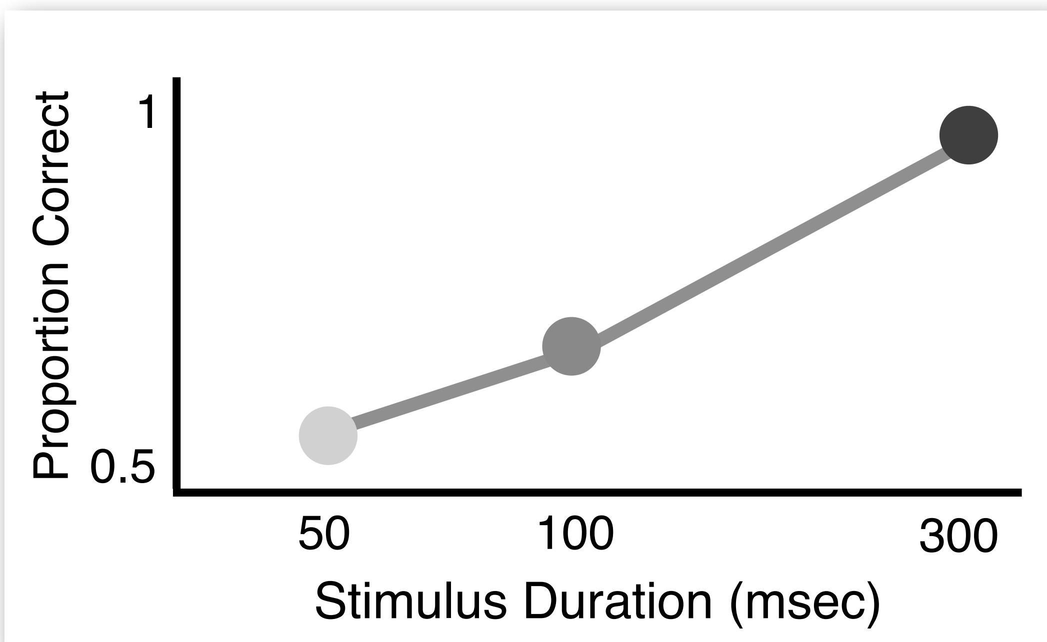

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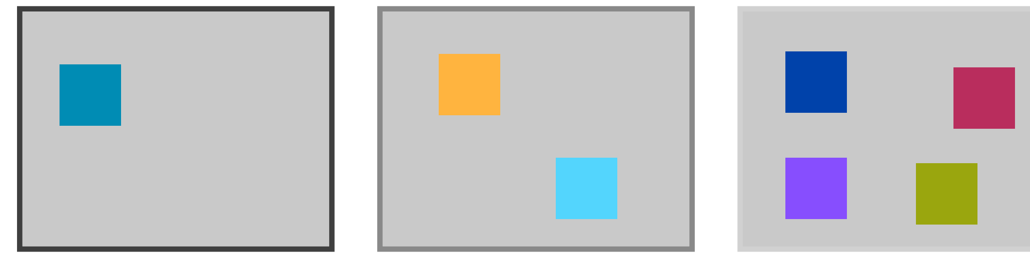
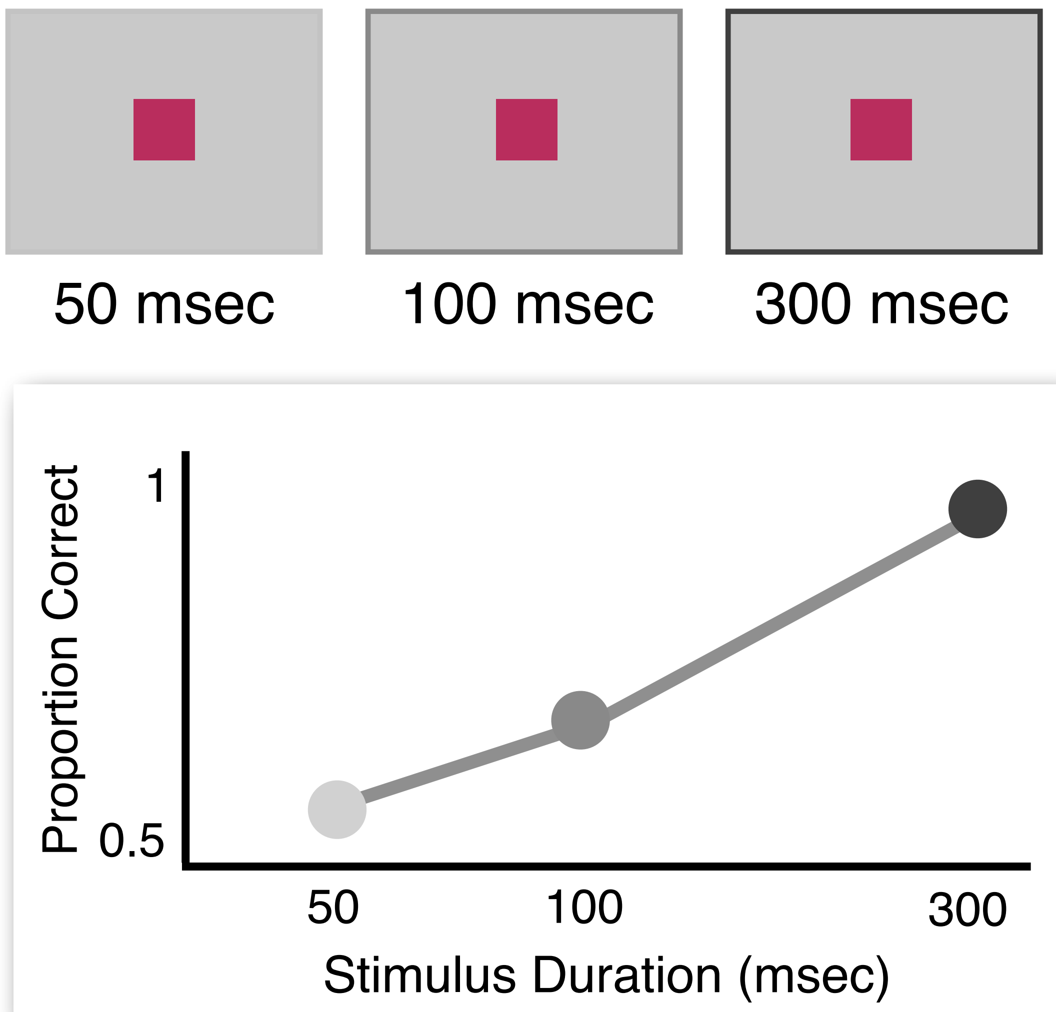


1 item 2 items 4 items

Two major factors that improve human visual decisions

Longer processing time



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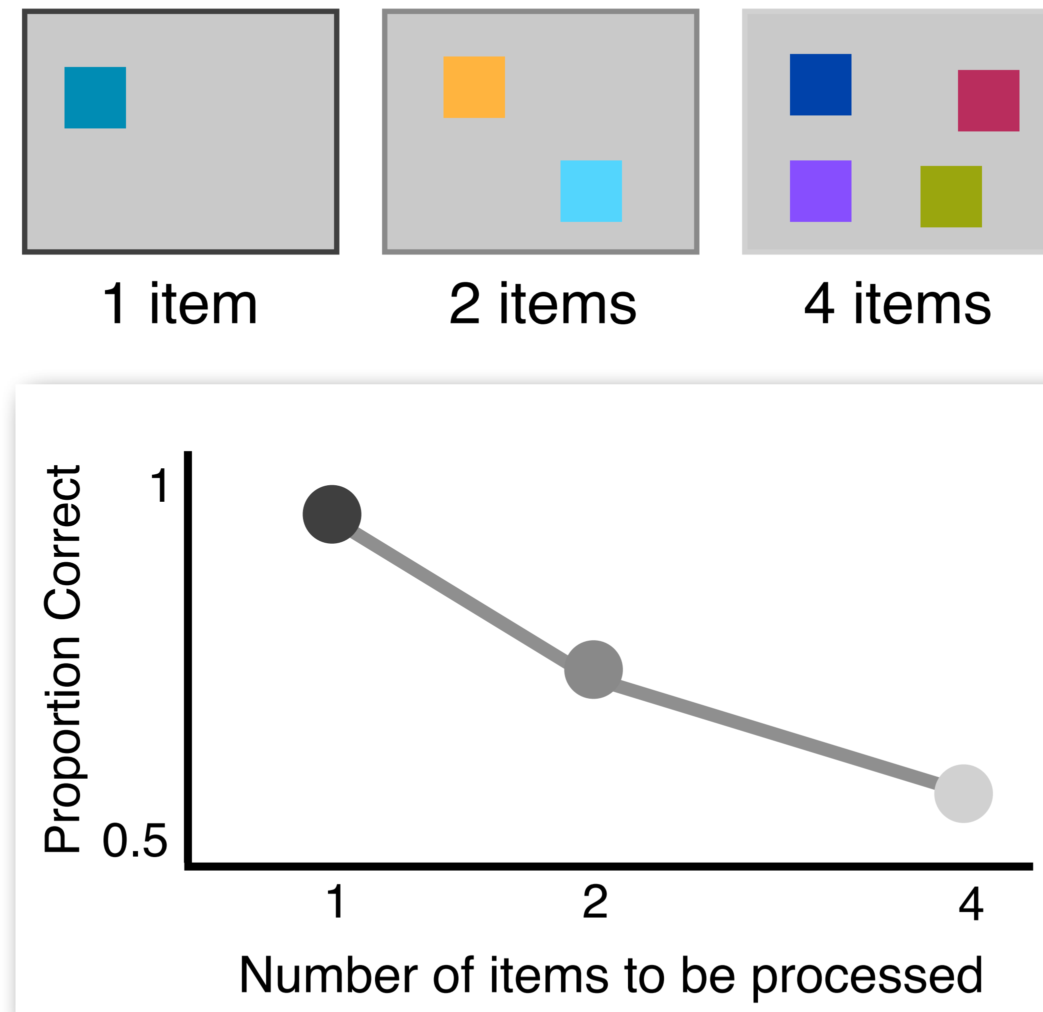
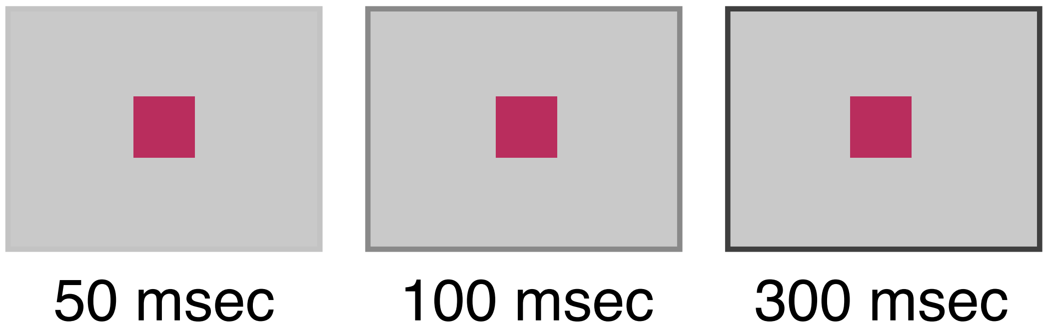


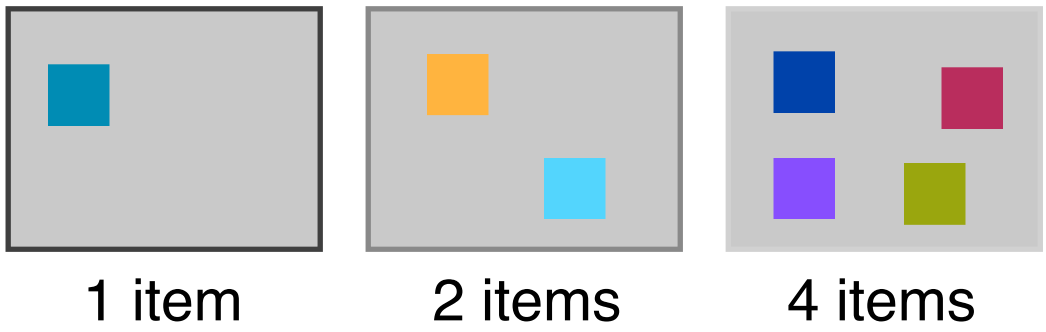
(e.g., Alvarez & Franconeri, 2007; Bays & Husain, 2008; Luck & Vogel, 1997; Palmer, 1990; Wilken & Ma, 2004)

How do these factors affect visual decisions?

Processing time



Information load



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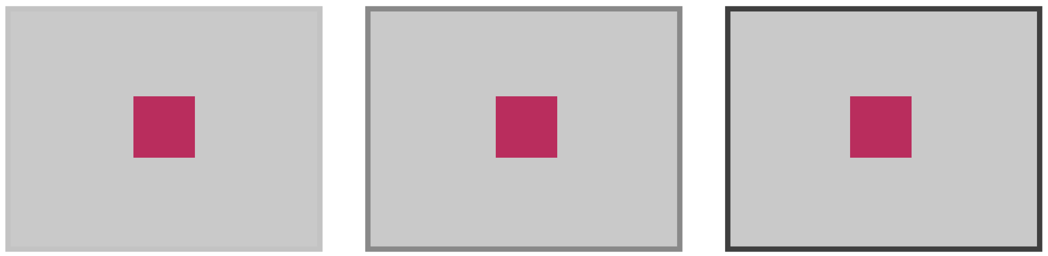
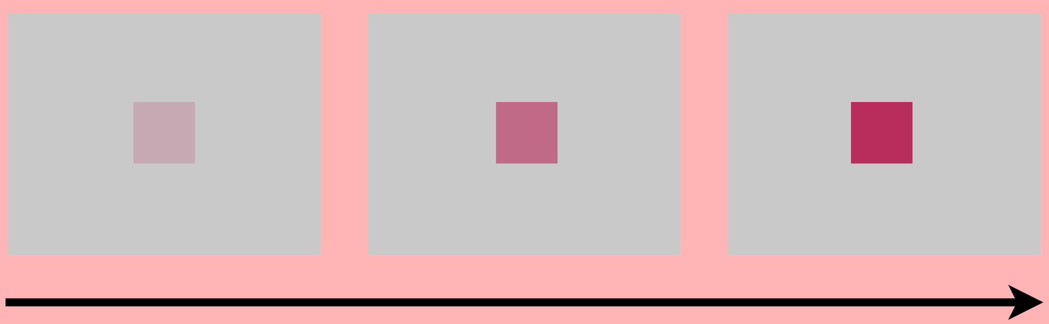


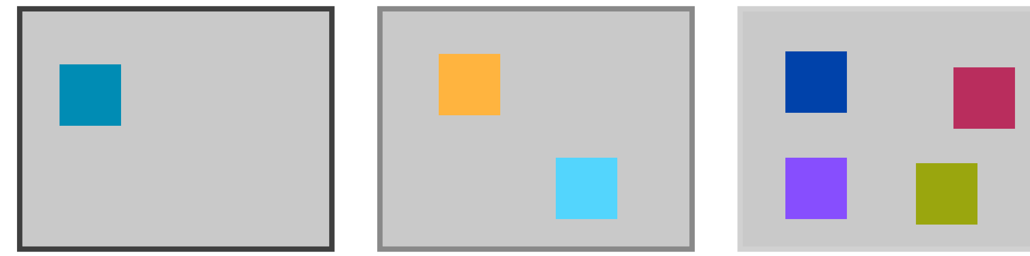
50 msec | 100 msec | 300 msec

Resolution becomes better



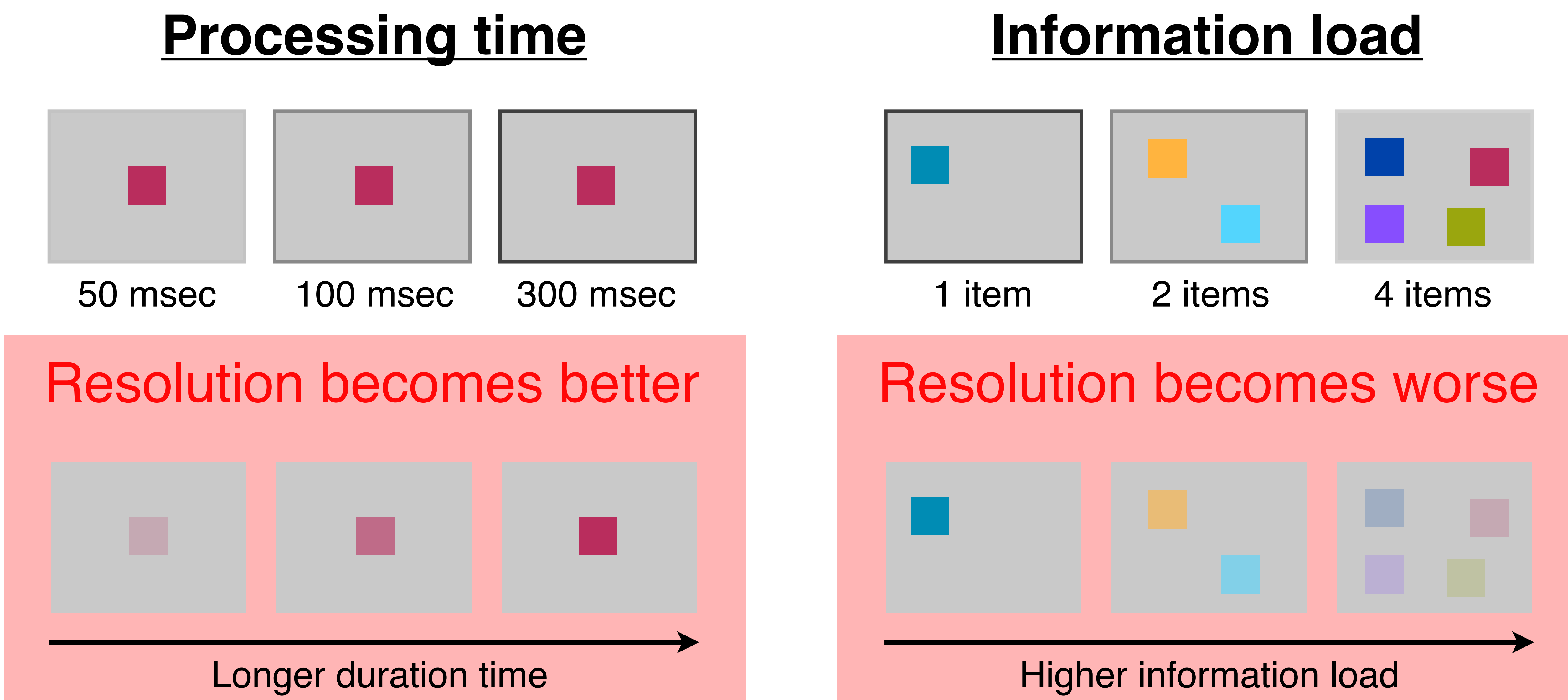
Longer duration time

Information load



1 item | 2 items | 4 items

How do these factors affect visual decisions?



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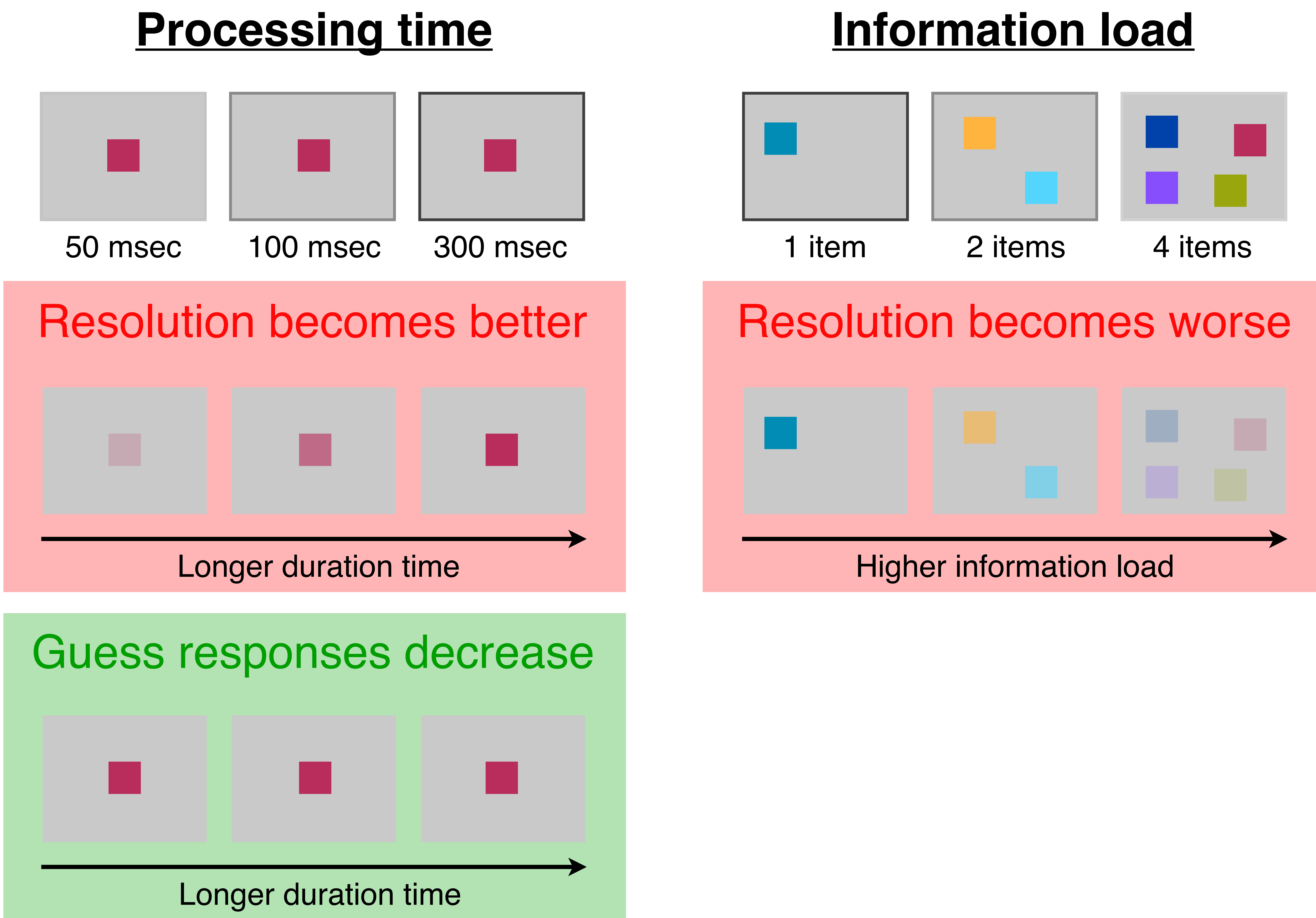
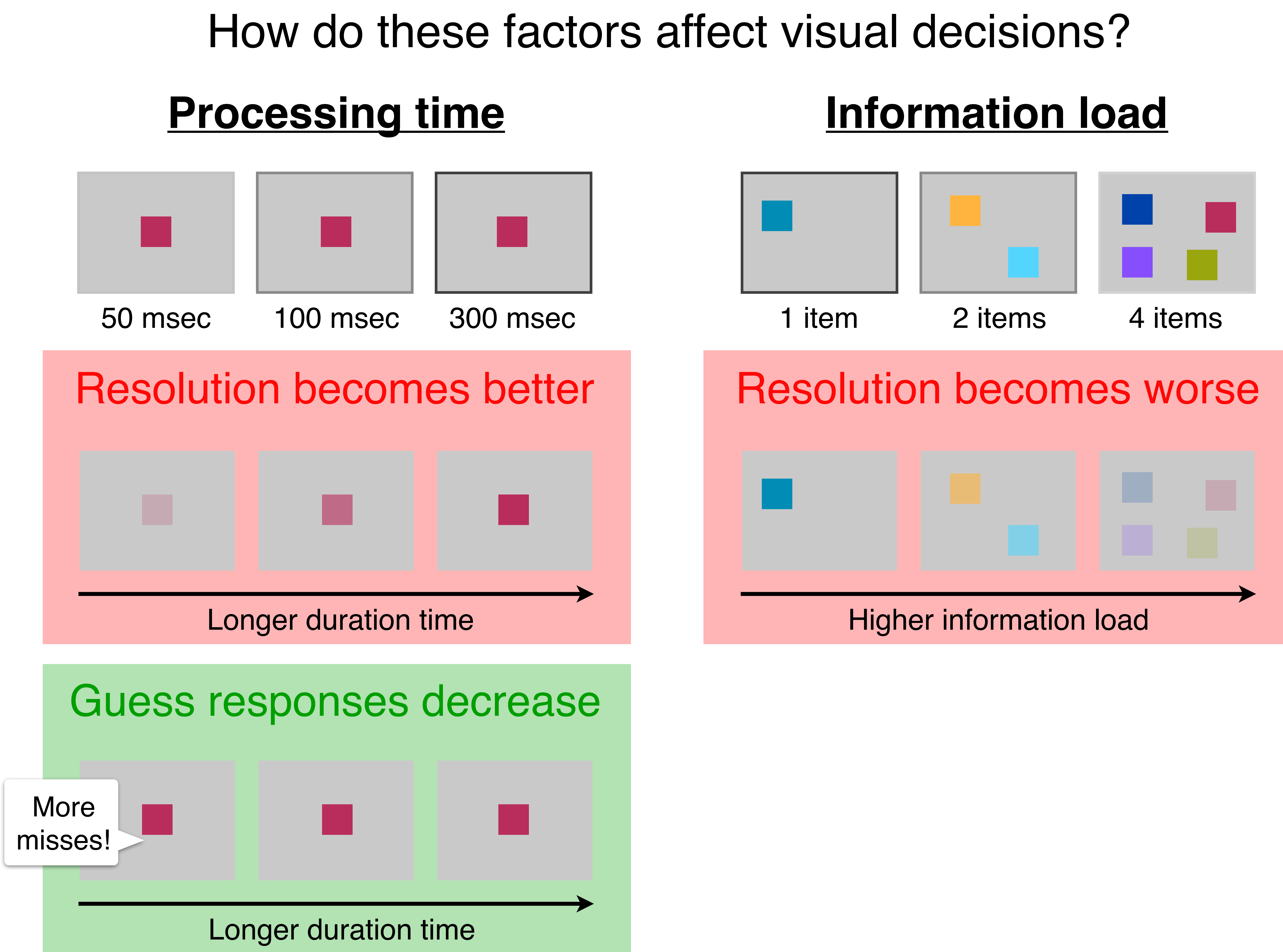
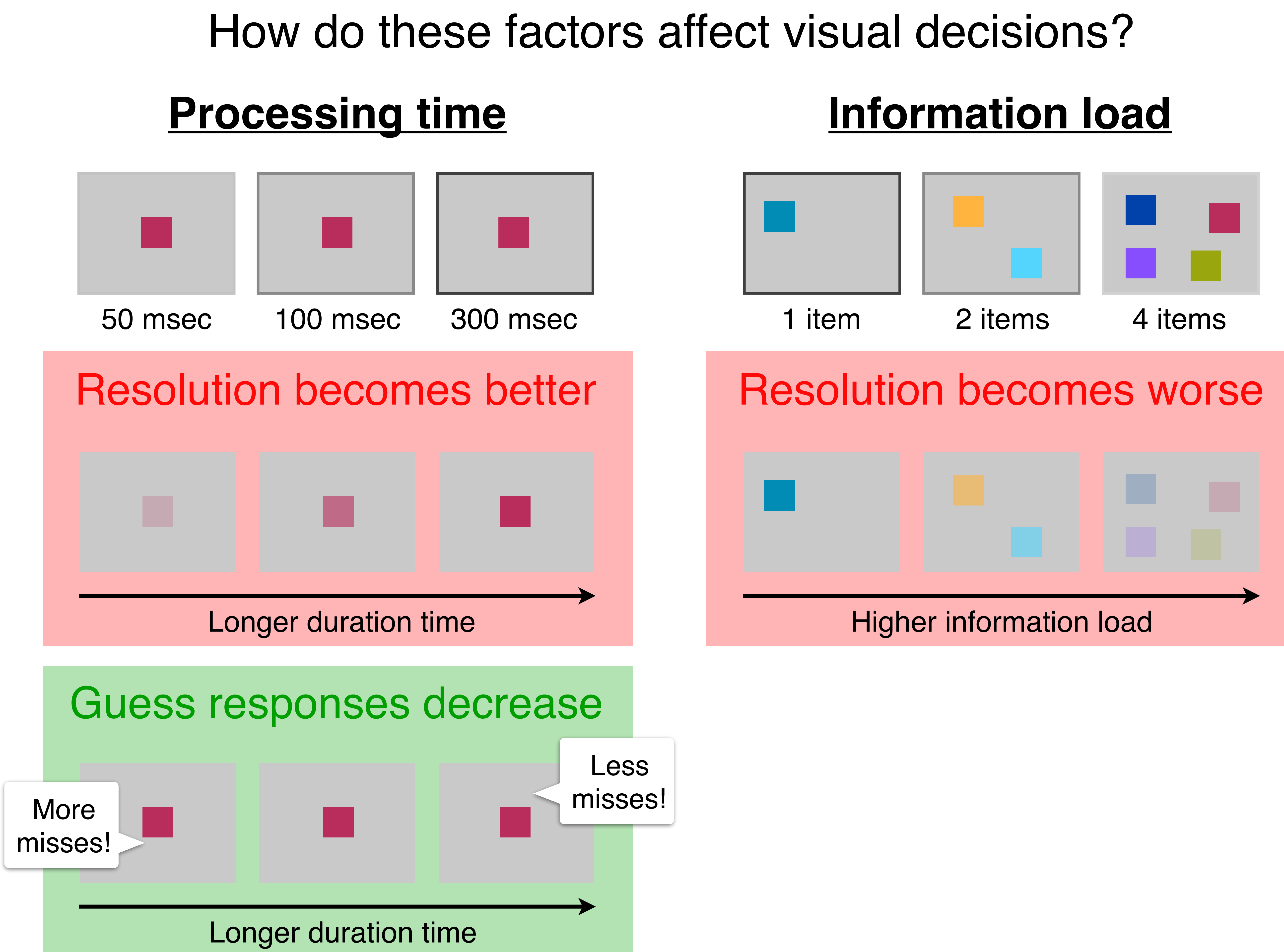



How do these factors affect visual decisions?
Processing time
Information load
50 msec
100 msec
300 msec
1 item
2 items
4 items
Resolution becomes better
Longer duration time
Resolution becomes worse
Higher information load
Guess responses decrease
More misses!
Longer duration time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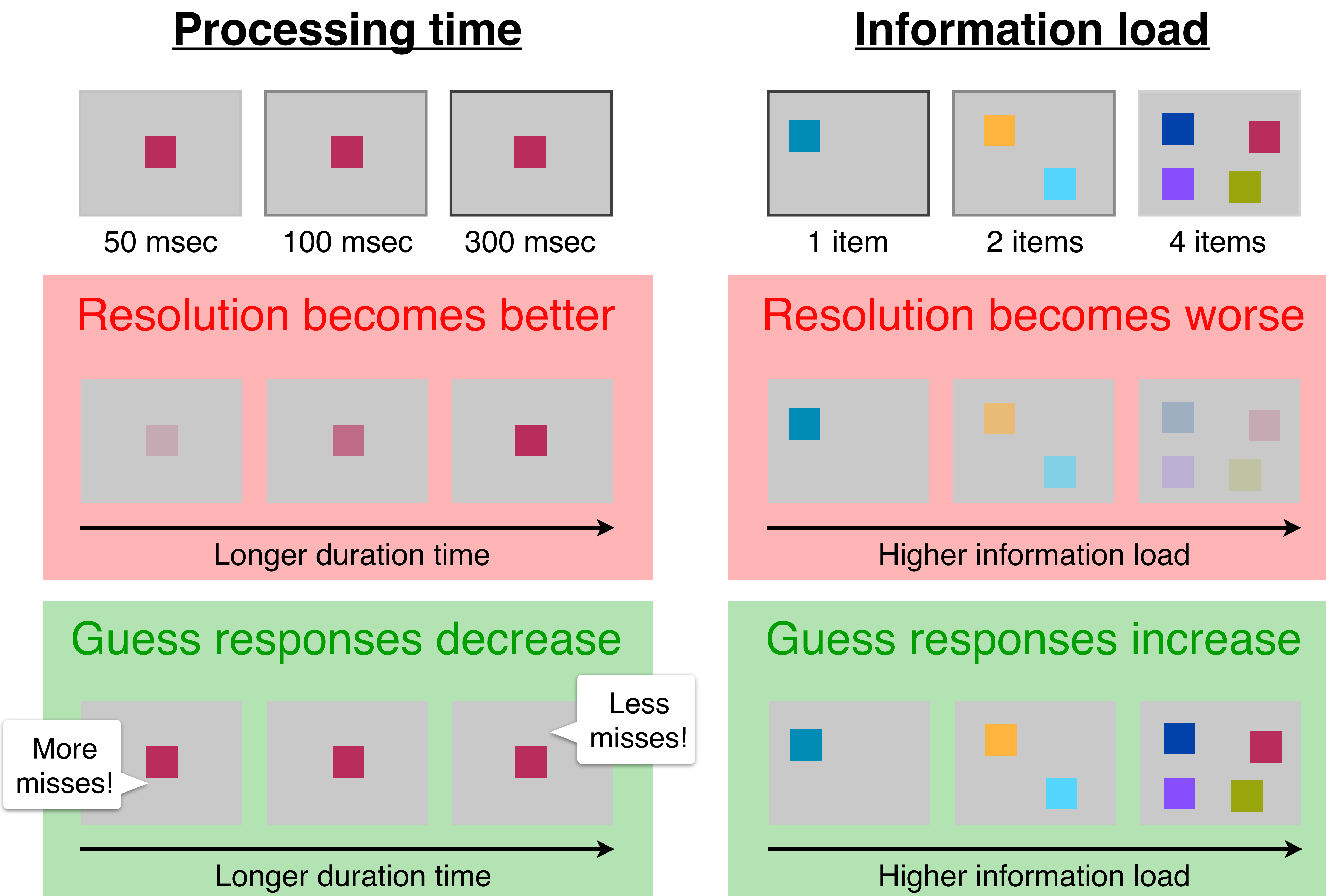

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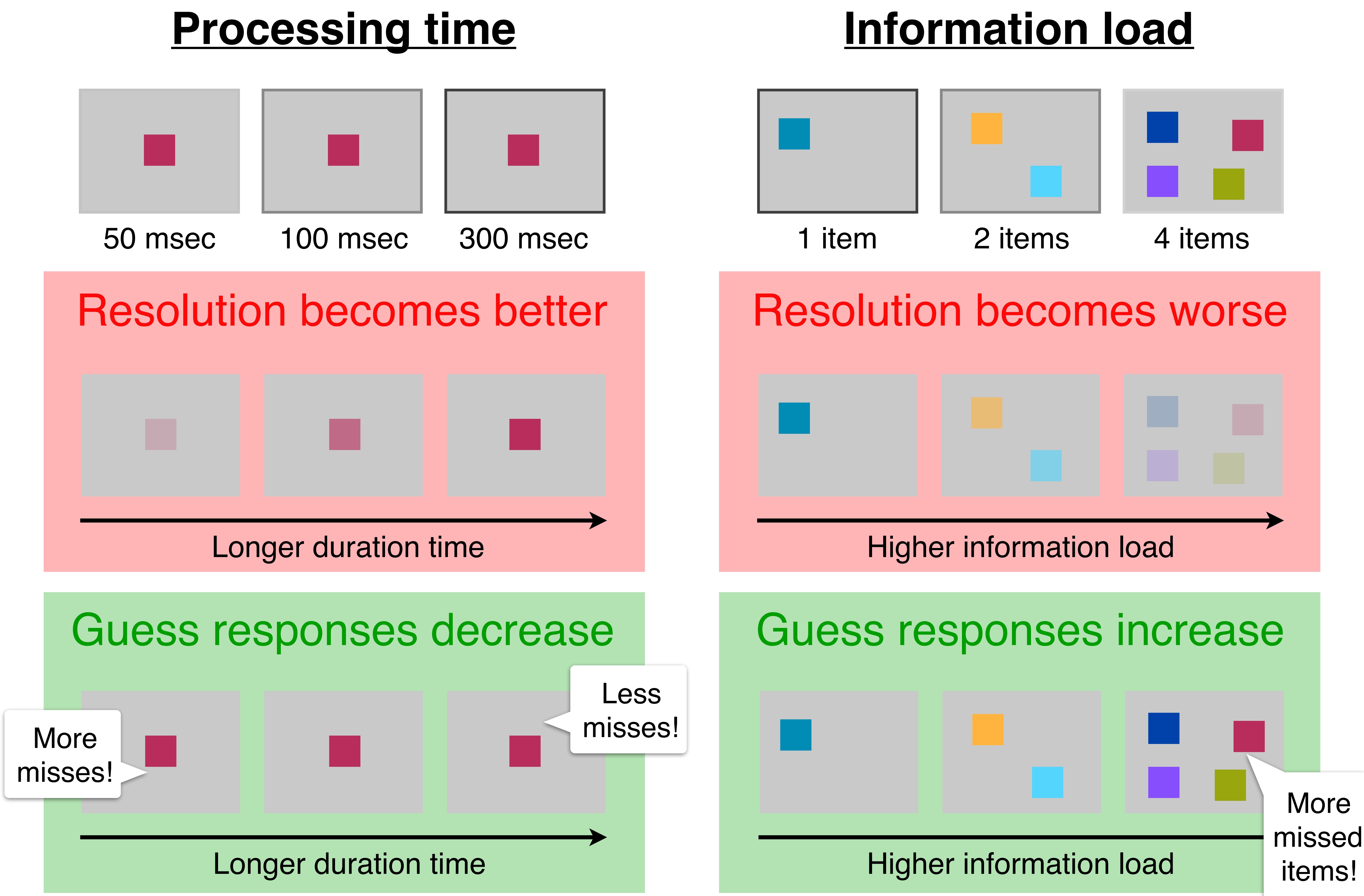
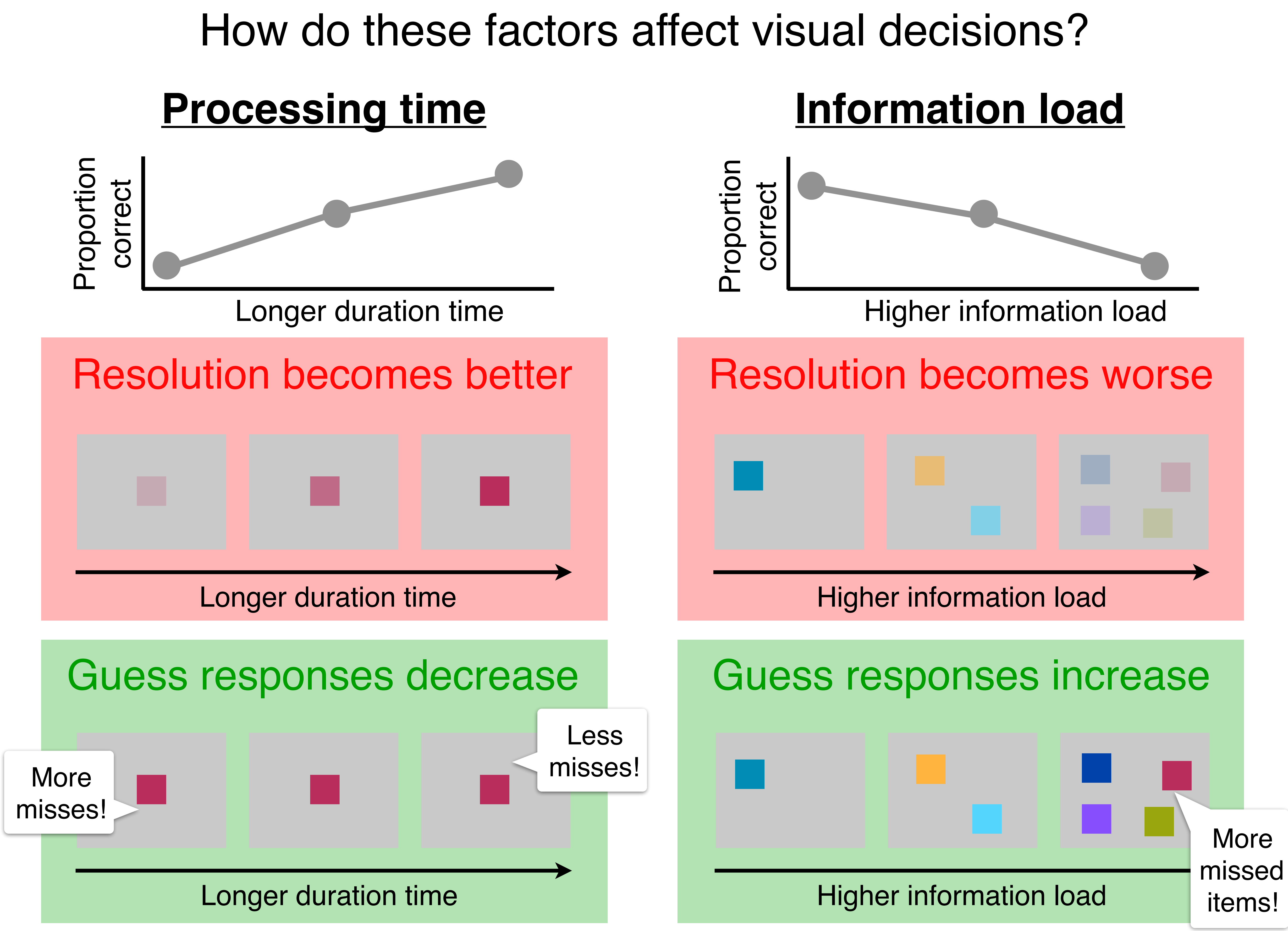
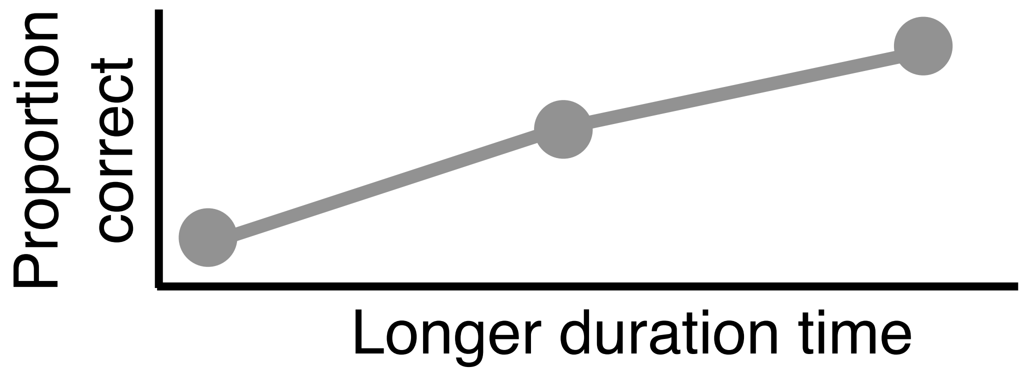
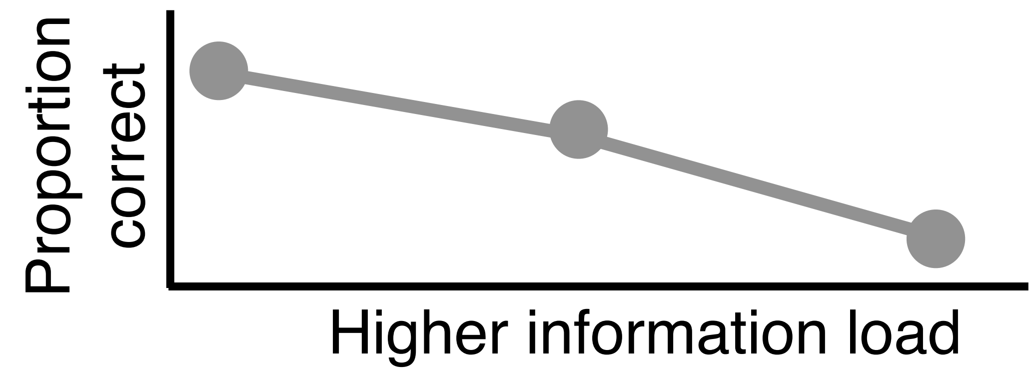



How do these factors affect visual decisions?
Processing time
Proportion correct
Longer duration time
Resolution becomes better
Longer duration time
Guess responses decrease
More misses!
Less misses!
Longer duration time
Information load
Proportion correct
Higher information load
Resolution becomes worse
Higher information load
Guess responses increase
More missed items!
Higher information load

Why is it a difficult problem?





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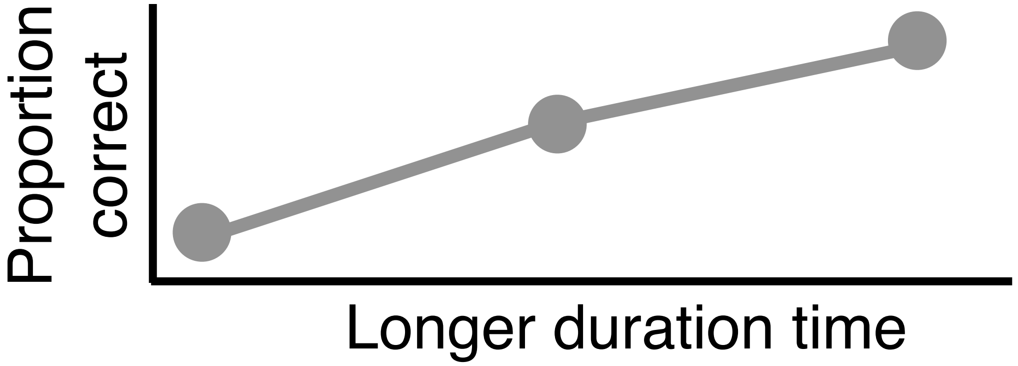

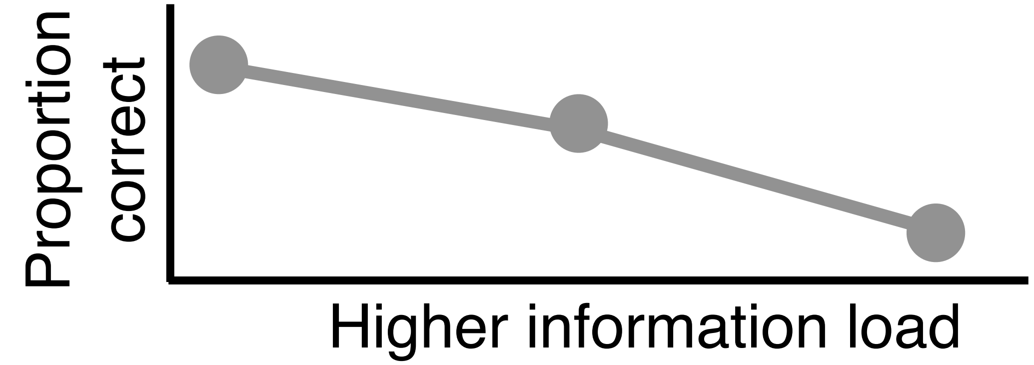

Because human response is a complex mixture of regular responses from internal representation and guess responses!

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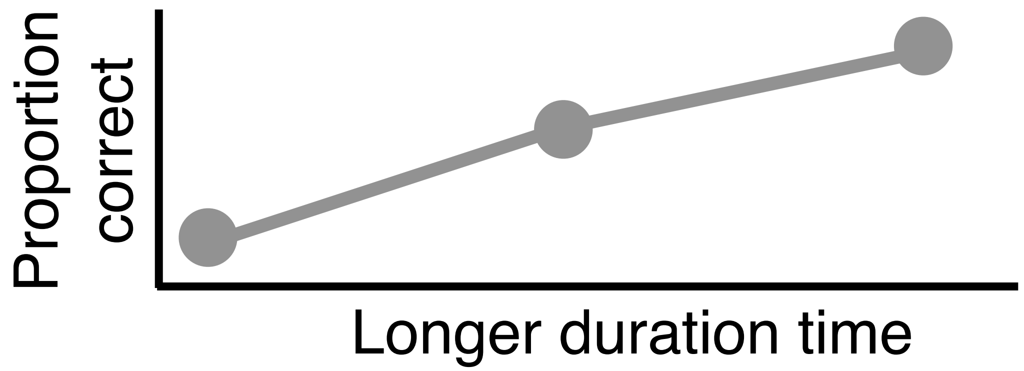

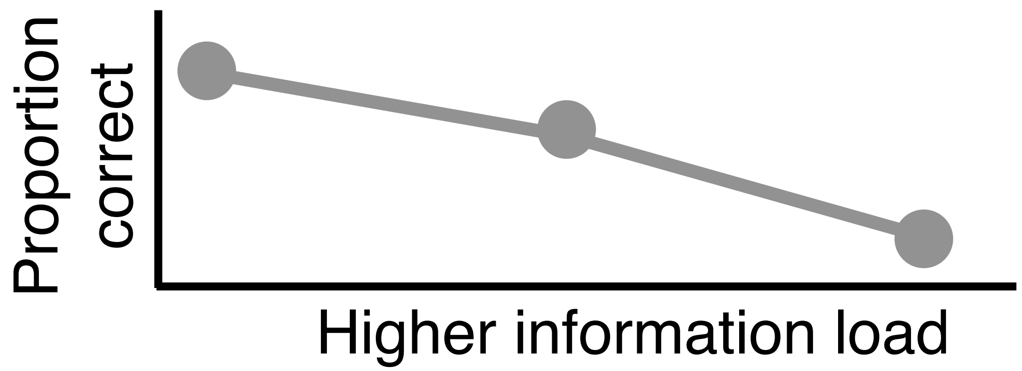

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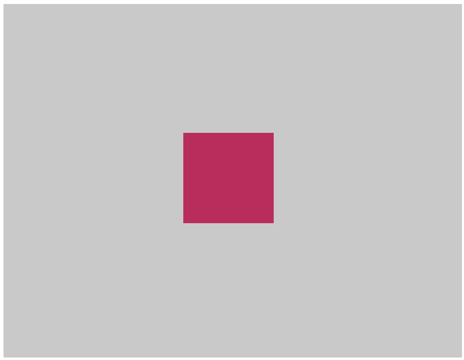

A given image

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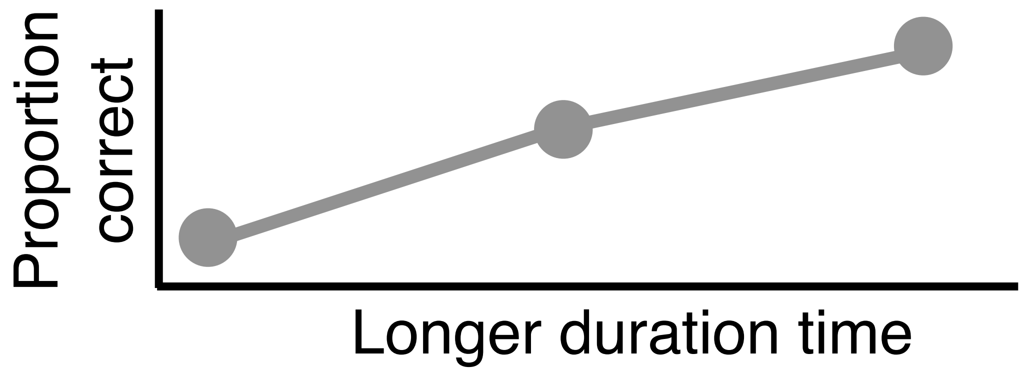

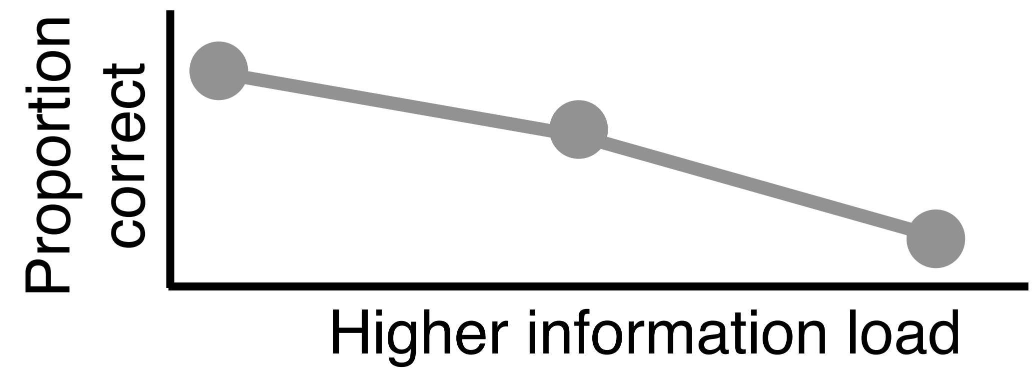

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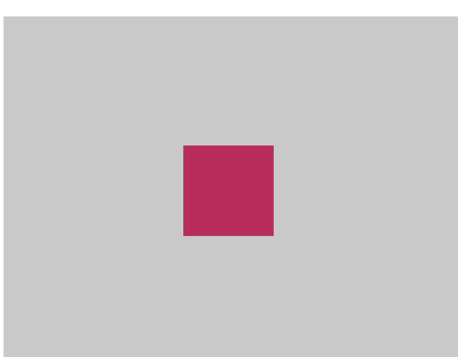
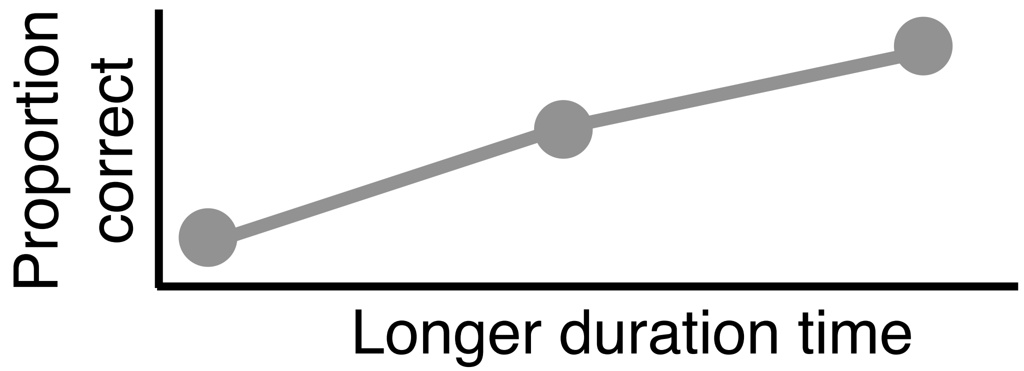
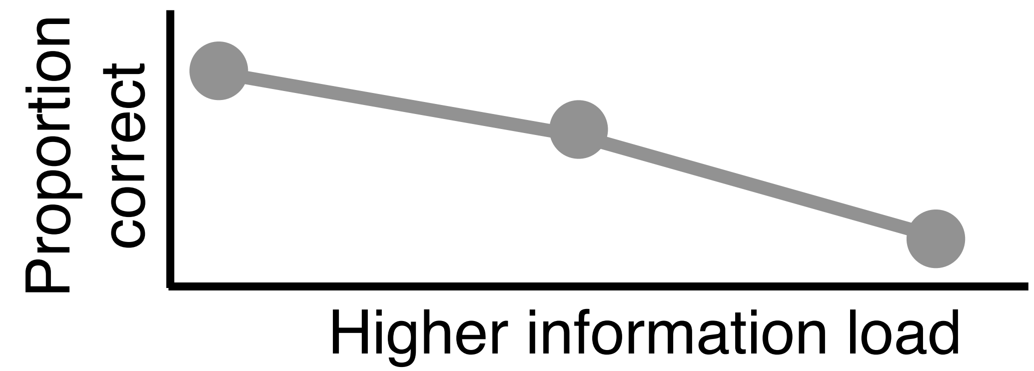


A given image

Response from an observer

Why is it a difficult problem?





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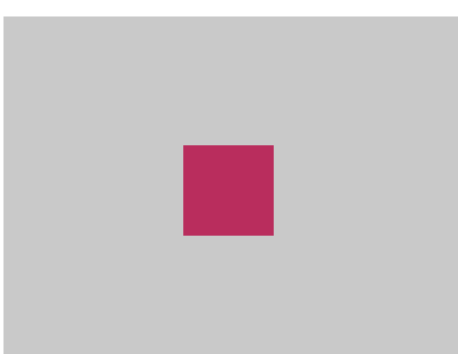


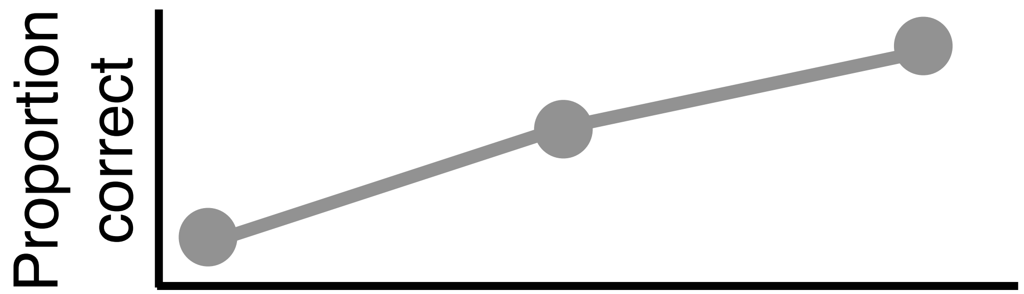
A given image

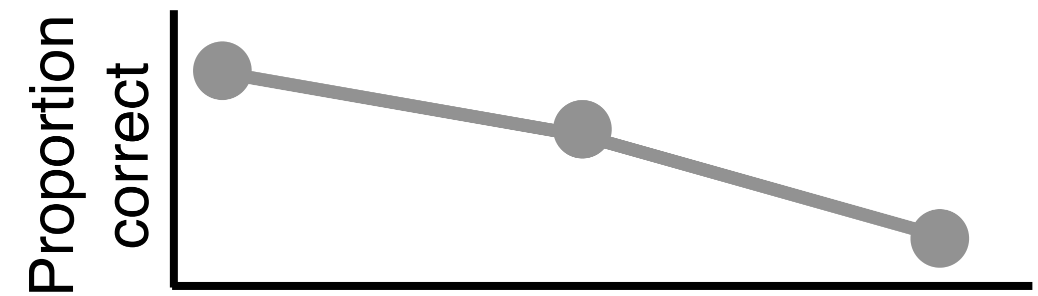
Response from an observer

Poor resolution of internal representation?

Guess response on a miss trial?

Why is it a difficult problem?





Because human response is a complex mixture of regular responses from internal representation and guess responses!

