A two-stage model of sensory discrimination: An alternative to drift-diffusion

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Sun & Landy, *J Neurosci*, 2016

Outline

- Reaction time, the DDM and S/N
- Expt. 1: RT as a function of S and N
- An alternative model: Estimate then Decide
- Expt. 2: Cued-response task vs. S and N

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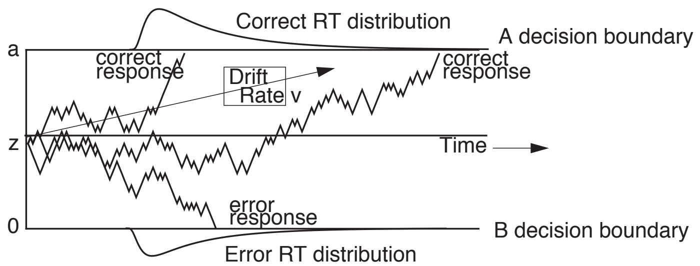
Reaction time (RT)

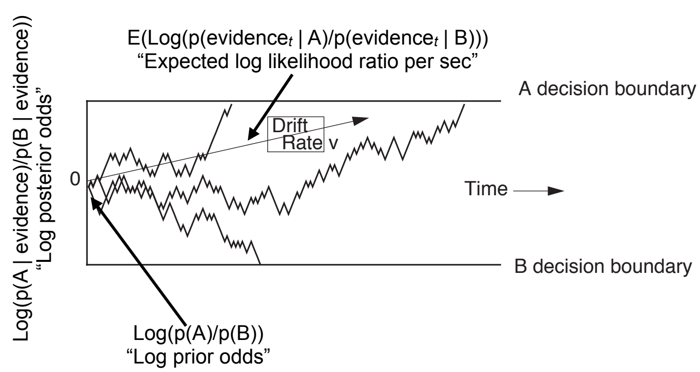
- Speed-accuracy tradeoff
- RT distributions for correct vs. error trials
- Curve-fitting vs. optimal behavior

The basic drift-diffusion model (DDM)



Ratcliff & McKoon (2008)

Bayesian DDM



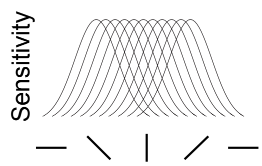
DDM and S/N: Intuition

- The drift rate is proportional to:
  E(Log(p(evidence$_t$ | A)/p(evidence$_t$ | B)))
- This is basically signal-to-noise ratio
- RT should be a function of S/N
- S/N is a ratio $\longrightarrow$ S and N should *interact*

Example task: Orientation discrimination

- Tilted Gabor with orientation $\pm\theta_0$
- Vary signal: vary θ_0 (e.g., ±45° vs. ±5°)
- Vary noise: vary contrast, for example

Toy model: Population code



- Homogeneous population
- Poisson noise
- Separable response: $\text{firing rate}_i = f_i(\theta)g(C)$
- Posterior ratio: Clockwise vs. counterclockwise

Toy model: Implications

For $\text{evidence}_t = p(\theta > 0 \mid \mathbf{n}_t) - p(\theta < 0 \mid \mathbf{n}_t)$

We derived a closed-form solution:

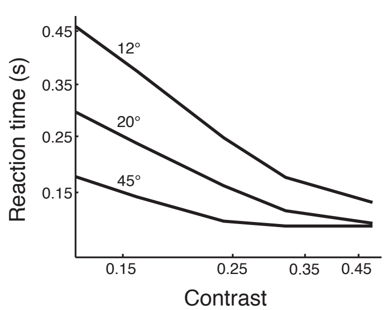
$$E(\text{RT}) = \frac{B}{2\Phi\left(\theta_0 f_C(C)\right) - 1}$$

That is, RT is a function of the product of signal θ_0 and noise $f_C(C)$, i.e., an *interaction*

Toy model: Implications

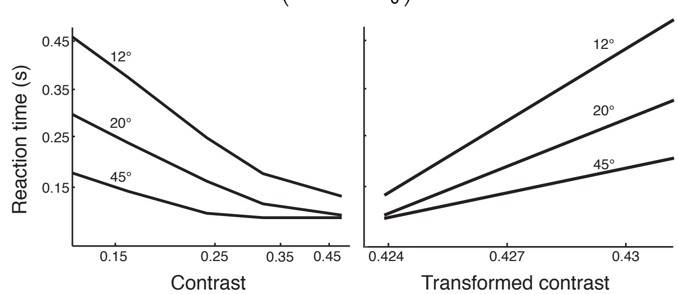
For $\text{evidence}_t = \dfrac{p(\theta > 0 \mid \mathbf{n}_t)}{p(\theta < 0 \mid \mathbf{n}_t)}$

