Serial vs parallel models of Visual Search: model comparison to RT-distributions

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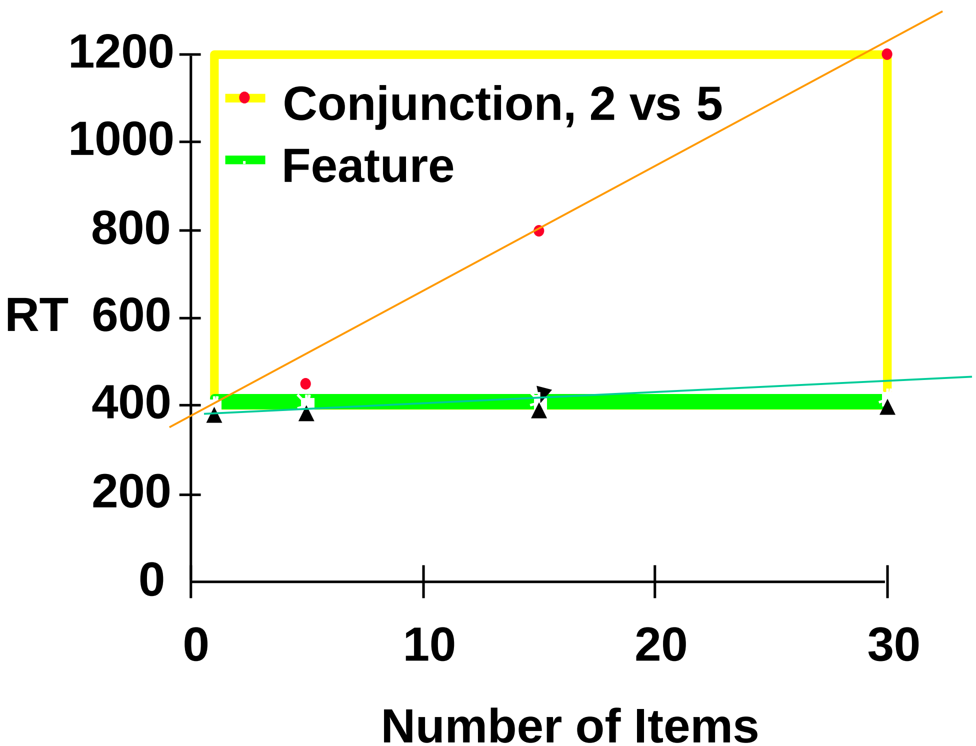
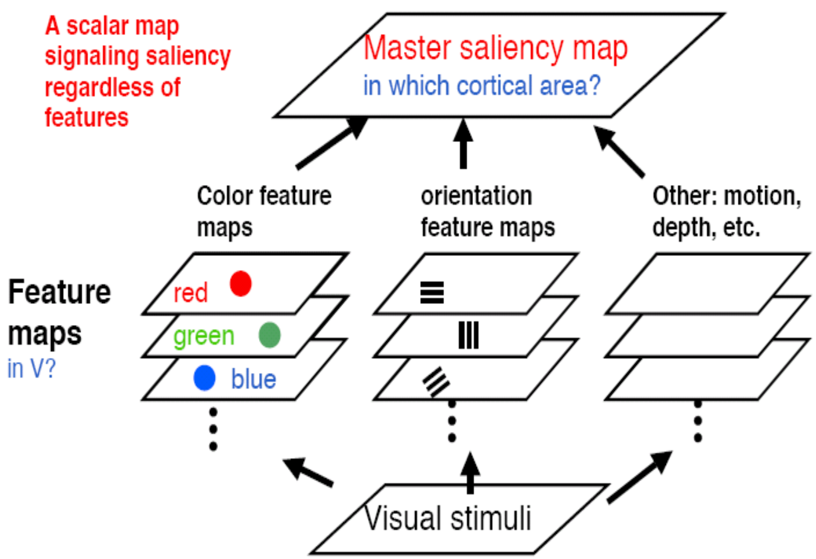
Classical theory(Guided-Search, FI, etc)

Stage-1: parallel computation of salience on master salience map
Stage-2: serial selection of visual items for target/non-target identification

Explains flat VS set-size functions for easy search, and steep slopes for difficult search; the Guidance-parameter (Wolfe, GS)





