Information pursuit as a model for efficient visual search

Hee Yeon Im, Sheng-hua Zhong, Bruno Jedynak, Lisa Feigenson, & Jonathan Flombaum

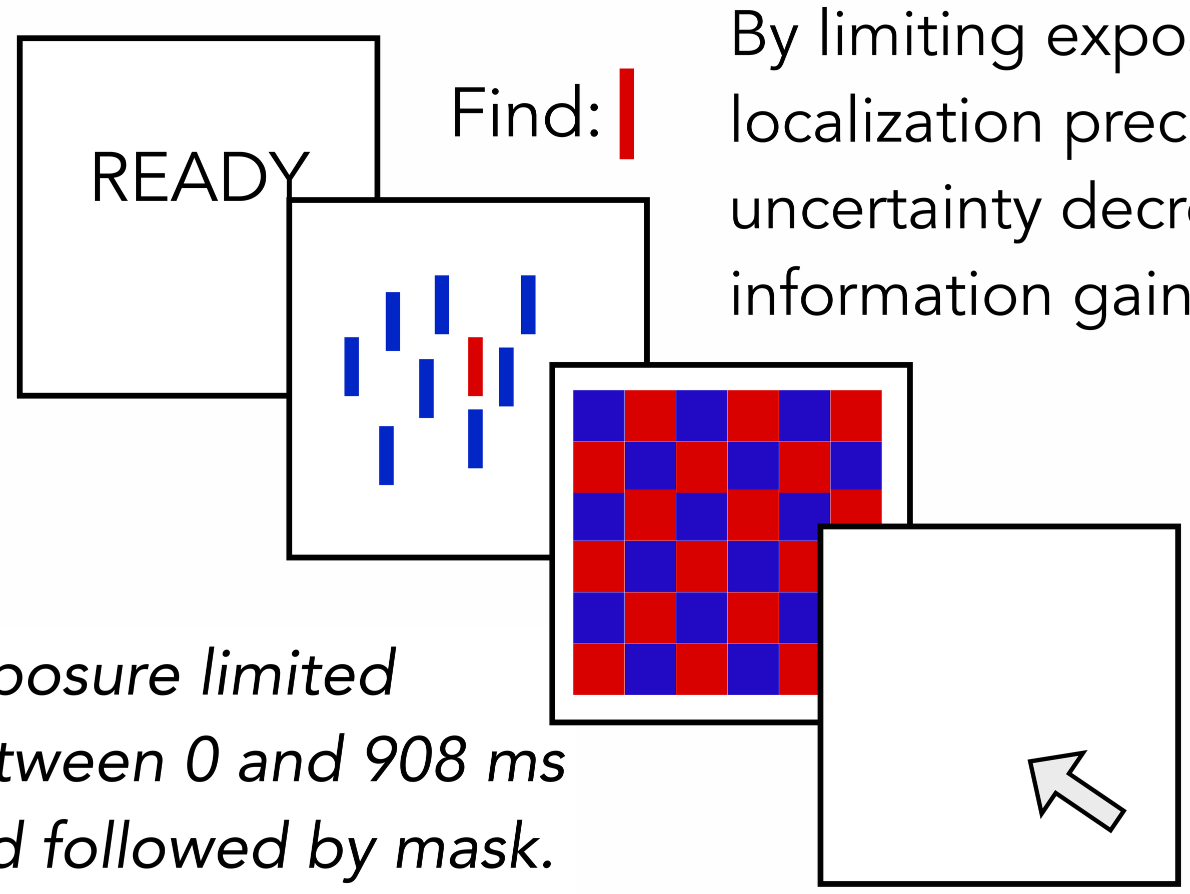
BROWN · BROWN INSTITUTE FOR BRAIN SCIENCE · The Vision Sciences Group Johns Hopkins University

The microgenesis of efficient search

Pop-out or 'efficient' visual search is fast because the target evokes a strong and easily discriminable signal.

But how knowledge of the target's position evolves over time -its microgenesis- has not been extensively investigated.