A given image

Response from an observer

<u>Poor resolution of internal representation?</u>

<u>Guess response on a miss trial?</u>

An approach should be able to appropriately identify human responses by decomposing them into the two states

Estimating the resolution of internal representations

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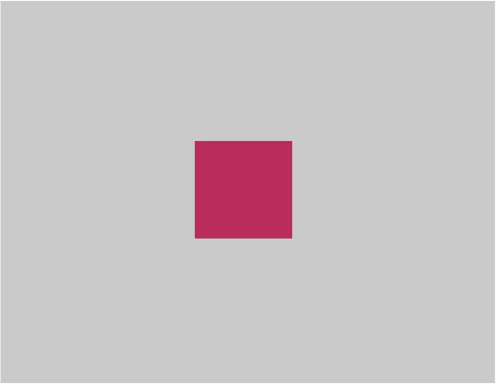

A given image

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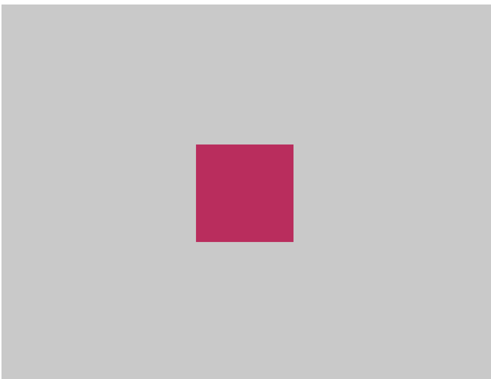
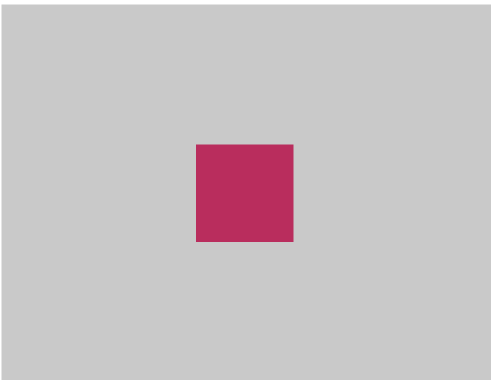


A given image

A good observer

A set of responses

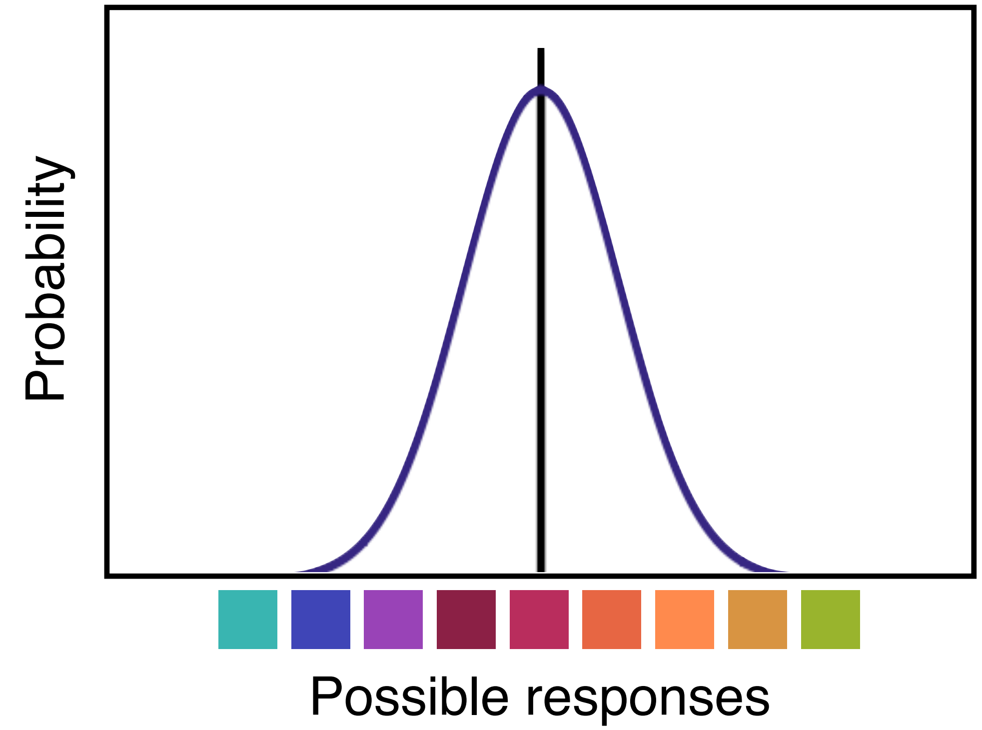
Estimating the resolution of internal representations



A given image

A good observer

A set of responses



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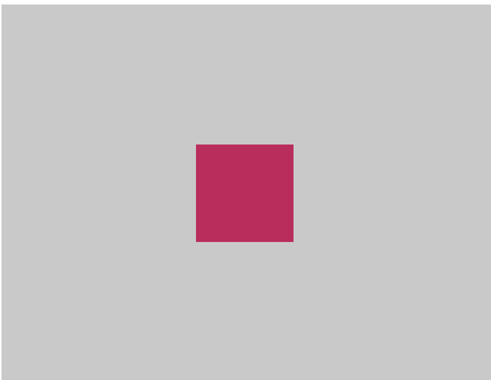

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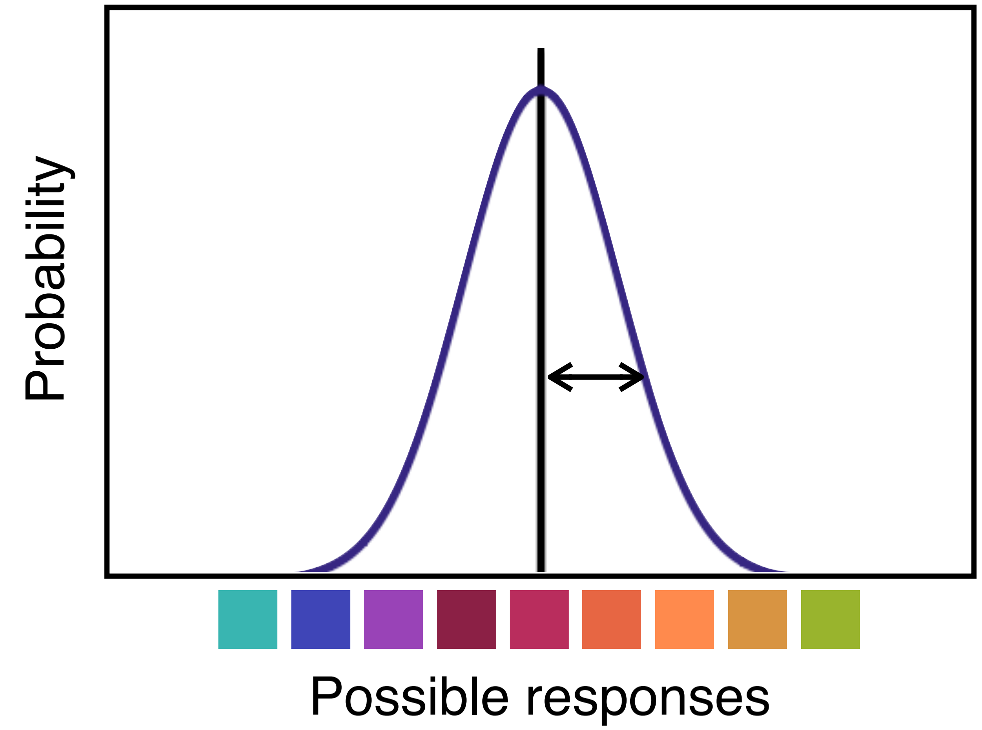

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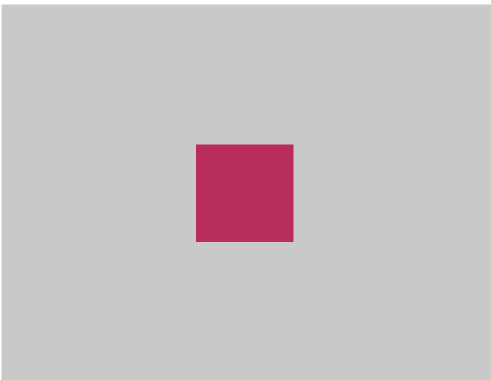

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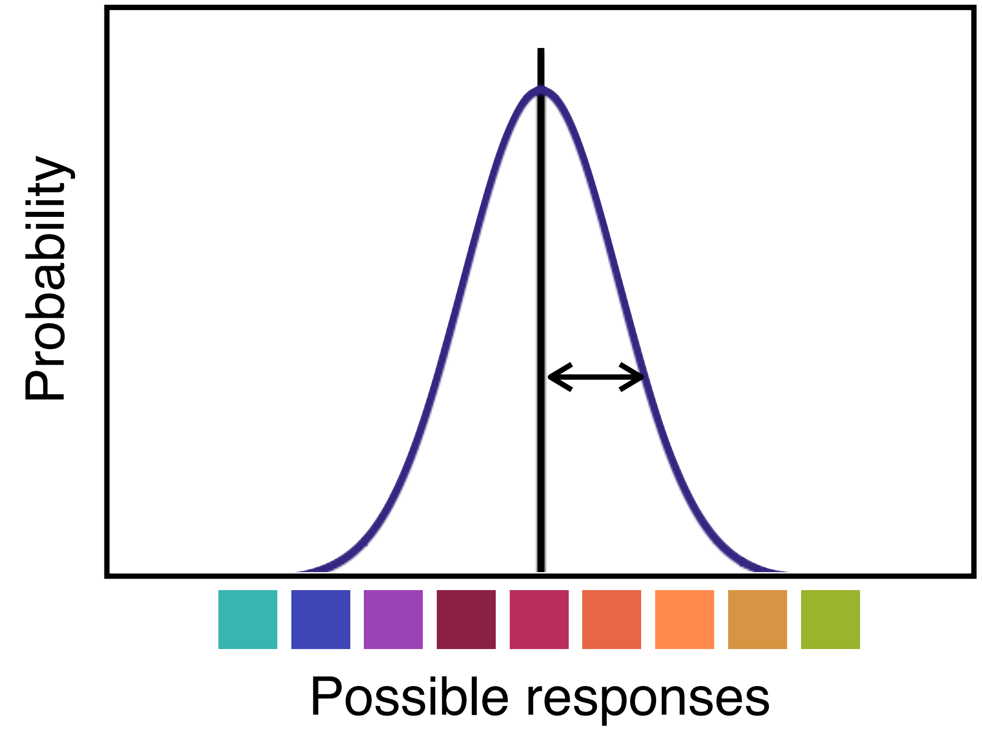

A poor observer

A set of responses

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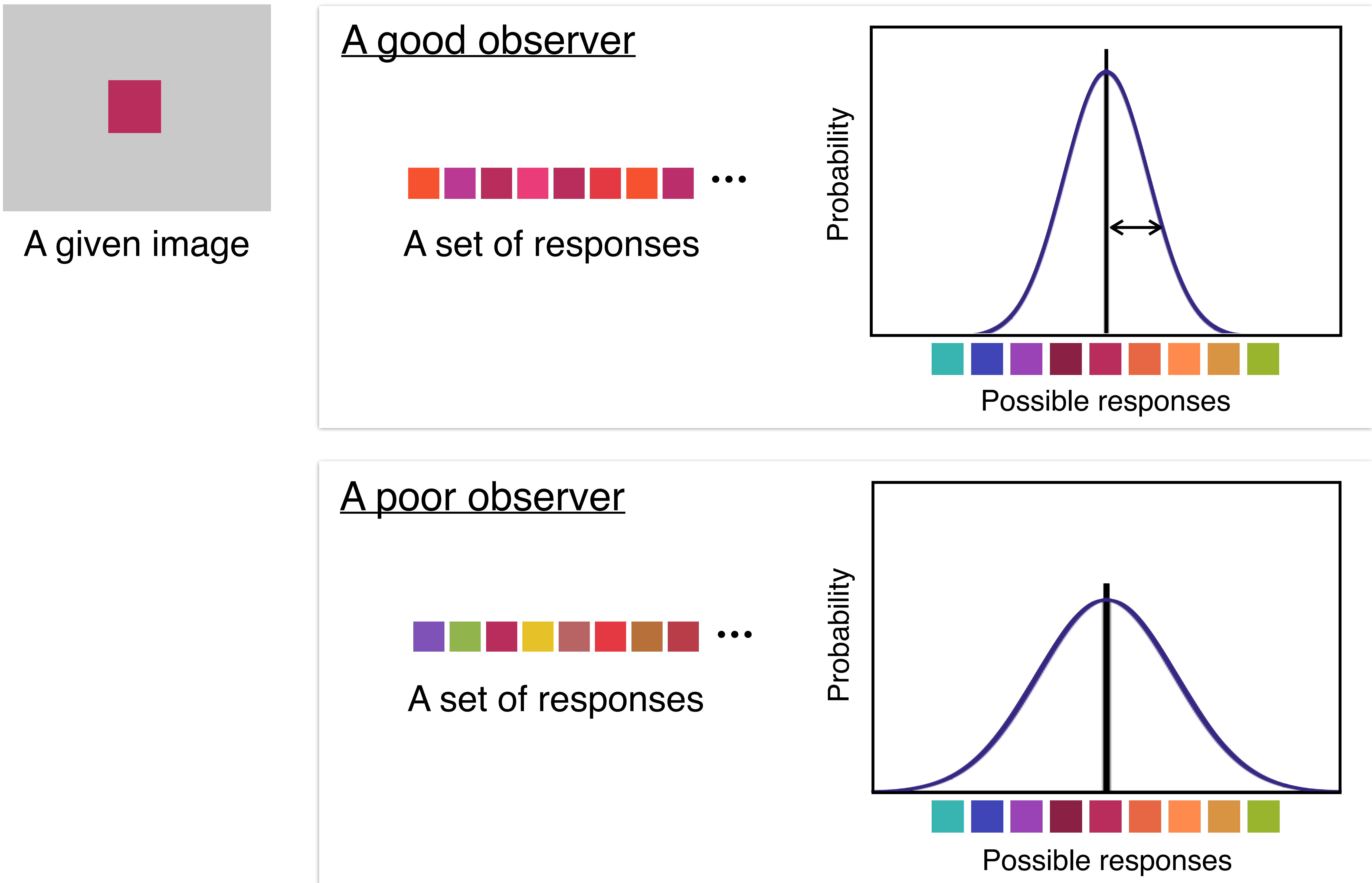

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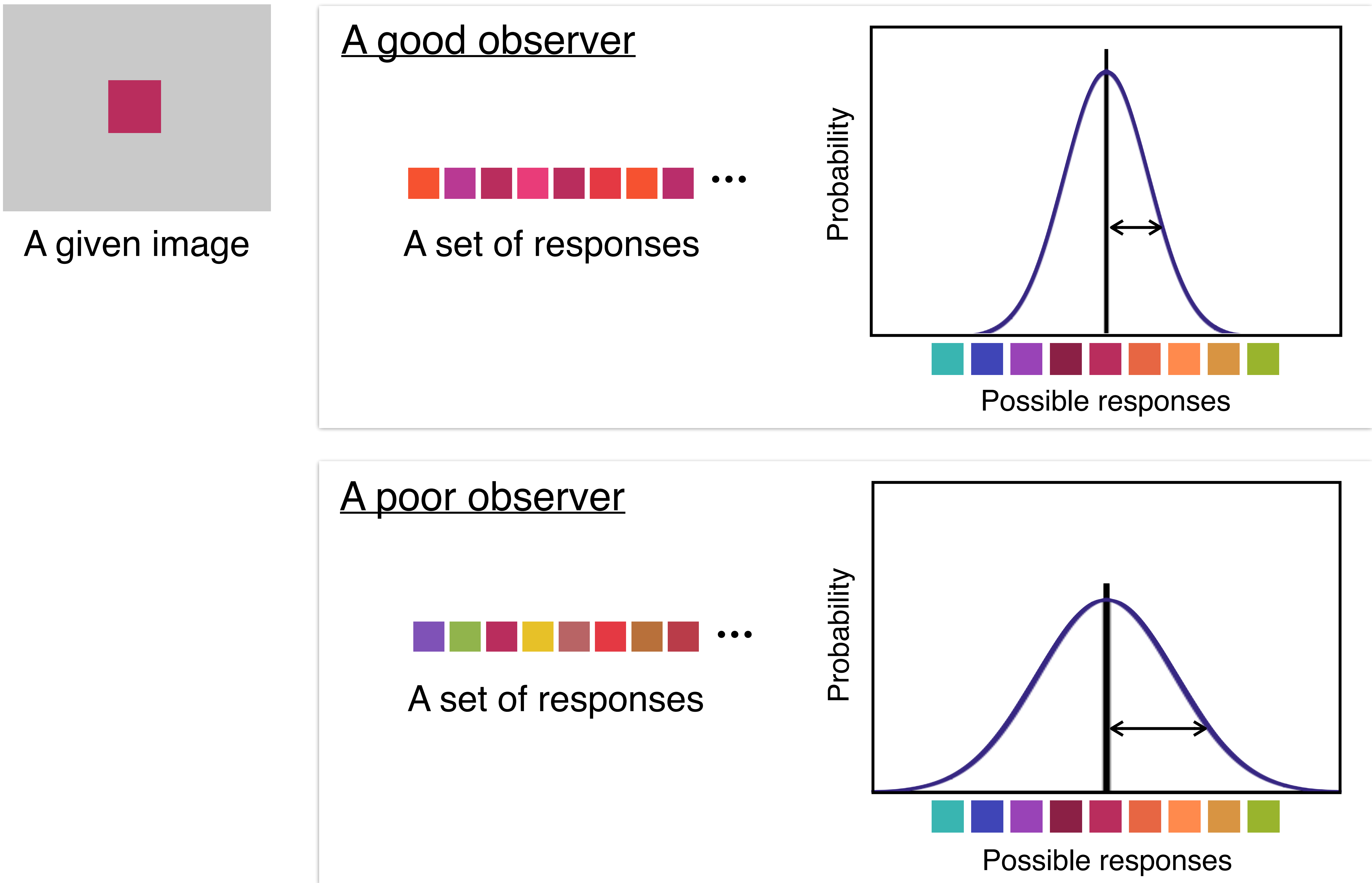
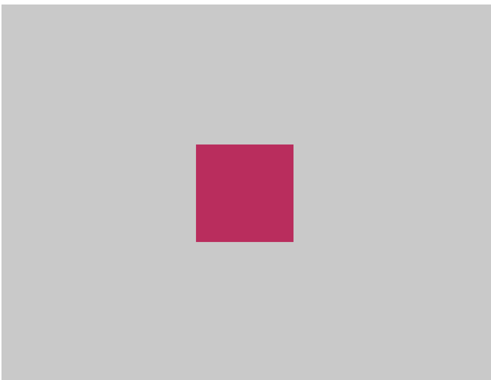


An assumption of guess responses



A given image

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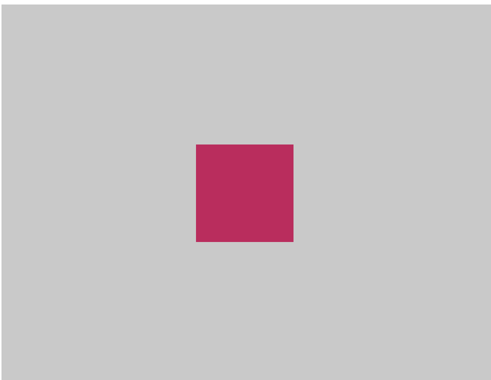
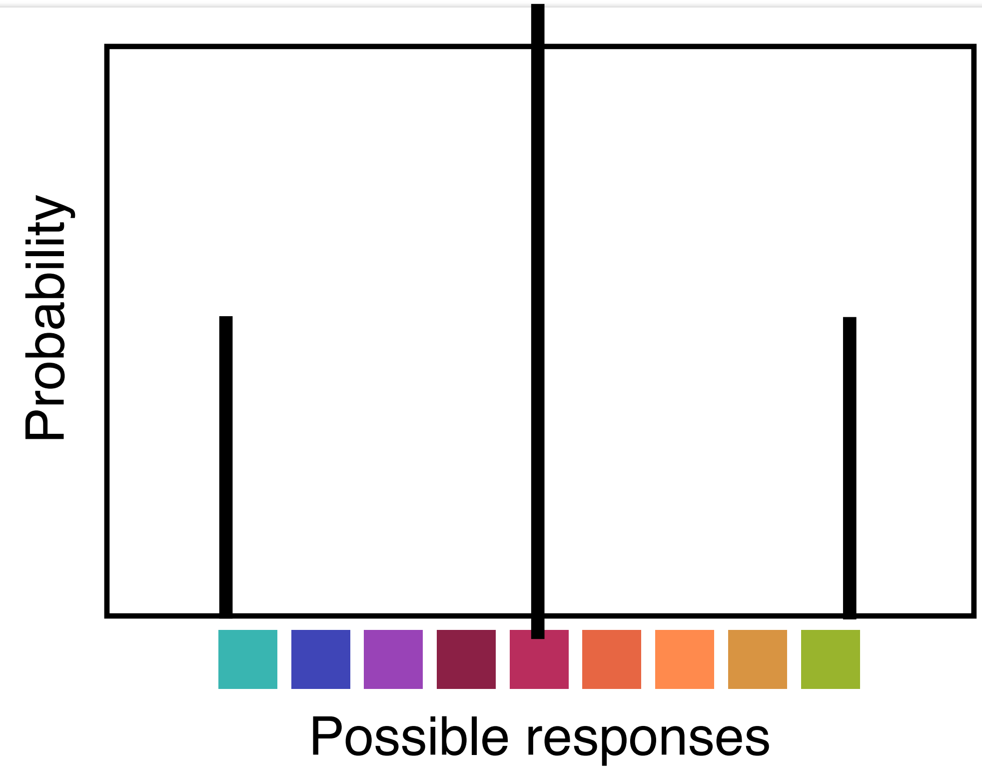


A given image

A good observer

A set of responses



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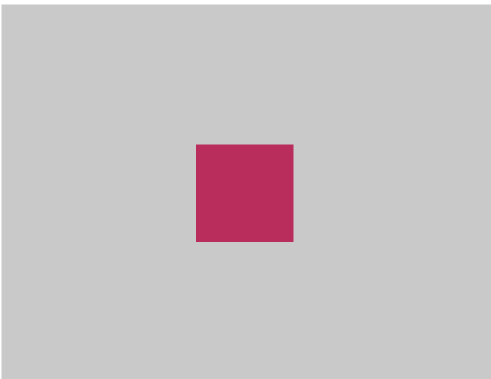
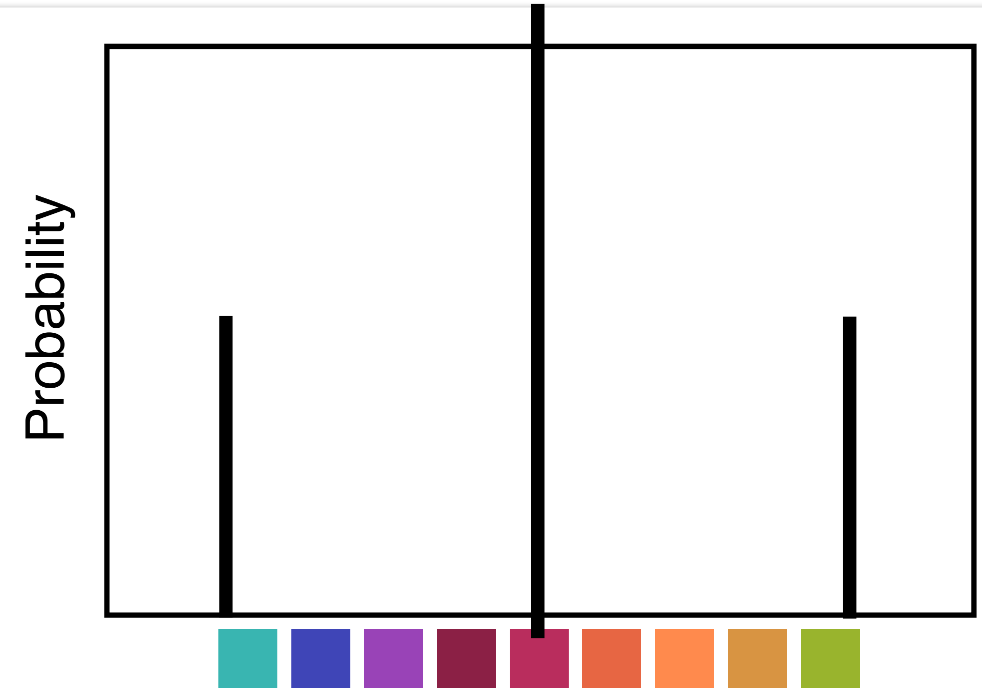


A given image

A good observer

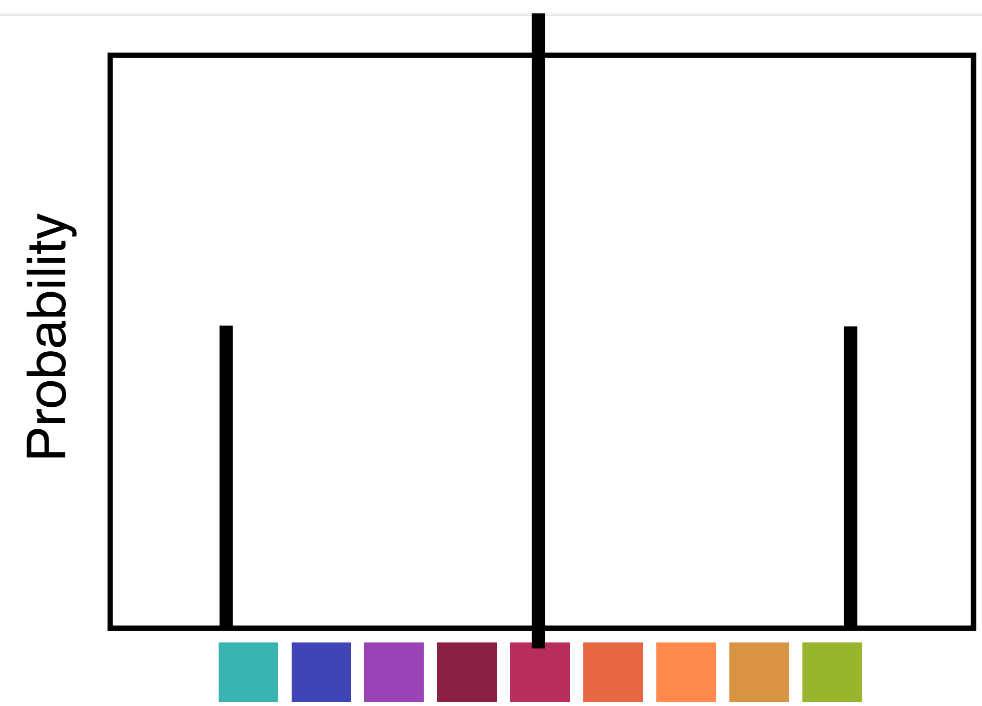
A set of responses



Possible responses

A poor observer

A set of responses



Possible responses

Fougnie & Alvarez, 2011;
Green & Swets, 1966;
Halberda & Feigenson, 2008;
Ludwig & Davies, 2011;
Wichmann & Hill, 2001;
Zhang & Luck, 2008

Decomposing human responses

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Comparing the probabilities for each response to be drawn from internal representation with those from random guessing

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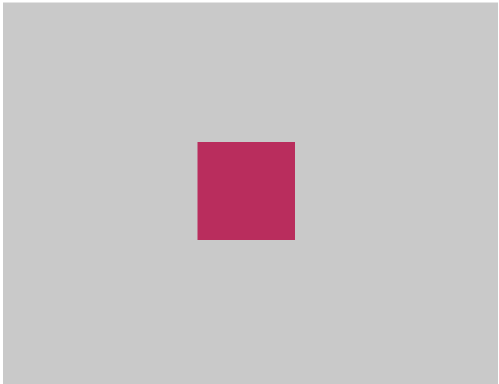

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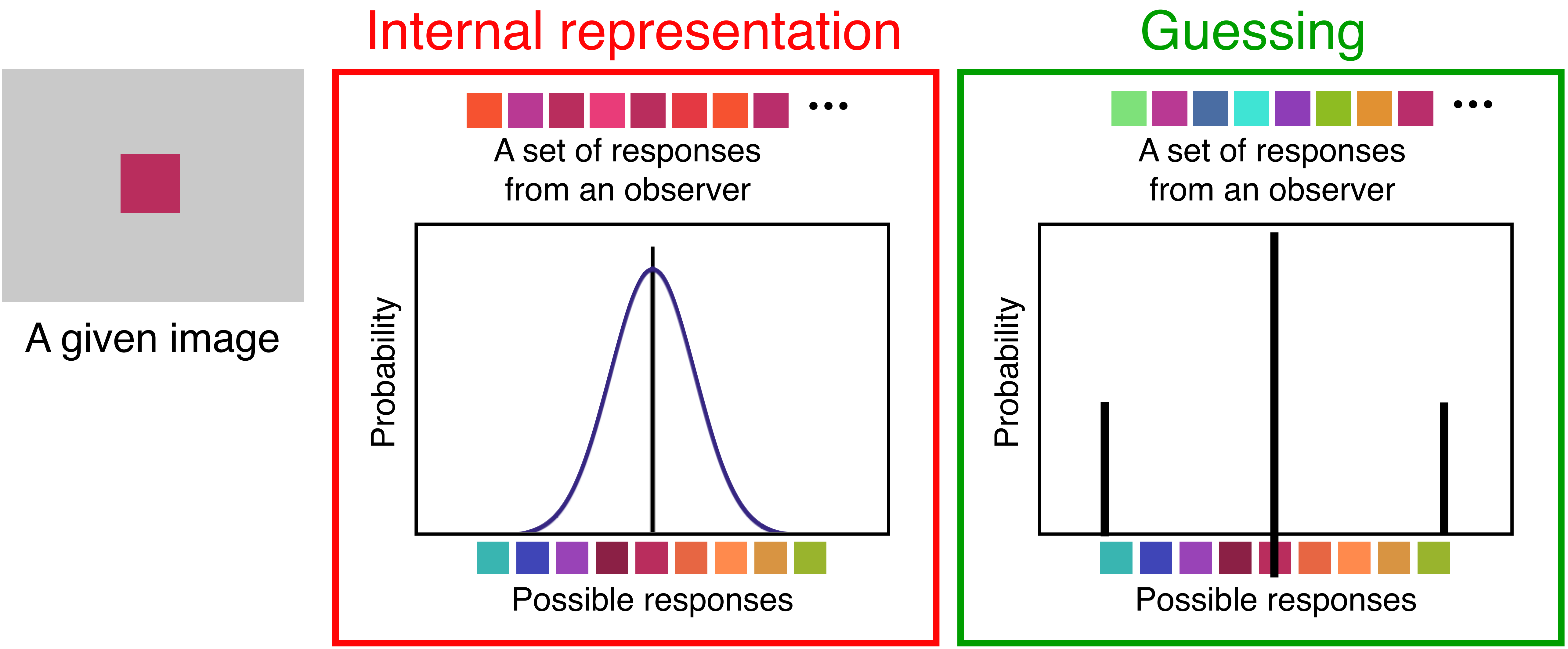

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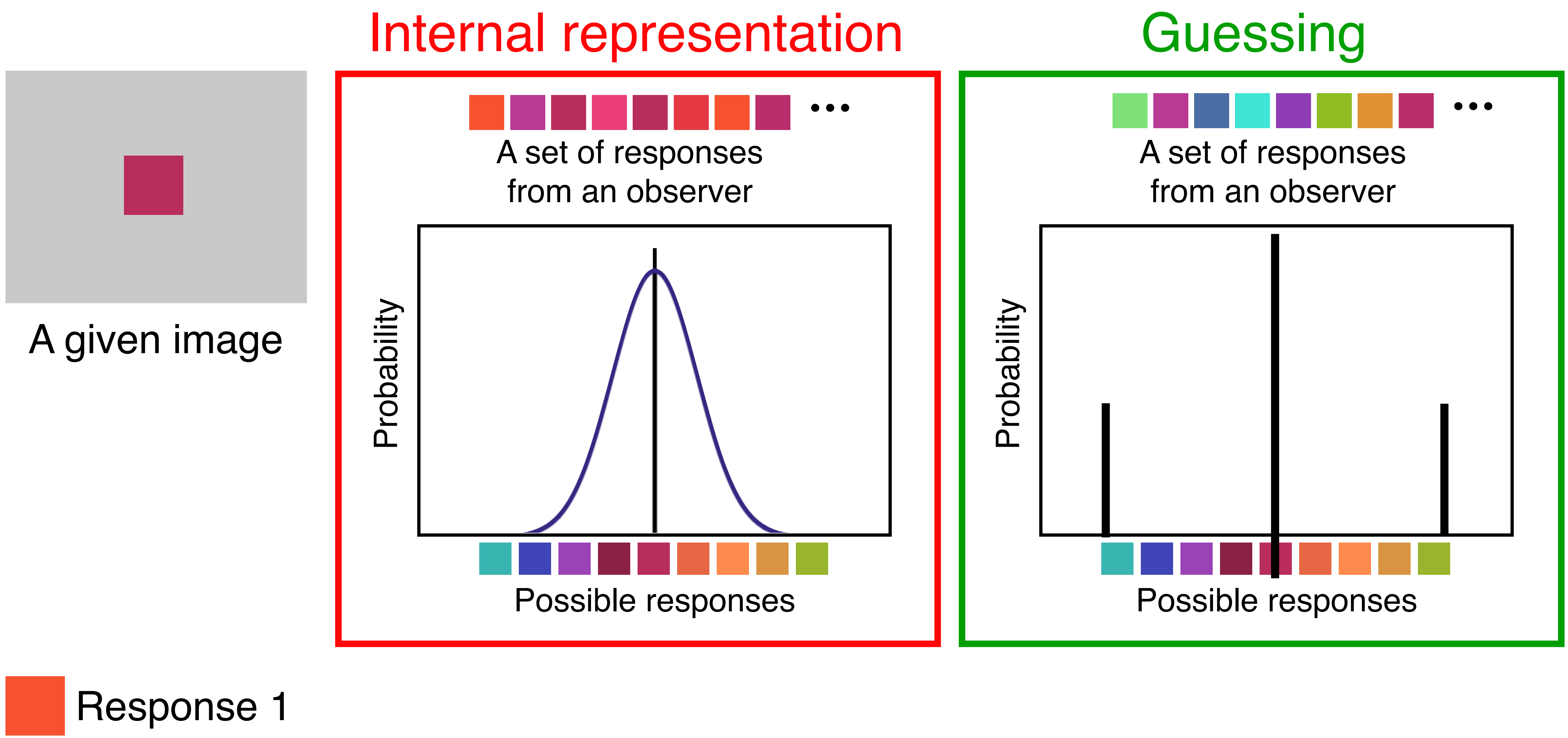

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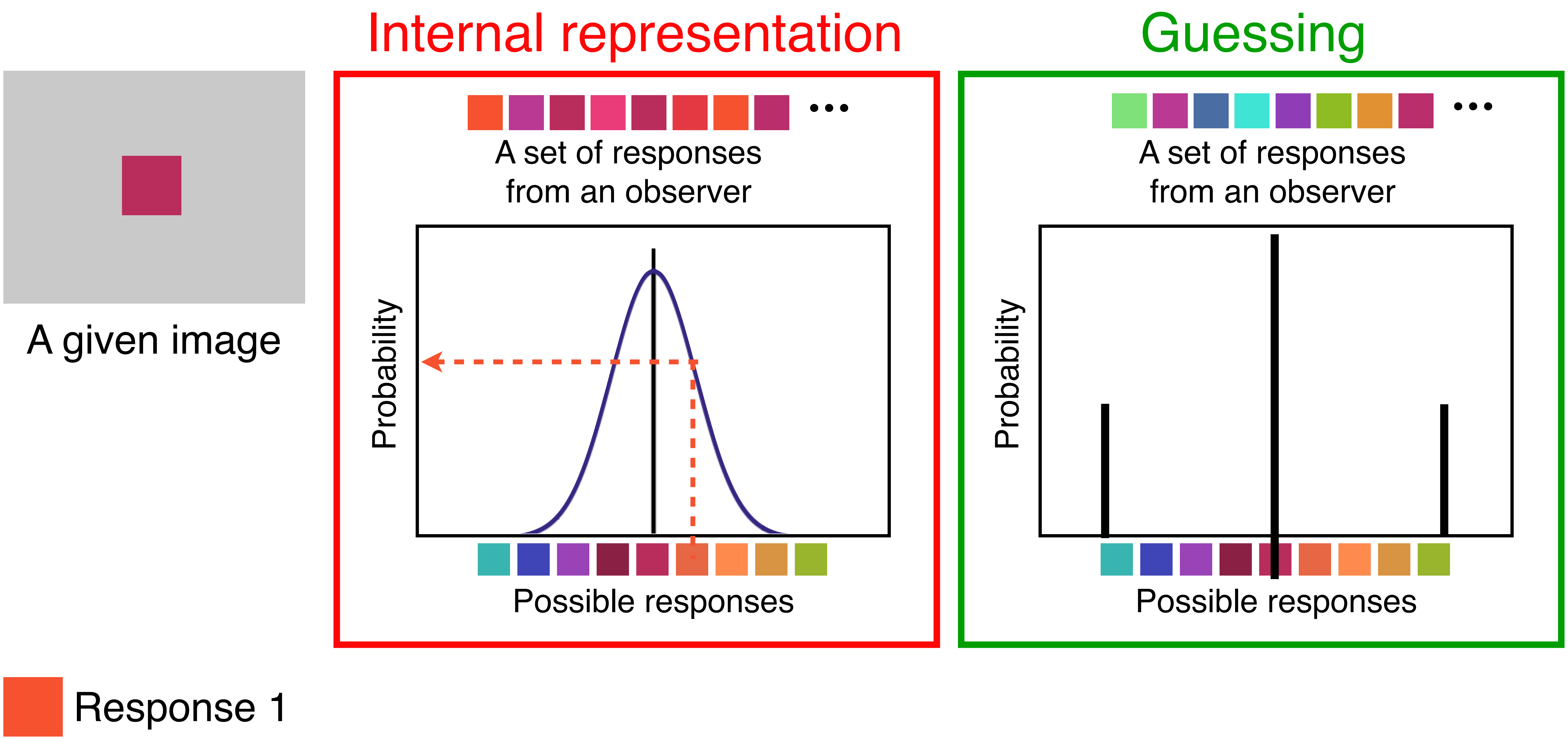

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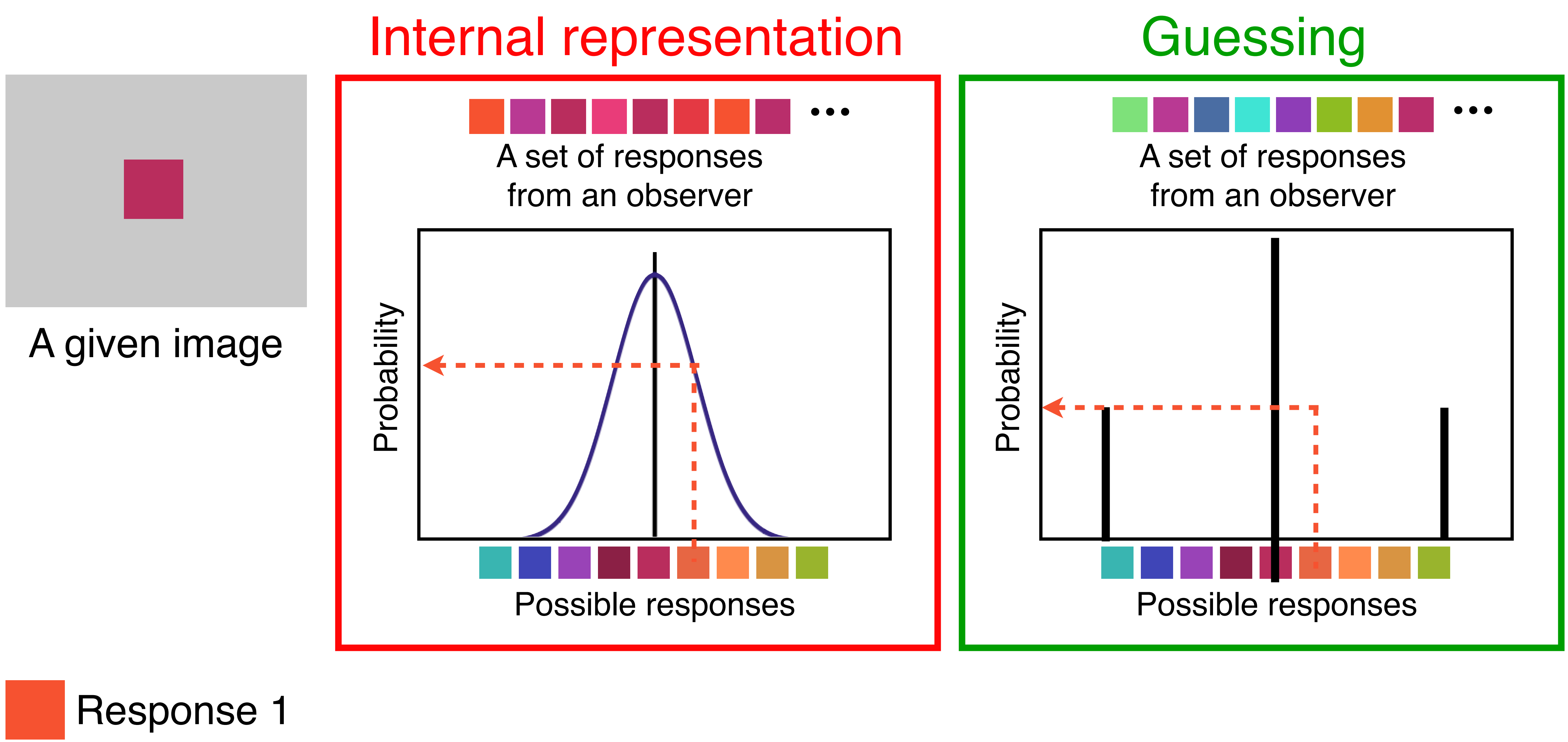

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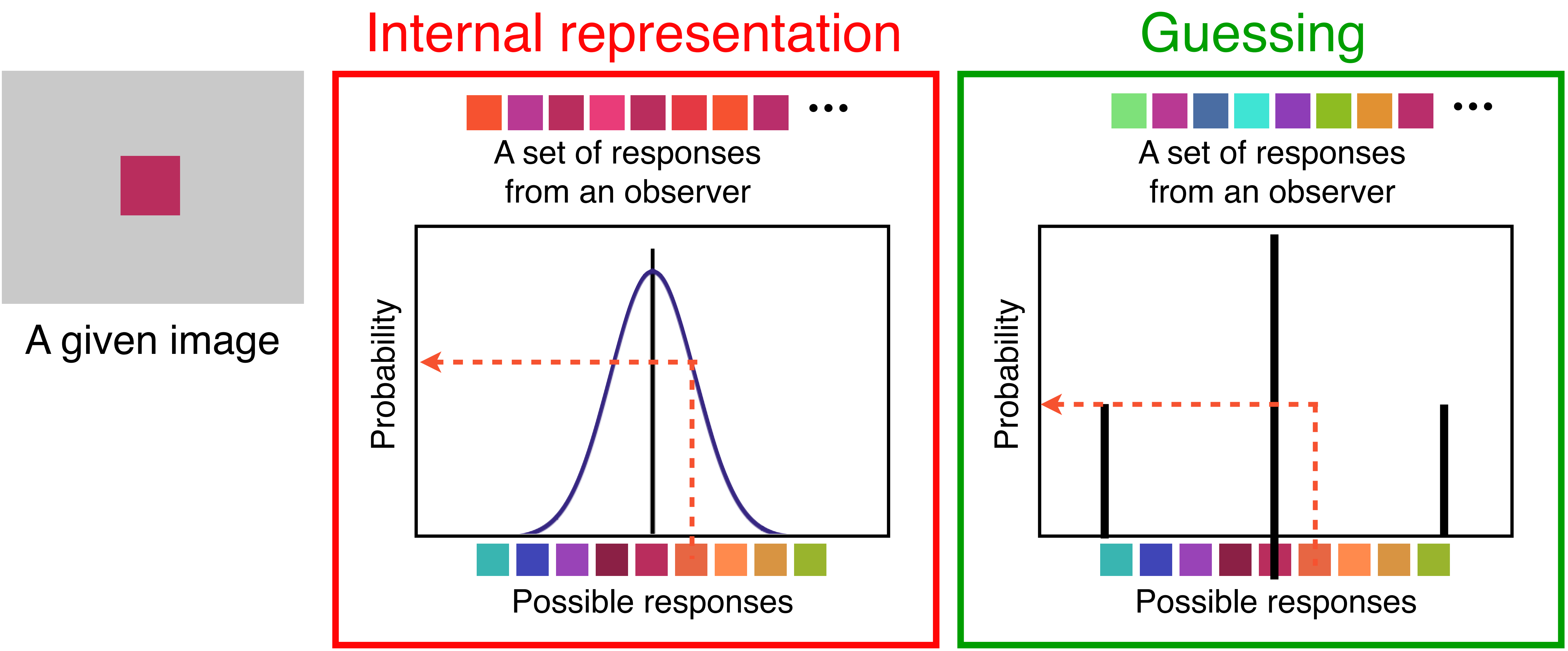

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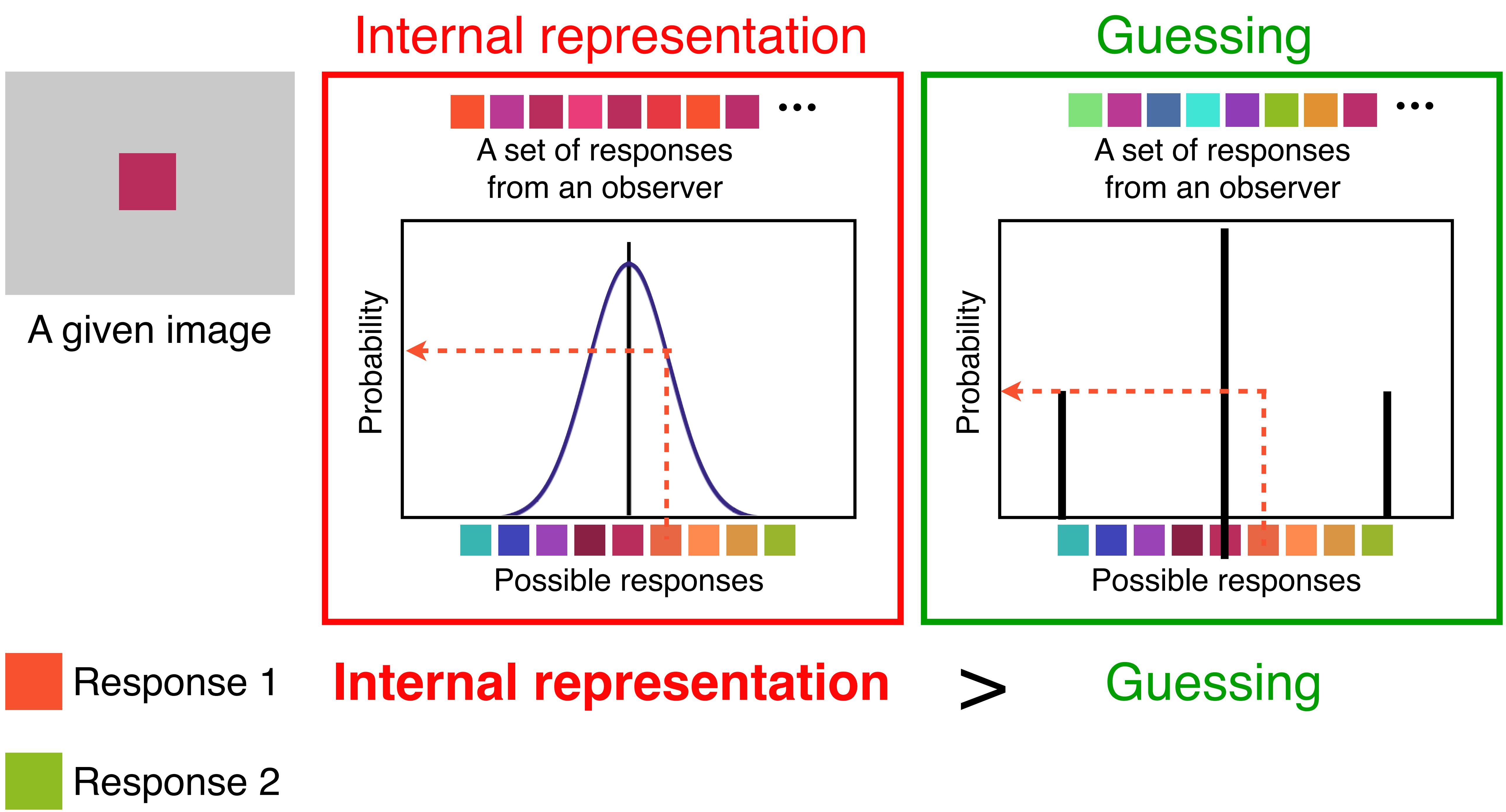

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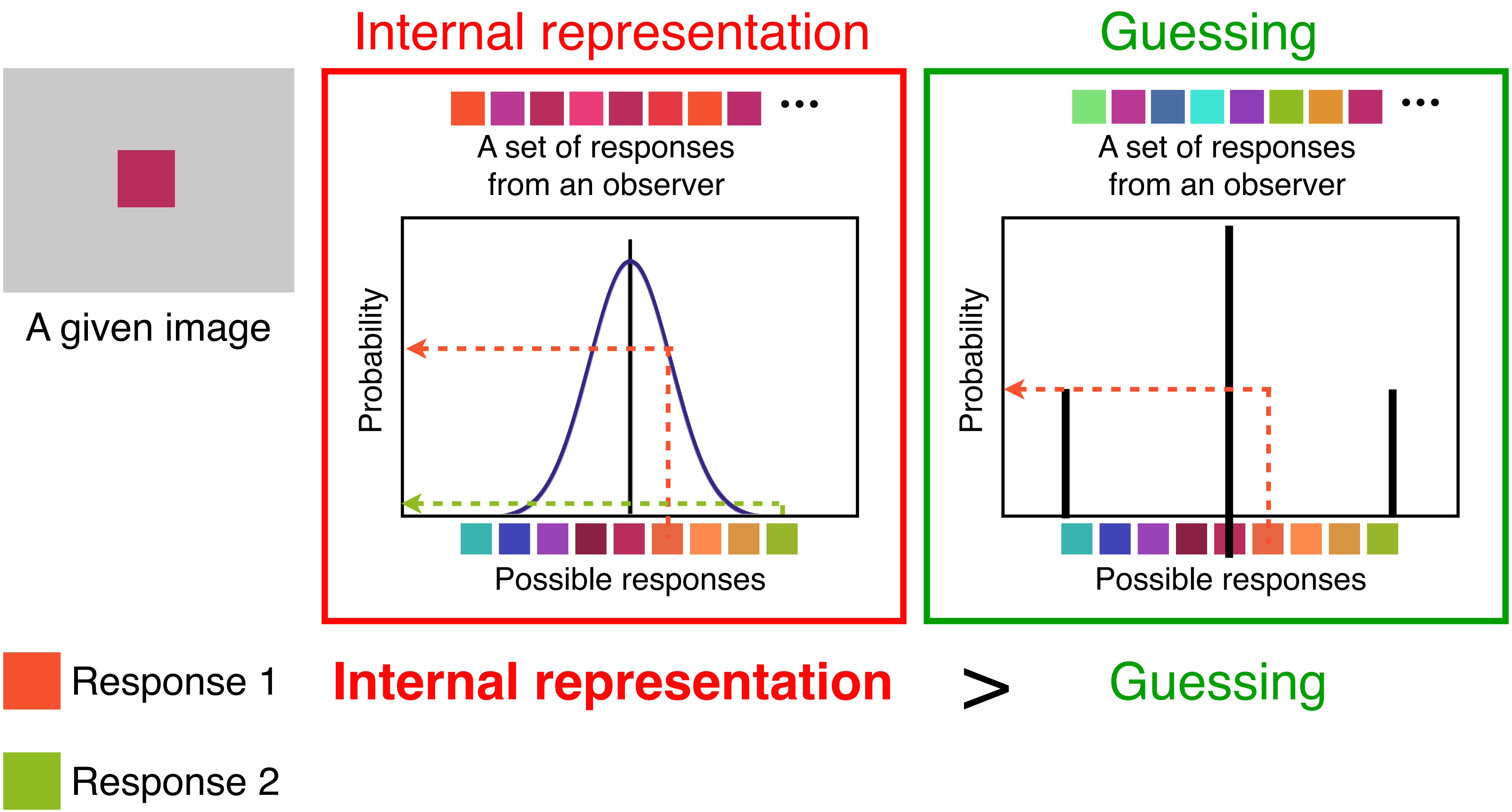
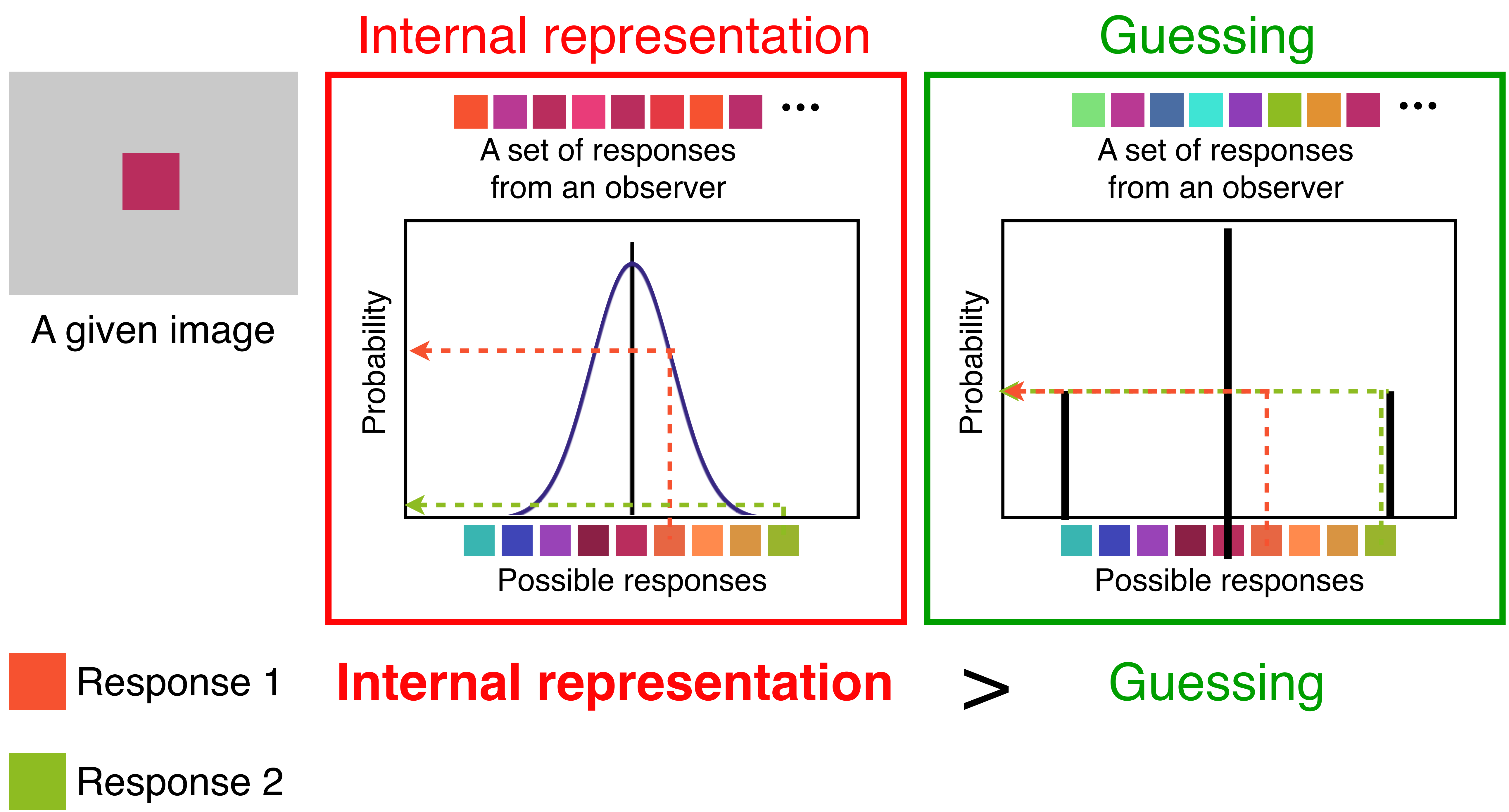


Decomposing human responses

Comparing the probabilities for each response to be drawn from internal representation with those from random guessing



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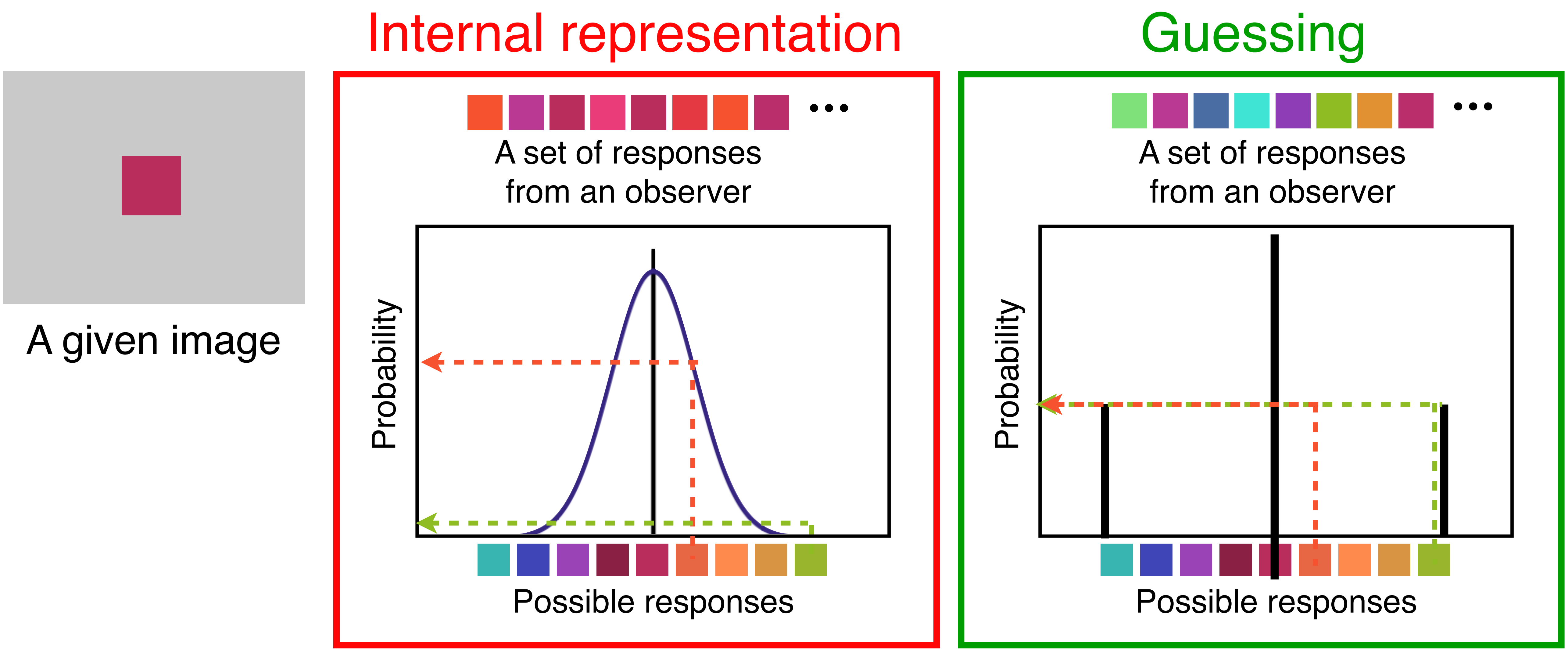
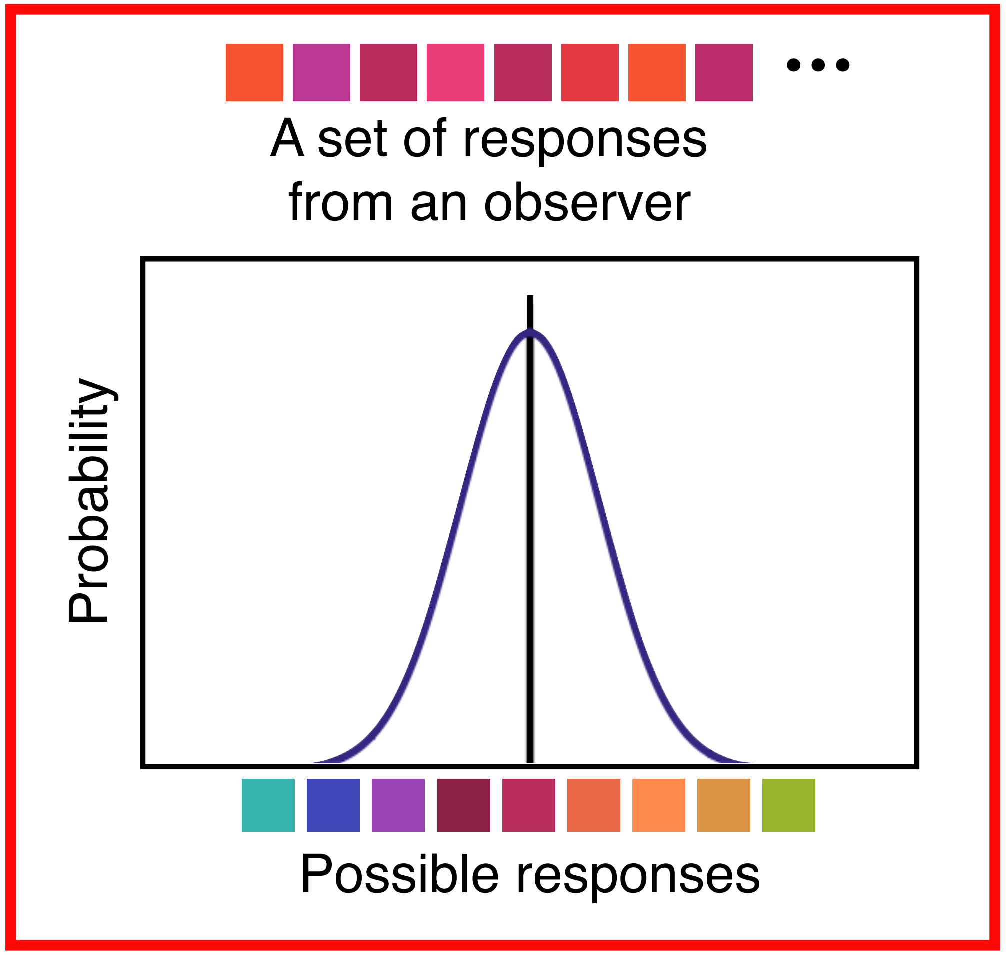


Response 1 **Internal representation** > Guessing

Response 2 Internal representation << **Guessing**

Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



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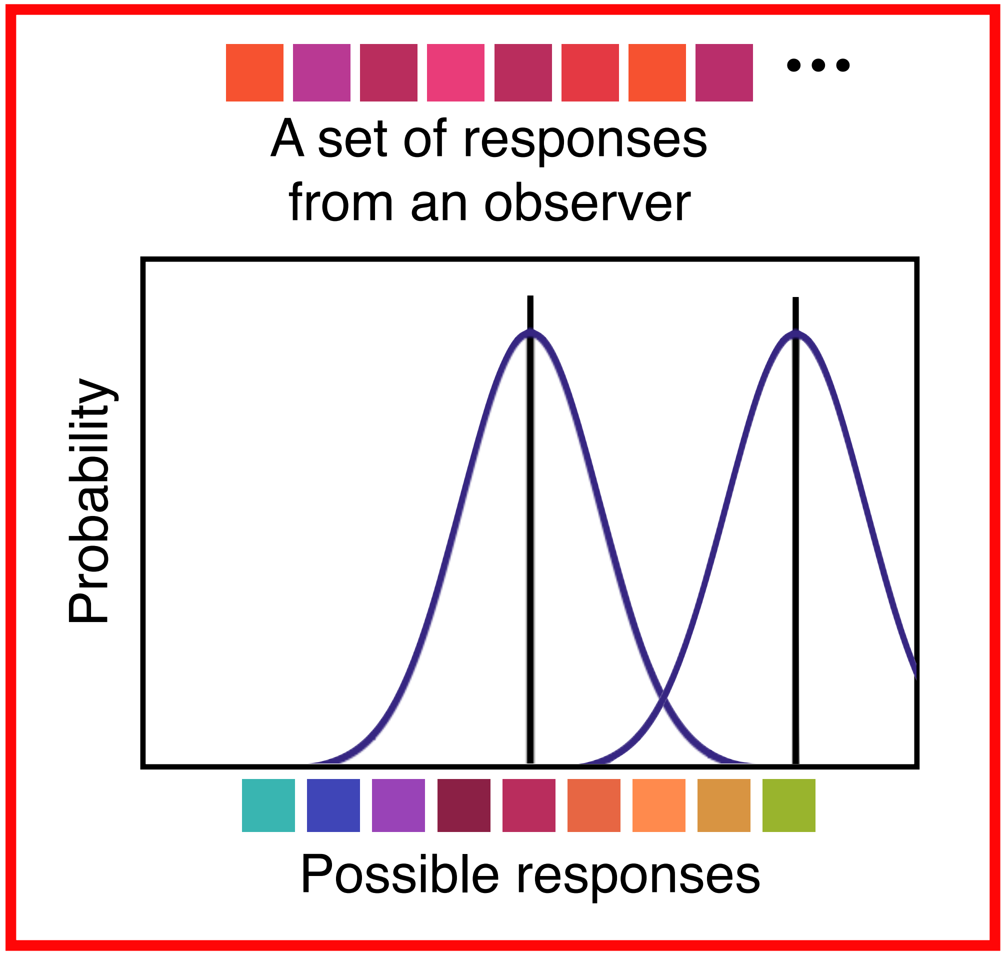
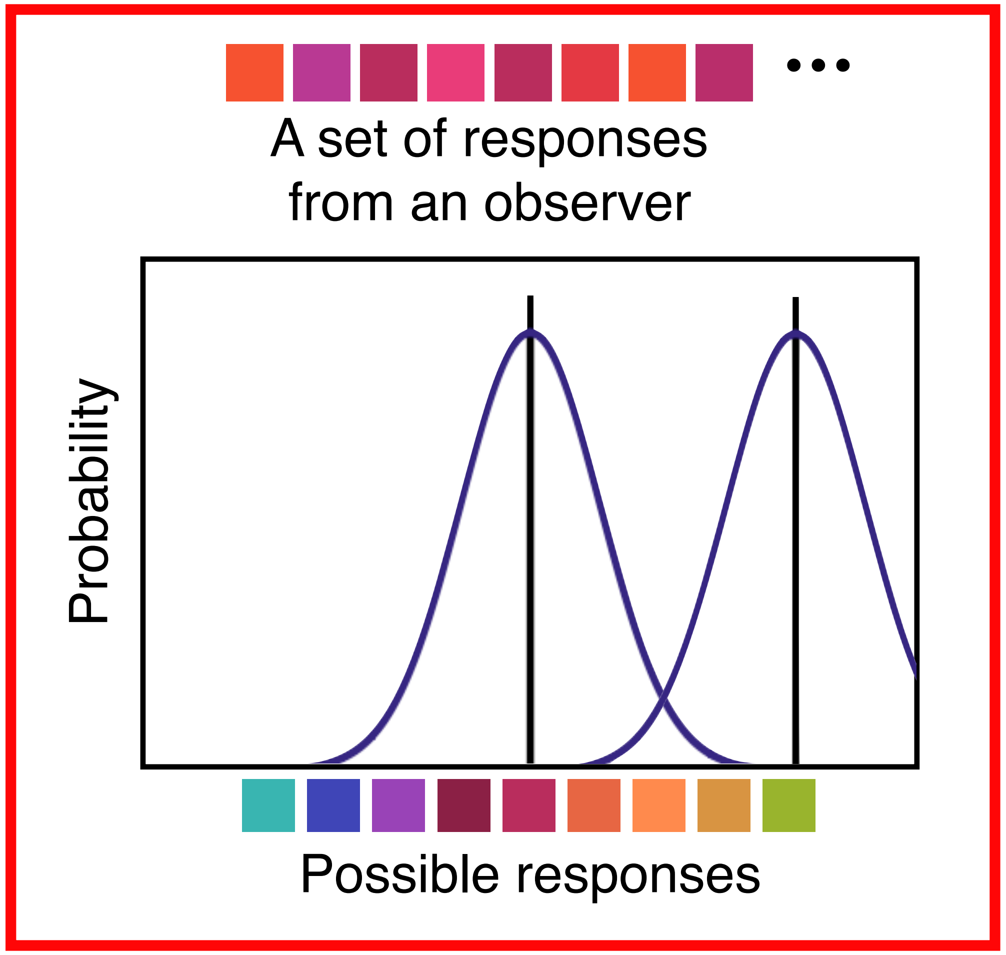
Internal representation



Appropriate models for internal representation and guessing are very important for precise decomposition

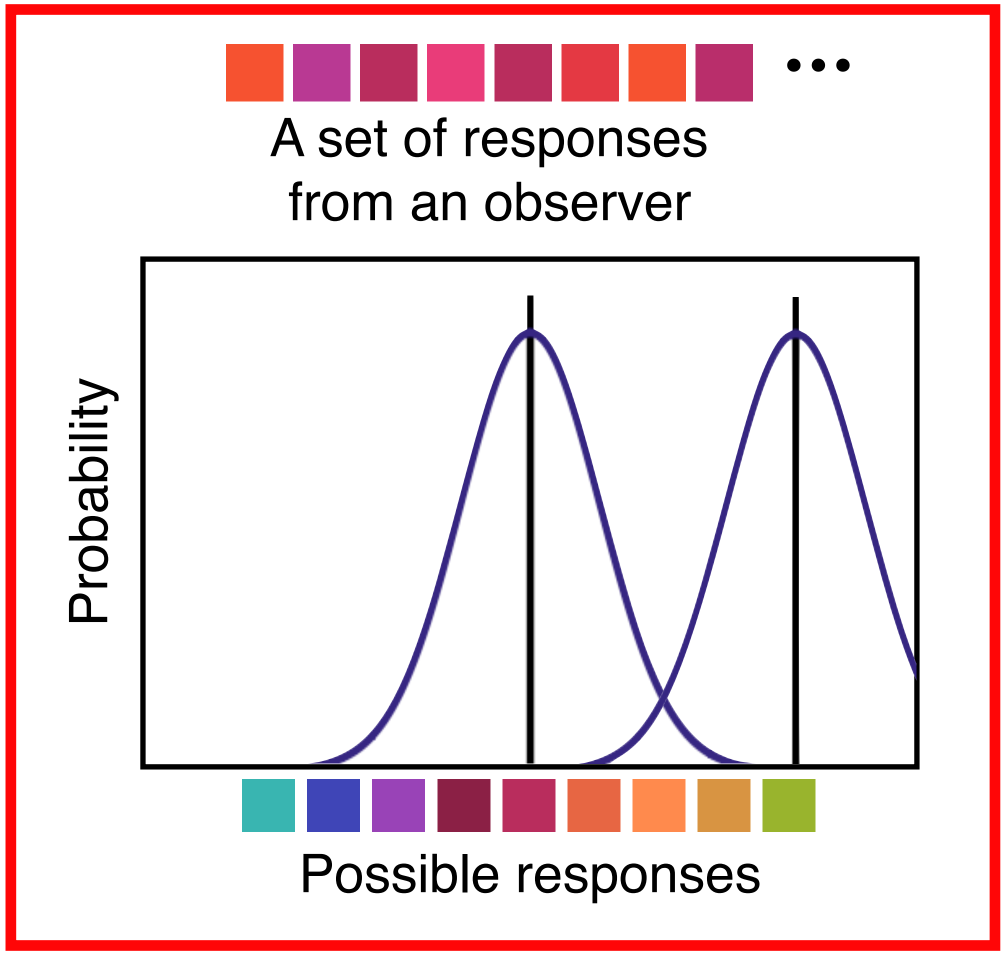
Internal representation



- Systematic variability across values

Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



- Systematic variability across values
- Different visual features require different assumptions

