Comparison of temporal models for spatial cuing

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Attention Computational models and Eye Movements (ACME) group

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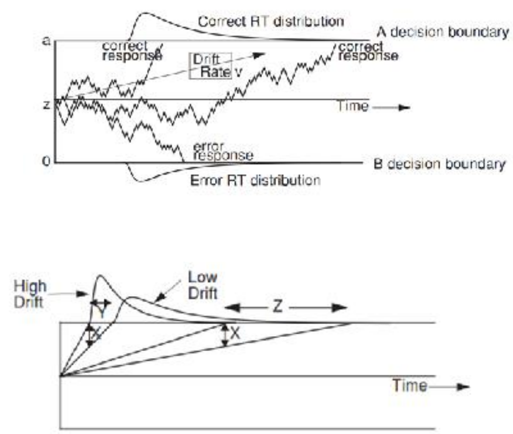
Responses as decision

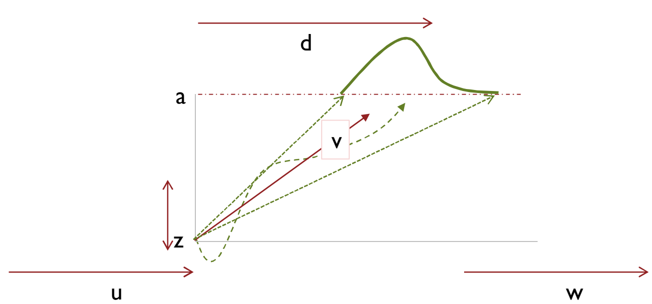
- Saccadic responses in perceptual tasks can be viewed as a build up evidence to reach a response criterion
- A variety of models have been proposed which model response times and errors with an accumulation of evidence
  - Leaky competing accumulator: Usher & McClelland, 2001
  - Diffusion: Ratcliff & McCoon, 2008
  - Linear ballistic accumulator: Brown, & Heathcote, 2008
- These models map onto activation in:
  - Superior colliculus (SC; Ratcliff et al., 2003)
  - Frontal eye fields (FEF; Hanes & Schall, 1996)
  - Lateral intraparietal area (LIP; Gold & Shadlen, 2003).

Diffusion models

- Drift rate is the signal that accumulates over time toward a correct response
- Variance (noise) around the signal causes distribution of possible response times
- Changing parameters results in different mean and shape of response distributions
  - Also decision errors



From Ratcliff, 2008



Decision components
z – starting point
a – decision boundary
v – drift rate signal
S(v) – variability (noise) in signal within trial
h – between trial variability
S(z) – flat distribution range for starting point

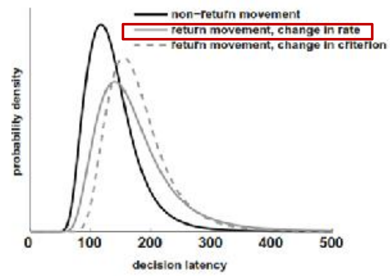
Non-decision components
S(t) = u+w – across trial variability of all other non decision components (Pre and post decision, possibly overlapping)

RT = (u+w) + d

Single threshold diffusion models typically do not require S(z) (Ratcliff 2011)

IOR Diffusion

- We can ask which parameters lead to a best fit of human data
- Also which parameter(s) best fit a particular experiment manipulation
- Ludwig et al modelled distributions from IOR/ISR
  - Saccadic response to cue and target
  - two cue/target locations
  - Both peripheral and central cues
- Reduced accumulation rate and increased threshold both result in delayed mean RT, and its only the distribution that differentiates the underlying mechanism
- Best fit was change in accumulation **rate (v)**
  - Interpreted as desirability of course of action

