

Adaptive Foraging: Effects of Resource Conditions on Search Paths in a Web-Based Foraging Game

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Abstract

Foraging is a search process common to mobile organisms, and foraging paths commonly exhibit statistical patterns akin to Lévy walks. There may be common factors and benefits underlying these patterns, but investigations are hindered by difficulty in assessing and manipulating search environments and task conditions. In the present study, a simple foraging game was developed to isolate and manipulate two factors hypothesized to make Lévy walks adaptive search strategies, sparsity and spatial clustering of targets in the search environment. The game entailed navigating a fuel-limited ship over a 2D grid to find as many targets as possible, rendered as asteroids in outer space. Over 1800 participants were recruited to play using Amazon's Mechanical Turk, in order to widely sample the parameter space defined by degrees of target sparsity and clustering. Observed search paths resembled Lévy walks with memory, and those of high performers were found to vary adaptively with clustering, but not sparsity. Results indicate that Lévy-like walks can emerge from search strategies and algorithms adapted to environments with clustered resources.

Keywords: Foraging; Lévy walks; crowdsourcing; adaptive search.

Introduction

Perhaps the most ancient kind of search function in biological organisms, in terms of evolutionary history, is foraging—moving about one's environment in search of resources like food, locales like shelter, or other organisms like mates. Studies of animal foraging have found a common statistical pattern in foraging paths known as a Lévy walk (Viswanathan et al., 1996). Paths are clustered such that most path segments are relatively short, but interspersed with longer segments, occasionally much longer. Intriguingly, the distribution of path lengths consistently follows an inverse power law, $P(l) \sim 1/l^\alpha$, where $\alpha \sim 2$. Lévy-like path lengths are observed for foragers from bacteria (Berg, 1993) to humans (Rhee, Shin, Hong, Lee, & Kim, 2011).

Lévy foraging paths can be modeled simply as random walks with path lengths sampled from a power law, although path directions may be correlated over time

(Viswanathan et al., 2001), and mechanisms of navigation are left unspecified. Despite their simplicity, Lévy walks have proven influential because they suggest that search benefits are conferred by power law path lengths, at least under certain foraging conditions (Viswanathan & Buldyrev, 1999). In particular, when $\alpha \sim 2$ and targets are sparsely and randomly distributed, Lévy walks are able to search spaces more completely compared with Gaussian-distributed random walks, and find targets at a maximal rate.

The potential benefits of Lévy walks recently have led cognitive scientists to investigate whether they occur in perceptual, memory, and decision-making search tasks. First were Rhodes and Turvey (2007), who investigated Lévy walks in a classic category recall paradigm (Bousfield & Sedgewick, 1944). Participants recalled as many animals as they could from long-term memory, for twenty minutes. Inter-response intervals were used as indirect measures of memory "path lengths", and they were found to be best fit by inverse power law functions with exponents near two. Then, Rhodes, Kello, and Kerster (2011) found that saccade lengths in visual foraging tasks also followed a heavy-tailed distribution resembling the optimal Lévy walk, although the lognormal function provided the best fit to data. A lognormal can be viewed as a constrained power law (Stephen & Mirman, 2010), which should be expected when search is constrained to a relatively small space (a computer monitor). Most recently, Radicchi and Baronchelli (2012) found search intervals to be Lévy-like when buyers searched the bid space in online auctions, and observed exponents were shown to maximize economic gains.

These and other similar studies raise the question of what mechanisms and factors give rise to Lévy-like search paths across so many different species and foraging conditions. Theoretical analyses suggest that sparsity of targets is a factor, but it is prohibitively difficult to test this hypothesis in natural foraging conditions, including visual and memory foraging of natural scenes and categories. Also, most theoretical analyses have assumed randomly distributed targets (Viswanathan & Buldyrev, 1999), but food and other resources may instead tend to be clustered in nature, as is the case with plankton distributions, for instance (Mackas &

Boyd, 1979). In terms of mechanism, Lévy-like foraging may be intrinsic to both biological and cognitive search functions, in which case Lévy walks would occur regardless of search conditions. Alternatively, Lévy walks instead may emerge as a result of interactions between search processes and their environments. These interactions may unfold over the course of minutes and even faster timescales.