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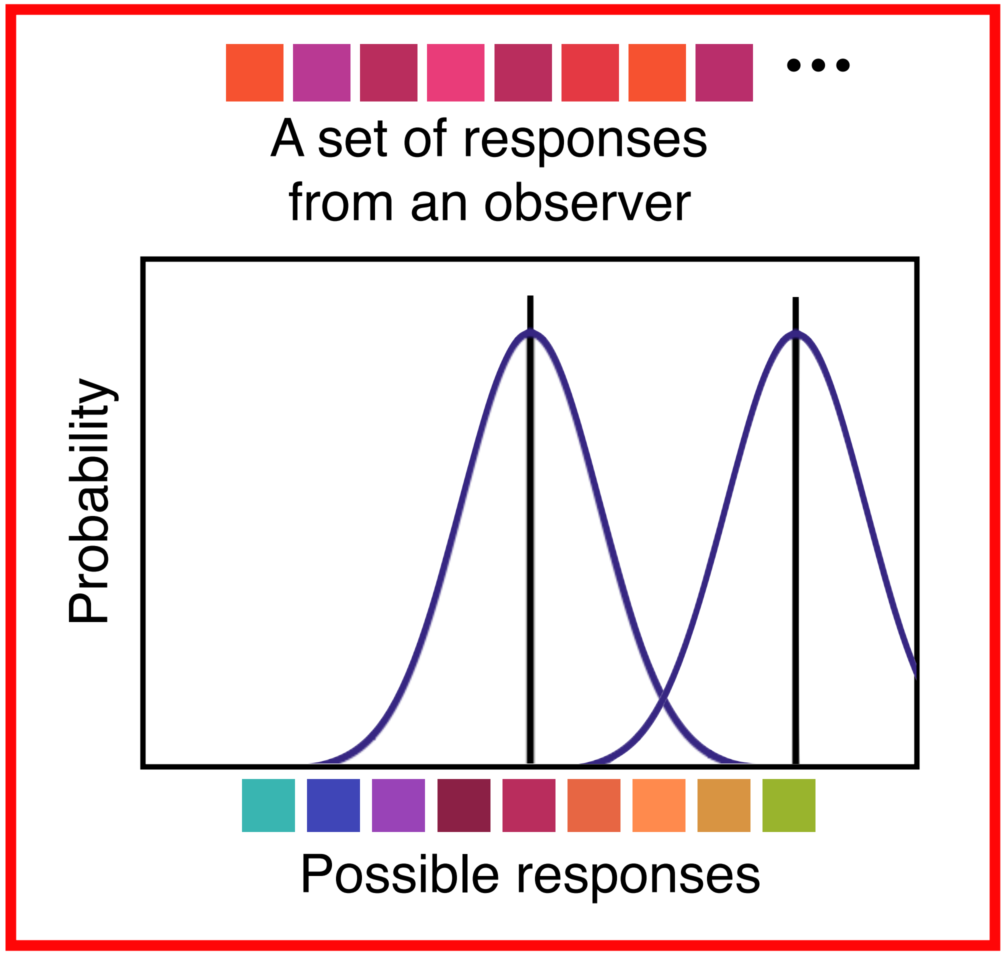
Internal representation



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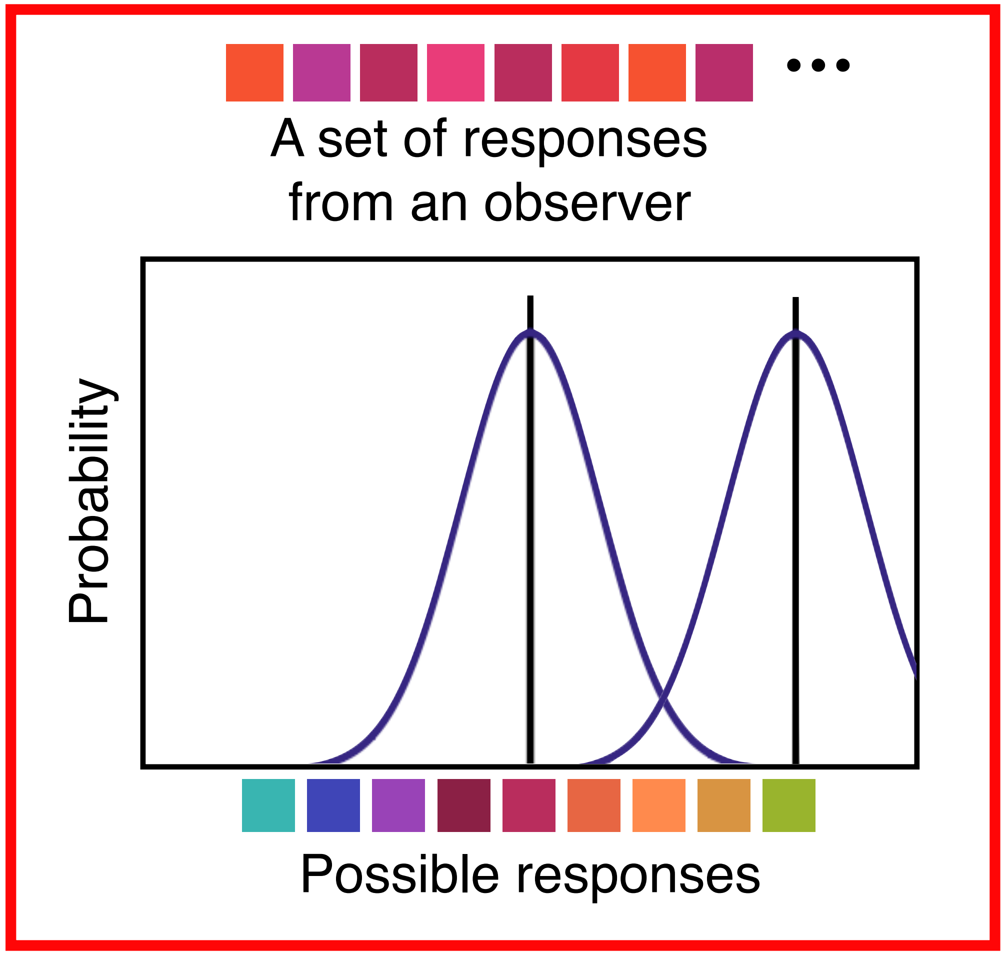
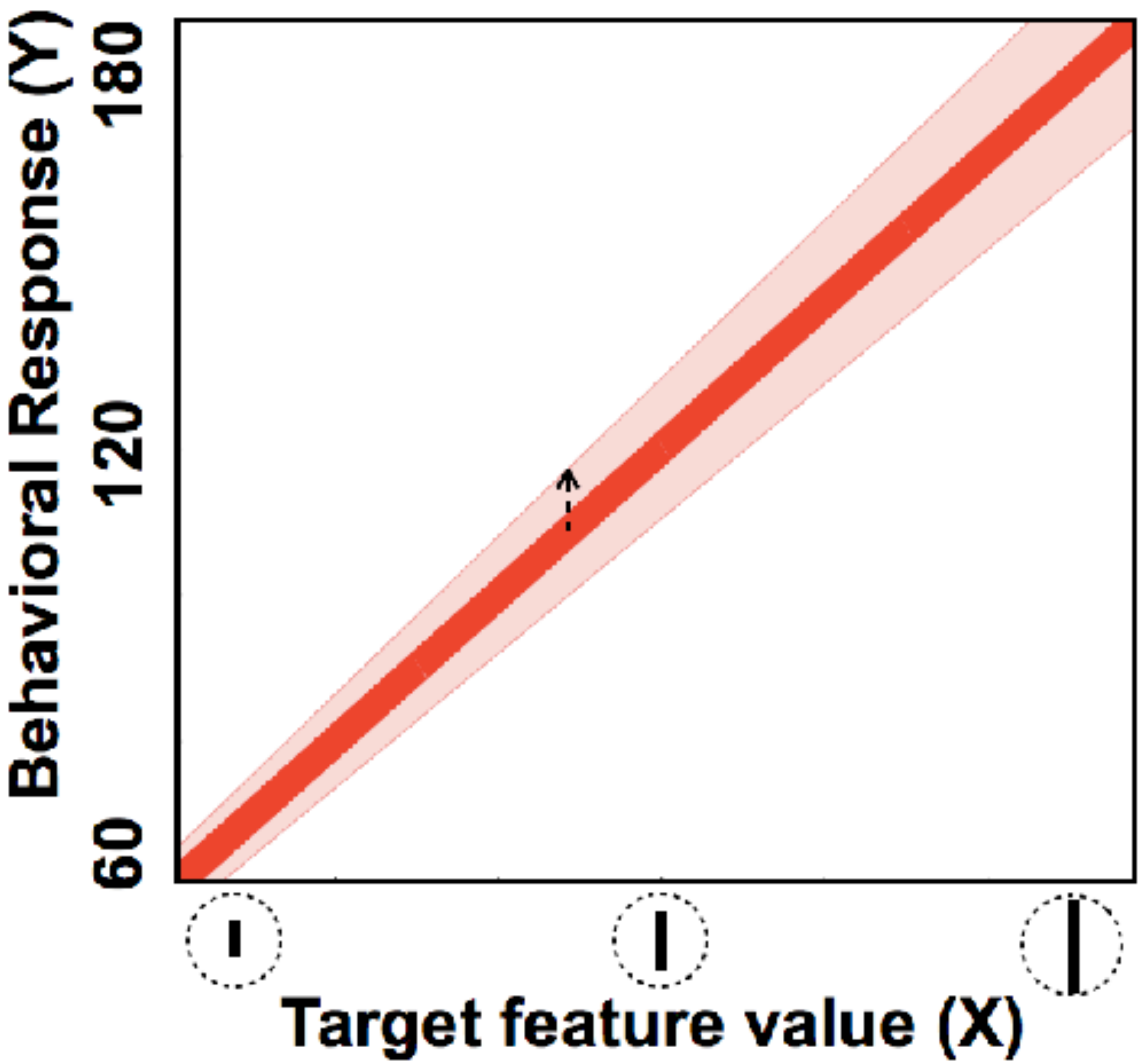


- Systematic variability across values
- Different visual features require different assumptions

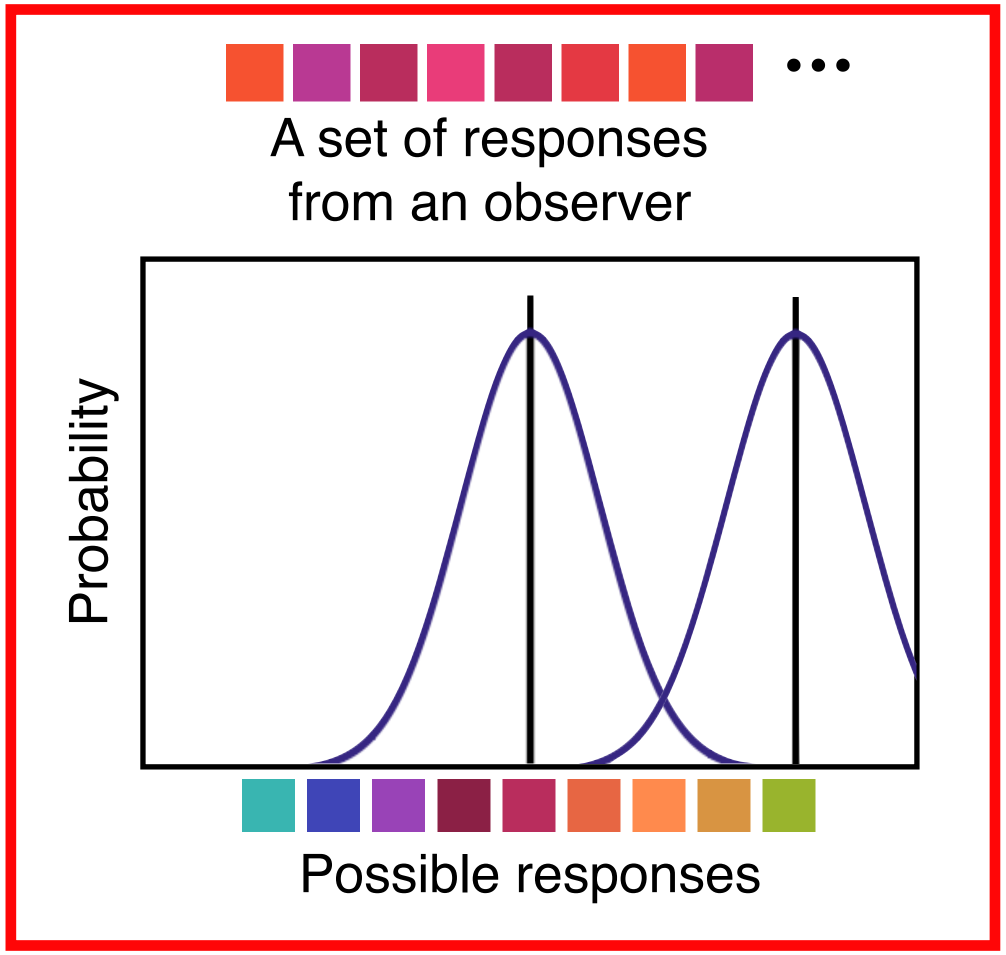
Length: scalar variability

Magnitude system. More precise at smaller values in its magnitude than larger values



Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



- Systematic variability across values
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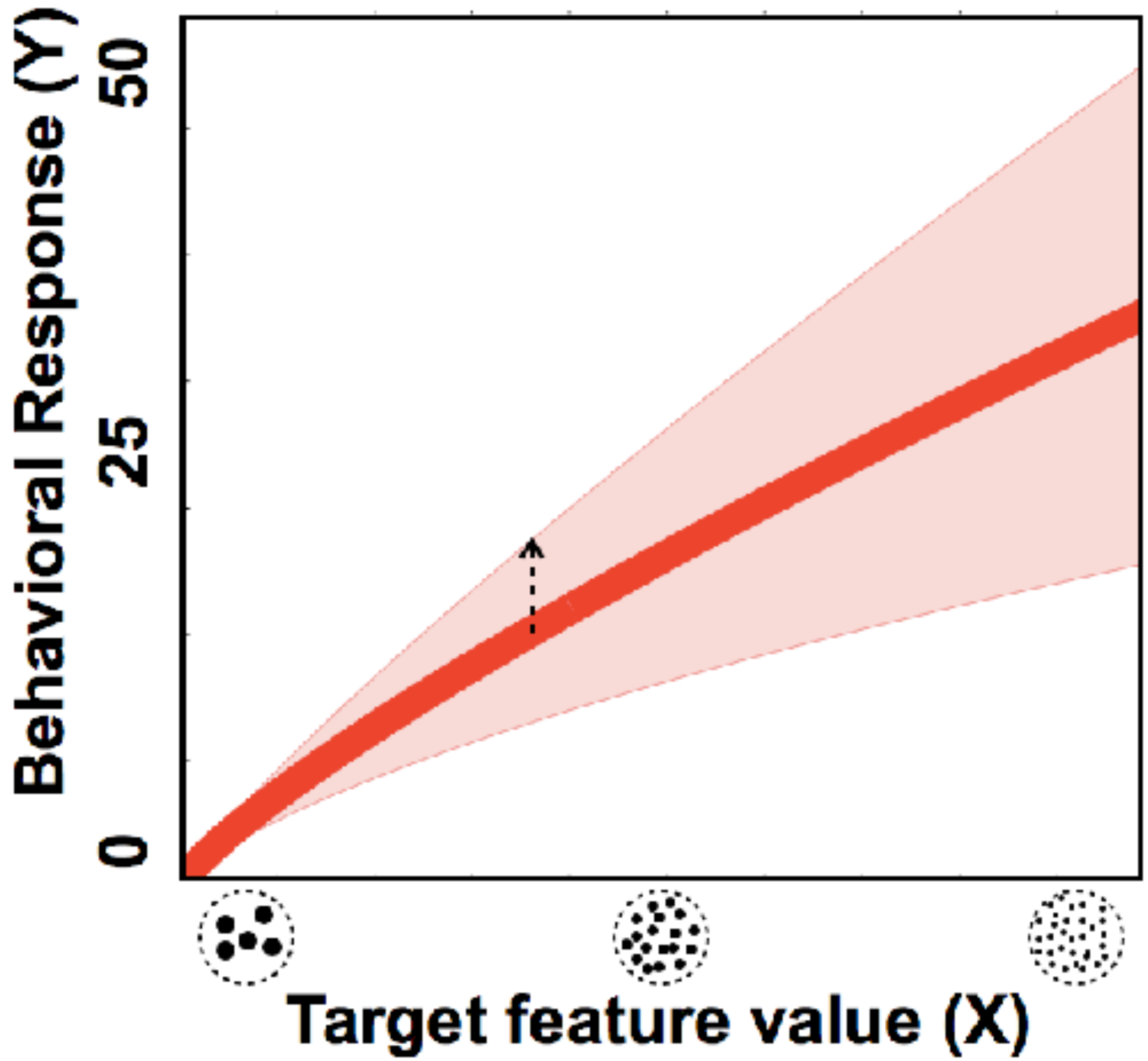
Numerosity: scalar variability

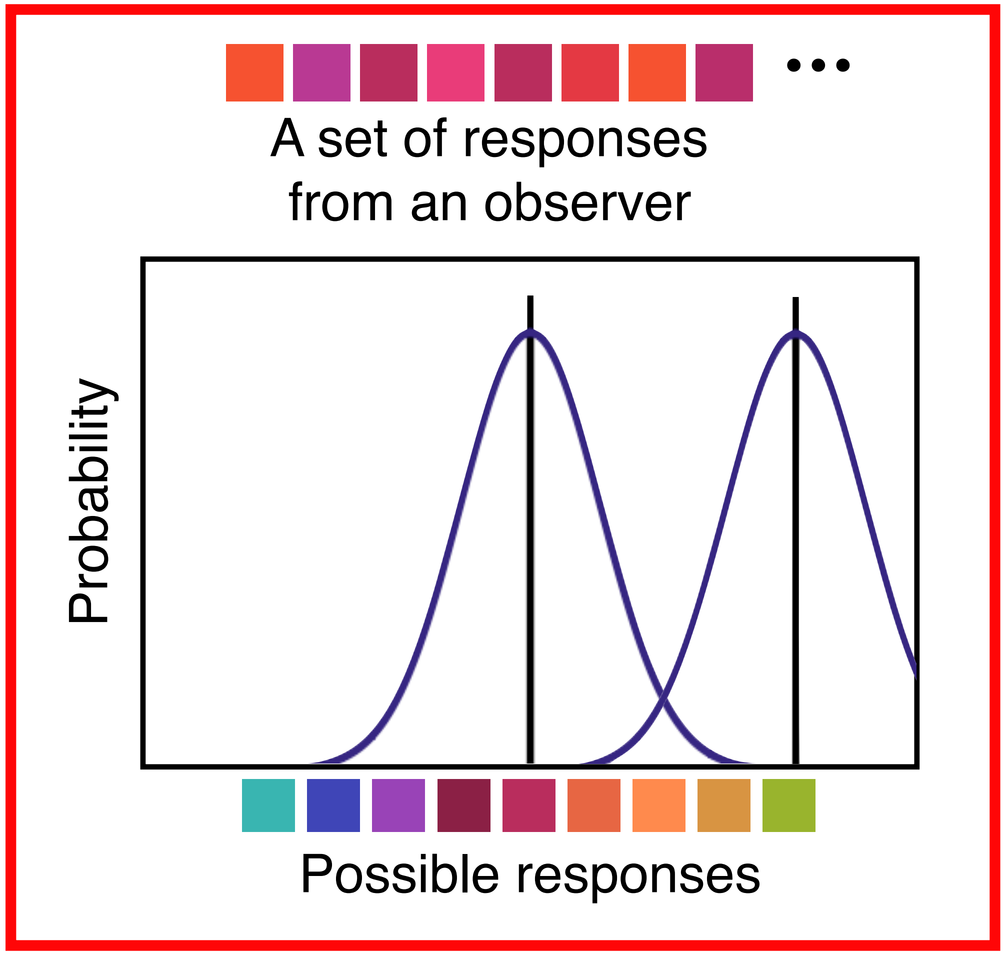
Magnitude system. More precise at smaller values in its magnitude than larger values

* basic visual feature



Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



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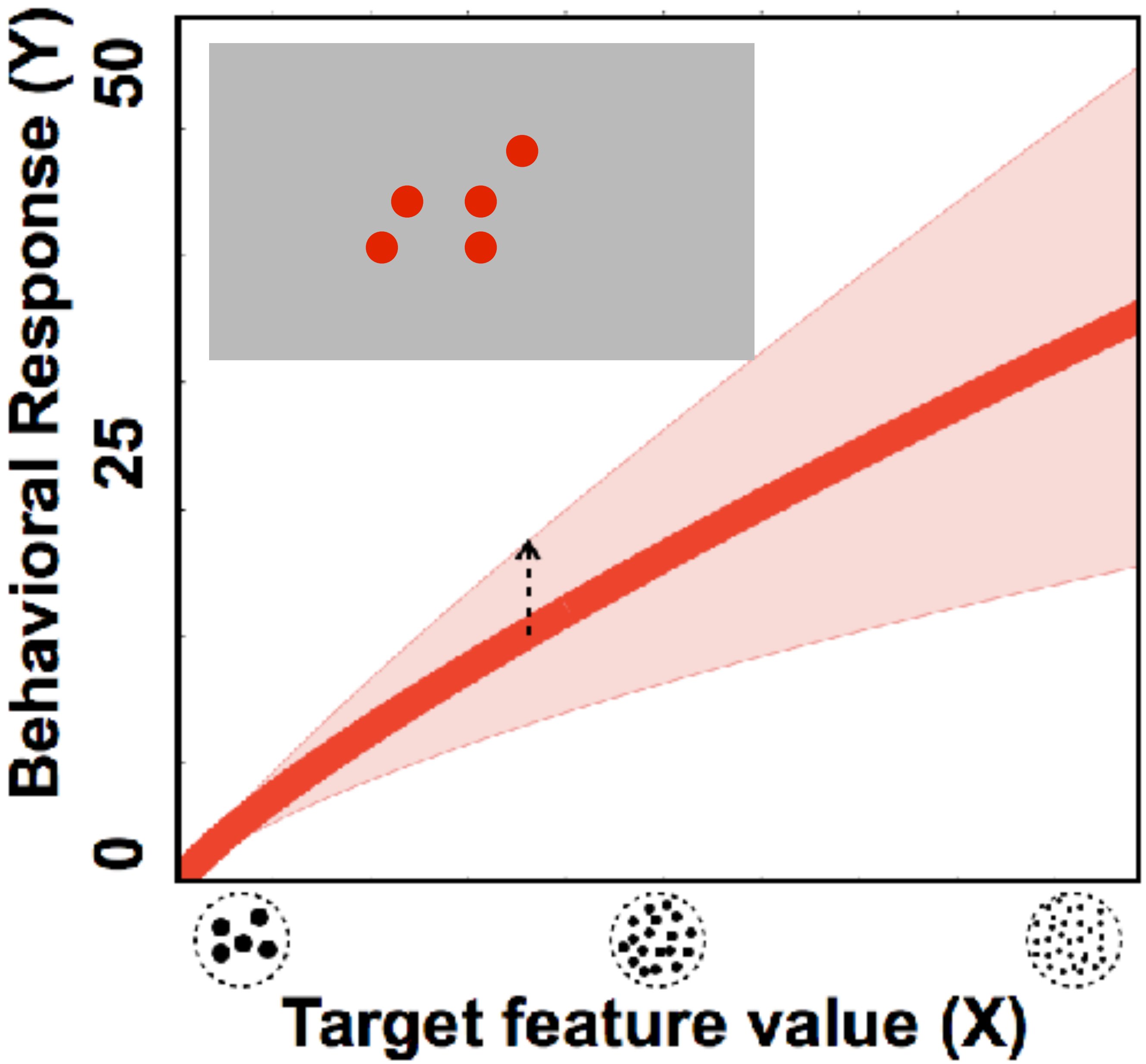
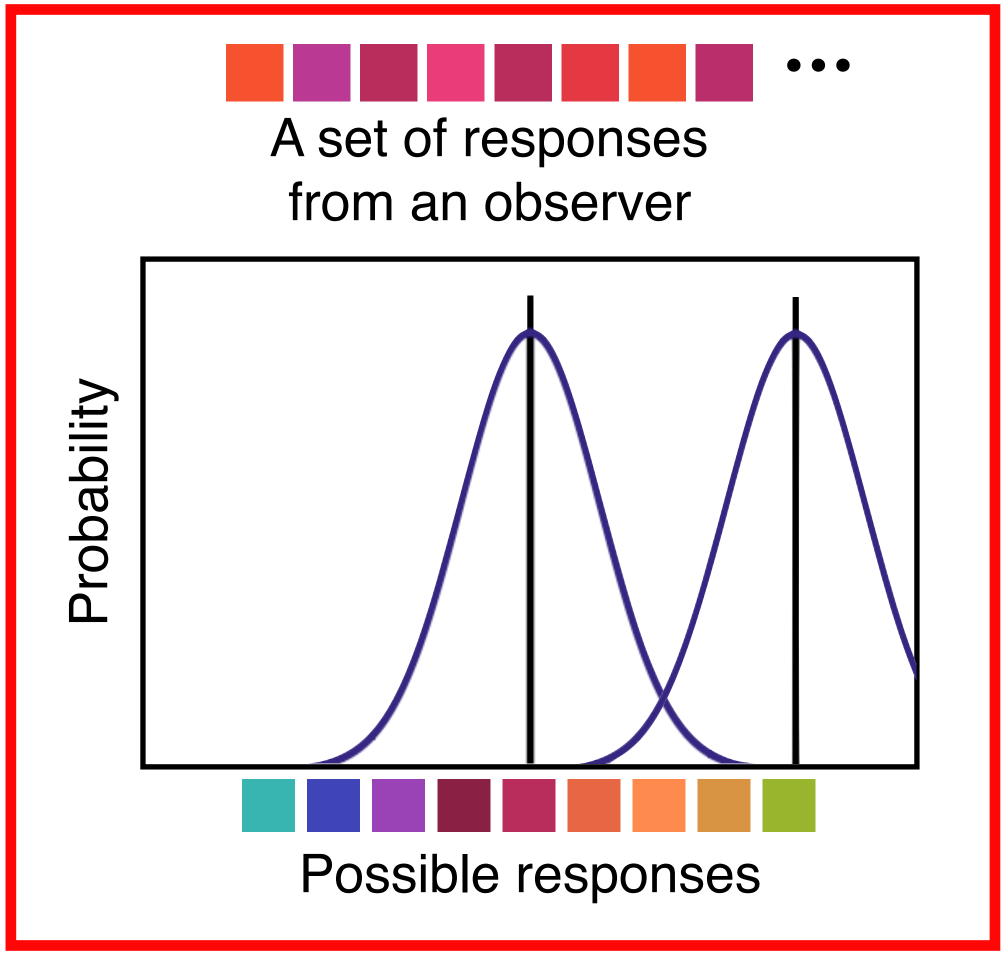


Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



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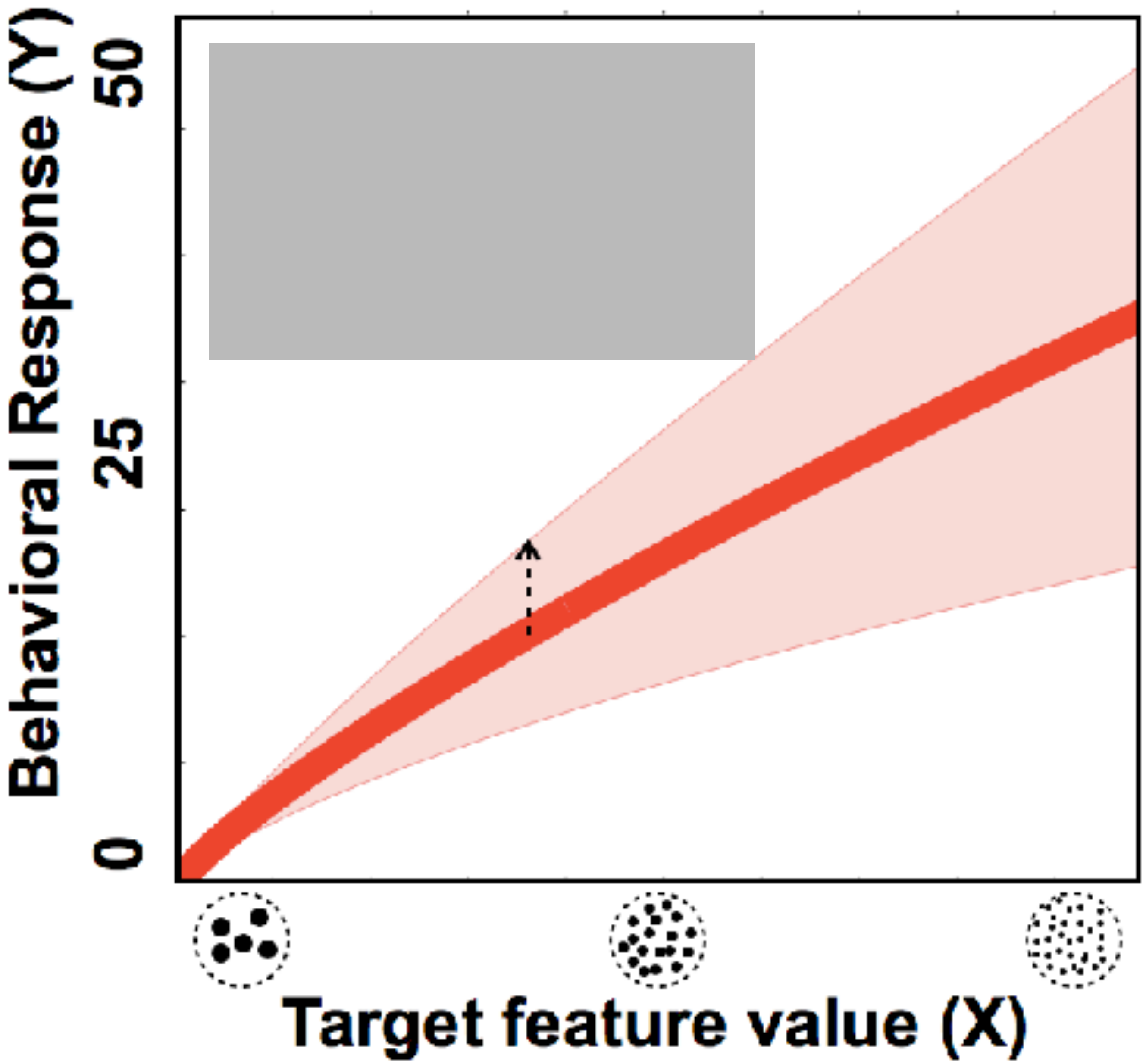
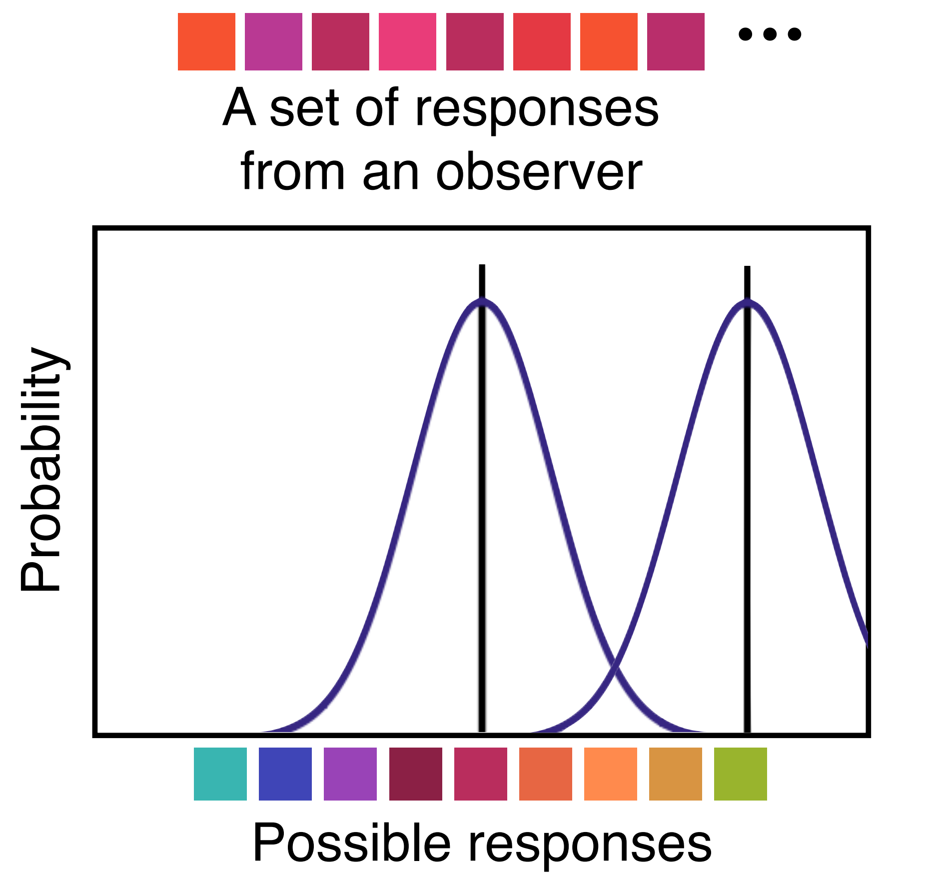


Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



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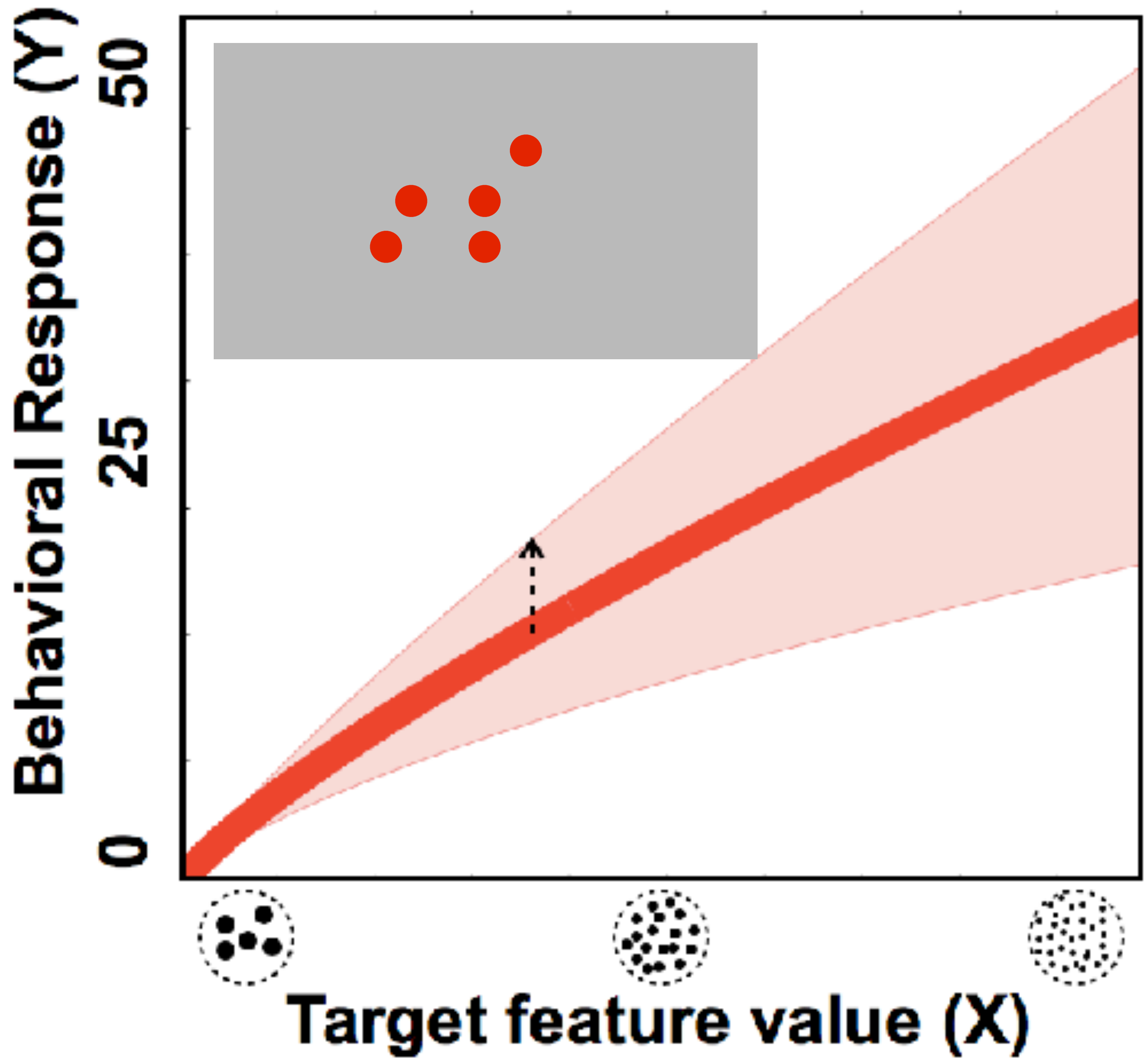
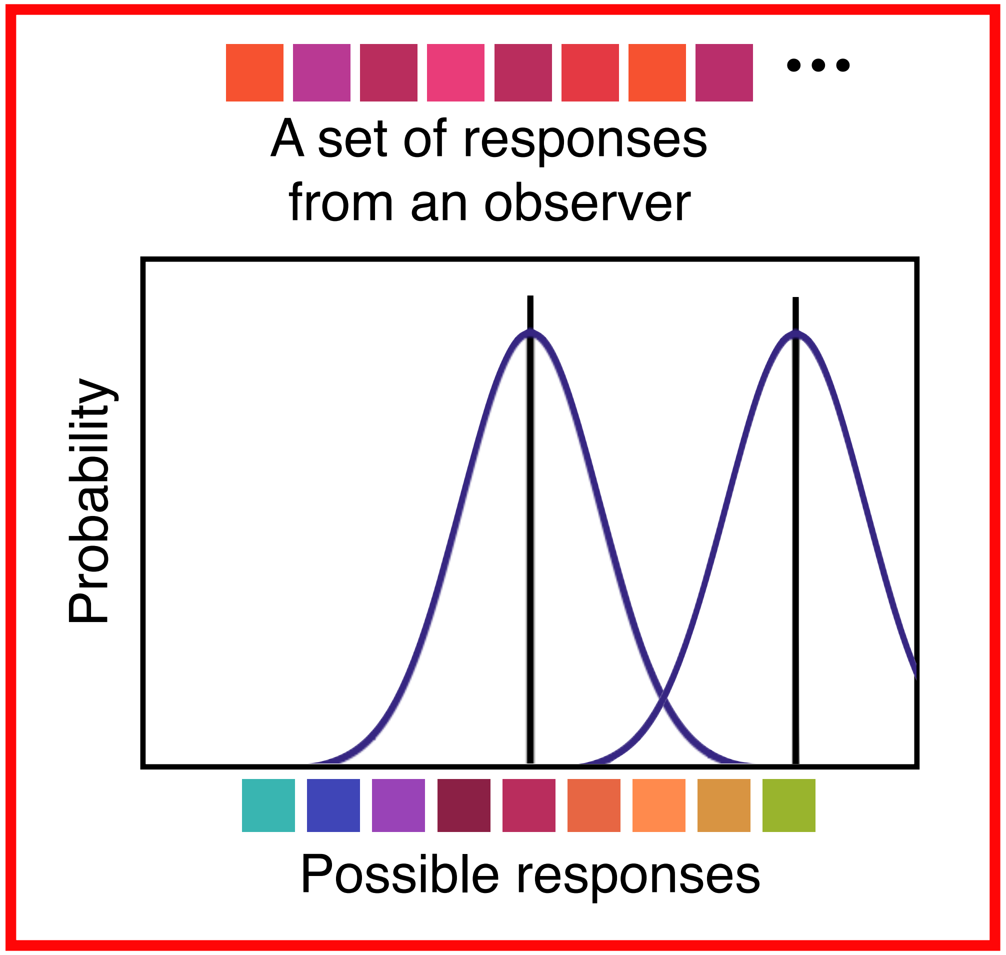


Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



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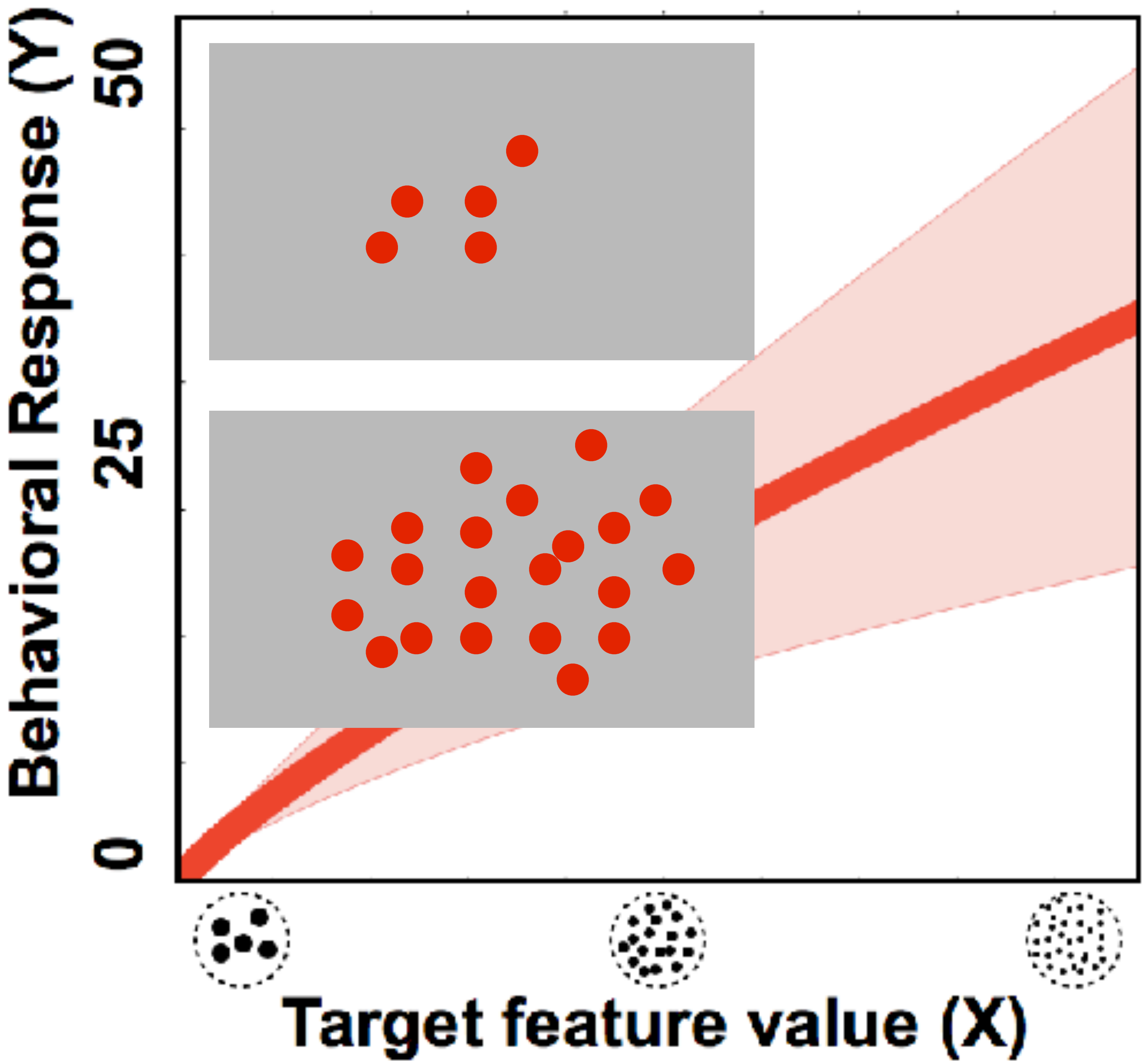
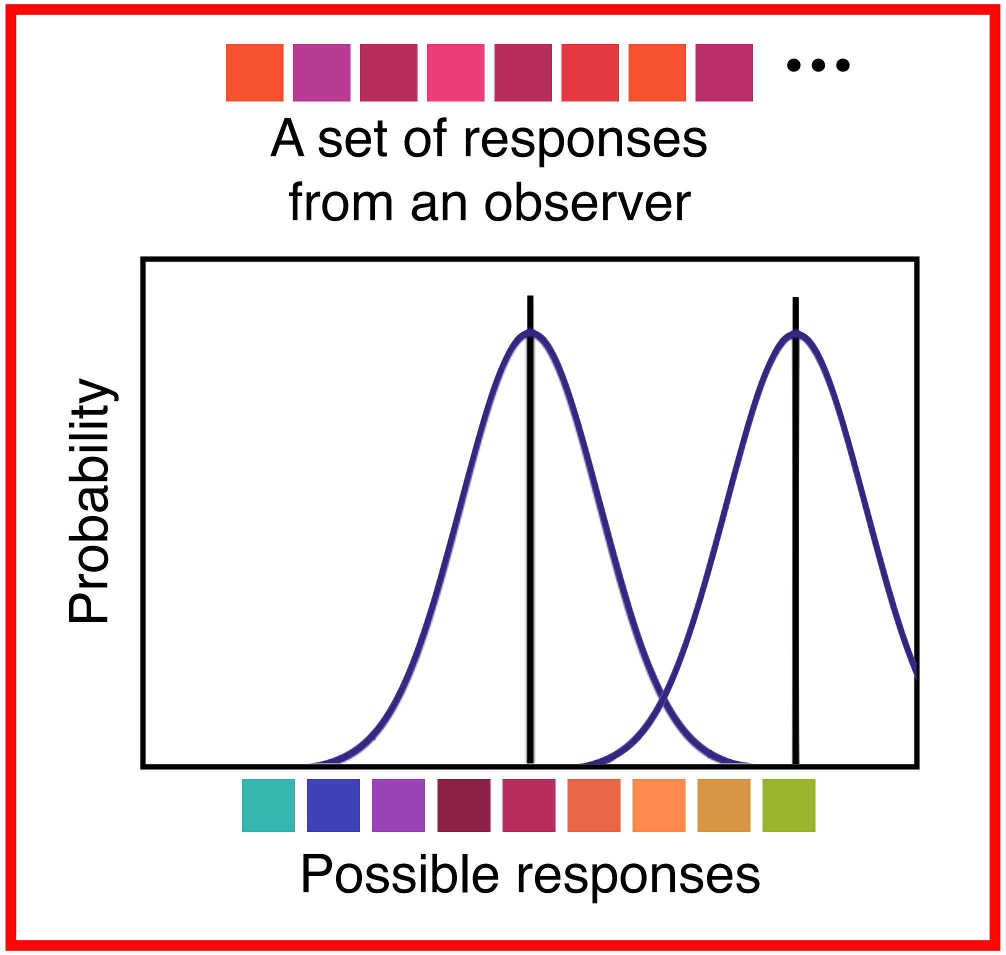


Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



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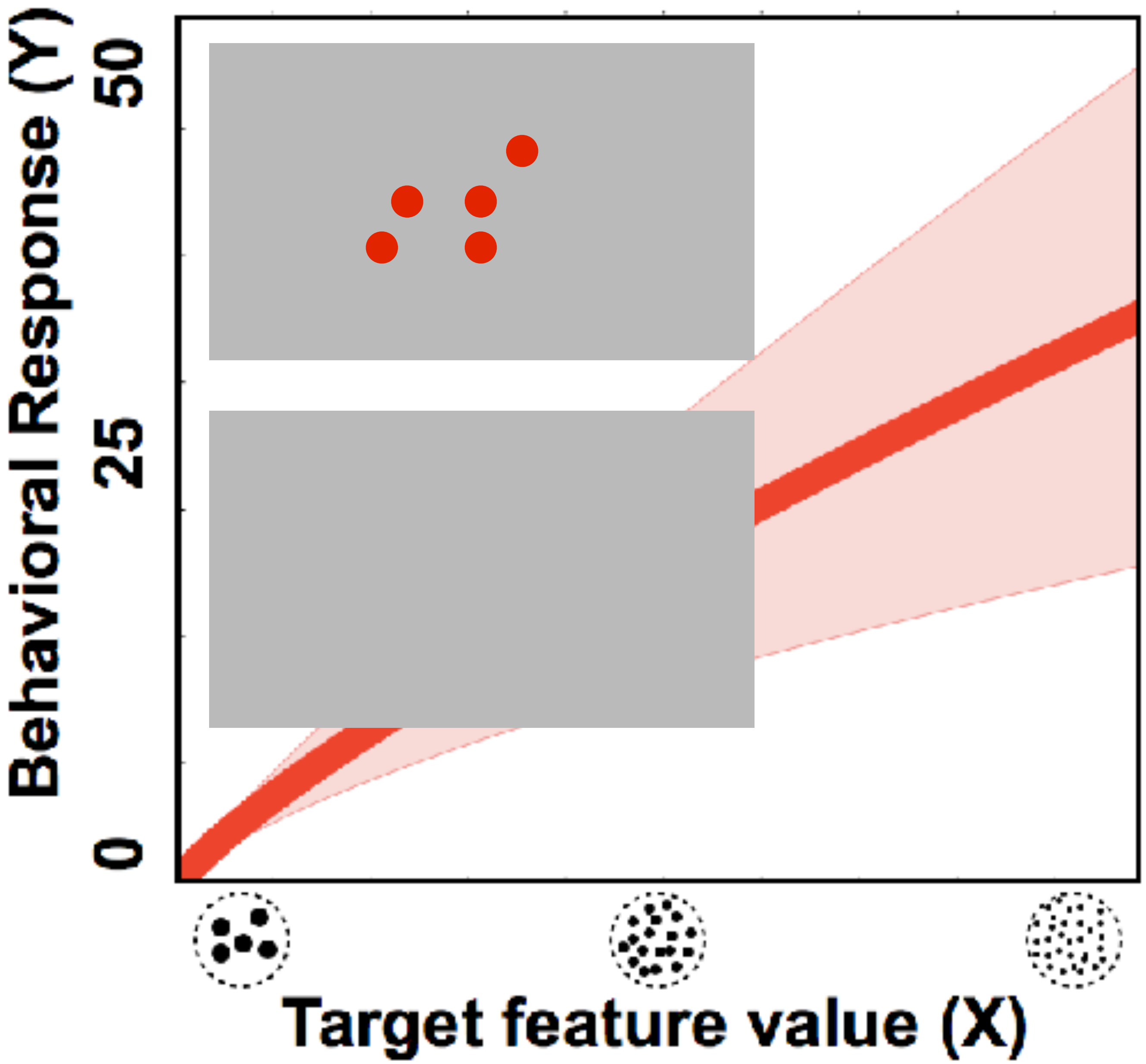
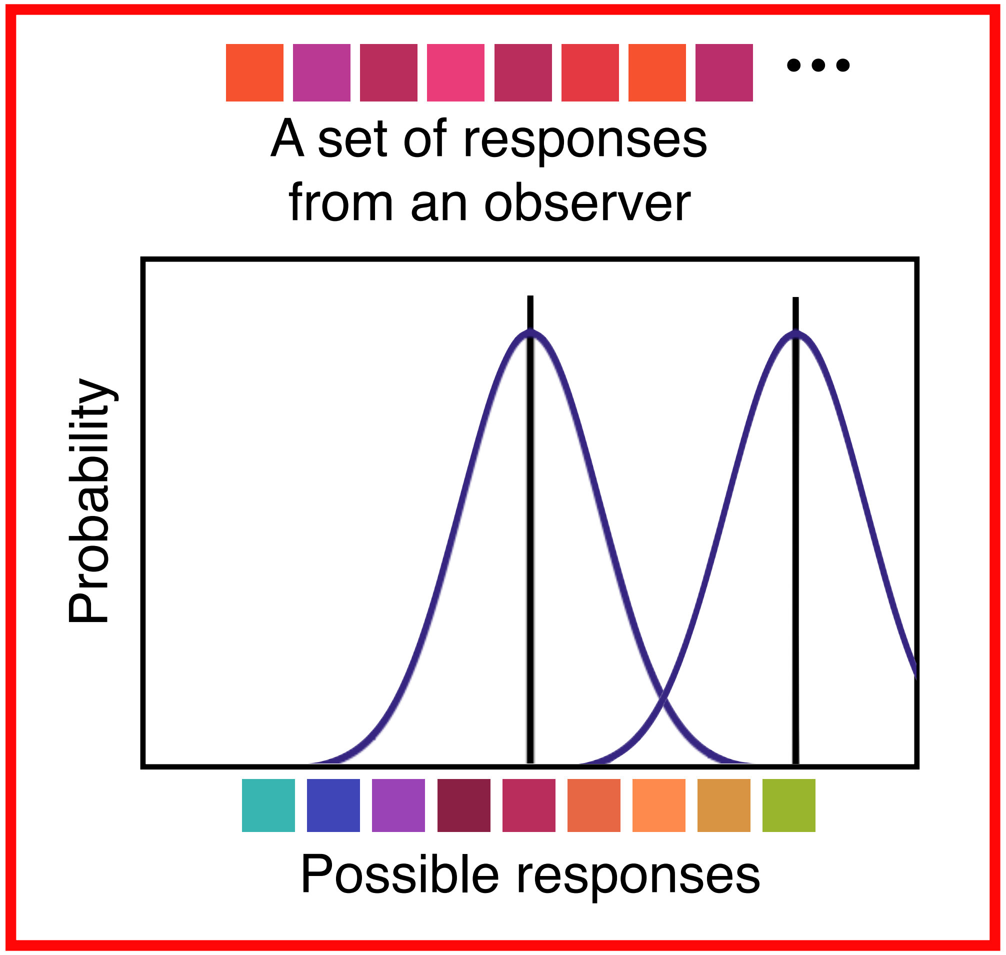


Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



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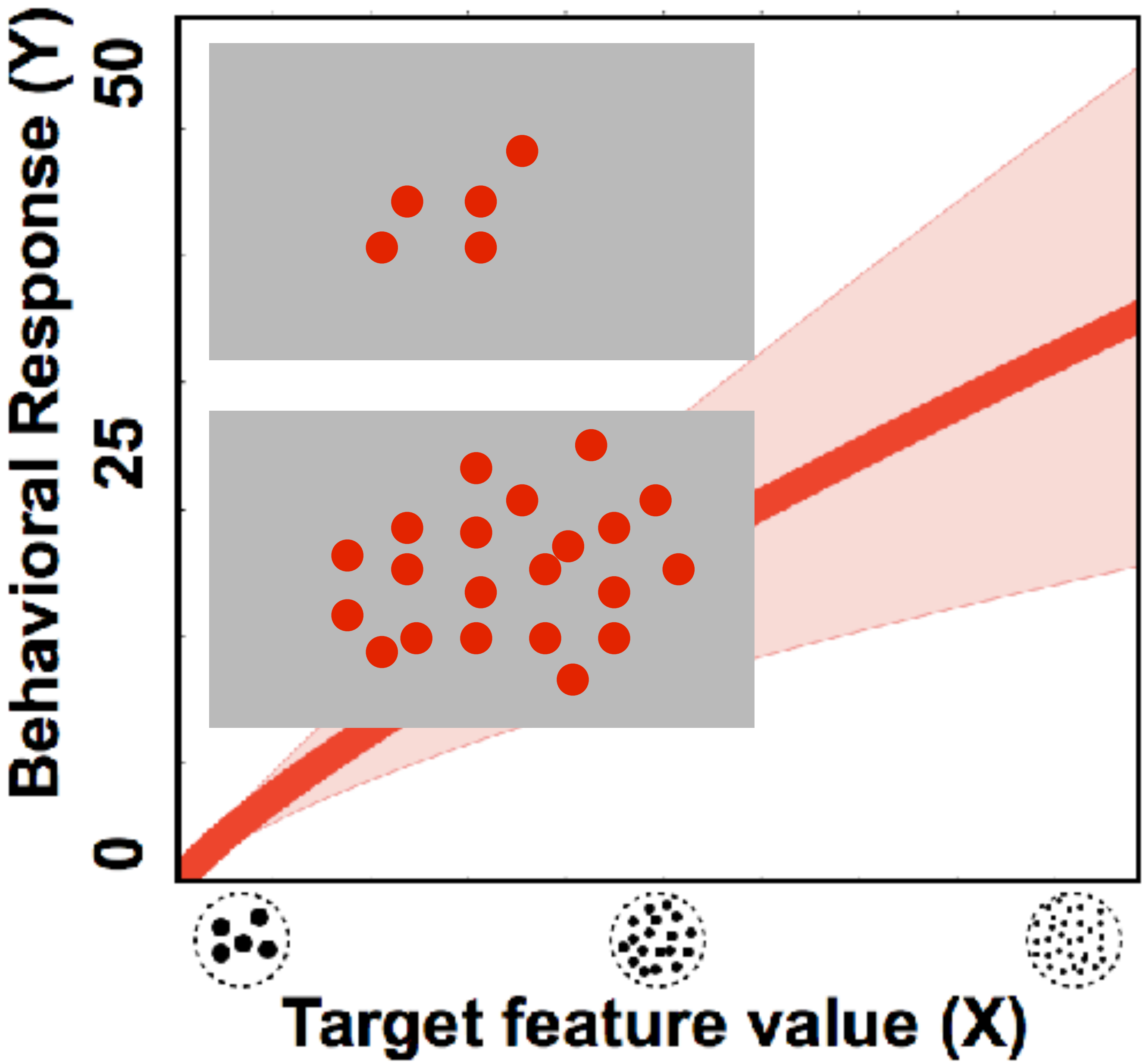

Appropriate models for internal representation and guessing are very important for precise decomposition

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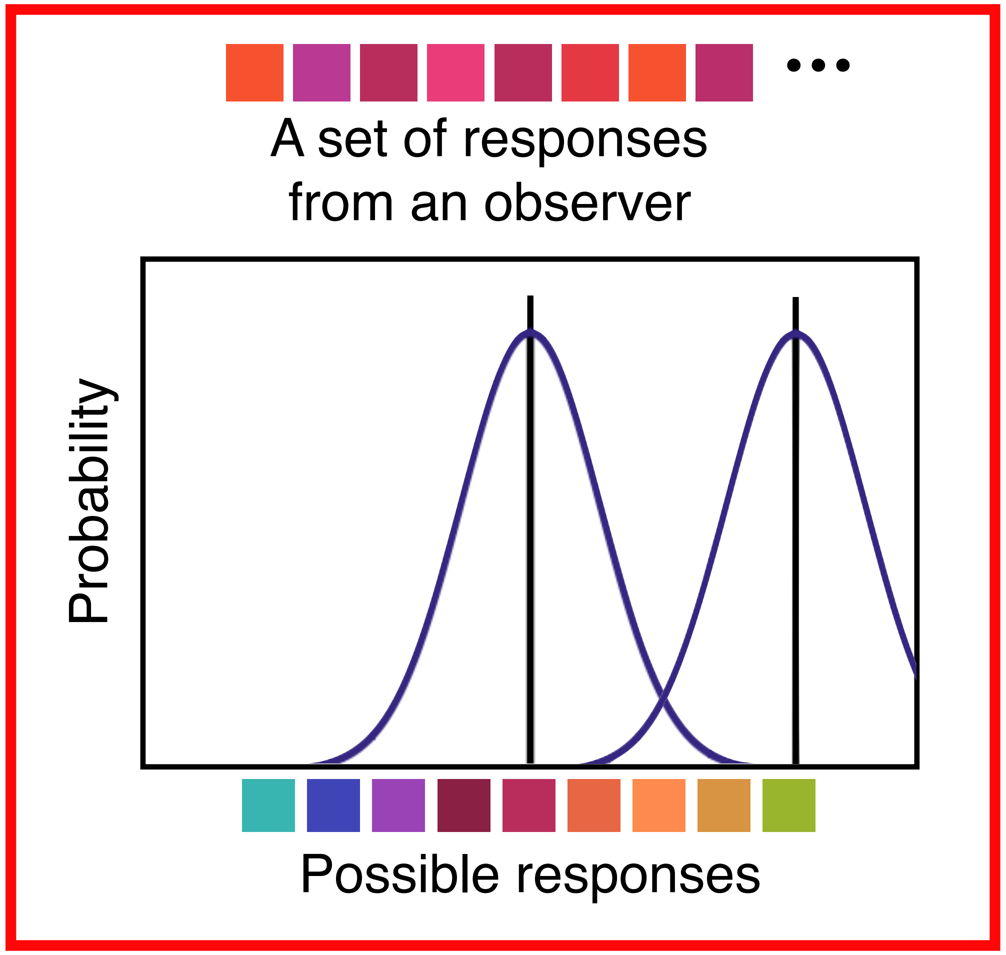
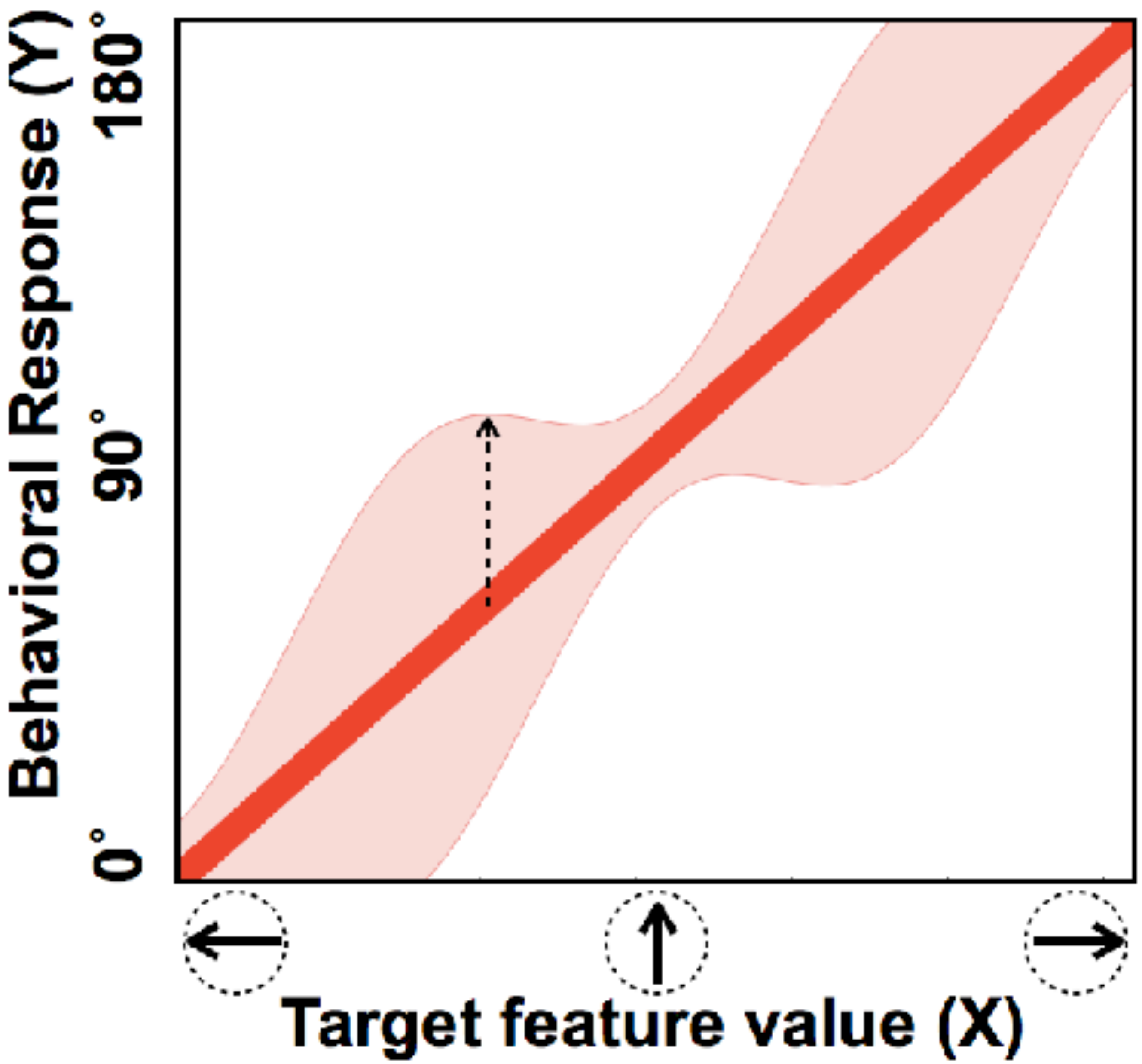


- Systematic variability across values
- Different visual features require different assumptions

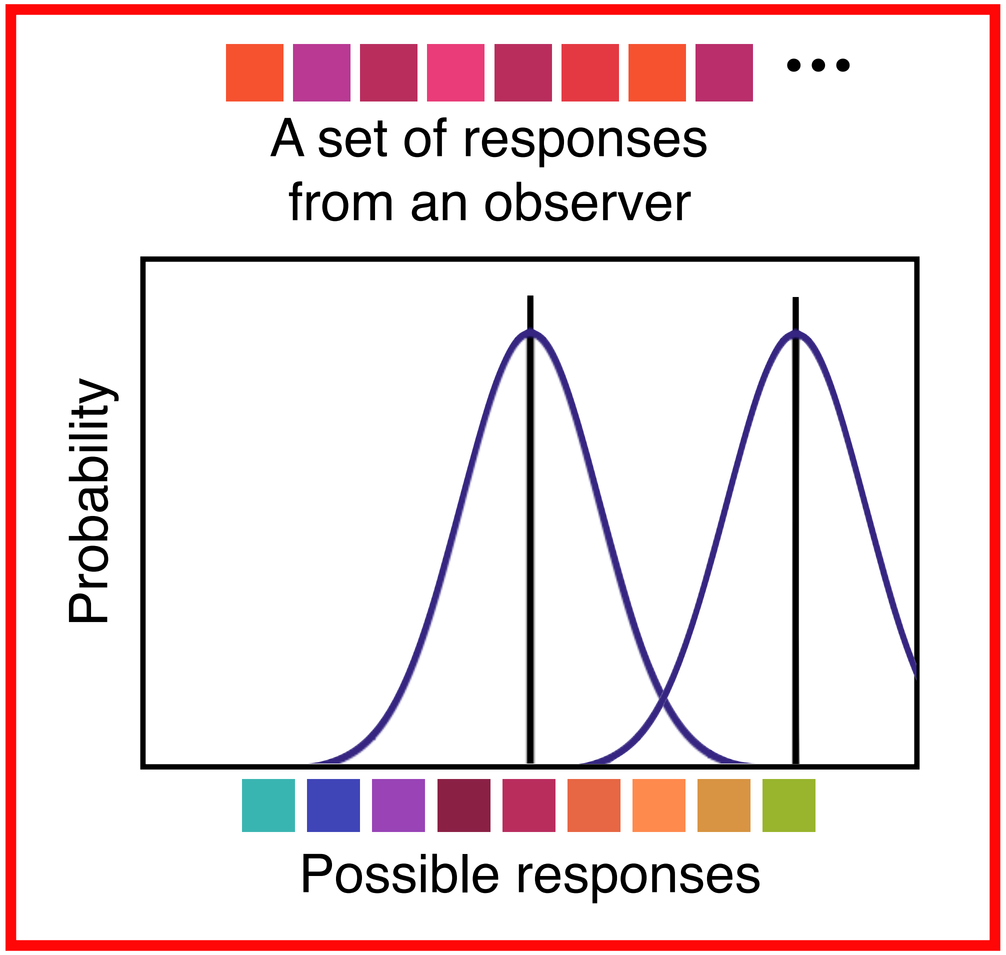
Orientation: oblique effect

More precise at 90° and 180° than other oblique orientations (e.g., 45° or 135°)



Appropriate models for internal representation and guessing are very important for precise decomposition

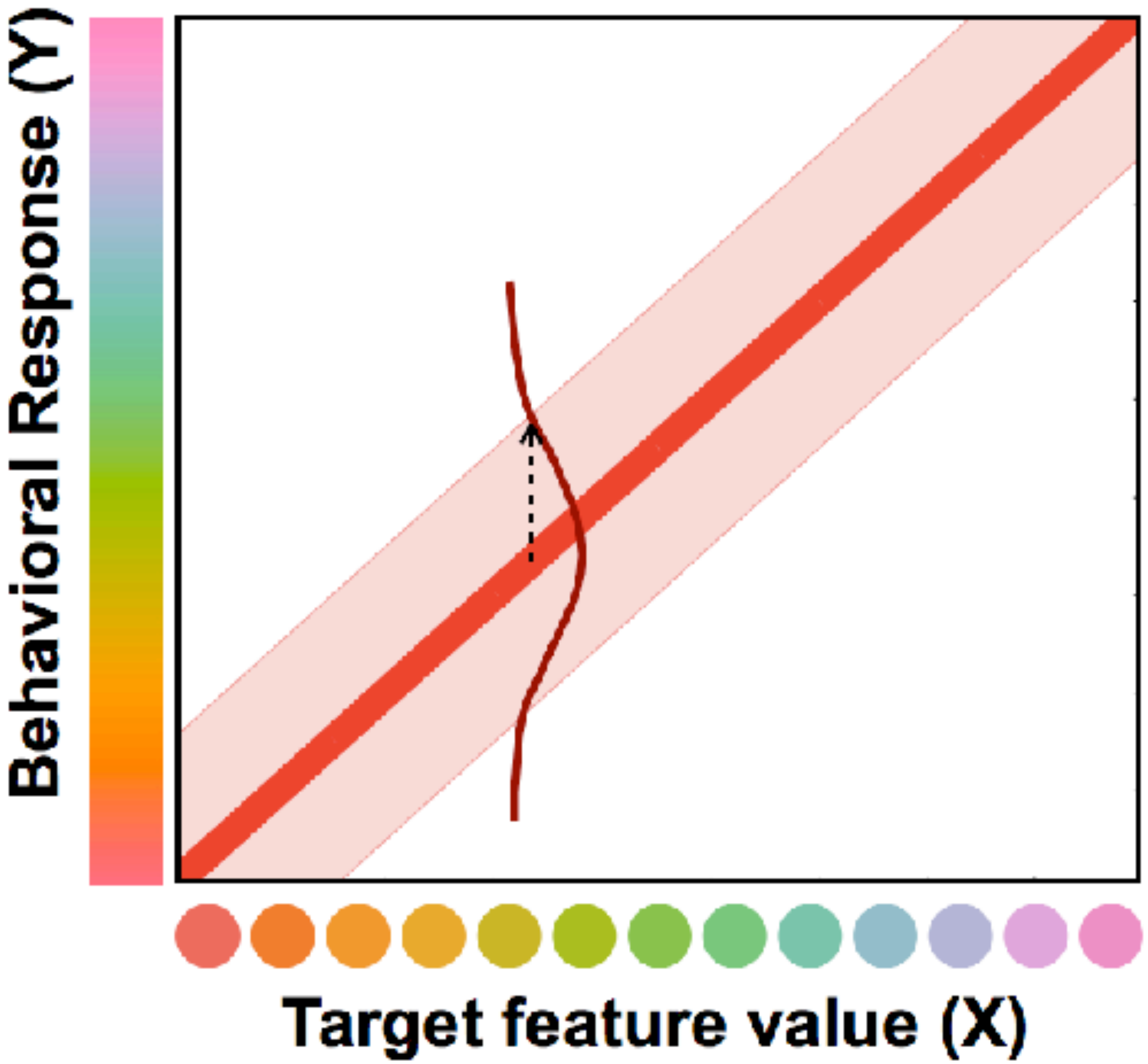
Internal representation



- Systematic variability across values
- Different visual features require different assumptions

Color: ???!??!?!?

