Capturing attentional capture with salience models

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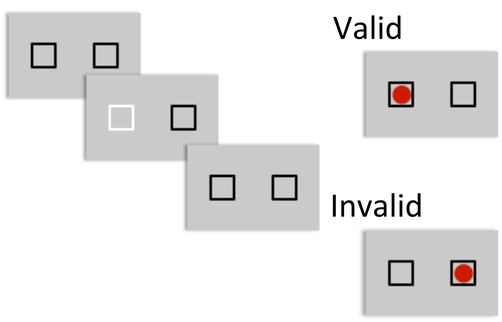
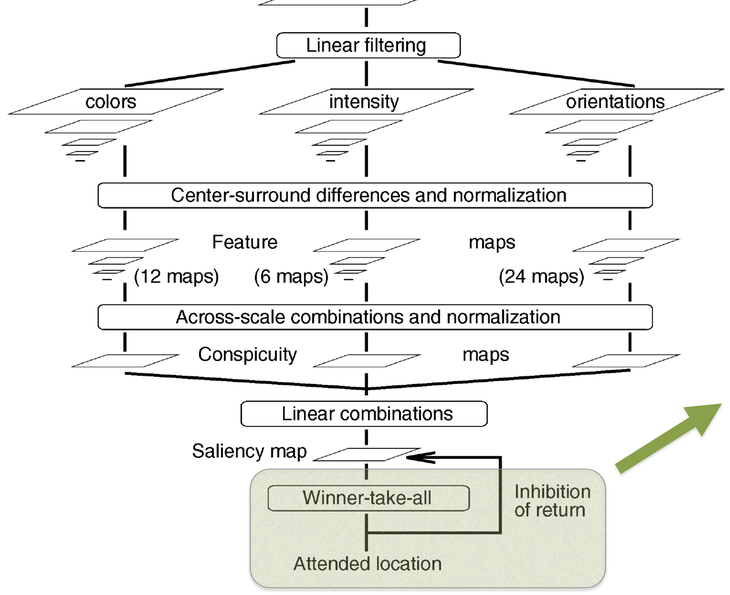
Salience models typically represent the various layers of visual processing and can predict the allocation of fixations to any given image by analysing its low level properties. Some of these models are capable of generating temporal predictions which can also be compared to human saccade distributions in image inspection and search.

Rather than test multiple saccades in static images, we test a modified the Itti & Koch (2001) Salience model on a task designed for attentional capture. This model was modified to accept changing spatial input, and respond using the standard Leaky Integrate and Fire (LIF) layer. Input to the model was from the classic Posner (2000) cuing paradigm and response times were compared to human data in a similar task.

