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# 1 **Reinforcement Learning Enables Resource-Partitioning in** 2 **Foraging Bats**

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4 Stefan Greif<sup>3</sup>, Rodrigo A. Medellin<sup>4</sup>, Yuval Emek<sup>5</sup>, Amos Korman<sup>2\*</sup> & Yossi Yovel<sup>1,3\*</sup>.

5

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16

## 17 **Summary**

18 Every evening, from late spring to mid-summer, tens of thousands of hungry lactating female  
19 Lesser long-nosed bats (*Leptonycteris yerbabuena*) emerge from their roost and navigate  
20 over the Sonoran Desert seeking for nectar and pollen [1,2]. The bats roost in a huge maternal  
21 colony which is far from the foraging grounds, but allows their pups to thermoregulate [3]  
22 while the mothers are foraging. Thus, the mothers have to fly tens of kilometers to the  
23 foraging sites - fields with thousands of Saguaro cacti [4,5]. Once at the field, they must  
24 compete with many other bats over the same flowering cacti. Several solutions have been

25 suggested for this classical foraging task of exploiting a resource composed of many  
26 renewable food-sources whose locations are fixed. Some animals randomly visit the food  
27 sources [6], some actively defend a restricted foraging territory [7–11], or use simple forms  
28 of learning such as ‘win-stay lose-switch’ strategy [12]. Many species have been suggested to  
29 follow a trapline, that is, to re-visit the food sources in a repeating ordered manner [13–22].  
30 We thus hypothesized that lesser long-nosed bats would visit cacti in a sequenced manner.  
31 Using miniature GPS devices, aerial imaging and video recordings, we tracked the full  
32 movement of the bats and *all* of their visits to their natural food-sources. Based on real data  
33 and evolutionary simulations, we argue that the bats use a reinforcement learning strategy,  
34 that requires minimal memory, to create small non-overlapping cacti-cores and exploit nectar  
35 efficiently, without social communication.

36

37 **Keywords:** Nectar feeding bats, reinforcement learning, resource partitioning, trapline,  
38 behavioral ecology, movement ecology.

39

## 40 **Results and Discussion**

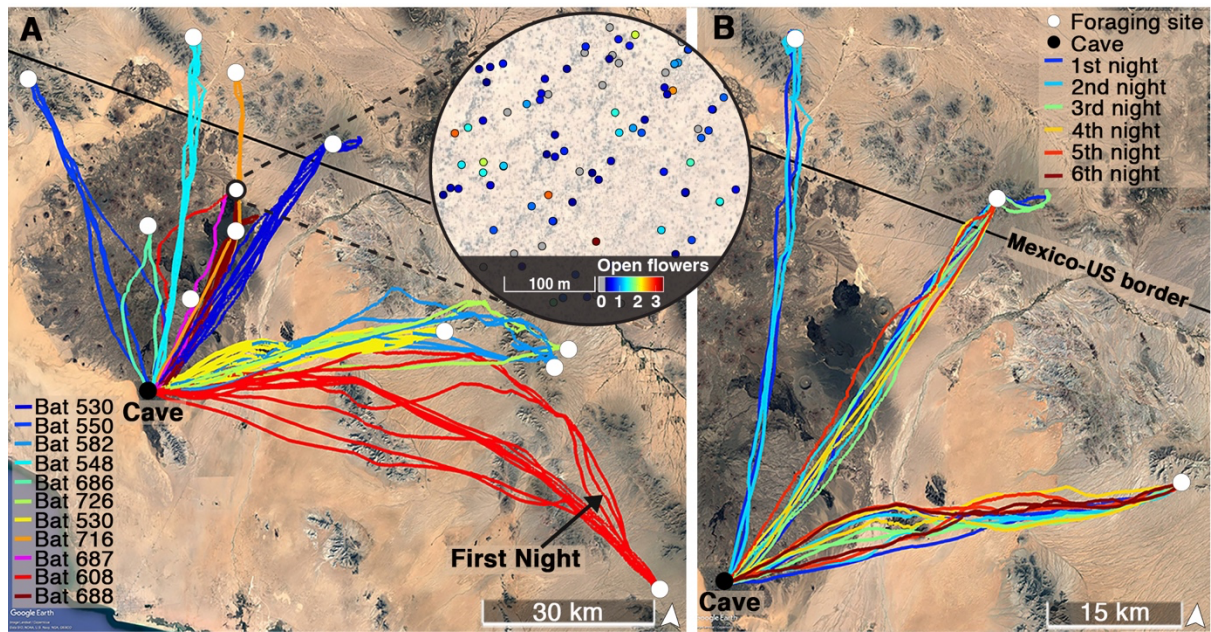
41 The foraging task of the Lesser long-nosed bat is particularly complex. Saguaro fields  
42 (*Carnegiea gigantea*) in the northern Sonora contain many hundreds of cacti per square  
43 kilometer [23]. The cactus flowers open in the evening and start producing nectar ca. 1.5  
44 hours after sunset at a constant rate of  $0.1 \pm 0.004$  ml/h per flower (Figure S1A, STAR  
45 Methods). The quality of a specific cactus can vary dramatically according to the number of  
46 flowers it opens on a given night, which translates linearly to its total rate of nectar  
47 production (flowers produce nectar at similar rates and sugar concentration is similar, see  
48 STAR Methods). Moreover, there is little correlation between the quality of neighboring cacti  
49 (Figure 1A).