Usually assumed to be constant across feature values (????)



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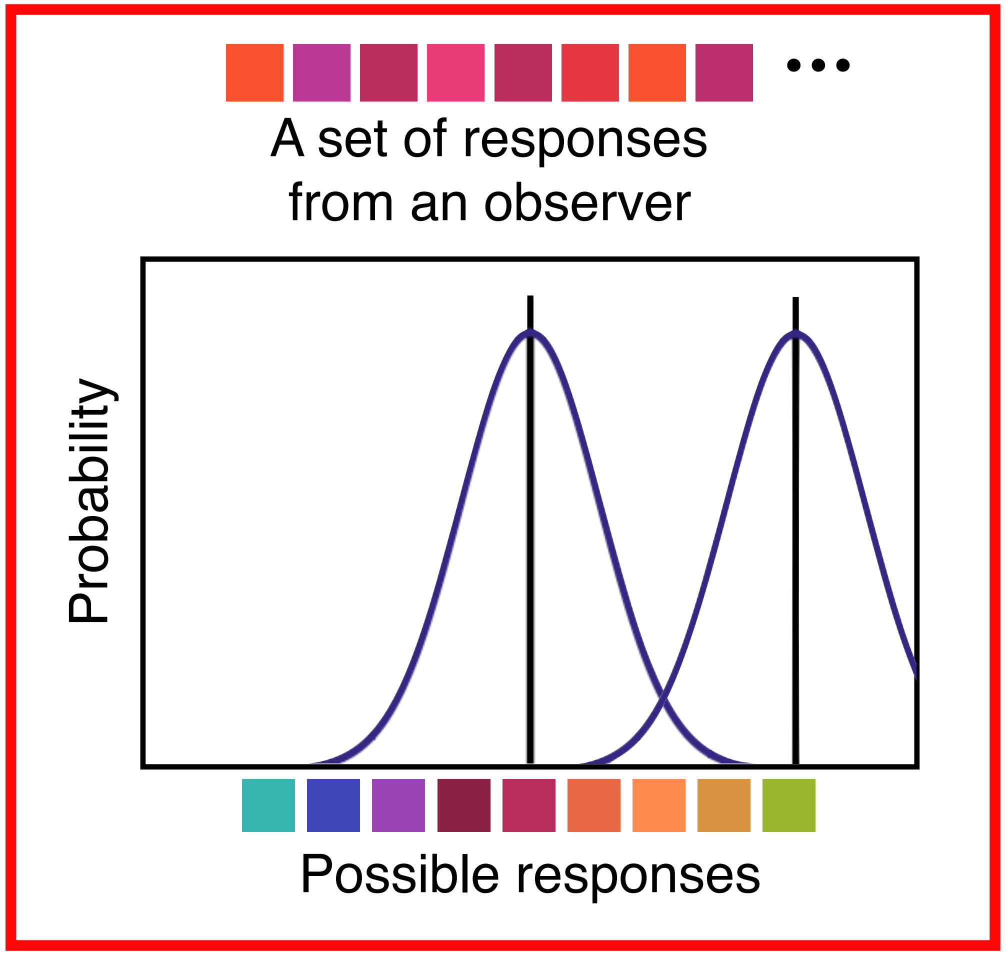
Internal representation



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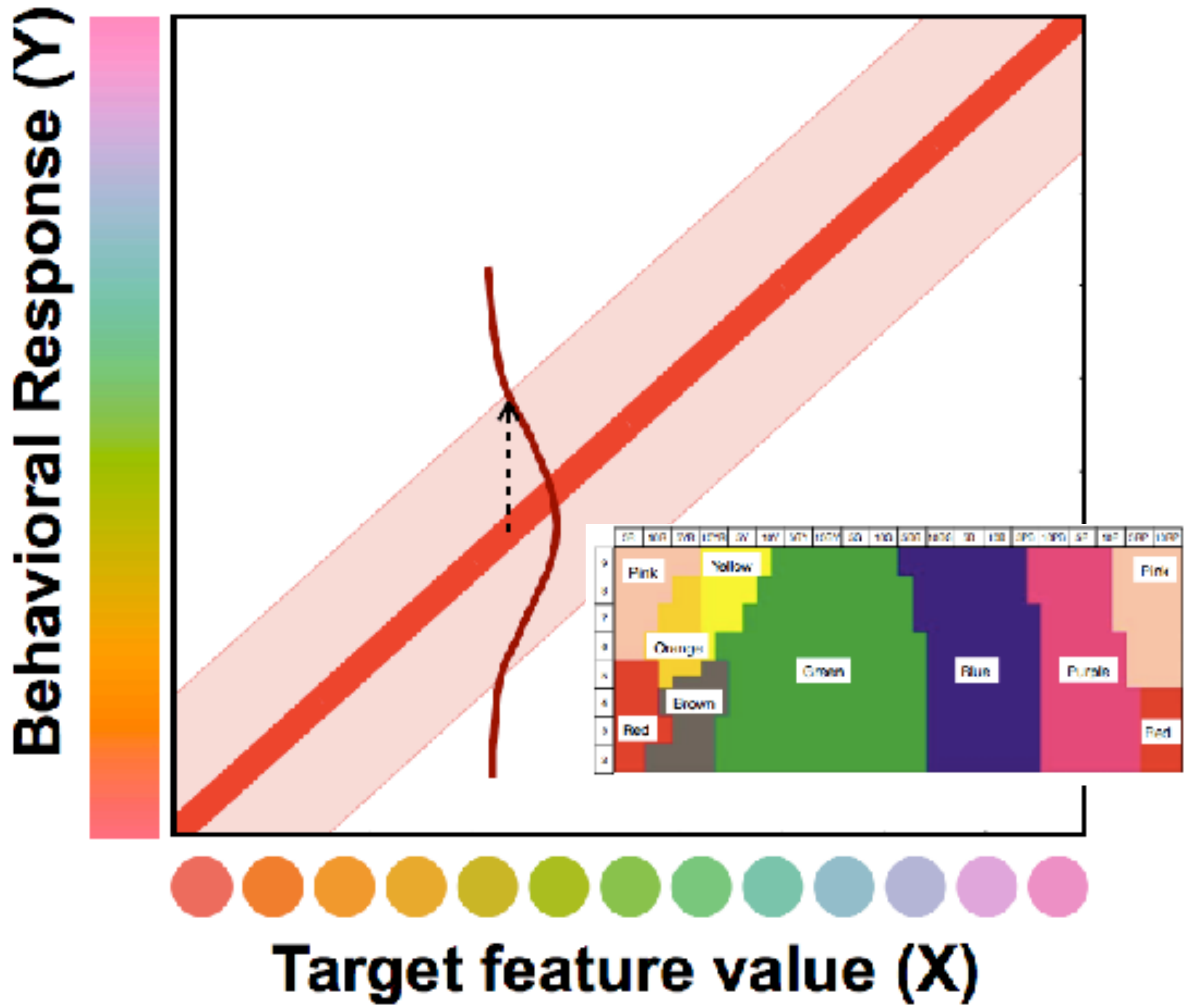

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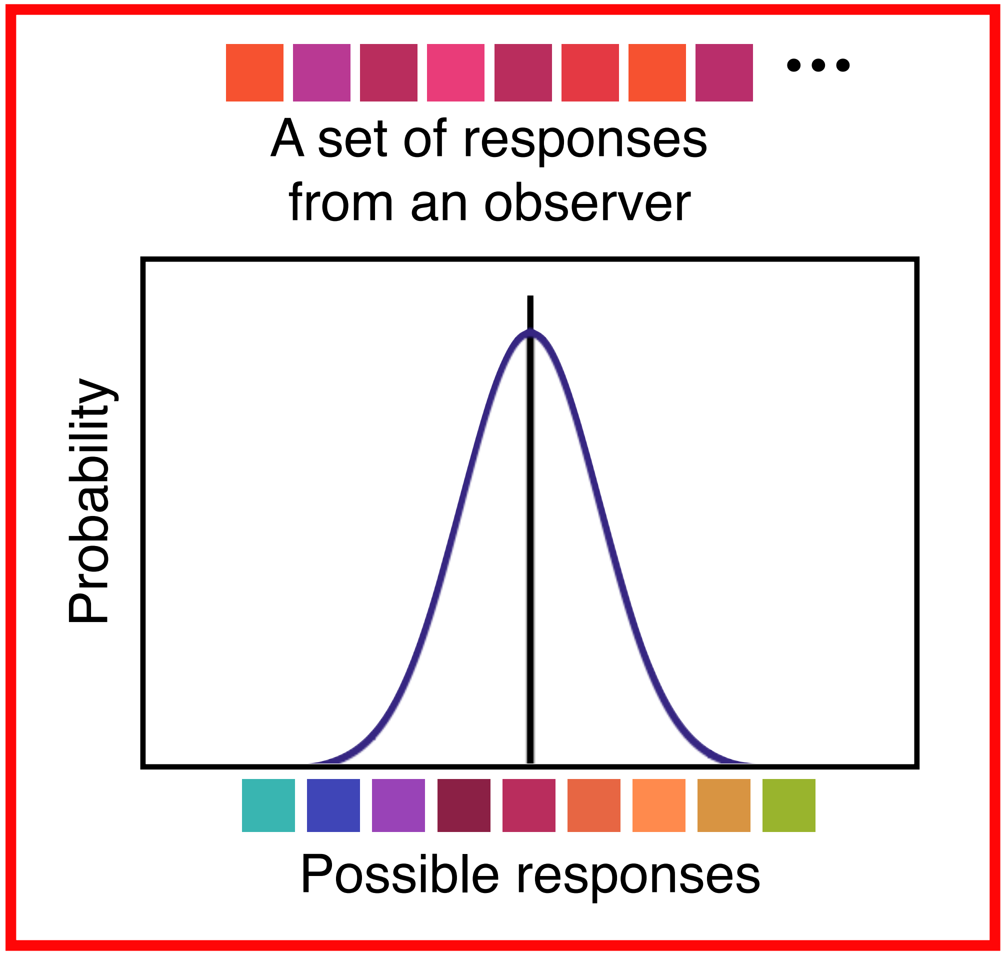
Internal representation



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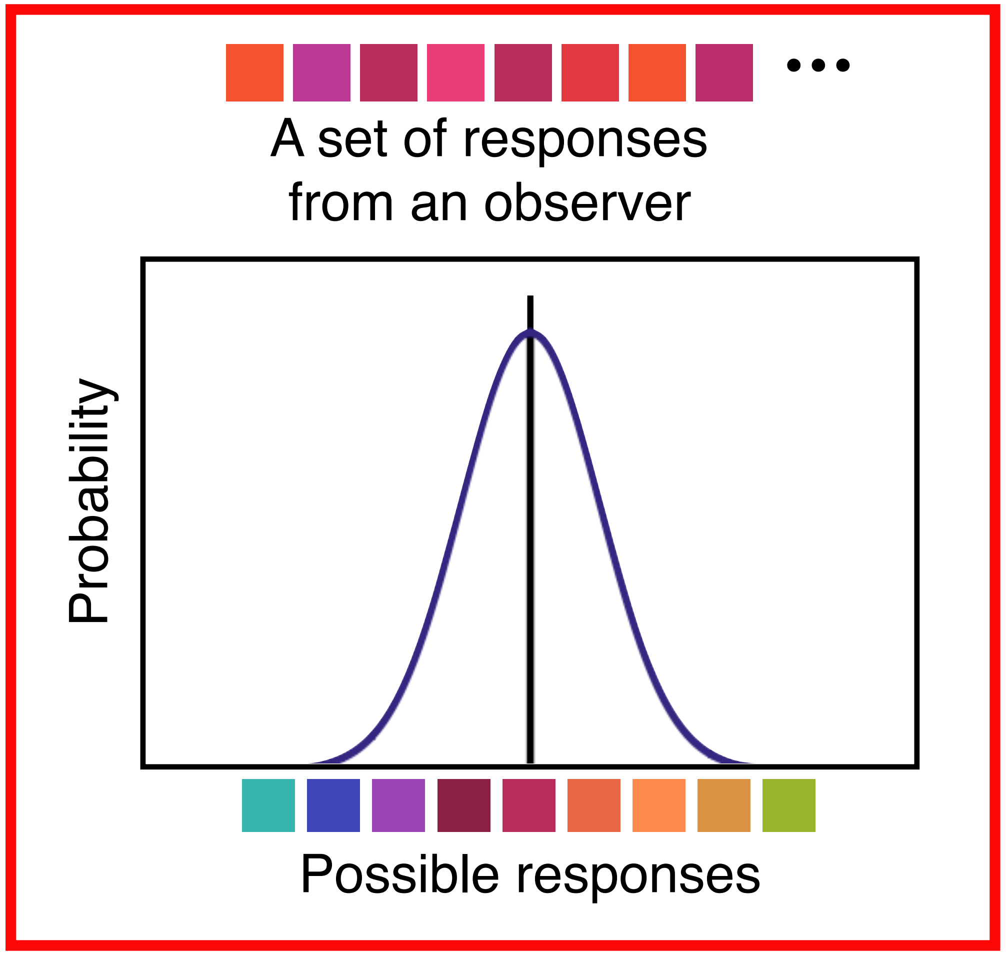


Length

Numerosity

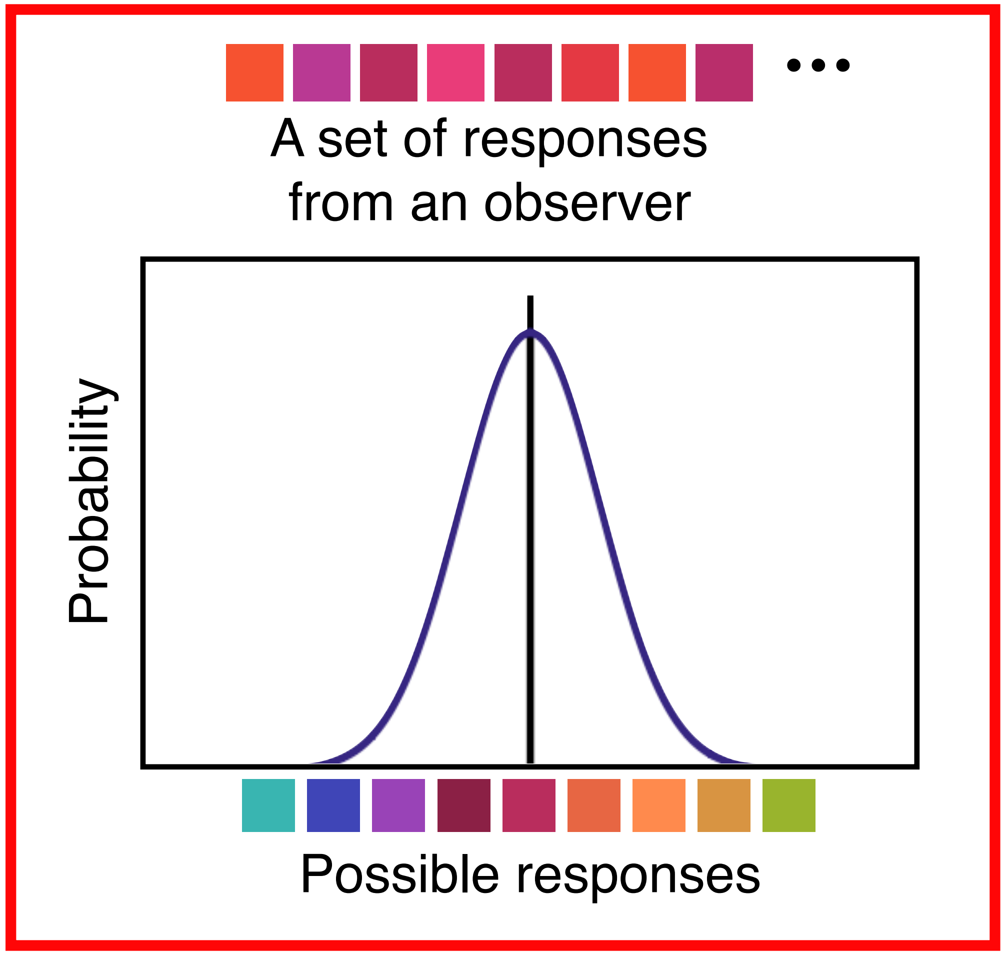
Orientation

Color

- Systematic variability across values
- Different visual features require different assumptions

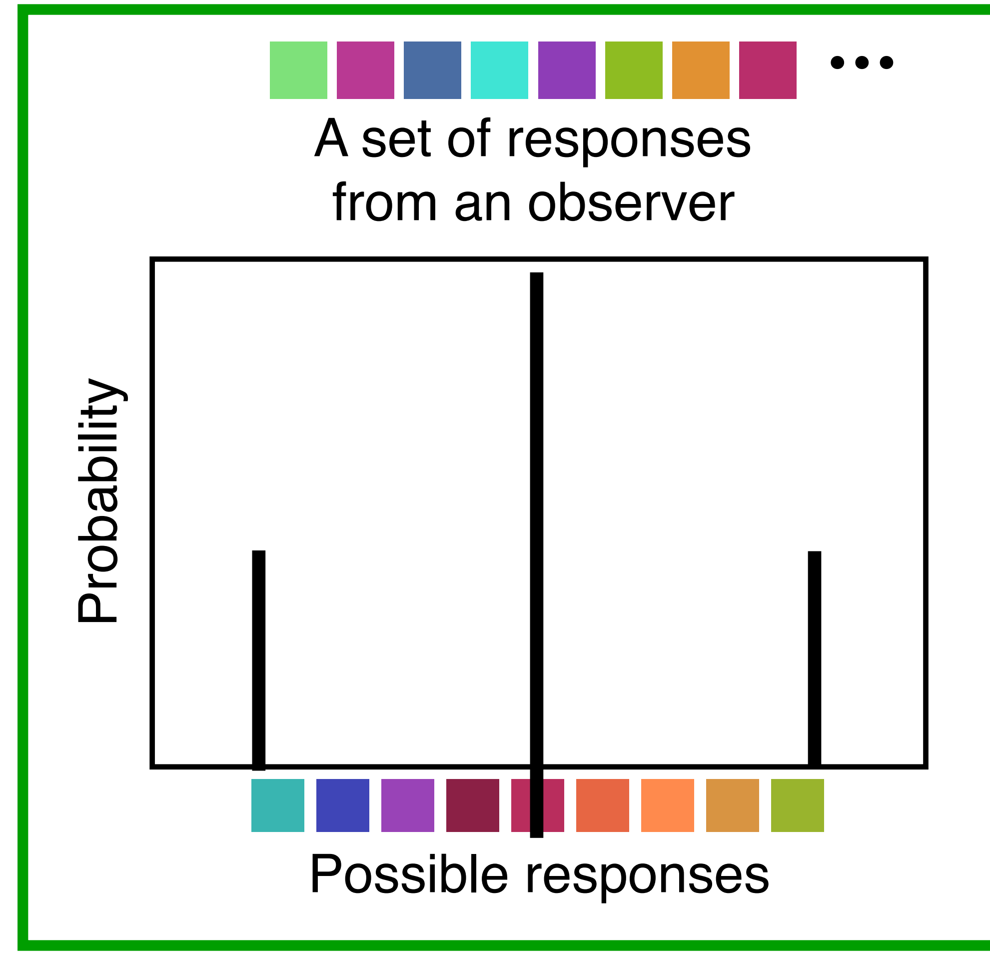
Appropriate models for internal representation and guessing are very important for precise decomposition

Internal representation



Length
Numerosity
Orientation
Color

Guessing



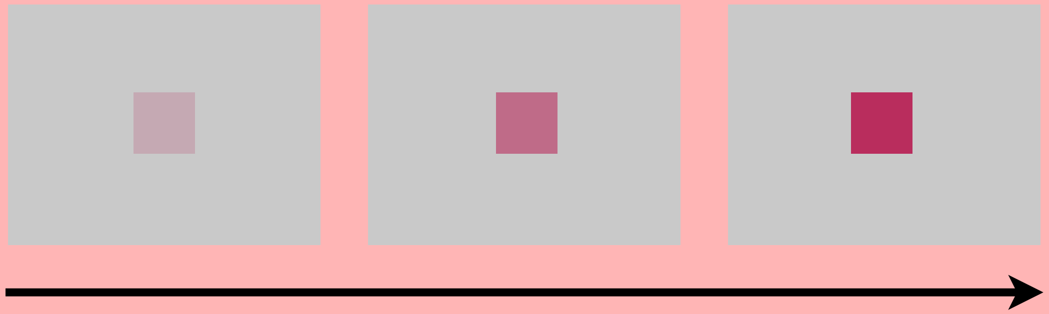
- Systematic variability across values
- Different visual features require different assumptions

- Educated guesses
- Humans are not good at producing uniformly distributed random responses anyway (Treisman & Faulkner, 1987)

How do these factors affect visual decisions?

Processing time

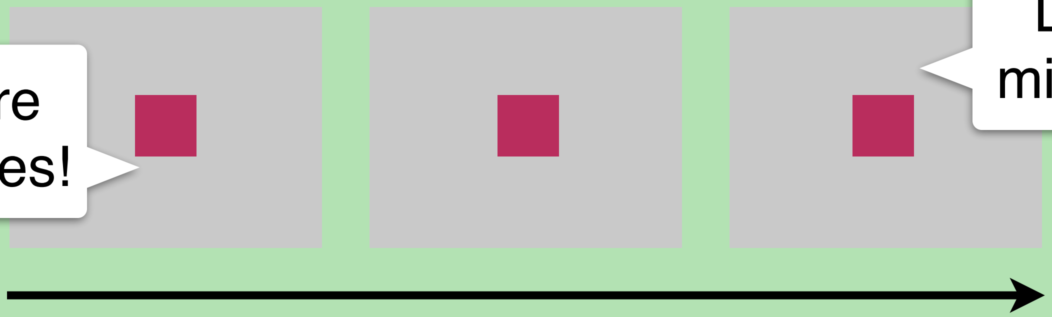
Resolution becomes better



Longer duration time

Guess responses decrease

More misses!

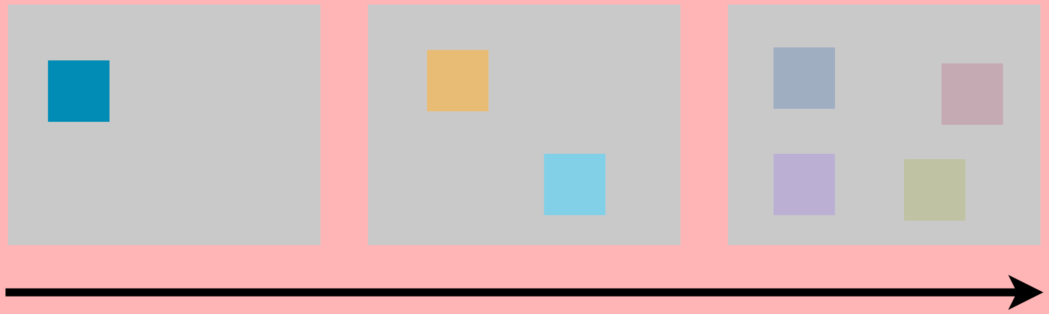


Less misses!

Longer duration time

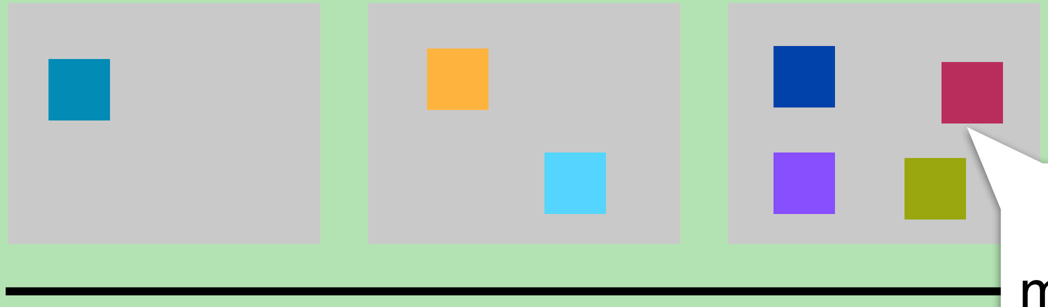
Information load

Resolution becomes worse



Higher information load

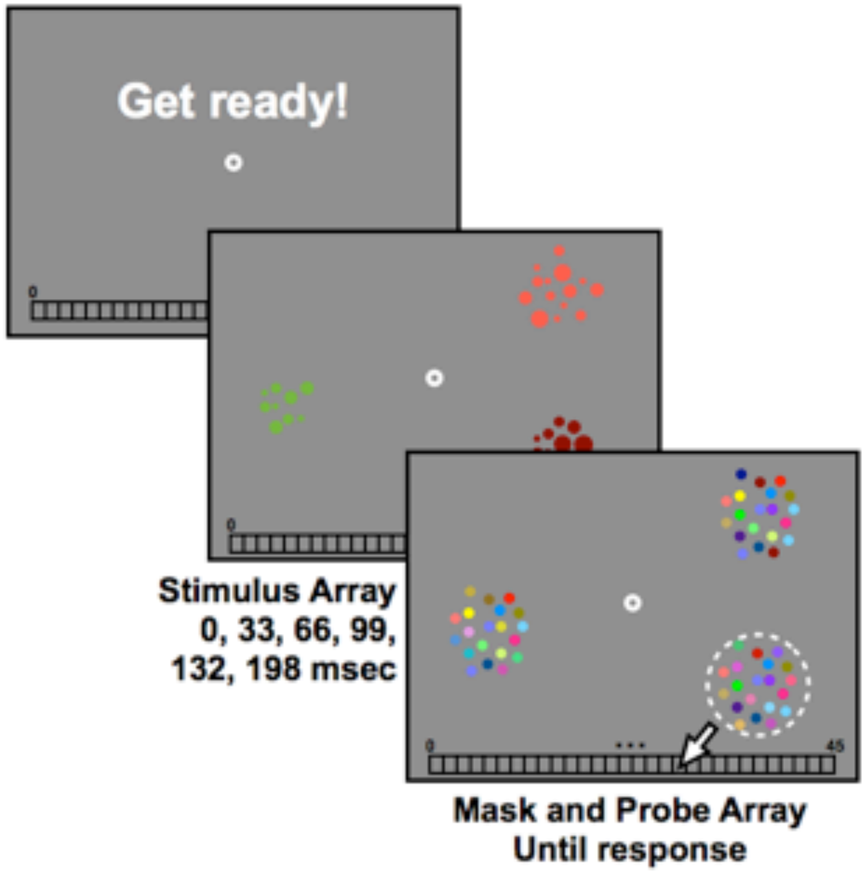
Guess responses increase



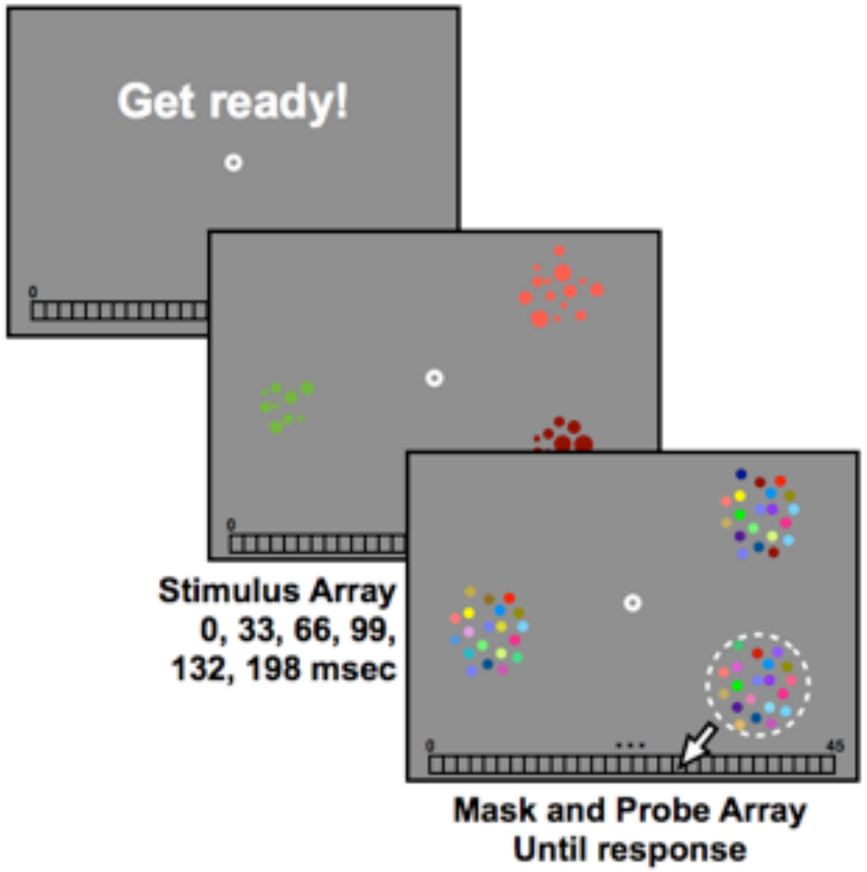
More missed items!

Higher information load

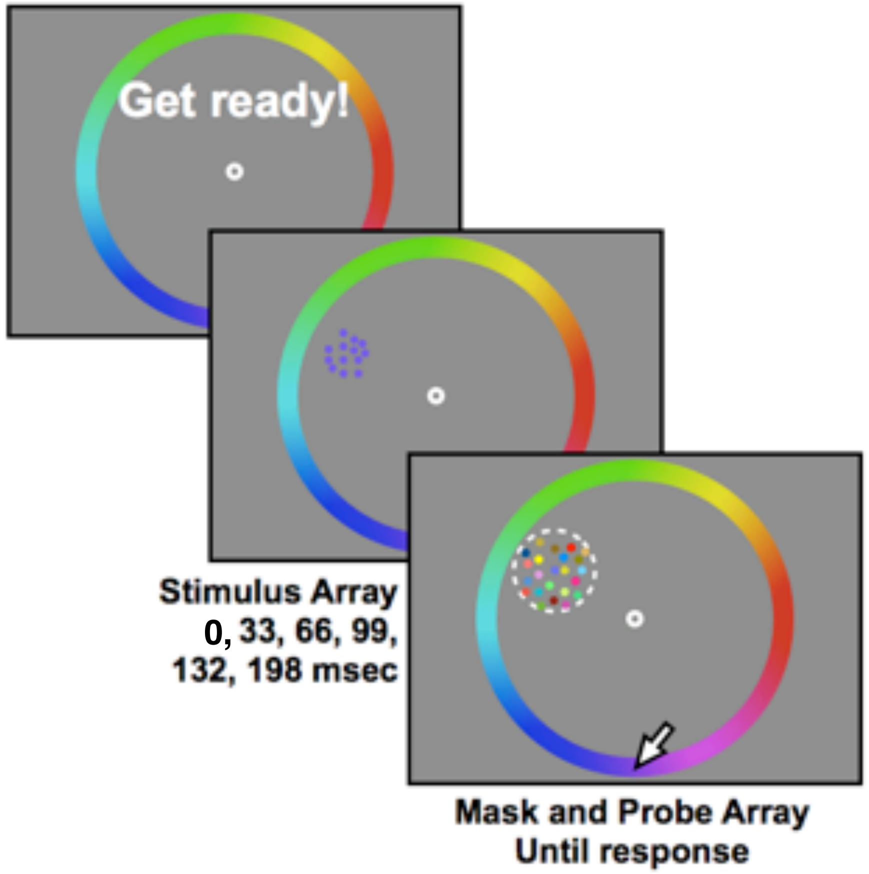
Numerosity


Get ready!
Stimulus Array
0, 33, 66, 99,
132, 198 msec
Mask and Probe Array
Until response

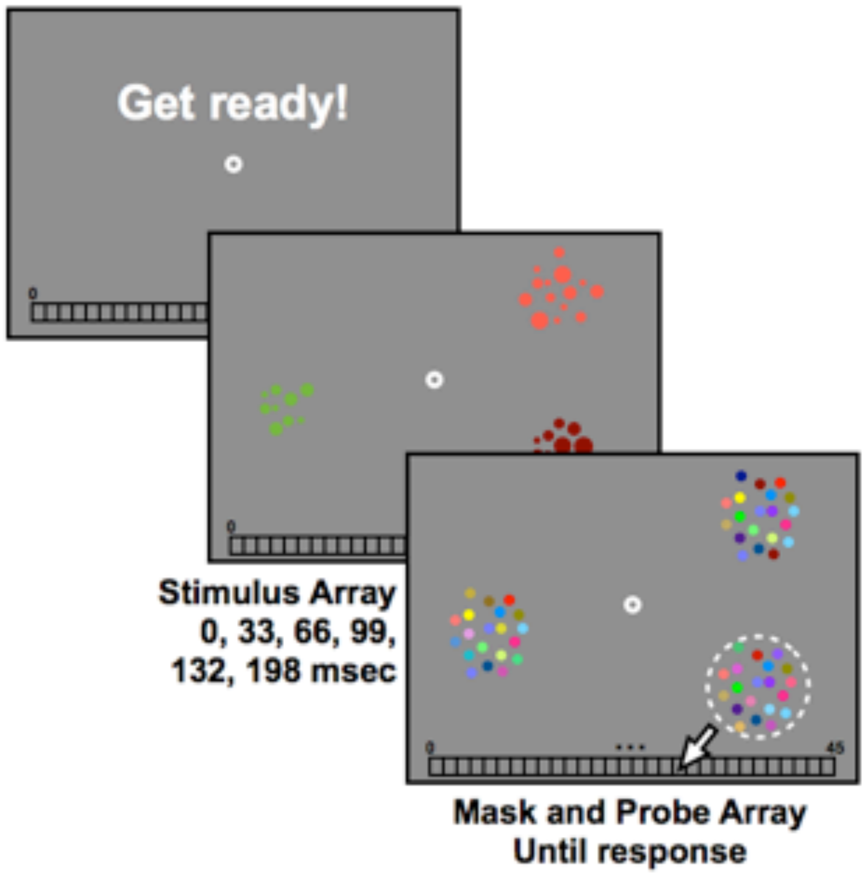
Numerosity



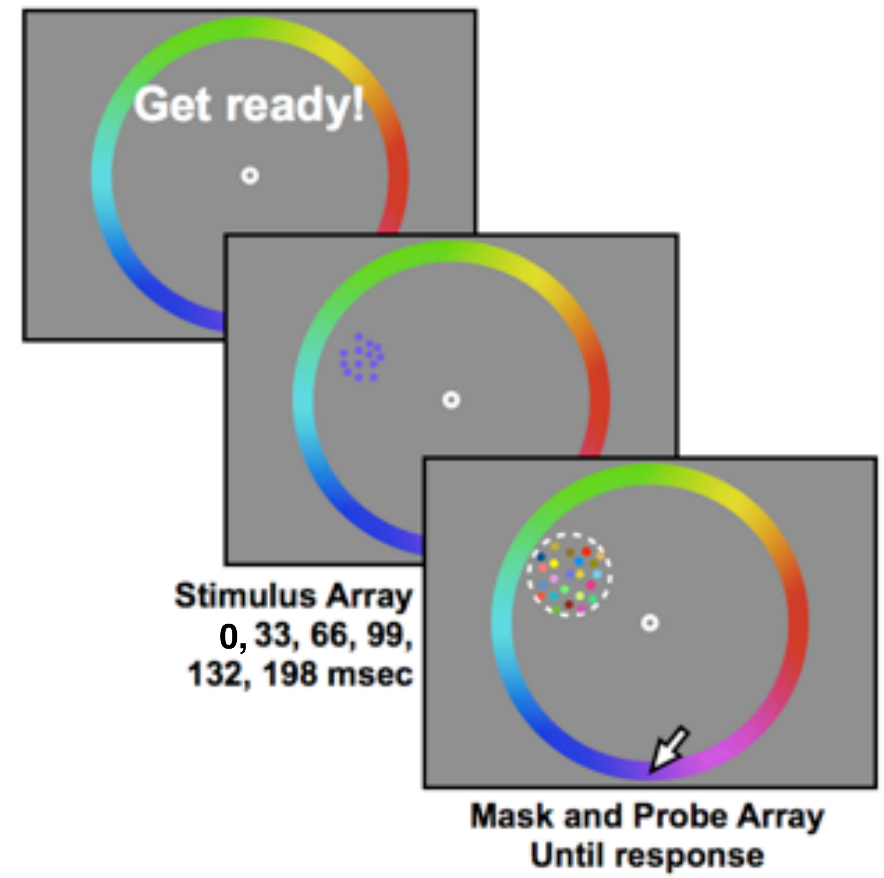
Color



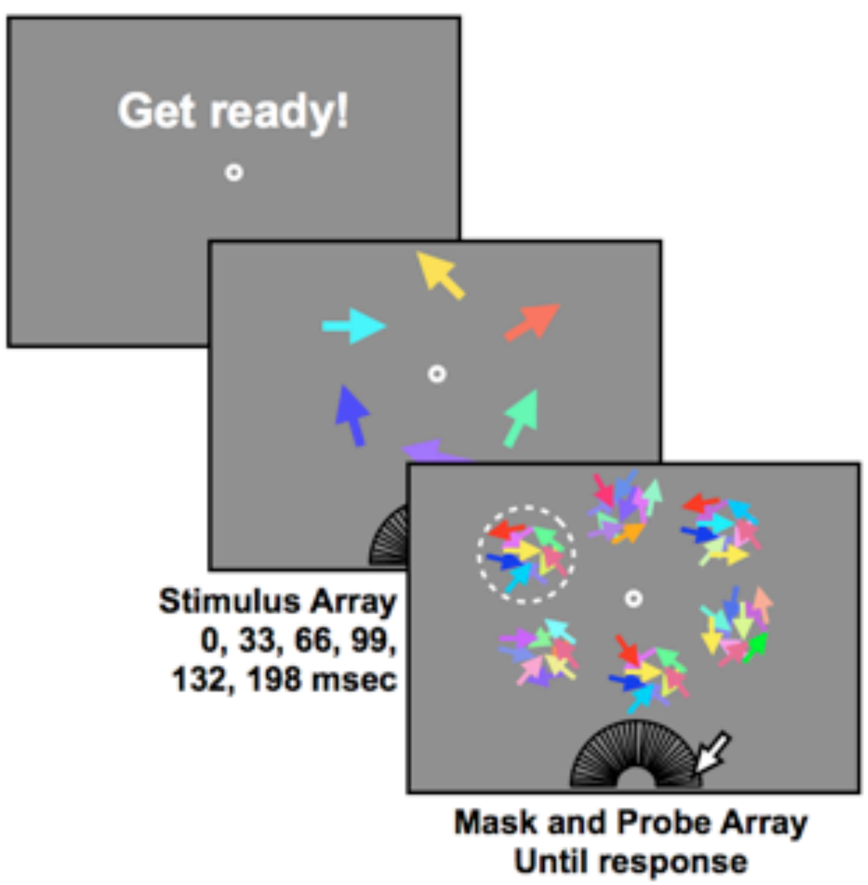
Numerosity



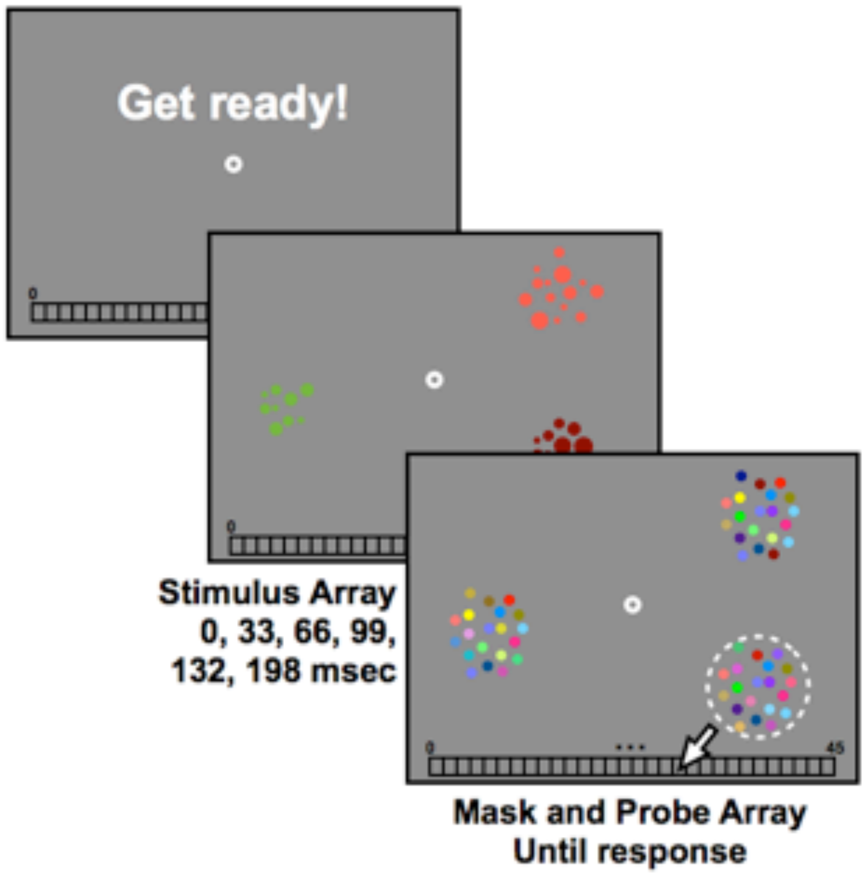
Color



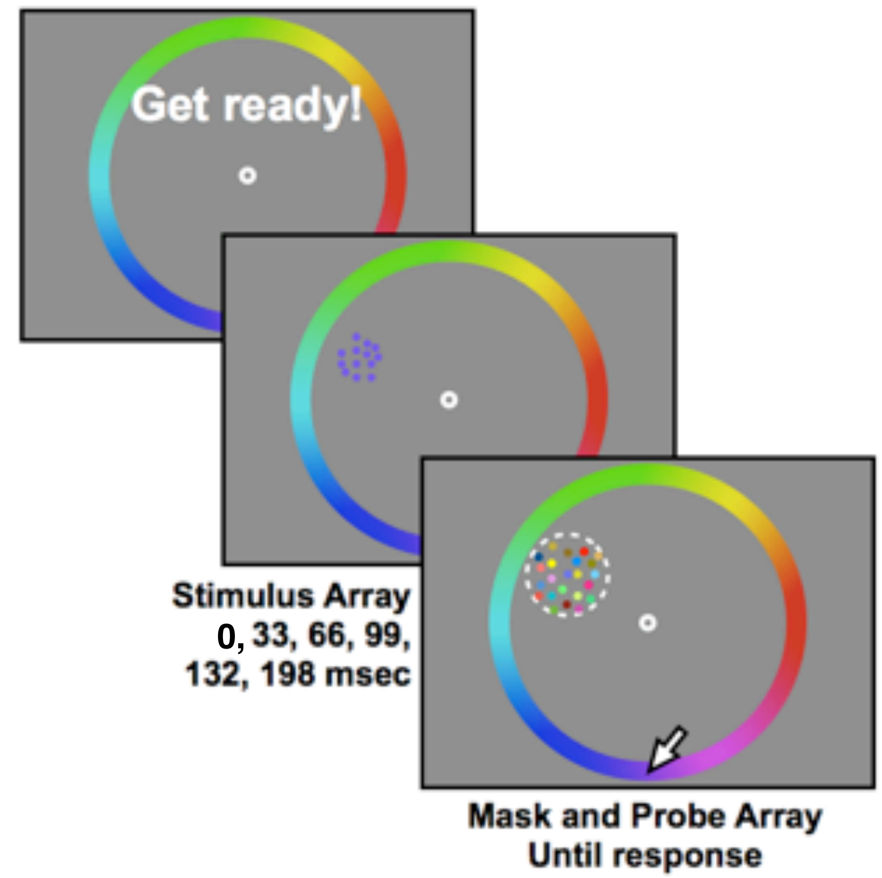
Orientation



Numerosity



Color



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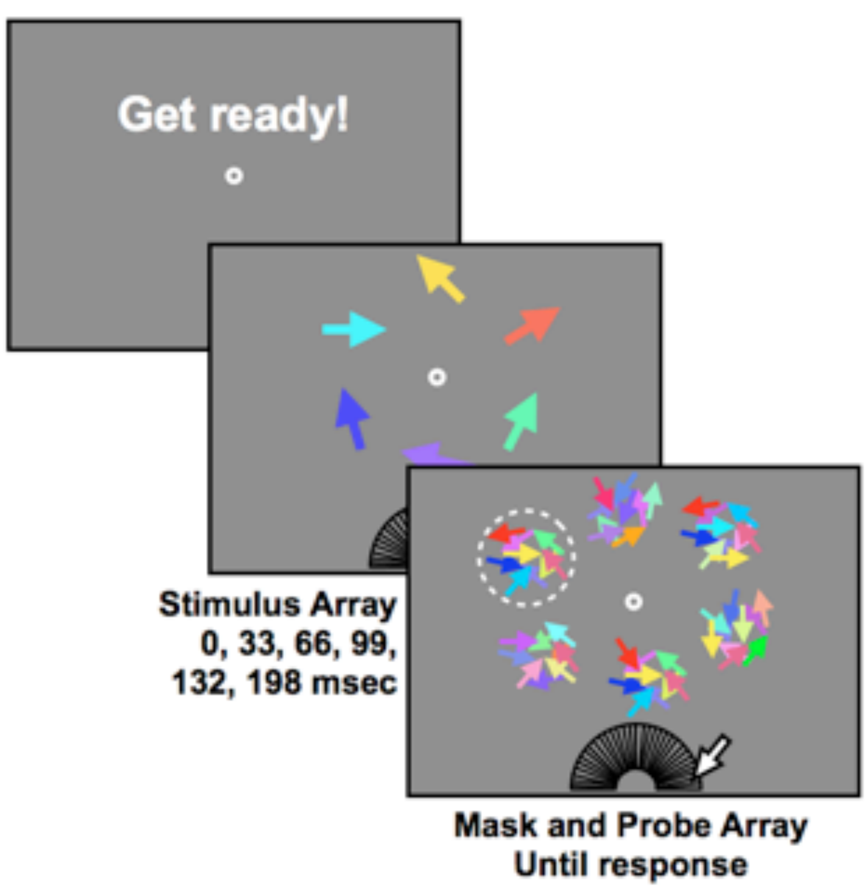
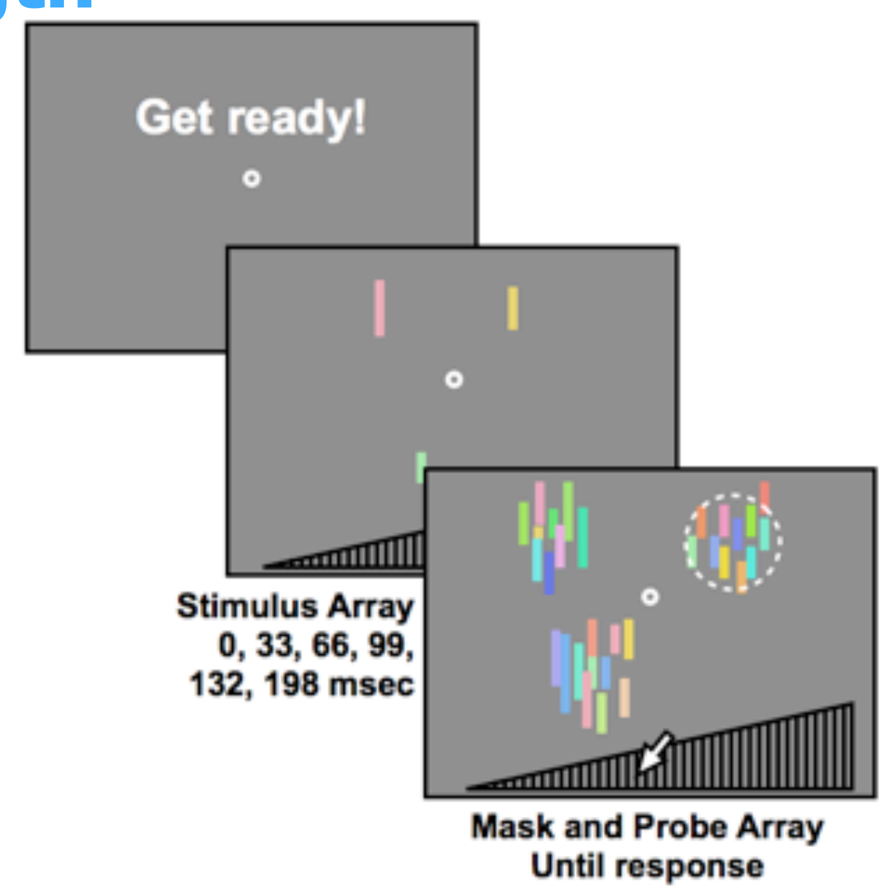
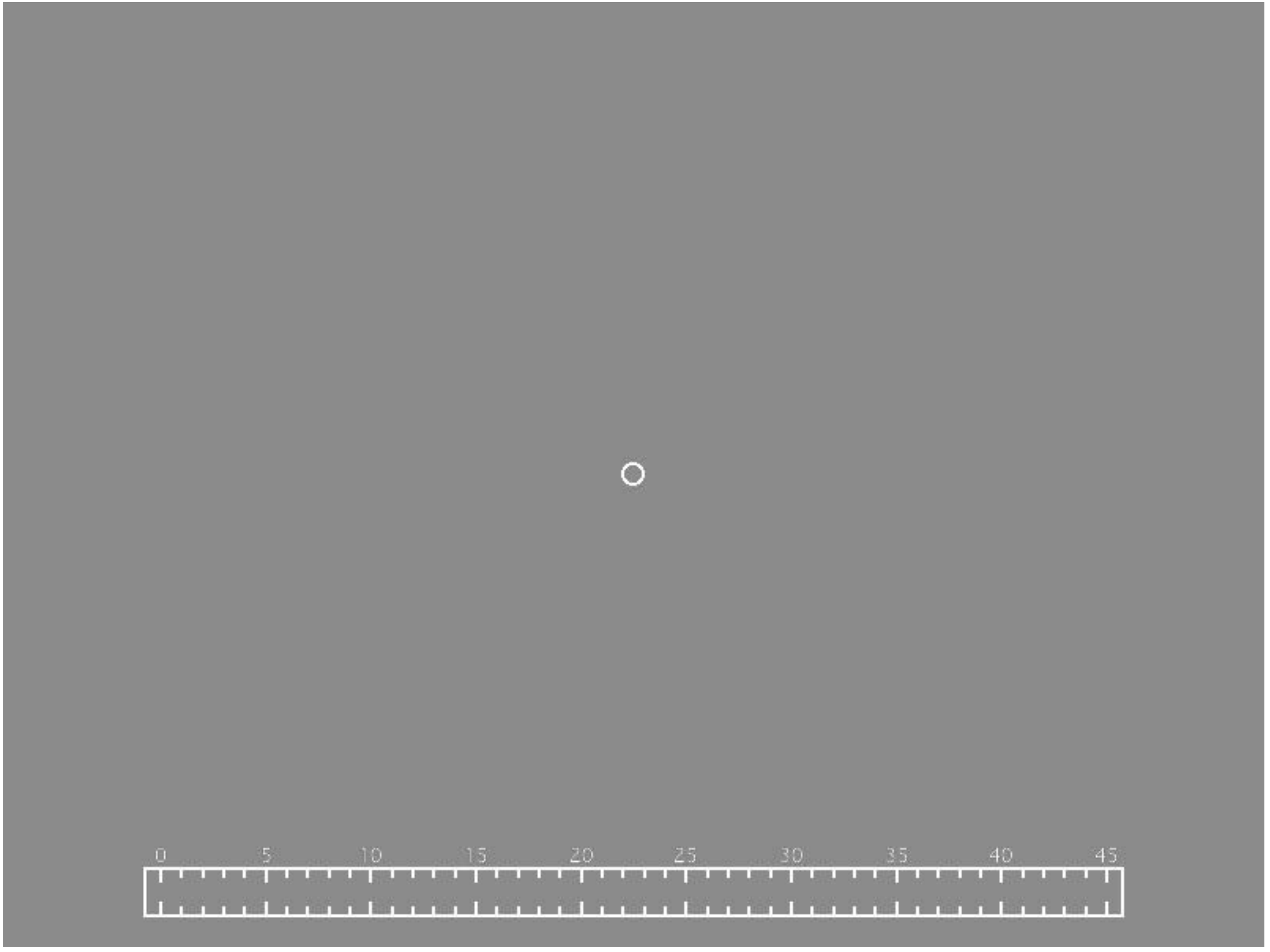


Length



Example trials



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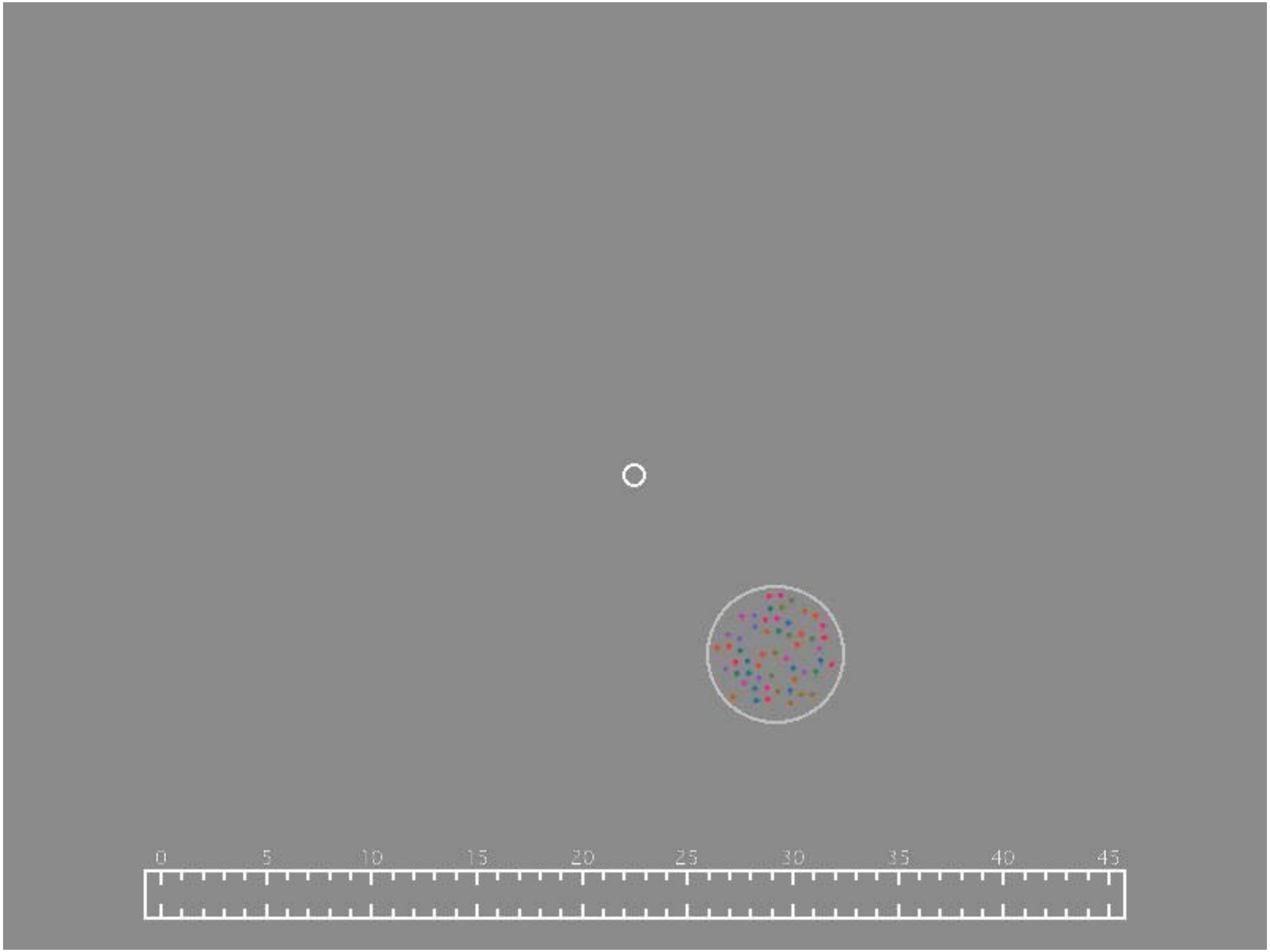

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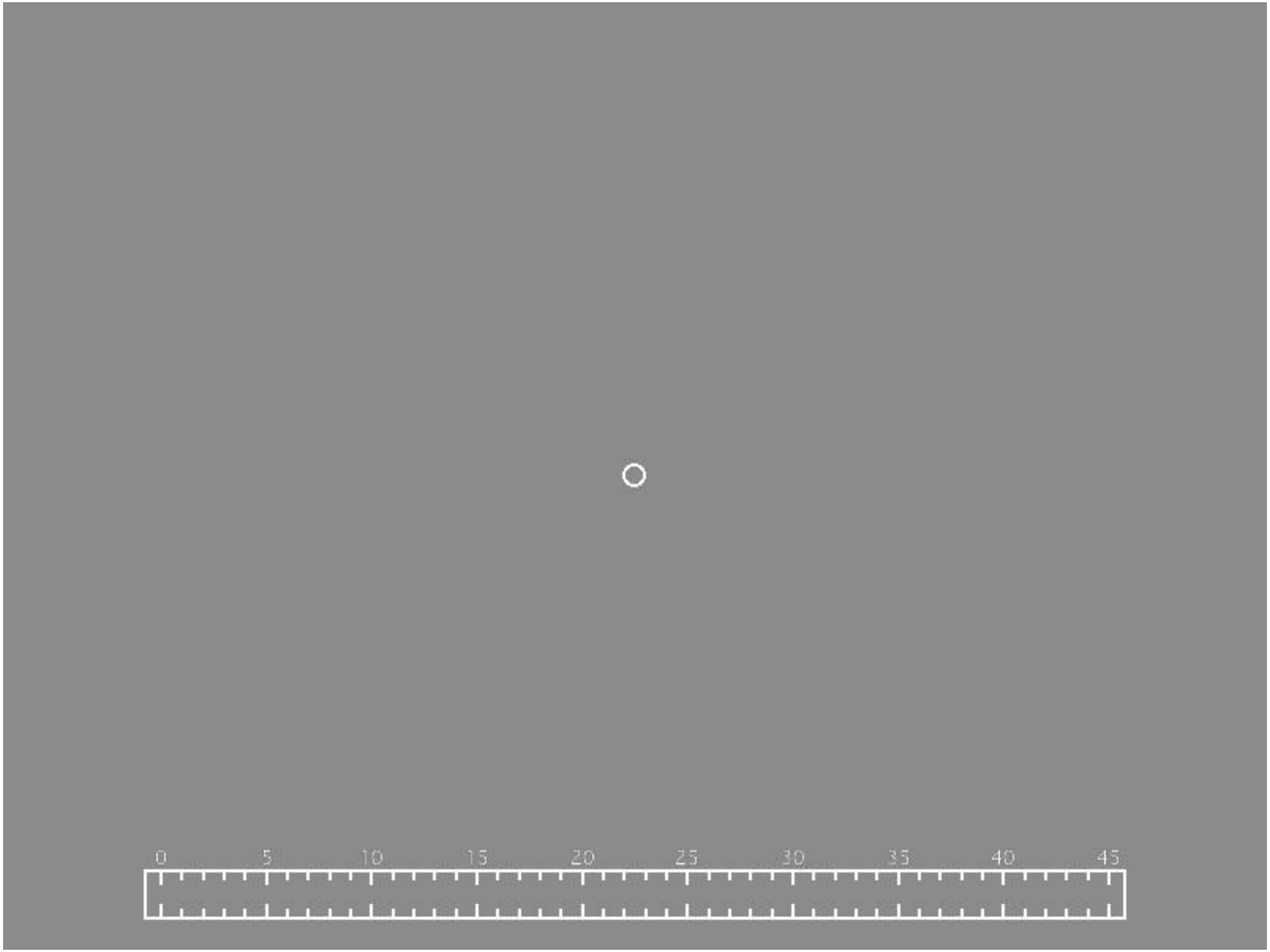

