How search in the mind guides search in the world

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How does capacity-limited hypothesis generation lead to biased information search?

The search for useful information in the world is guided by the hypotheses a learner wants to test (e.g., when a doctor orders a diagnostic test based on a potential disease). This external search process is commonly shown to be biased (e.g., the positive test strategy, Klayman and Ha 1987).

One explanation for biased information search is that people have a limited capacity to generate alternative hypotheses (Mynatt et al. 1993). However, prior work has focused on tasks where ongoing generation of multiple hypotheses (and an internal limit on that process) is difficult to measure during information search.

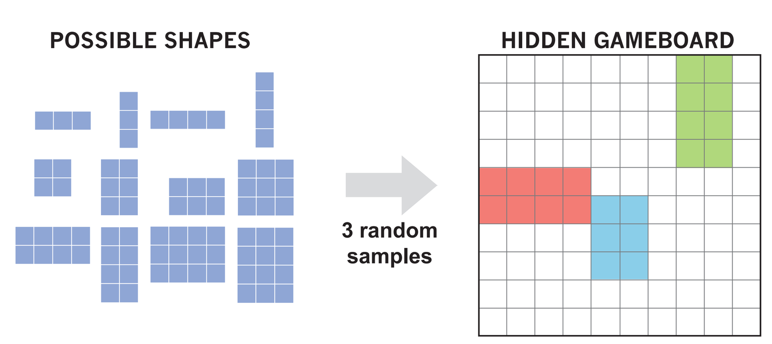
GOALS OF THE STUDY

Using behavior in a spatial search task, we model how an intrinsic limit on the capacity to represent alternatives affects information sampling decisions.

- We measure information search in a task with a well-defined hypothesis space and large number of alternatives
- Use an ideal observer model to characterize suboptimal sampling decisions
- Develop a model of the hypothesis generation process that explains the effects of limited capacity on information sampling decisions

The Rectangle Search Game

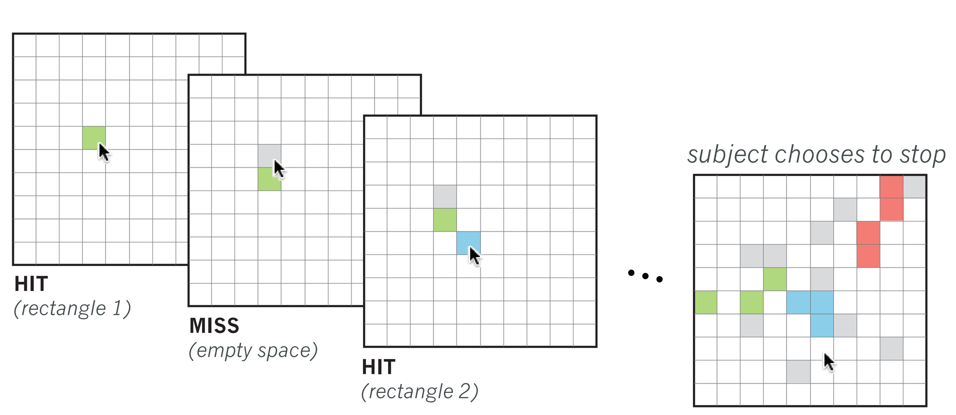
OBJECTIVE: With the fewest number of observations possible, learn the shape and location of three rectangles hidden in a 10x10 grid:



SAMPLING PHASE

Participants learn about the hidden shapes by "sampling" information at any location in the grid, revealing either an empty square (a "MISS") or part of a colored rectangle (a "HIT").

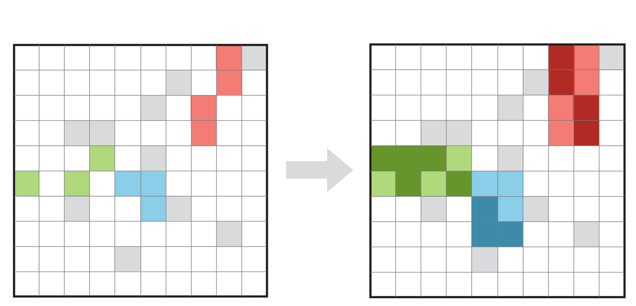
For every observation, 1 point is added to the score (goal is to get lowest score possible).