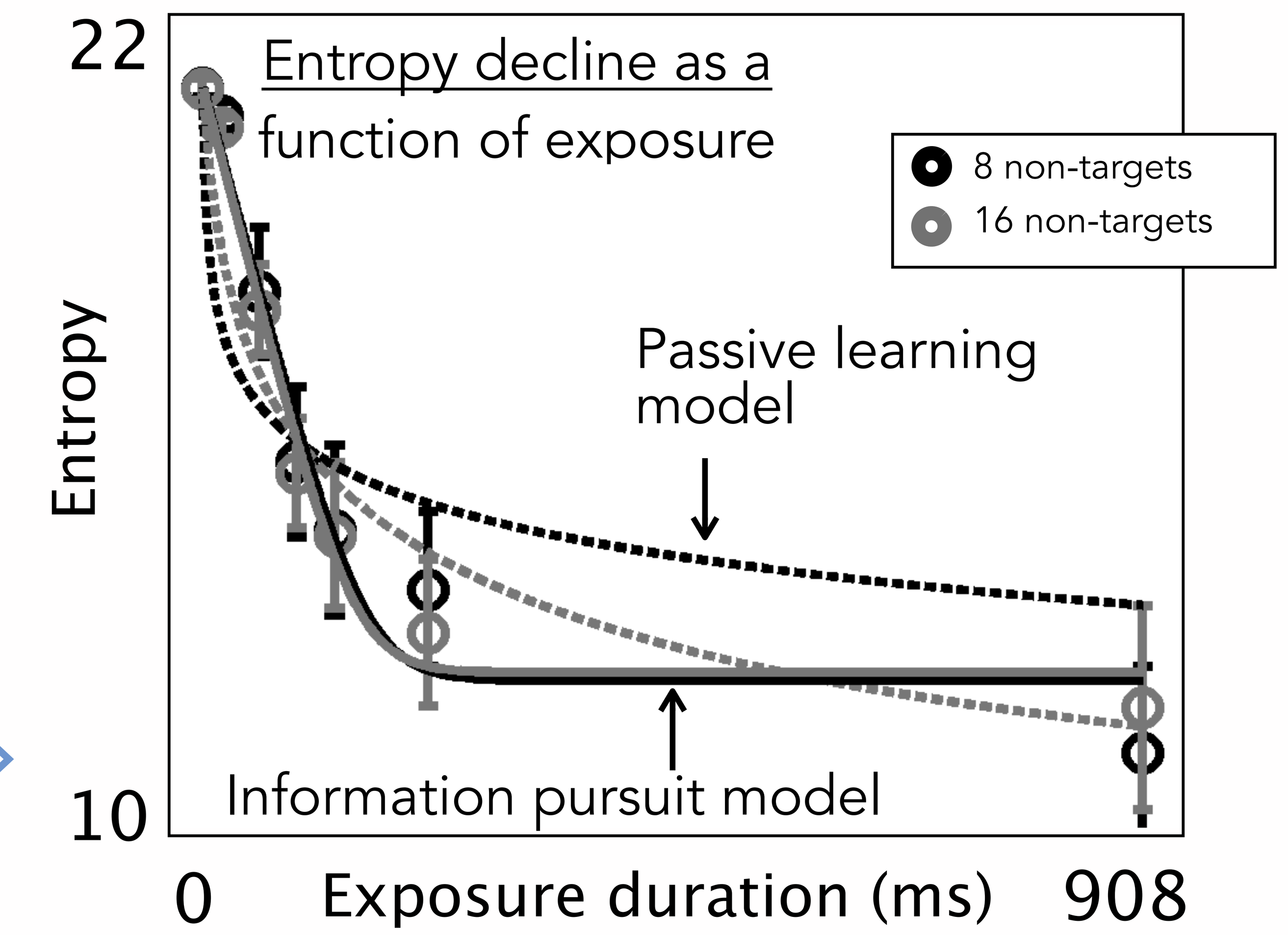
Method: Exposure limited search and localization



By limiting exposure time and measuring localization precision, we can measure how uncertainty decreases with exposure time = information gain / entropy decline .