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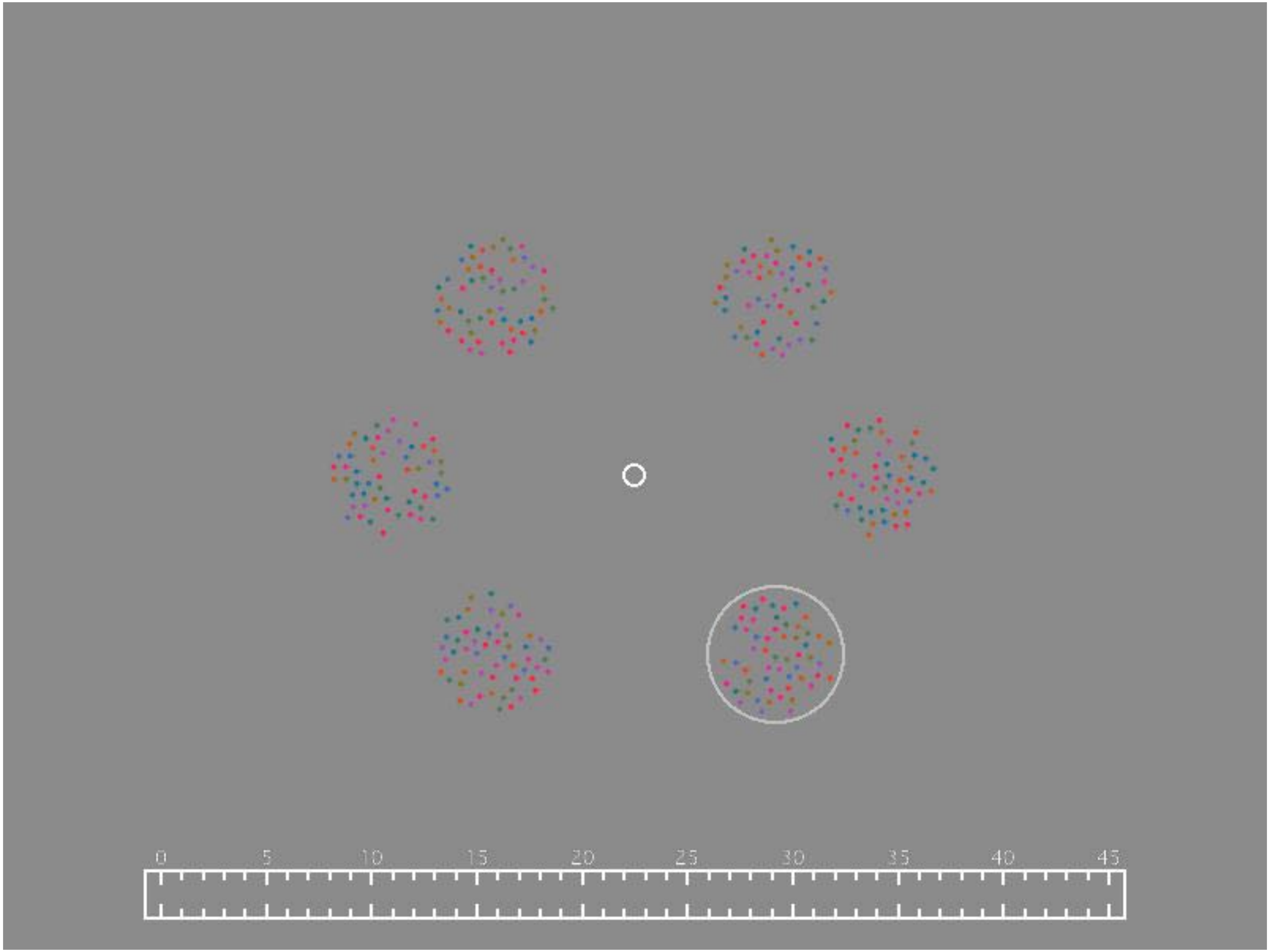
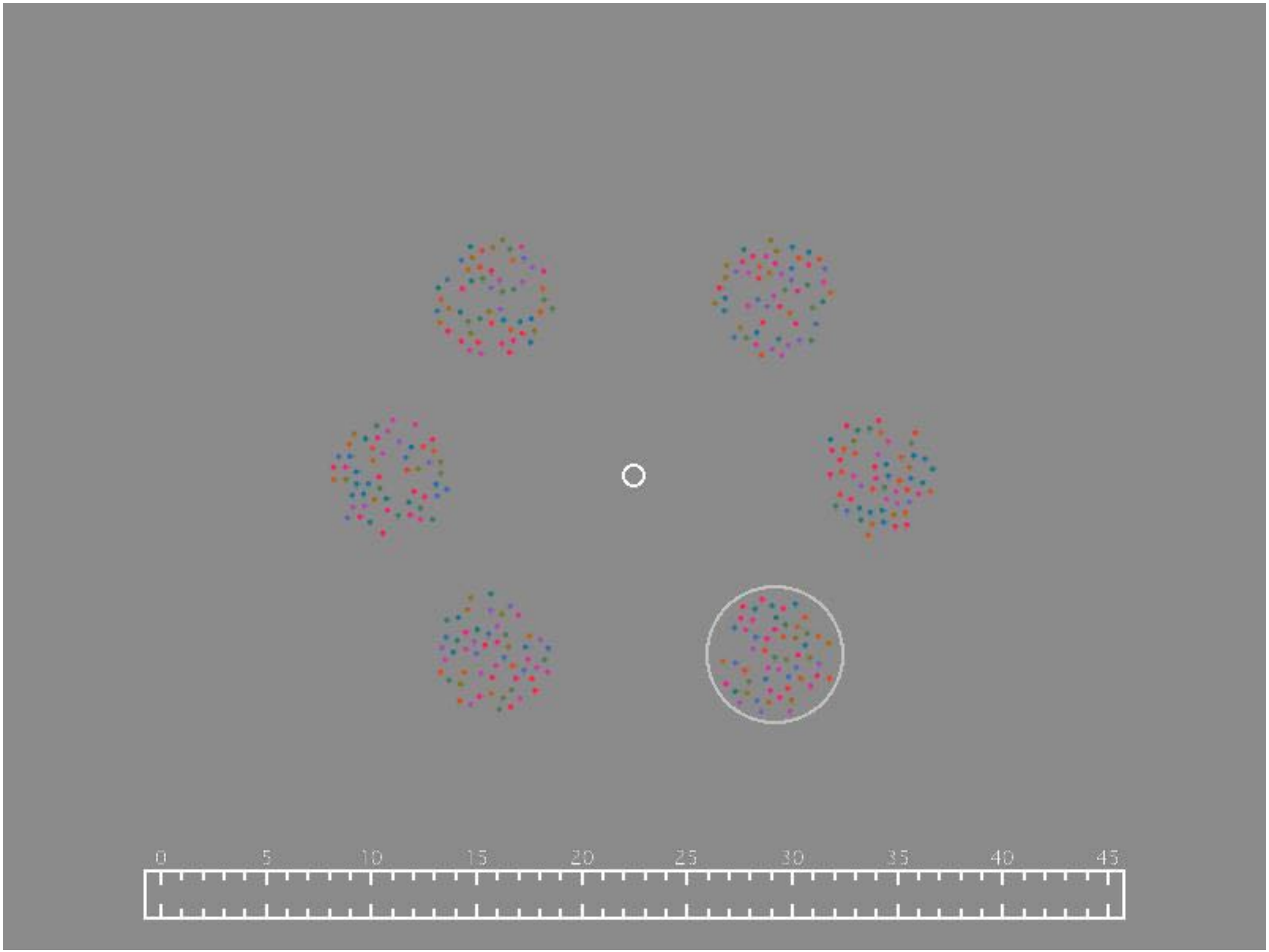
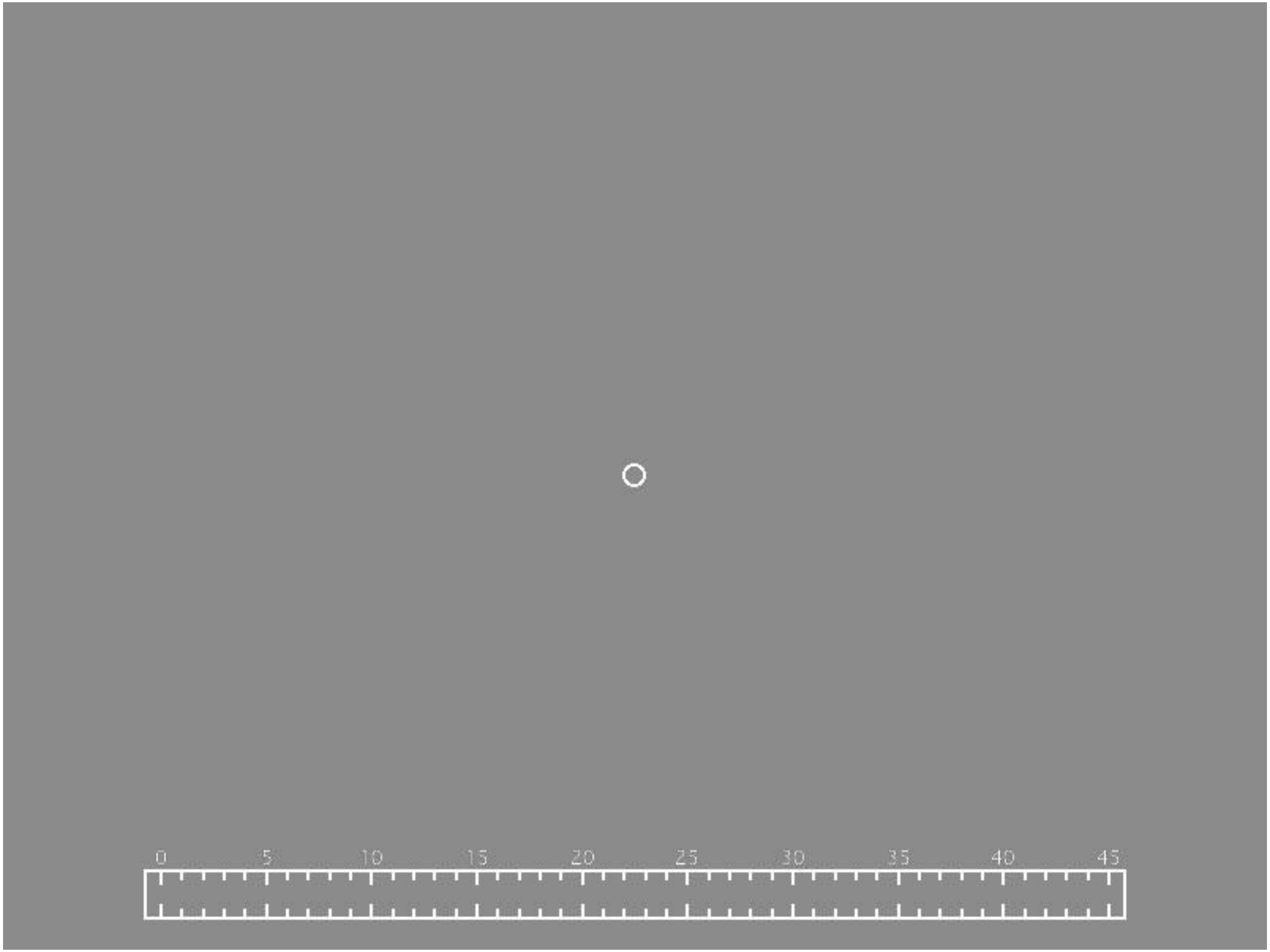


Example trials

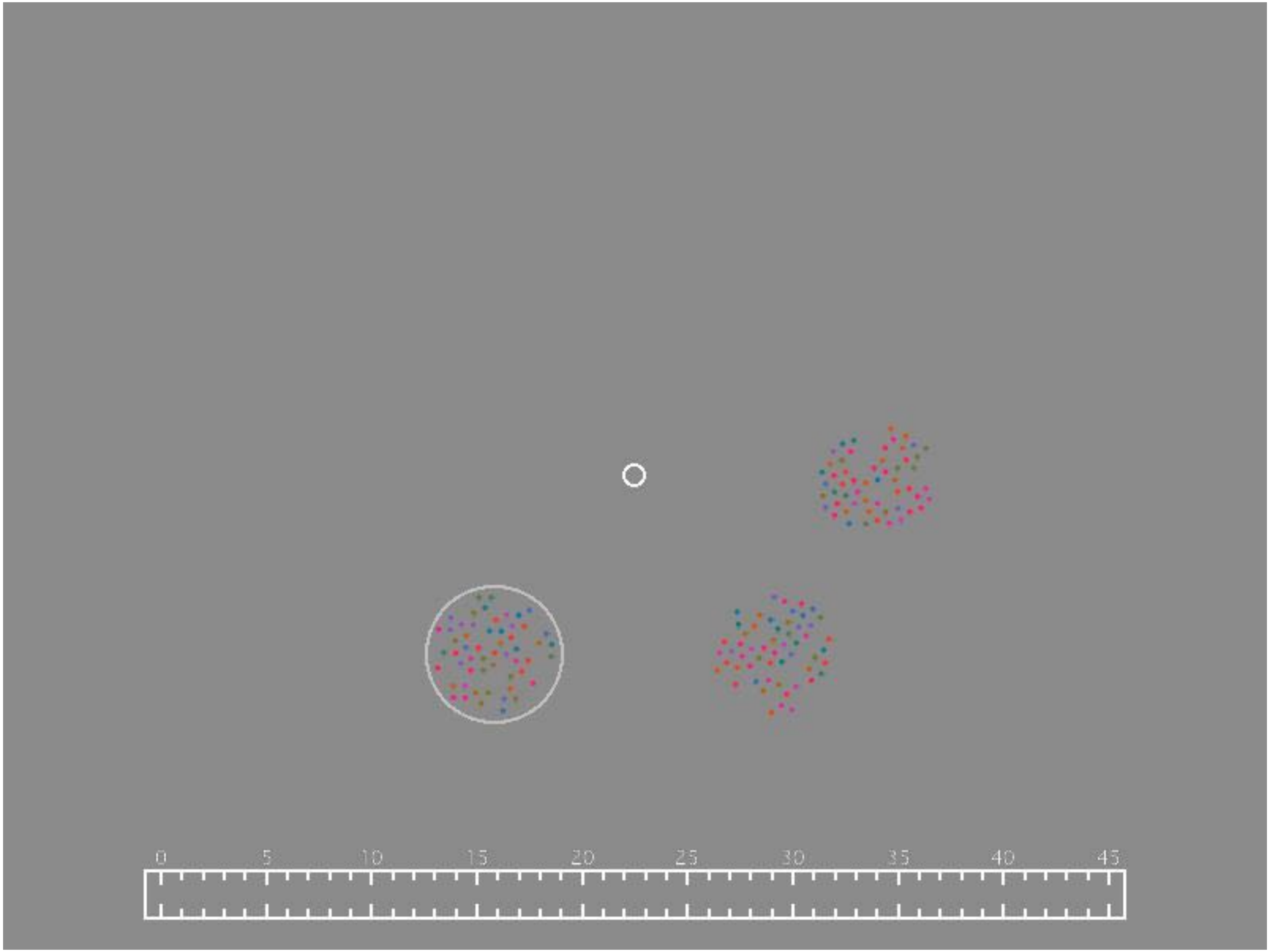
Set size 6 Dur: 198 msec



Example trials

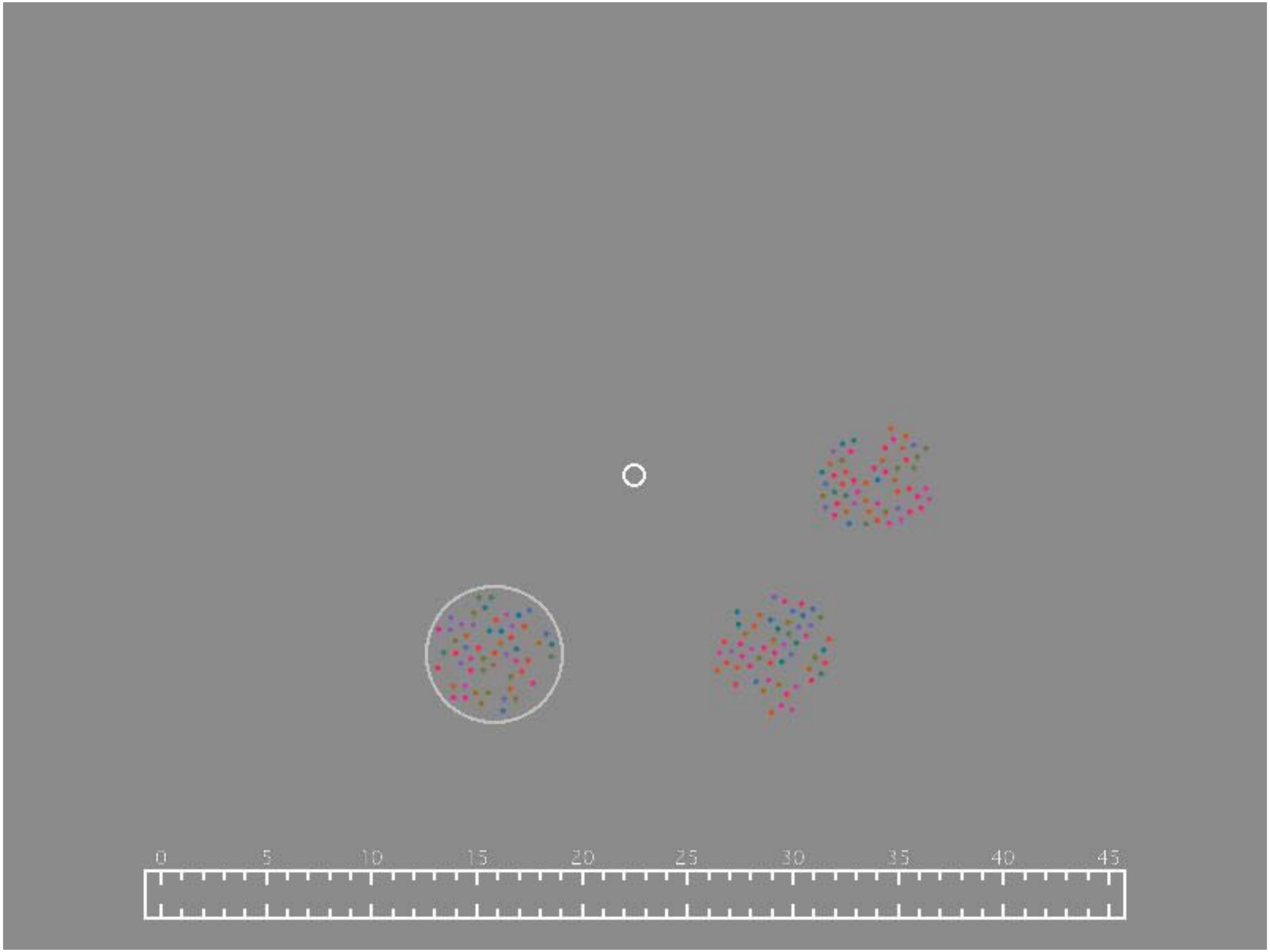


Example trials

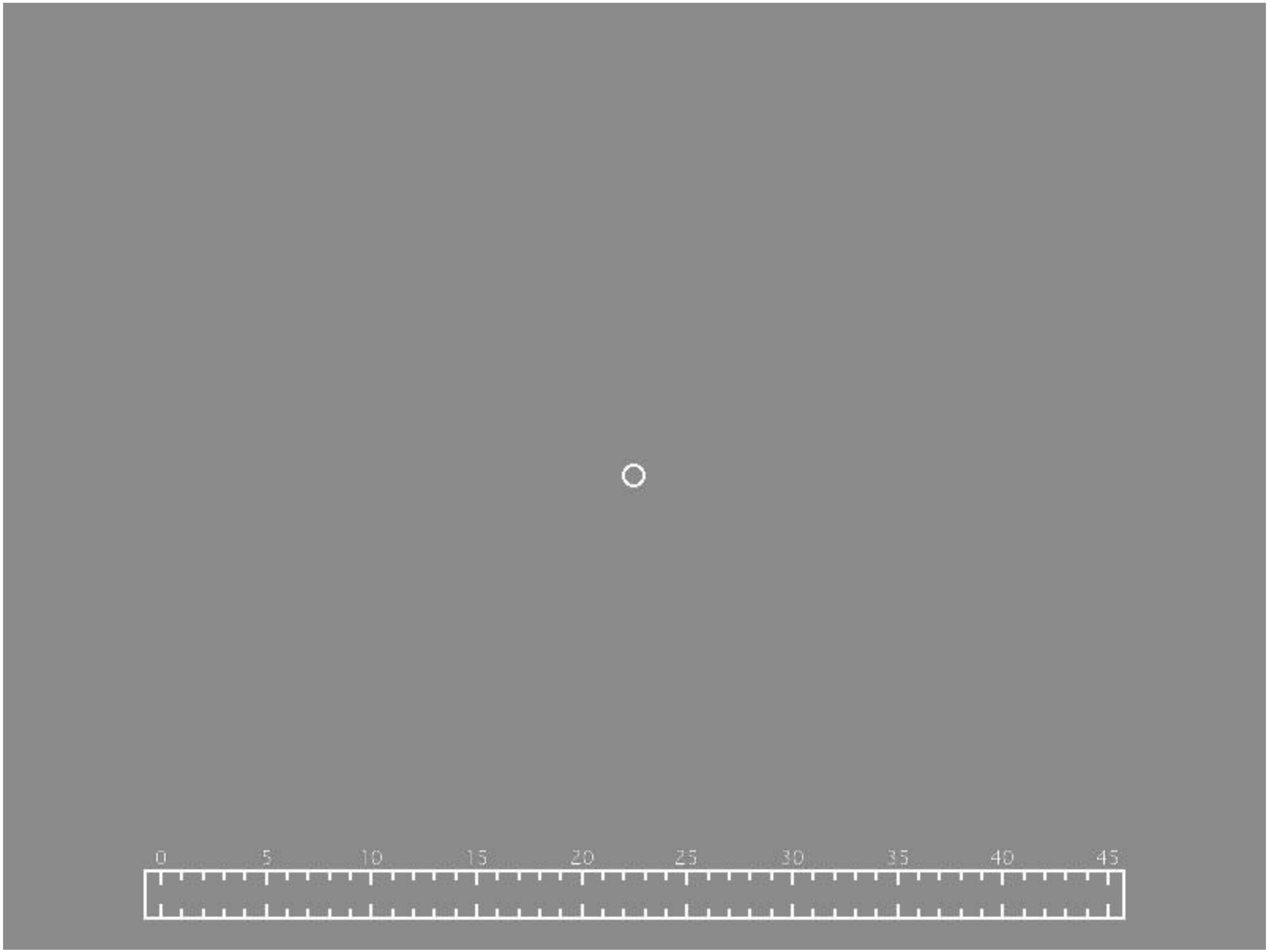


Example trials

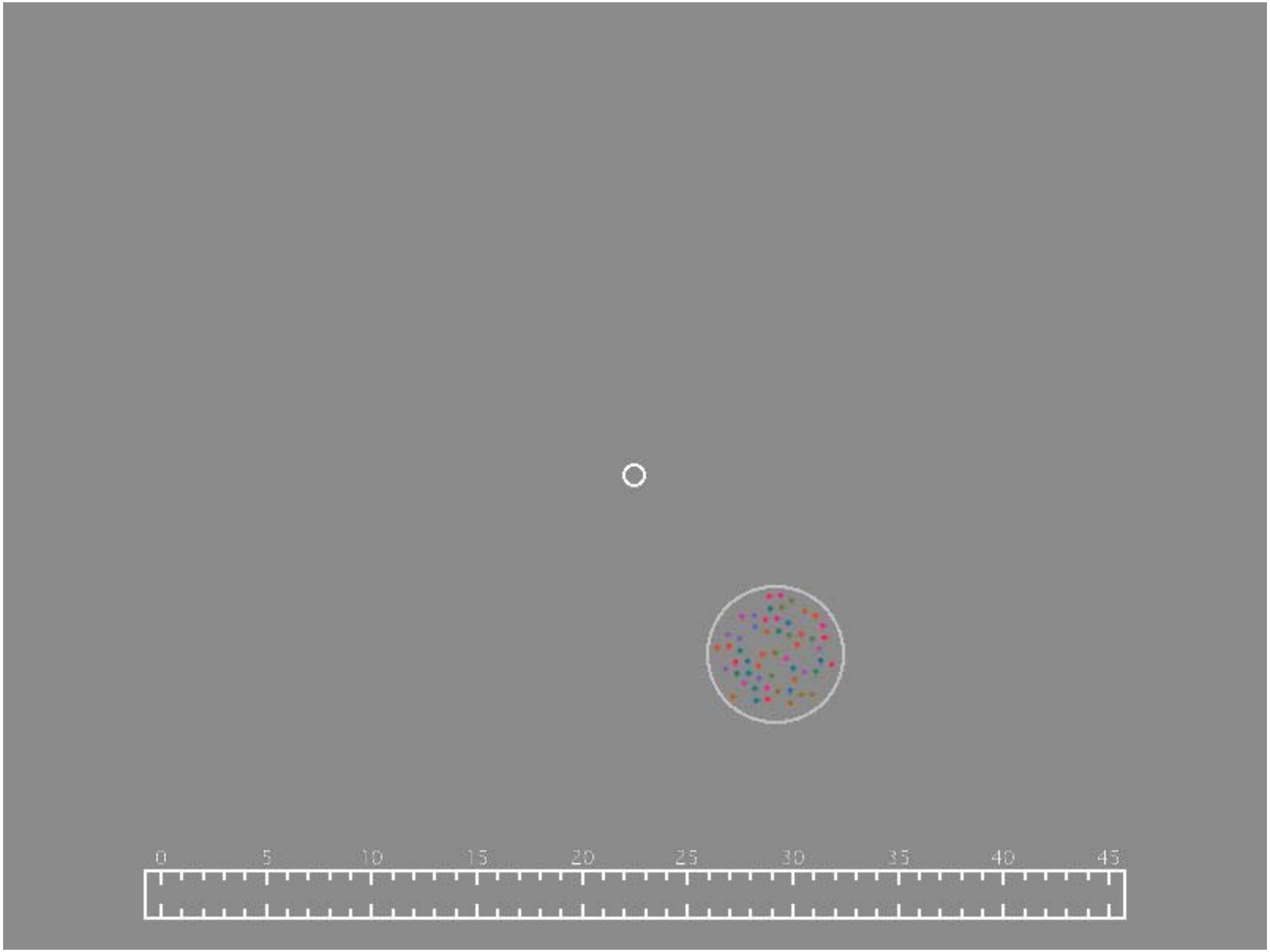
Set size 3 Dur: 100 msec



Example trials

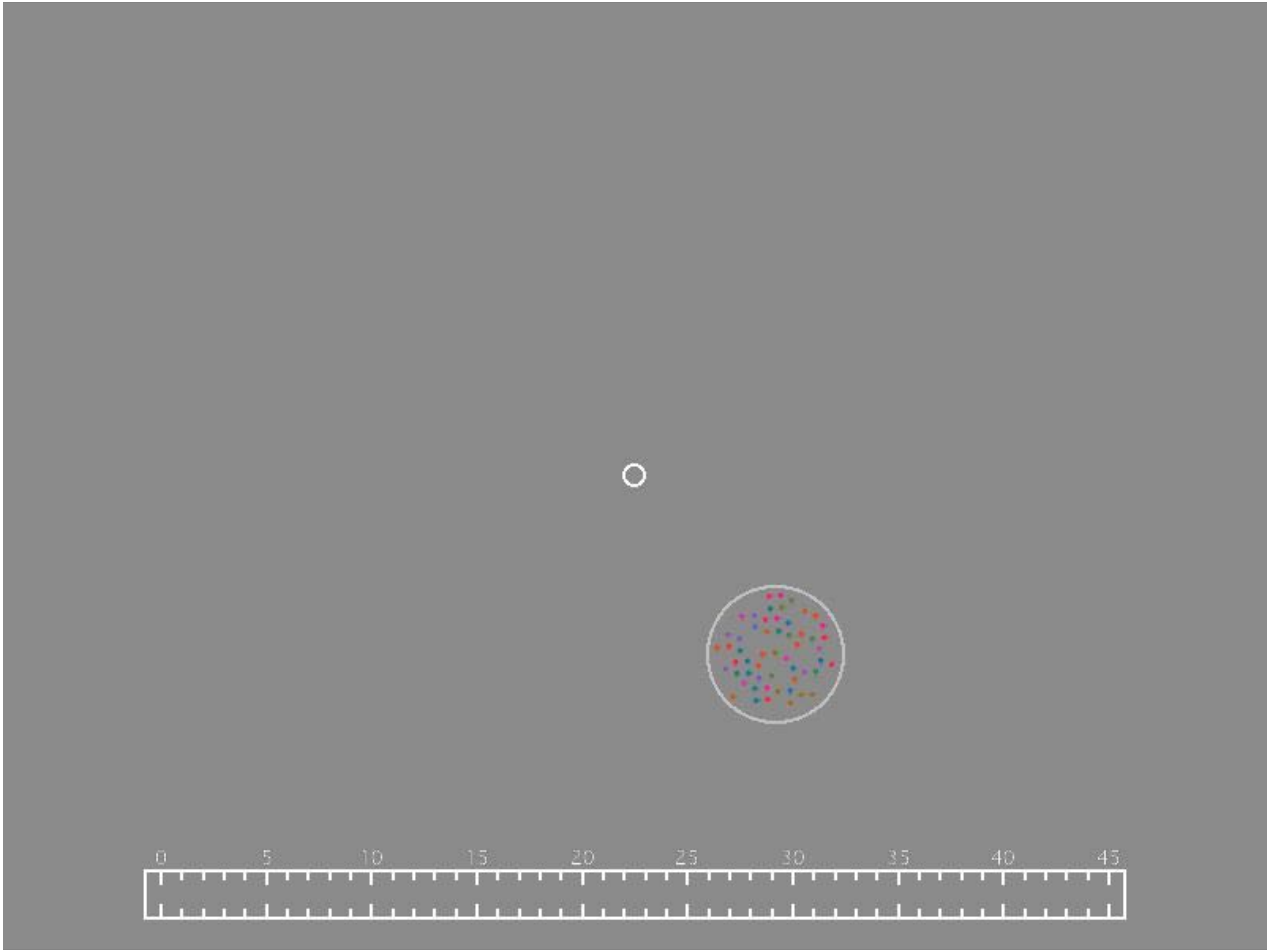


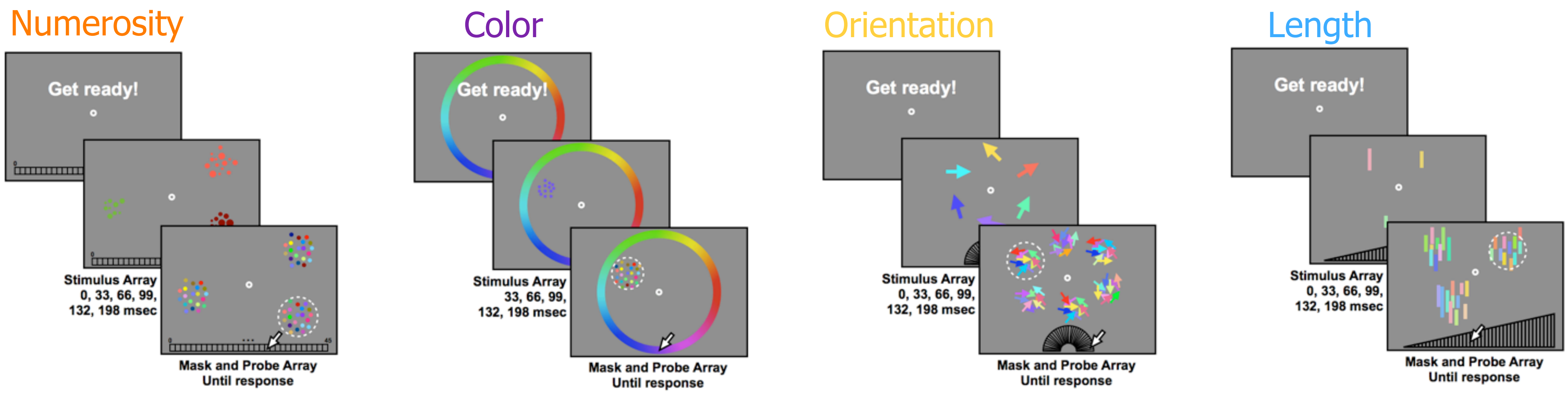
Example trials

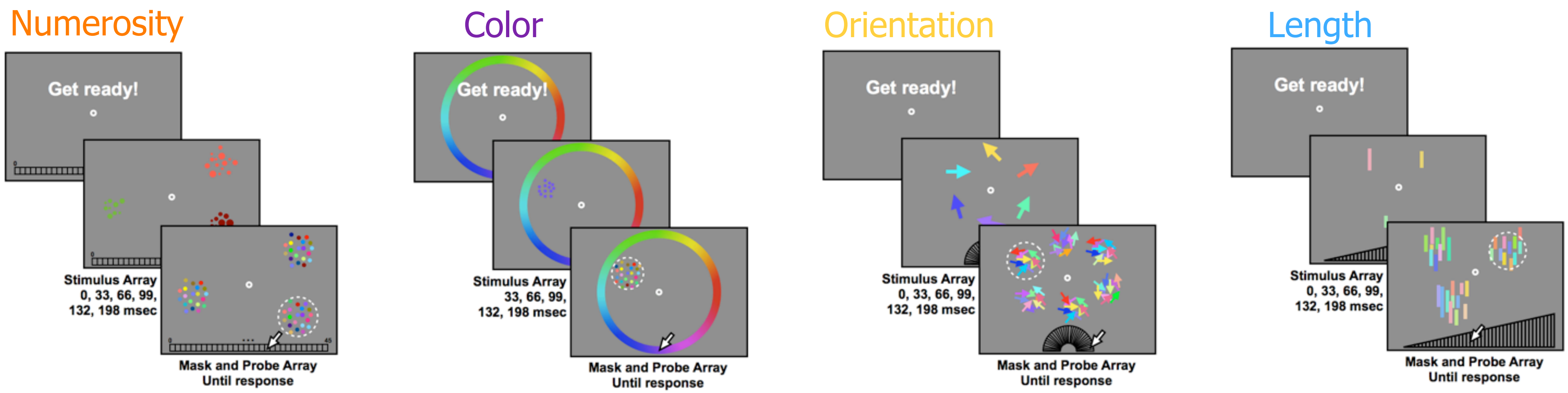


Example trials

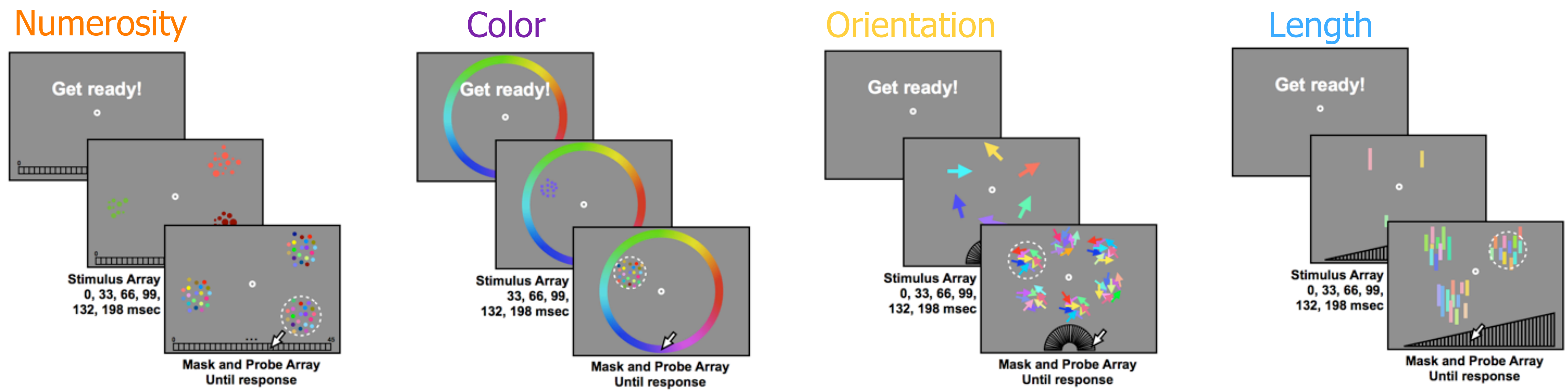
Dur: 0 msec



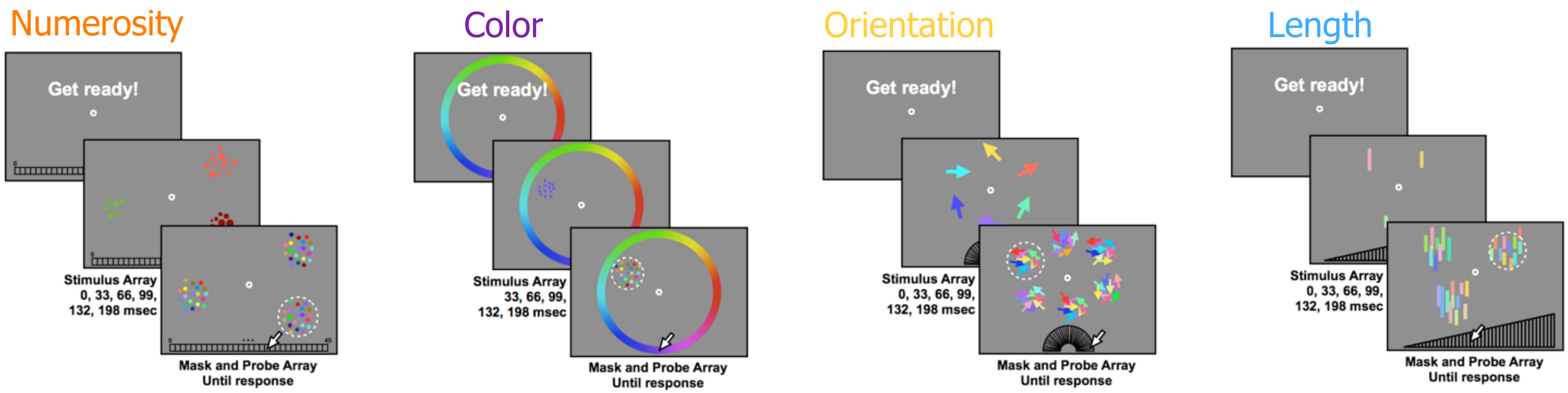

Numerosity
Get ready!
Stimulus Array
0, 33, 66, 99,
132, 198 msec
Mask and Probe Array
Until response
Color
Get ready!
Stimulus Array
33, 66, 99,
132, 198 msec
Mask and Probe Array
Until response
Orientation
Get ready!
Stimulus Array
0, 33, 66, 99,
132, 198 msec
Mask and Probe Array
Until response
Length
Get ready!
Stimulus Array
0, 33, 66, 99,
132, 198 msec
Mask and Probe Array
Until response



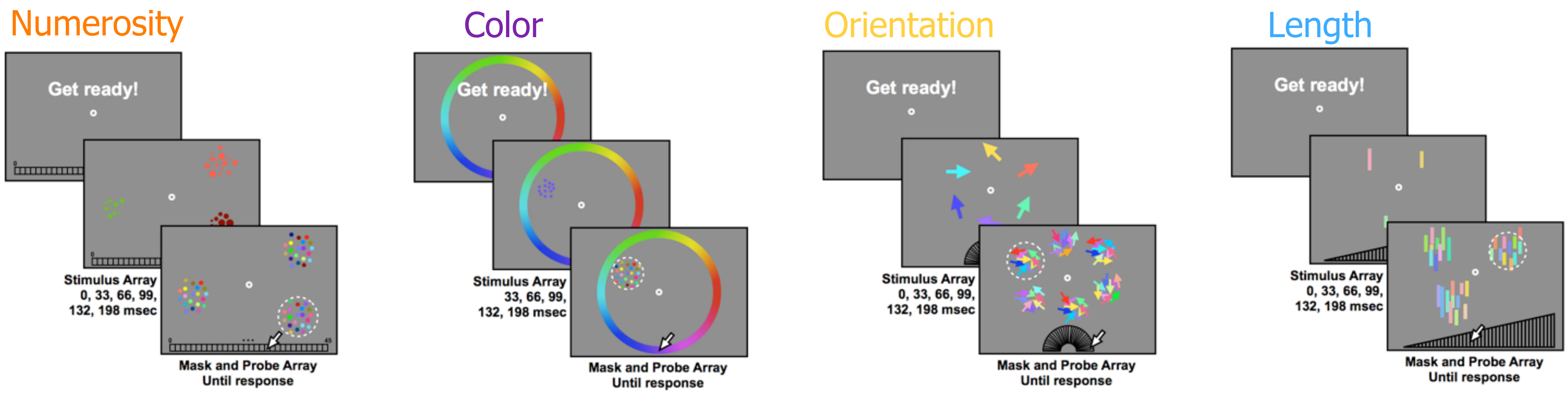
- Four different features: Numerosity, Color, Orientation, and Length



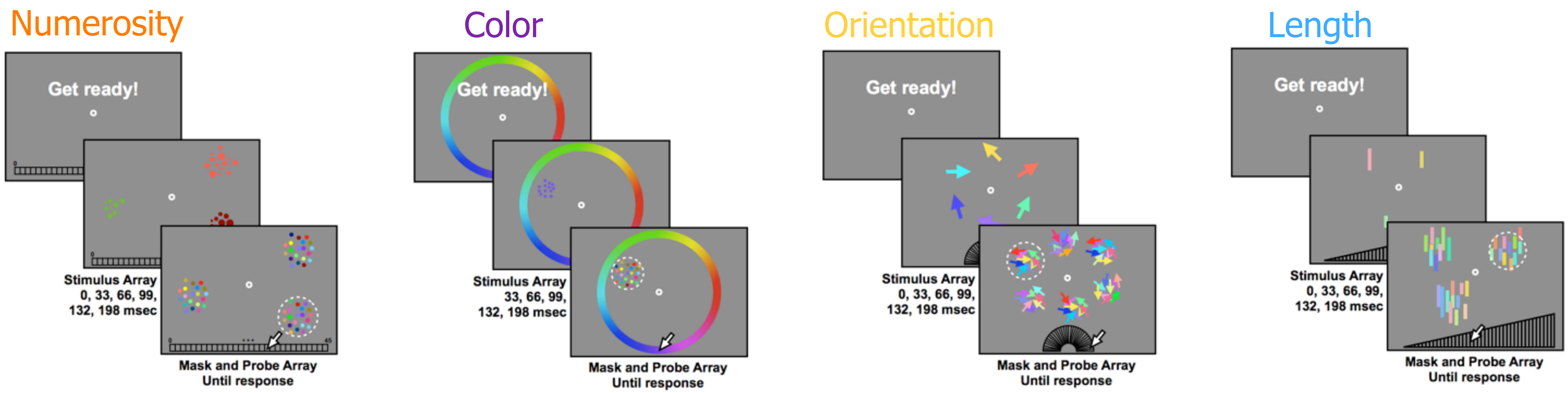
- Four different features: Numerosity, Color, Orientation, and Length
- Continuous response scale



- Four different features: Numerosity, Color, Orientation, and Length
- Continuous response scale
- Set sizes: 1,3, and 6



- Four different features: Numerosity, Color, Orientation, and Length
- Continuous response scale
- Set sizes: 1,3, and 6
- SOA's: 33, 66, 100, 133, 198, and **0 msec**



- Four different features: Numerosity, Color, Orientation, and Length
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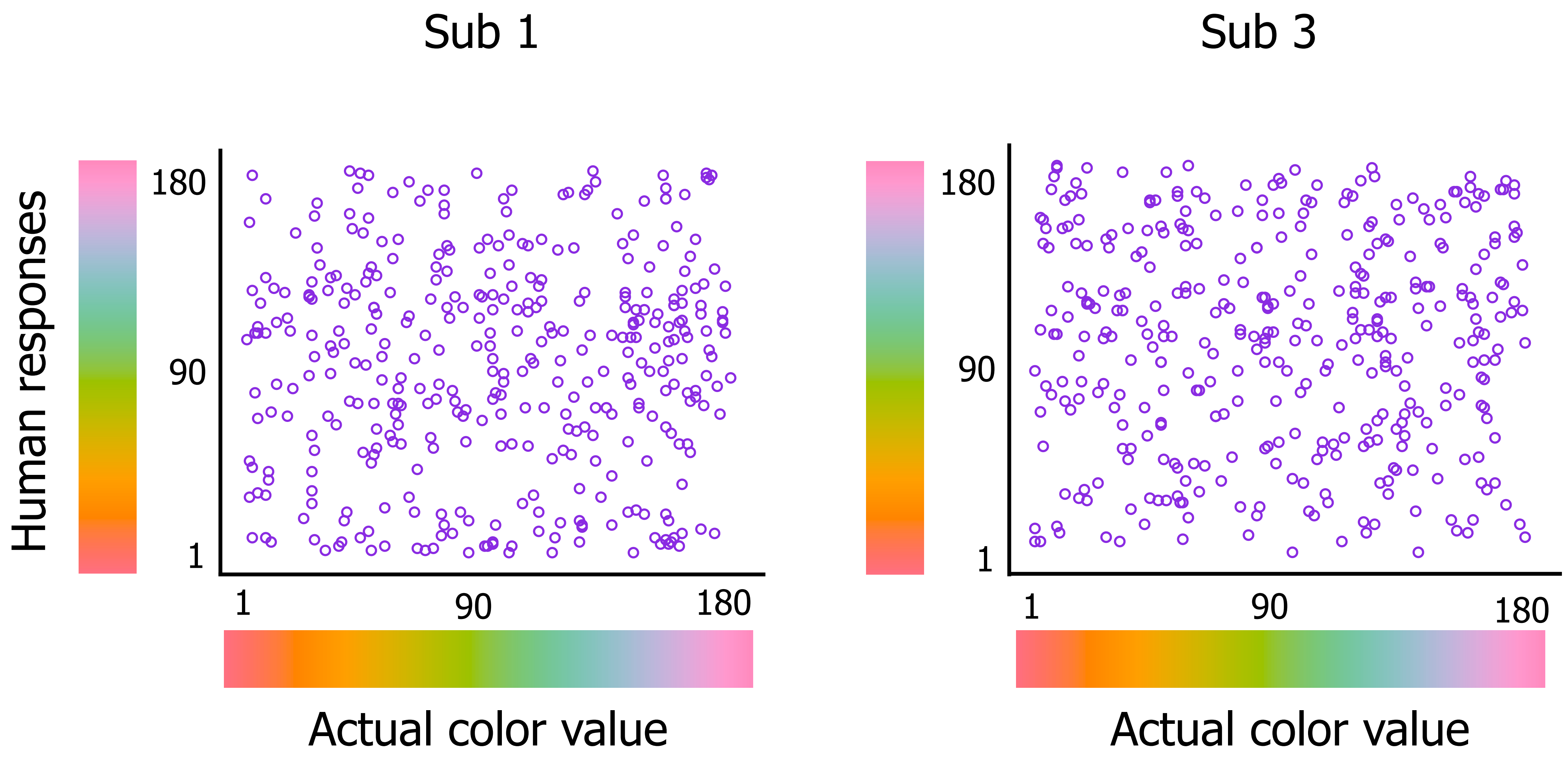
Why use 0 msec?

Results from 0-msec-trials: pattern of pure guesses

Color

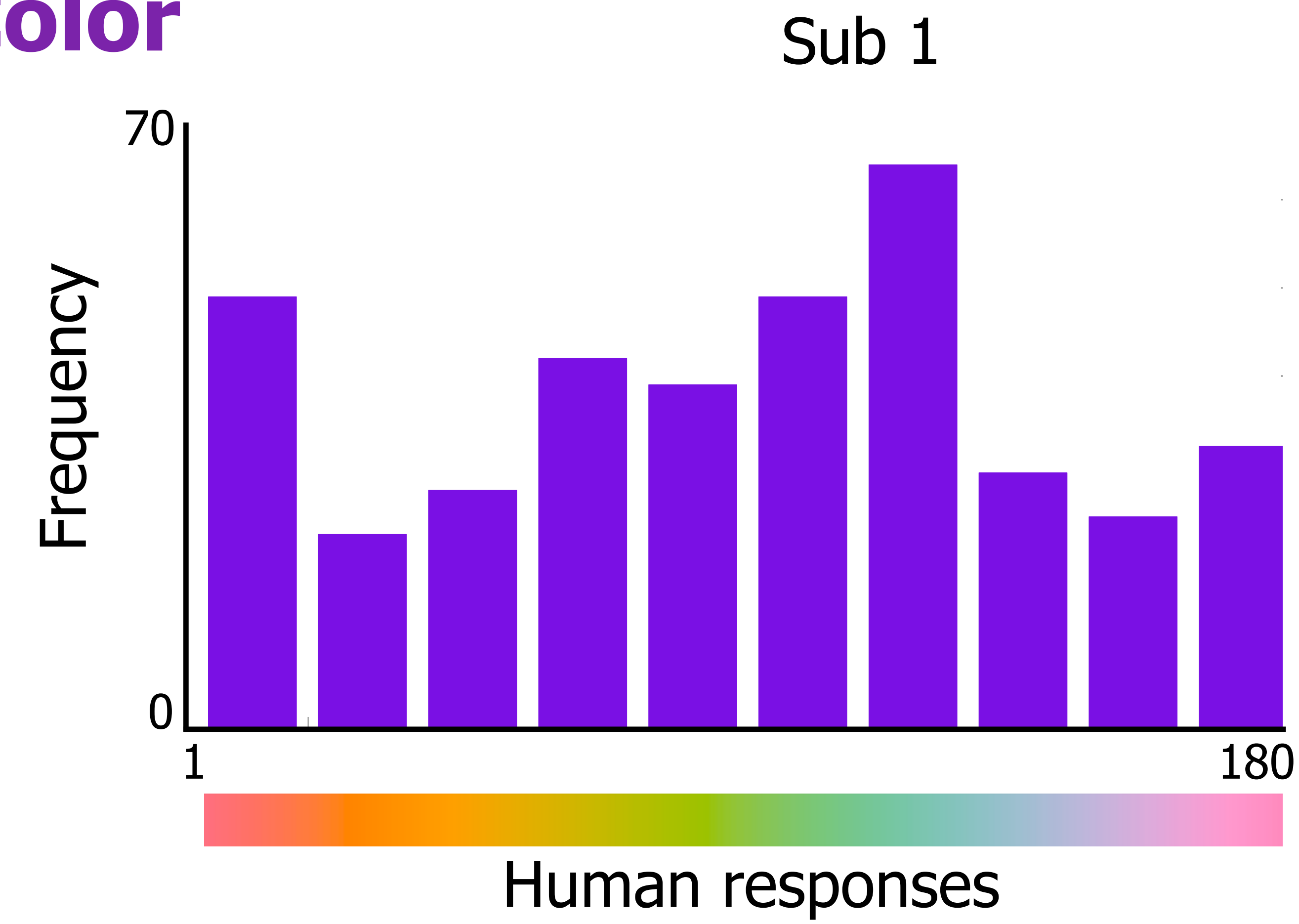
Results from 0-msec-trials: pattern of pure guesses

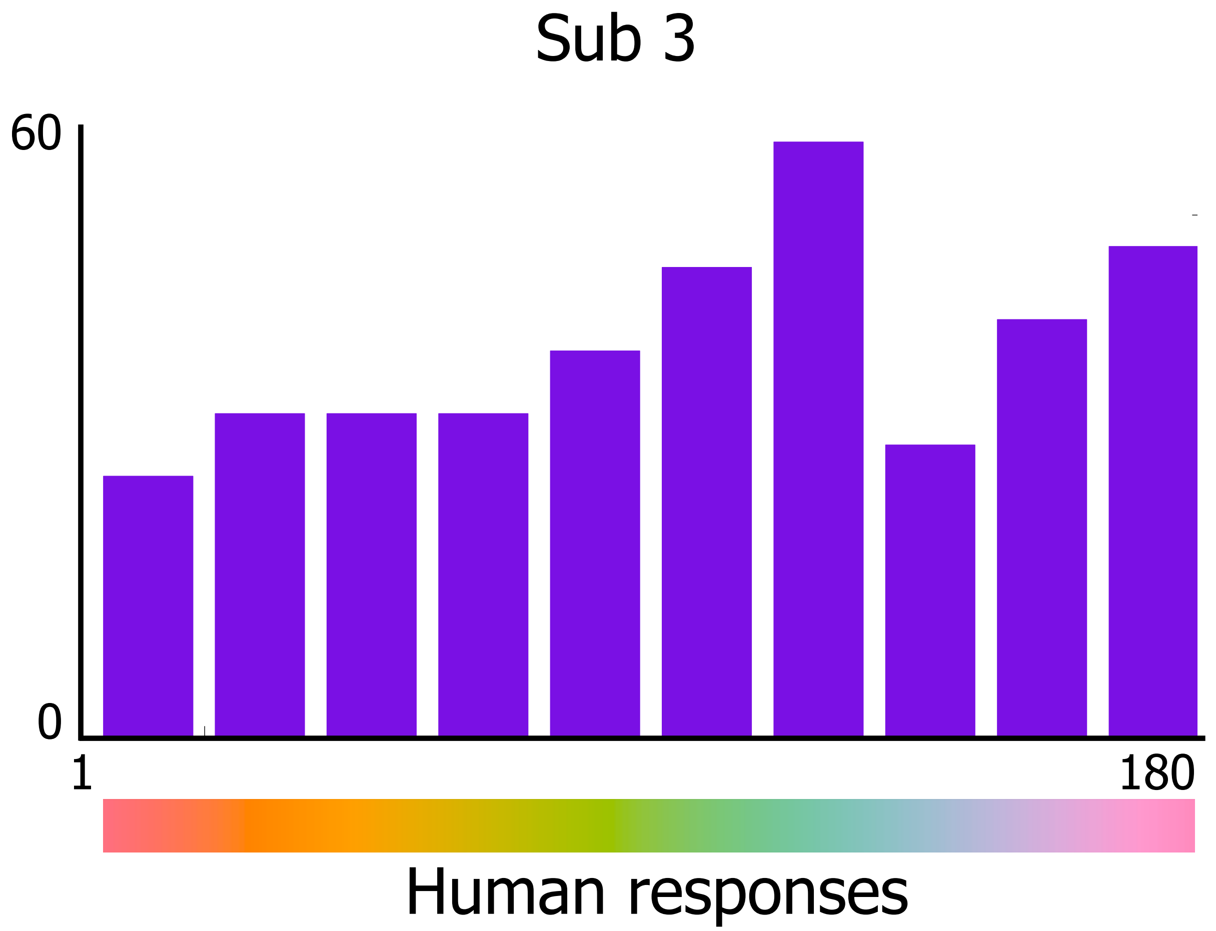
Color



Results from 0-msec-trials: pattern of pure guesses

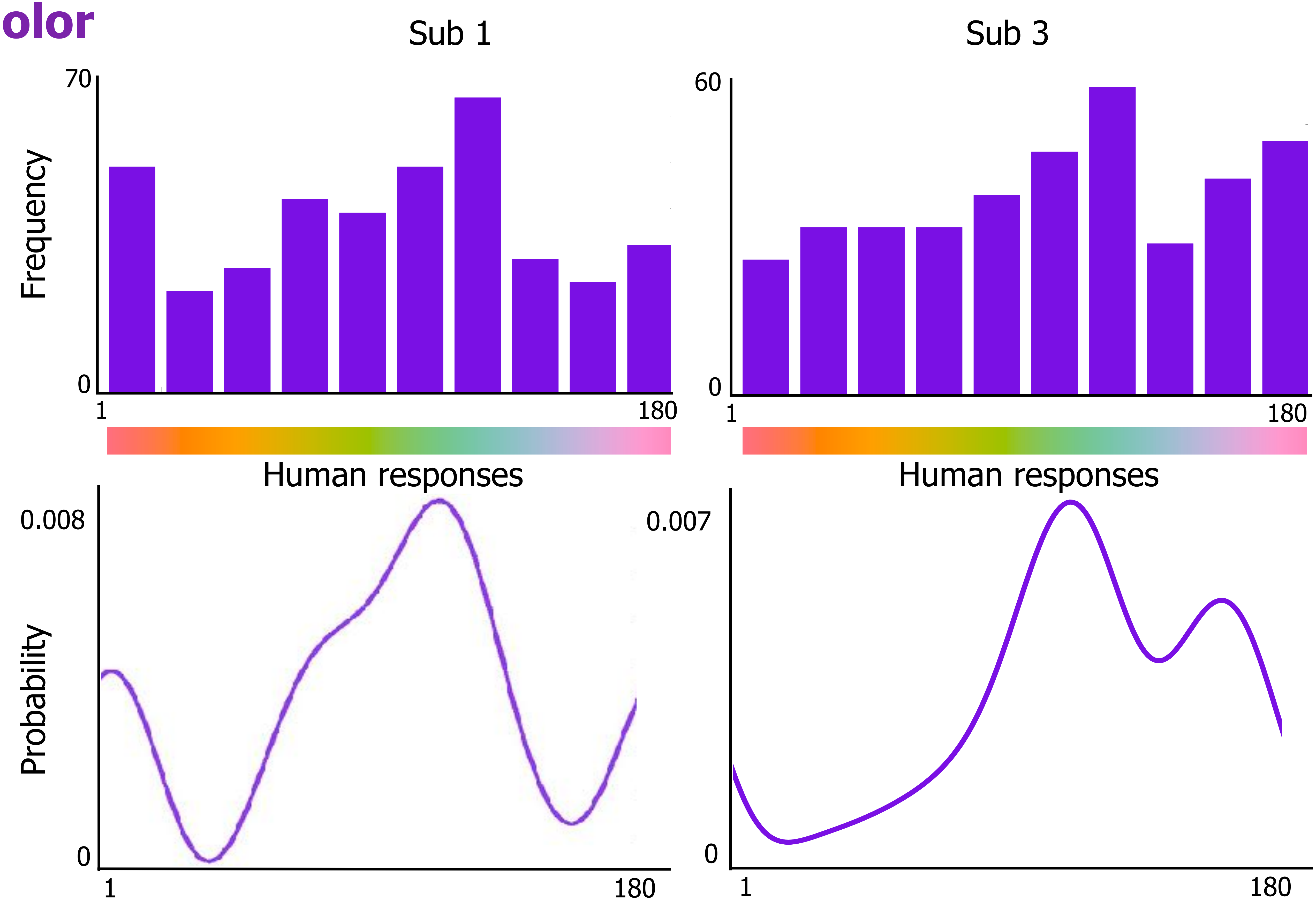
Color





Results from 0-msec-trials: pattern of pure guesses

Color

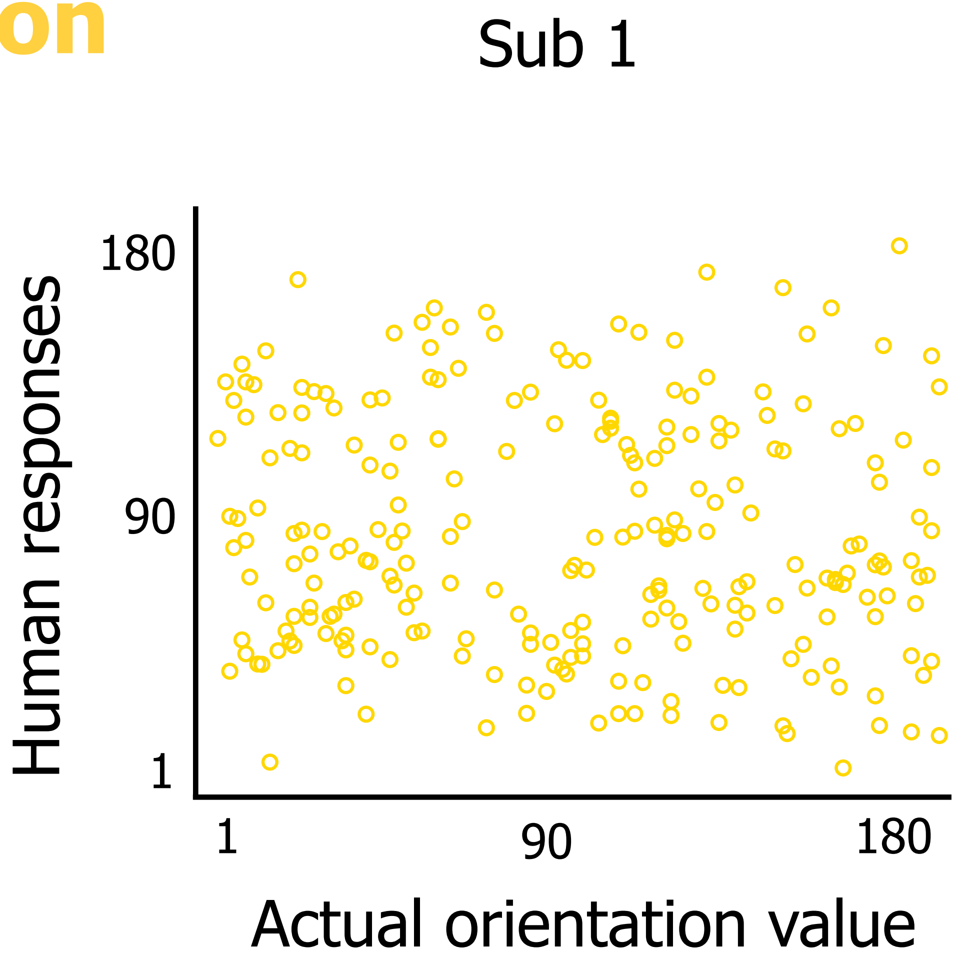


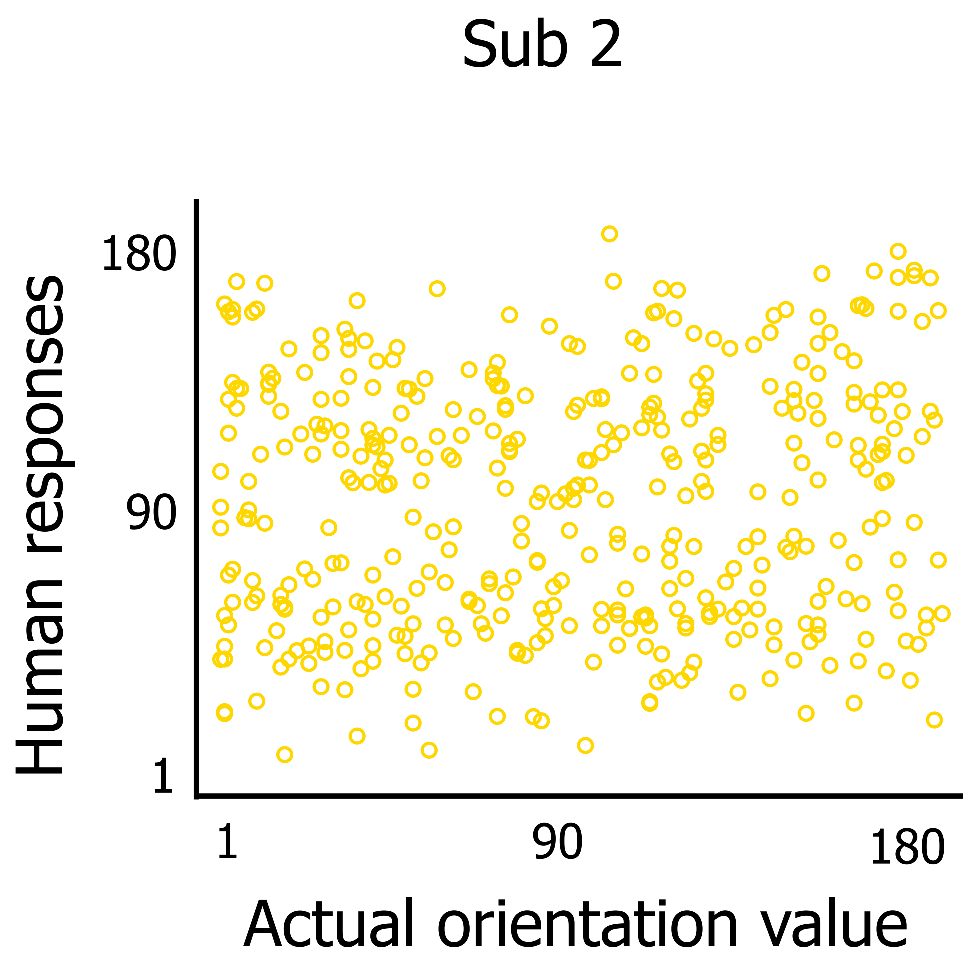
Results from 0-msec-trials: pattern of pure guesses

