

# Toward Online Measurement of Decision State

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## A New Method

### Goals

Develop a behavioral measure of decision state that:

- tracks the development of decisions over time
- allows observers to indicate uncertainty with graded responses

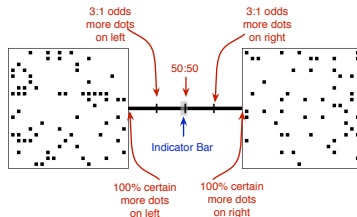
Track influences of top-down and bottom-up information over time

### Task

Observers determined which of two patches of dots had more dots.

Observers were asked to indicate their confidence that more dots were on the right or left by positioning a small bar with a joystick.

Observers were asked to respond as quickly as possible.

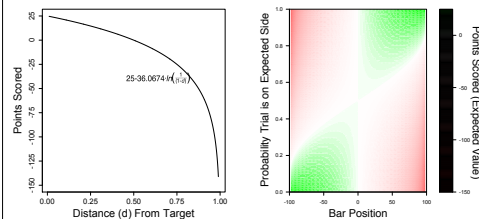


### Scoring

#### Accuracy

Observers received points as a function of their distance from the correct response.

The function gave the highest expected value when observers accurately reported the probability they were correct.

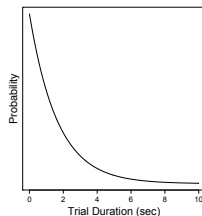


#### Speed

Trials ended at a random point in time, not controlled by the observer.

Observers received a score based on the bar position at the end of the trial.

Thus observers had to move the bar as quickly as possible when new information became available.



### Design

We manipulated bottom-up discriminability across trials. One patch always had 50 dots, the other had 51, 52, 54, 58 or 66.

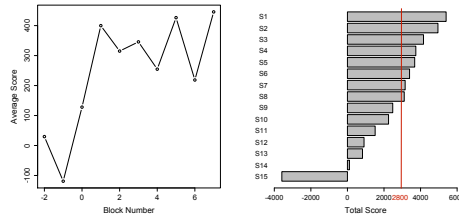
We manipulated top-down expectation across blocks. One patch was three times as likely to have more dots as the other.

Observers saw 10 blocks of 82 trials. The first 3 blocks of the session and the first 2 trials of every block were discarded. The remaining 80 trials/block contained 15 trials of each discriminability level on the expected side and 5 on the unexpected side.

## How well does the method work?

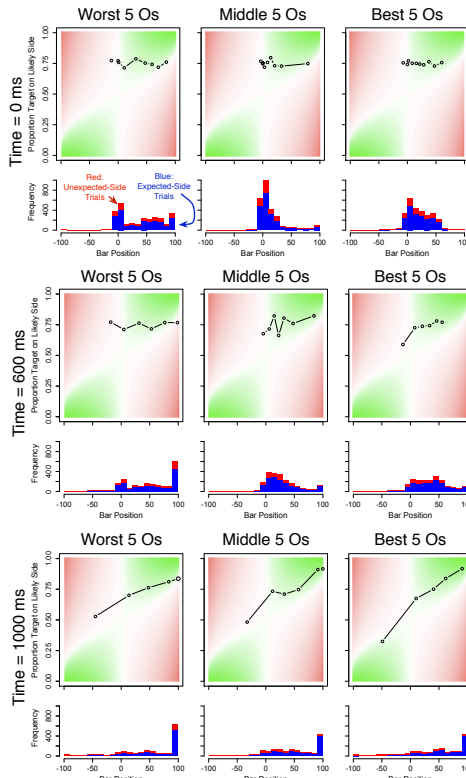
### Overall Performance

Performance reached asymptote after about 3 blocks (246 trials). Some observers performed much better than others. Almost half of the observers scored fewer points than could have been scored by leaving the bar indicating 3:1 odds more dots will be on the expected side (2800 pts).



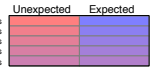
### Reporting of Confidence

No observers were close to optimal in the absence of perceptual information (e.g., before stimulus onset). With perceptual information, all observers showed some degree of graded responding, with the best observers reporting their confidence fairly accurately.



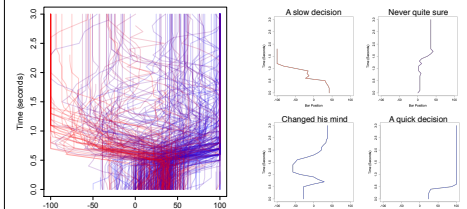
## What can we learn using this method?

The data presented below is colored according to this convention.



### Looking at Individual Trials

Unlike traditional methods, we can get some idea of observer's state of mind on individual trials.

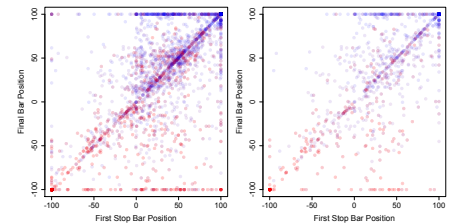


## Examining patterns: How often do observers change their mind?

If you find a particular data pattern of interest you can pull out the corresponding trials and characterize them. Here we look at the first place the observer set the bar plotted against the final bar position on which the observer changed their mind.

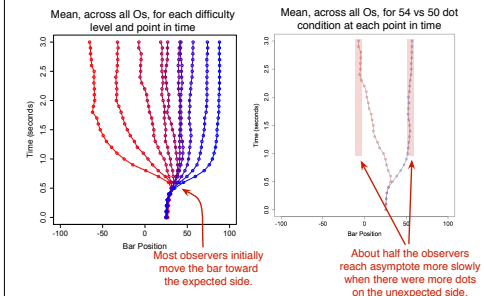
All Os, Trials > 1.5 sec

Best 5, Trials > 1.5 sec



## Expected and unexpected trials can be looked at independently.

One can separate bias from sensitivity more easily than with signal detection.



## Conclusions

We have created a paradigm that allows us to capture the evolution of observer decision state over time. While not all observers accurately estimated the probability that they were correct, we can, for all observers, track the time course of their decision process. Doing so gives us an ability to examine single trials at a level of detail that is not captured with traditional psychophysical techniques.

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