Challenge: parallel models can produce positive slopes

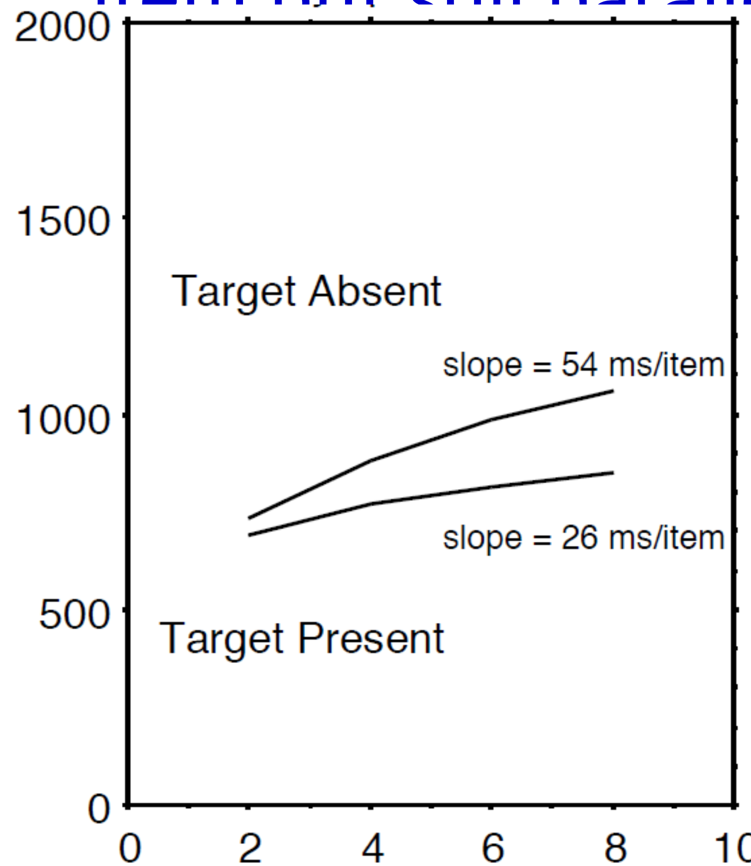
Serial and parallel models can mimic each other: •

Capacity issues (Townsend:Tweedle-Dee & Tweedle-dum): larger set-size → lowers processing rates per item but still parallel

Noisy decision processes •

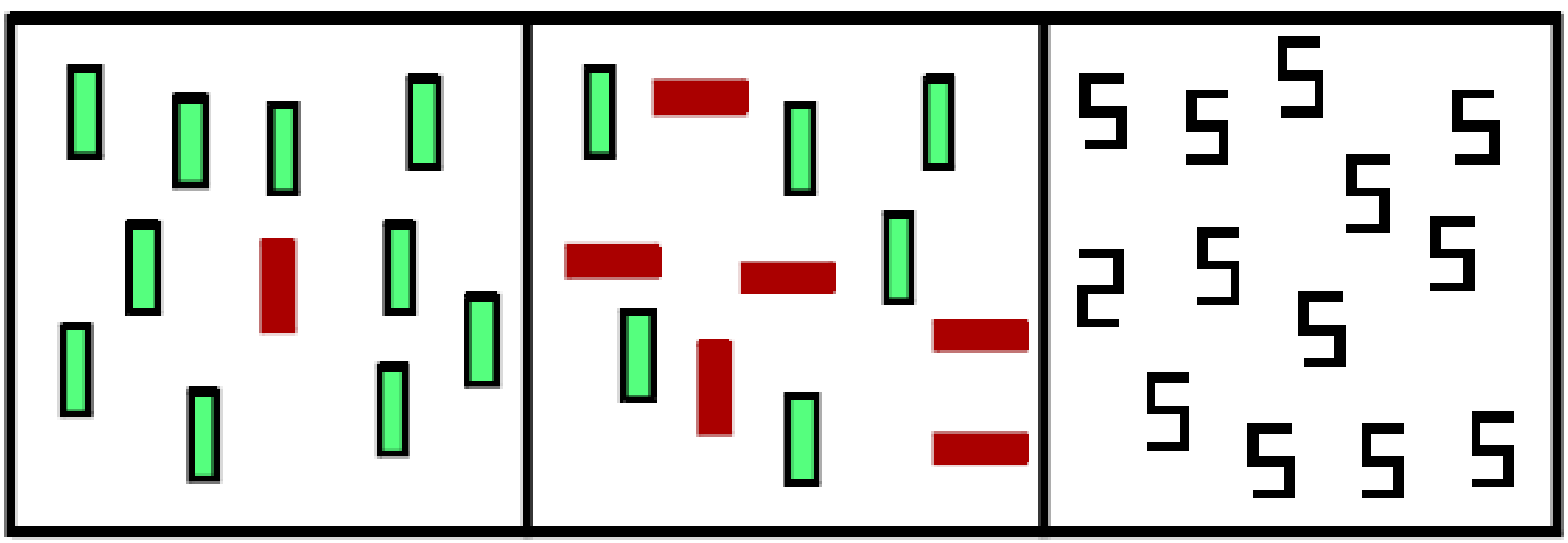
John Palmer:

with more items to search there is more opportunity for decision errors (e.g., distracter misidentification leading to FA), which requires more stringent decision criterion to maintain error-rate → longer search times.