We used simulation and also found a clear interaction between S and N:



Toy model: Implications

We linearize these curves using transformed contrast $g(C) = K\log\left(1 + C / C_0\right)$



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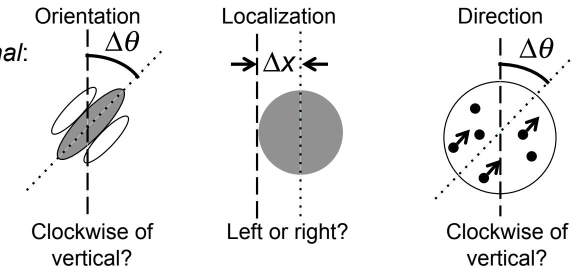
Three discrimination tasks

Signal:

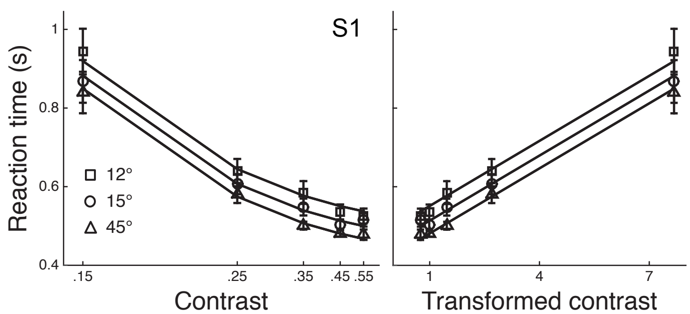


Noise: Contrast Contrast Coherence

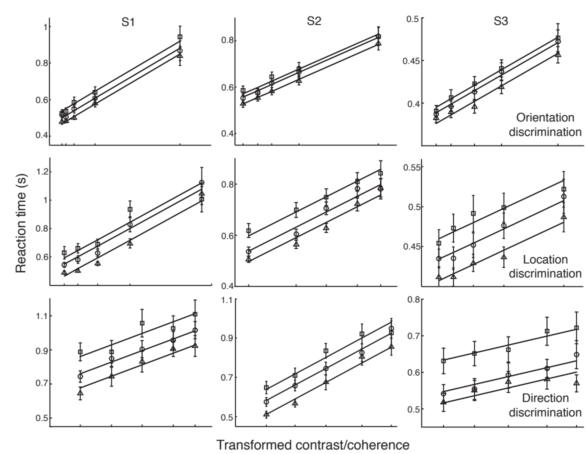
Mixed-list design, in each block of trials: One task
3 signal strengths
5-6 noise levels

Full feedback. Maintain 95% accuracy

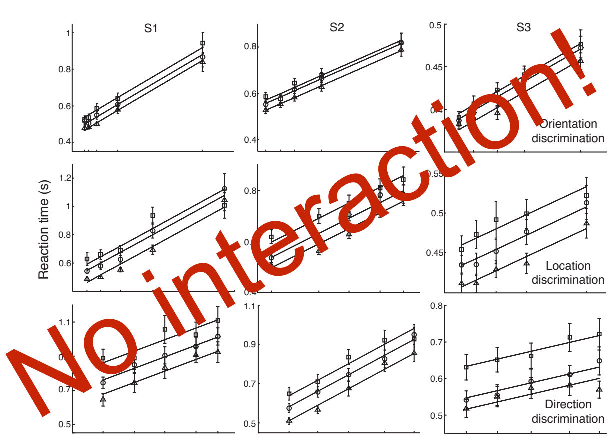
Sample data: Orientation discrimination



Full dataset: Three tasks



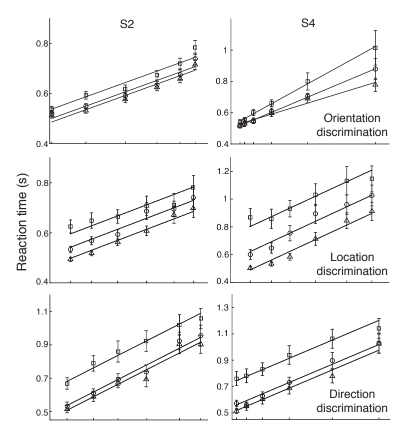
Full dataset: Three tasks



More data

One new naive subject (S4)

