Greater than Parallel:

Distinguishing features can be combined for efficient object identification in dual-target search

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Object Identification in Visual Search

Two major processes in visual search: *Attentional guidance* and *object identification.*

- Guidance biases our attention toward relevant and away from irrelevant visual information (e.g., find shiny things and ignore pillows if looking for car keys). Once the eyes land on a relevant item, it must then be identified and confirmed or disconfirmed as the object of interest. Many studies have examined attentional guidance (e.g., Duncan & Humphreys, 1989; Wolfe, et al., 1989). **However, object identification has largely been a black box in studies of visual search.**
- Recently, however, Godwin, et al. (2015) examined object identification processes, comparing identification efficiencies when people looked for single items versus two items simultaneously. Results revealed that **object identification is more efficient in dual- than in single-target search when people are looking for complex, real-world objects** (see also Hout & Goldinger, 2015).
- **Why are people more efficient when looking for multiple, complex objects than when looking for singular objects?**

The Capacity Coefficient

- Quantitative index of processing efficiency (Townsend and Wenger, 2004; Wenger & Townsend, 2000) that can be used to compare single- and dual-target detection performance.
- Although RTs will usually be slower in dual-target search due to statistical slowdown, the Capacity Coefficient determines the extent of this slowdown, in single-target relative to dual-target search.
- **Ratio of single-target to dual-target distractor rejection efficiency,** derived from cumulative distribution of RTs.
- Baseline = Unlimited capacity, independent parallel (UCIP) model.

Three Possible Outcomes:

- ***C(t)* = 1:** UCIP baseline. Single- and dual-target comparisons are equally efficient.
- ***C(t)* < 1:** Limited capacity. Single-target comparisons are more efficient than dual-target comparisons.
- ***C(t)* > 1:** Supercapacity: Dual-target comparisons are more efficient than single-target comparisons. Benefit in multiple-target search (e.g., processing *shared features* simultaneously). **We predicted supercapacity search for more complex objects.**

Computing *C(t)*:

Cumulative Distribution Function for UCIP baseline:

$$P\{T_{12} \le t\} = P\{T_1 \le t\} \times P\{T_2 \le t\} \quad (1)$$

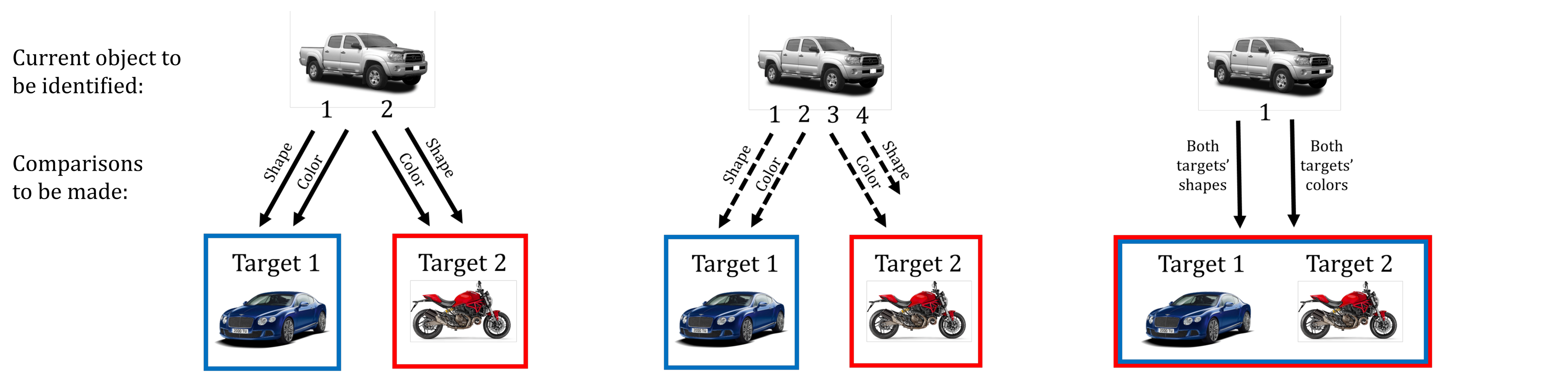
Cumulative reverse hazard function; logarithm of Equation 1:

$$K_{12}(t) = K_1(t) \times K_2(t) \quad (2)$$

Capacity Coefficient:

$$C_{AND}(t) = \frac{K_1(t) + K_2(t)}{K_{12}(t)} \quad (3)$$

Why was object identification more efficient for complex objects? Shared individuating features:



$C(t) = 1$
UCIP; equivalent to two independent, single-target comparisons

$C(t) < 1$
Limited capacity; less efficient than processing single targets in isolation. Serial or cascaded processing of each feature for each target, for example.