Outline

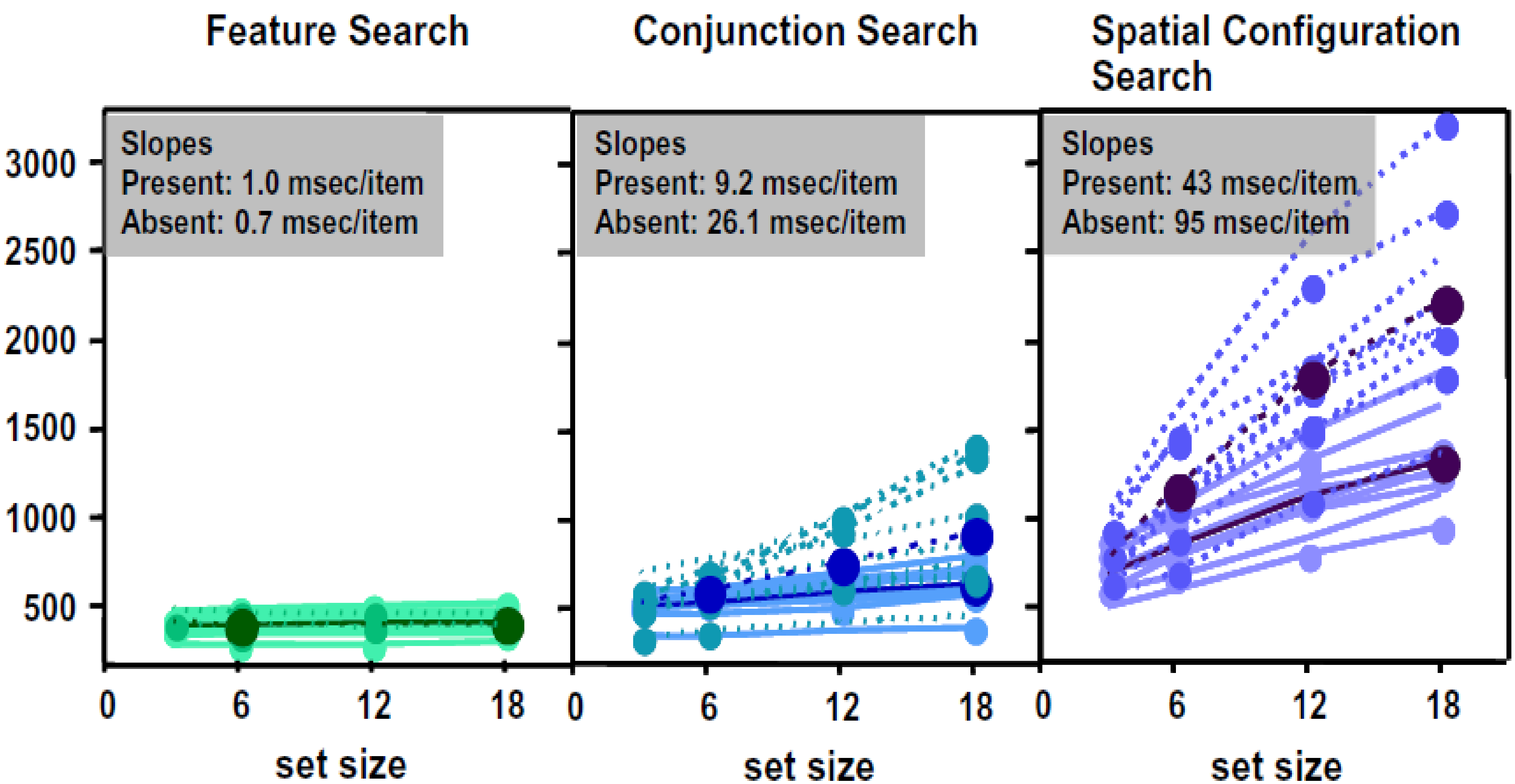
- Formal comparison of a serial (2 stage) and a parallel (1 stage) model of VS to standard search tasks
- Account not only for mean-RT and error-rate but also for RT-distributions (more constraint for mode comparison)



VS-data with RT-distributions

- Wolfe J.M., Horowitz T.S., & Palmer E.M. (2010). Reaction time distributions constrain models of visual search. *Vision Research*. 50 (14): 1304-1311.
- 28 participants (~9 per task)
- Factorial design: 4 set sizes (3,6,12,18)* 2 target presence conditions
- All 8 cells mixed within blocks.
- ~500 trials per cell per participant.

What is usually reported: mean RT



e data: lighter lines show data for individual observers. Darker lines and data points show mean data. Solid lines show target present results.
t. Since all tasks are plotted on the same *y*-axis, feature search present and absent data overlap nearly completely.