Orientation

Results from 0-msec-trials: pattern of pure guesses

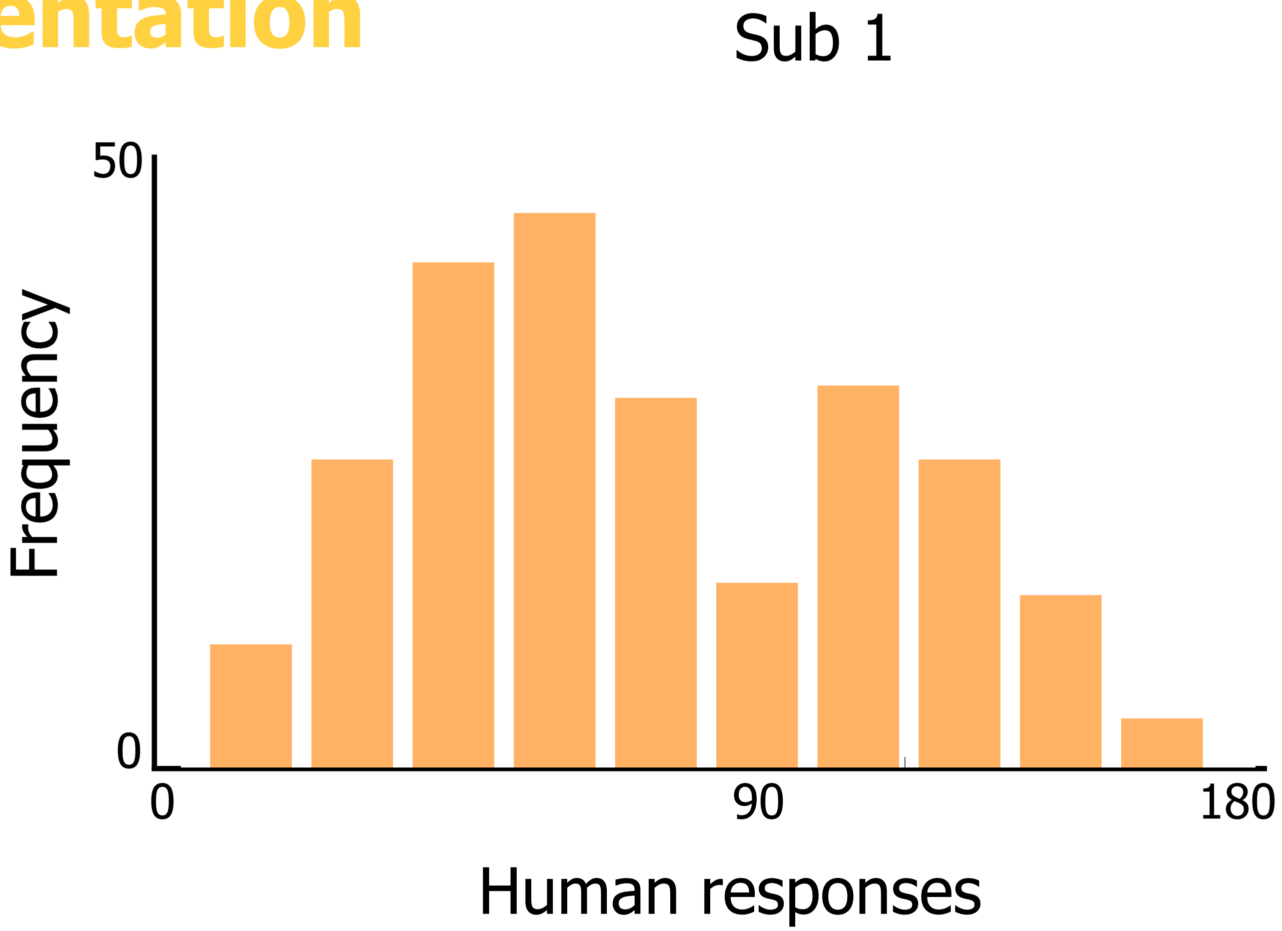
Orientation

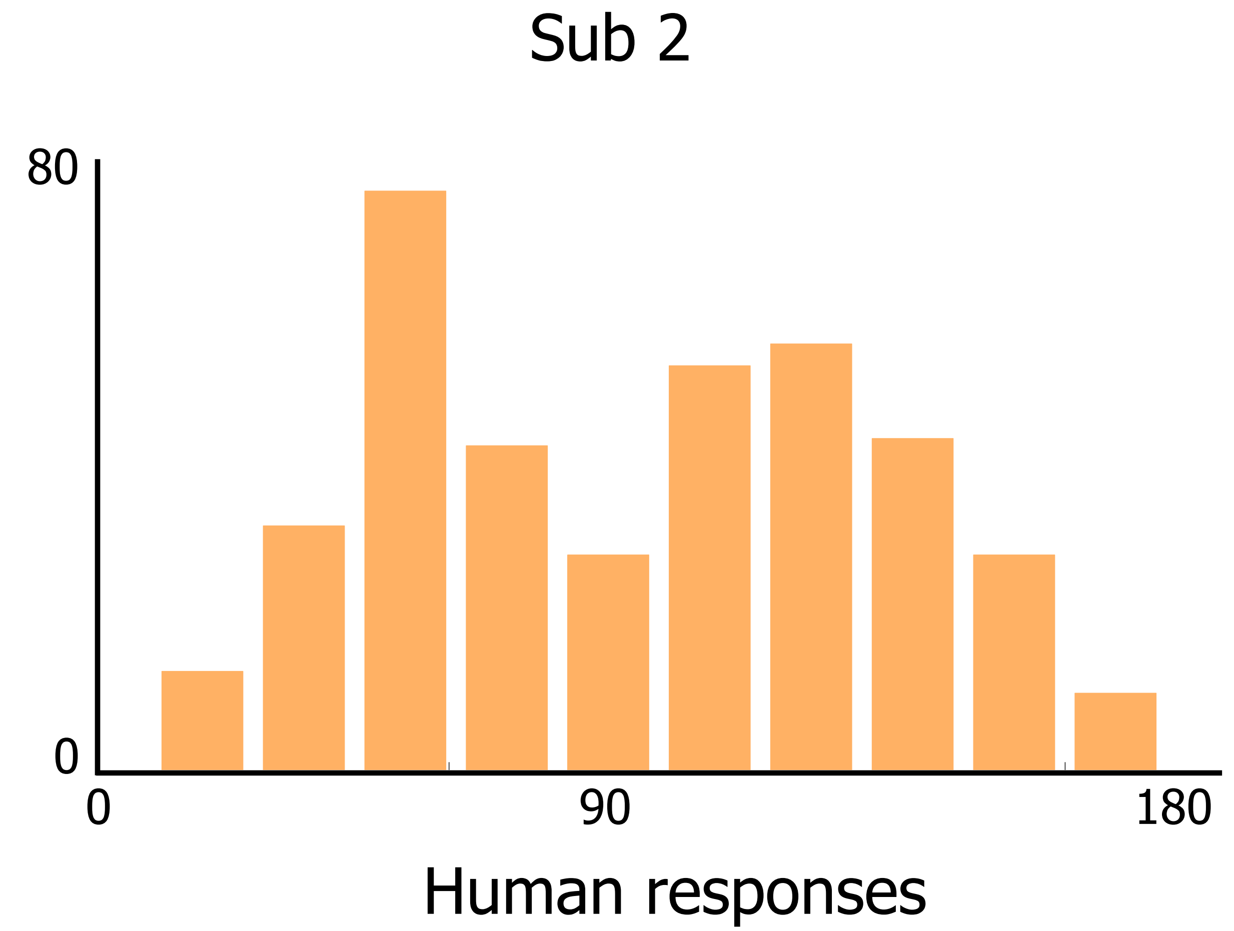




Results from 0-msec-trials: pattern of pure guesses

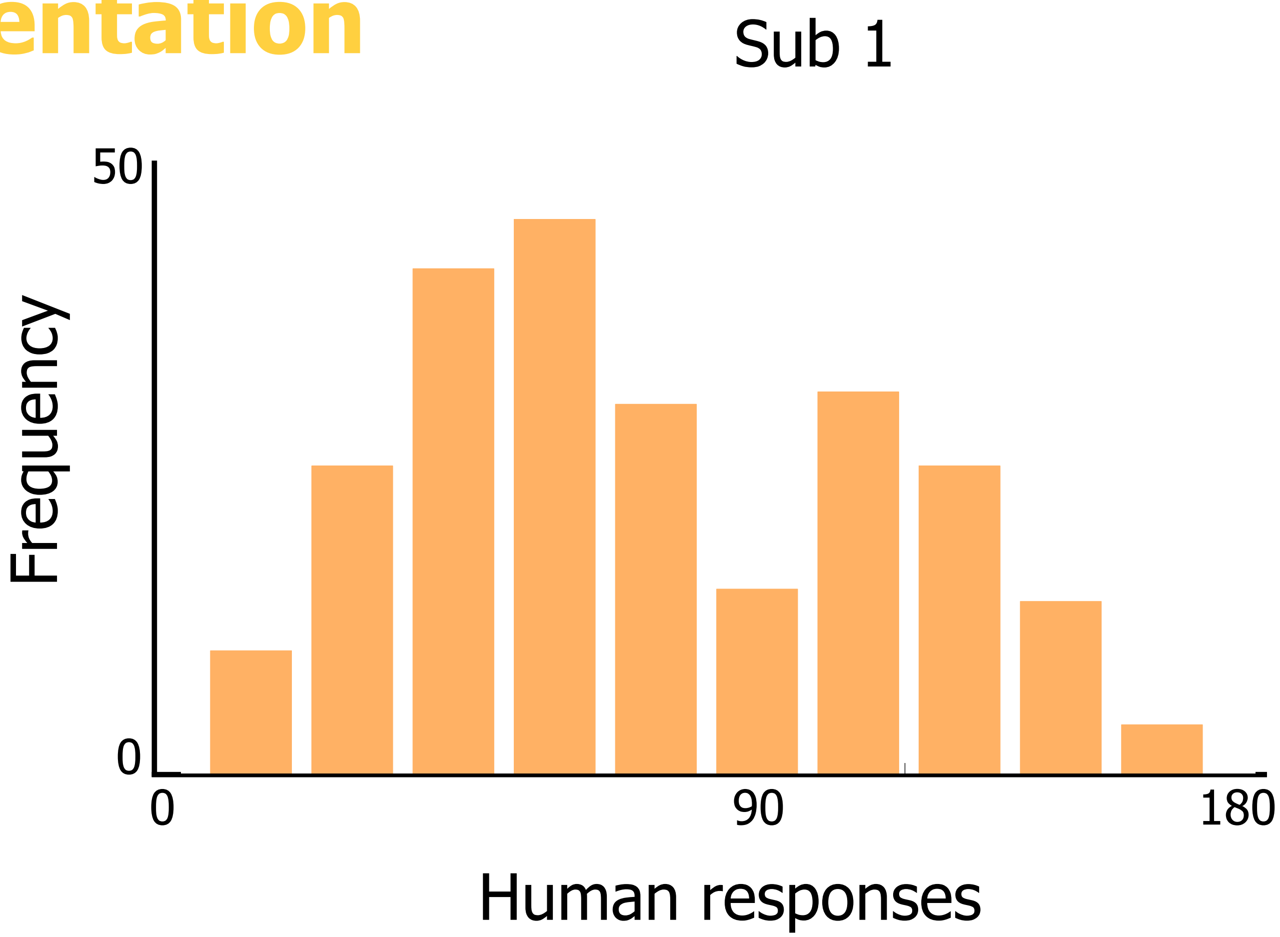
Orientation

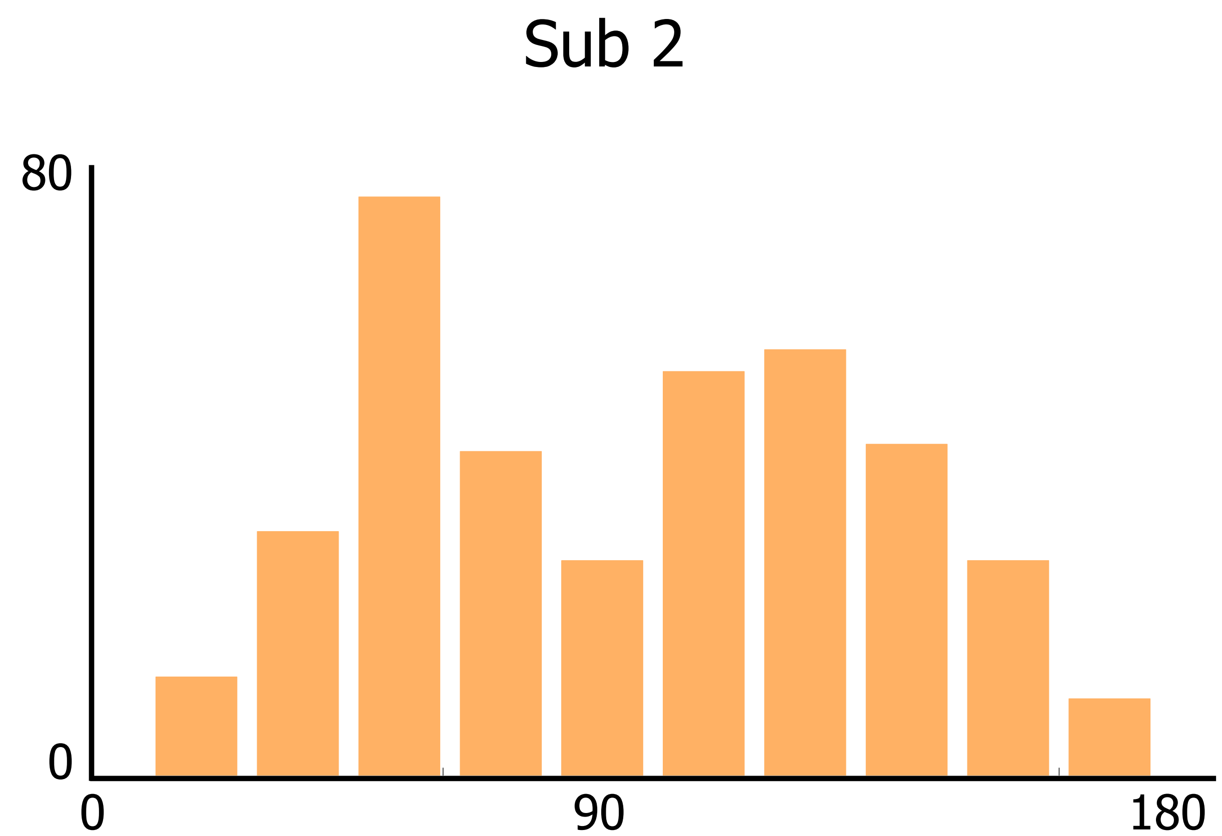


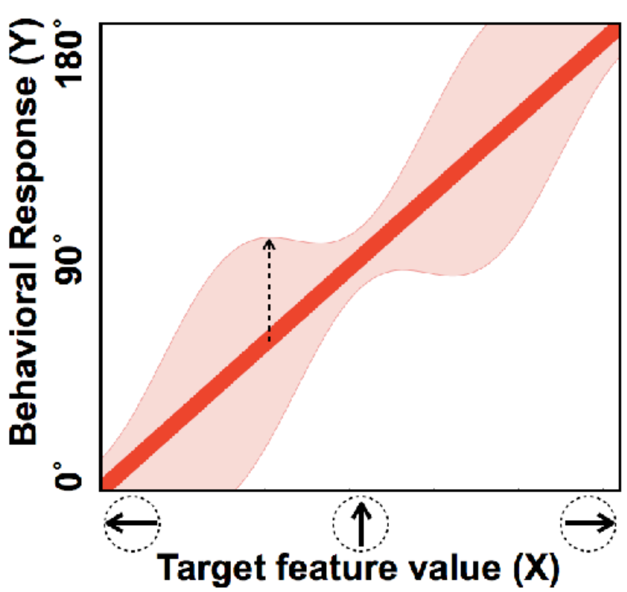


Results from 0-msec-trials: pattern of pure guesses

Orientation

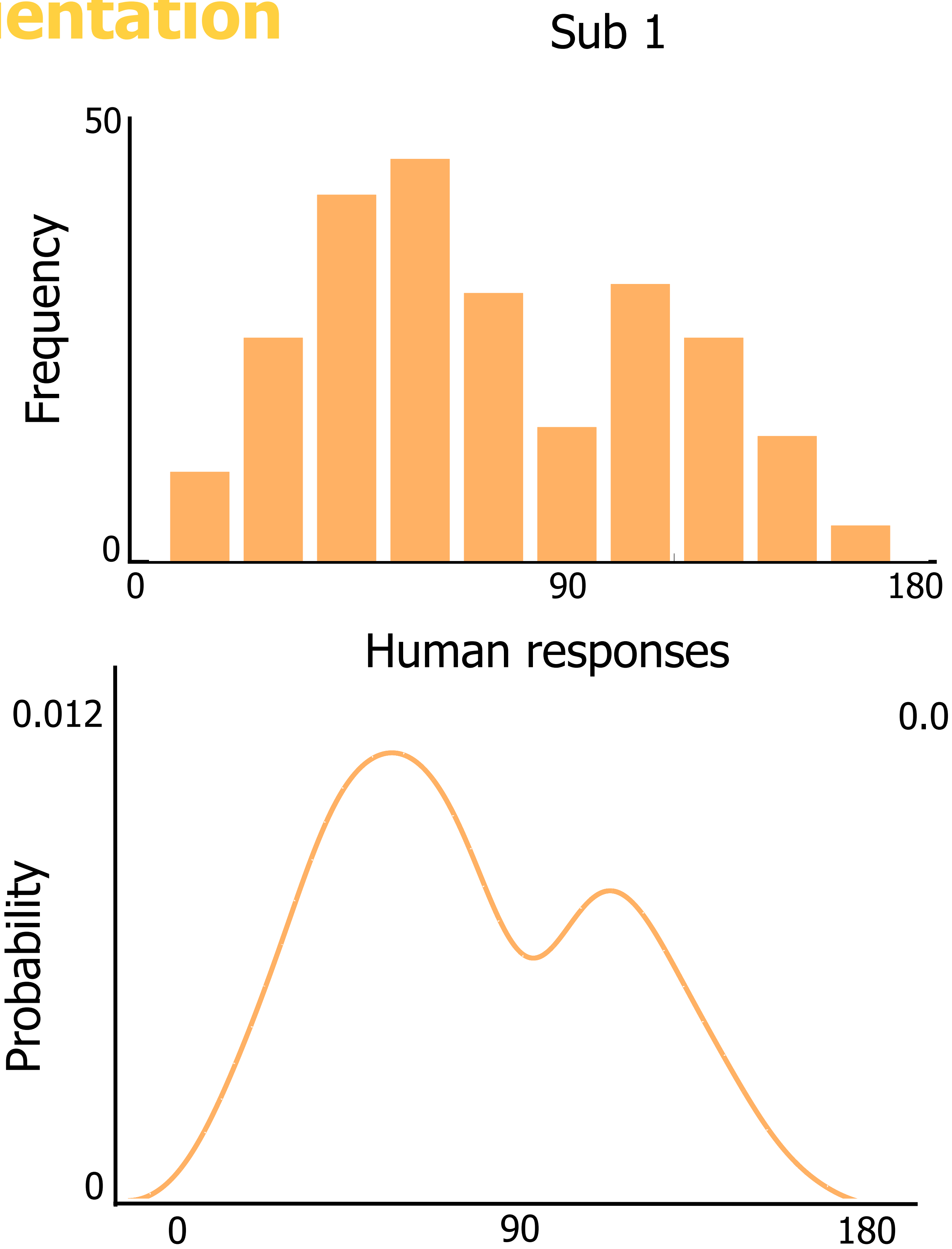


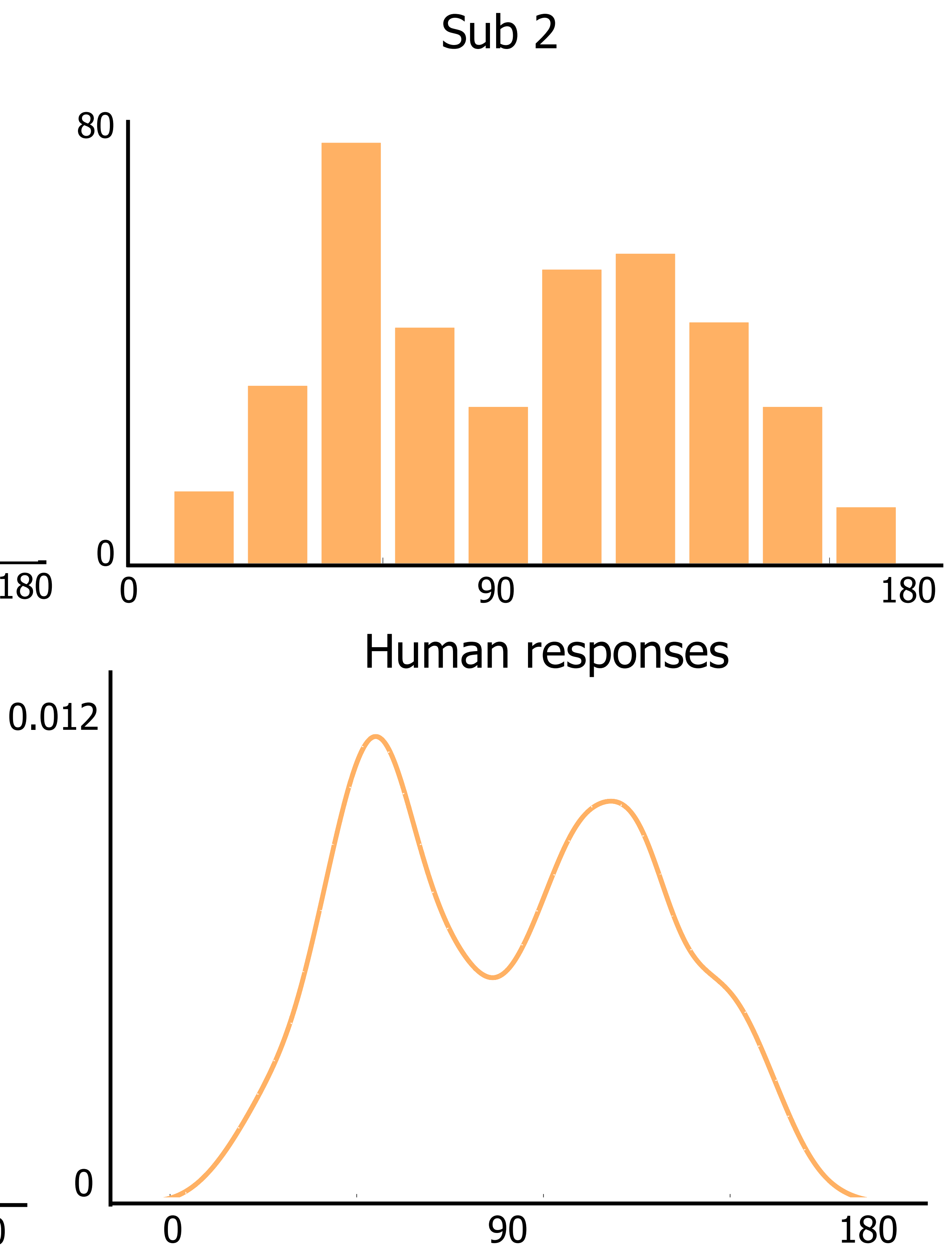




Results from 0-msec-trials: pattern of pure guesses

Orientation



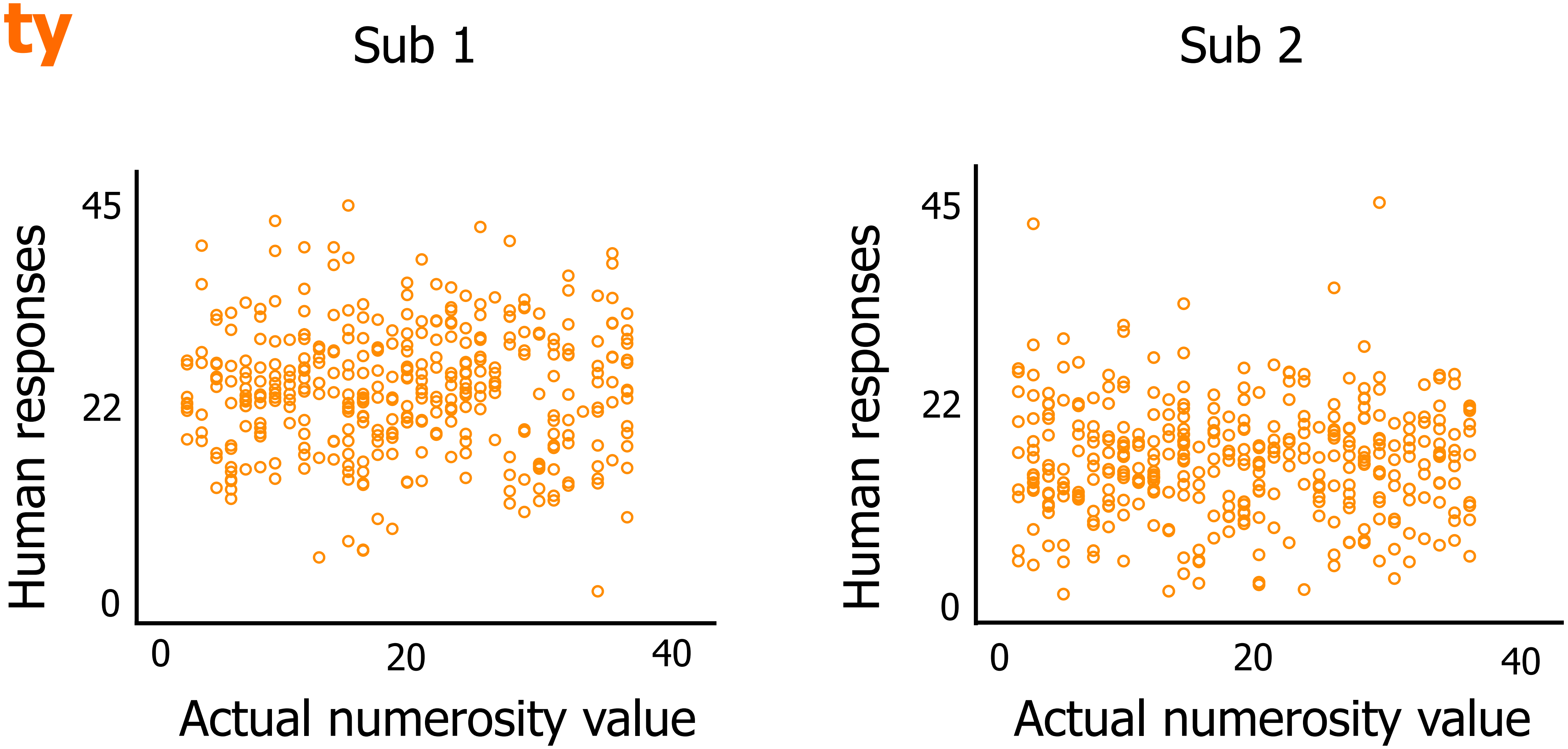


Results from 0-msec-trials: pattern of pure guesses

Numerosity

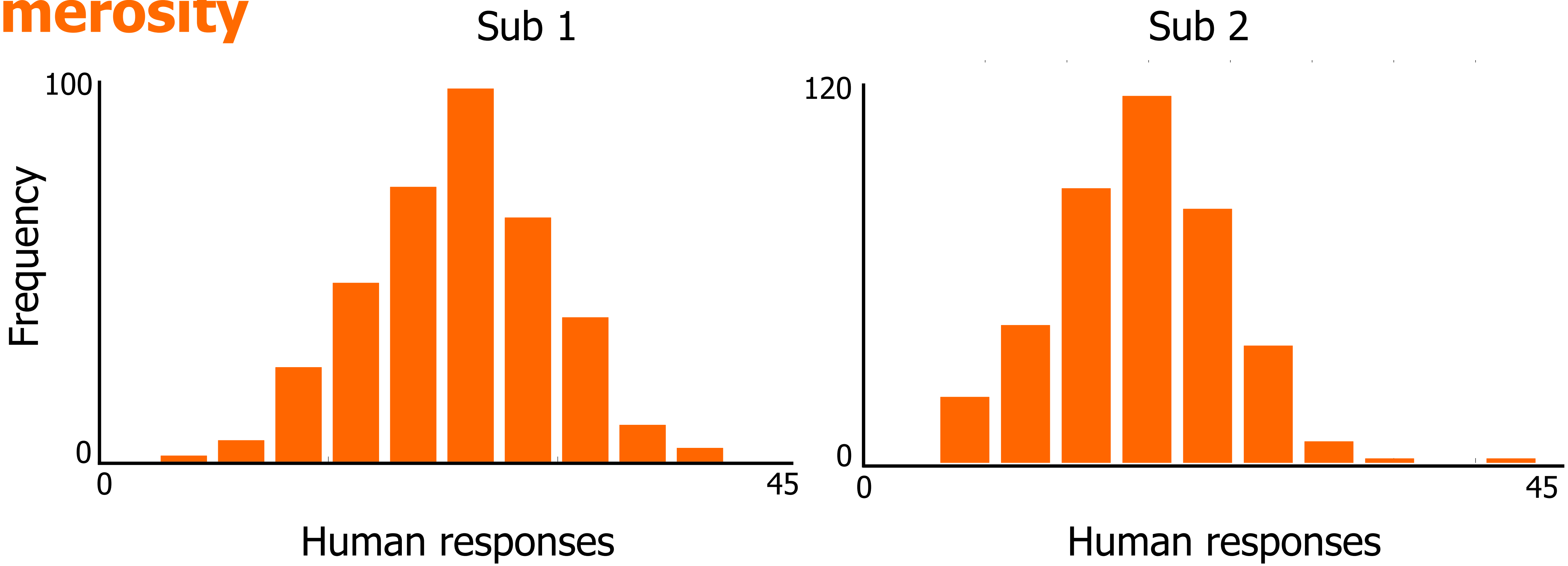
Results from 0-msec-trials: pattern of pure guesses

Numerosity



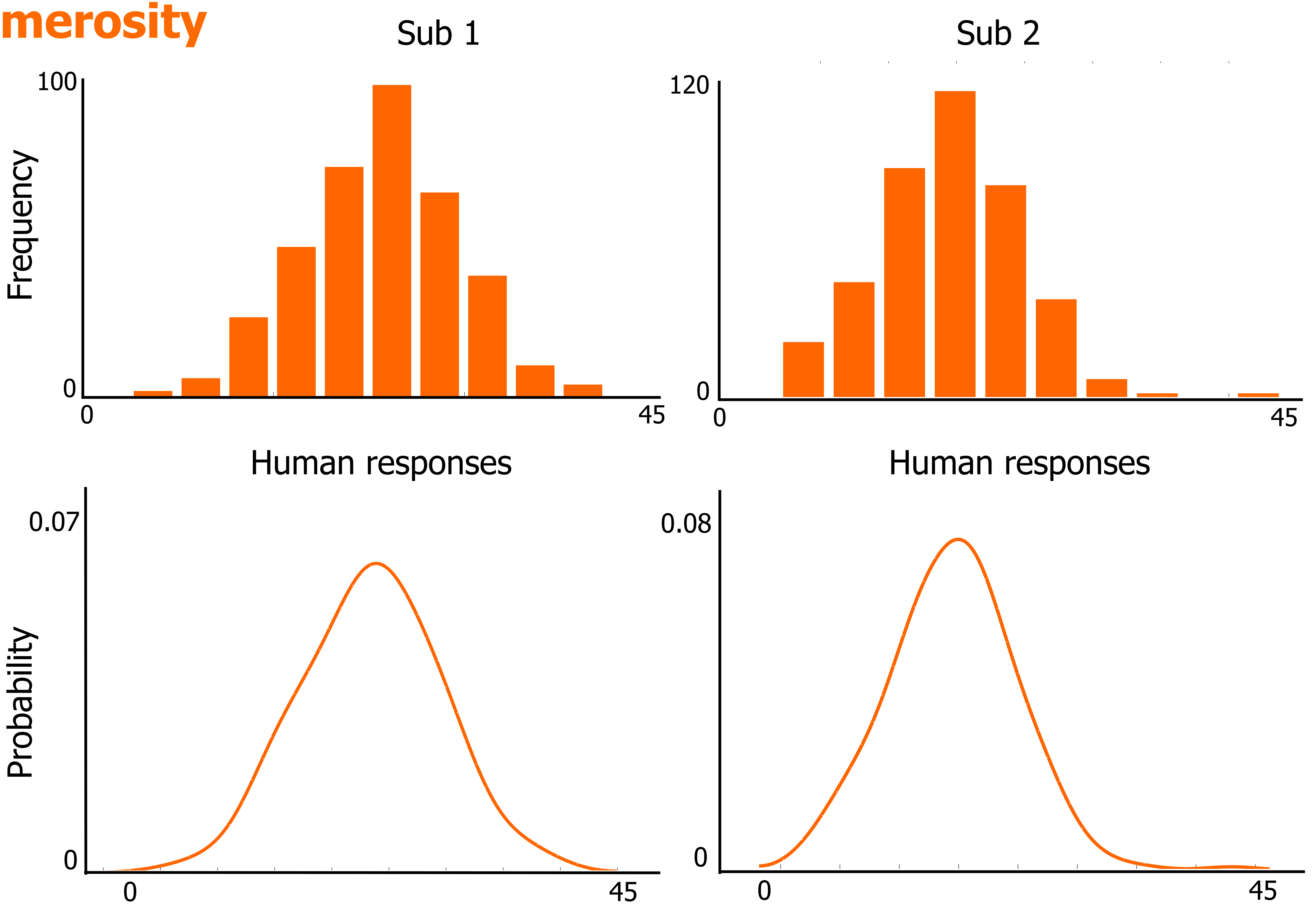
Results from 0-msec-trials: pattern of pure guesses

Numerosity



Results from 0-msec-trials: pattern of pure guesses

Numerosity

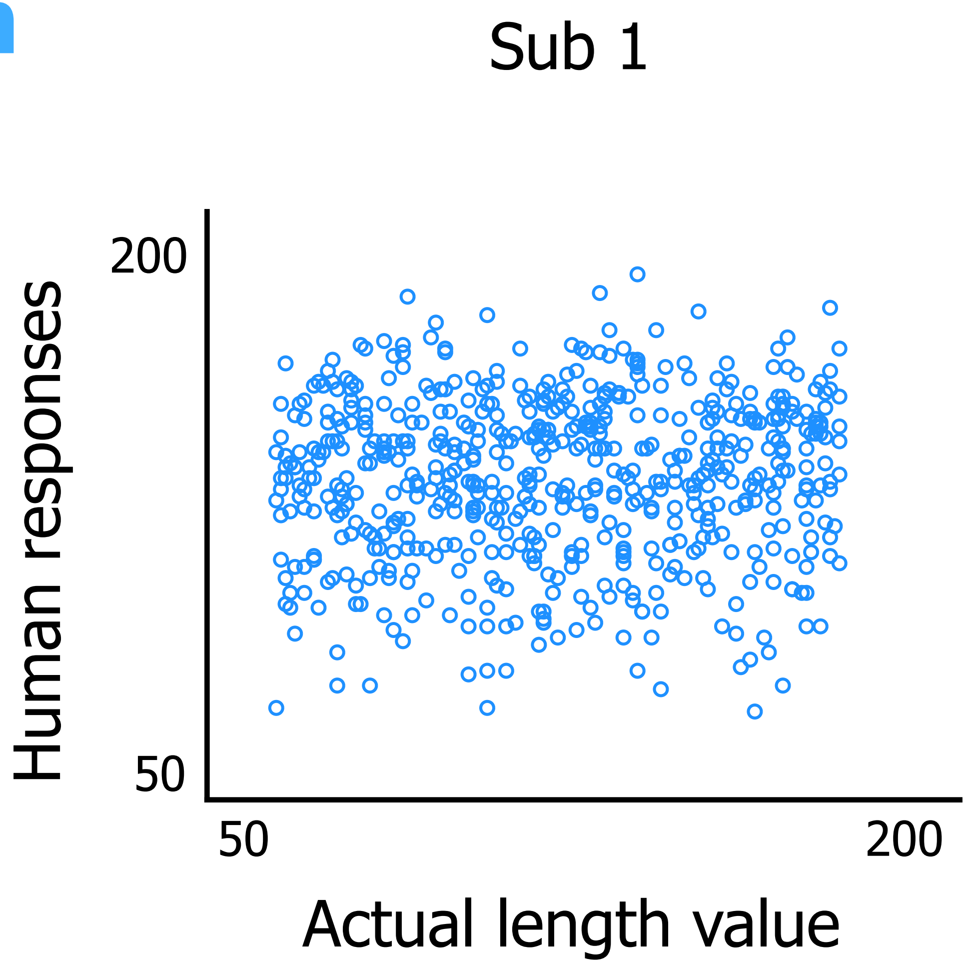


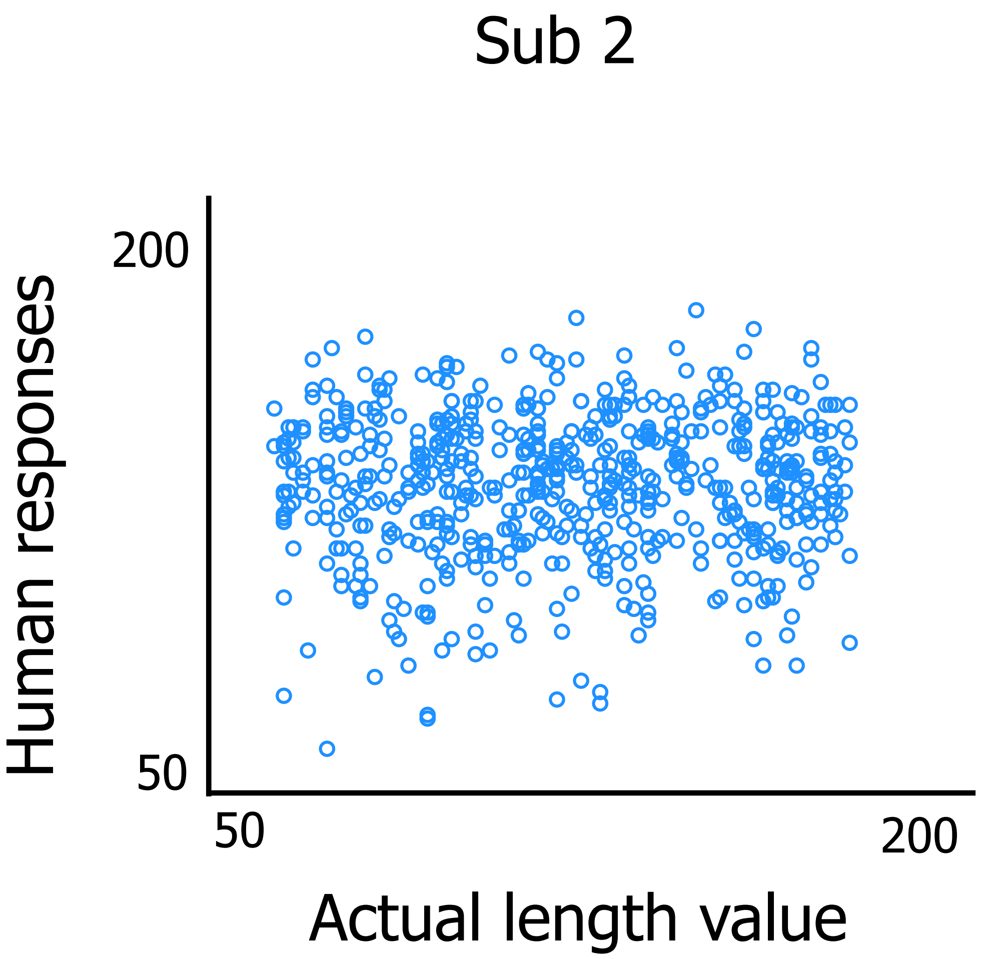
Results from 0-msec-trials: pattern of pure guesses

Length

Results from 0-msec-trials: pattern of pure guesses

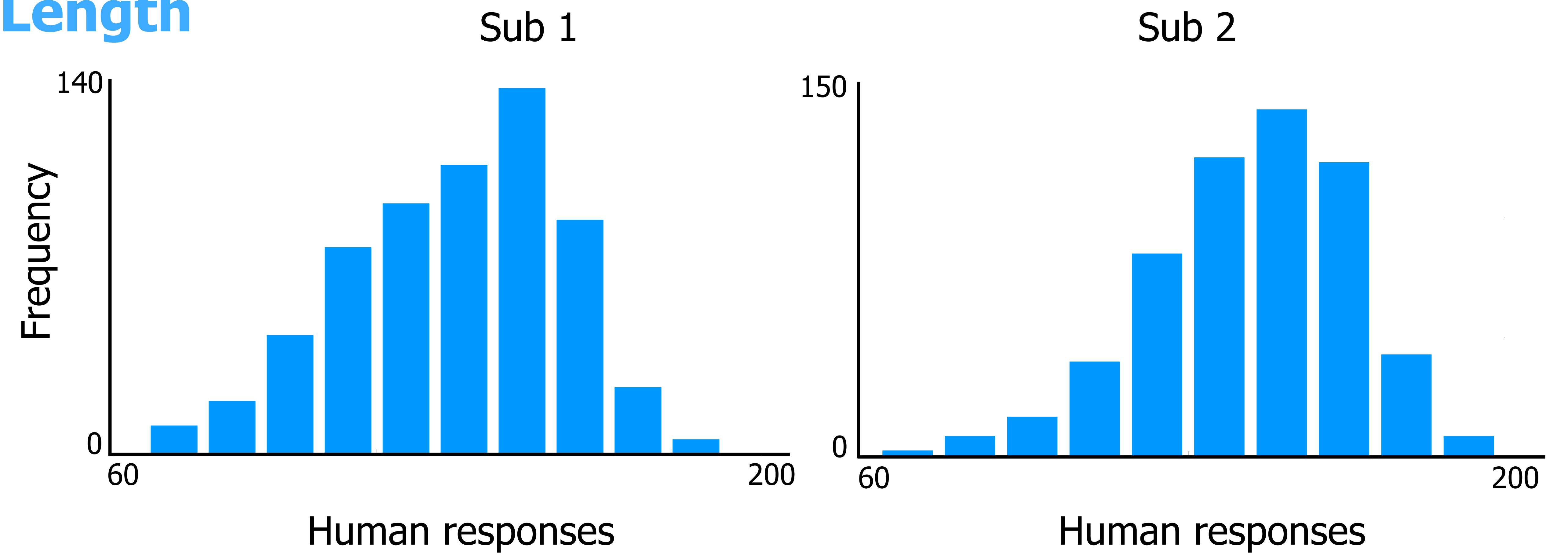
Length



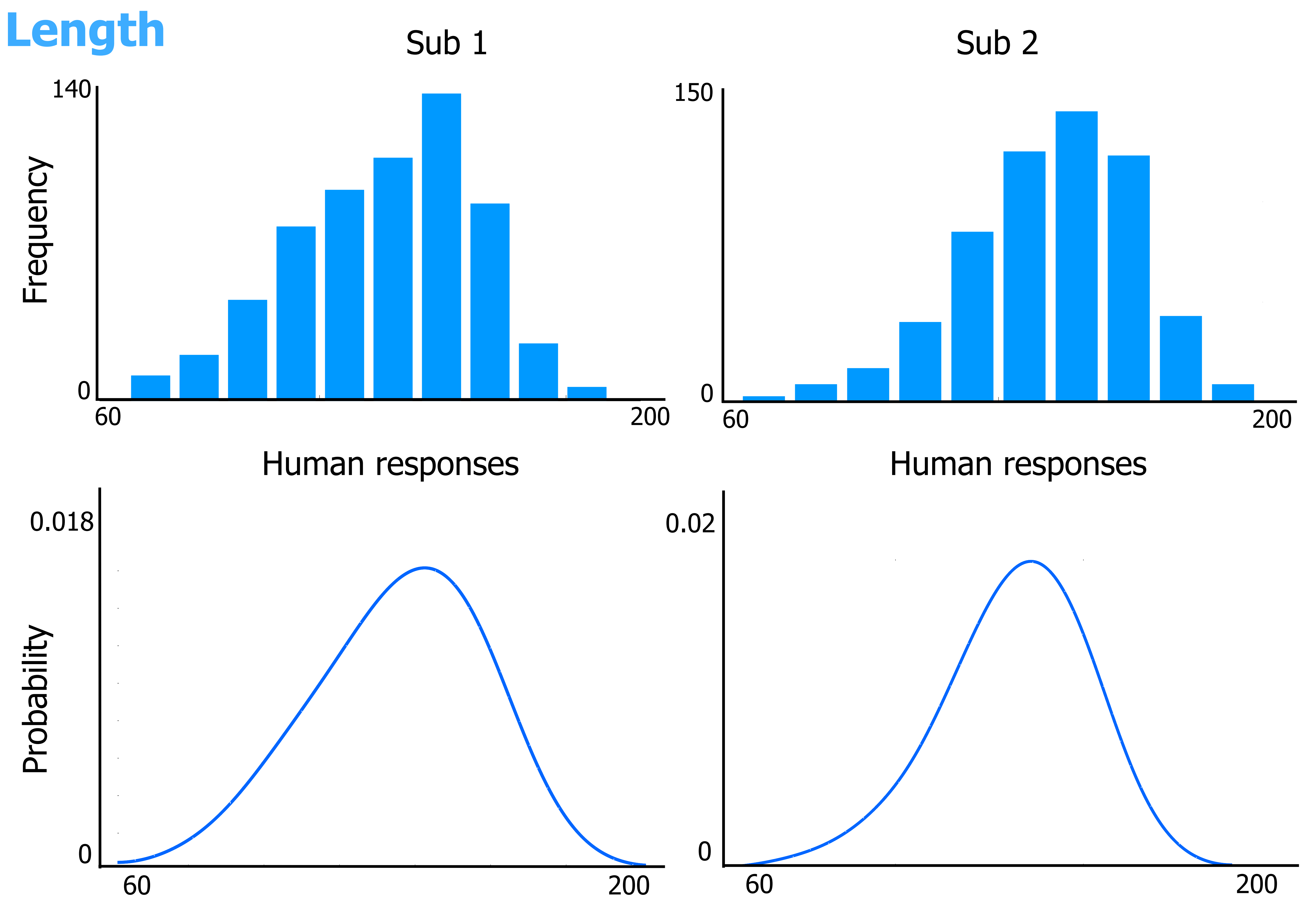


Results from 0-msec-trials: pattern of pure guesses

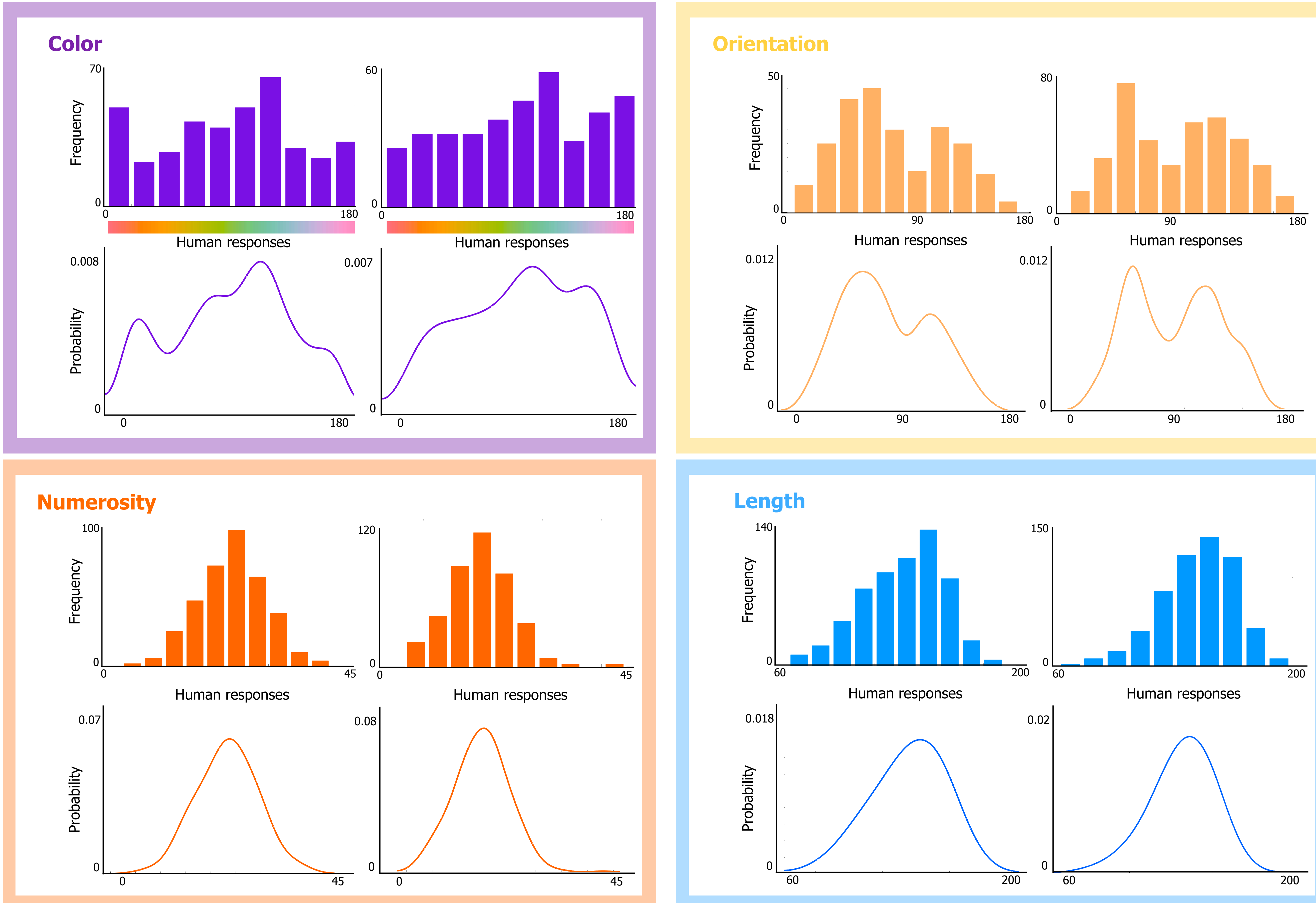
Length



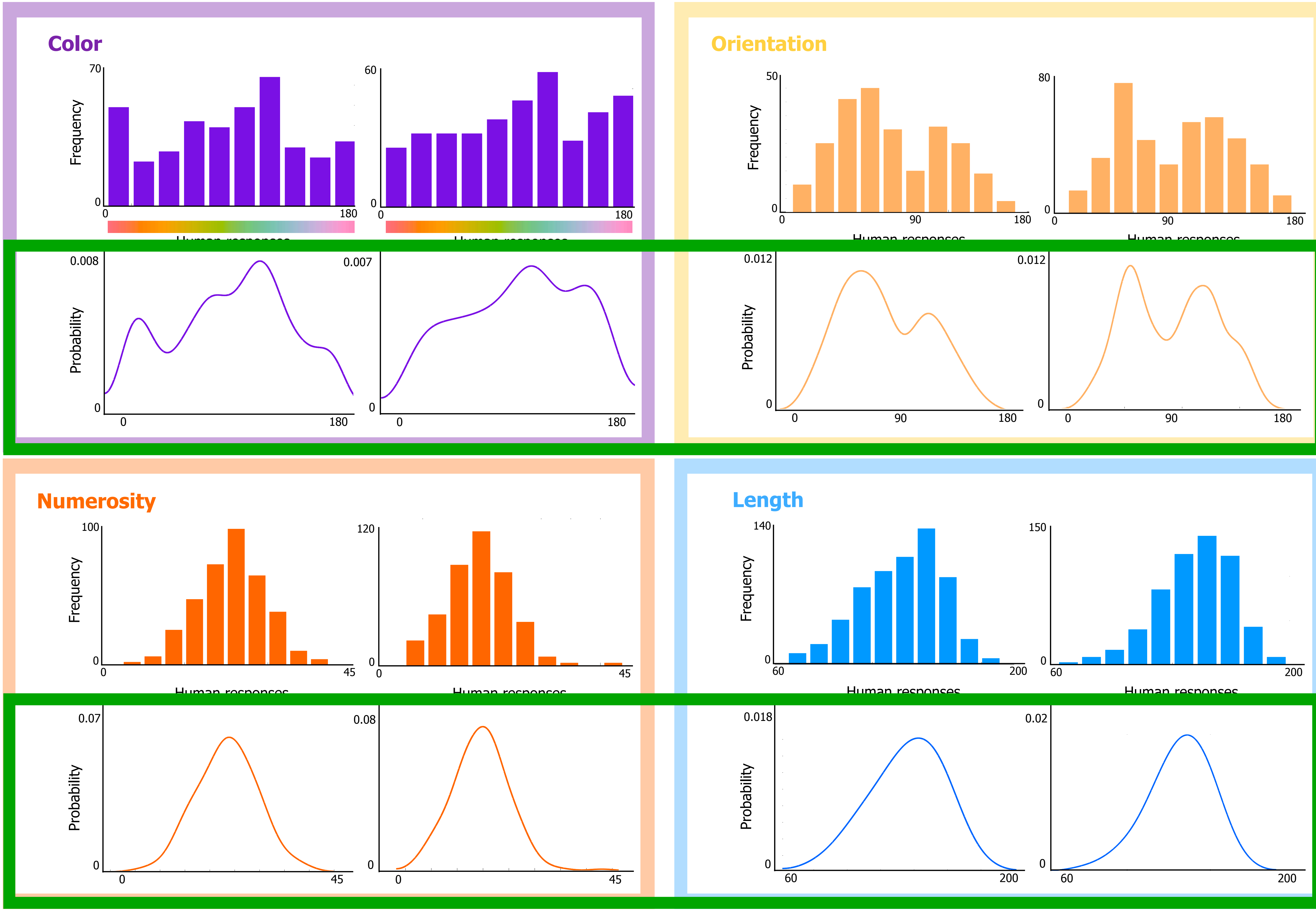
Results from 0-msec-trials: pattern of pure guesses

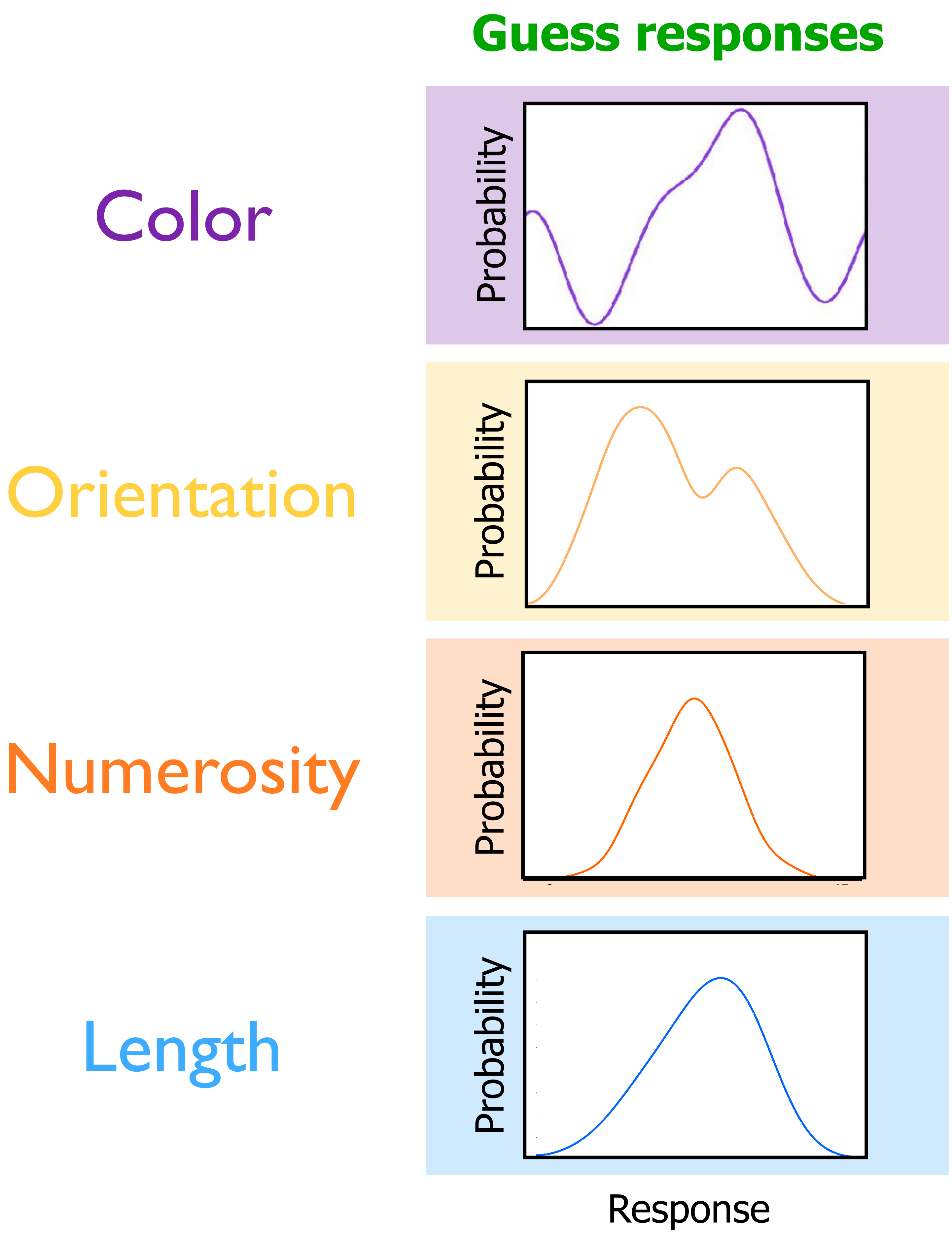


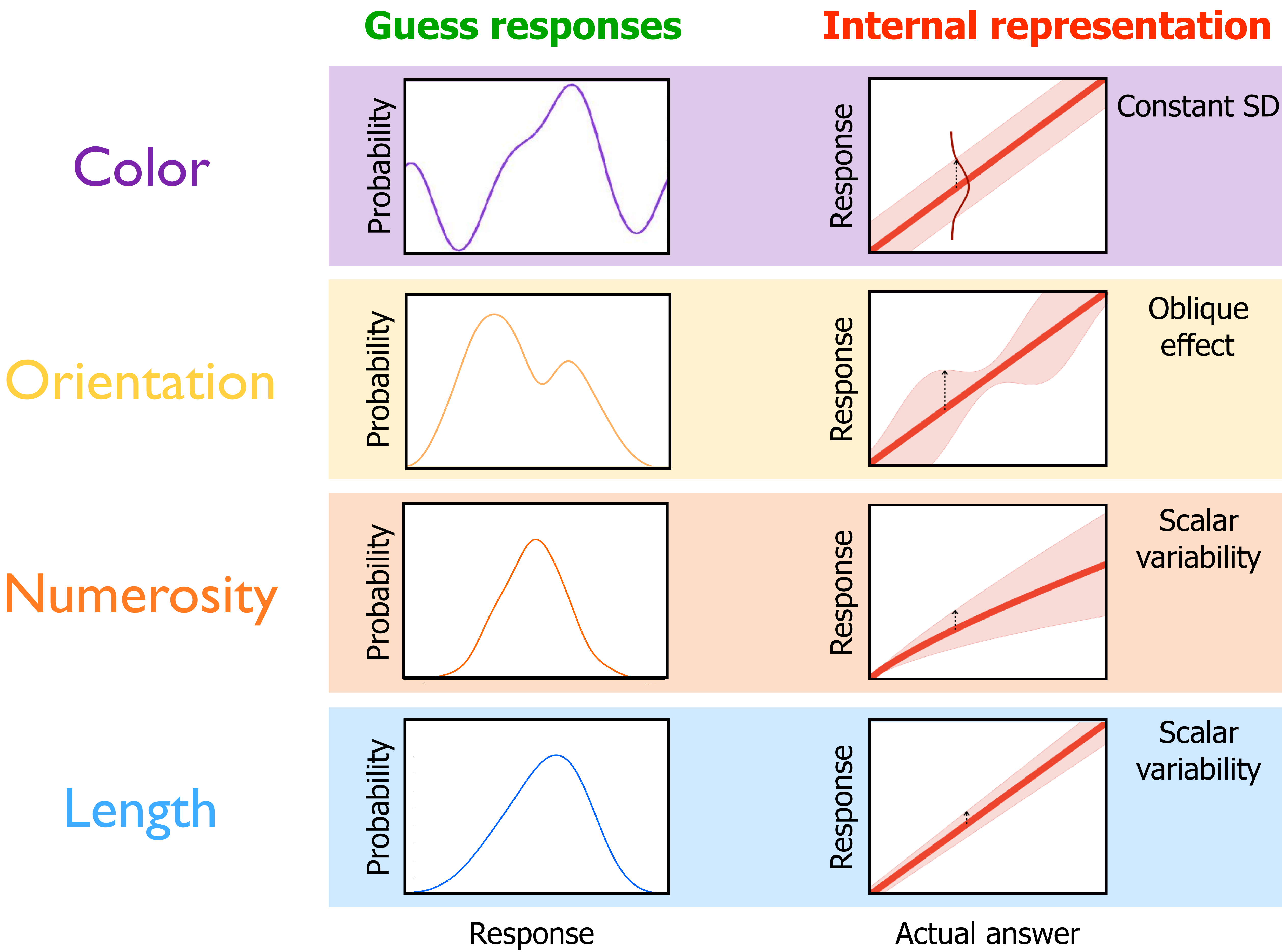
Results from 0-msec-trials: pattern of pure guesses



Results from 0-msec-trials: pattern of pure guesses



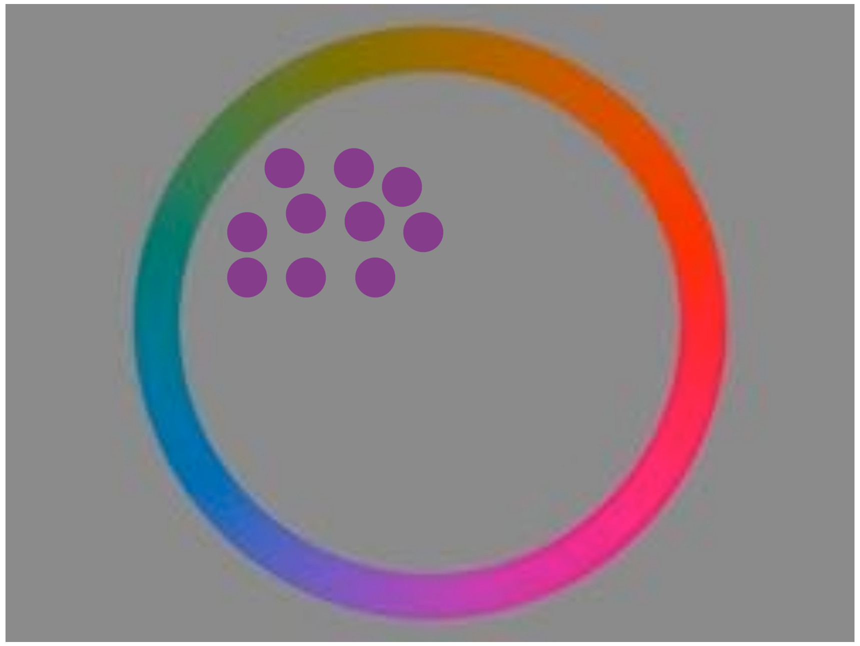

Guess responses
Color
Orientation
Numerosity
Length
Probability
Probability
Probability
Probability
Response



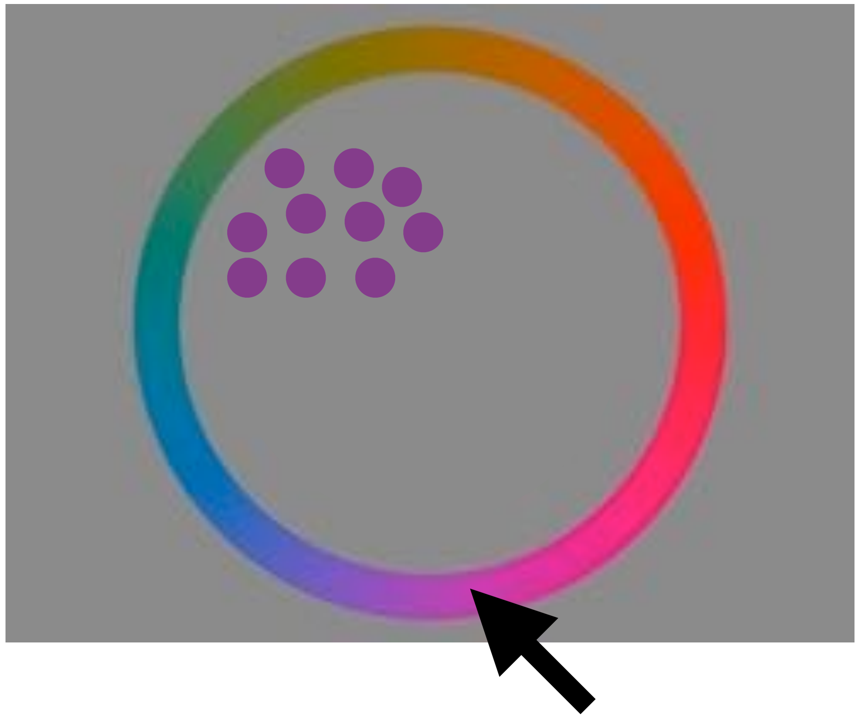
Guess responses
Internal representation
Color
Orientation
Numerosity
Length
Probability
Response
Constant SD
Oblique effect
Scalar variability
Scalar variability
Response
Actual answer

Modeling: decomposing mixed responses from longer durations

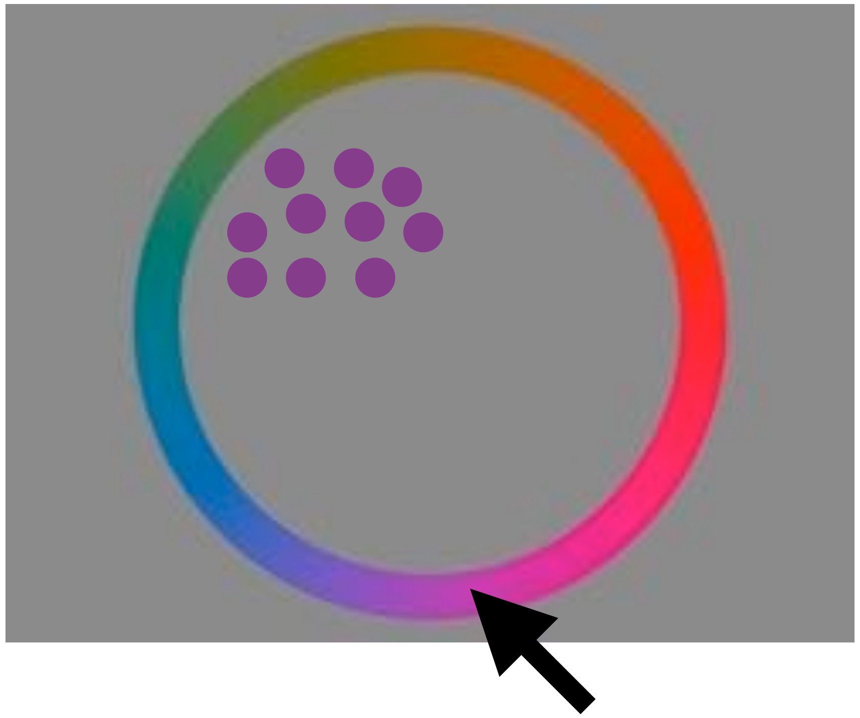
Modeling: decomposing mixed responses from longer durations

