# Optimal eye movement strategies in visual search (Najemnik & Geisler, 2015)

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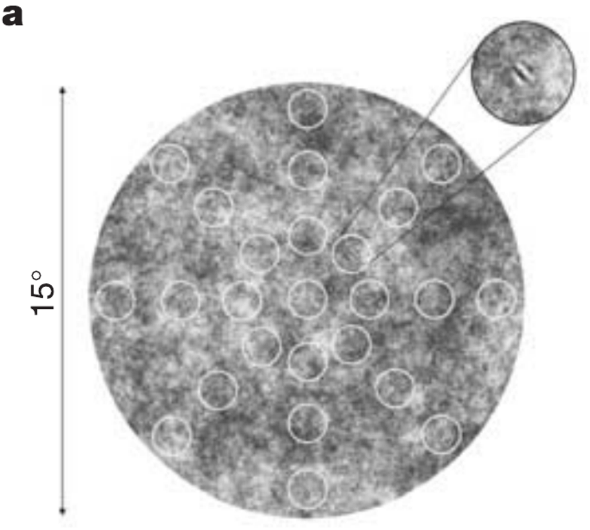
# Context

- Old question in vision science: how good is the human visual system?
  - Different from "how many receptors do we have on the retina?"
  - Rather, how well do we do process the information that we do have
- "Ideal observer theory": formulate models that perform optimally given the constraints
  - for example, what is the minimum number of photons we should be able to detect?
  - optimal threshold for Vernier acuity given receptor density?
- Here: optimal visual search

# The task



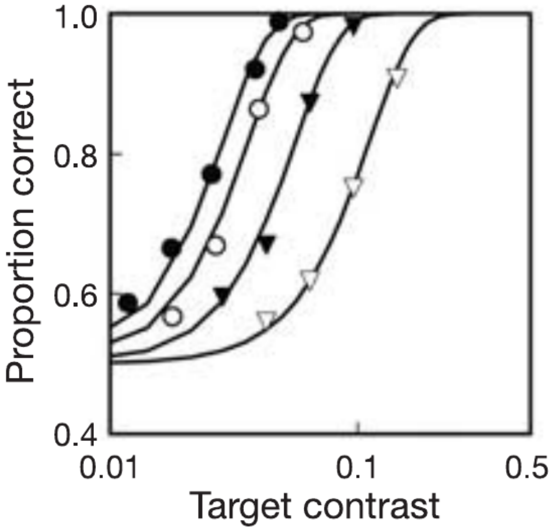
# Defining optimality

- Main constraint for the visual system: visual acuity drops off with eccentricity
- That's why we have to move our eyes to find the target
- Optimal searcher: best searcher under true acuity constraints of the visual system
- First step is to measure acuity

# Measuring acuity

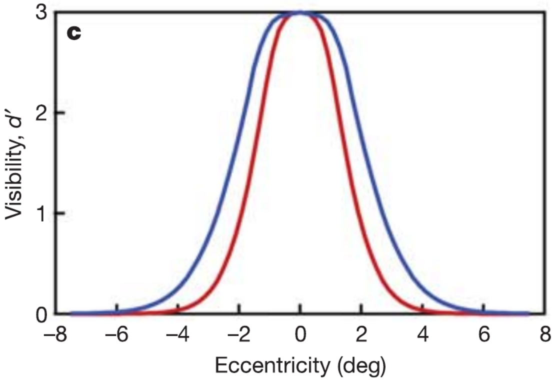
- N&G measured visual acuity as a function of:
  - location
  - signal contrast
  - noise contrast
- Two subjects: N&G.
- Task: 2IFC detection of the target in noise

# Acuity: results




Increasing levels of external noise (filled circles: no noise)

# Acuity: results




(different levels of background/target contrasts)