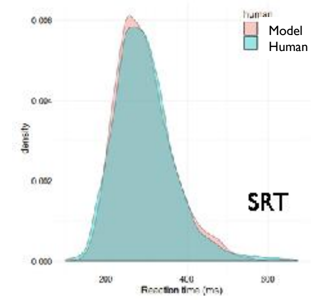


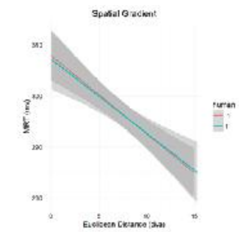
Ludwig et al, 2009

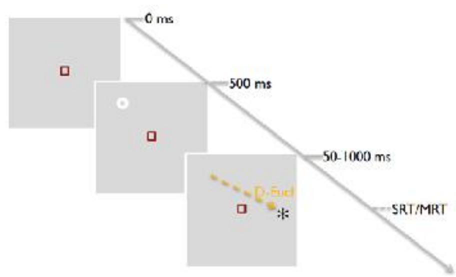
- SRT – Standard diffusion
- Parameter optimization with genetic algorithm

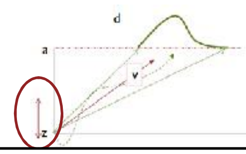
Gradient(s) of IOR

- IOR has a spatial and temporal gradient
  - IOR decreases as distance from the cue increases
- Diffusion modelled spatial and temporal gradients for manual and saccadic responses
- Gradient best described as change in starting point variance for both modalities







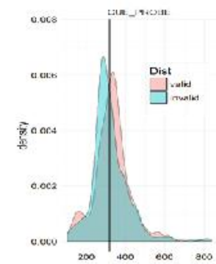


MacInnes, Neural Computation, 2016

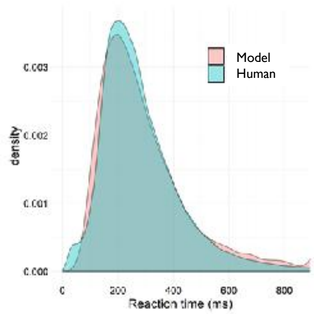
- Temporal diffusion

Log-abnormal

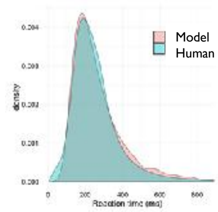
- Some RT distributions are more difficult for the basic model
- Multiple decisions?
- Distribution not log-normal?
- Change in decision criteria?
- Express saccades?



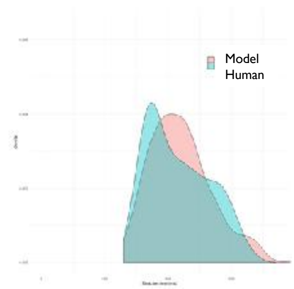
MRT data, Kruger, MacInnes & Hunt, 2014



MIT saccade dataset, Bylinskii etal, 2016



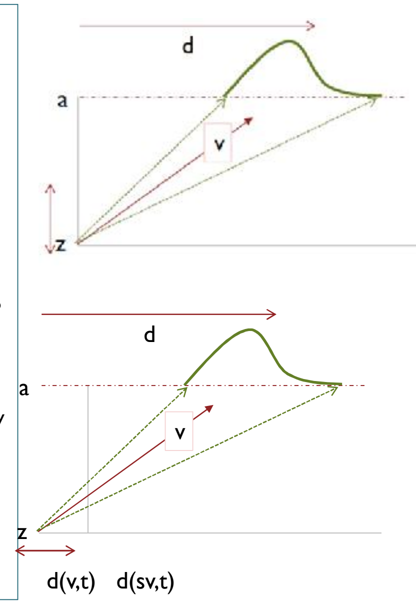
LabelMe, MacInnes& Gordienko



SRT, antisaccade condition, Alena Kulikova & MacInnes (Poster)