In the present experiment, we examined the roles of sparsity and clustering in a web-based video game designed to mimic canonical foraging. We used a video game because it allowed us to know and manipulate search conditions. We made the game web-based so that we could collect data from very large numbers of participants on Amazon's Mechanical Turk. Recent studies have shown that Turk yields data comparable to university participant pools (Germine et al., 2012; Snow, O'Connor, Jurafsky, & Ng, 2008), and we confirmed this in a pilot study of our video game run through the UC Merced participant pool (not reported). Turk allowed us to robustly sample the parameter space created by factorial manipulation of sparsity and clustering. Turk also allowed us to collect enough data to compare players who find greater versus fewer numbers of targets, i.e. high versus low performers.

Comparisons of high versus low scorers are critical because they test whether adaptive search is associated with closer-to-optimal (i.e. higher scoring) performance. That is, do high performers adapt their search strategies, as measured by path length distributions, to changes in sparsity and clustering? Do high scoring foraging paths more closely resemble Lévy flights with the theoretically optimal exponent of two? Addressing these questions will provide evidence on 1) whether Lévy-like foraging paths can emerge from searcher-environment interactions on timescales no longer than minutes, and 2) whether adapting paths to sparsity or clustering is associated with better performance.

Methods

The foraging game was framed as a task of exploring outer space to find resources on asteroids (see Figure 1, and <http://cogmech.ucmerced.edu/downloads.html> to play). Participants used a mouse (or functionally equivalent device) to move a spaceship over a 1280x1024 grid of space. Movement was controlled at two scales, *zoomed in* and *zoomed out*. When *zoomed out*, the entire space was visible at once, and participants clicked on a location to "fly" the ship to that spot (shown by animation). Participants pressed the space bar to zoom in 15X at a given location, at which point they again could navigate the ship via point-and-click. Hubble images were used as background to help engage players by giving the sense of outer space, and to provide environmental cues that are, in general, ubiquitous to natural search conditions. These cues may encourage use of memory in navigation (e.g. Vinson, 1999), which shall be discussed later.

Asteroids were visible only when zoomed in, and resources were harvested by moving to them such that

collision occurred between the asteroid and ship graphics. A set amount of fuel was provided for each play of the game, and fuel usage (shown by a fuel bar) was a linear function of distance traveled, plus a small constant for each zoom in/out. The amount of fuel provided was determined based on pilot work to allow for about 5 minutes per play, and to enable players to find some but not all asteroids. Each successful harvest was indicated by sight and sound, and asteroids could only be harvested once (the un/harvested status of asteroids was not displayed). Each harvest added one point to the score (no fuel was added), and play continued until all fuel was expended.

