



Visual search with heterogeneous distractors

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The psychophysics of visual search with heterogeneous distractors

 Andra Mihali,  Wei Ji Ma

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Explaining the effects of distractor statistics in visual search

 Joshua Calder-Travis,  Wei Ji Ma

doi: <https://doi.org/10.1101/2020.01.03.893057>

Visual search



Photo by Johannes Eisele/AFP—Getty Images



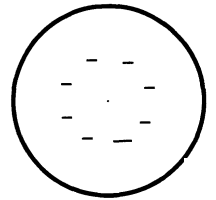
Photo by Lucy Orloski, Flickr



Photo from QLP Locksmith

Psychophysics / Signal detection approaches to visual search

- Deliberately very simple stimuli: *Palmer, Verghese, and Pavel (2000)*
 - unidimensional stimuli, parametrically varied
 - brief stimulus presentation times to prevent eye movements
 - stimuli at equal retinal eccentricities
 - wide spacing between stimuli



*Palmer, Ames
and Lindsay, 1993*

- SDT models
 - dissociate component processes (encoding and decision stages)
 - can predict accuracy as a function of set size and target-distractor similarity *Palmer, 1990, Shaw, 1982; Palmer et al., 1993; Eckstein et al., 2000; Verghese, 2001*

Distractor type	Psychophysics / SDT approach	Ecological validity
Homogenous	Extensive work, well understood	Lower
Heterogeneous	Less work, Less well understood	Higher

Visual search with heterogeneous distractors

- Distractor heterogeneity increases search time

Gordon, 1968; Gordon, Dulewicz, & Winwood, 1971; Farmer & Taylor, 1980, Lleras et al, 2019

- *Duncan & Humphreys (1989)* proposed that search performance
 - decreases as target-distractor similarity increases
 - decreases as distractor heterogeneity increases
 - interaction
- Tests: *Duncan and Humphreys 1989, Duncan 1989, Nagy & Thomas, 2003; Vincent et al., 2009*
- But:
 - heterogeneity has not been systematically varied (e.g. letters)
 - no process-level understanding of observer decision-making like in SDT

Psychophysics / Signal detection approaches to visual search with heterogeneous distractors

Some work with heterogeneous distractors within the SDT approach:

*Rosenholtz, 2001, Vincent et al, 2009, Ma et al, 2011,
Mazyar, van den Berg and Ma, 2012, 2013
Bhardwaj, van den Berg, Ma, and Josic, 2016*

But detailed characterizations of search performance with respect to distractor statistics and task types are still lacking

Outline

1. Assess in a comprehensive fashion which summary statistics related to distractor heterogeneity affect performance. Compare with *Duncan and Humphreys, 1989*
 - Two task types within subject: localization and detection *Liu, Healey and Enns, 2003, Cameron et al, 2004, Dukewich and Klein, 2009, Vincent 2011*
2. Fit an optimal-observer model and see if it accounts for these effects *Ma et al, 2011, Mazyar, van den Berg and Ma, 2012, Ma et al, 2015, Calder-Travis et al, 2020*
3. Visual search in memory: comparison with perception *Kuo, Rao, Lepsin and Nobre, 2009; Kong and Fougny, 2019*

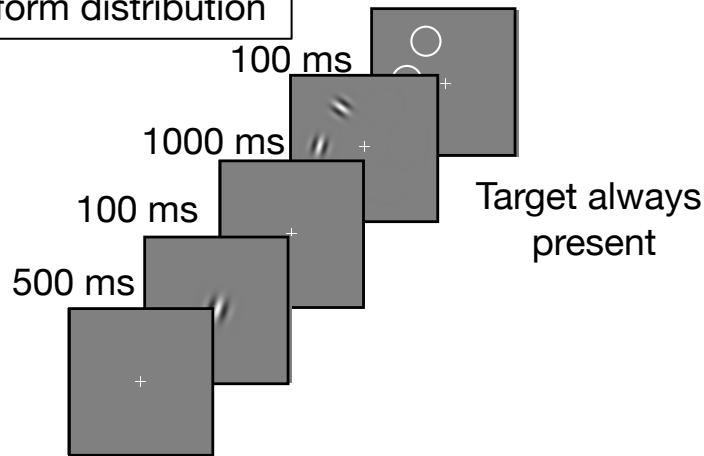
Visual search task: n-AFC localization and detection

Localization

Where was the target?

Mouse click

Set size: 2, 3, 4 or 6
Uniform distribution

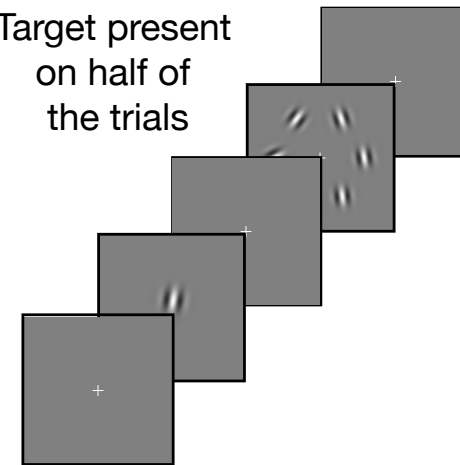


Detection

Target present or absent?

Button press

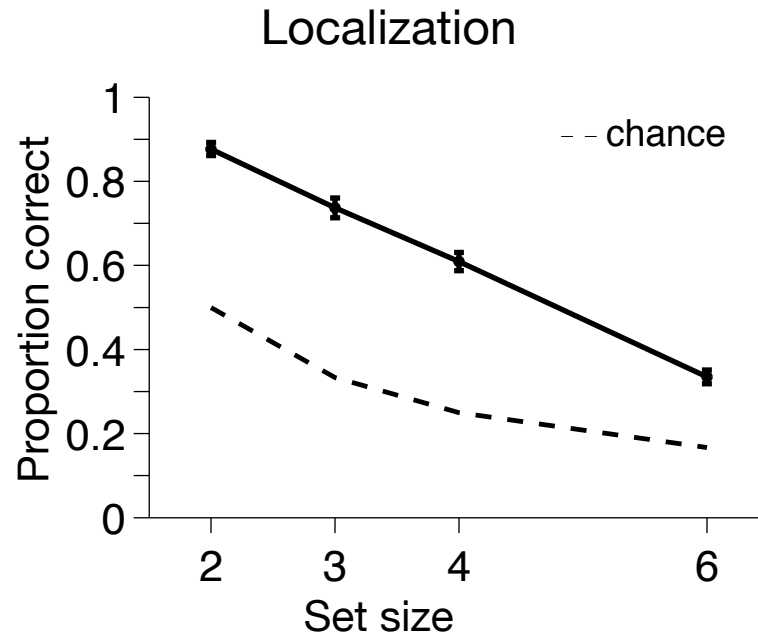
Target present
on half of
the trials



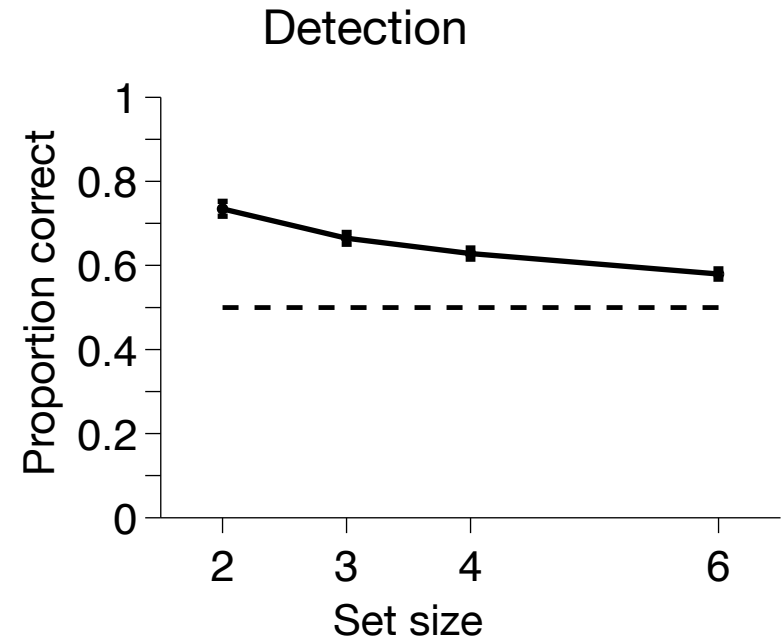
Observers also did a Memory condition, which we will discuss later

Accuracy as a function of set size

11 observers



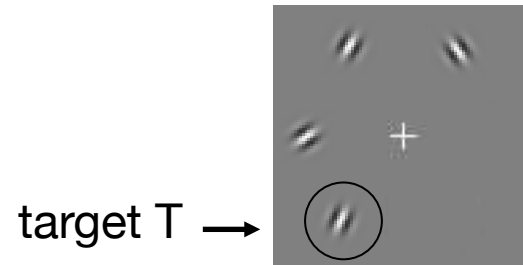
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Effect of set size: $p < 0.001$

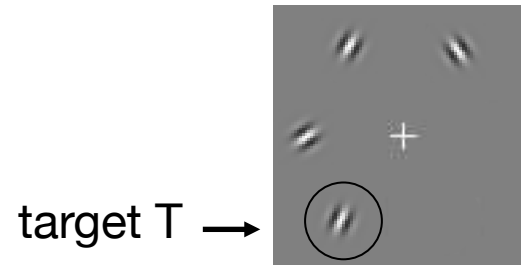
- However, many factors besides set size may affect performance
- More so than homogenous distractors, heterogeneous distractors afford rich summary statistics, which we will use to characterize behavior

Trial-by-trial summary statistics



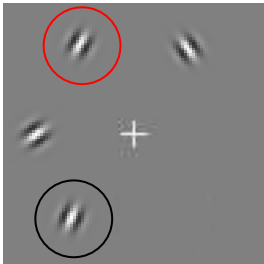
Within a trial, what distractor statistics can we extract?

Trial-by-trial summary statistics



Within a trial, what distractor statistics can we extract?

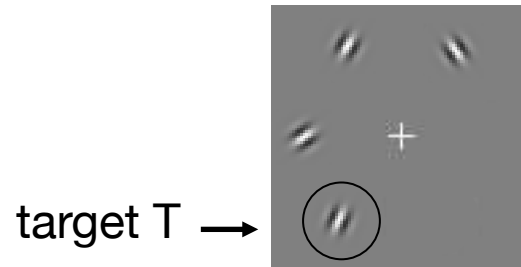
Most similar
distractor



Min T-D difference (°)

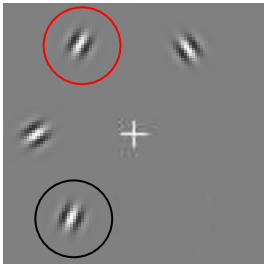
For both localization and detection

Trial-by-trial summary statistics



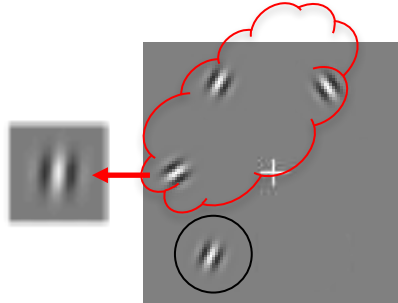
Within a trial, what distractor statistics can we extract?