And accuracy

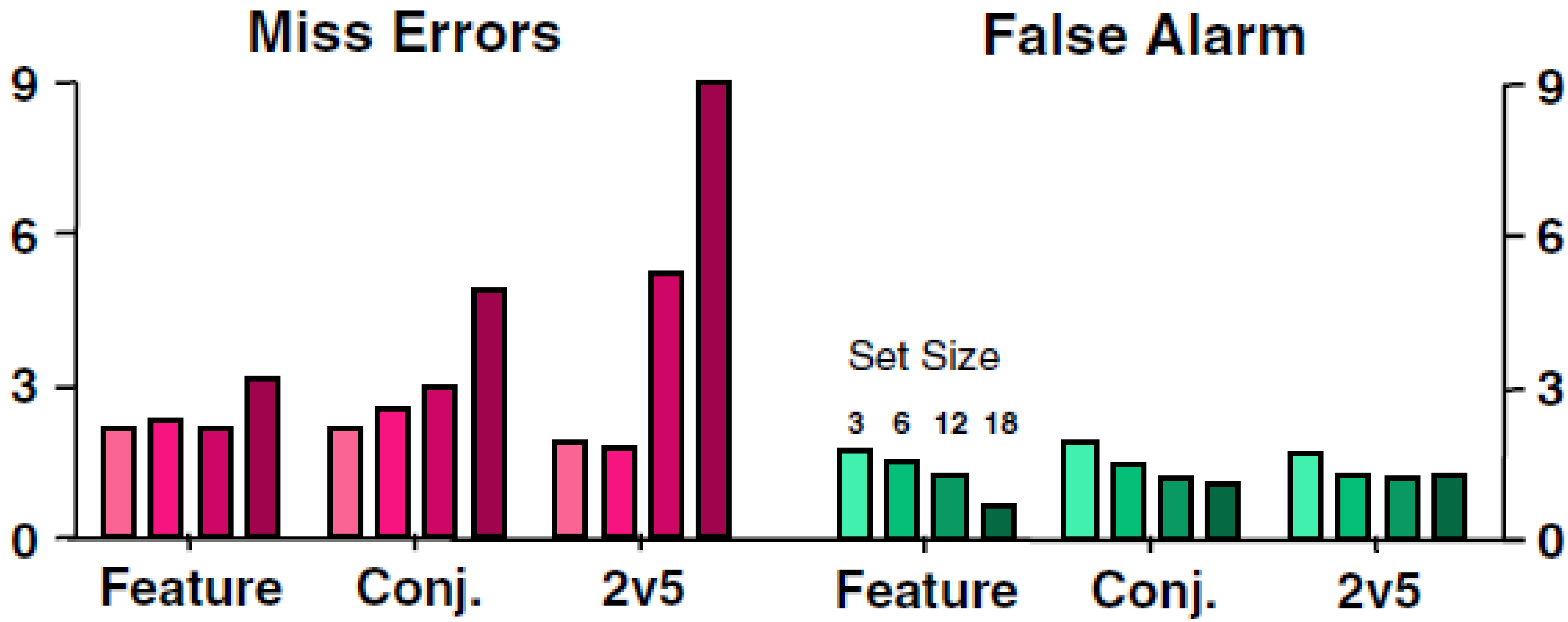
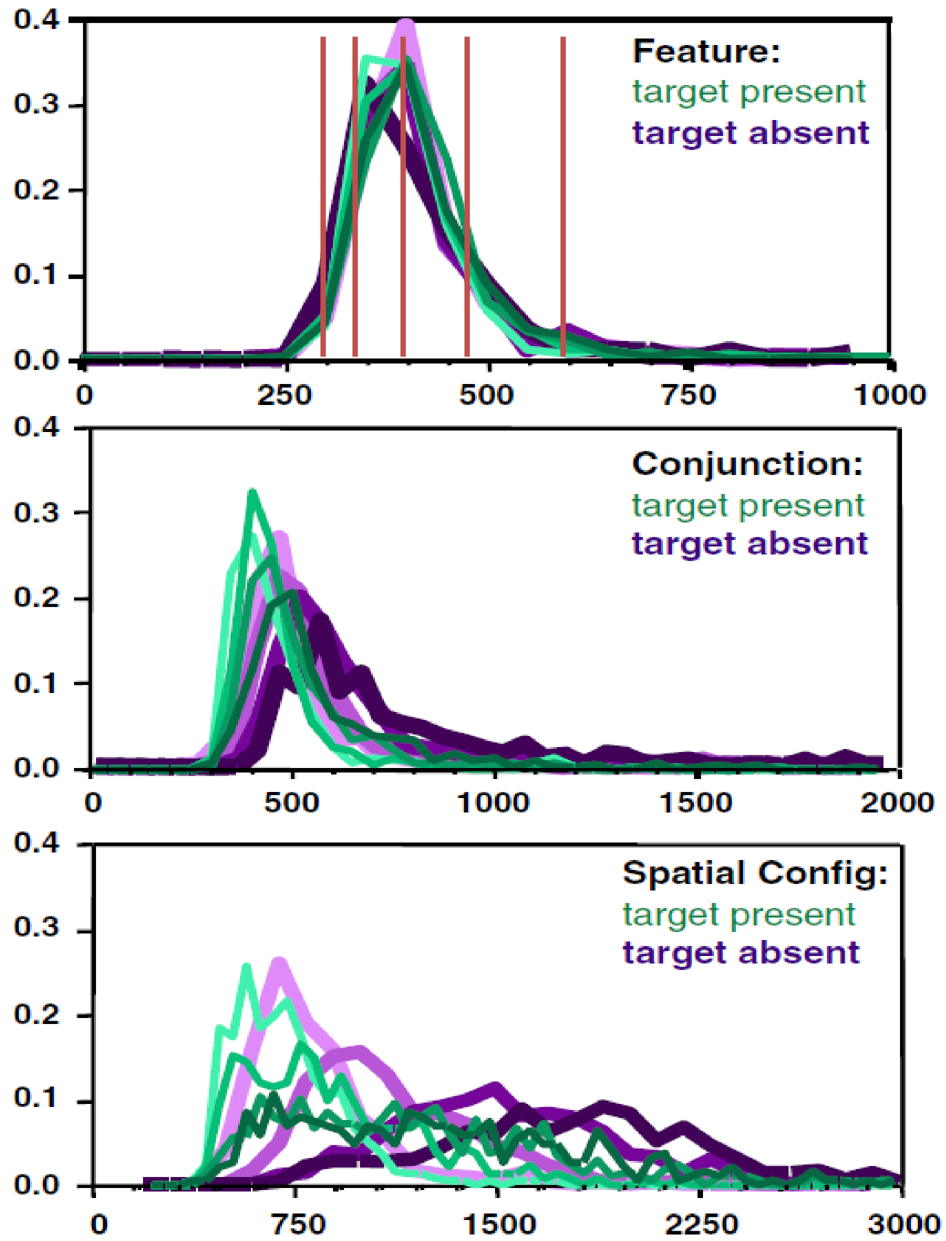


Fig. 3. Mean error rates for each set size and for each task. The four bars for each task represent the four set sizes. Thus, for example, it can be seen that error rates are highest for spatial configuration miss errors and that these rise with set size.