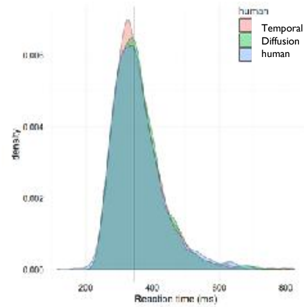
Temporal diffusion

- Assumptions of standard diffusion
  - Evidence accumulation begins at t = 0
  - single signal event or equivalent (events easily averaged)
  - No change in event strength
- t – event at time t. provided by relative timing of events in experiment design (cue or probe onset)
  - Since we are modelling the neural accumulation of evidence, the actual event happened prior to t = 0.0. t represents the time when visual signal of that event begins to influence the accumulation at the neurons being modelled
- d(v,t) - change in v at time t
- d(sv,t) - change in s(v) at time t
- S(z) - removed this is now accounted for by new parameters
- z - removed, but we still keep *a* to account for initial bias
- Variations on this theme –Wolfe, guided search 4.0 (Object recognition component with staggered feature onsets)



SRT Cuing random CTOA

SRT



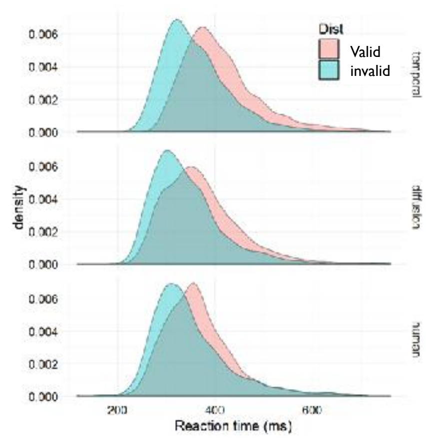
- Very close match with model and experiment distributions
  - Not surprising, since distribution was what we were optimizing with our fitness function
  - K.0123; p=.98
- Starting range (S(z)) and minimal inter-trial variability *h* were needed in top models
- Non decision component (S(t)) had mean of
  - SRT (153)
  - 41 ms higher than simple response model (MacInnes, 2016)

- Both diffusion and temporal diffusion showed excellent fit to data
- Temporal diffusion took 30% longer (Generations) to converge on parameters
- No difference in distribution accuracy between two diffusion models
- Temporal Onset Diffusion
  - Small temporal decrease in signal and signal variance –s, -s(v)
  - Followed by slightly larger increase in signal variance +(s(v)
  - Roughly 40 ms apart, soon after onset

driftmean	.0116
driftsd	.0597
trialsd	0.005
trialstartmin	4.1443
trialstartrange	2.7288
threshold	10
UVMean	153

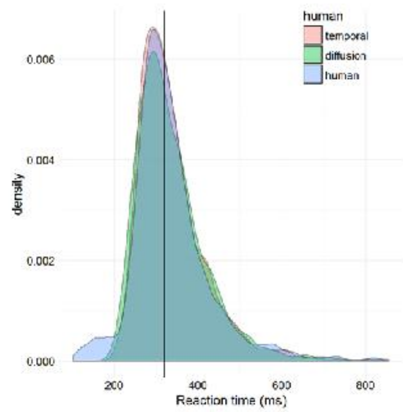
Modelling IOR

- Valid/invalid split
- Single parameter explanations of validity change the distribution in addition to the mean
- Diffusion only
  - Previous success with S(v) can match the mean results, but not distribution
- Temporal diffusion
  - Delayed onset of t results in distribution not distinguishable from human data (LME) p(human) = .16
- Simple change of U+V might be best fit here and relate to 'Output' type of IOR



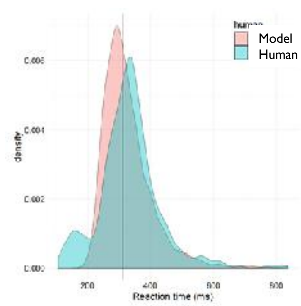
Kruger 2014

- Valid/Inlalid
- Pre-cue/Post-cue
  - Pre-cue showed typical cuing effect
  - Post-cue showed slow RTs at valid location
  - Perceptual merging due to feedback signal of first event
- Learned parameters for full dataset does not account for non-typical distribution at early RTs
- These are primarily found at pre-cue/valid