TEST ("PAINTING") PHASE

When the participant thinks they know the shape and location of all three hidden shapes, they can choose to stop sampling.

After sampling is over, they then "PAINT" in any remaining squares they believe belong to one of the hidden shapes. For every square they paint incorrectly, 2 points are added to the score.



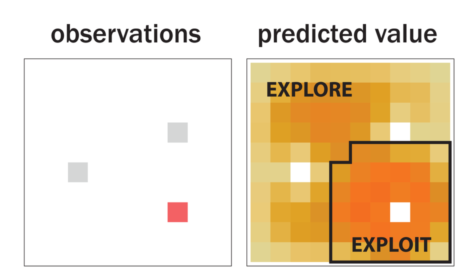
Ideal observer analysis

How does people's search behavior compare to an ideal observer that has perfect knowledge of the hypothesis space (i.e., the set of all possible gameboards)?

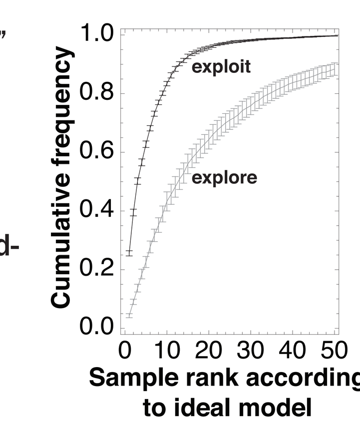
1. Ideal observer model represents the full set of gameboard hypotheses possible in the task and optimally updates its belief following each observation using Bayes' rule
2. The value of a future observation is measured by the degree to which hypotheses disagree on the predicted outcome of that observation
3. Since observations in SAMPLING phase are less costly than errors during PAINTING phase, will continue sampling until there is no longer uncertainty about the true gameboard

EFFICIENT SEARCH IN "PATCHES" OF INFORMATION

1. After the learner uncovers part of a hidden rectangle, the model predicts that the most informative observations are clustered in a surrounding "patch"



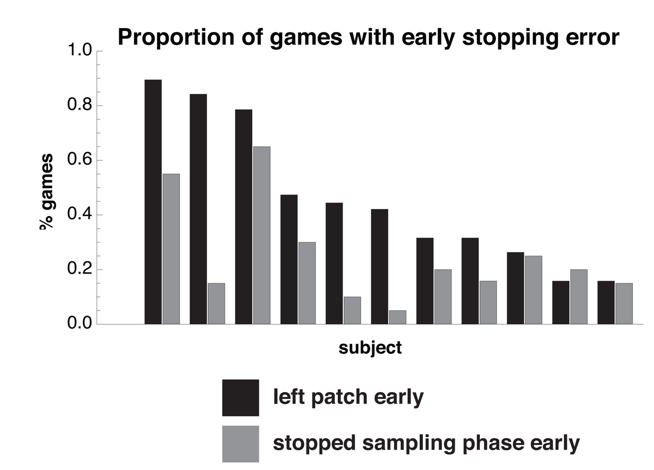
2. Observations within a patch are classified as "EXPLOIT" trials, while observations outside patches classified as "EXPLORE" trials
3. Overall, participants are more efficient during EXPLOIT trials than EXPORE trials. In half of EXPLOIT trials, participants chose one of the top 5 ranked samples according to the ideal model (in contrast to only 15% of EXPLORE trials ranked in top 5)