But they don't usually report



Rules out naïve serial self terminating search:2vs5

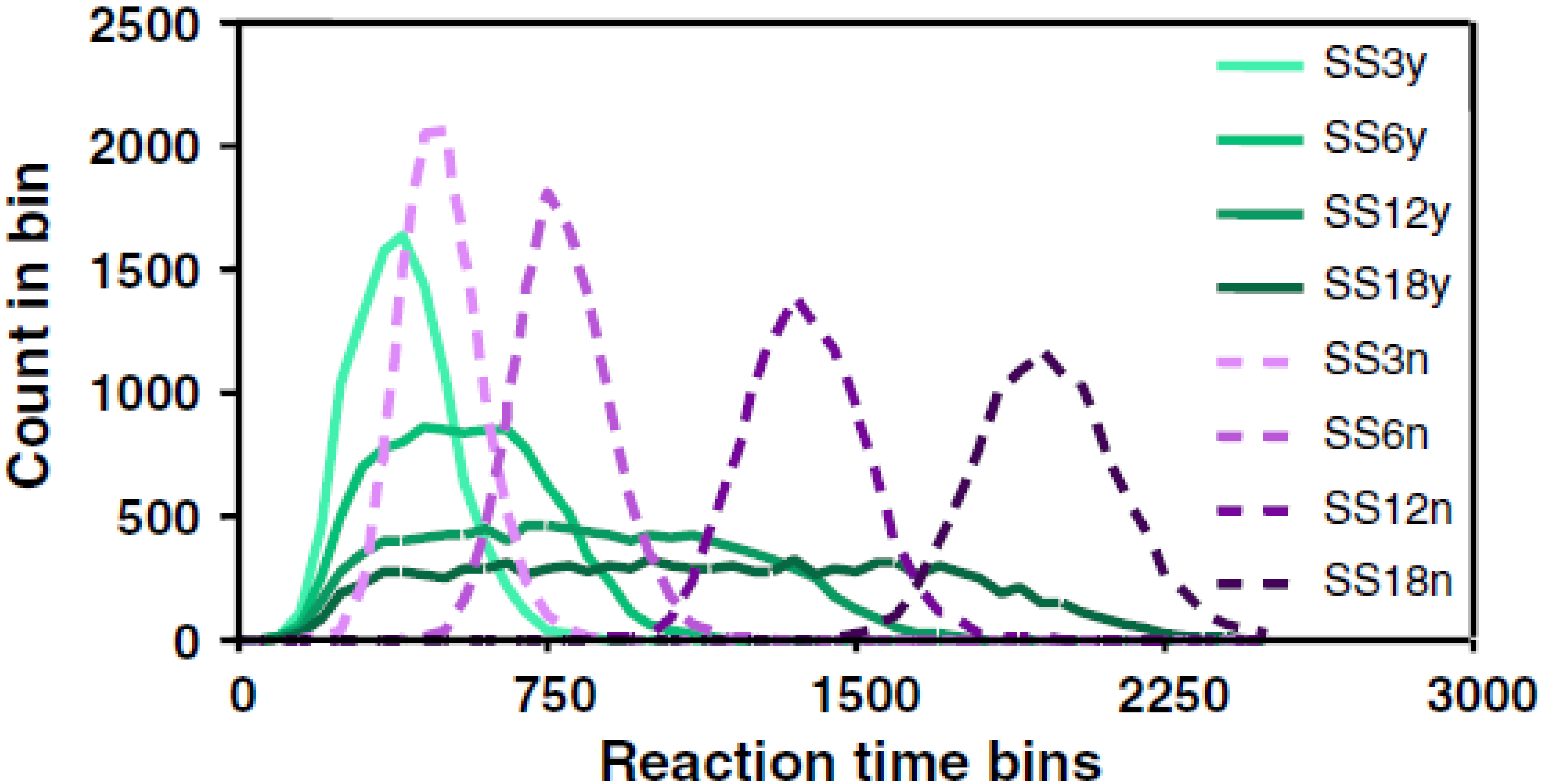


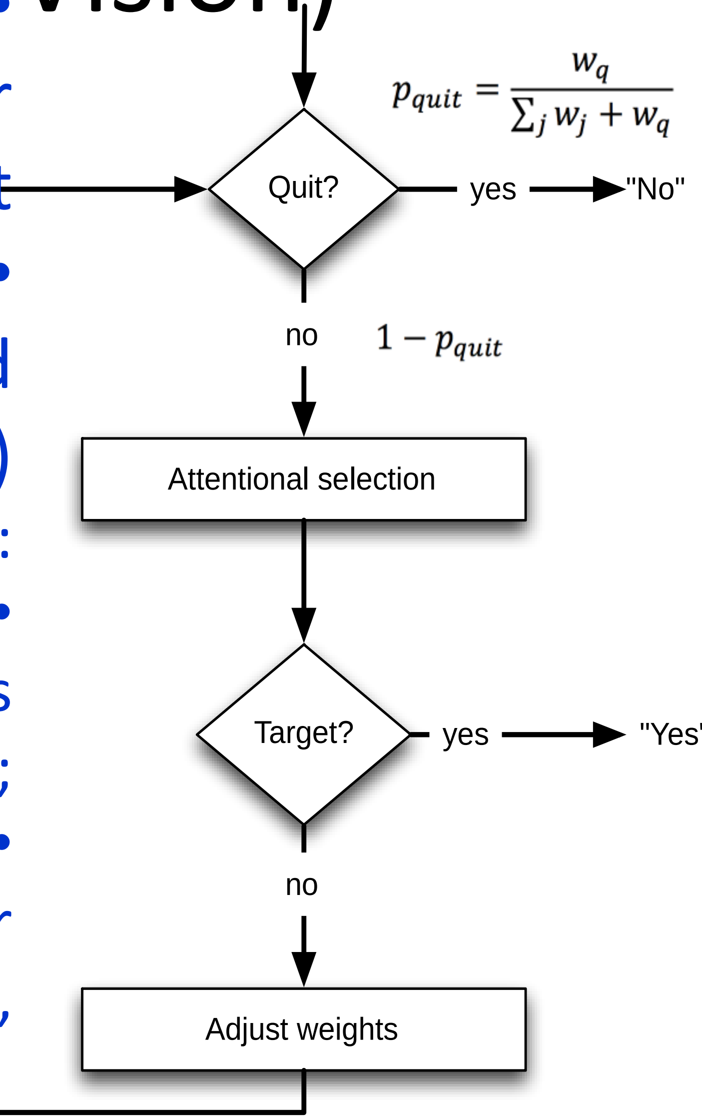
Fig. 7. RT distributions for simulated serial, self-terminating search. Solid lines represent target present distributions; dashed, target absent. Lighter lines represent smaller set sizes.

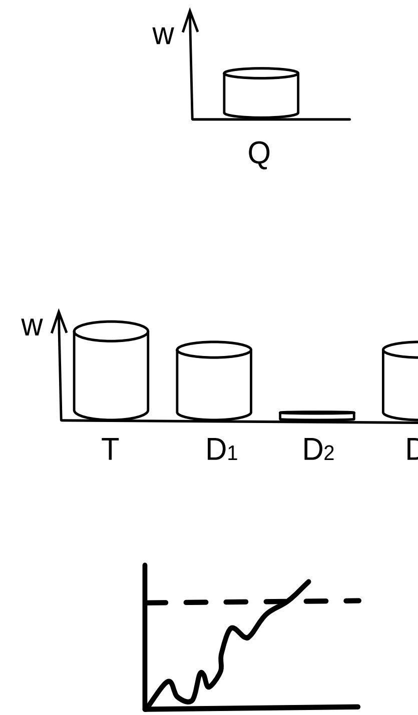
Serial (2 stage) model: Competitive guided search (Moran et al, 2014; J. of Vision)

- Stage-1: salience with guidance parameter for target
- Stage-2: selection and identification (Wald process)