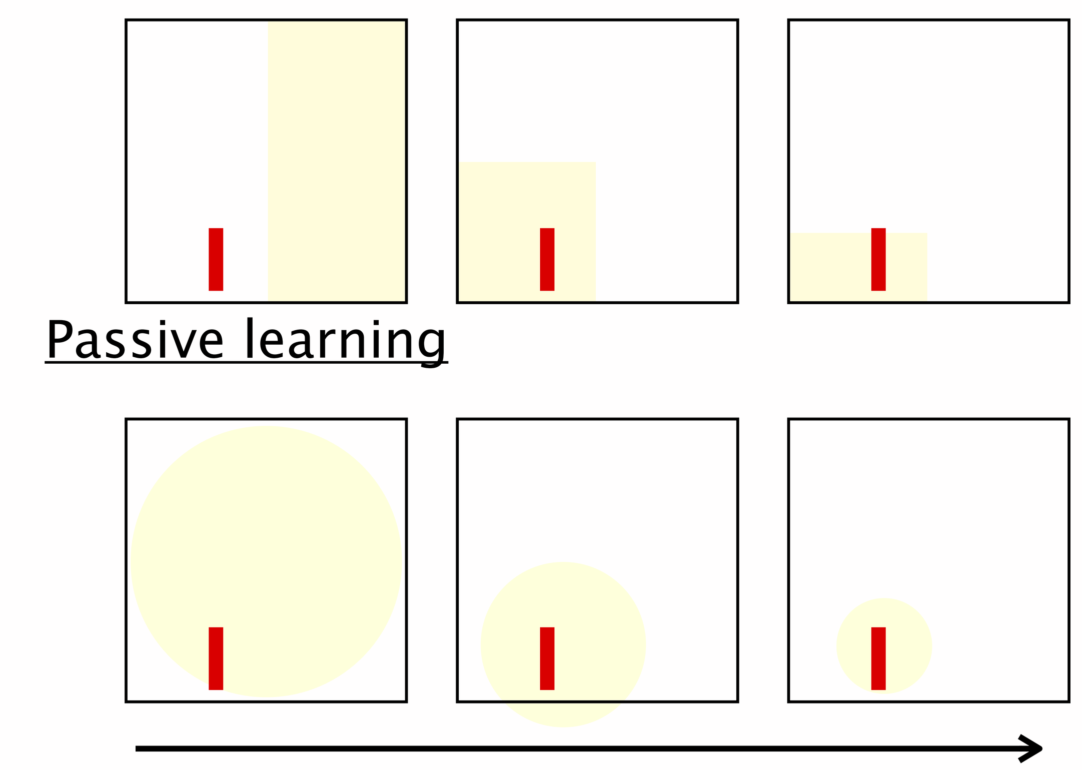
Exposure limited between 0 and 908 ms and followed by mask.

Blank display.
Task: Click in the position closest to where you think you saw the target.



* *Information pursuit model provides significantly better fits (Wilcoxon rank sum test: $p < .01$)*