Most similar
distractor



Min T-D difference (deg)

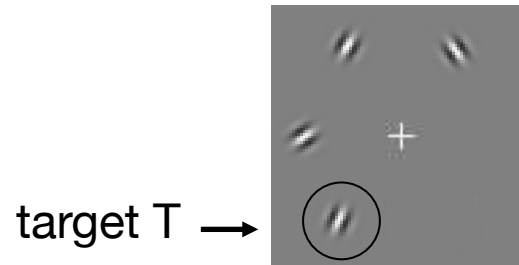
Circular mean
of distractors



T-D mean (deg)

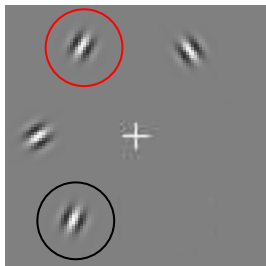
For both localization and detection

Trial-by-trial summary statistics



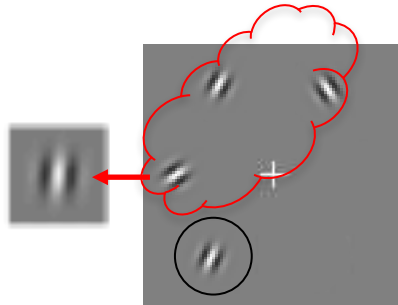
Within a trial, what distractor statistics can we extract?

Most similar
distractor



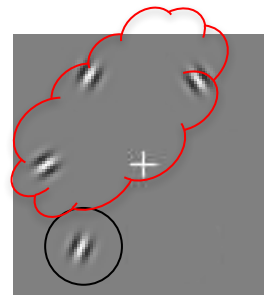
↓
Min T-D difference (deg)

Circular mean
of distractors



↓
T-D mean (deg)

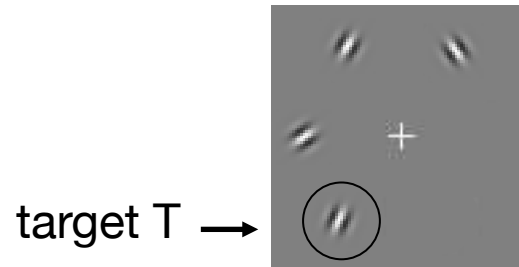
Circular variance (CV)
of distractors



↓
Distractor variance
>0, <1

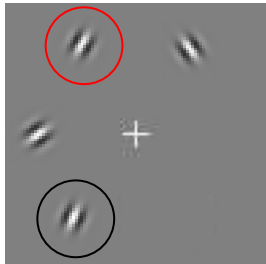
For both localization and detection

Trial-by-trial summary statistics



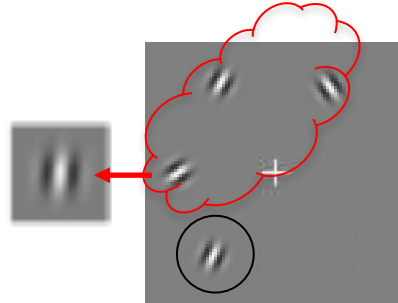
Within a trial, what distractor statistics can we extract?

Most similar
distractor



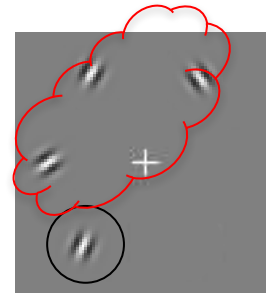
Min T-D difference (deg)

Circular mean
of distractors



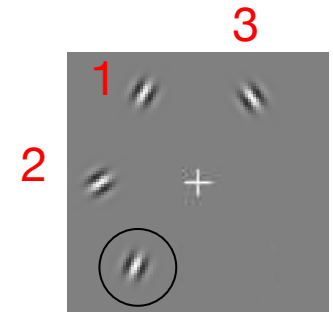
T-D mean (deg)

Circular variance (CV)
of distractors



Distractor variance
>0, <1

response to T?



Rank of similarity of
response to the target

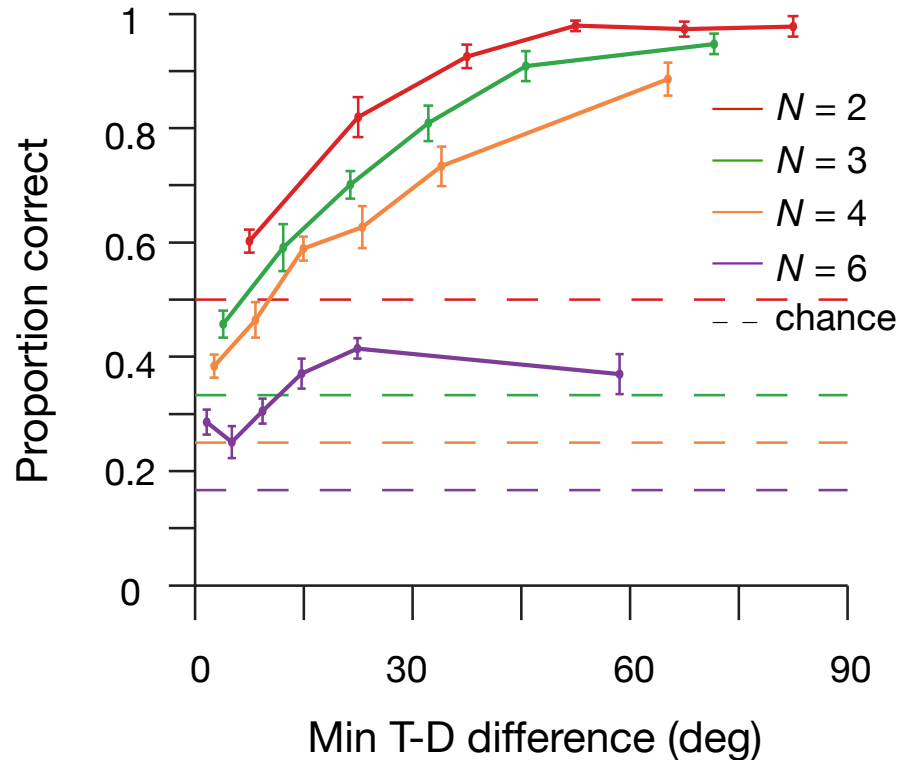
For both localization and detection

For localization
errors only

How does performance depend on these 4 trial-by-trial summary statistics?