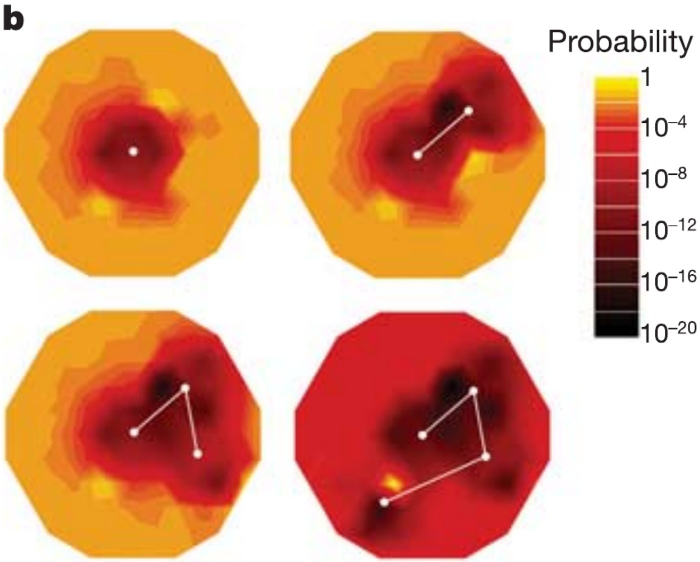
# Limiting factors

- N&G assume that the factors limiting performance are:
  - external noise (that they themselves add)
  - internal noise (in subject's head)
- At each new fixation, internal noise is updated. External noise stays fixed (the stimulus doesn't change)

# Defining the ideal observer

- Before we have an ideal searcher, we need an ideal observer
- The ideal *observer* gives its best guess as to where the target is.
- The best guess comes from the (Bayesian) posterior distribution
$$p(s|\mathbf{y}_t) \propto p(\mathbf{y}_t|s)p(s)$$
- $s$: target position, $\mathbf{y}$ visual data up to time $t$

# Updating posterior distributions



# Ideal searcher

- Ideal searcher chooses search point such as to maximise prob. correct at next step.
- Best possible guess: $\hat{s} = \text{argmax} p(s|\mathbf{y}_t)$, most likely location
- Prob. that the best guess is correct: $p(\hat{s}|\mathbf{y}_t)$
- Find next location $l_{t+1}$ such that:

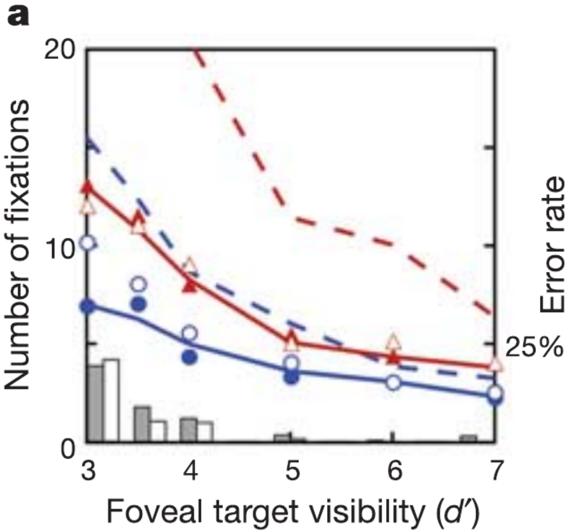
$$l^\star = \text{argmax}\, E_{\mathbf{y}_{t+1},s}\left(\max p(\hat{s}|\mathbf{y}_t, \mathbf{y}_{t+1}, l_{t+1}, s)\right)$$

# Ideal searcher: summary

# Ideal searcher: behaviour

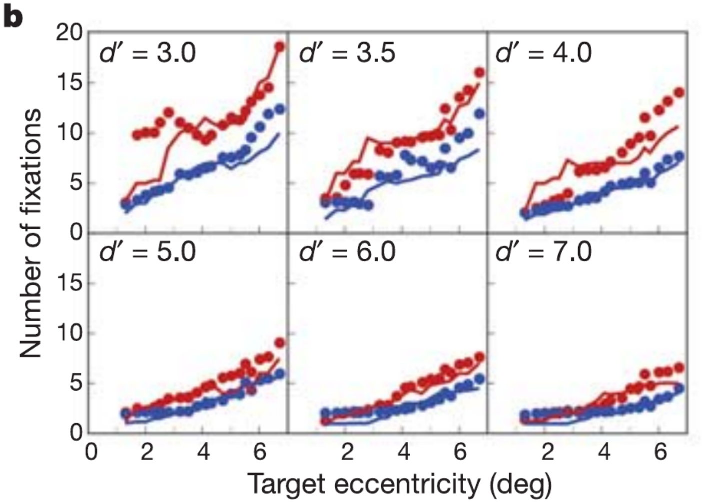
- Performs a “random-looking” search
- MAP vs. center-of-gravity fixations:
  - sometimes goes to have a look at the most likely location (Max. A Post., MAP)
  - sometimes fixates at the centroid of a cluster of likely locations (center-of-gravity)
- Makes saccades of moderate length
- Exhibits Inhibition-of-Return (IOR)
- Sometimes moves to low-probability regions (“exclusion saccades”)