Quit-mechanism:

- Quit-unit competes for selection with other items (Luce rule);
- Target found? “yes”, otherwise: Inhibit distracter by setting it’s weight to 0, activate Quit

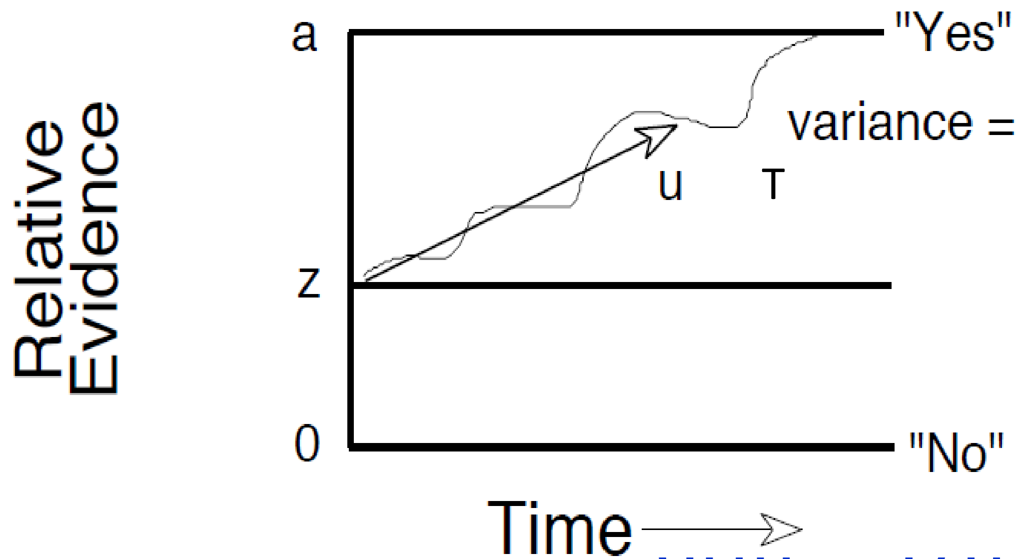




8- free parameter

The parallel model (**13 free parameters**)

N-identification processes taking place in parallel (2 •



Boundary and starting point parameters free to vary •
with set-size (assumes S attempt to regulate RT-
errors)

Quit mechanism to relax exhaustive rule •
termination: 'th item reaches the lower boundary,
search quits with probability: (the search exhaustive;