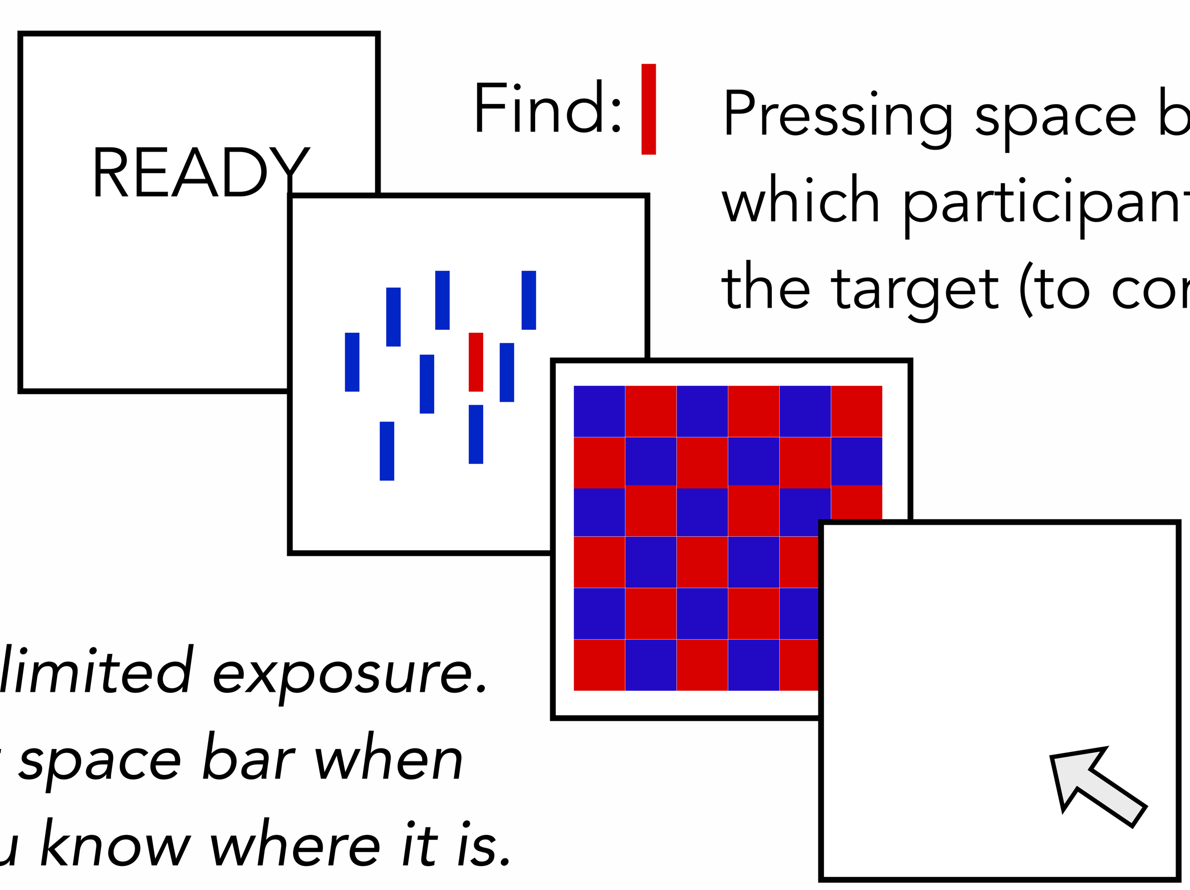
Information pursuit (conceptually, math below)



The observer recursively queries the display, choosing the questions for which she is the most uncertain of the answer

The observer interrogates each signal to produce an improved estimate of its source given knowledge of her own noise.

A more standard paradigm

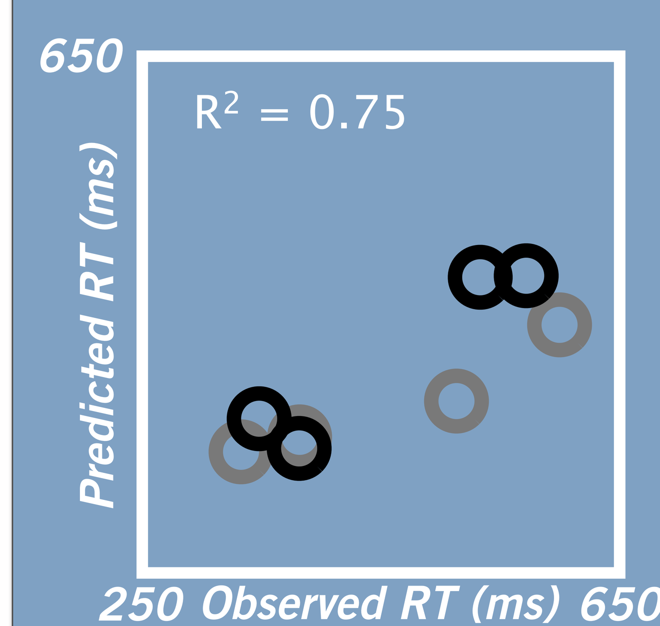


Pressing space bar induces a mask, after which participant clicks where she saw the target (to confirm successful search).

Unlimited exposure. Hit space bar when you know where it is.