Summary statistic 1: most similar distractor

Localization



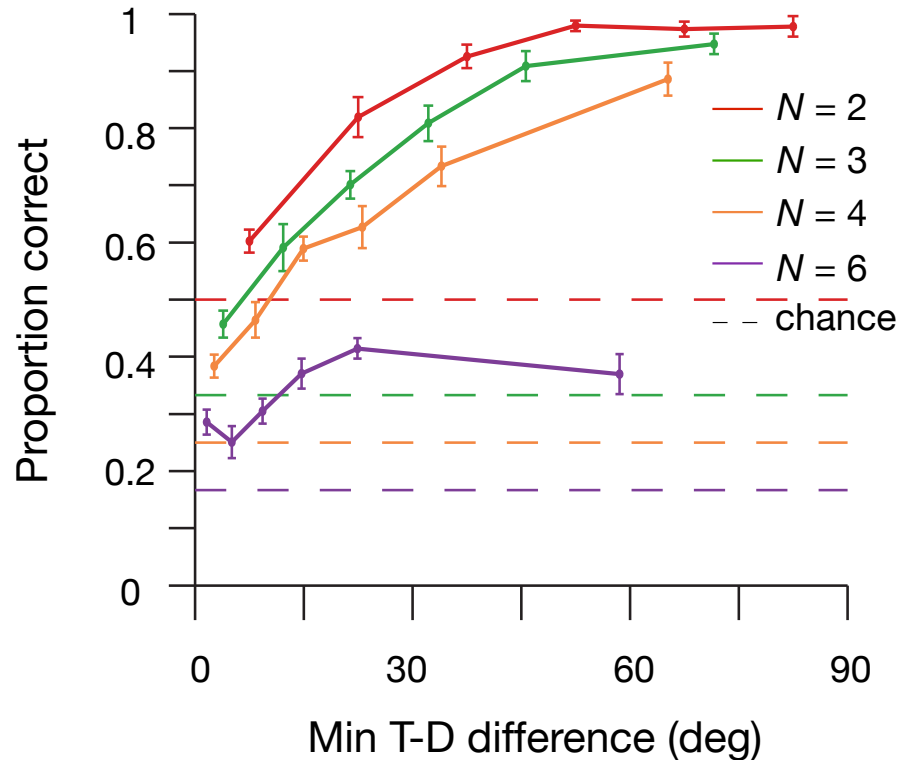
Effect of set size: $p < 0.001$

Effect of min T-D difference : $p < 0.001$

Interaction: $p < 0.001$

Summary statistic 1: most similar distractor

Localization

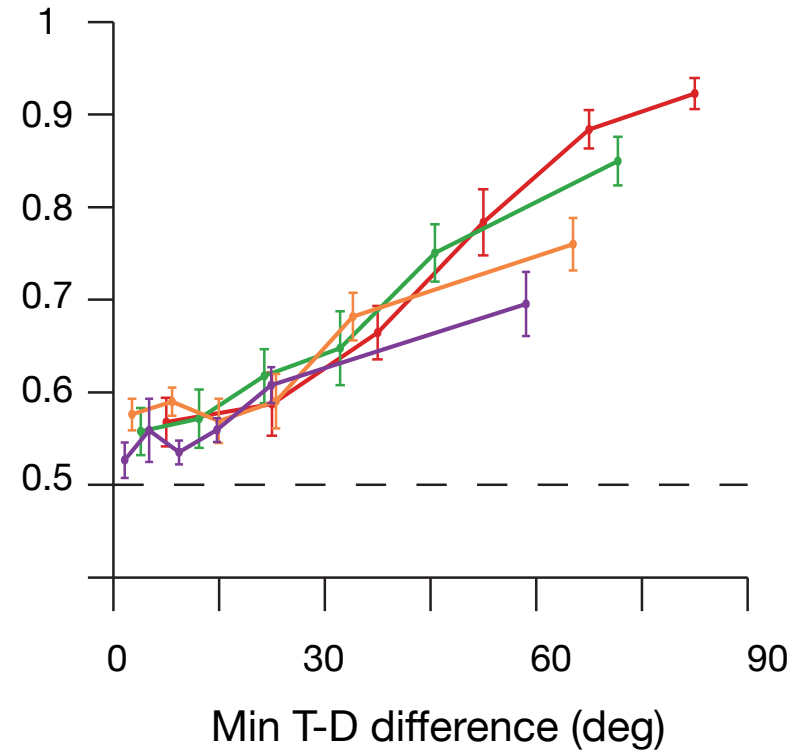


Effect of set size: $p < 0.001$

Effect of min T-D difference : $p < 0.001$

Interaction: $p < 0.001$

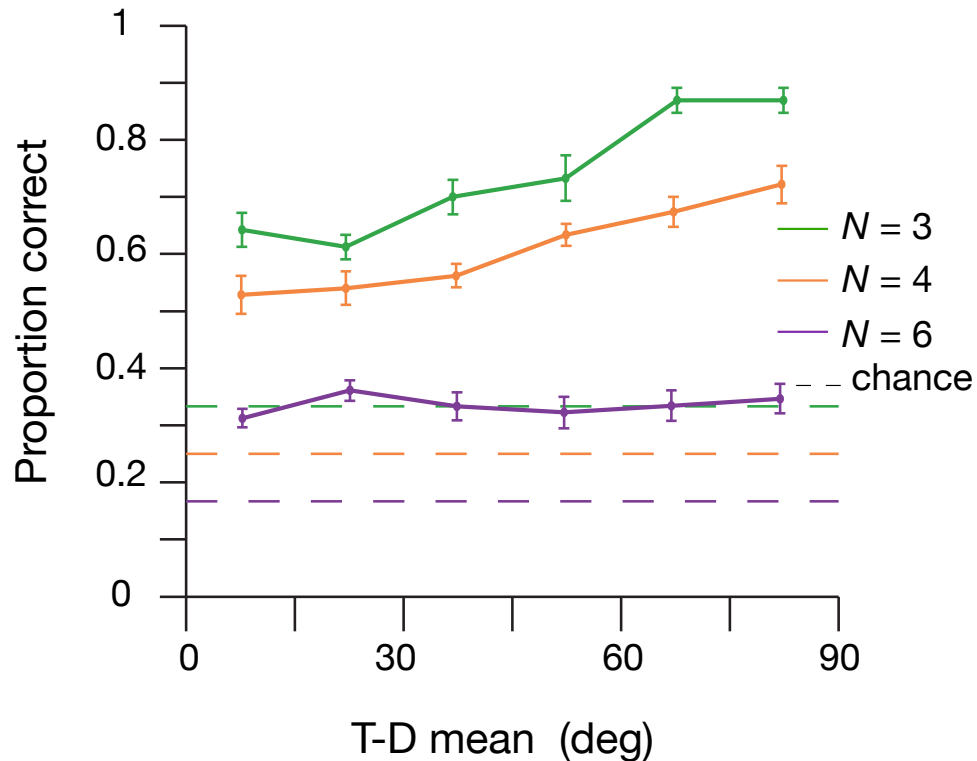
Detection



Effect of min T-D difference : $p < 0.001$

Summary statistic 2: based on the mean of distractors

Localization



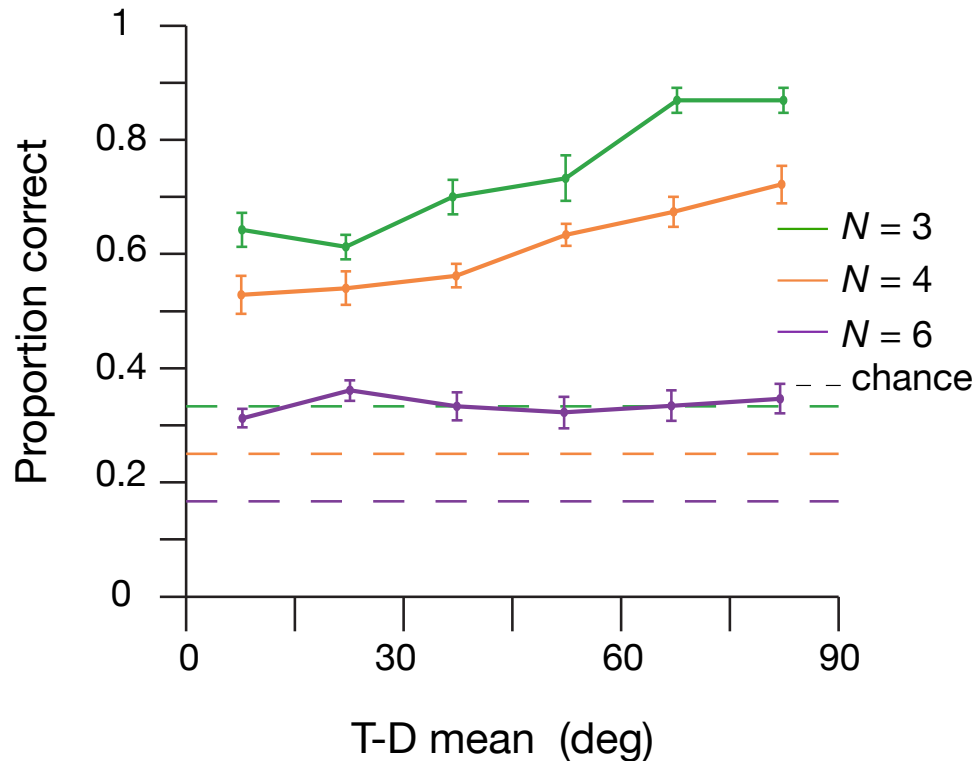
Effect of set size: $p < 0.001$

Effect of T-D mean: $p < 0.001$

Interaction: $p < 0.001$

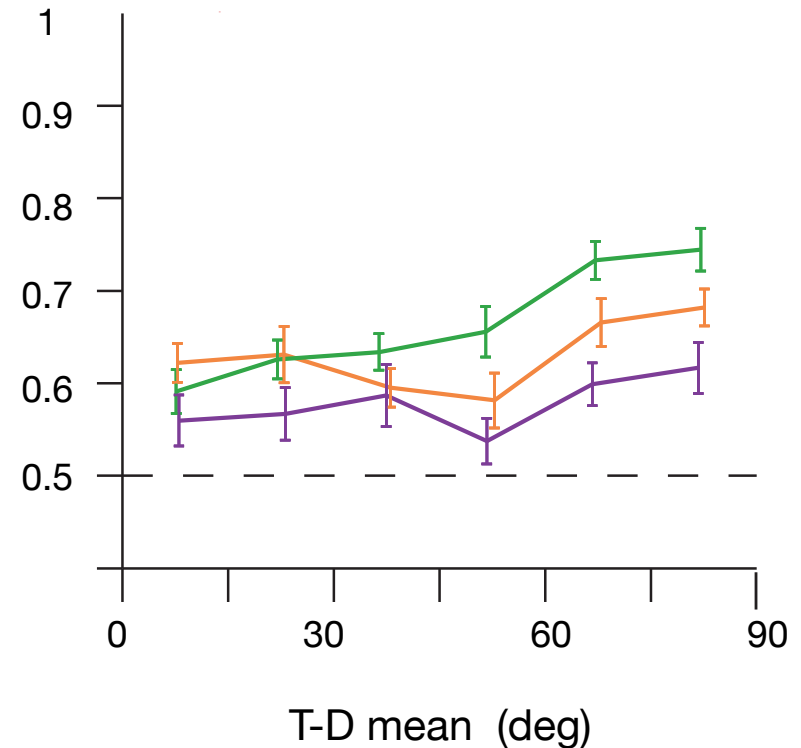
Summary statistic 2: based on the mean of distractors

Localization



Effect of set size: $p < 0.001$
Effect of T-D mean: $p < 0.001$
Interaction: $p < 0.001$

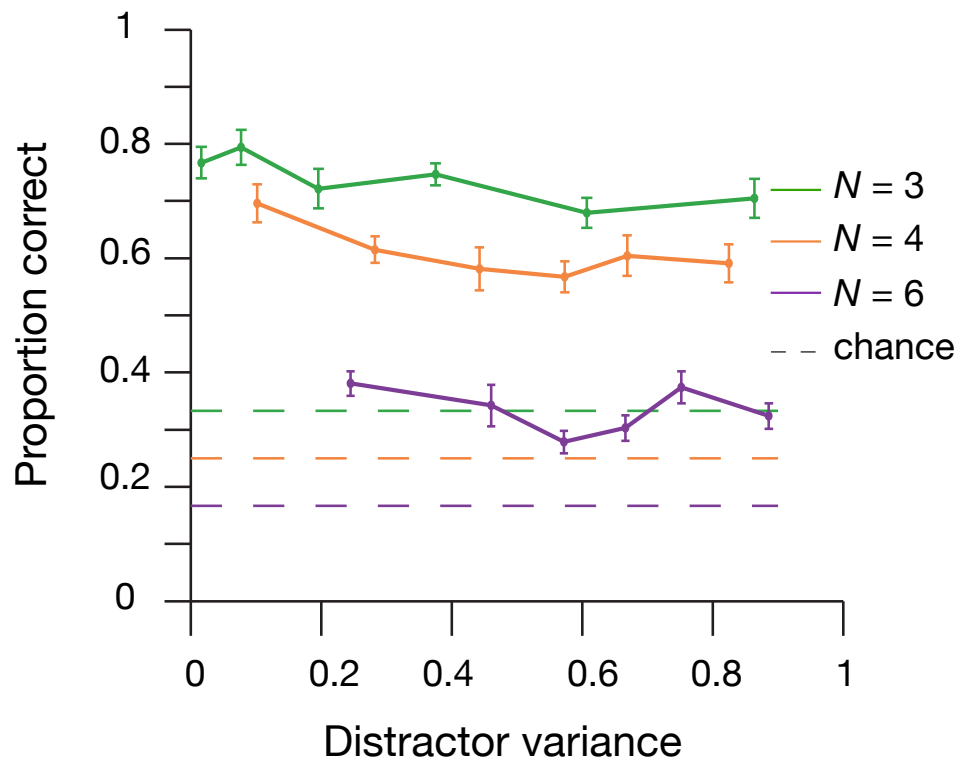
Detection



Effect of set size: $p < 0.001$
Effect of T-D mean: $p < 0.001$
Interaction: $p < 0.05$