50 Energetic estimates (see STAR Methods) suggest that a lactating female needs to drink 14.1-  
51 18.9 ml of nectar per night. Because a single cactus provides no more than 0.65 ml during the  
52 hours that a bat spends in the field, a bat must visit many cacti. As high-quality cacti are rare  
53 and most cacti have 0-1 open flowers (Figure 1A and Figure S1B), it is worthwhile for a bat  
54 to invest time in exploring the field. Moreover, bats have to re-map the field every night.  
55 Although we found a significant correlation between the number of flowers on a cactus on  
56 consecutive nights, there was much inter-night variability (Spearman correlation test:  $r=0.6$ ,  
57  $P<0.001$ , Figure S1C-D). Importantly, even if the exploration is effective, the corresponding  
58 exploitation might not be trivial. In theory, a bat could memorize when it last visited a  
59 profitable cactus [24] and plan to revisit it after some time interval, but it cannot be certain it  
60 will find the expected nectar, since a conspecific might deplete it in the meanwhile (the bats'  
61 behavior suggests that they do not know if a flower was recently visited, Figure S1E-F). We  
62 thus set out to examine how bats make foraging decisions under such uncertainty.

63 We used miniature GPS devices to track bats' movement. We employed drone and aerial  
64 imaging (of ~3600 cacti) to identify all resources available to the bats, that is, the positions of  
65 the cacti that they visited and the estimated distribution of flowers. To complete our  
66 understanding at the population level, we video-monitored tens of cacti over full nights,  
67 recording all bat (and other pollinator) activity. Finally, all of these data were used to develop  
68 a mathematical model that aims to explain the bats' foraging strategy.

69 In total, we GPS tracked 17 lesser long-nosed females. We then used aerial imaging to  
70 reconstruct the location of all cacti at the foraging sites of eight bats (STAR Methods).  
71 Henceforward, unless stated otherwise, all foraging analyses were conducted for these  $n=8$   
72 bats, with a mean of  $2.9\pm 2.1$  nights per bat. Tracking revealed extreme commutes of tens of  
73 kilometers, from the colony to the cacti fields (the average one-way commute was  $55.4\pm 17.2$   
74 km, Mean $\pm$ SD,  $n=17$  bats, with a record-holding bat that flew ~104 km to reach the field,

75 Figure 1A). On consecutive nights, bats typically returned to the same field (in 25 out of the  
76 28 consecutive nights that we monitored for 8 bats, Figure 1B).