Human data from Krueger, MacInnes & Hunt, 2014, JOV

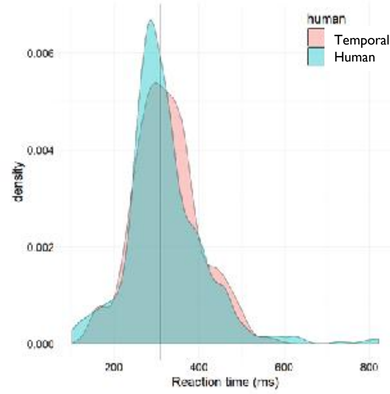
- Genetic algorithm did not converge on parameter solution
- Fitness functions not sensitive to bimodal distributions
- Ktest treats portions of distributions equally and will still dismiss null hypothesis if 'most' sections are similar



GA solution, k = .19
LME human = .65

Kruger etal, 2014

- Guided convergence
- Human guided machine learning
  - MacInnes etal, 2010, Computer Graphics and Applications

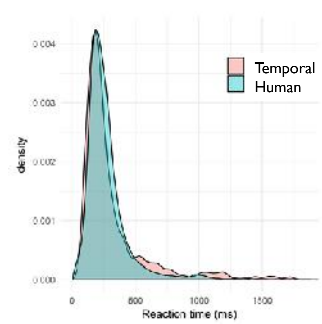


Perhaps less convincing visually, but still statistically not different

Z = .04, p= .96
k = .06, p = .20
LME human = .85

LabeIme Search

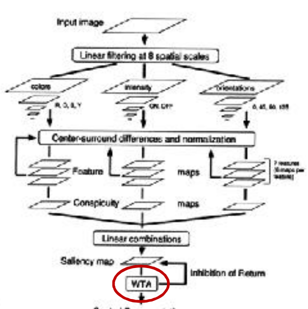
- Early saccades (small amplitude)
- Typically not found in target onset/SRT experiment
  - or excluded as anticipations
- T = 25ms
- D(s(v),t) = -2/3
- Reduction in system noise 25ms after completion of previous saccade



- Salience + leaky integrate and fire (LIF)

Salience + leaky integrate and fire

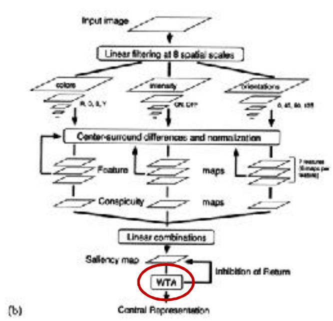
- Salience models (eg. Itti & Koch, 2000)
  - Low accuracy compared to recent deep learning
  - But still discussed due to high neural and theoretical match
- Integrate and Fire layer for random component + timing
- Similar to accumulation of evidence, but with improvements
  - Spatial array of neurons simulates visual map, as compared to abstract decision locations
  - Leaky property explains loss of signal
  - Allows for lateral inhibition with adjacent neurons

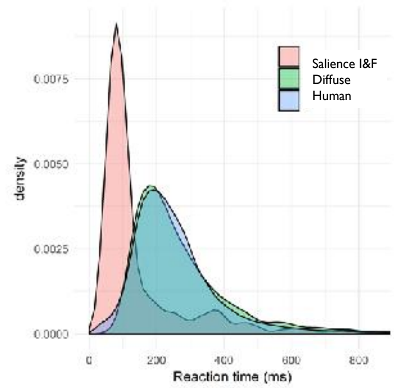


(b)

Salience + leaky integrate and fire

- Salience models (eg. Itti & Koch, 2000)
- Integrate and Fire + IOR as part of winner take all + timing
- I&K focus has been on spatial accuracy, not temporal





Next steps

Closer look at error rates (fitness function for speed/accuracy tradeoff?)

Best combination of spatial and temporal models

Test predictions of temporal model

Accumulation rates that change over time

Periods of shorter lasting, stronger changes in accumulation

these can be tested with neural data

- Thank you

- Students working on various eye tracking projects
- ACME group: Liuba, Tanya, Alena, Elena, Lya, Liz, Anastasia, Roopali
- Katya Gordienko on original Labelme paper
- Hannah Krueger and Amelia Hunt on original Cuing paper