More evenly spaced noise levels



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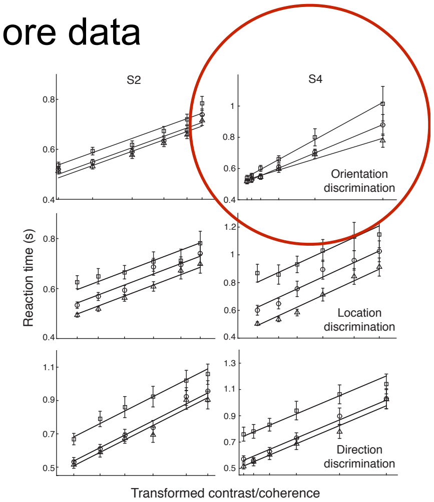

Intermediate conclusions

- In almost all cases, signal and noise show no interaction in RT
- This is at odds with predictions of the DDM
- It suggests separate stages of processing affected by signal vs. noise

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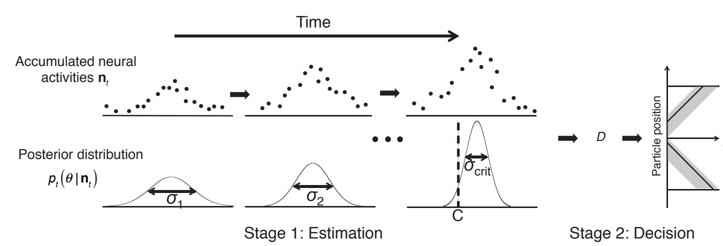
The estimate-then-decide (ETD) model



Where $D = p(\theta_0 > 0 \mid \mathbf{N}_t) - p(\theta_0 < 0 \mid \mathbf{N}_t)$ (a bounded quantity)

and 2nd-stage $RT \propto B - k \bullet |D|$

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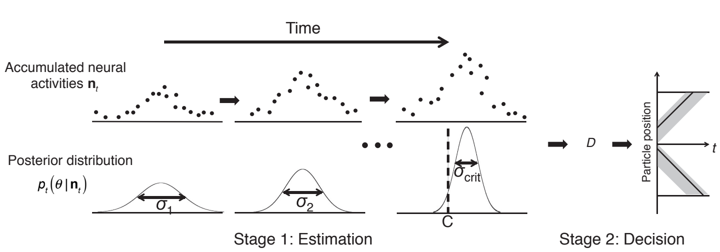


Where $D = p(\theta_0 > 0 \mid \mathbf{N}_t) - p(\theta_0 < 0 \mid \mathbf{N}_t)$ (a bounded quantity)

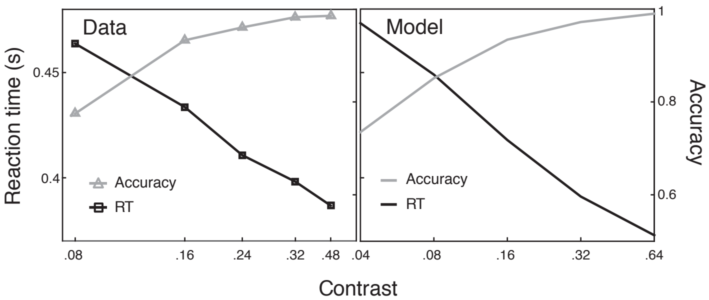
and 2nd-stage $RT \propto B - k \bullet |D|$

This 2nd stage is a work in progress. Its duration depends on *S/N*, but since *N* is fixed by the first stage, it only depends on $\hat{S}$, consistent with the lack of interaction.