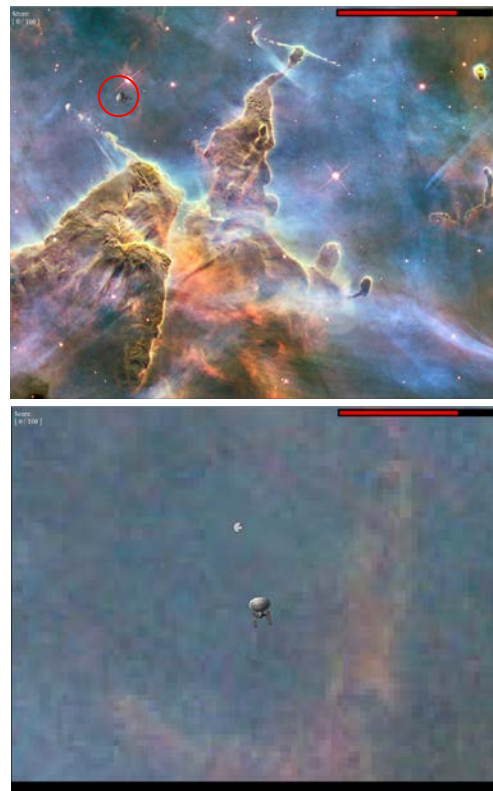


Figure 1: Example game space shown zoomed out (above), along with the corresponding zoomed in view (below). Current score is shown in upper left corner, and fuel bar with remaining fuel in red is shown in upper right corner.

The game was designed to mimic foraging as exemplified by aquatic birds hunting for fish, or the eyes scanning a scene to gather visual information. Relatively short movements are made during resource acquisition (while in the water and close to the surface, or during fixations), interspersed with longer-scale movements when no resources are acquired (while flying high above the water, or during saccades when visual information uptake is attenuated; Ross, Morrone, Goldberg, & Burr, 2001). Foraging costs in natural searches (e.g. risk and energy expenditure) were lumped into the fuel cost of travel, although time costs were also a factor, given the natural tendency to minimize time spent.

The game was coded in Flash so it could be distributed via the web, with game data collected on a local server. We used Amazon’s Mechanical Turk to find people willing to play the game twice (plus a 1 minute practice session to learn) for 75 cents in compensation. Pilot work indicated that the availability and quality of Turk workers fell off precipitously for tasks lasting more than 10-15 minutes. A step-by-step demo, along with instructions in English, was presented at the beginning of play, and each play was set to last about 5 minutes (assuming no breaks). Two plays were required for each paid work session.

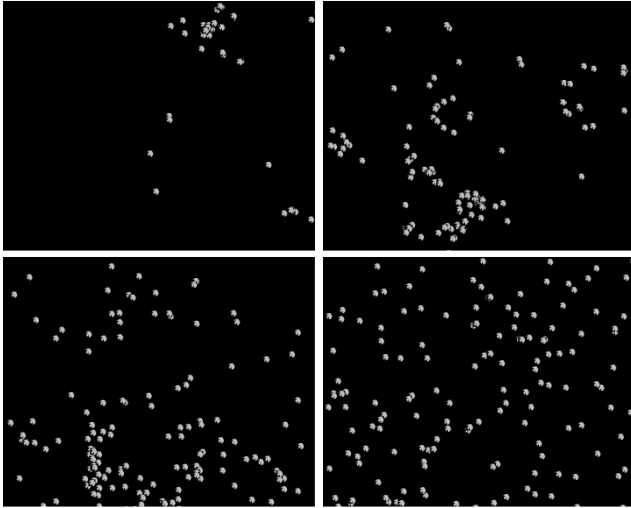


Figure 2: Example of 150 asteroids clustered at 0.05, 0.15, 0.25, and 0.5, left to right, top to bottom.

The number of asteroids per play was set at four different levels: 25, 50, 100, and 150. Pilot work indicated that 25 asteroids meant that players occasionally found only a few of them (or even none), and 150 meant that players found asteroids nearly every time the zoomed in. Clustering of asteroids was manipulated at four different levels of a probabilistic parameter: 0.05, 0.15, 0.25, and 0.5. This parameter controlled the probability of dividing asteroids evenly (0.5) or entirely to one side (0.0) in an algorithm that divided a given set of asteroids recursively into alternating horizontal and vertical splits of a given 2D space. Asteroids were placed when only one remained in a given recursively split section of the space (placed at random in the section), and/or when the space could be split no further (see Figure 2 for example asteroid distributions, and Figure 3 for pseudocode). This algorithm created clusters whose sizes followed a nested scaling relation to varying degrees, consistent with findings of scaling law clustering of natural resources (Humphries et al., 2010; Mackas & Boyd, 1979). The algorithm also created asteroid distributions that were independent of Hubble image backgrounds, and participants were informed of this independence during the demo/instruction period.