Using the data from the limited exposure experiment and the information pursuit model, we can predict **reaction time distributions.**

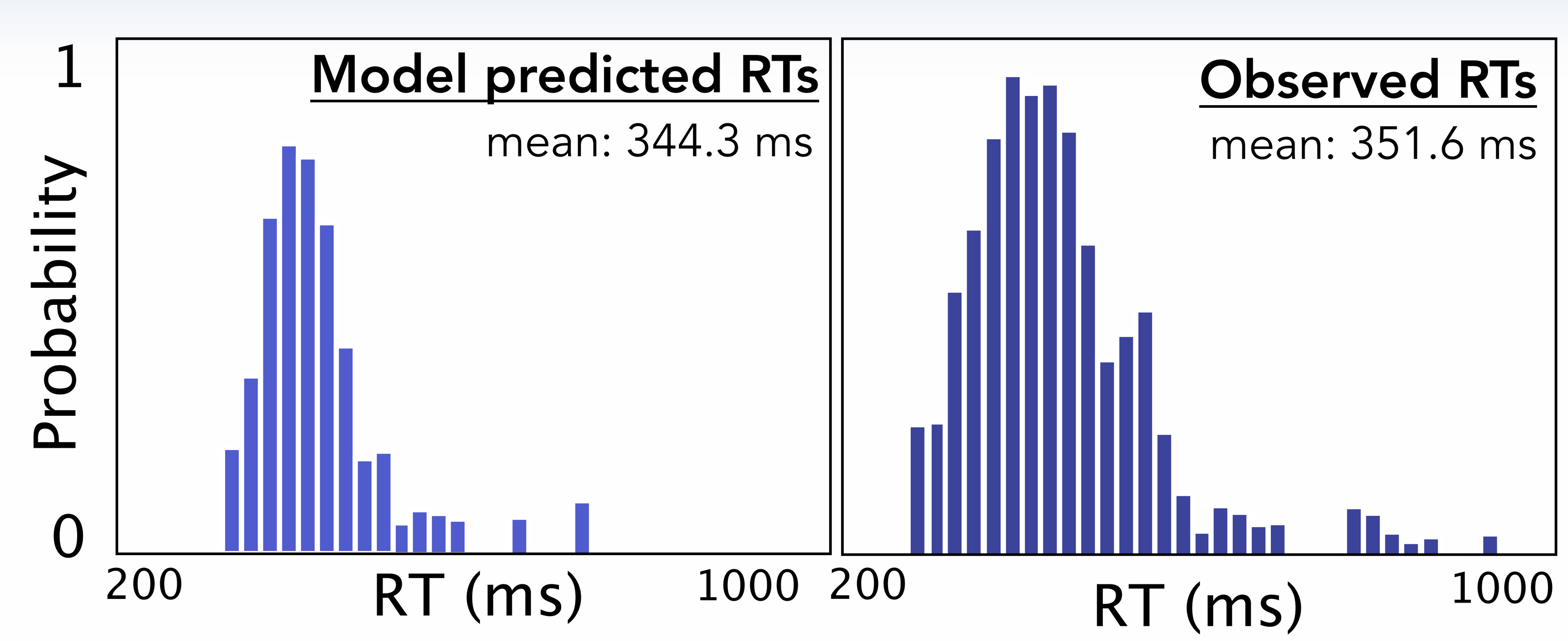
Advantages of information pursuit as an algorithm for search



Maximal information gain in situations where search time is limited or unknown
A constant rate of information gain
Savings when searching for more than one thing

Empirically

Predicts reaction times, even fast ones.
Also predicts shallow slope in efficient search (not shown, but ask...)



Math of information pursuit and passive learning

t = time, $h(t)$ = entropy at a given time
So, $h(0)$ = complete uncertainty
$h(\infty)$ = minimal uncertainty
ß = rate of information gain

Information pursuit continuous time function

$$h(t) = \log(2^{h(0)-\beta t} + 2^{h(\infty)})$$

Passive learning continuous time function

$$h(t) = \log(2^{h(0)-0.5\cdot\log(1+\beta t)} + 2^{h(\infty)})$$

Reprints: http://goo.gl/HoR6oc