Summary statistic 3: the circular variance of distractors

Localization

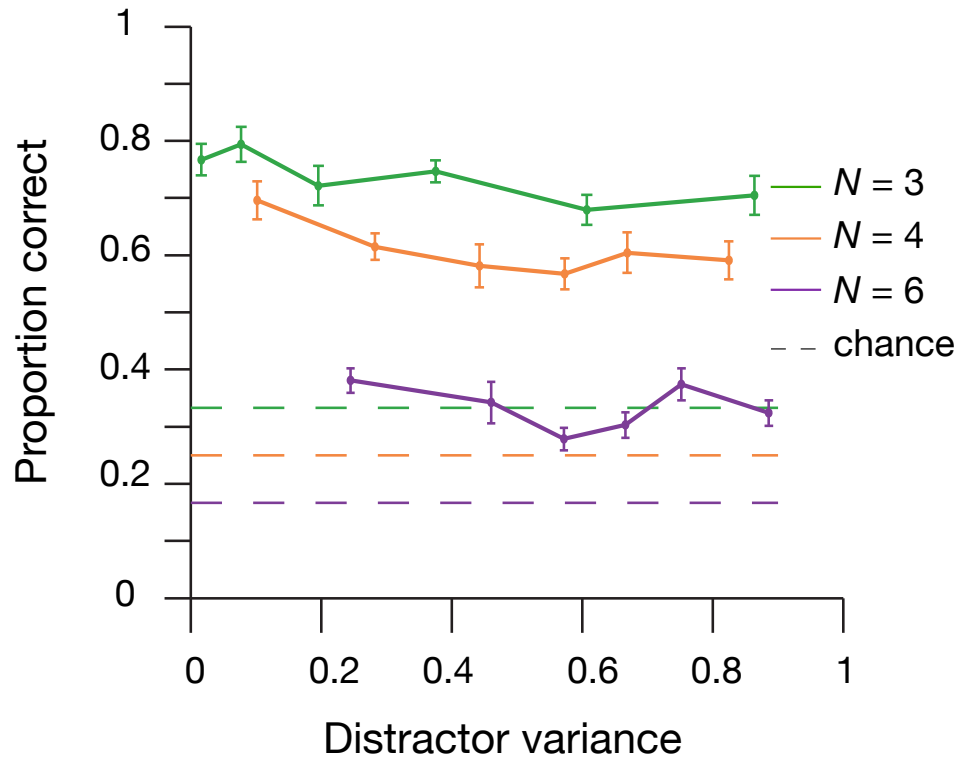


Effect of set size: $p < 0.001$

Effect of distractor variance: $p < 0.001$

Summary statistic 3: the circular variance of distractors

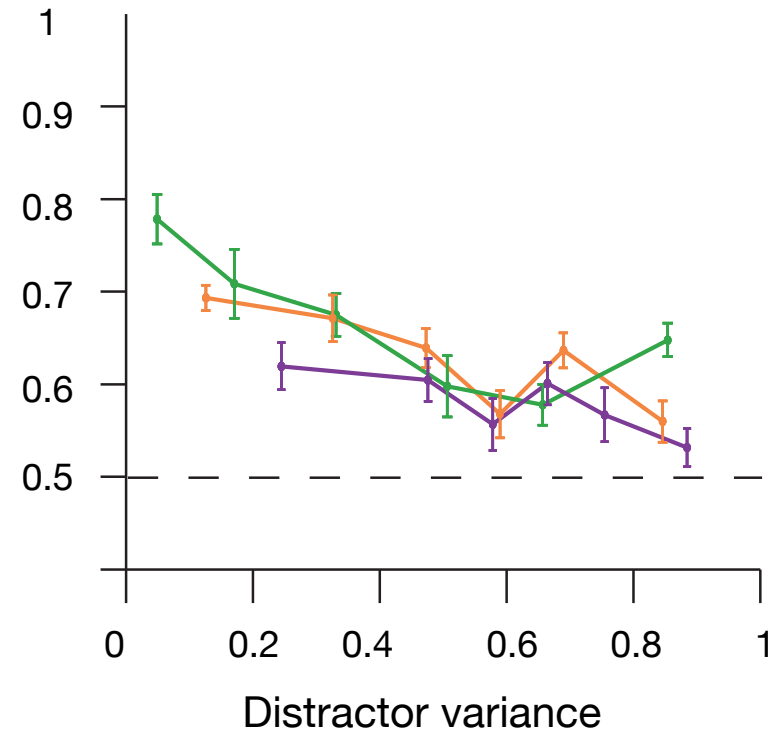
Localization



Effect of set size: $p < 0.001$

Effect of distractor variance: $p < 0.001$

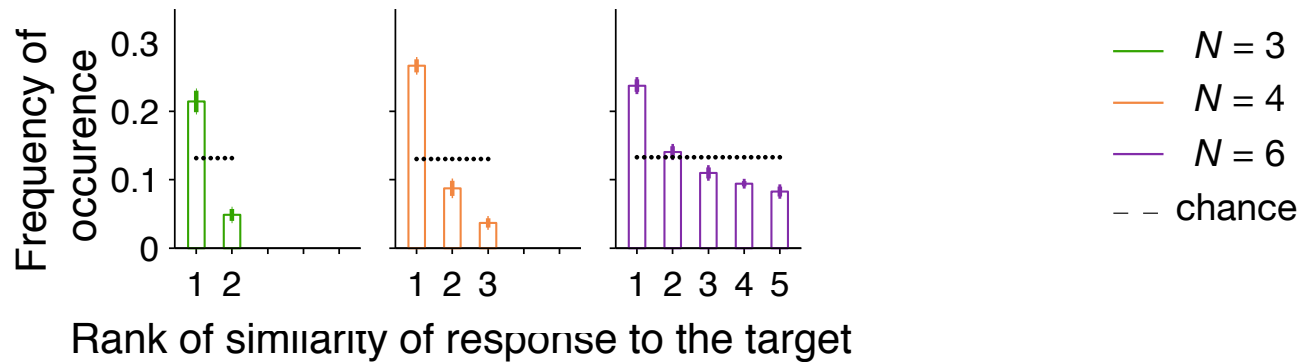
Detection



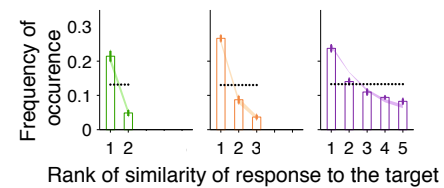
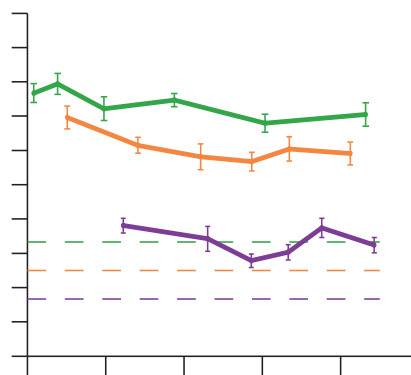
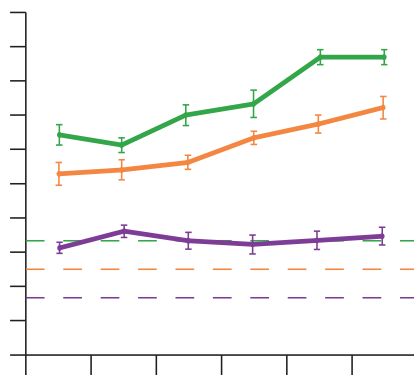
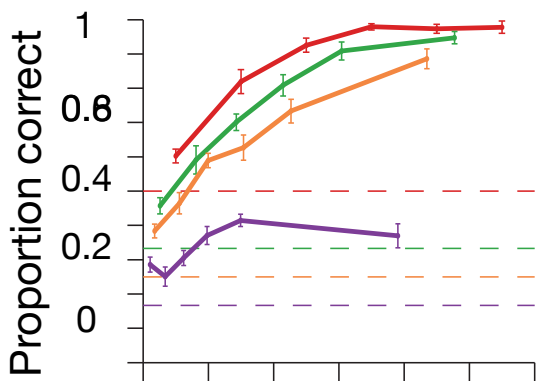
Effect of set size: $p < 0.05$

Effect of distractor variance: $p < 0.001$

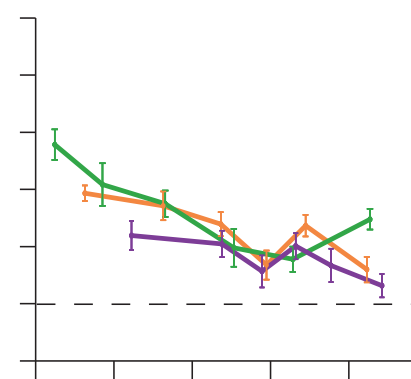
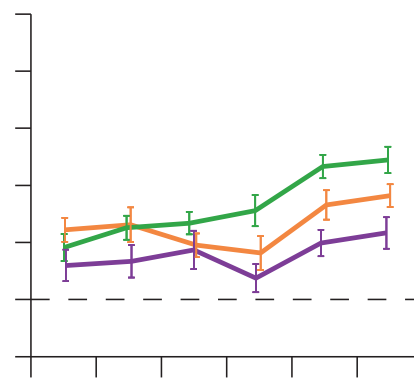
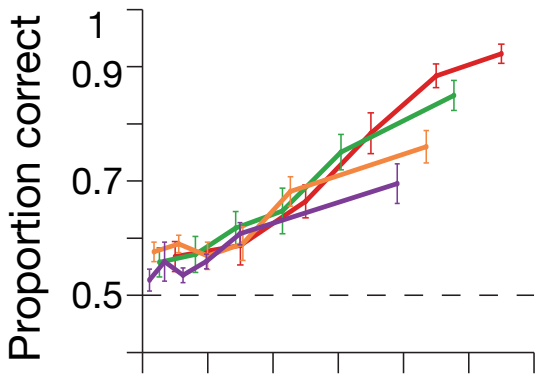
Summary statistic 4 (Localization errors only): Rank of similarity of response to the target



Localization



Detection



Min T-D difference (deg)

T-D mean(deg)

Distractor variance

Which summary statistics are *useful and necessary* for explaining performance?