The full 4x4 factorial of sparsity and clustering levels was tested. Each participant played twice in only one of the 16

possible conditions, chosen at random at the start of each Turk session. The demo and instructions included an example asteroid distribution for the condition the participant was in, to help them formulate an informed foraging strategy. Players were also encouraged to achieve the best score possible by maintaining a high score board, and allowing high scorers to enter their initials for display to other players.

```
function distributeResources(rectangle, prob_split)
{
  if (rectangle.stars_remaining < 1) return
  else if (rectangle.size < 1 pixel) {
    place remaining stars at pixel
    return
  }
  else if (rectangle.stars_remaining == 1) {
    place star randomly in rectangle
    return
  }

  // alternate between vertical and horizontal splitting
  (rectangle1,rectangle2) = splitRectangle(rectangle,alternate)

  for each star {
    if (random_prob() < prob_split) star in rectangle1
    else star in rectangle2
  }

  // bias direction is randomized each split
  if (random_prob() < 0.5) prob_split = 1 - prob_split

  distributeResources(rectangle1, prob_split)
  distributeResources(rectangle2, prob_split)
}
```

Figure 3: Pseudocode for asteroid distribution algorithm

Results

A total of 1,825 play sessions were administered on Turk. Participants who did not produce more than 80 zoom in actions per play were excluded from analysis (603 participants). Pilot work indicated that participants who simply expended fuel to complete the task, rather than endeavored to find asteroids, were usually revealed as making mostly large zoom out movements to expend fuel quickly. Of the remaining 1,222 participants, it was determined that 393 of them were participants who played in two or more Turk sessions. Analyses with and without these repeats indicated no qualitative change in results, so all plays were included in the reported results. Analyses combine zoomed in and zoomed out path lengths.

Visual inspection of zoomed out flight paths revealed directional movements that ranged in their temporal correlations, which are a basic expression of memory in search paths. Two example paths at the two ends of this range are shown in Figure 4. Paths that consisted of highly regular directional movements were seen as “sweep” strategies designed to systematically cover the space in left-right, top-down, spiral, and other search patterns. Paths at the other end of the range consisted of seemingly haphazard directional movements, akin to random walks. In the middle were mixtures of the two, plus directional movements that followed irregular contours of Hubble images (despite instructions that distributions were independent of images).

To minimize effects of practice and learning, only the second of two plays per Turk session was analyzed (unless specified otherwise). Performance was measured as the

proportion of available targets harvested, and plays were divided into three categories of performance, for each of the 16 game conditions: Top 20, middle 20, and bottom 20 scores. More than 60 Turk sessions were randomly assigned to each game condition, so any additional plays were excluded from reported analyses. The constant of 20 plays per cell simplified statistical analyses, and excluding plays in between performance categories helped to make those categories distinct.