The estimate-then-decide (ETD) model

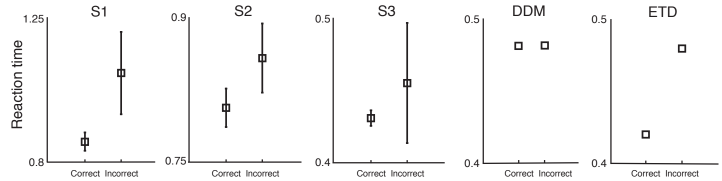
- Both stages contribute variability to RT
- 2nd stage reminiscent of LATER model (Carpenter, 2004)
- Separates estimation from task; easily extended to more than two response categories
- Predicts no interaction by default; Can add flexible bounds based on the current estimate $\hat{S}$ to get an interaction
- DDM predicts parallel curves *only* if raise the boundary for large values of $\hat{S}$, which seems counterintuitive
- Doesn't require perfect integration; a leaky integrator works

Speed-accuracy tradeoff



ETD naturally predicts speed-accuracy tradeoff: more difficult trials (higher *N*) take longer to reach criterion precision, yet still is more likely to lead to errors

Slower RT for error trials



- ETD predicts slower RT for error trials (distance to criterion in the 2nd stage is, on average, smaller)
- Standard DDM predicts identical RTs
- Typical fixes to DDM don't apply or don't work for our population-code DDM model

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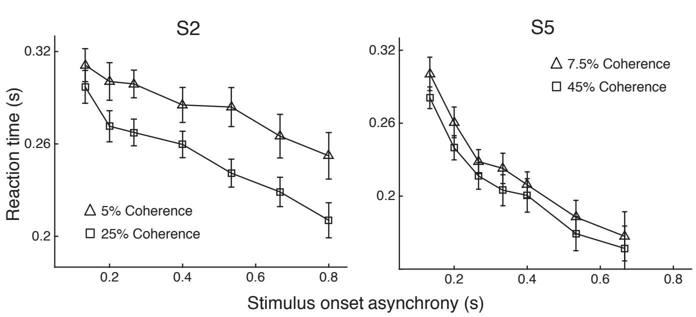
Cued-response task

- The 2nd stage of our ETD, the decision stage, needs further development
- The critical aspect of the decision stage is that RT depends on *S*/*N* at the time of the decision
- In a cued-response task, integration of stimulus information is halted by the cue to respond
- In ETD: post-cue RT will depend on *S*/*N* at the time of the cue
- In standard DDM, the prediction is less clear and requires specification of a decision stage

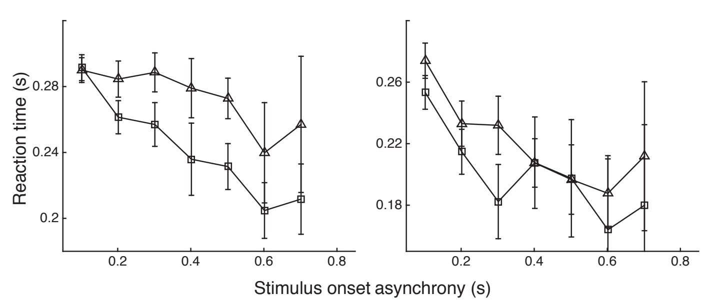
Cued-response task: Results

For method of constant stimuli:



Cued-response task: Results

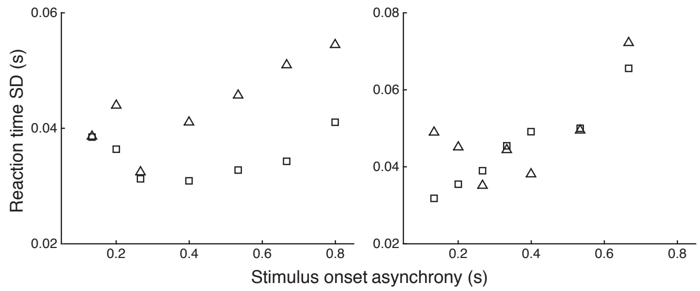
For constant hazard rate:



Cued-response task: Variance of RT

- DDM: Post-cue evidence accumulation until hit bound is consistent with these results
- However, this suggests that the DDM predicts that variance of t post-cue RT should increase with mean RT
- ETD predicts that RT variance increases with cue SOA: Longer cue SOA leads to larger variance in the *S*/*N* achieved by the time of the cue that, in turn, determines post-cue RT

Cued-response task: Variance of RT



Conclusions

- We've introduced the Estimate-then-Decide model of perceptual decision-making
- It is a work in progress, but so far has done a good job of making predictions consistent with previous results accounted for by the DDM, while also accounting for the lack of interaction of signal and noise in RT and the dependence of post-cue RT on signal and noise as well
- It is a model that is flexible, adaptable to other tasks