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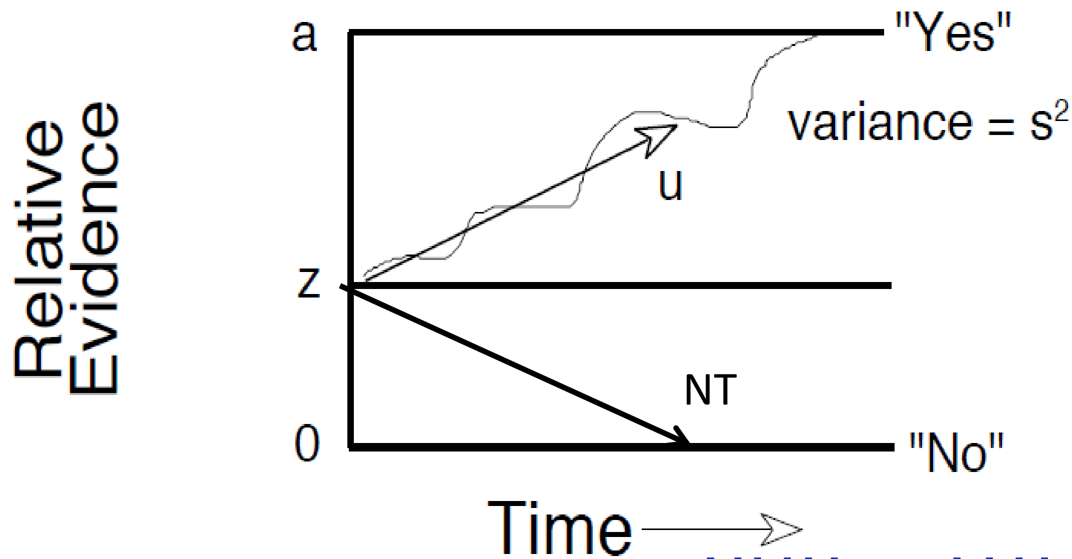
- g e o r