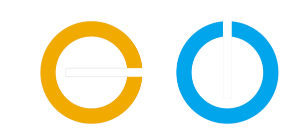
$C(t) > 1$
Supercapacity; features of both targets are pooled for efficient distractor rejection.

Godwin, et al. (2015):

Targets:

Simple: Two features (color, orientation)

Complex: Many features (color, shape, pattern, etc.)



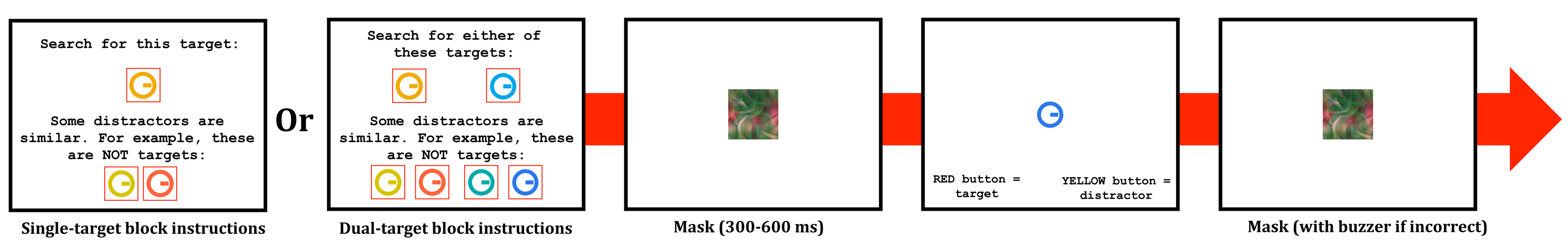
$C(t) < 1$ Limited Capacity

$C(t) > 1$ Supercapacity

Does adding features result in more efficient object identification?

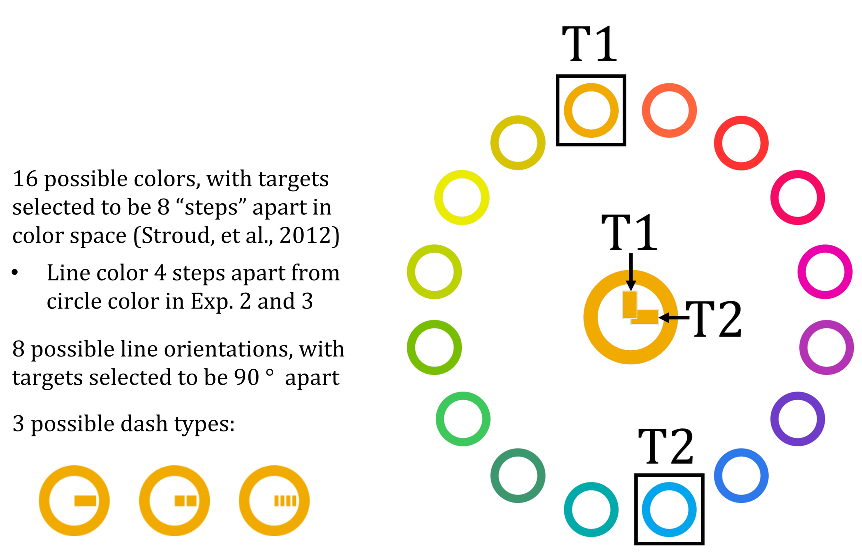
- Features of real objects are difficult to quantify. Solution: Use artificial stimuli, adding features incrementally.