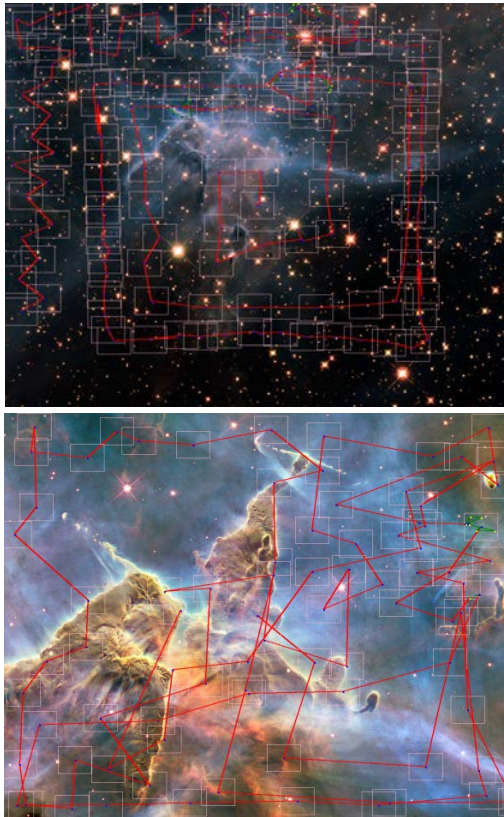


Figure 4: Two example flight paths of more versus less directionally correlated movements (top versus bottom). Red and green lines indicate zoomed out and zoomed in movements, respectively. Blue dots indicate clicked locations, and yellow dots indicate points of harvest. White boxes indicate areas of zoom in.

All results are graphed and analyzed as a function of sparsity, clustering, and performance category. A three-way analysis of variance was conducted for each dependent measure, and only main effects and two-way interactions are reported because these are the statistical tests relevant to our research questions and hypotheses. First, we examine score as function of these three factors, shown in Figure 5. The main effect of performance category is itself based on score, and is so large throughout our analyses that reporting its reliability was unnecessary.

As for the other two main effects, sparsity was not reliable, $F(3,18) = 2.1, p > 0.1$, but clustering was, $F(3,18) = 38.42, p < .05$. The interaction of performance category with

sparsity was also not reliable, $F(6,18) = 0.84, p > 0.5$, but it did interact with clustering, $F(6,18) = 55.41, p < .05$. Visual inspection shows that scores improved with clustering for high performers, but the opposite effect occurred for low performers. These results show that foragers adapted to clustering but not sparsity, and low performers appeared to adapt counterproductive strategies in terms of score. Thus we have initial evidence that high performers took advantage of the spatial correlations in clustering, suggesting that foraging paths emerged from interactions between search processes and game conditions.

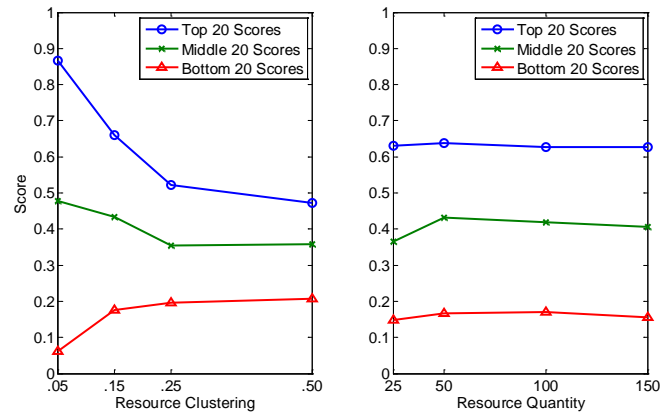


Figure 5: Proportional score as a function of quantity (i.e. sparsity), clustering, and performance category.

However, one might argue that each forager has an intrinsic strategy, or a strategy chosen without regard to conditions. Effects of clustering merely may show that the consequences of good versus bad strategies increase with clustering. We tested this possibility by examining the change in score from first to second play. We found that score increased over time for high performers (+19%), but decreased for low performers (-14%), $t(638) = 17.7, p < .01$. This difference suggests that strategies changed over the course of play, for better or worse, indicative of interactions between search processes and game conditions.

Next we examine mean path length, shown in Figure 6. High performers had shorter path lengths overall, which indicates that shorter path lengths allowed for greater coverage of the space (confirmed by coverage analyses not reported). This main effect would be expected to diminish, and possibly even reverse, if fuel cost more per zoom.

There were no main effects of sparsity on mean path length, $F(3,18) = 2.19, p > .1$, and neither of clustering, $F(3,18) = 1.7, p > .2$. The interaction of performance category with sparsity again was not reliable, $F(6,18) = 1.66, p > .15$, but it interacted reliably with clustering once again, $F(6,18) = 4.61, p > .05$. Visual inspection shows that path lengths for high performers increased with clustering, whereas they decreased for low performers. The increase for high performers presumably reflects the increased need for larger jumps as clusters became more tight and scattered.