Model comparison: method inspired by stepwise regression, from *Shen and Ma, 2019*

- Min T-D difference is the most *useful* regressor
- No regressor is *necessary*

Outline

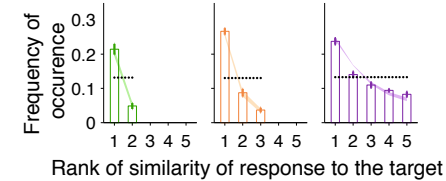
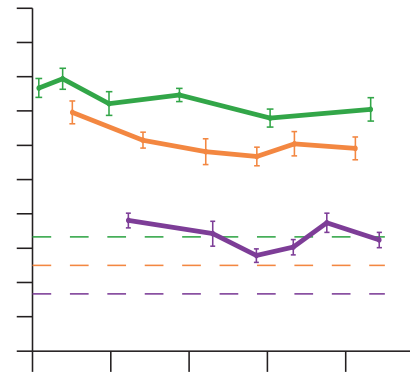
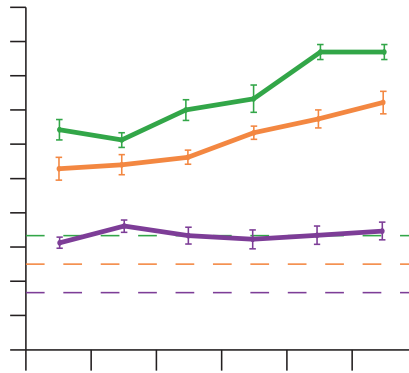
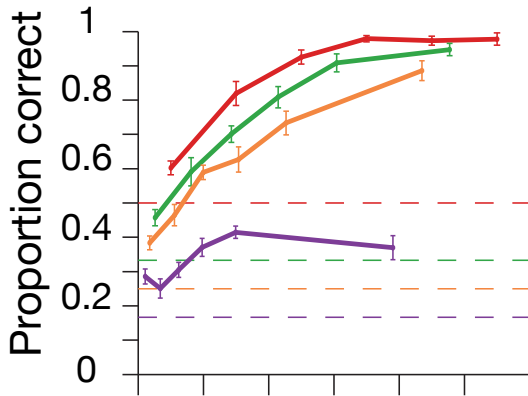
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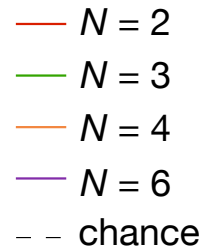
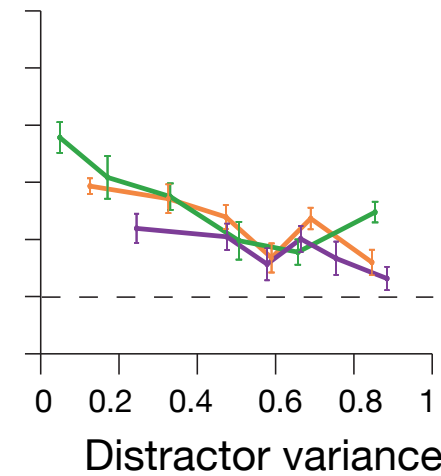
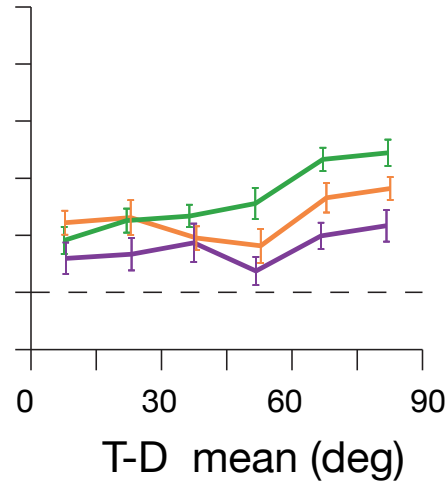
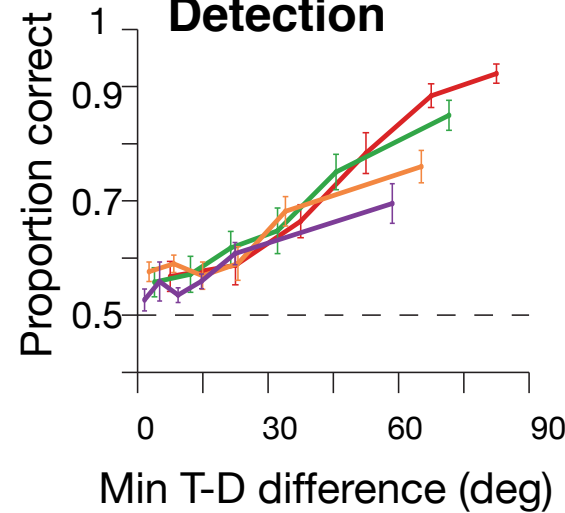
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Summary statistics

Localization



Detection



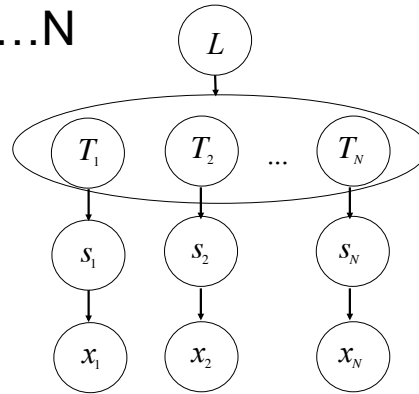
- Not just qualitative trends
- We will use the exact shapes of these curves to constrain the optimal-observer model.

Bayesian optimal-observer model

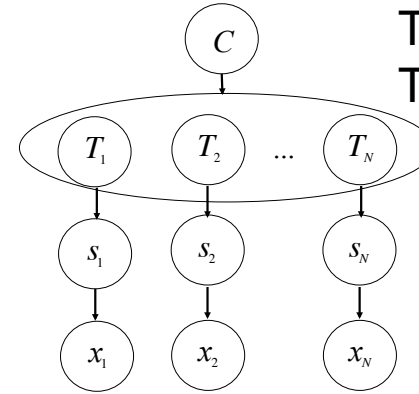
1. Encoding stage

- Stimuli \longrightarrow noisy measurements
- Same structure in Localization and Detection

Location $L = 1, 2, 3 \dots N$



Target present $C = 1$
Target absent $C = 0$



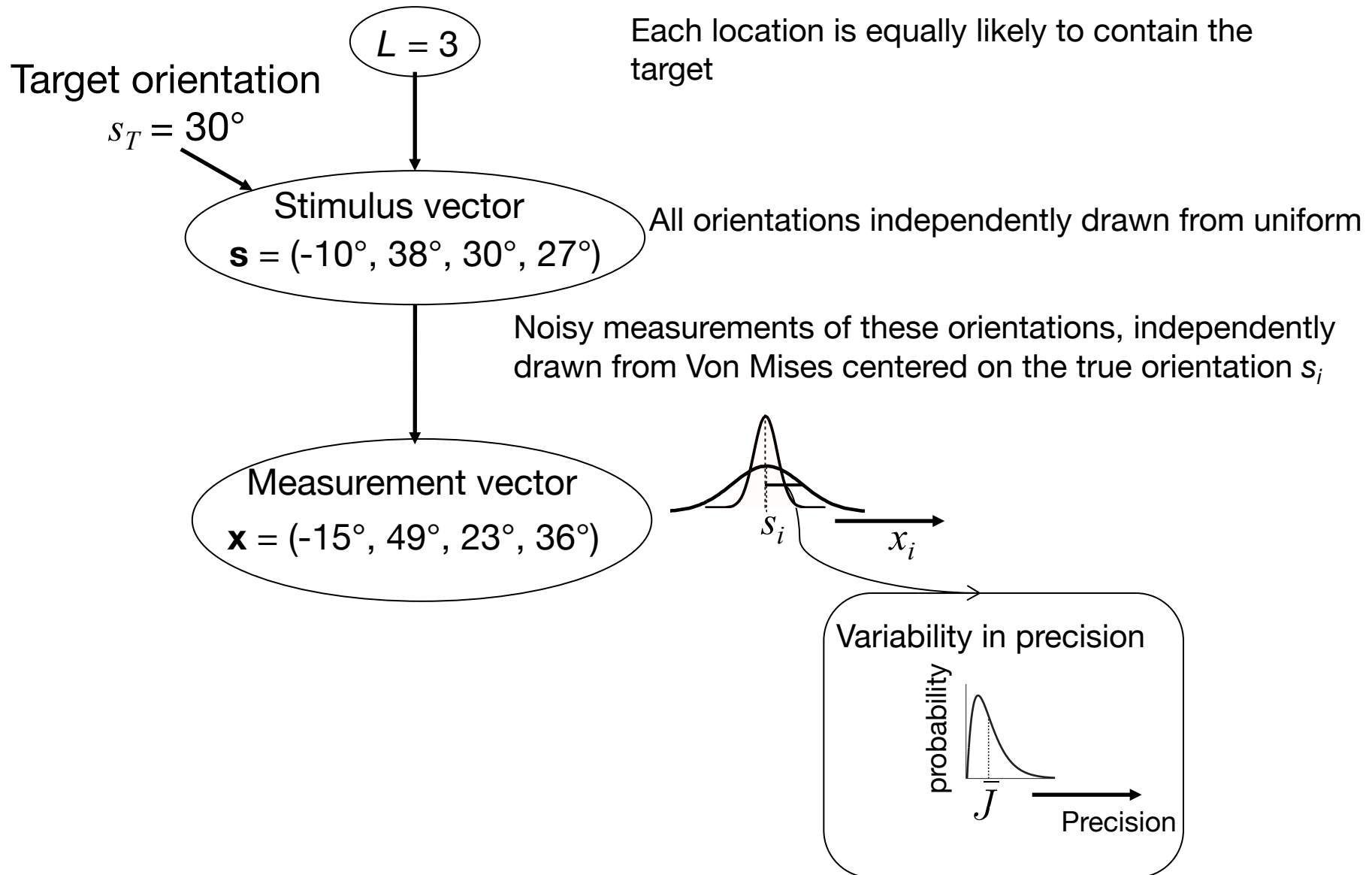
2. Decision stage

Based on the noisy measurements and knowledge of the encoding process:

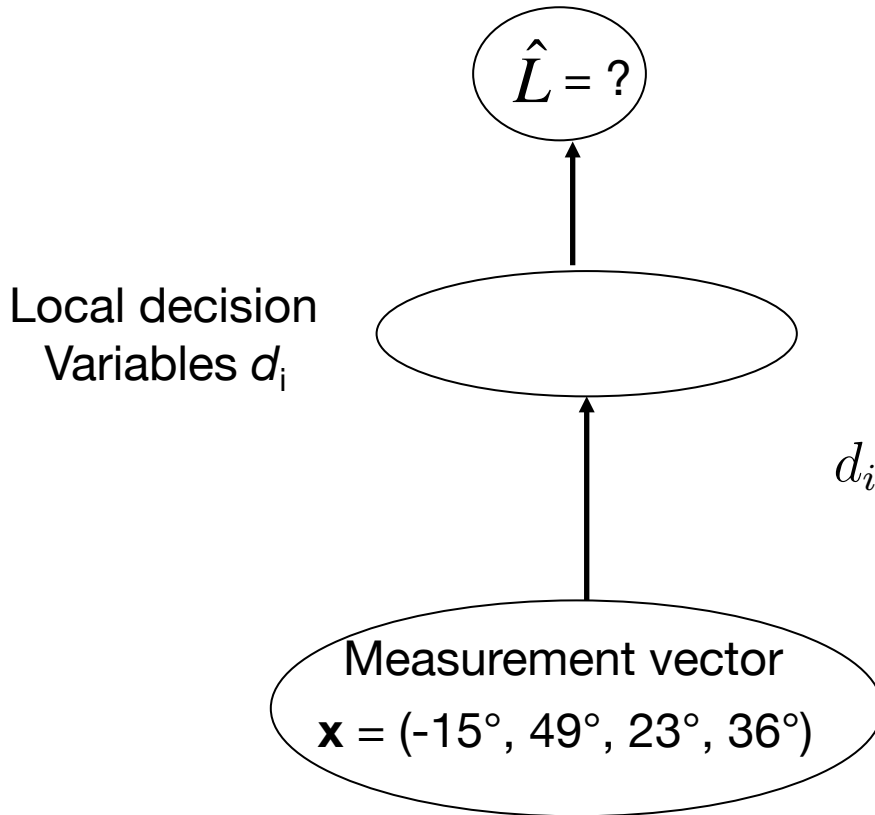
- Localization: The observer calculates the probability of each possible target location, chooses the most probable location.
- Detection (*Ma et al. 2011, Mazyar, van den Berg and Ma 2012*): the observer calculates the probability that the target is present and reports “target present” when it exceeds a criterion.