Procedure: All experiments



Single-target block instructions — Dual-target block instructions — Mask (300-600 ms) — Mask (with buzzer if incorrect)

- 16 possible colors, with targets selected to be 8 "steps" apart in color space (Stroud, et al., 2012)
  - Line color 4 steps apart from circle color in Exp. 2 and 3
- 8 possible line orientations, with targets selected to be 90 ° apart
- 3 possible dash types:

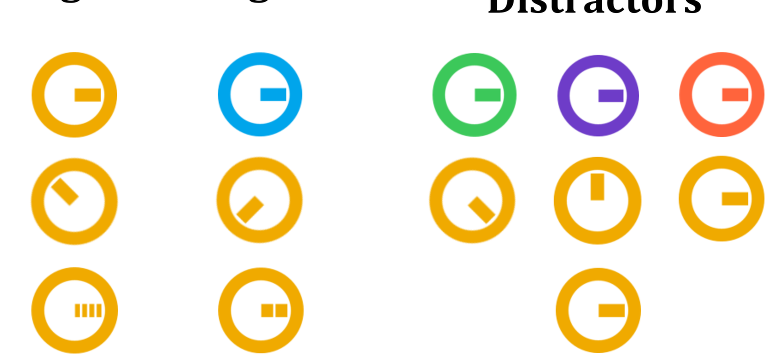


Experiment 1: Single Feature Search

- Feature types counterbalanced between-subjects

Target 1 | Target 2 | Example Distractors

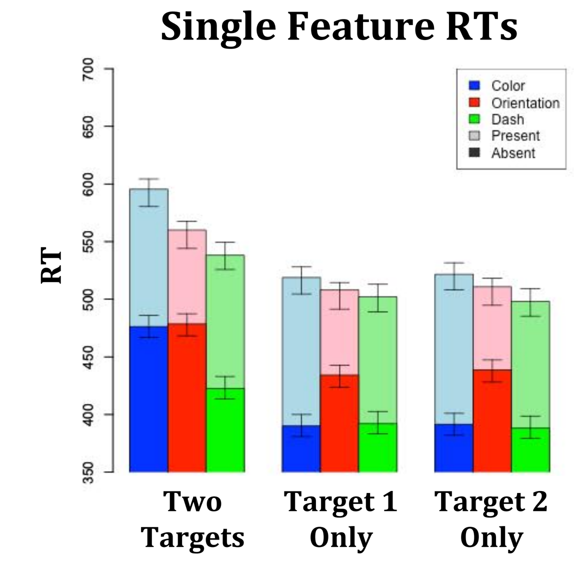
1. Color
2. Orientation
3. Dash Type



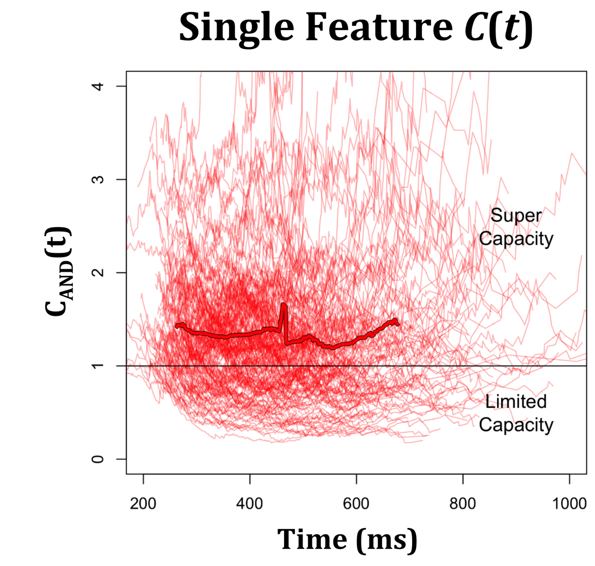
Results

- First, individual *Cz* computed for each subject using the Houpt-Townsend capacity test (Burns, et al., 2013; Houpt & Townsend, 2012).
- Next, Bayesian *t*-tests compare relative likelihood of models with non-zero group-averaged *Cz* to models with zero-centered average *Cz*.

Single Feature RTs



Single Feature *C(t)*



Supercapacity Performance

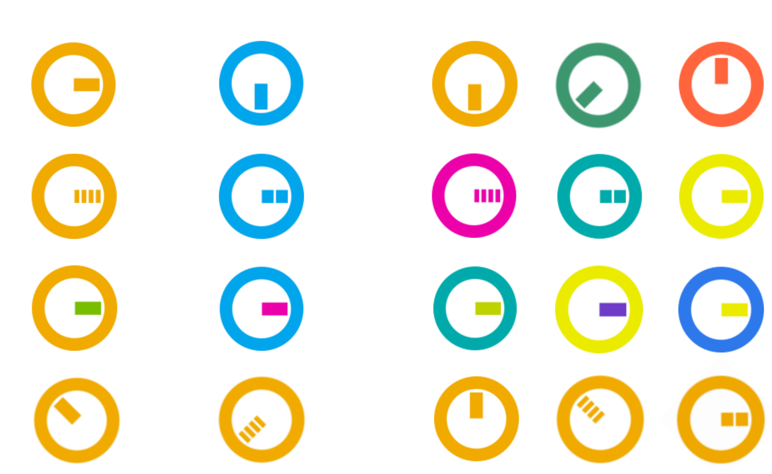
BF (Bayes Factor) = 4.90 × 10^7

M_{Cz} = 2.02, 95% HPD: [1.43, 2.63]