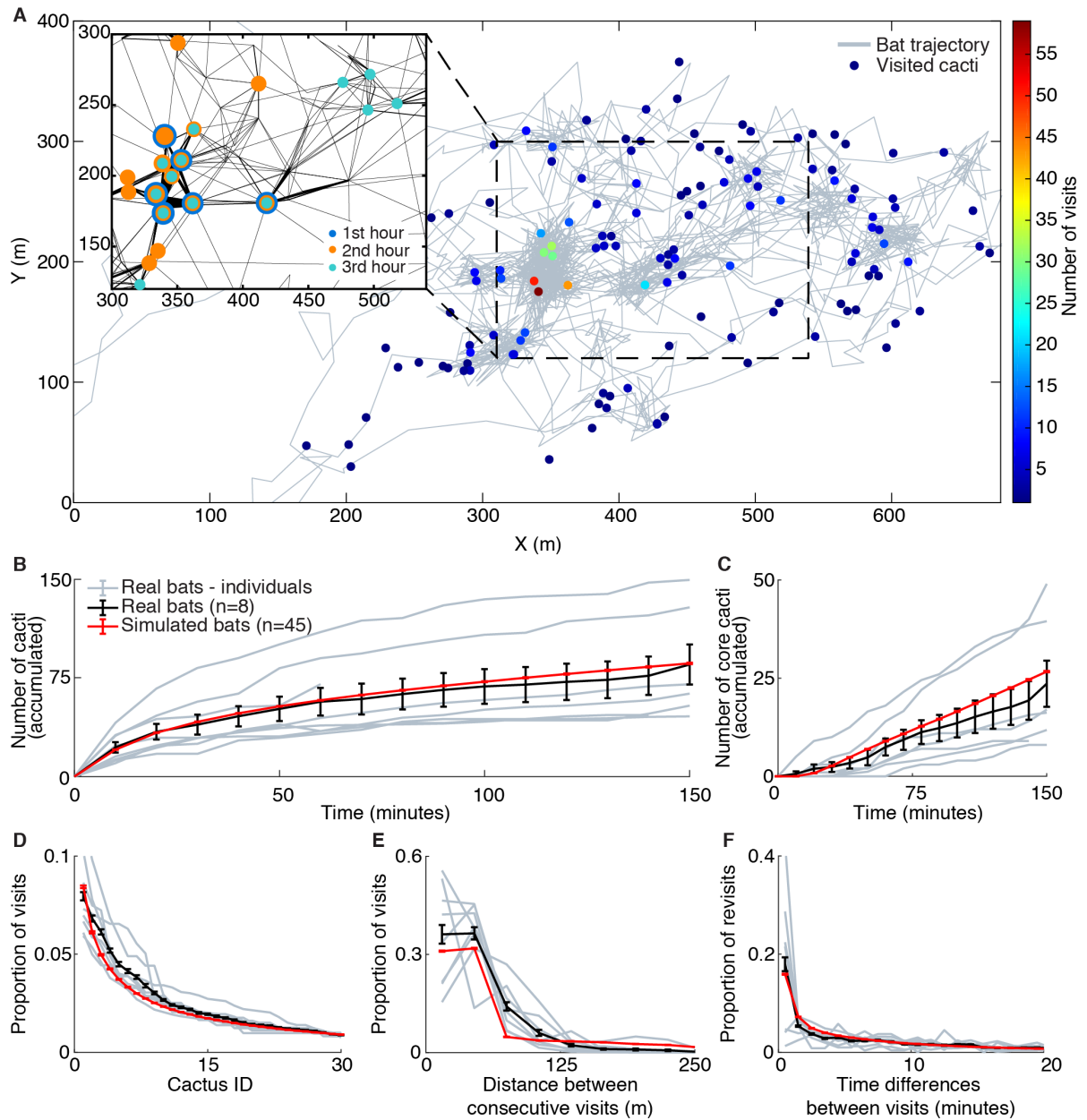


77  
78 Commuting to the foraging fields took  $1.6 \pm 0.8$  hours, in which bats flew at a mean ground  
79 speed of  $8.7 \pm 0.8$  m/s, mean air speed of  $9.1 \pm 0.9$  m/s, and a mean altitude of  $126 \pm 75$  m above  
80 ground (Mean $\pm$ SD, n=17 bats, maximum ground speed was 18.3 m/s and maximum altitude  
81 was  $\sim 1045$  m). These long commute flights account for an average of  $\sim 46\%$  of the total time  
82 a bat spends out-doors, implying that the bats should use the remaining time for exploiting  
83 the field efficiently.