The optimal observer maximizes performance given the noise.

Optimal-observer model: encoding stage



Optimal-observer model: decision stage



$$\begin{aligned} d_i &= \log \frac{p(x_i | \text{target at location } i)}{p(x_i | \text{distractor at location } i)} \\ &= -\log I_0(\kappa_i) + \kappa_i \cos(x_i - s_T) \end{aligned}$$

Parameters and model fitting

- Parameters:
 - Mean precisions at set sizes 2, 3, 4, 6
 - Parameter for variability in precision
 - For detection: extra p_{present} parameter
 - decision noise parameters
- } Both separate and joint for Localization and Detection
- We fit the localization and detection data both separately and jointly
 - Maximum-likelihood estimation of parameters
 - Fit individual-subject data
 - Trial-by-trial predictions obtained through simulations
 - Algorithm: Bayesian Adaptive Direct Search, *Acerbi and Ma, 2017*

<https://github.com/NYUMaLab>

<https://www.cns.nyu.edu/malab/resources.html>

https://github.com/lianaan/Vis_Search

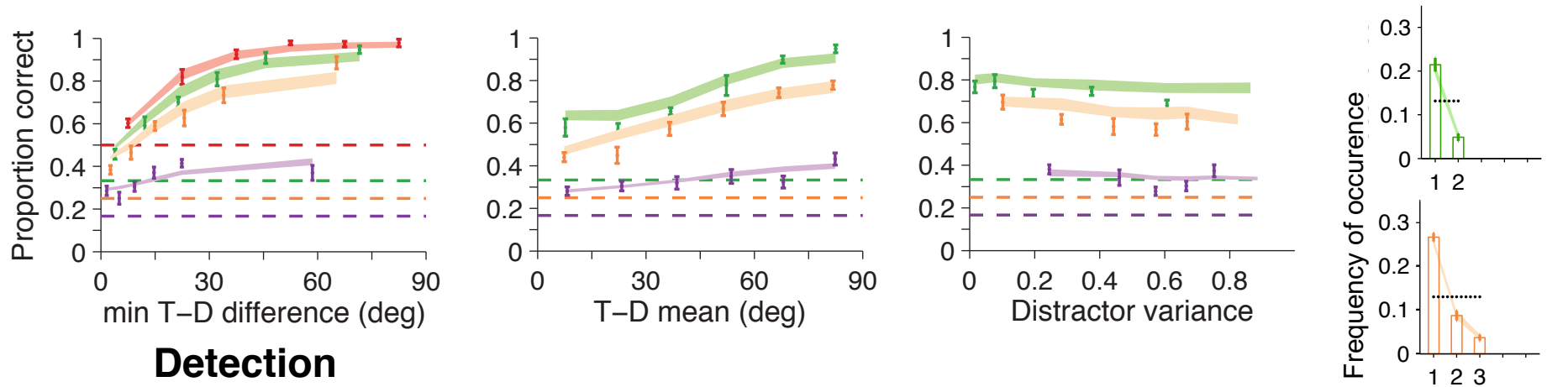
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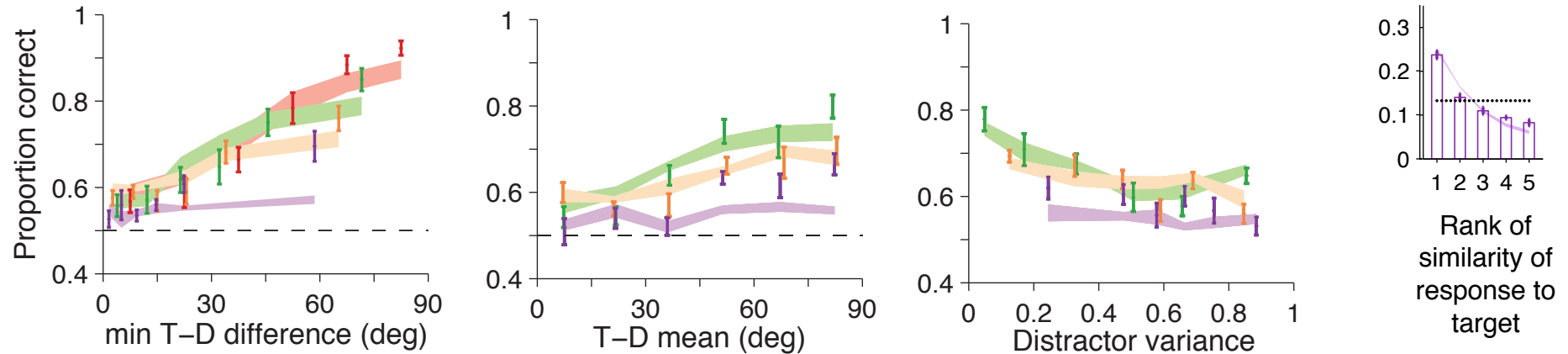
How well does the fitted optimal-observer model
account for the summary statistics?

Optimal-observer model fits – jointly to Localization and Detection

Localization



Detection

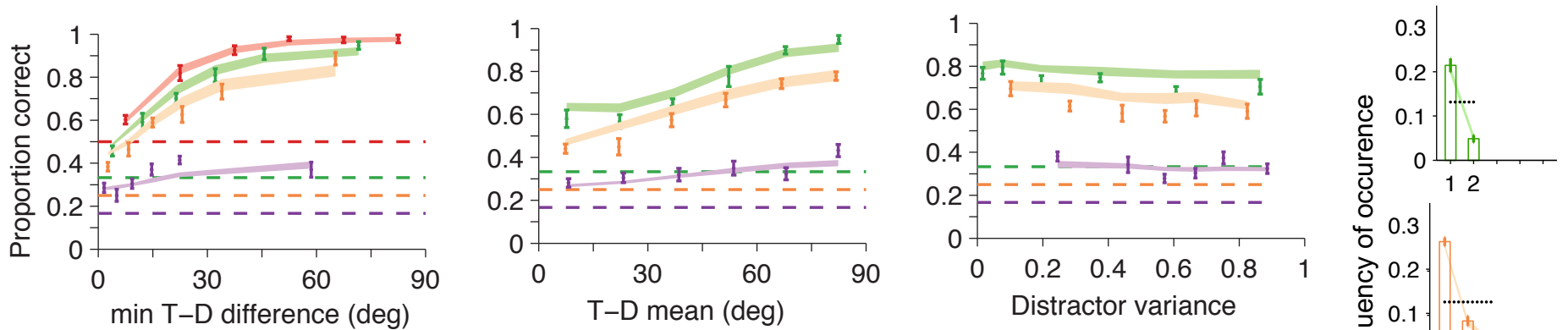


● data: mean and sem
■ model

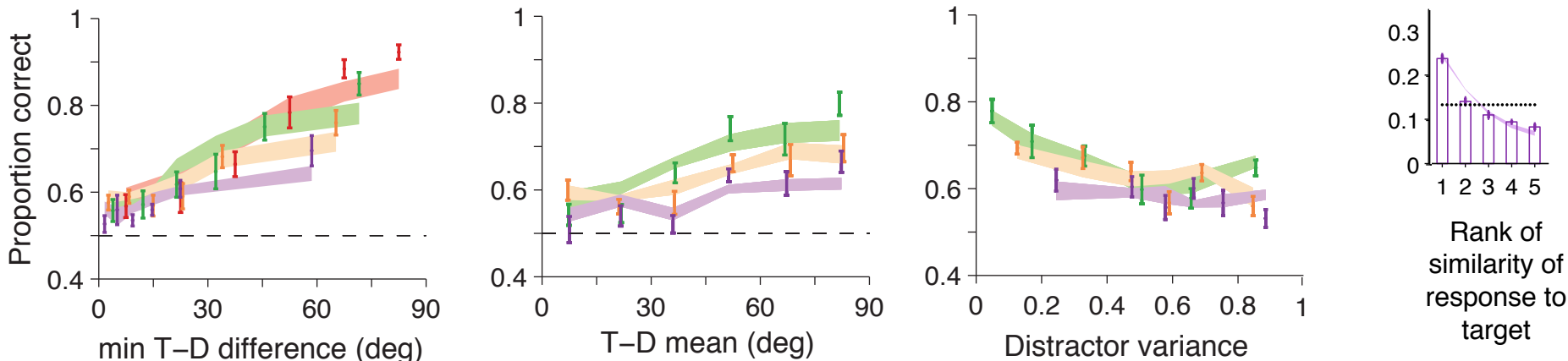
$N = 2$
 $N = 3$
 $N = 4$
 $N = 6$
--- chance

Optimal-observer model fits – separately to Localization and Detection

Localization



Detection



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2. Fit an optimal-observer model and see if it accounts for these effects
Ma et al, 2011, Mazzyar, van den Berg and Ma, 2012
 - Optimal-observer model captures the localization and detection data, separately and also jointly
 - Accounts for rich summary statistics in both task types
3. Visual search in memory: comparison with perception *Kuo, Rao, Lepsin and Nobre, 2009; Kong and Fournie, 2019*

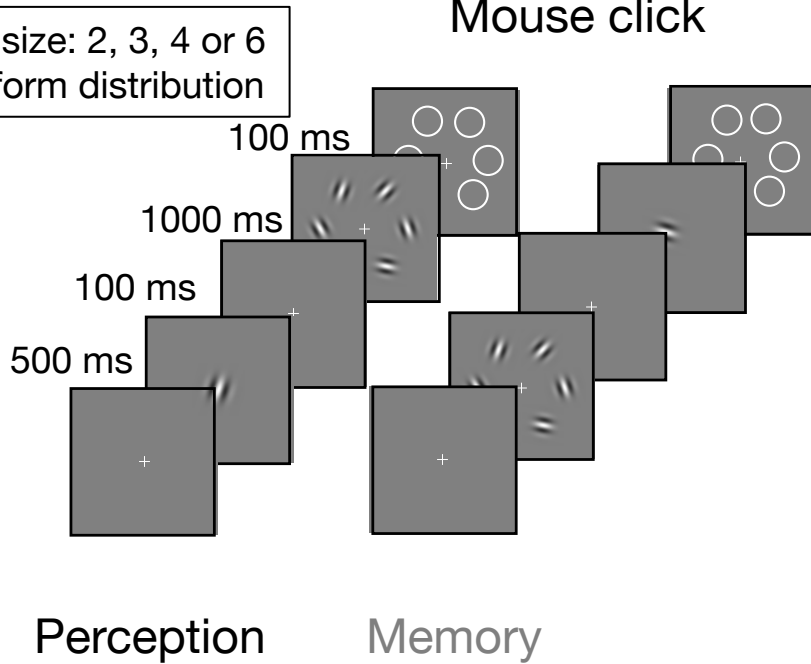
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Memory-based search