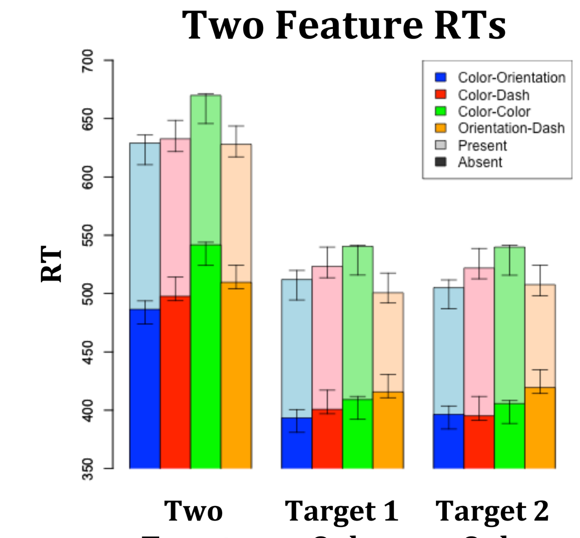
Experiment 2: Two Feature Conjunction Search

- Replication of Godwin, et al. (2015)

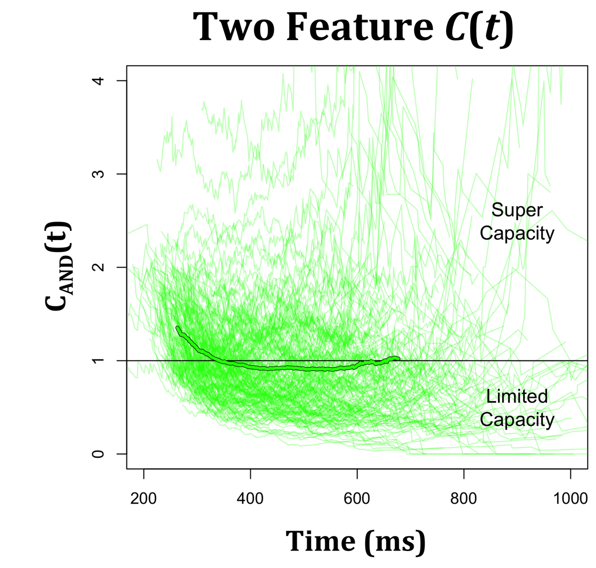
1. Color, Orientation
2. Color, Dash Type
3. Circle Color, Line Color
4. Orientation, Dash Type



Two Feature RTs



Two Feature *C(t)*



Limited Capacity Performance

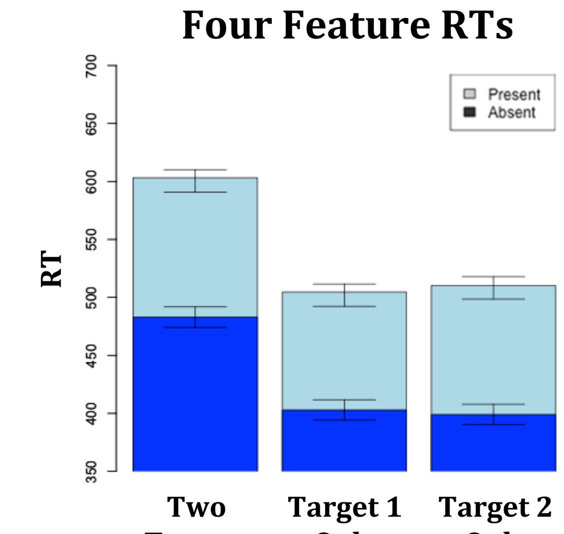
BF = 3.71

M_{Cz} = -0.78, 95% HPD: [-1.30, -0.22]