# Ideal vs. human




dashed: random searcher solid: ideal. dots: human. red/black : high vs. low noise contrast

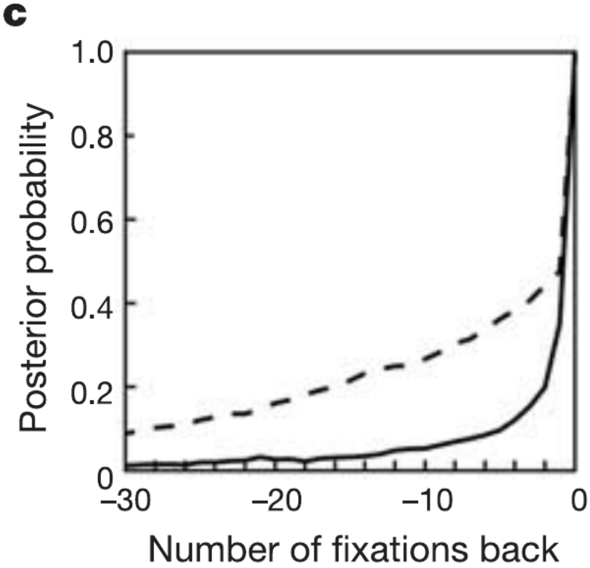
# Ideal vs. human



# Ingredients of ideal searcher

- Ideal searcher has:
  1. completely parallel search at all locations
  2. infinite memory
  3. ability to maximise complicated function for choosing next location
- Which features do humans really have?
- Authors argue (1) for sure, (2) not really needed, (4) can be approximated. They don't talk about (3)

# Do we need infinite memory?

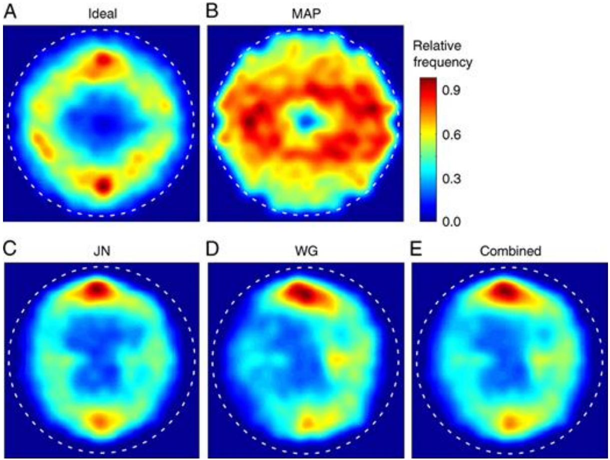



solid: ideal. dashed: random

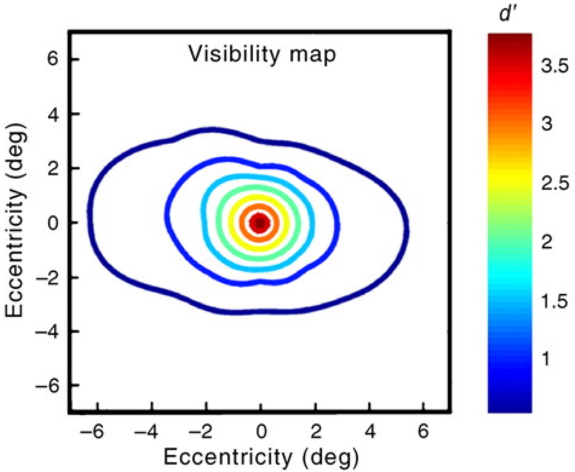
# Do we need to optimise exactly?

- Heuristic: MAP searcher, just looks at the most likely location
- MAP searcher does almost as well as ideal searcher
- MAP is more realistic in a brain implementation
- However: follow-up paper (N&G, JoV)

# Fixation locations



# Visibility field is elongated



# Conclusion

- Ideal observer analysis lets you compare what humans do to what they should be doing.
- Surprisingly good performance in this task (but *very* small sample size).
- Observers seemed to have a notion of what their visibility field is and how to place gaze accordingly.
- If "center-of-gravity" fixations occur with some frequency it's problematic for how we fit models
- Spatial biases observed in this task completely different from usual