FREQUENT EARLY STOPPING ERRORS

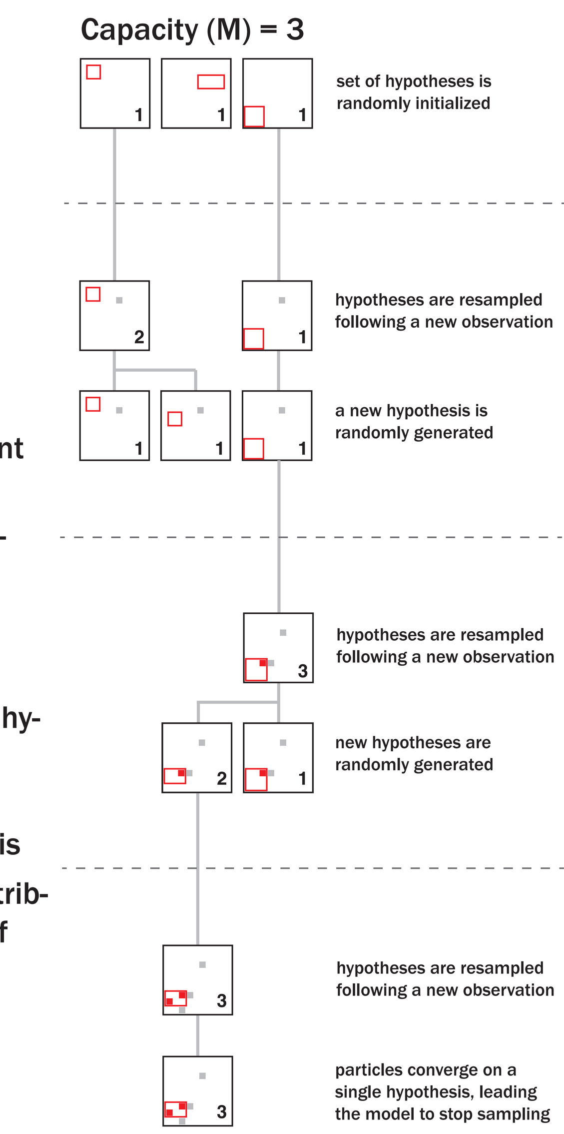
Another measure of how participants diverged from the ideal model is their tendency to make the following errors:

1. *Leaving a patch early:* the participant decided to stop sampling within a "patch" of information before uncertainty about that shape was resolved
2. *Stopping the sampling phase early:* the participant decided to stop sampling even though the ideal model predicts that there are informative observations remaining



Hypothesis generation model

Can a limited capacity to generate alternative hypotheses account for suboptimal information search?

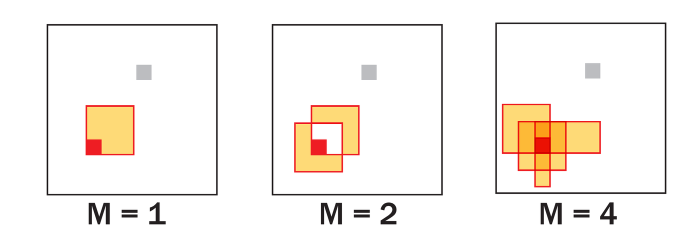


SEQUENTIAL HYPOTHESIS SEARCH

1. Model represents small number of hypotheses about one of the three target shapes
2. The capacity (M) is the number of "particles" or units of weight that are divided among competing hypotheses
3. Hypothesis set is updated following a new observation, such that any inconsistent hypotheses are discarded
4. New hypotheses are generated by making "proposals" based on the previous hypothesis set, leading to an incremental, local process of hypothesis generation

SAMPLING BY UNCERTAINTY

1. Value of a future observation determined by disagreement between the current hypothesis set
2. If only a single hypothesis is represented (M = 1), the model employs a "positive test strategy" by sampling any uncovered locations that belong to that hypothesis
2. As capacity of the model increases, greater number of possible hypotheses contribute to the measurement of uncertainty, biasing the sampling decision in favor of more informative observations



EARLY STOPPING WHEN HYPOTHESES CONVERGE

Low capacity
↓
Increased chance of hypotheses randomly converging
↓
Decision to stop sampling before all alternatives have been considered

1. When there is no disagreement between the current set of hypotheses (i.e., all the weight is on a single hypothesis), the learner stops sampling by either switching to a new target (if there are targets that have not yet been found) or ending the sampling phase (if all targets have been found).
2. If capacity is low, model is more likely to randomly converge on a single hypothesis (even if multiple shapes are still possible). As a result, a low-capacity model will tend to stop sampling earlier than predicted by the ideal observer model.