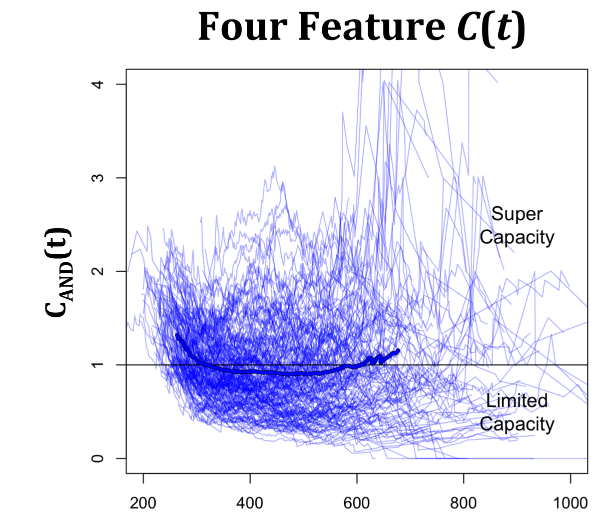
Experiment 3: Four Feature Conjunction Search

1. Circle color, Line Color, Orientation, Dash Type

Four Feature RTs



Four Feature *C(t)*



Limited Capacity Performance

BF = 11.10

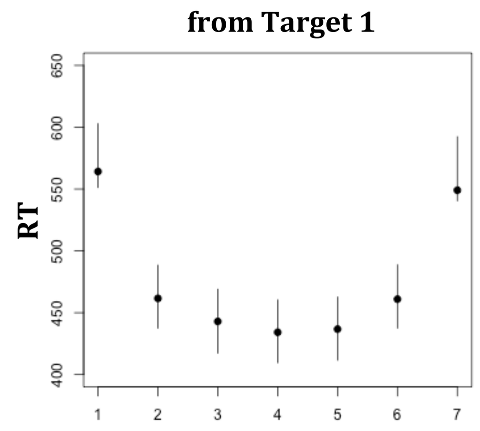
M_{Cz} = -0.81, 95% HPD: [-1.32, -0.30]

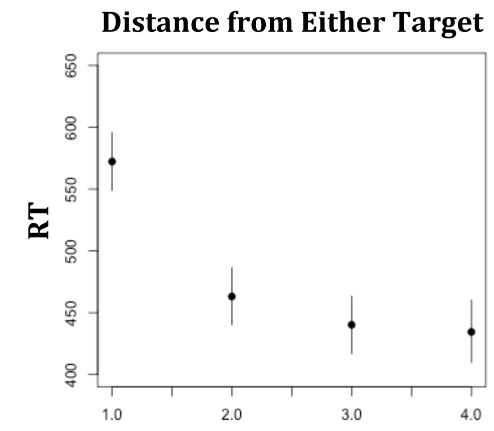
Why is *C(t)* reduced for more complex objects?

- Possibly due to nonequivalent color and shape feature distances

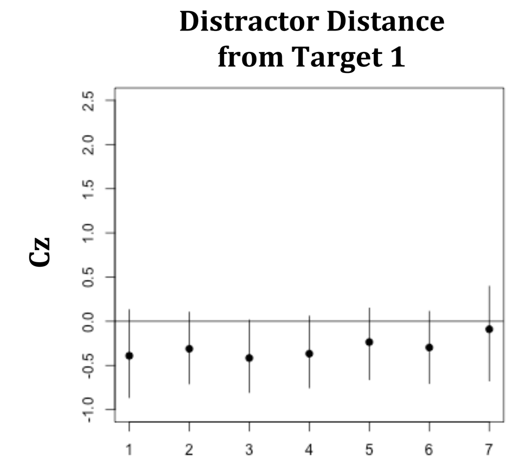
Experiment 1: Color Breakdown

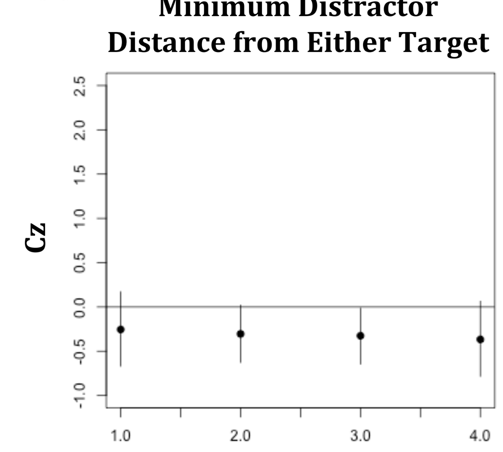
RTs





C(t)