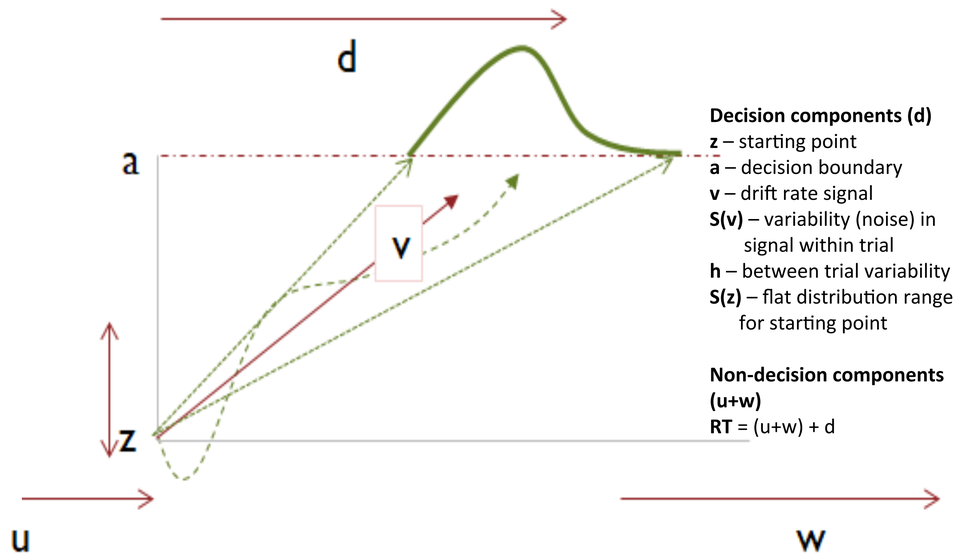
Methods



A structure of a virtual trial
**Proportions are not preserved*



Classic Salience model
used for spatial component



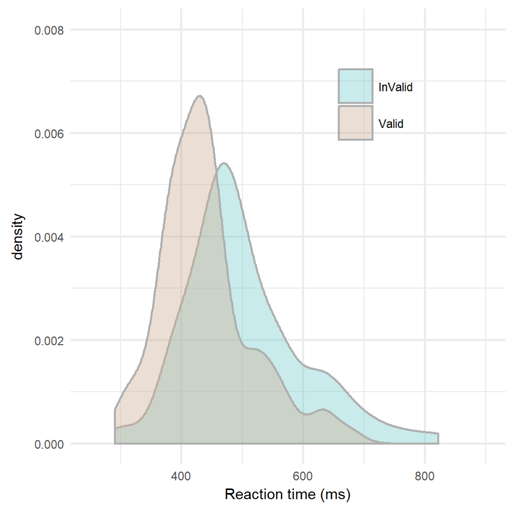
Diffusion model
replaces WTA

Results

* ns

‘Salience rate’

- Drift rate is calculated from trial onset
- Drift value is calculated as salience difference of locations
- Negative values (such as invalid cue) can lead to ‘negative’ accumulation toward incorrect threshold

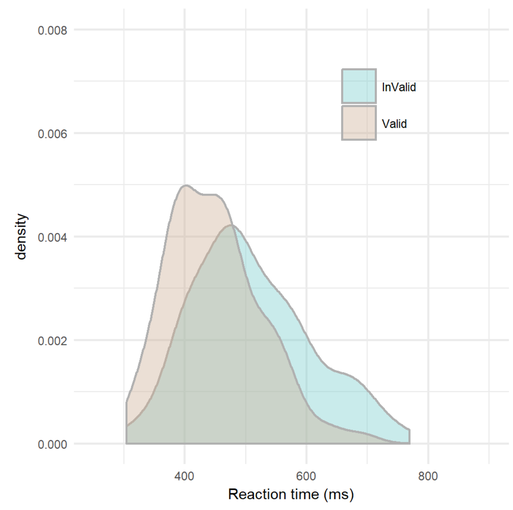


	RT	%corr	%inc	%antic
Valid	445	93.8	6.2	Removed
Invalid	511	94.4	5.6	Removed
Valid	445	88.2	5.9	5.9
Invalid	511	93.2	5.1	1.3

Speed/accuracy trade-off only emerges when considering anticipations

‘Threshold bias’

- Drift rate is 0 until target onset
- Bias parameter is modified at the time of the cue onset
- Value of the change depends of salience difference (valid-invalid)



	RT	%corr	%inc	%antic
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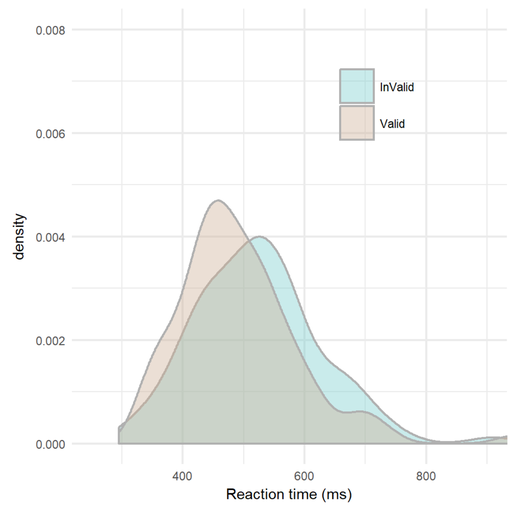
Invalid	498	95.4	4.6	Removed
Valid	452	88.5	6.3	5.2
Invalid	498	93.6	4.5	1.9

Consistent speed/accuracy trade-off with and without anticipations

‘Speeded attention’

- Drift rate is 0 until target onset
- Value of the drift rate is adjusted by proportional salience and validity of cue



	RT	%corr	%inc	%antic
Valid	468	96.1	3.9	Removed
Invalid	505	94.8	5.2	Removed
Valid	468	94.7	3.8	1.5
Invalid	505	93.2	5.1	1.8

Consistent performance gain with and without anticipations

Discussion

- Salience models can be combined with temporal diffusion to generate accurate RT distributions
- Some top down attentional (feature choice) can be learned and modeled at the salience map level
- Temporal onset of diffusion parameters matches traditional diffusion, and makes predictions on anticipations
- Errors of anticipation and errors of decision correctness can both be diagnostic of theory
- Strength of a model is not just in its accuracy of matching human data, but in its ability to make predictions and distinguish different theories

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