Again, low performers appeared to adjust strategies as well, but in counterproductive ways.

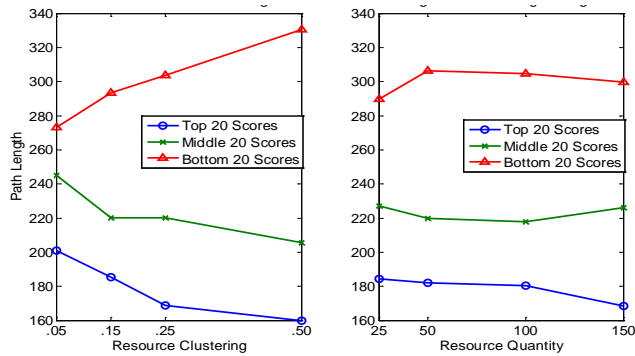


Figure 6: Proportional score as a function of quantity (i.e. sparsity), clustering, and performance category.

Next we examine whether foraging paths resembled Lévy walks, in the sense that path length distributions were power law distributed with estimated exponents near two. We used multi-model inference (Symonds & Moussalli, 2010) to test which of four different functions provided the best fit to the distribution of path lengths for each participant (mean of 217 path segments per participant): Normal, exponential, lognormal, and Pareto. Only the latter two are heavy-tailed and Lévy-like, and the method uses Akaike's information criterion (AIC) to find the function with the shortest information-theoretic distance to the data.

The lognormal function provided the best fit for 68% of the participants, with the remaining trials roughly evenly split between normal and exponential fits (Pareto never provided the best fit). As mentioned earlier, the lognormal is akin to a constrained power law, and the foraging game constrained movements in terms of a limited amount of space. An example distribution from one participant is plotted in Figure 7 in logarithmic coordinates, which is representative of the majority of participants. The constrained, normal-like portion of the distribution is seen as a slight hump on the left side, and the power law-like tail is seen as a negatively sloped line on the right.

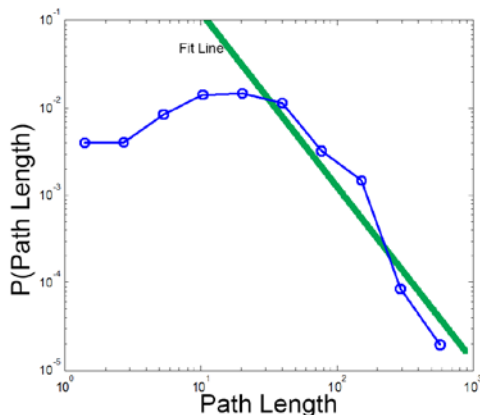


Figure 7: An representative path length distribution for one participant, plotted in logarithmic coordinates

We further examined the tails of path length distributions in two ways. First, the fitted lognormal functions have μ and σ parameters, where the latter roughly corresponds with the heaviness of the tail. Heavier tails indicate more Lévy-like distributions. Best-fitting σ 's are shown in Figure 8 for all participants, including those whose data were better fit by normal or exponential distributions.

The overall pattern of results was similar to previous ones. There was no main effect of sparsity, $F(3,18) = 1.17, p > .35$, but clustering was again reliable, $F(3,18) = 10.52, p < .05$. Visual inspection reveals the possibility of an effect in the high/mid performers which was supported by a reliable interaction of performance category with clustering, $F(6,18) = 12.29, p < .05$. Once again, there was no reliable interaction with sparsity, $F(6,18) = 1.77, p > .15$. Visual inspection shows that the tails of path length distributions were heavier overall for low performers, but they *became* heavier with greater clustering *only* for high performers.