Localization

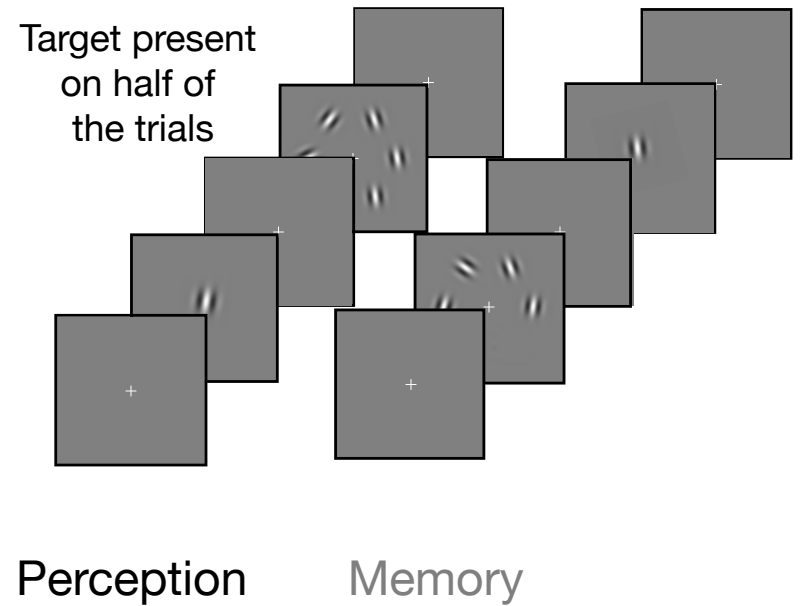
Where was the target?
Mouse click



Mihali and Ma, 2020

Detection

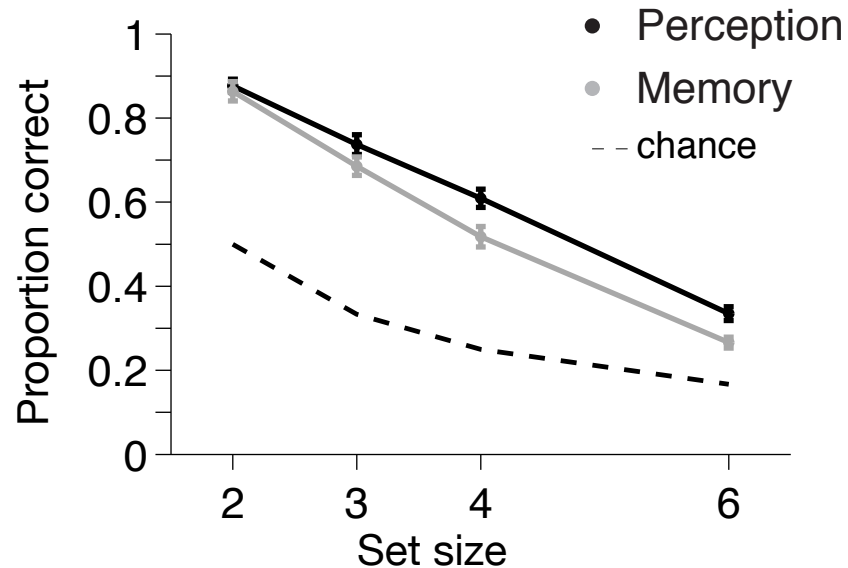
Target present or absent?
Button press



Mazyar, van den Berg and Ma, 2012

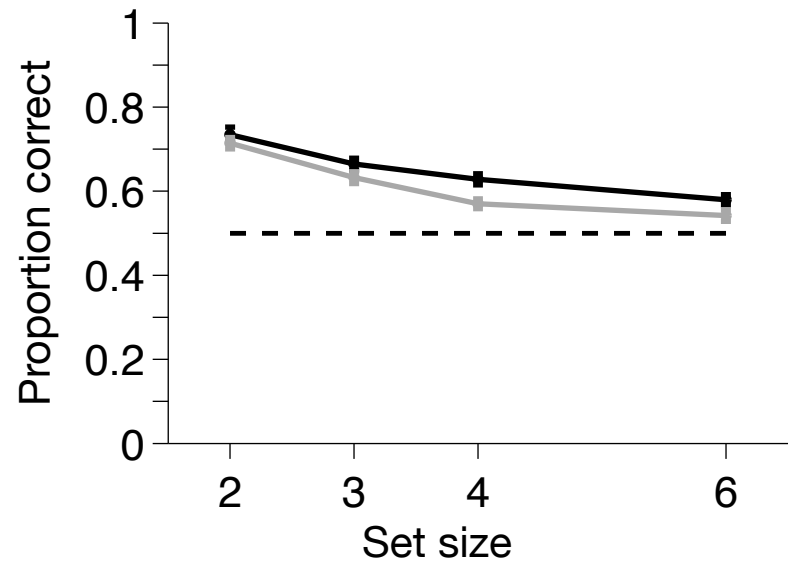
Accuracy as a function of set size

Localization



Effect of set size: $p < 0.001$
Effect of Perception/Memory: $p < 0.001$

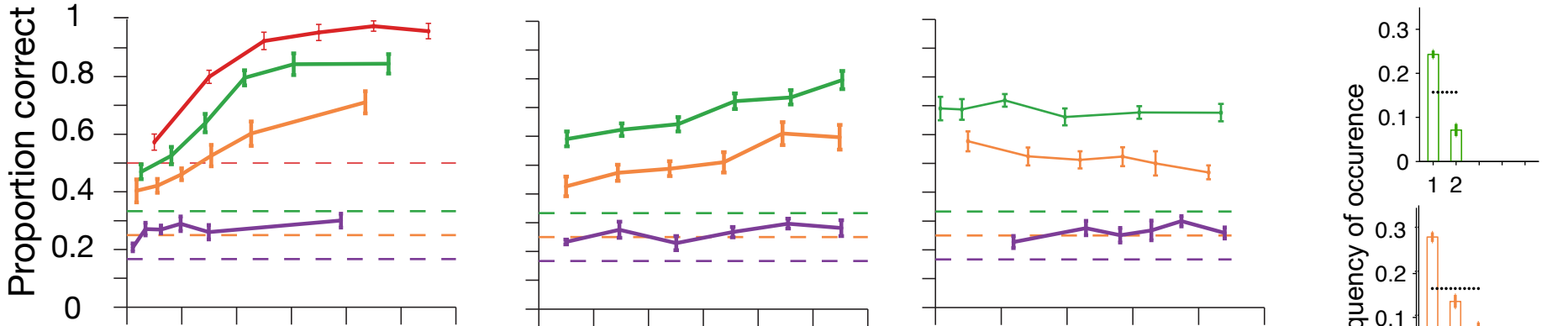
Detection



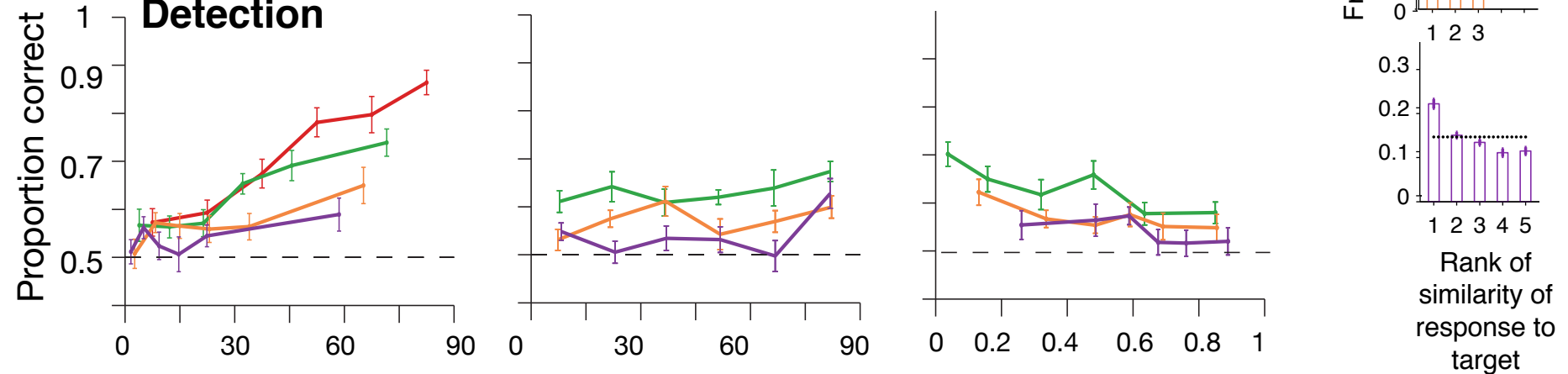
Effect of set size: $p < 0.001$
Effect of Perception/Memory: $p < 0.001$

Summary statistics: Memory

Localization



Detection



Min T-D difference (deg)

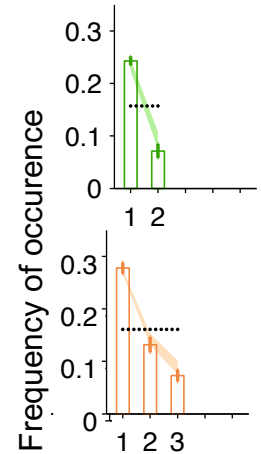
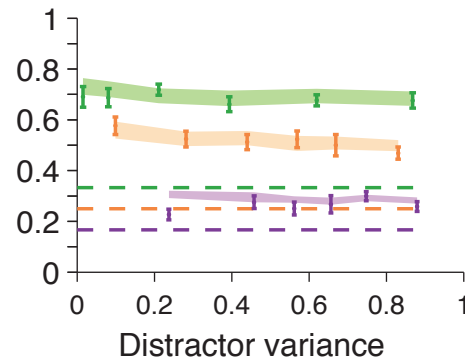
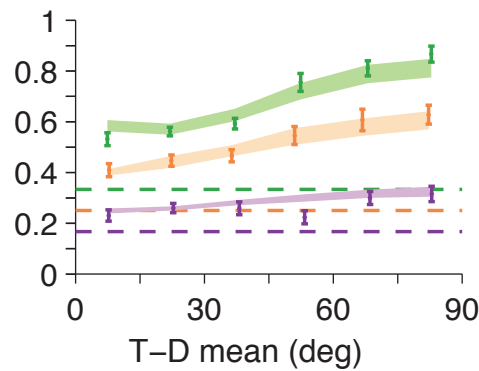
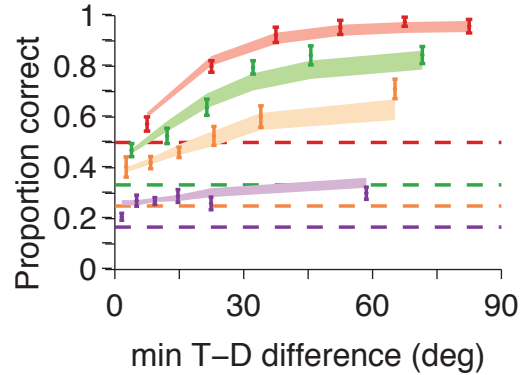
T-D mean(deg)