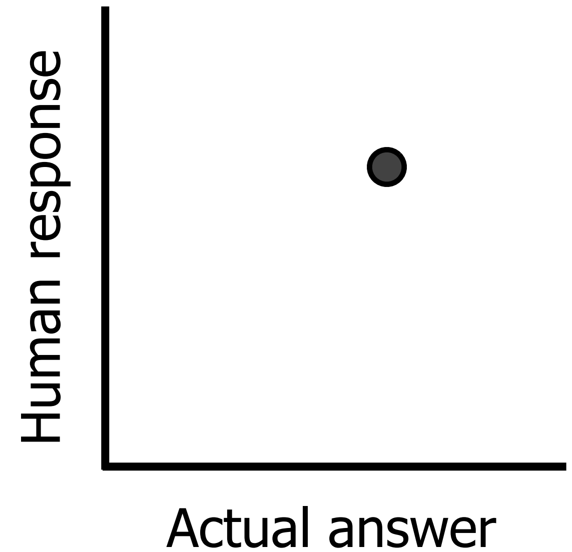


Modeling: decomposing mixed responses from longer durations

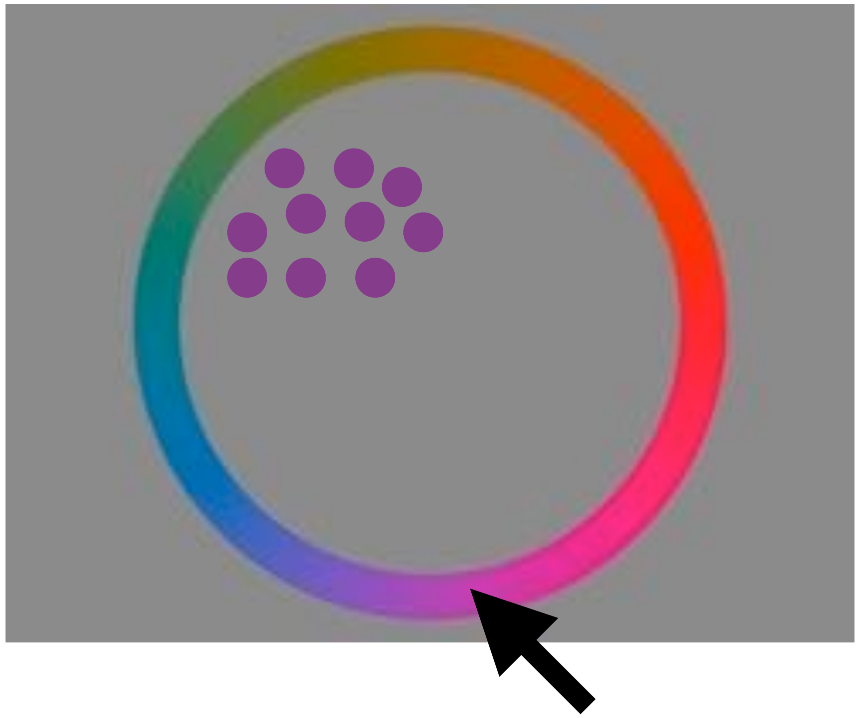


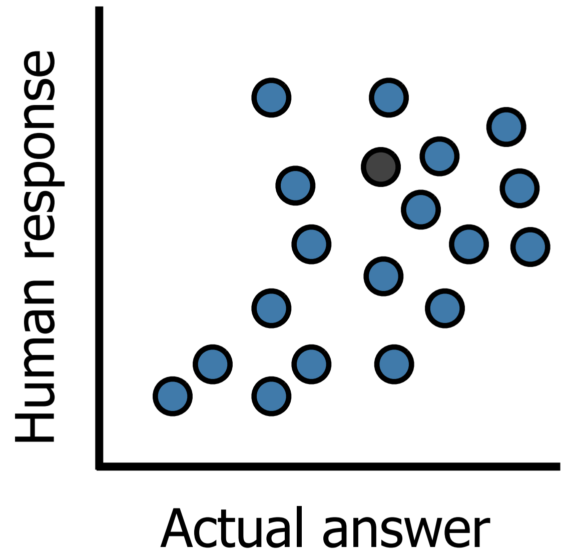
Modeling: decomposing mixed responses from longer durations



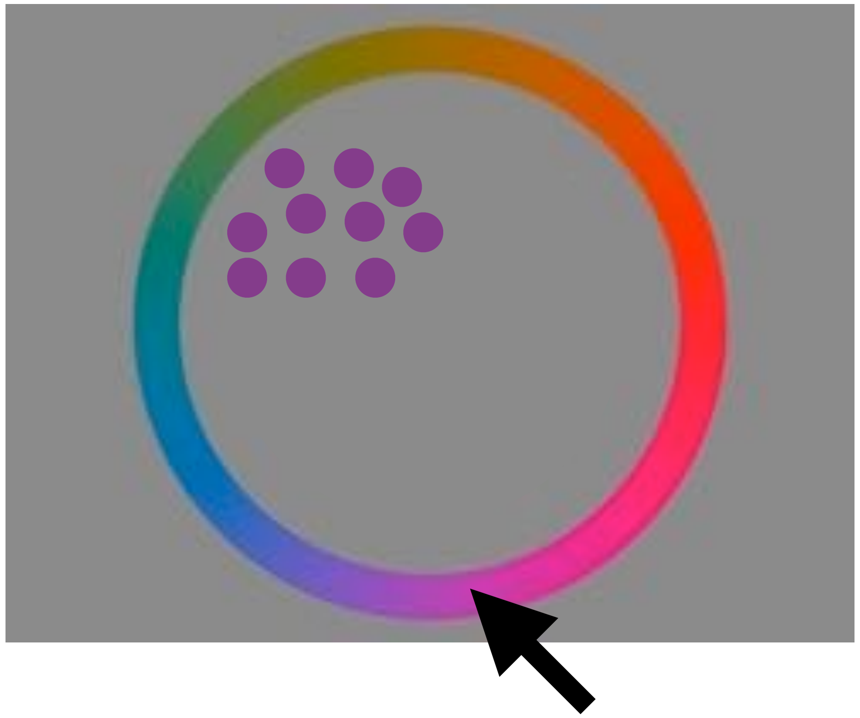


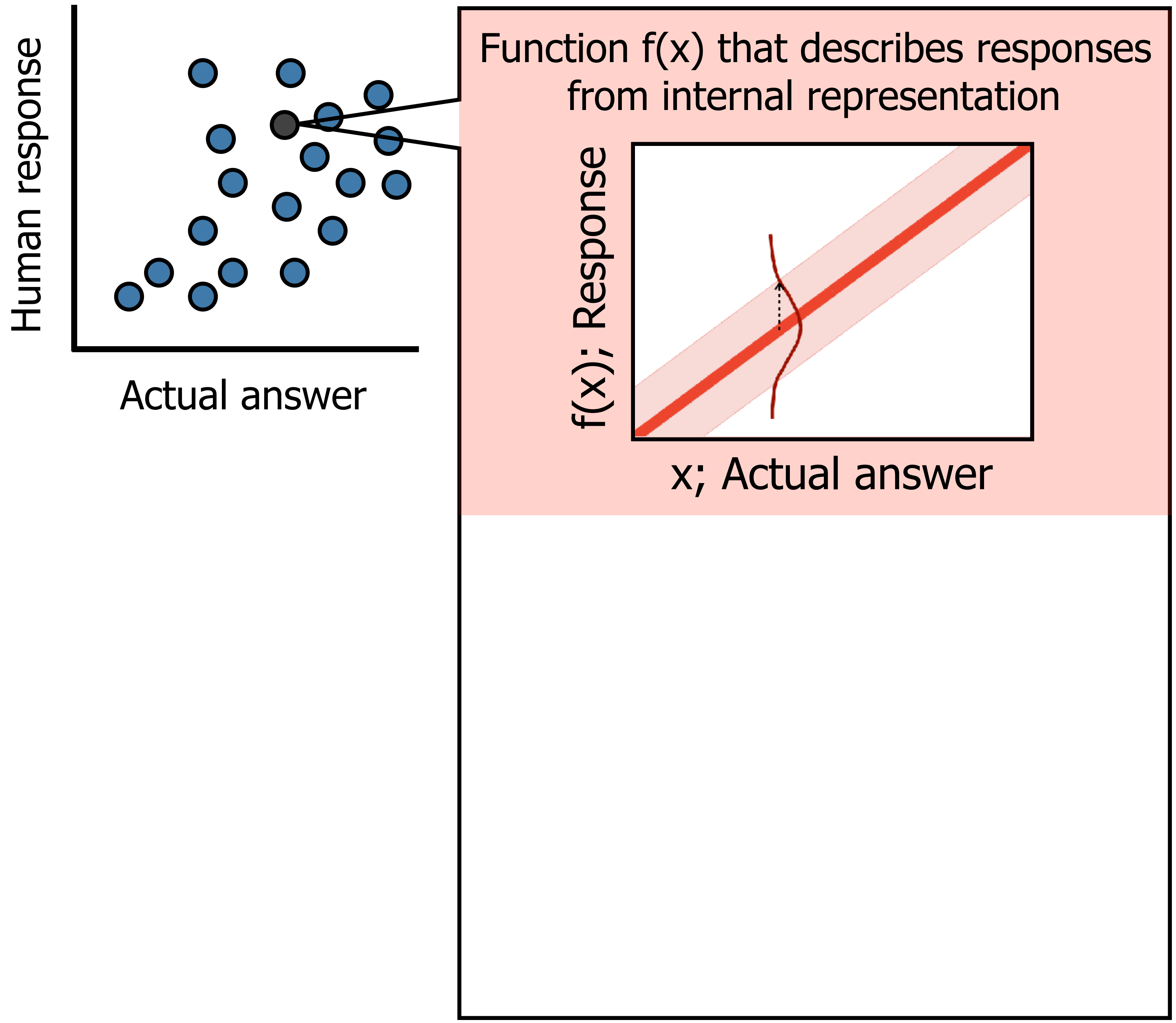
Modeling: decomposing mixed responses from longer durations



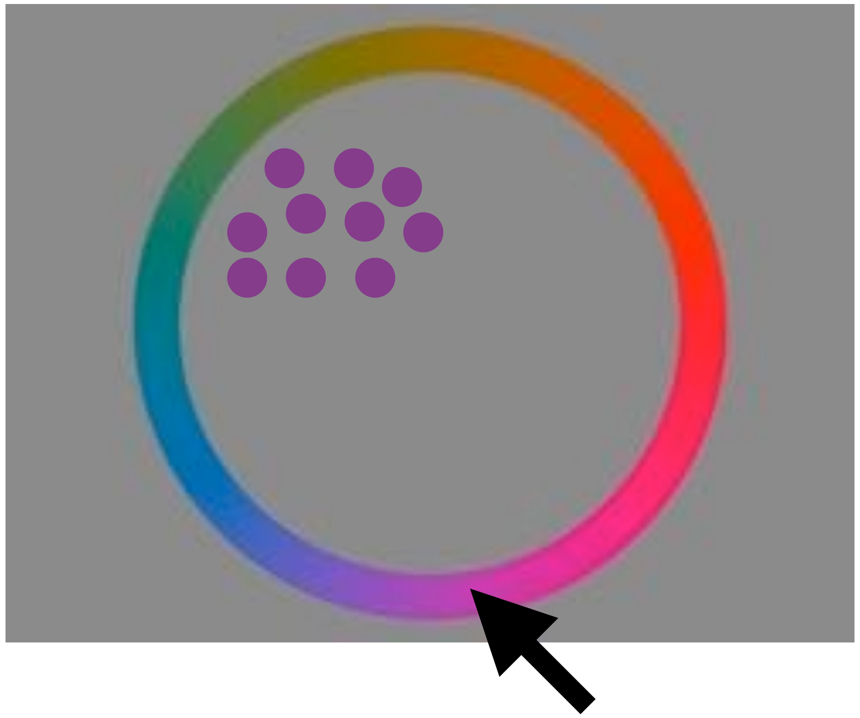


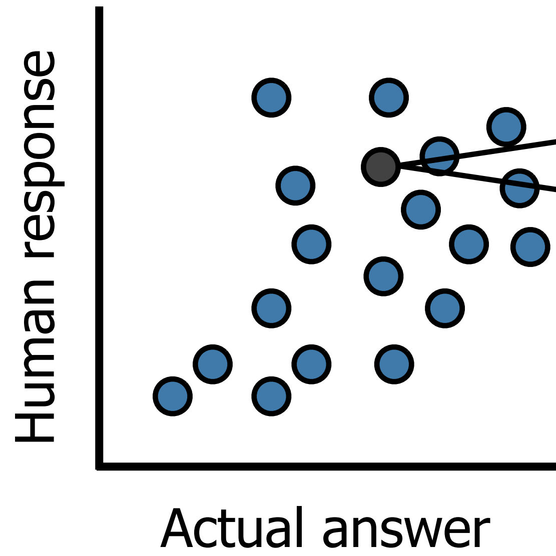
Modeling: decomposing mixed responses from longer durations

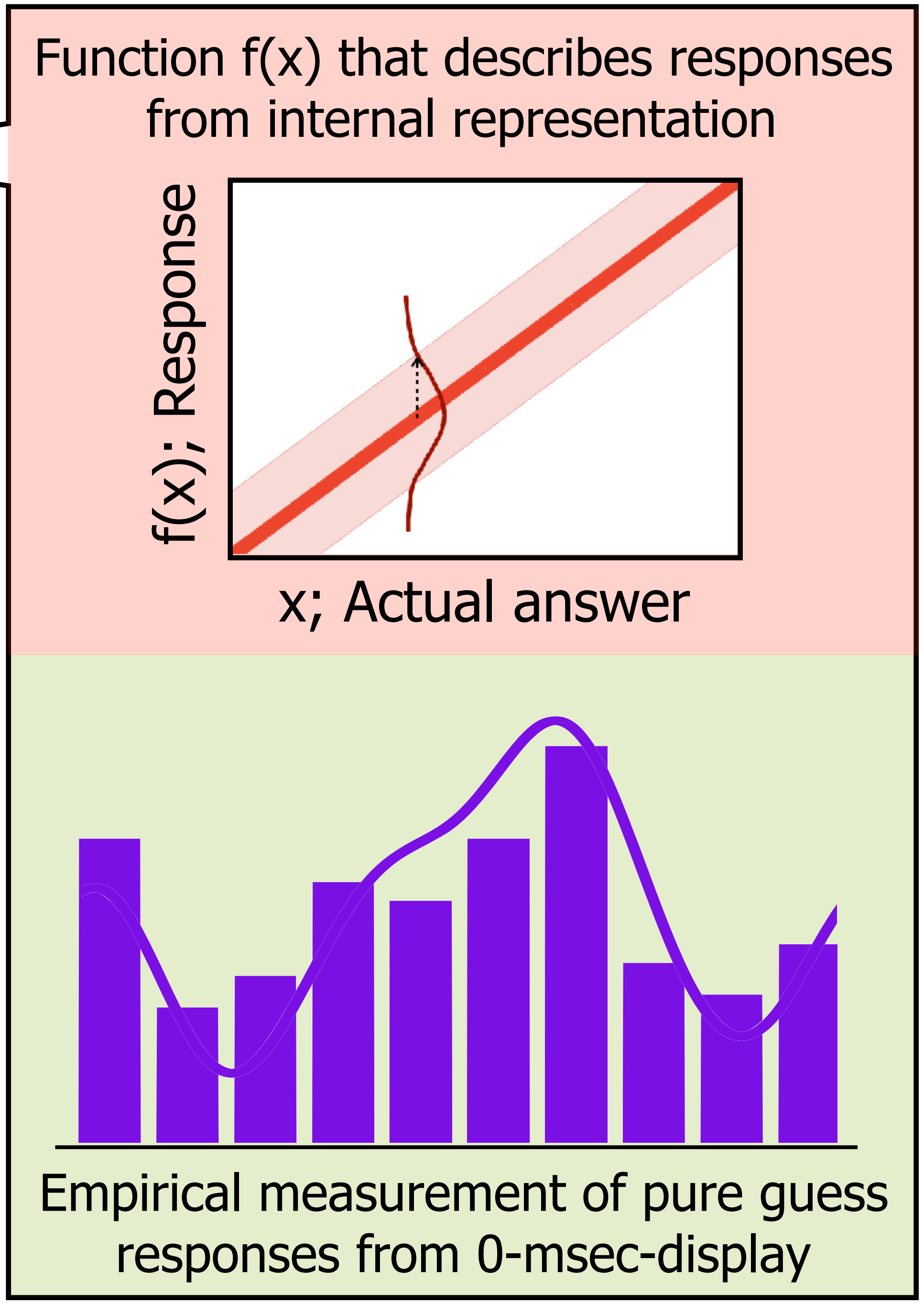




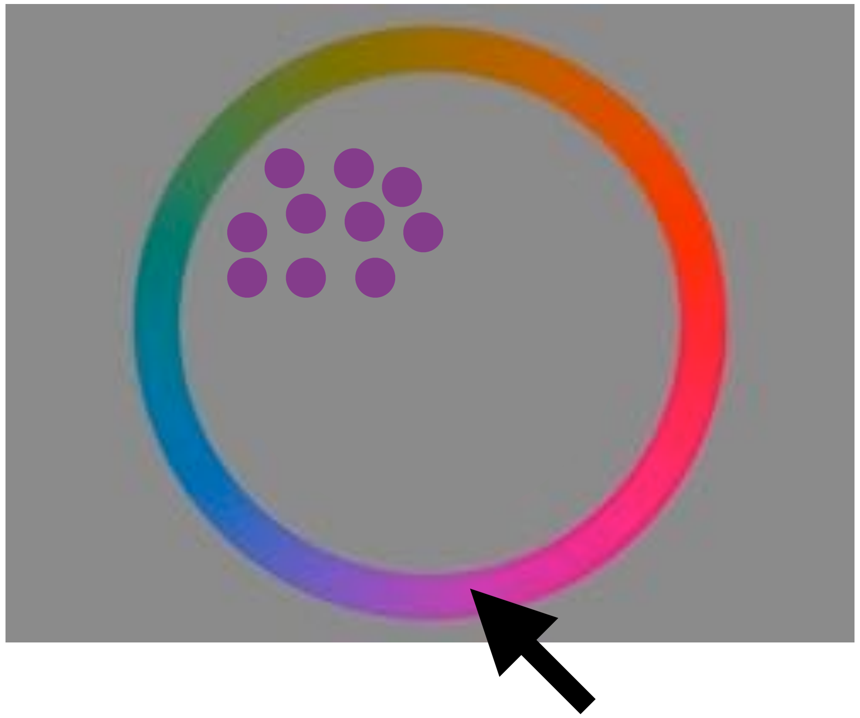
Modeling: decomposing mixed responses from longer durations

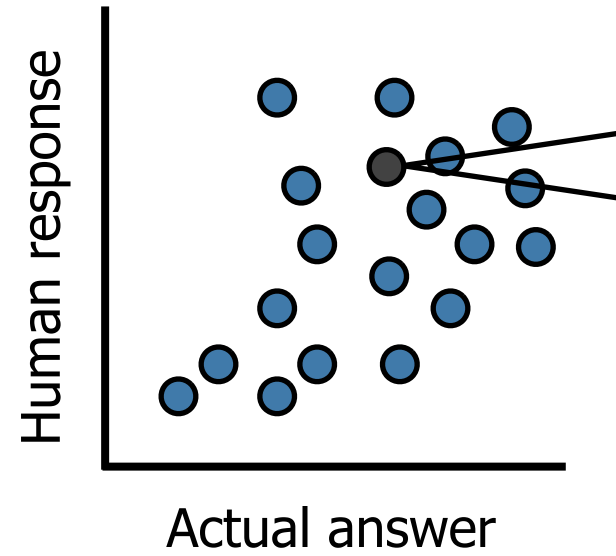


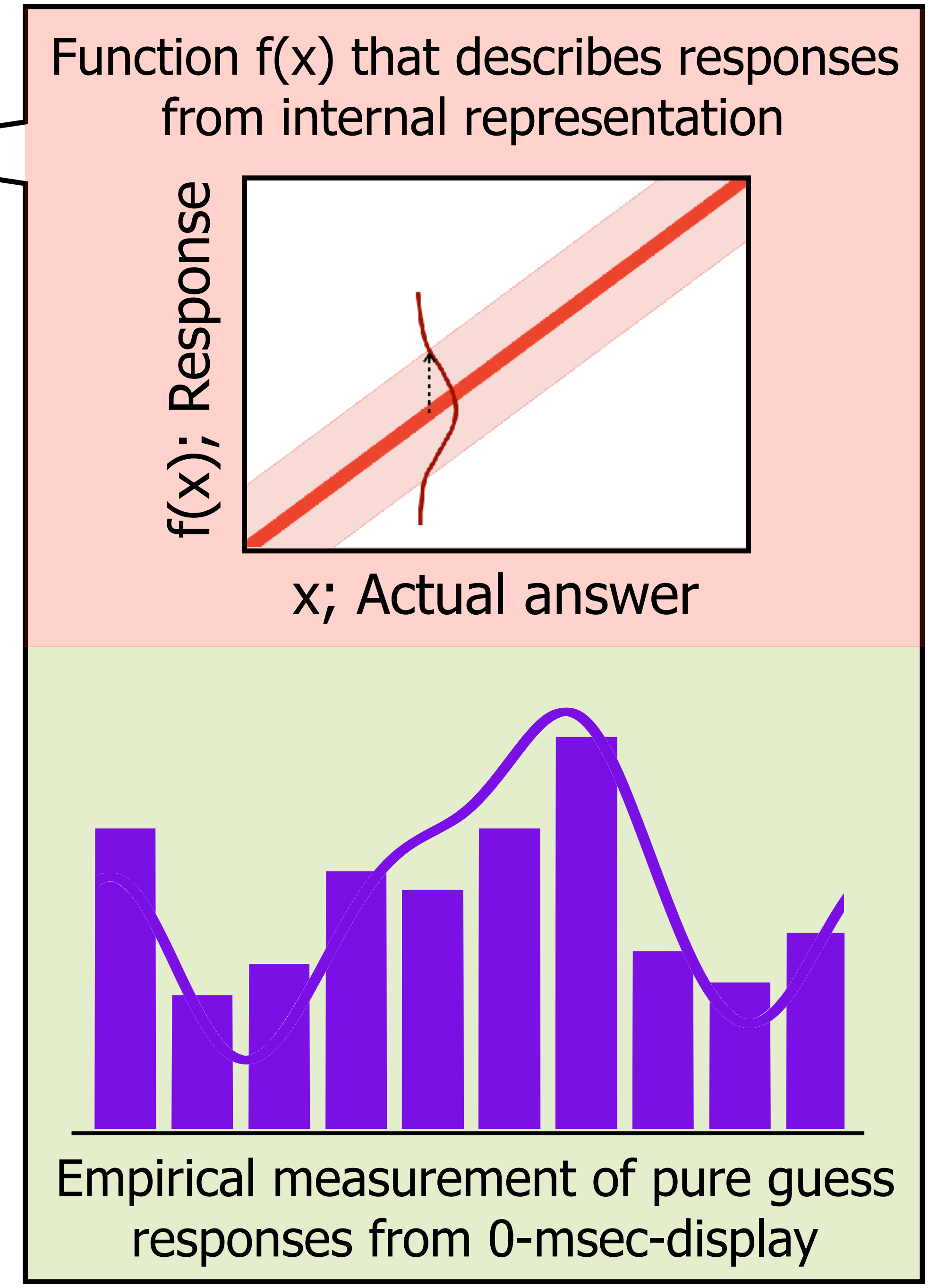




Modeling: decomposing mixed responses from longer durations

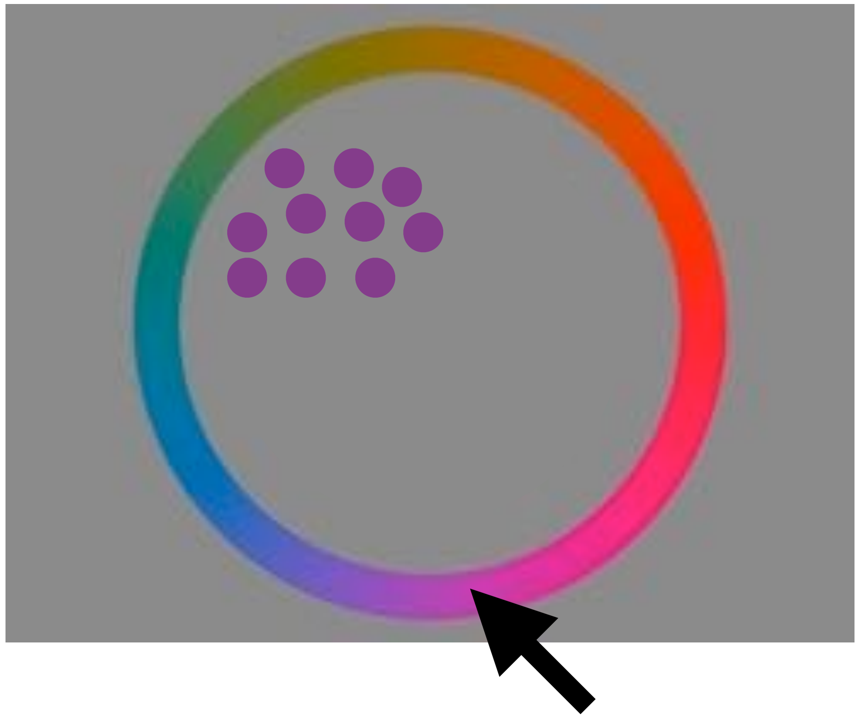


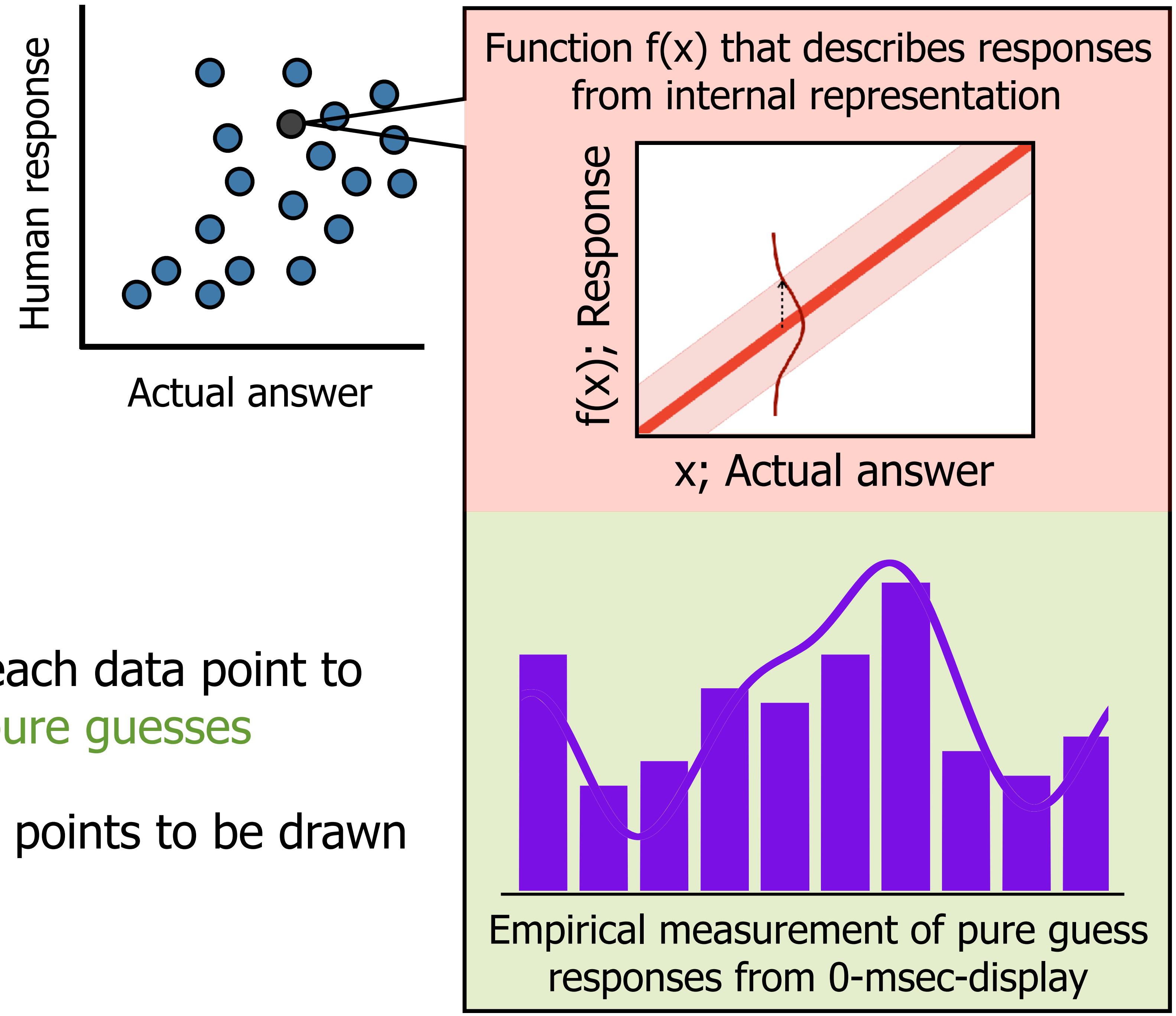




- Maximum likelihood estimation of each data point to be from internal representation vs. pure guesses

Modeling: decomposing mixed responses from longer durations

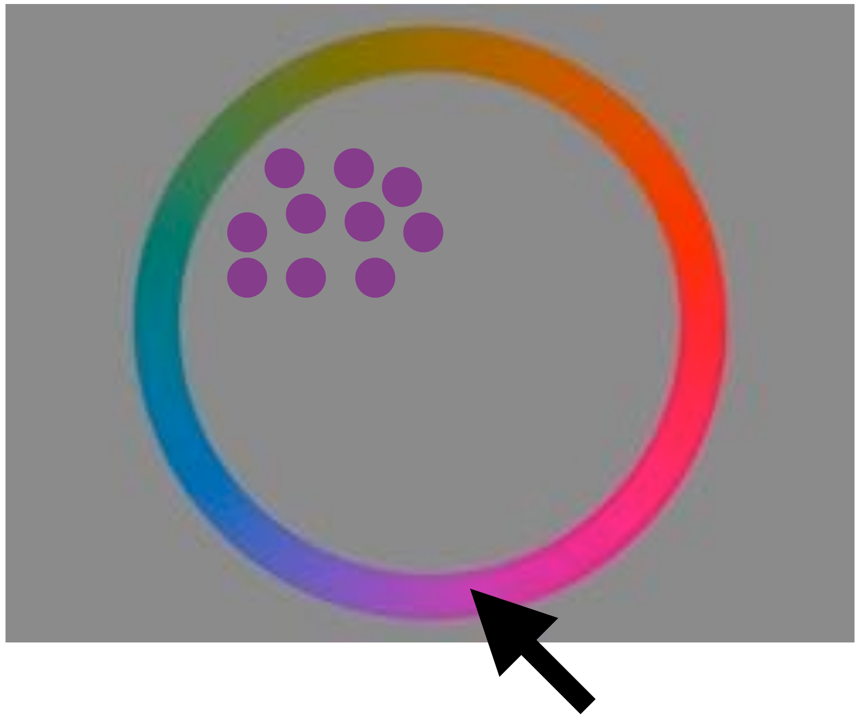


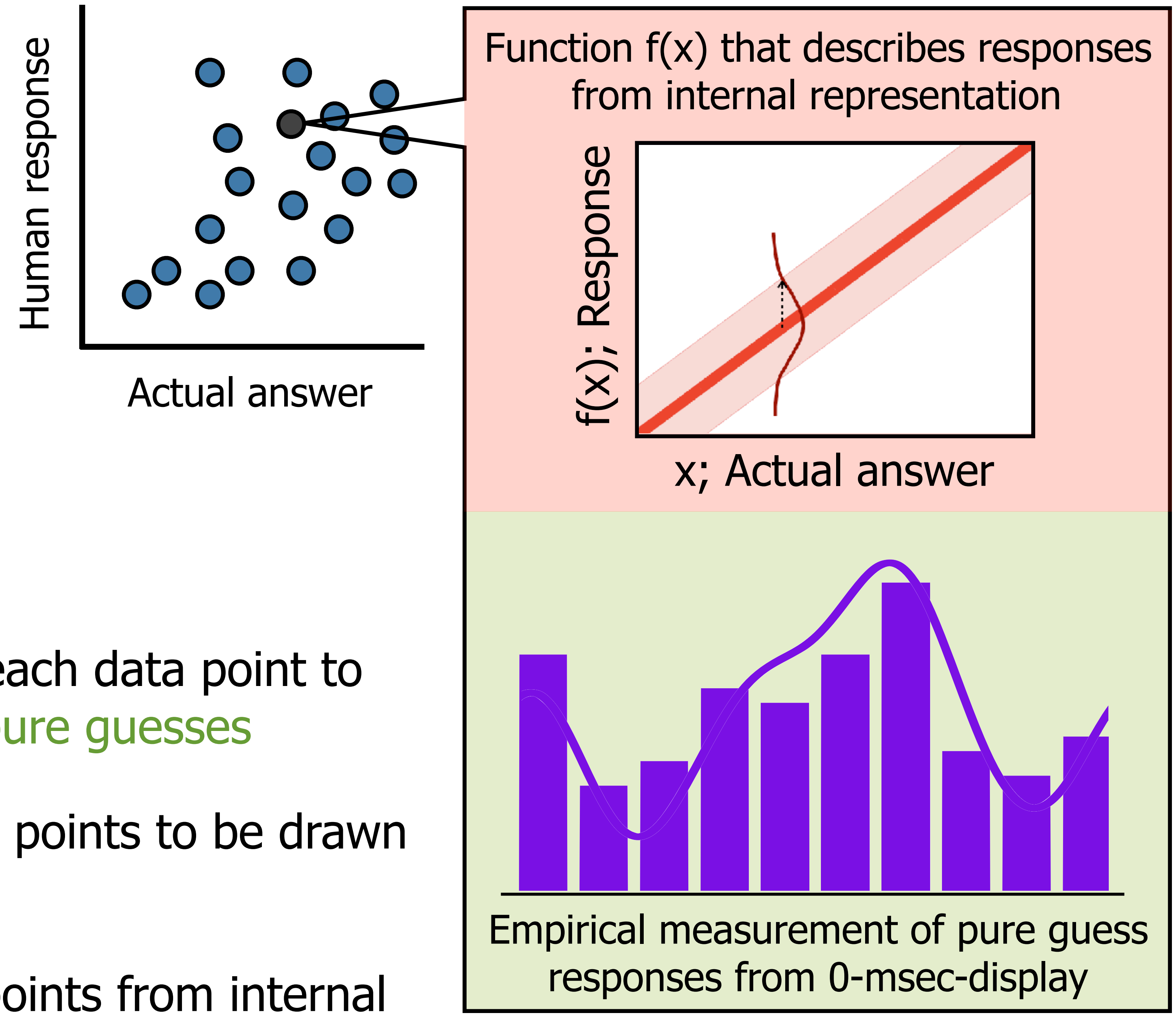


- Maximum likelihood estimation of each data point to be from internal representation vs. pure guesses

- P_{Int} : The overall probability of data points to be drawn from internal representation

Modeling: decomposing mixed responses from longer durations





- Maximum likelihood estimation of each data point to be from internal representation vs. pure guesses

- P_{Int} : The overall probability of data points to be drawn from internal representation

- SD_{Int} : Standard deviation of data points from internal representation, weighted by the likelihood of each data point

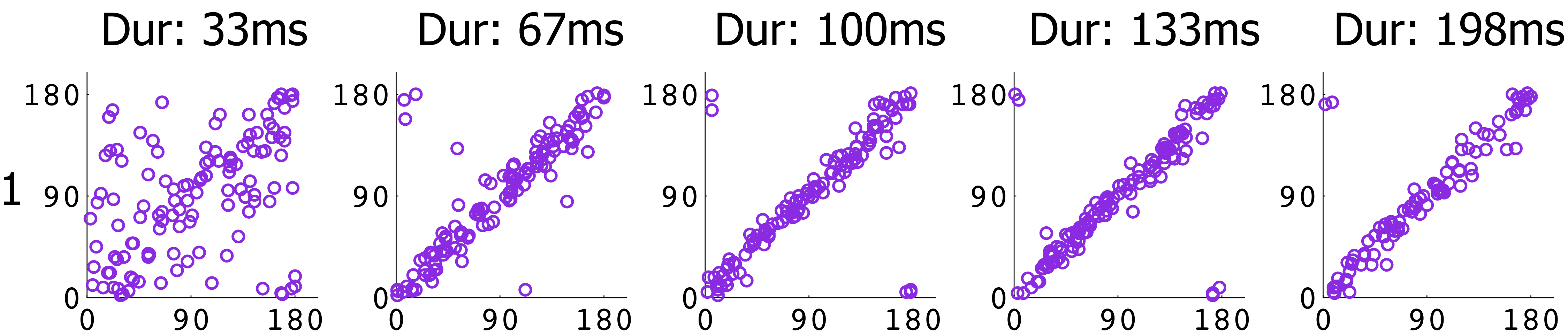
Results from longer durations: guess + internal representation

Color

Results from longer durations: guess + internal representation

Color

Sub 1



Set size 1

Set size 3

Set size 6

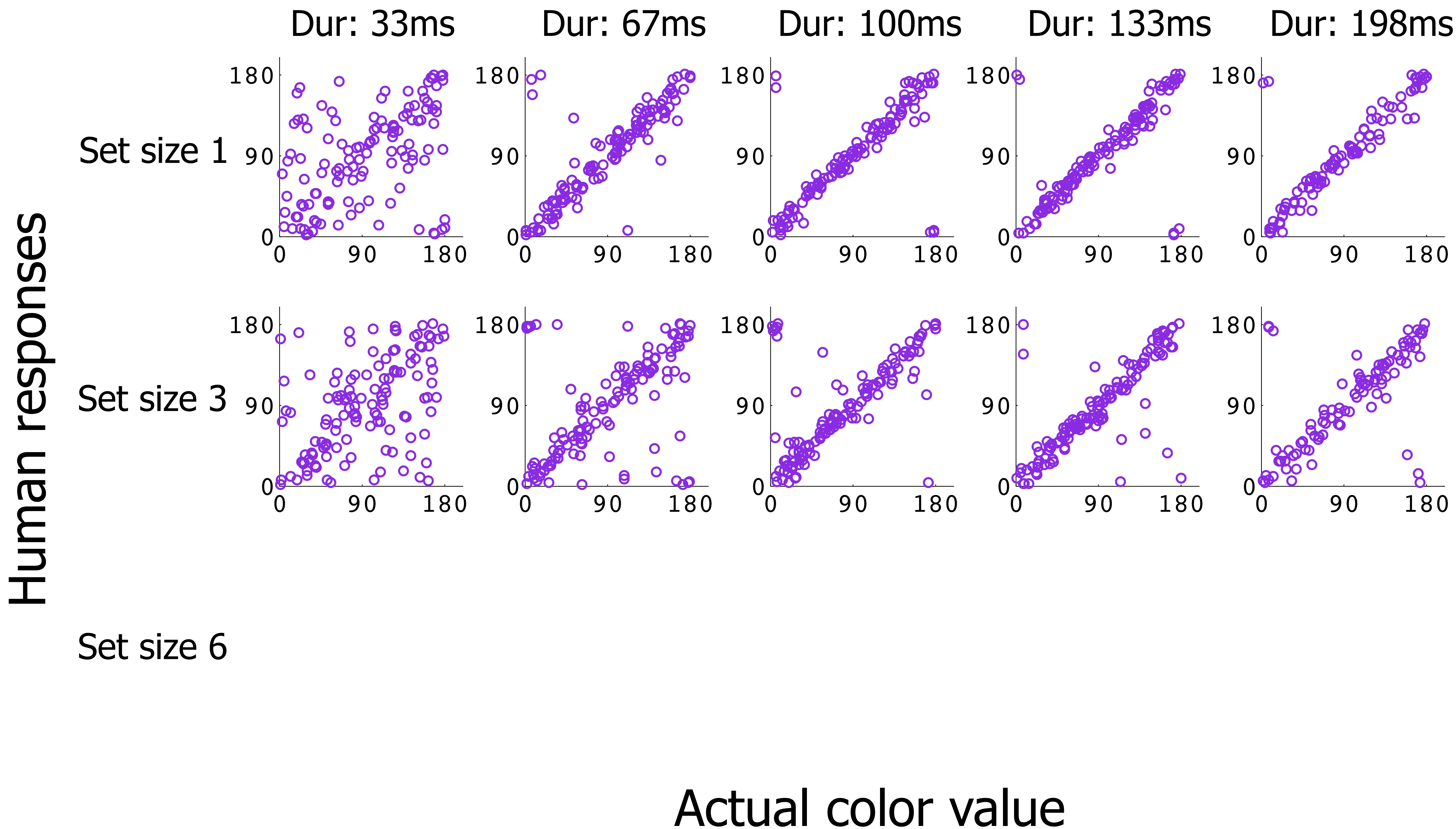
Human responses

Actual color value

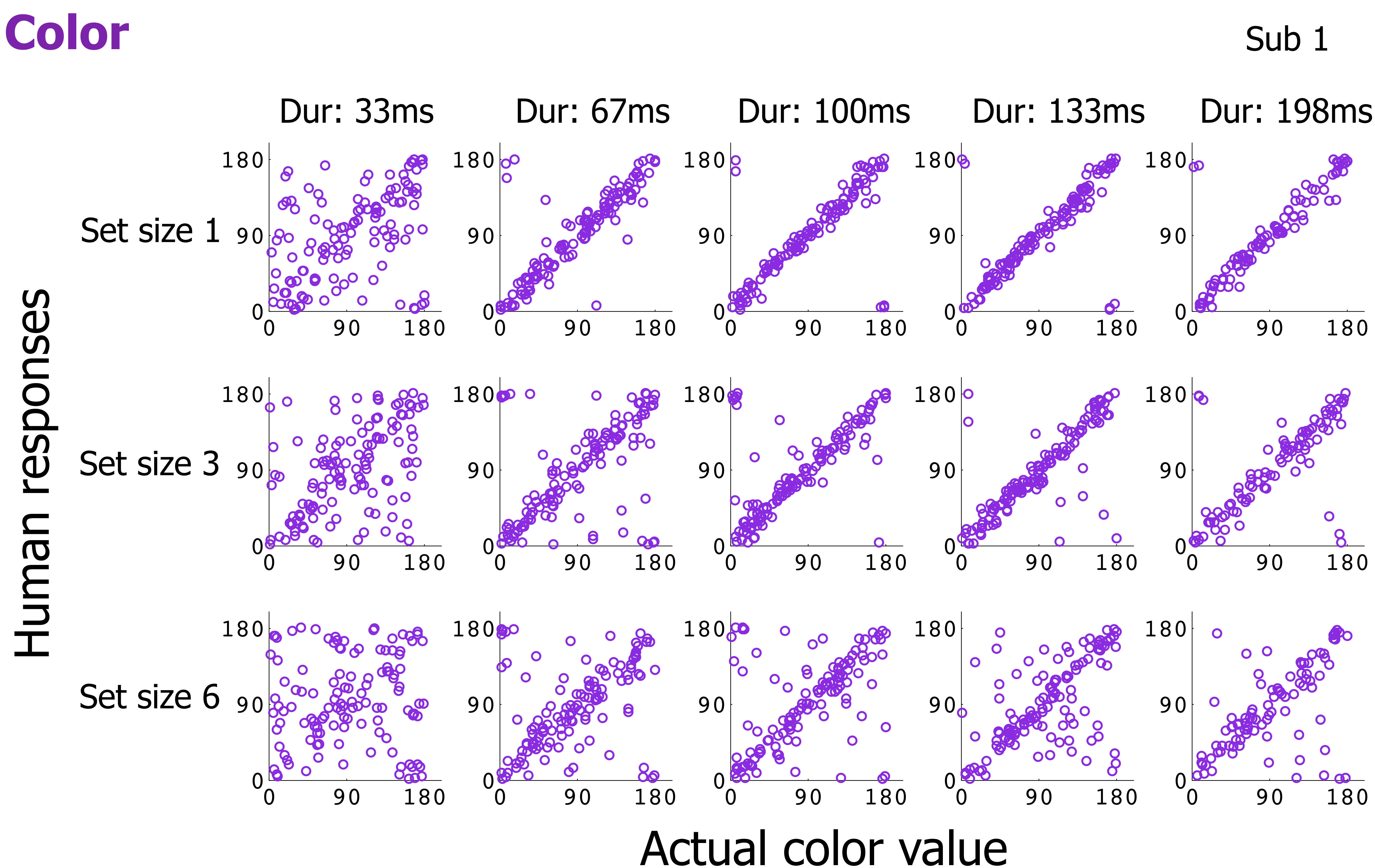
Results from longer durations: guess + internal representation

Color

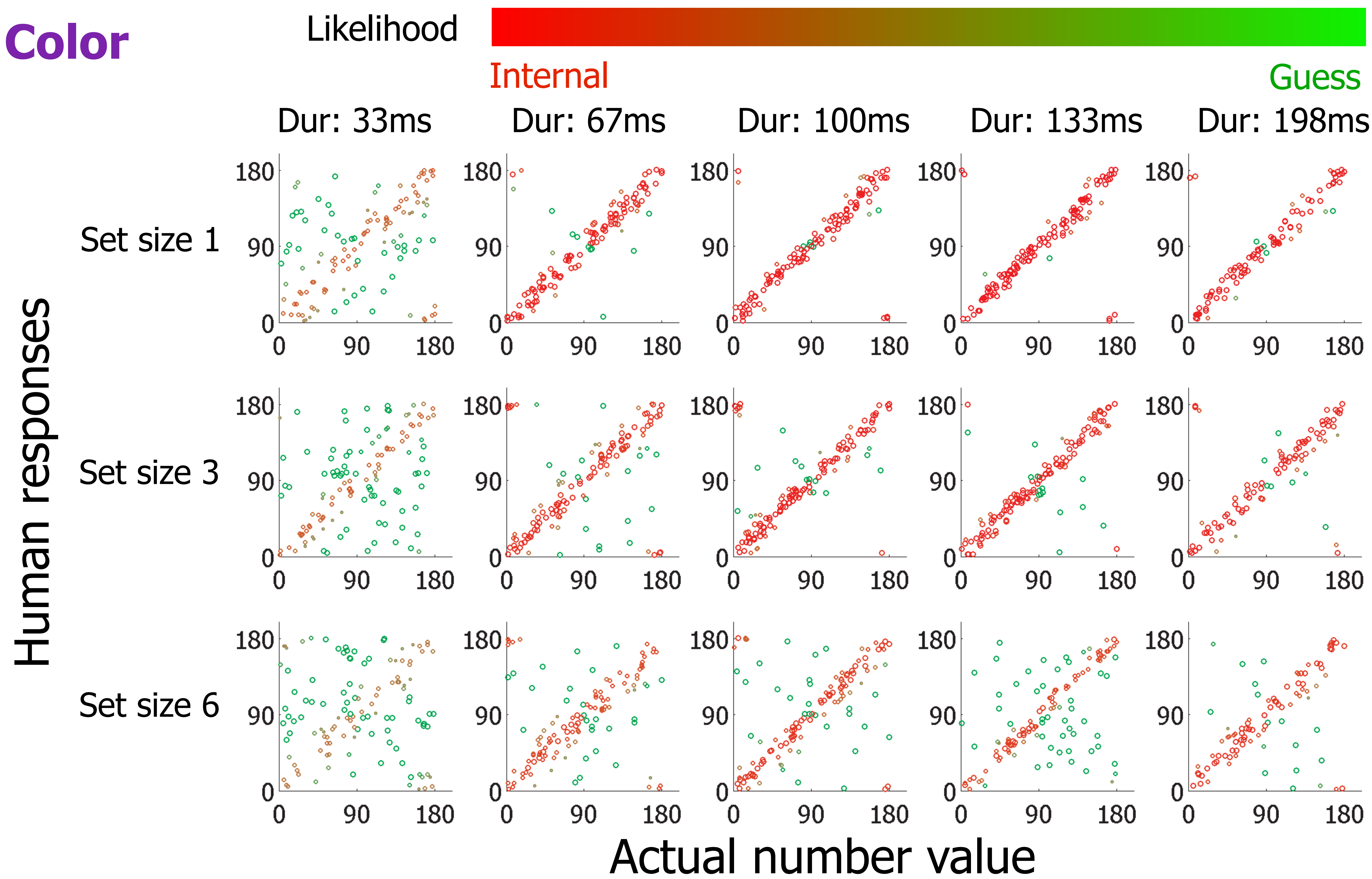
Sub 1



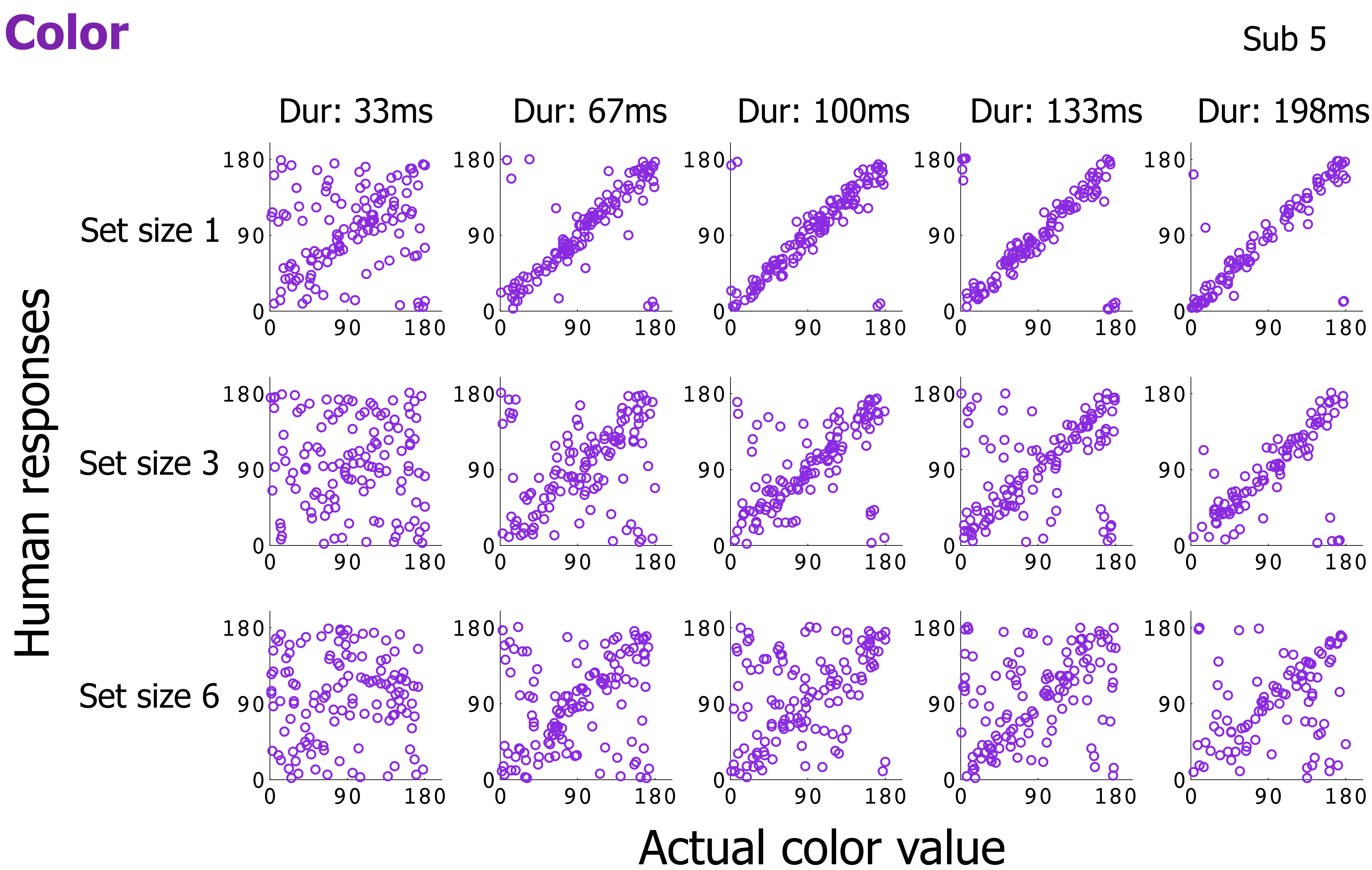
Results from longer durations: guess + internal representation



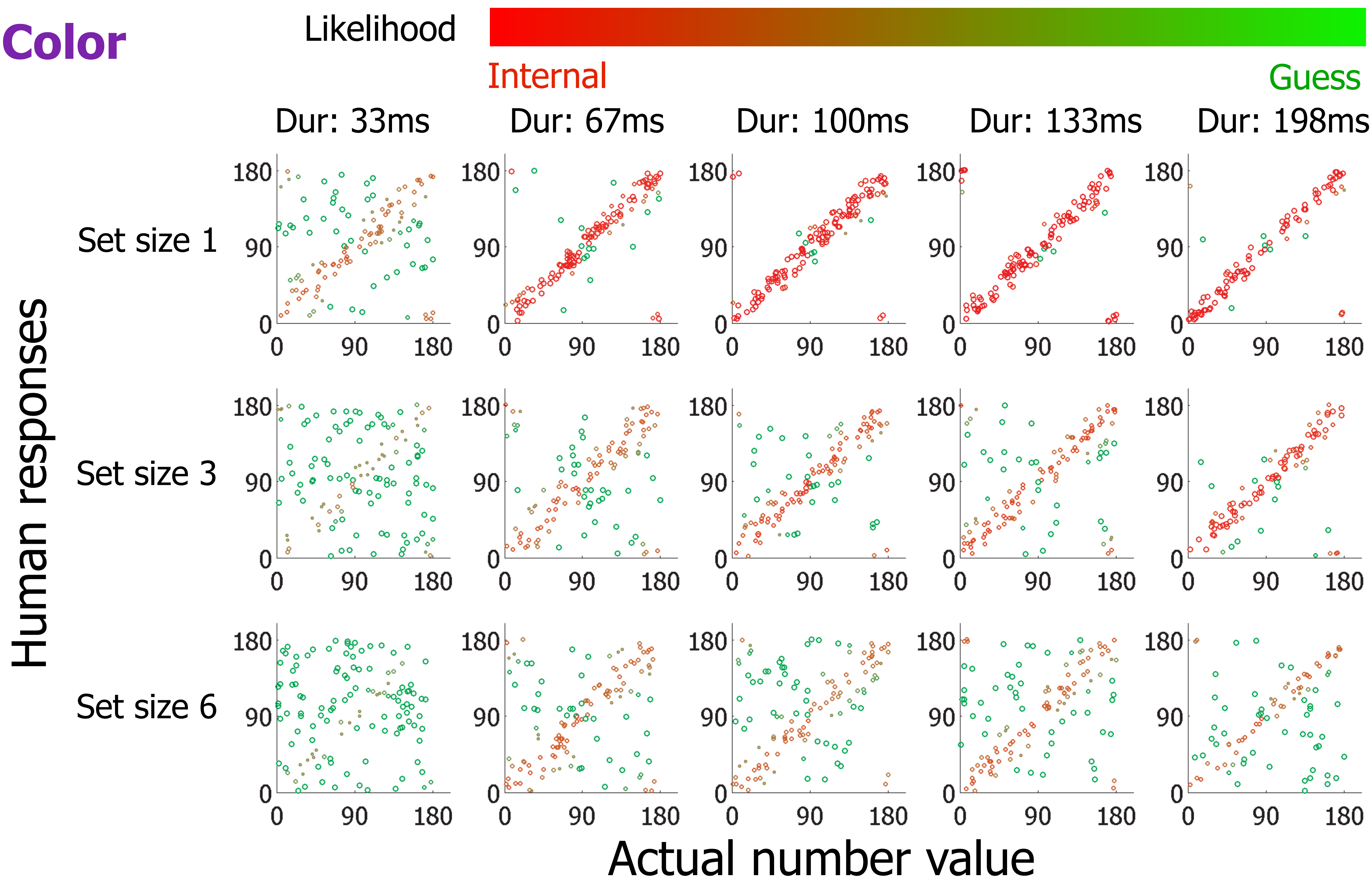
Model results: decomposed responses



Results from longer durations: guess + internal representation

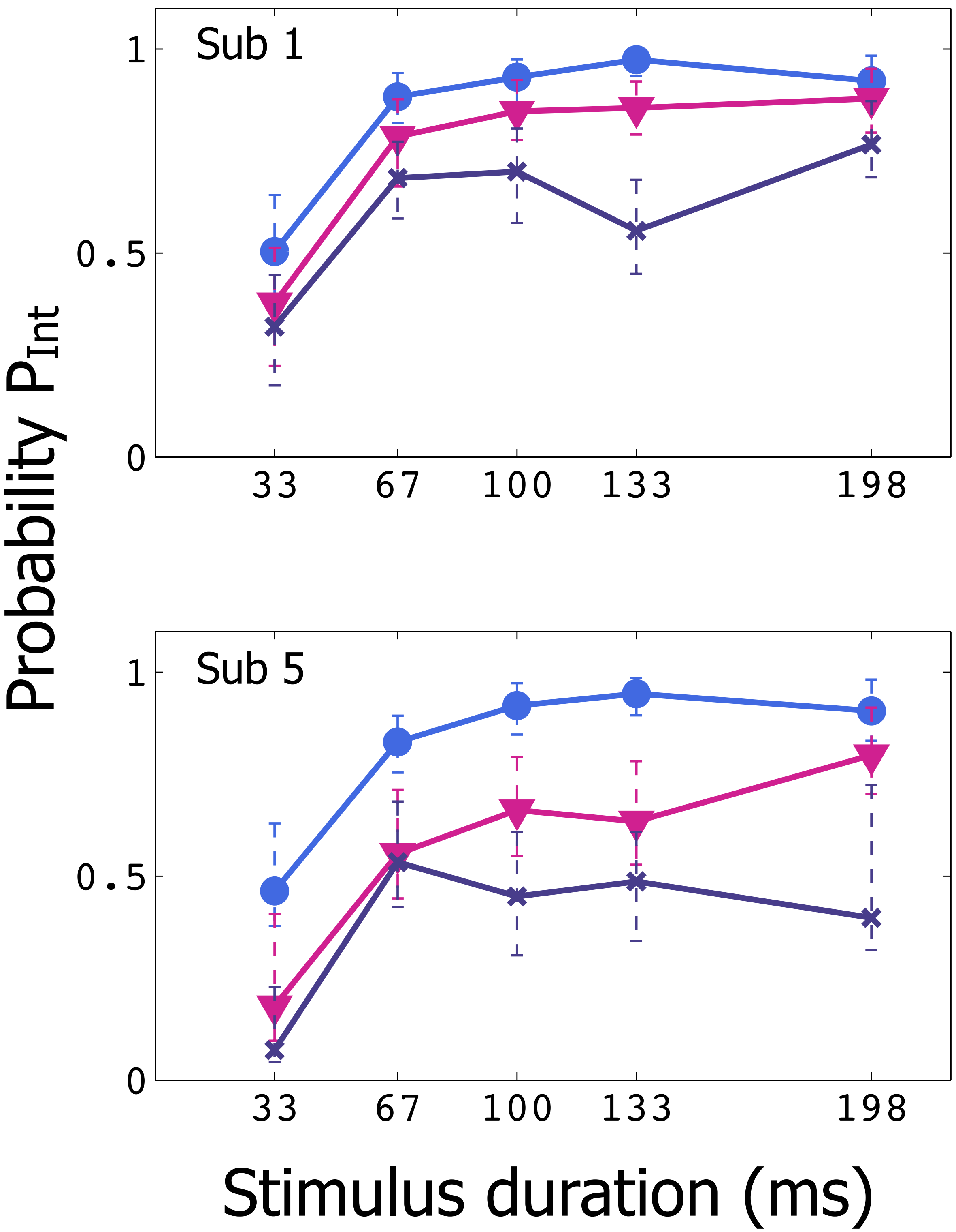


Model results: decomposed responses



The proportion of guess responses changes, but not the precision!