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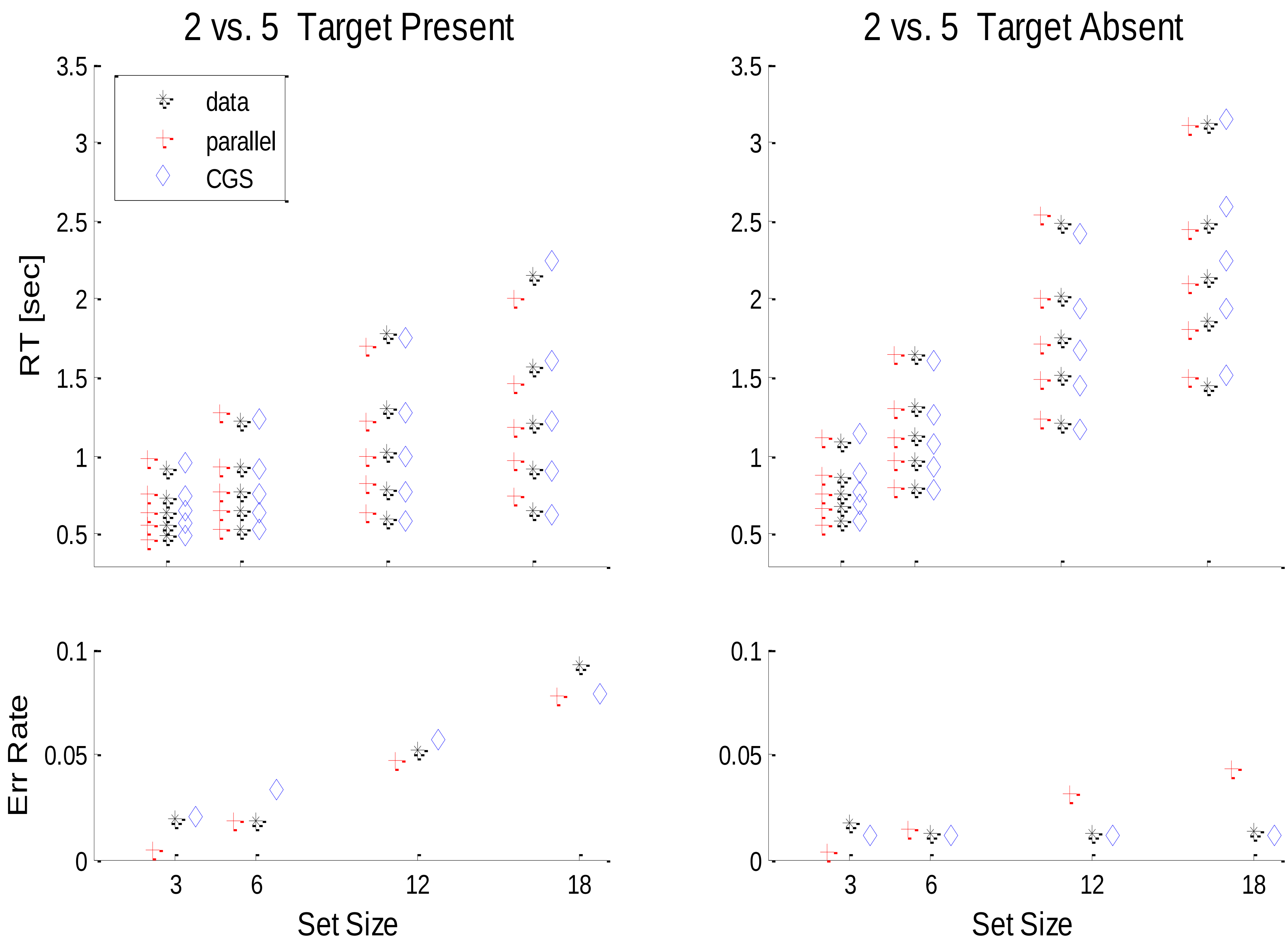
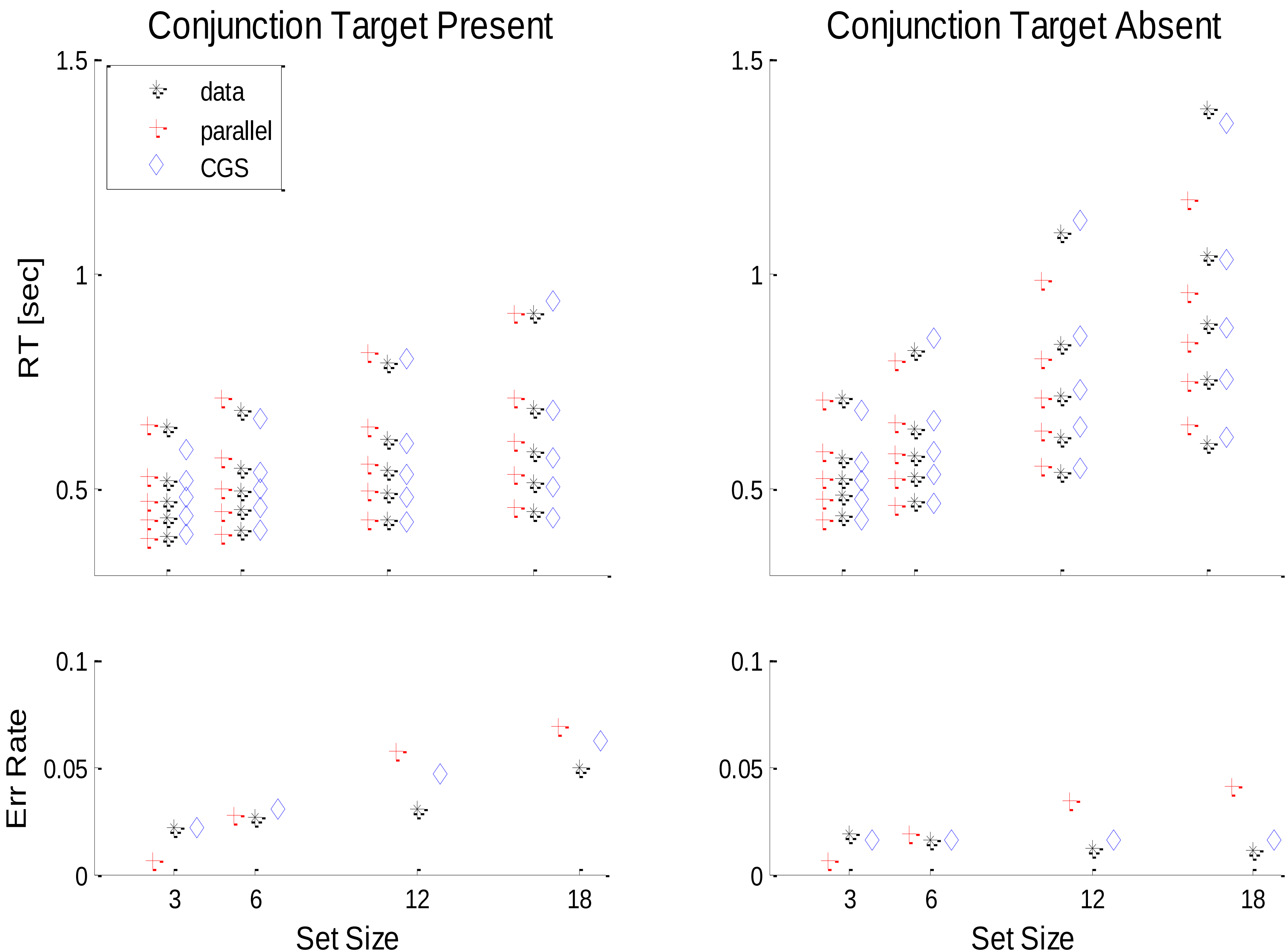
Methods of model fitting

- Quantile Maximal Probability Estimation (QMPE; Heathcote, Brown, & Mewhort, 2002)- Maximal likelihood based on RT-quantiles: accounts simultaneously for RT distributions and error rates
- For both models we developed analytic formulas error rates and RT (Hit, CR) distributions.

Results: 2 vs 5



Results: conjunction



Results: feature-search

Model-comparison conclusions

- Despite less model flexibility (8 compared with 13 free parameters), CGS accounts better (less deviance) for the data in all 3 tasks
- The parallel model can account for positive or flat slopes, but cannot account as well for the quantitative aspects of the RT-distributions together with error-rates
- Interestingly, the parallel model could not account well for the zero-slope feature search task: when n-diffusors go in parallel we have statistical facilitation for self terminated processes, or slowdown for exhaustive ones.

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