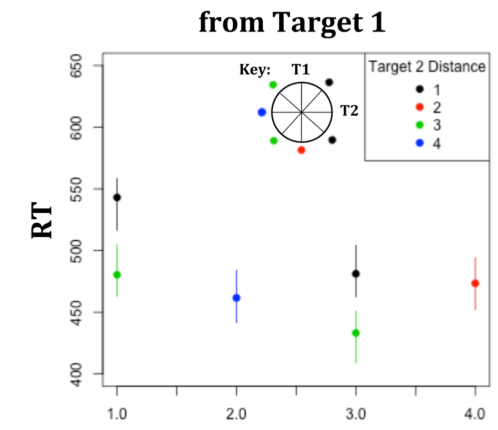


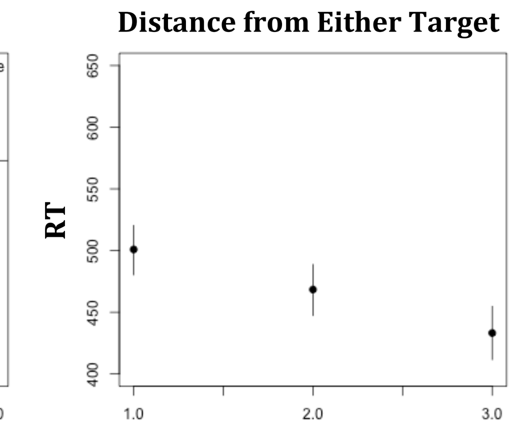


- Minimum distance from either target better accounts for Color RT than distance from Target 1 (BF = 18).
- **Neither** color distance measure accounts for *C(t)* (BF = 80).

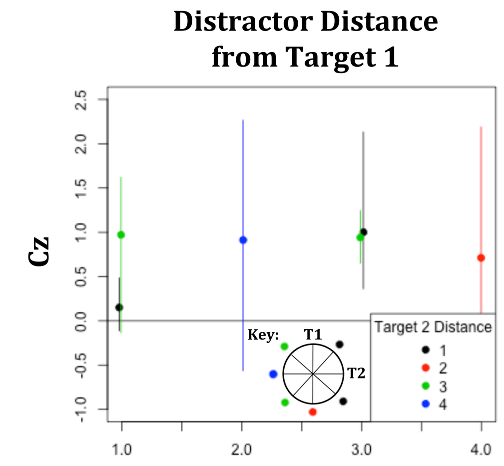
Experiment 1: Orientation Breakdown

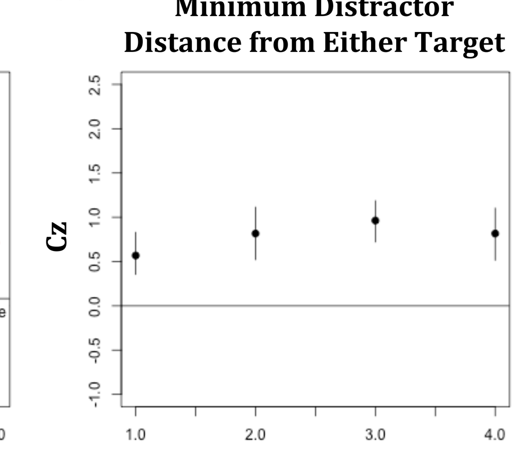
RTs





C(t)





- Distance from Target 1 better explains orientation RTs than minimum distance from either target (BF > 100).
- Target 1 Distance × Minimum Distractor Distance interaction accounts for *C(t)* (BF = 8).
- No effect on *C(t)* if model only considers minimum distance (BF = 4.93).

Conclusions

- Object identification was efficient when people searched for multiple objects, but only when these targets were very simple and defined by single features (Exp. 1). While Exp. 2 replicated Godwin, et al. (2015), demonstrating limited capacity with simple, two-feature objects, the finding of limited capacity with more complex objects in Exp. 4 was contrary to our predictions.
- Two possible reasons for these findings: (1) The targets in Experiment 1 were entirely unique, sharing no overlapping features with any distractors. In contrast, conjunction targets in Exp. 2 and 3 shared overlapping features with distractors, possibly negating the benefit of *shared individuating features.* (2) Target colors and orientations were not equally distant (180° and 90°, respectively), evident in discrepant identification efficiencies for each.
- Future directions: (1) Examine *C(t)* when targets share no overlapping features with distractors. (2) Equate target distance on different feature dimensions, and examine *C(t)* for each.

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