Color



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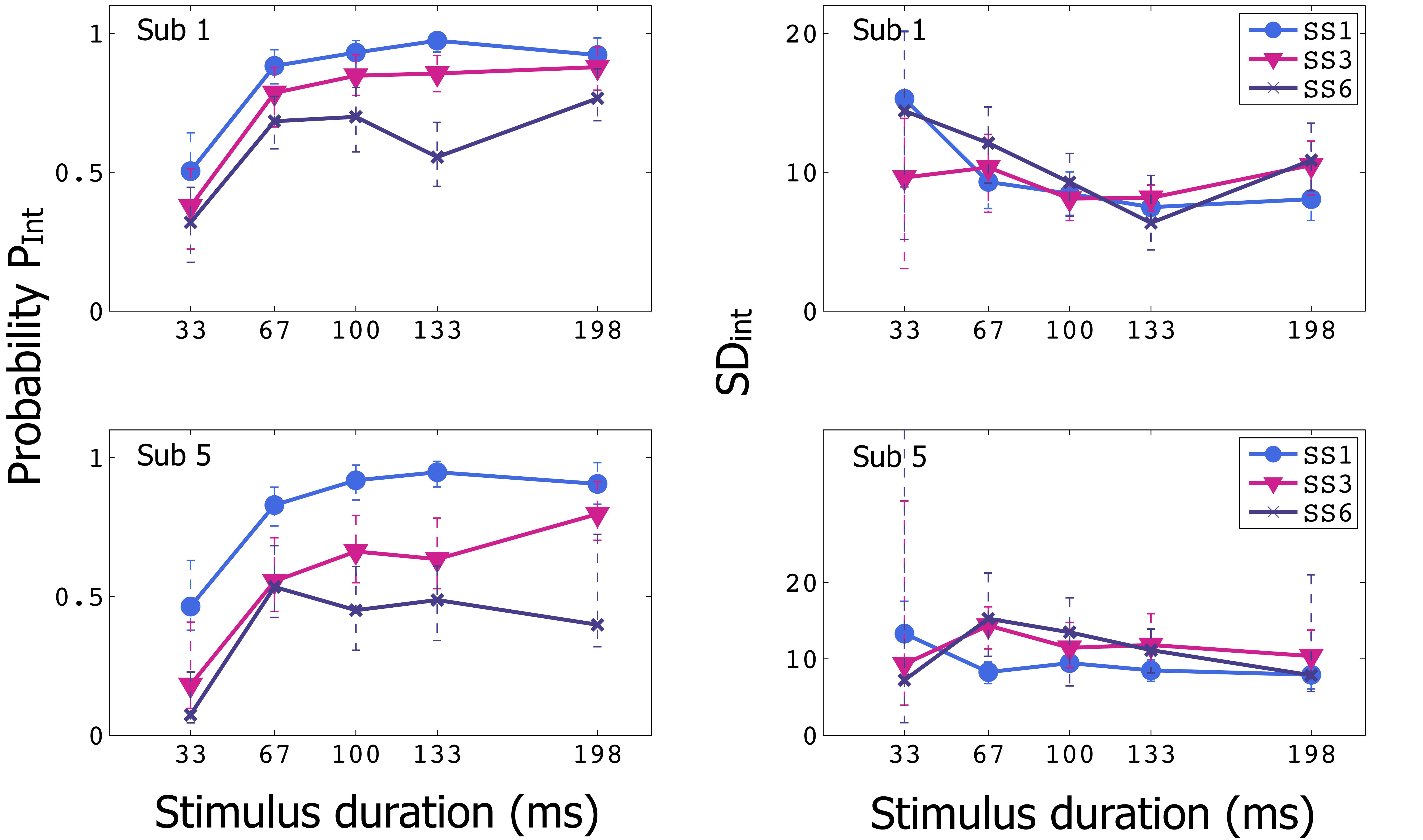
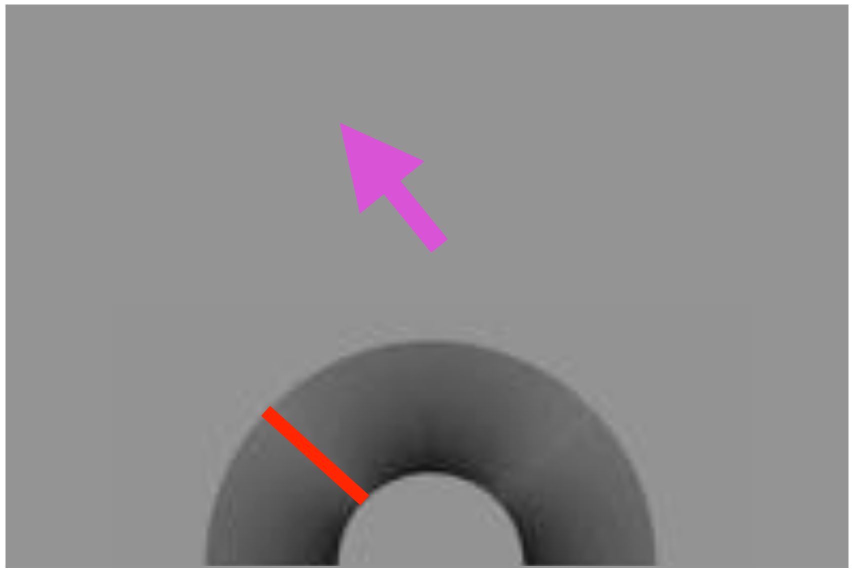
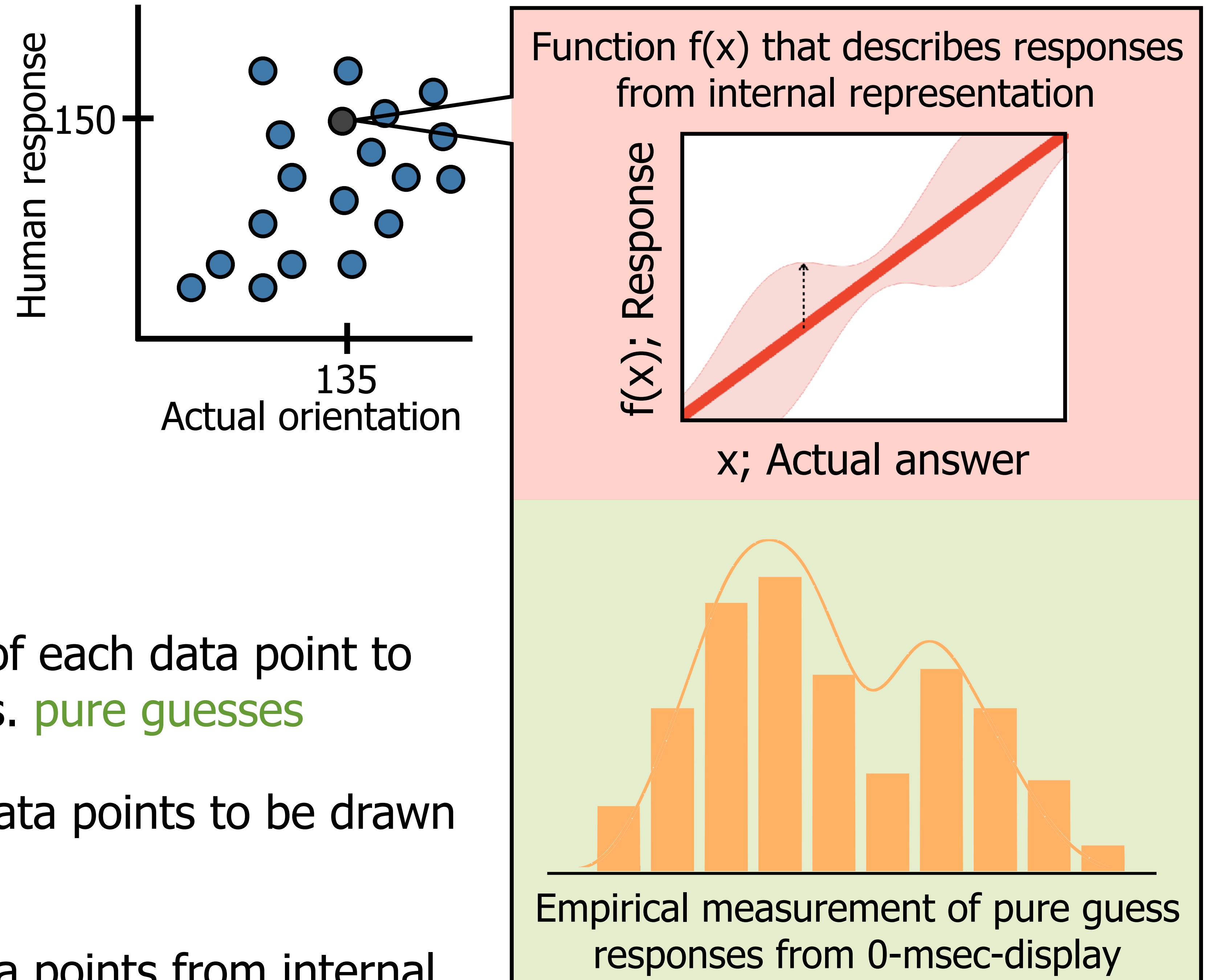
Color



Modeling: decomposing mixed responses from longer durations





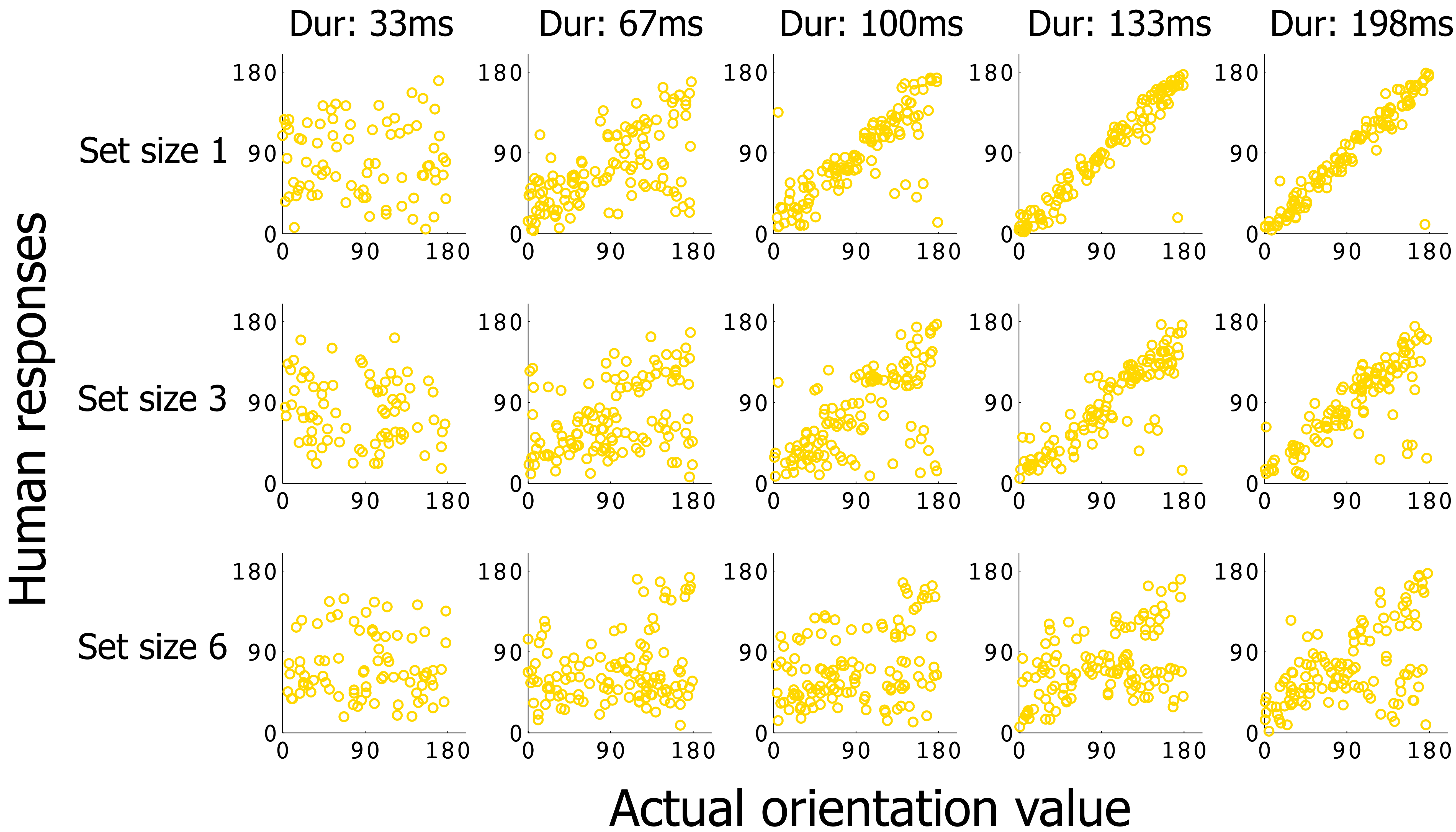
- Maximum likelihood estimation of each data point to be from internal representation vs. pure guesses

- P_{Int} : The overall probability of data points to be drawn from internal representation

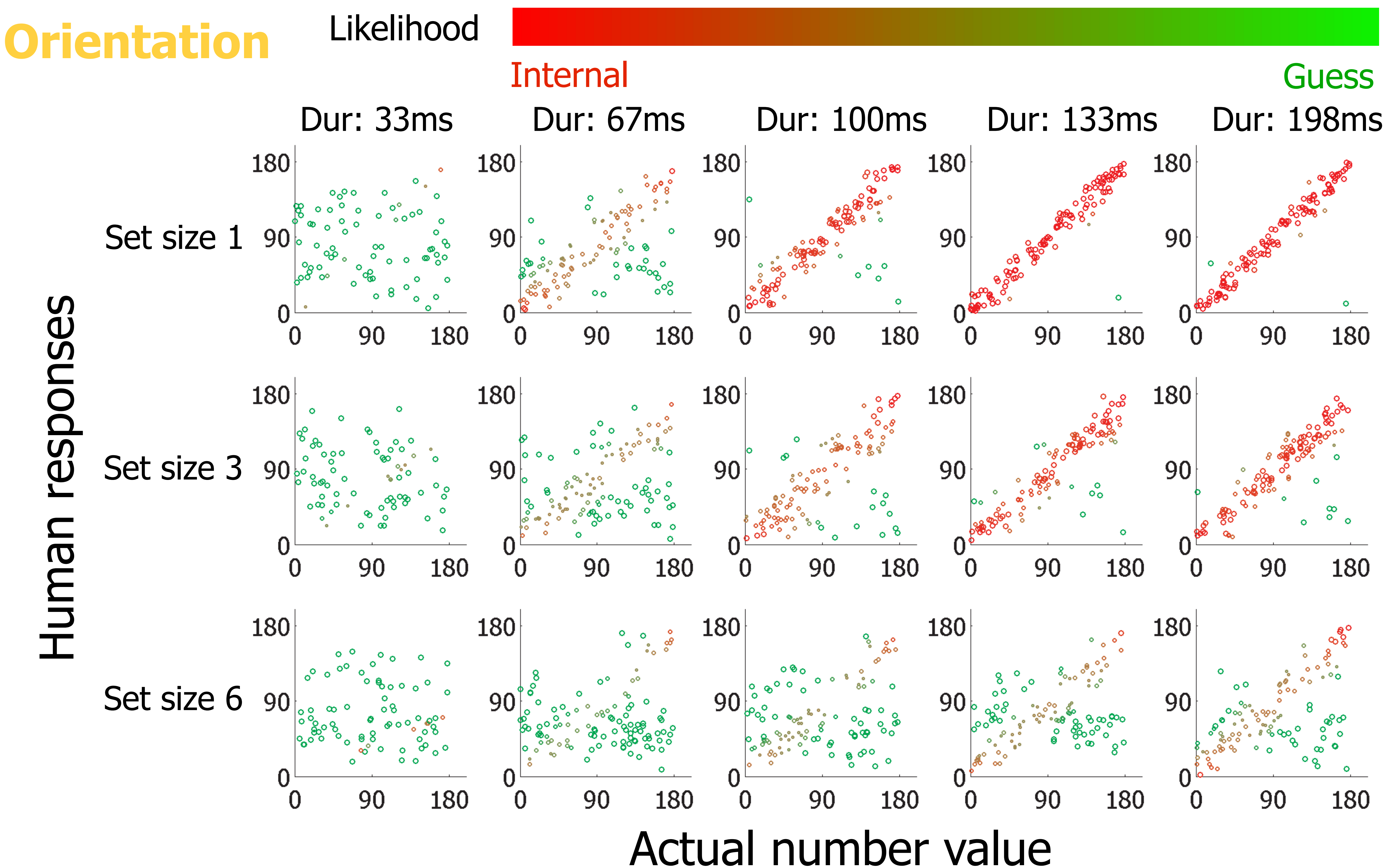
- SD_{Int} : Standard deviation of data points from internal representation, weighted by the likelihood of each data point

Results from longer durations: guess + internal representation

Orientation

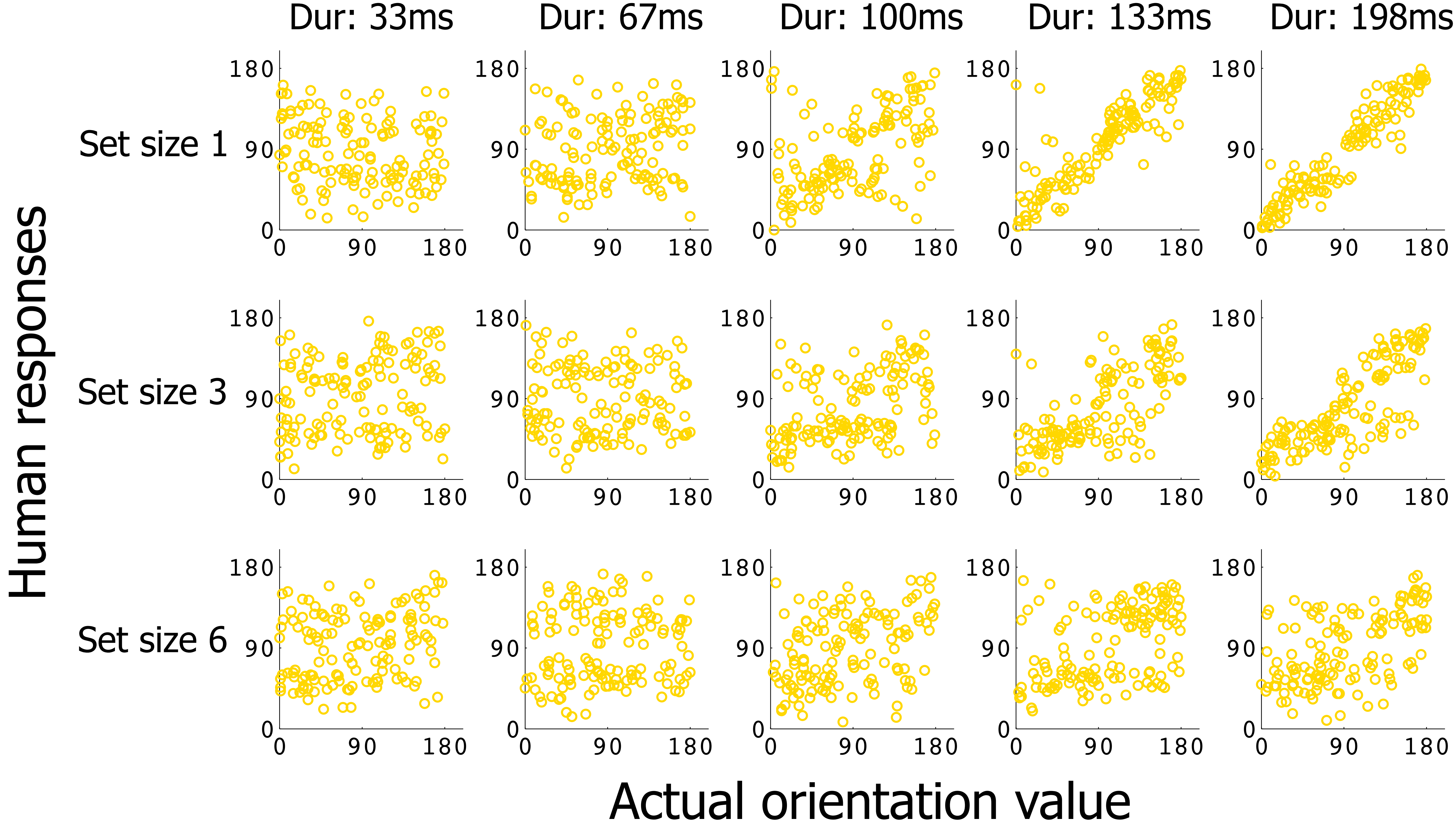


Model results: decomposed responses

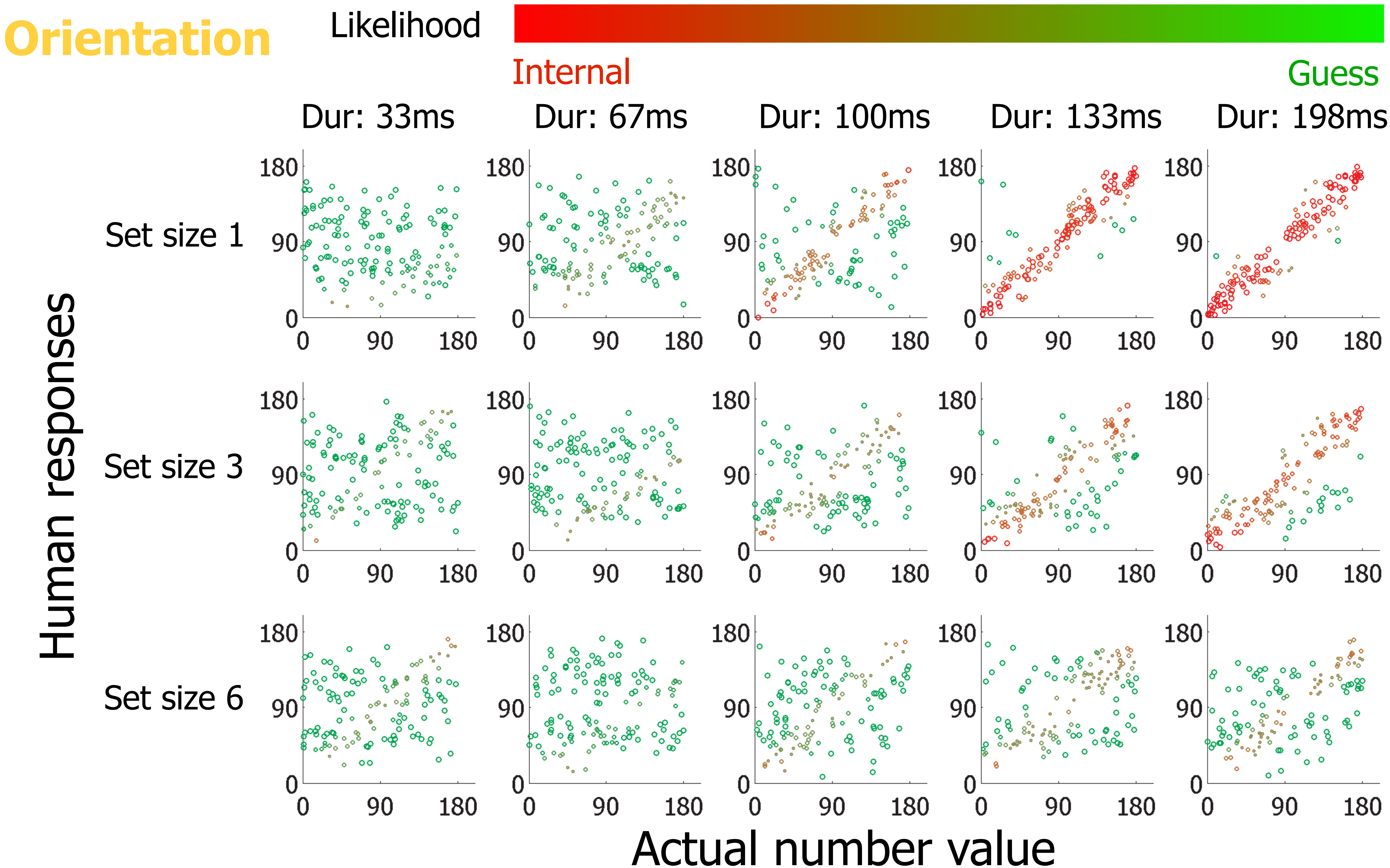


Results from longer durations: guess + internal representation

Orientation

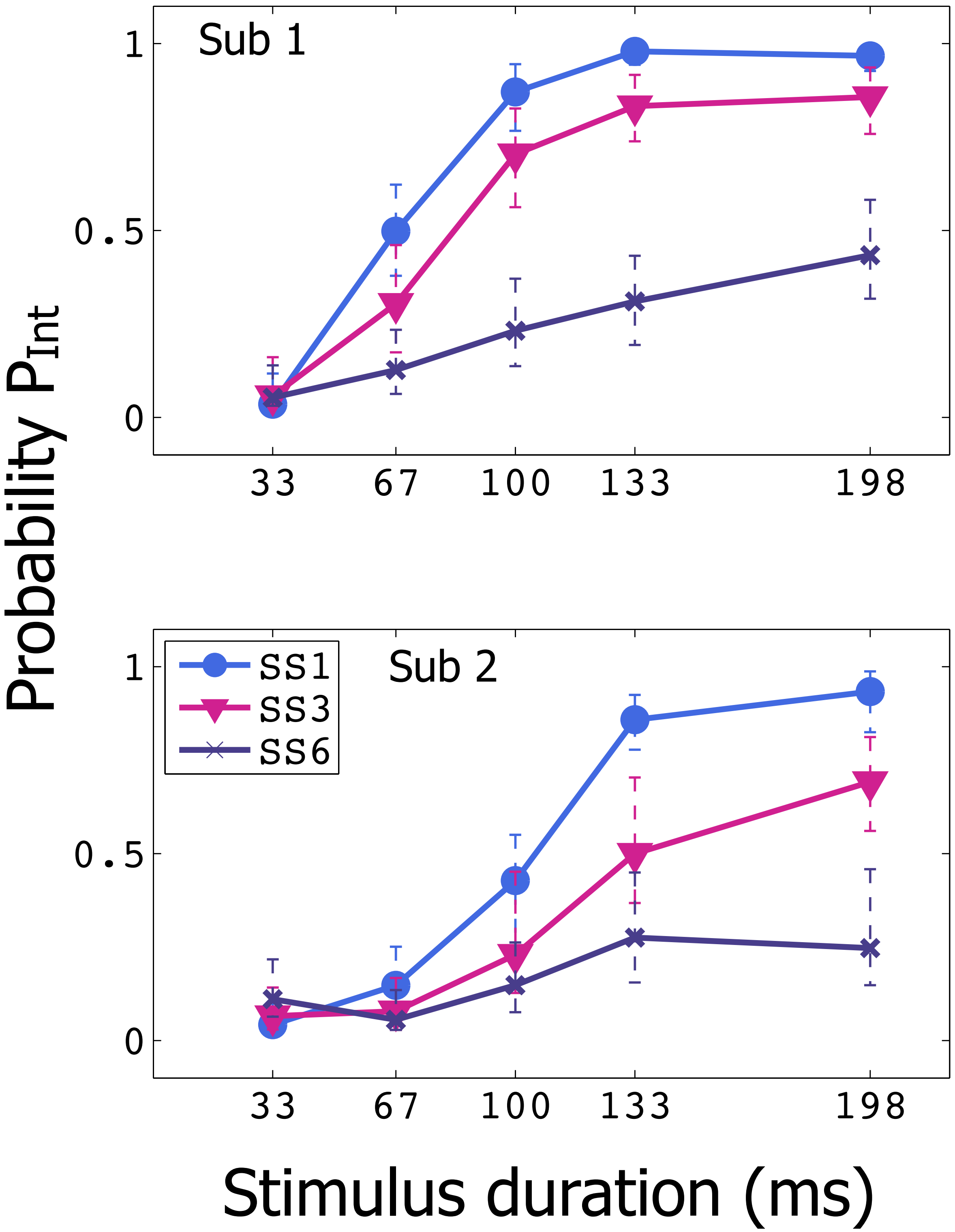


Model results: decomposed responses



The proportion of guess responses changes, but not the precision!

Orientation



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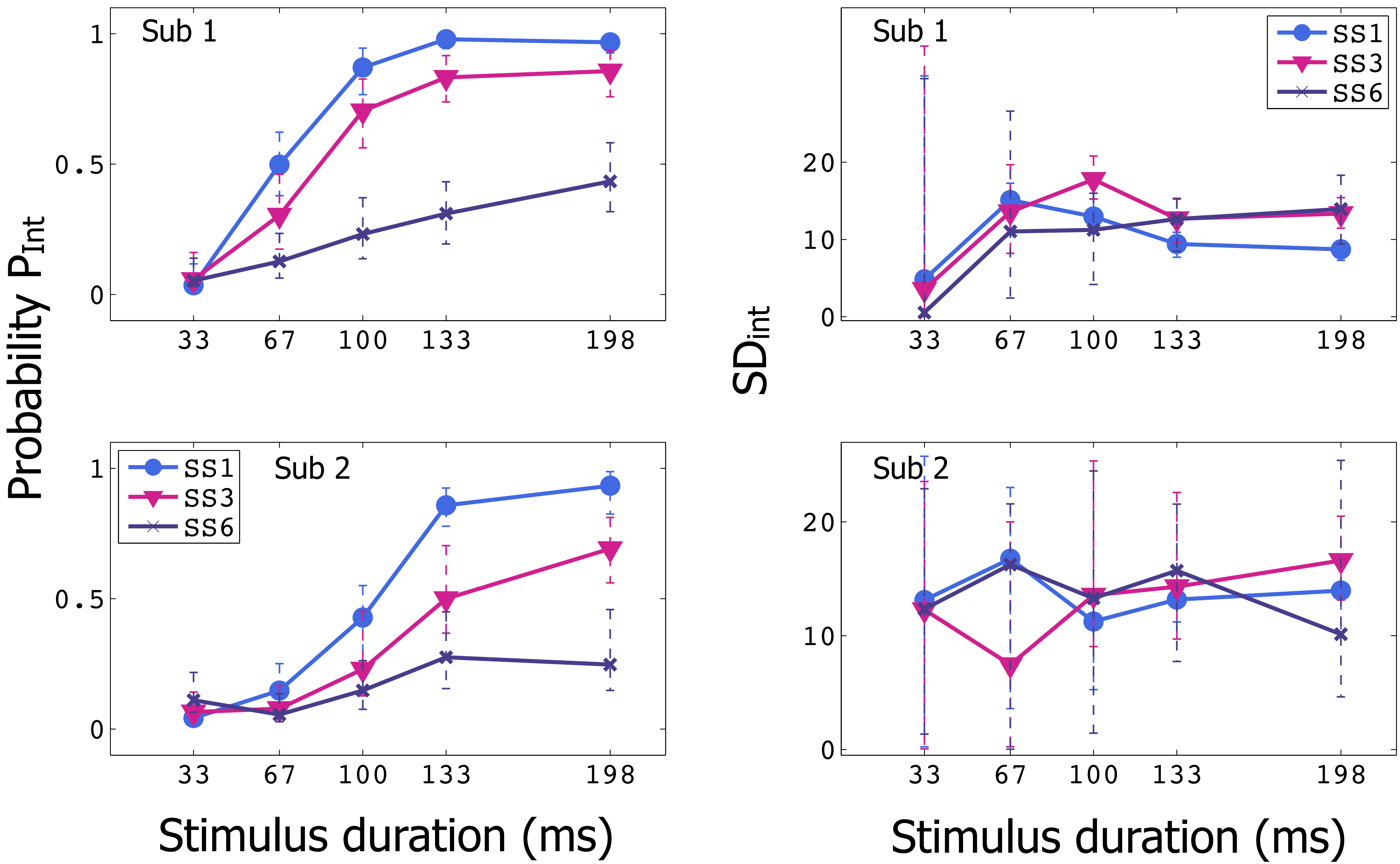
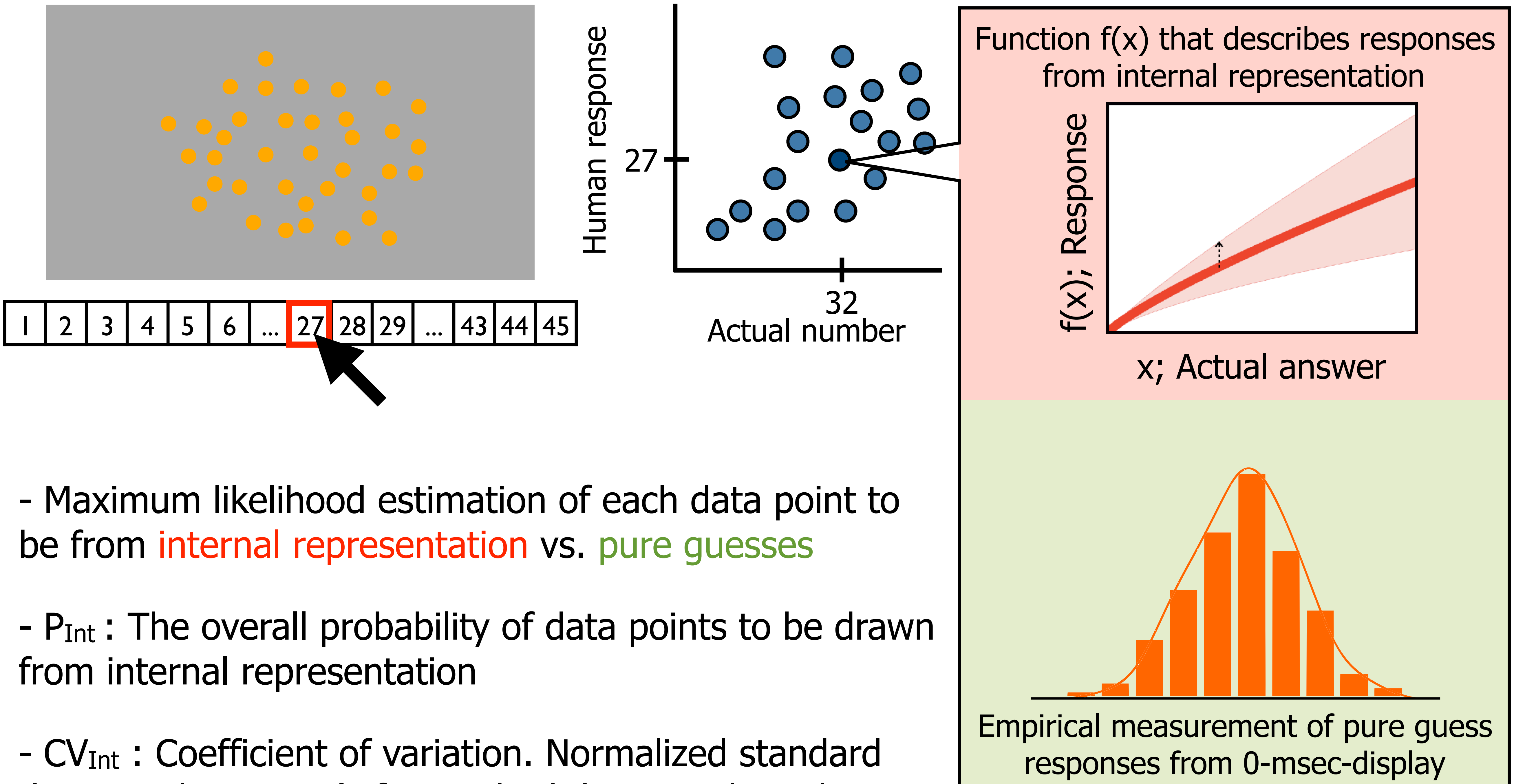
Orientation



Modeling: decomposing mixed responses



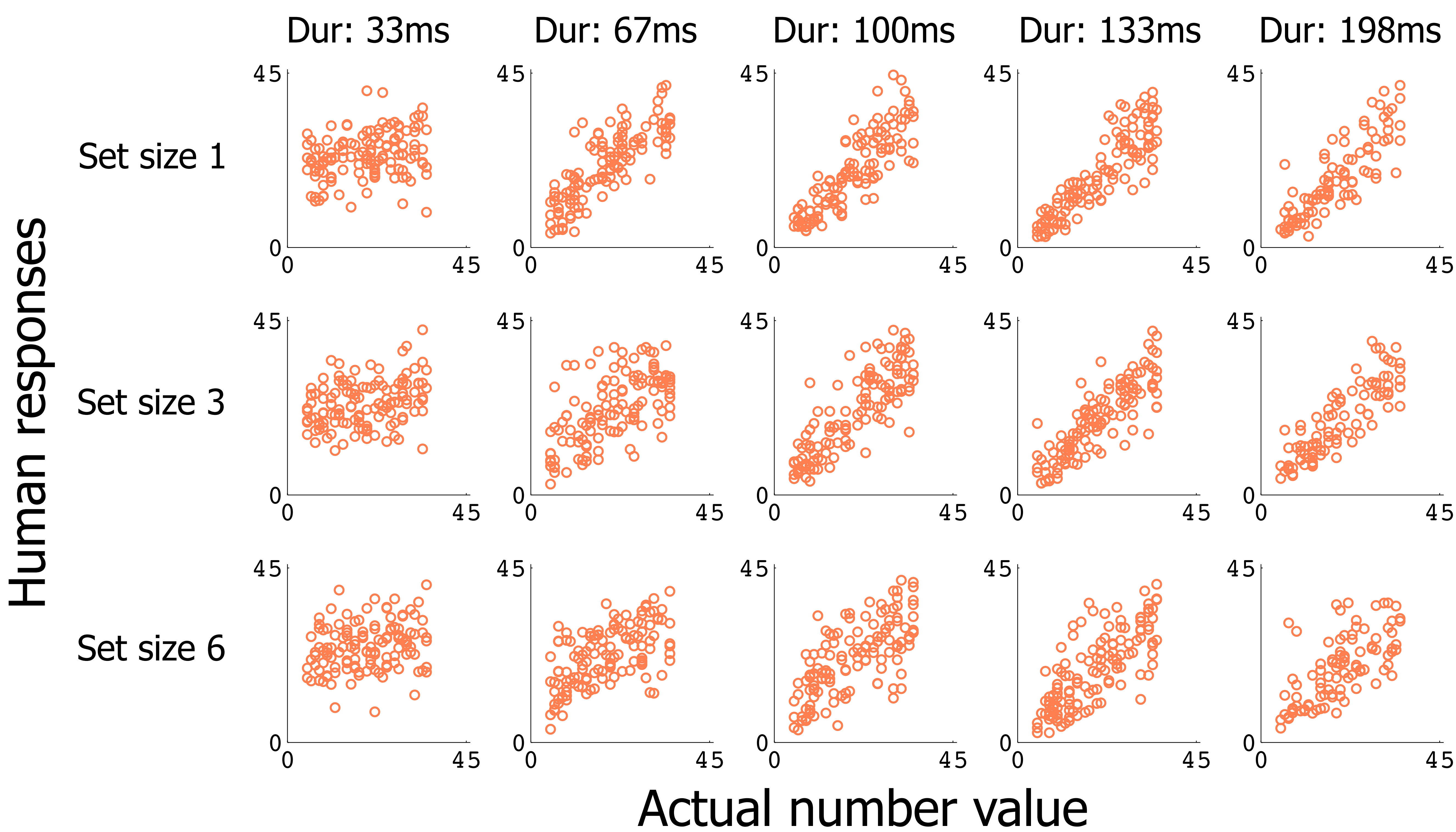
- Maximum likelihood estimation of each data point to be from internal representation vs. pure guesses

- P_{Int} : The overall probability of data points to be drawn from internal representation

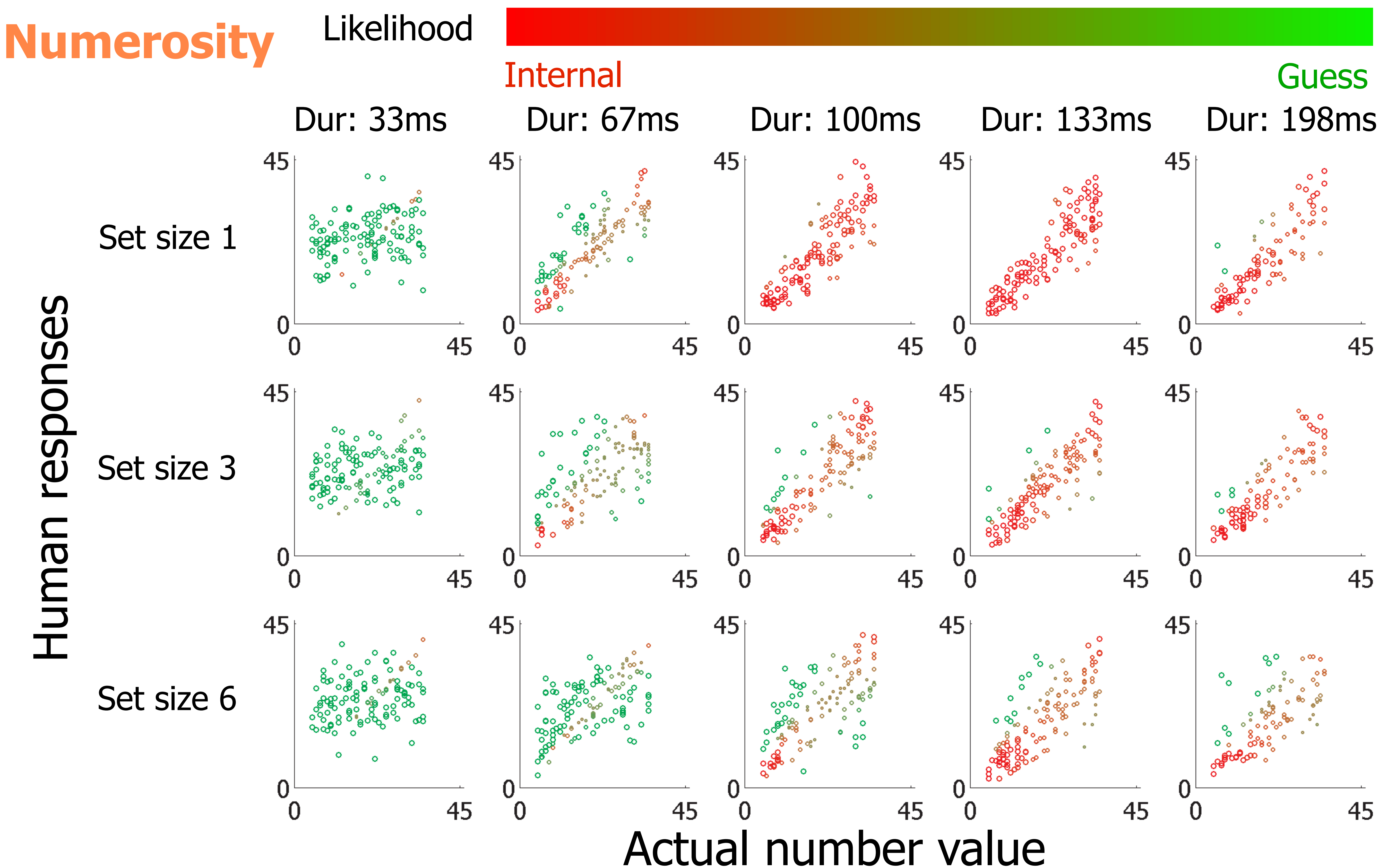
- CV_{Int} : Coefficient of variation. Normalized standard deviation by mean (c.f., standard deviation linearly increases with feature values in numerosity and length dimensions)

Results from longer durations: guess + internal representation

Numerosity

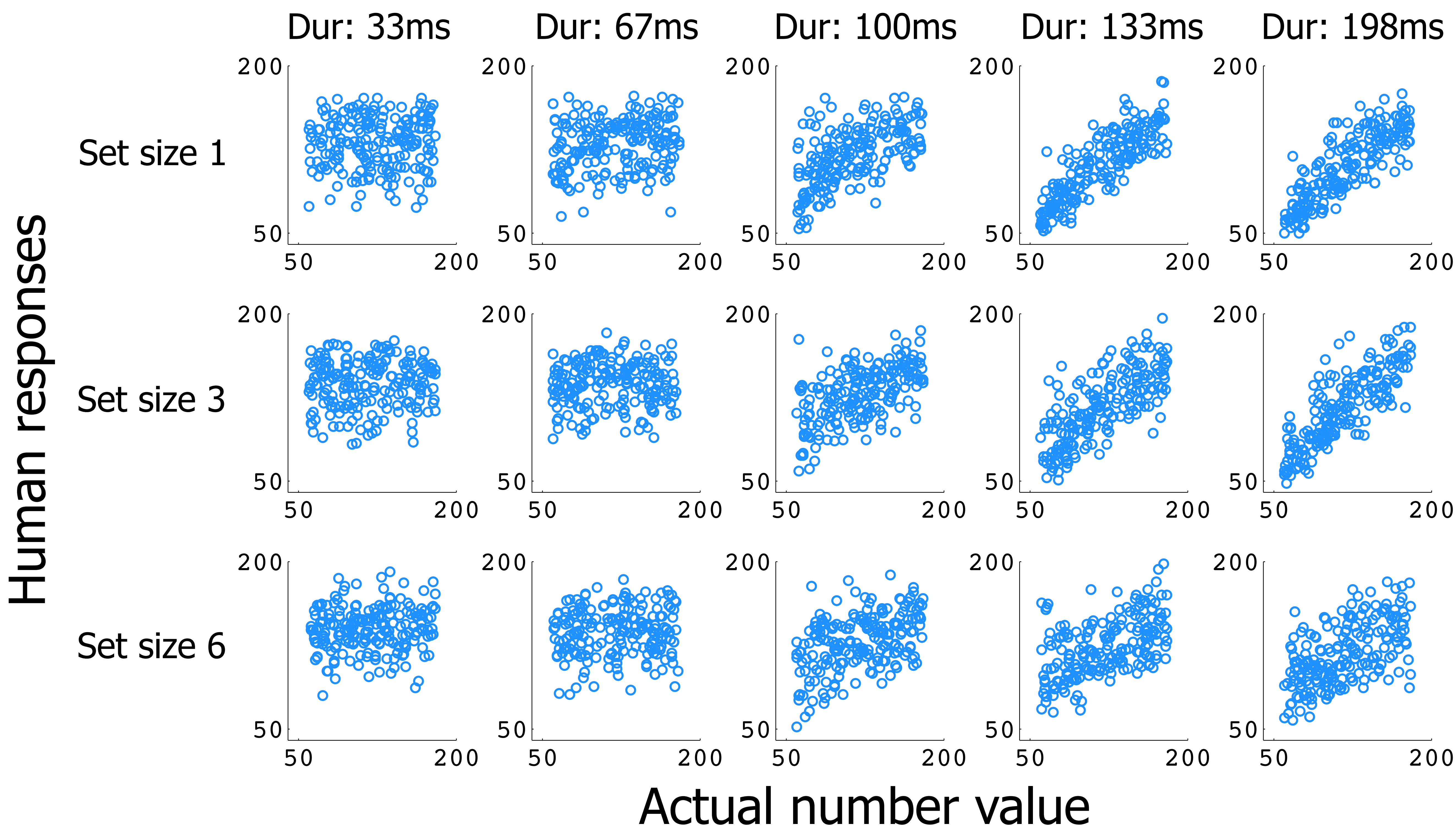


Results from longer durations: guess + internal representation

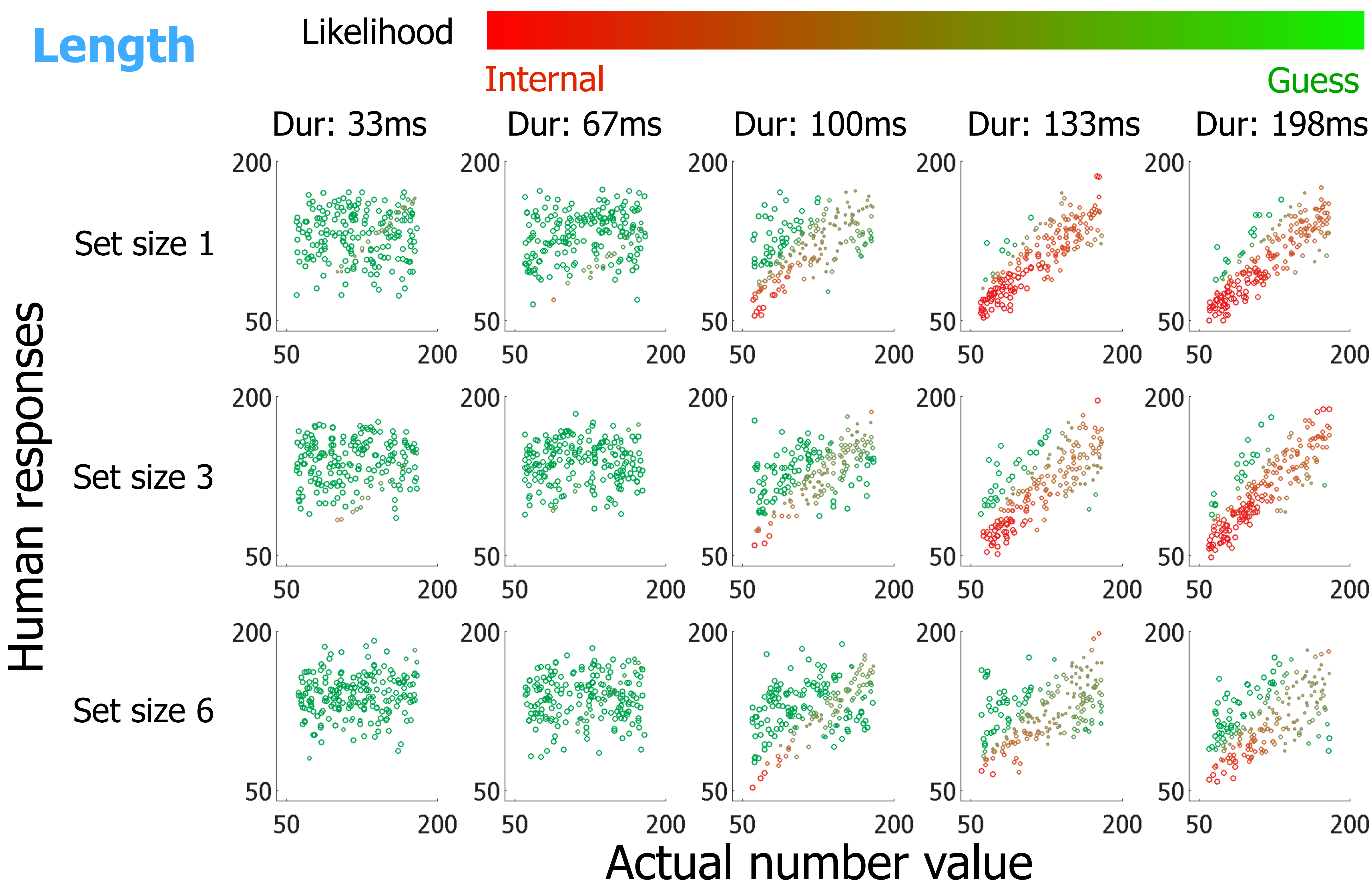


Results from longer durations: guess + internal representation

Length

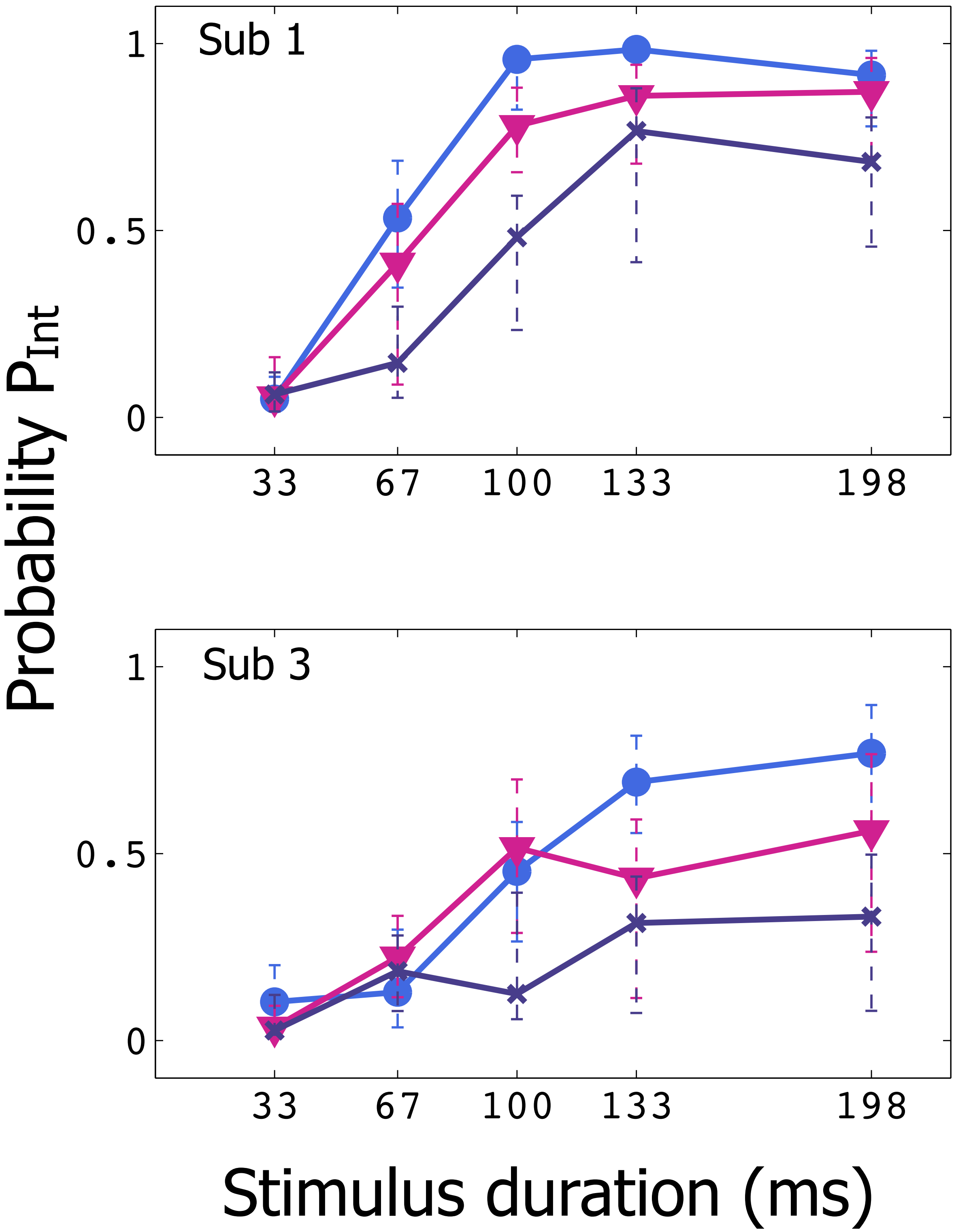


Results from longer durations: guess + internal representation



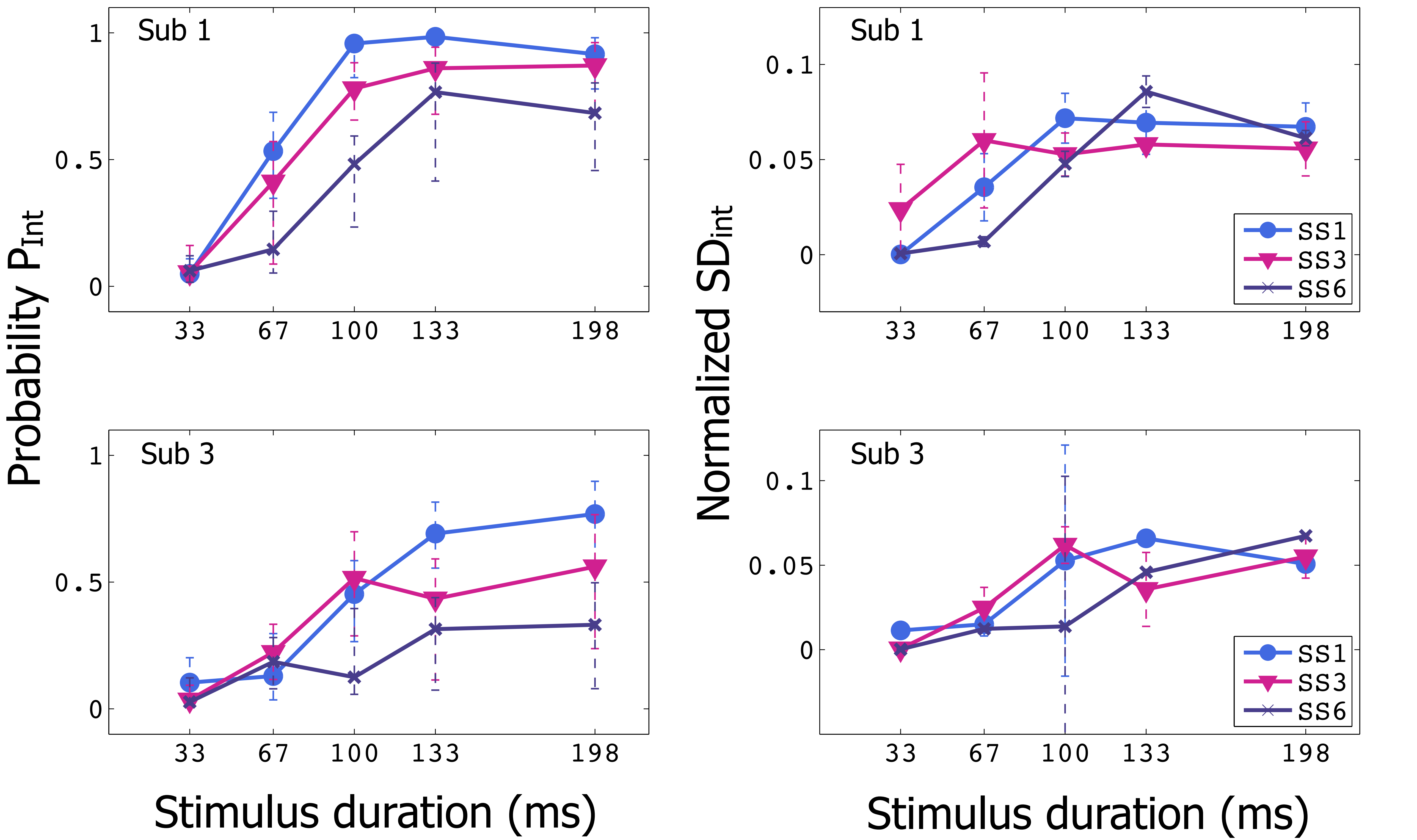
The proportion of guess responses changes, but not the precision!

Numerosity



The proportion of guess responses changes, but not the precision!

Numerosity



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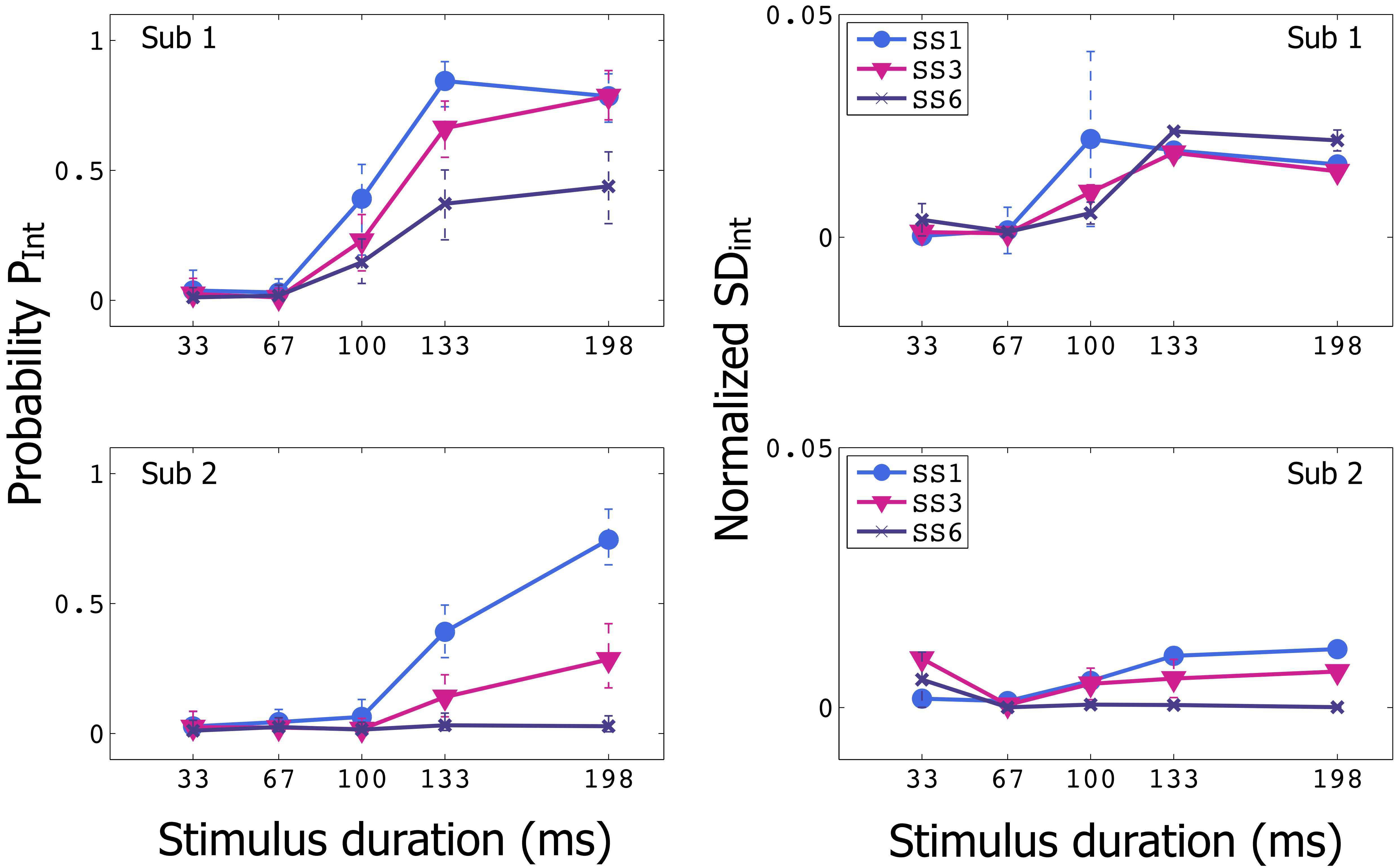
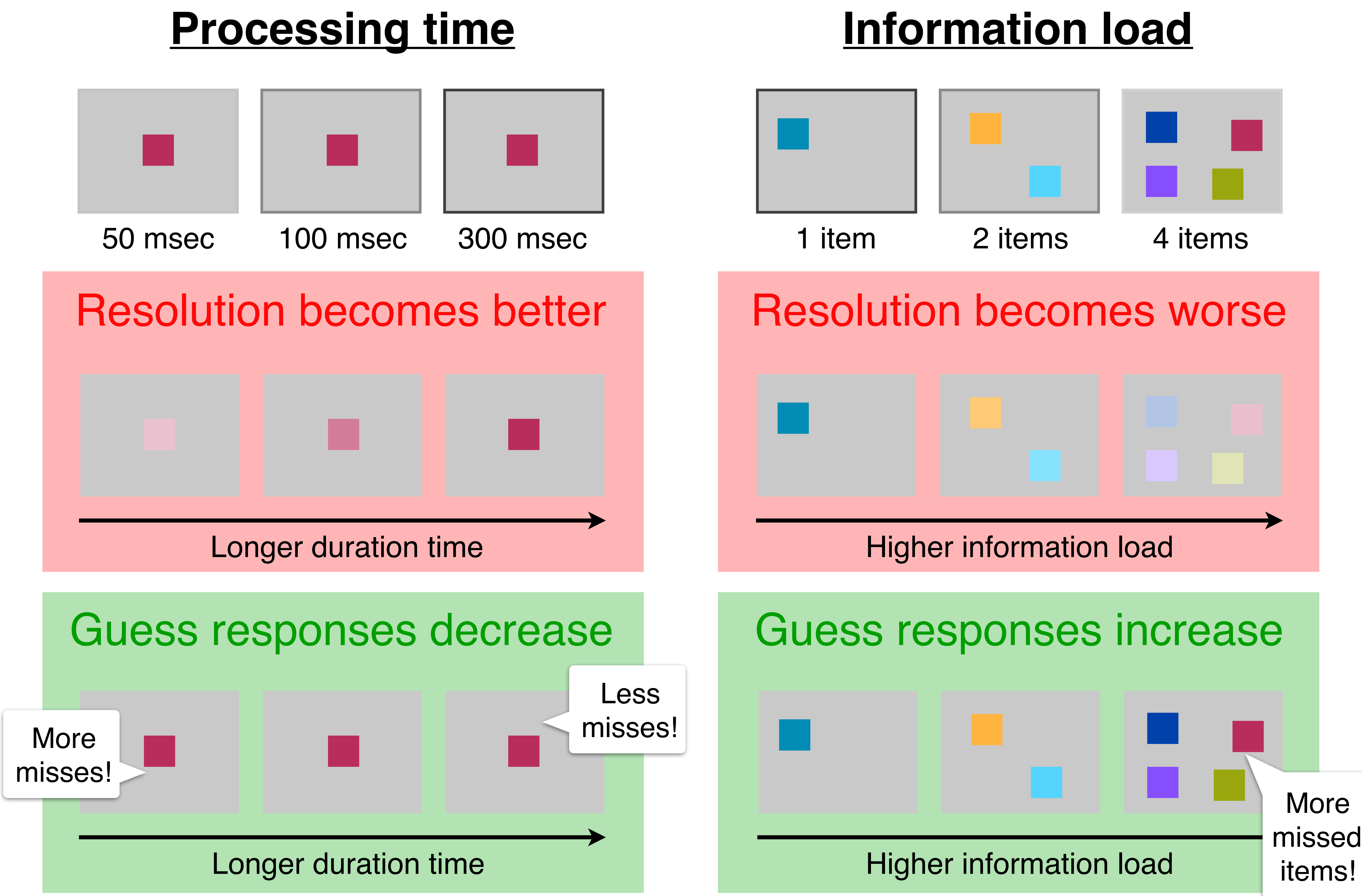
Length

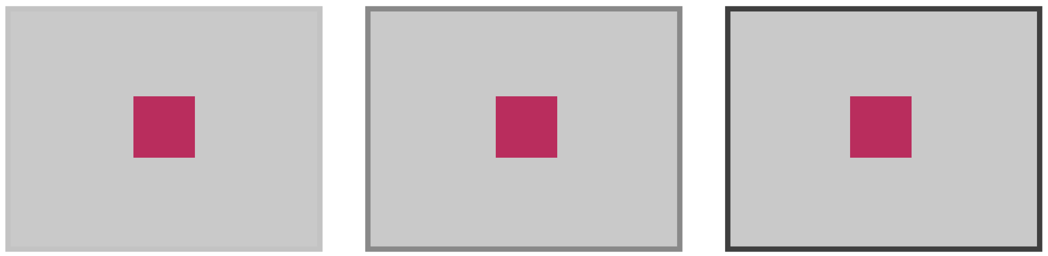


So, how do these factors affect visual decisions?



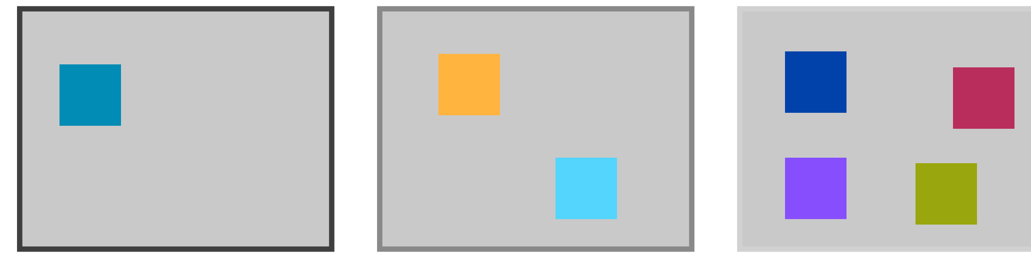
So, how do these factors affect visual decisions?

Processing time



50 msec | 100 msec | 300 msec

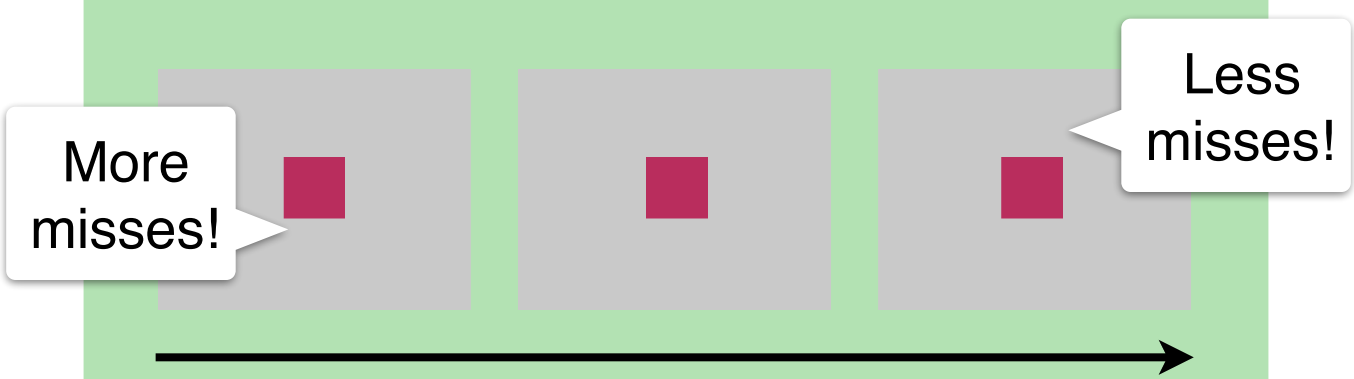
Information load



1 item | 2 items | 4 items

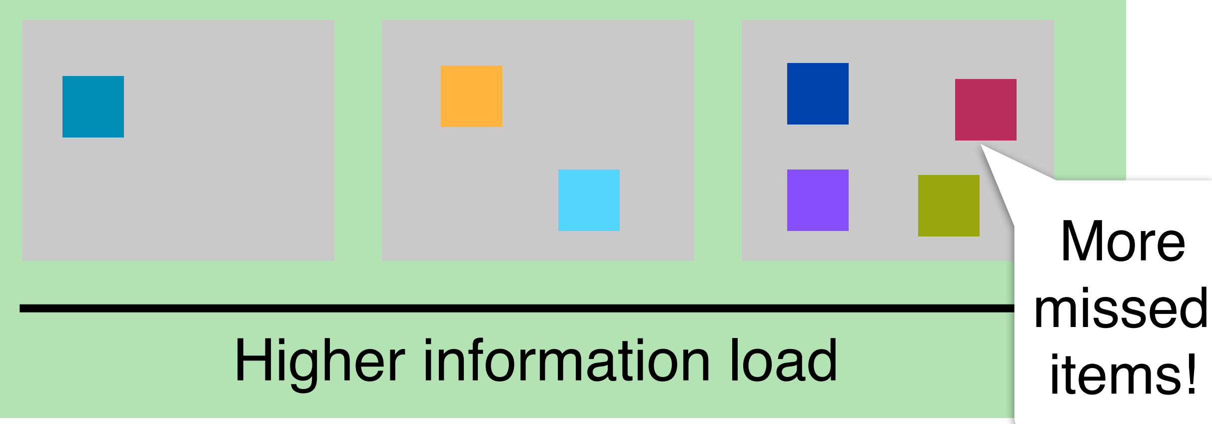
The resolution of internal representation does not progressively change, but the proportion of non-visual responses (guess responses) changes

Guess responses decrease



Longer duration time

Guess responses increase



Higher information load

Take-home messages

Take-home messages

1. Humans' guess responses are not noise, nor are they random.

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Take-home messages

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2. The resolution of visual representations is fixed and discrete.

The discrete nature of visual representation may benefits in the dynamic, noisy visual world

The discrete nature of visual representation may benefits in the dynamic, noisy visual world

1. It is more categorical and more easily verbalizable

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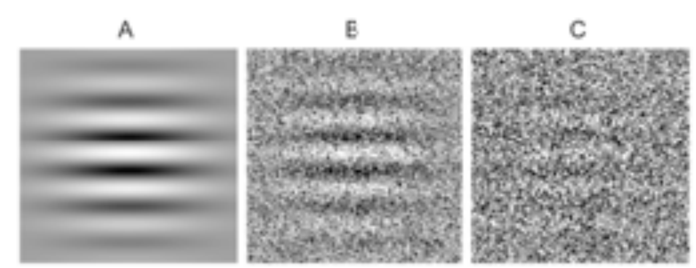

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2. It makes a fast perceptual-decision making possible

3. It is robust especially when the input signal is weak or when the information is ambiguous

4. It makes storage and retrieval easier by reducing additional computational load

Our impression of gradually evolving visual representations with variable levels of precision may be a grand illusion

Thank you

RA's: Robert Eisinger, Grace Kim, and Jordana Goldman

... and Subjects G.K., S.K., and J.G. (who worked hard on 3600 trials...)