Distractor variance

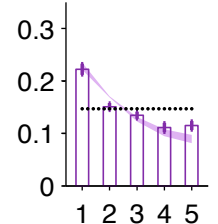
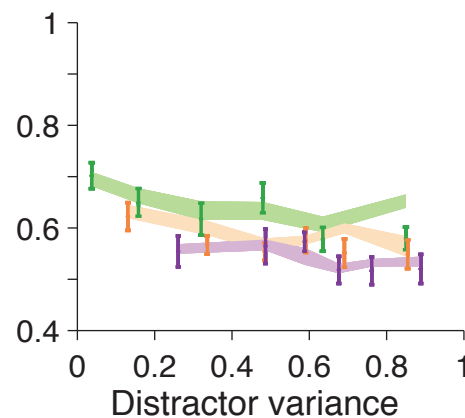
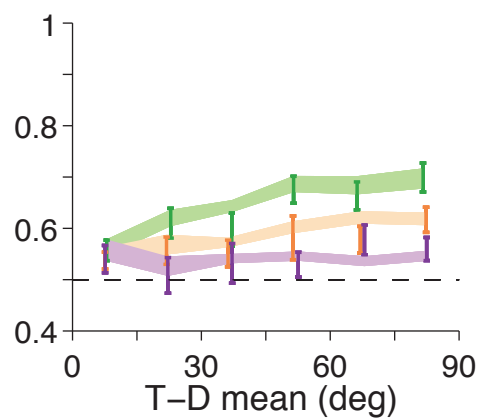
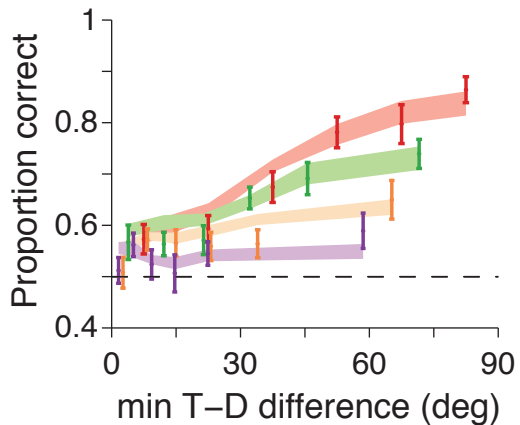
- $N = 2$
- $N = 3$
- $N = 4$
- $N = 6$
- chance

Optimal-observer in Memory – joint fits to Localization and Detection

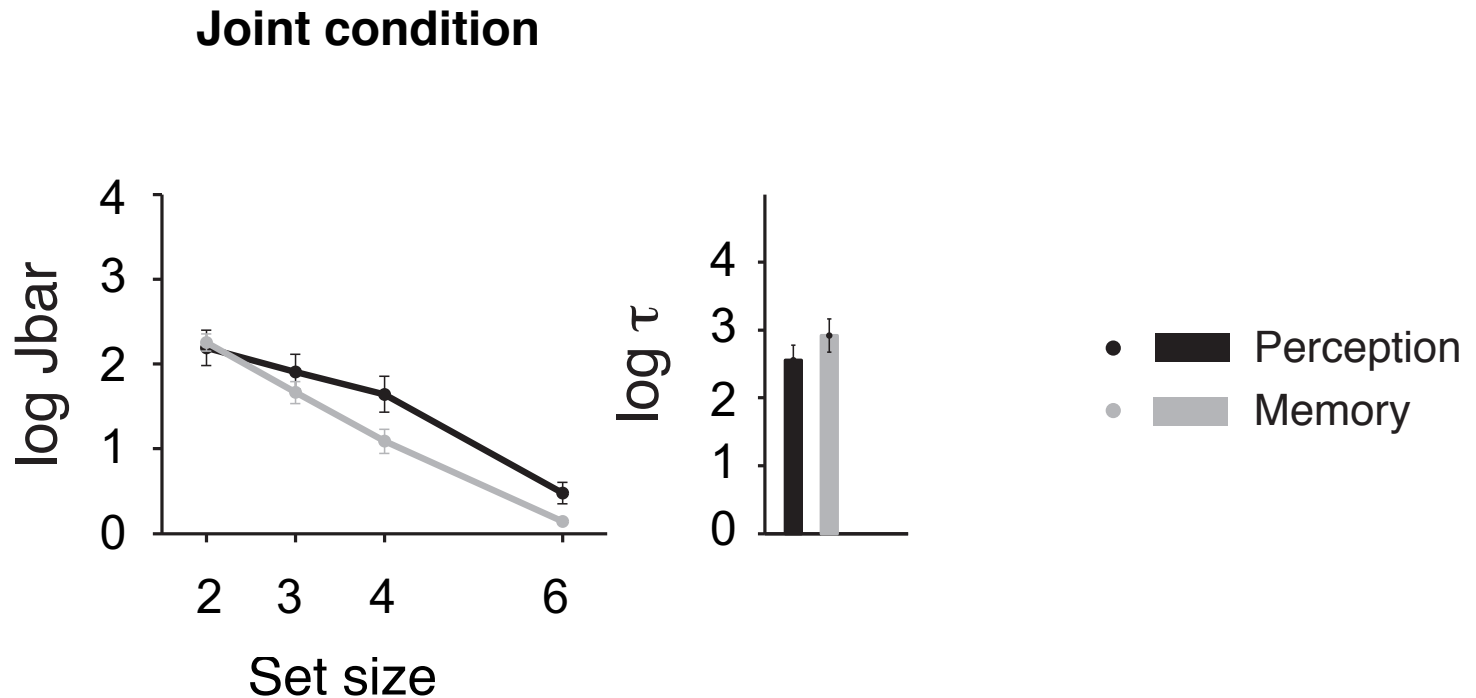
Localization



Detection



Mean precision parameter decreases with set size in perception and memory



Effect of set size: $p < 0.001$

Effect of Perception/Memory: $p < 0.05$

Outline

1. Assess in a comprehensive fashion which summary statistics related to distractor heterogeneity affect performance. Compare with *Duncan and Humphreys, 1989*
 - Two task types within subject: localization and detection *Liu, Healey and Enns, 2003, Cameron et al, 2004, Dukewich and Klein, 2009*
 - Strong effect of min T-D difference, weaker effects of circular mean and circular variance of the distractors. Min T-D difference was the most useful factor.
 - Consistent to some extent with Duncan and Humphreys (1989)

2. Fit an optimal-observer model and see if it accounts for these effects *Ma et al, 2011, Mazyar, van den Berg and Ma, 2012*
 - Optimal-observer model captures the localization and detection data, separately and also jointly
 - Accounts for rich summary statistics in both task types

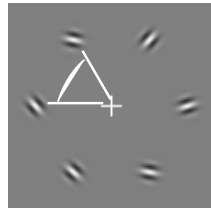
3. Visual search in memory: comparison with perception *Kuo, Rao, Lepsin and Nobre, 2009; Kong and Fournie, 2019*
 - Effect of summary statistics on performance very similar between Perception and Memory
 - Optimal-observer model also fits well to Memory
 - Accuracy and precision tend to be lower in Memory than in Perception

Experiment 2:

Consistent pattern of results with smaller stimulus spacing
(still outside the Bouma limit)

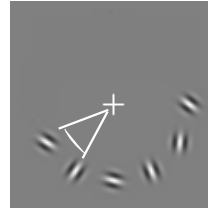
Experiment 1

60 deg



Experiment 2

30 deg



Conclusions

1. Assess in a comprehensive fashion which summary statistics related to distractor heterogeneity affect performance. Compare with *Duncan and Humphreys, 1989*
 - Two task types within subject: localization and detection *Liu, Healey and Enns, 2003, Cameron et al, 2004, Dukewich and Klein, 2009*
 - Strong effect of min T-D difference, weaker effects of circular mean and circular variance of the distractors. Min T-D difference was the most useful factor.
 - Consistent to some extent with Duncan and Humphreys (1989)

2. Fit an optimal-observer model and see if it accounts for these effects *Ma et al, 2011, Mazyar, van den Berg and Ma, 2012*
 - Optimal-observer model captures the localization and detection data, separately and also jointly
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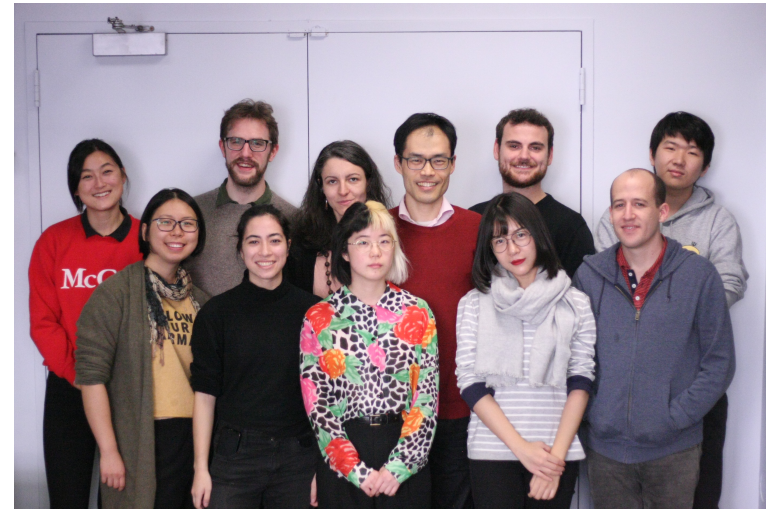
Limitations and open questions

- Interactions between summary statistics? Not enough trials to assess
- Why decision noise in detection, but not localization?
- Comparison with alternative models? either based on heuristics *Ma et al, 2011, Shen and Ma, 2016, Calder-Travis and Ma, 2020* or summary statistics *Rosenholtz, 1999, Avraham, Yeshurun, & Lindenbaum, 2008*
- Towards naturalistic visual search, but how close? *Wolfe, 1994, Najemnik and Geisler, 2005, Wolfe, 2010, Biggs and Mitroff, 2014, Yang et al, 2017, Boettcher et al, 2018, Geng and Witkowski, 2019, Radulescu, van Opheusden et al, 2020*
- Nevertheless, revisiting psychological theories with optimal-observer models can contribute to our understanding of visual search, and more broadly to psychology and neuroscience.

Thanks:

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Thank you for your
attention!