Model comparison

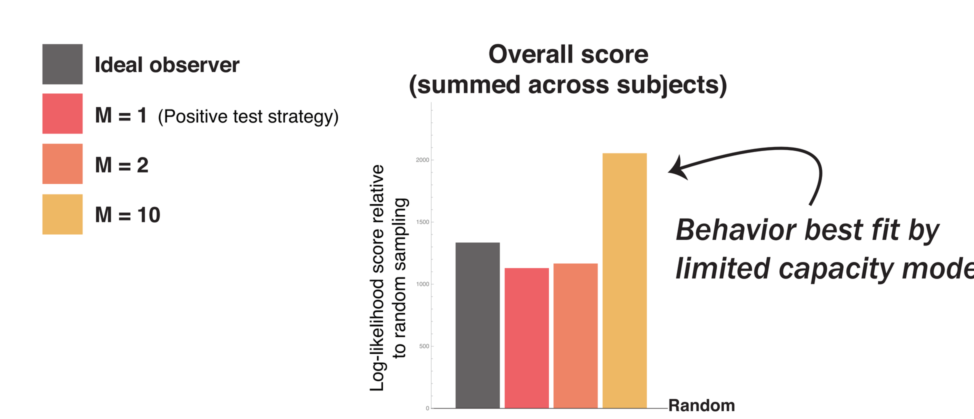
	IDEAL OBSERVER	LIMITED CAPACITY
Efficient exploitation of information "patches"	YES	YES
Early stopping errors	NO	YES

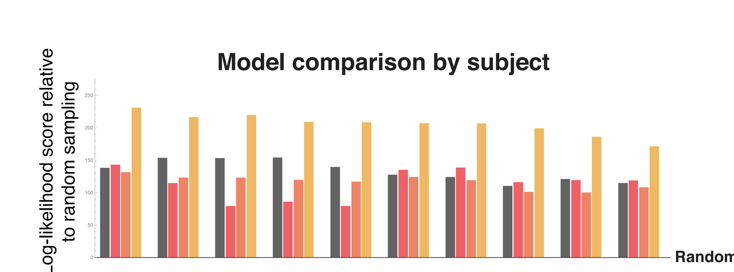
We compared the prediction of the ideal observer to the hypothesis generation model with three settings of the capacity parameter (M = 1, 2, 10)

Since the capacity parameter probabilistically determines when the model switches between target shapes, each model was simulated for 200 runs and the predicted value of participants' choices averaged over runs

- On each trial, value of all remaining observations is calculated using *label entropy*, a sampling norm that measures disagreement between hypotheses' predictions
- Likelihood of participant's choice calculated using probabilistic ("softmax") choice rule
- Log-likelihood of individual samples summed across all games played by a participant for model's overall score

EXAMPLE GAME and MODEL PREDICTIONS





CONCLUSIONS

- Found systematic divergence between participants' behavior and the ideal learner:
  1. People are more efficient when exploiting patches of information related to a single target
  2. People frequently leave a patch or stop sampling altogether before reducing uncertainty completely
- Across 10 participants, a limited capacity hypothesis generation model better predicted search behavior than the ideal observer due to its limited representation and sequential process of switching between target shapes
- Performance was best captured by a hypothesis generation model with an intermediate capacity (M=10) as compared to a low-capacity (M=2) and "confirmatory" model (M=1)
- Future work will measure ongoing changes in capacity limit as a result of extrinsic task demands (e.g., working memory load)