To gauge whether distributions were becoming more similar to the theoretical power law exponent of two, we fit regression lines (see Figure 7) to the right half of distributions in logarithmic coordinates, and results are shown in Figure 9. None of the main effects (excluding performance category) or interactions were reliable, but slopes were generally in the neighborhood of the theoretical optimum of -2 (negative of the optimal exponent). Moreover, slopes for high performers were closest in their approach towards -2 with greater clustering.

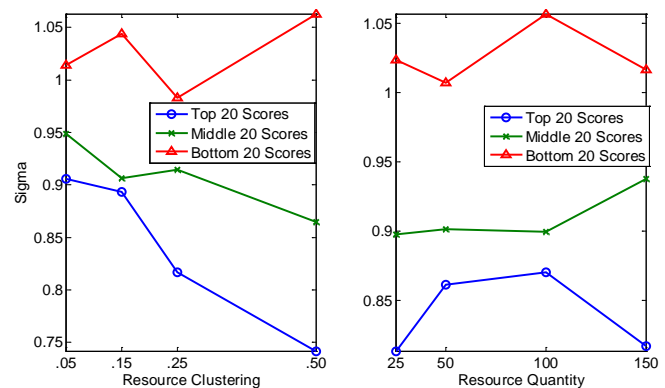


Figure 8: Lognormal σ as a function of quantity (i.e. sparsity), clustering, and performance category.

To summarize, search paths generally resembled the optimal Lévy walks predicted to occur, to some degree. The majority of path length distributions were heavy-tailed, and tails resembled power laws with exponents near two, to some degree. Distributions most closely resembled Lévy walks for high performers in the most clustered resource conditions. Foraging paths also departed from Lévy walks, in that directions were never drawn purely at random. Example paths (Figure 4) showed that directions tended to be correlated in time. This tendency can be quantified simply by computing the proportion of times that next steps went in the same direction, within some threshold. Angular changes were between 0 and 180 degrees (collapsing left

versus right turns) and divided evenly into 45 bins. The proportion of movements falling into the smallest angular bin was 25%, about 10X greater than chance. Thus foraging paths had memory in terms of directional correlations.

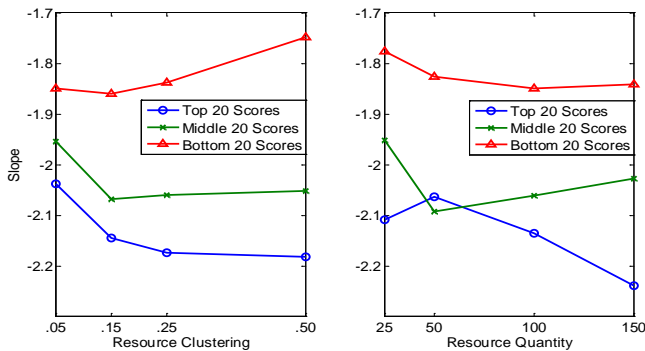


Figure 9: Regression slopes as a function of quantity (i.e. sparsity), clustering, and performance category.

Discussion

In the present study, analyses of data from a web-based foraging game showed that Lévy-like search paths emerge from search processes that change depending on the clustering of resources. This was true for both high and low performers, although only high performers changed their search processes adaptively. The lack of a sparsity effect was conspicuous because prior theoretical analyses suggest that the benefits of Lévy-like search paths are most prevalent when items are rare to be found. However, prior analyses focused on random Lévy walks, whereas observed foraging paths clearly had memory. Memory sometimes manifested as “sweep” searches, but more generally, directions of next steps depended on previous steps.

Our results suggest that the prevalence of Lévy-like walks in both animal and cognitive searches can be better modeled by processes with memory that attend to target and task conditions, as opposed to random walk processes. The observed effects of clustering indicate that search processes take advantage of spatial correlations in resource distributions when they exist and are known or learned. A simple approach to modeling an effect of spatial correlations is for search processes to follow a gradient of resource density. These and related modeling ideas (e.g. Ferreira, Raposo, Viswanathan, & da Luz, 2012) will be pursued in future research.

Acknowledgments

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