#### 84 **Foraging dynamics throughout the night**

85 Once in the field, bats spent  $2.2 \pm 0.7$  hours foraging (n=11, Mean $\pm$ SD). Even though a single  
86 Saguaro field in this region can spread over a few square kilometers, each bat concentrated its  
87 foraging on a relatively small area ( $0.14 \pm 0.09$  km<sup>2</sup>, the convex hull of all locations defined as  
88 foraging, STAR Methods). Moreover, even within this restricted site, the bat did not visit all  
89 cacti uniformly, but clearly preferred some cacti over others (Figure 2A). We defined a cactus  
90 that was visited by a specific bat at least five times throughout the night as belonging to this

91 bat's *core cacti* (see STAR Methods and Figure S1G-H for the reasoning behind this  
 92 definition).



93  
 94  
 95 The bats combined exploitation of their core cacti with exploration of new unvisited cacti  
 96 (Figure 2B-C and insert in Figure 2A), and they gradually increased the exploitation to  
 97 exploration ratio at a steady rate throughout the night (Figure S1I). By the end of the night, a  
 98 bat visited an average of  $86 \pm 48$  cacti, out of which,  $28 \pm 26$  (~33%) cacti were part of its core

99 cacti (Mean±SD, Figure 2B-C, Figure S1J). This accounts for drinking ~18 ml of nectar per  
100 night, approximately the amount required by a lactating female (see STAR Methods).

101

### 102 **Information-based foraging**

103 Bats clearly did not visit cacti in the field in a deterministic ordered sequence, as a trapline  
104 strategy would suggest (see Figure S1K-L for more details). However, the bats also did not  
105 visit the cacti at random. Indeed, video analysis revealed that cacti with more flowers were  
106 visited significantly more often (Spearman correlation test,  $r=0.40$ ,  $P=0.02$ ,  $n=33$  cacti,  
107 Figure S1M), suggesting that some kind of a reinforcement mechanism underlies the bats'  
108 behavior.

109 In order to unravel the bats' visitation strategy, we developed a mathematical model that  
110 simulates a single night of foraging under competition in a space with multiple replenishing  
111 food-sources, using a rule inspired by reinforcement learning [25]. In the simulations, bats  
112 start without prior knowledge on cacti quality, and remember the value ('nectar-weight') and  
113 positions of the ten best cacti they experienced (see Figure S1J). At each visit, the bat updates  
114 the nectar-weight of the cactus depending on the cactus' nectar yield as experienced by the  
115 bat in previous visits and according to a learning rate  $\alpha$ . Then the bat samples its next visit  
116 from the set of cacti that includes the ten remembered best cacti and the other cacti around it  
117 (STAR Methods). The probability to pick a cactus in this set is proportional to its nectar-  
118 weight, i.e., to the amount of nectar it provides, and inverse-proportional to its distance from  
119 the current location of the bat.

120 Importantly, we did not fit the data in order to find the learning-rate  $\alpha$ . We ran evolutionary  
121 simulations, in which multiple bats with different individual learning-rates competed with  
122 each other. Bats that accumulated more nectar had higher chances to reproduce; and the  
123 learning-rates in each generation were slightly mutated. After many generations, the

124 simulated bats converged to a learning-rate of 4.6, see STAR Methods. The simulated bats  
125 with this  $\alpha$  behaved very similarly to the real bats (compare the red and black lines in Figure  
126 2B-F).

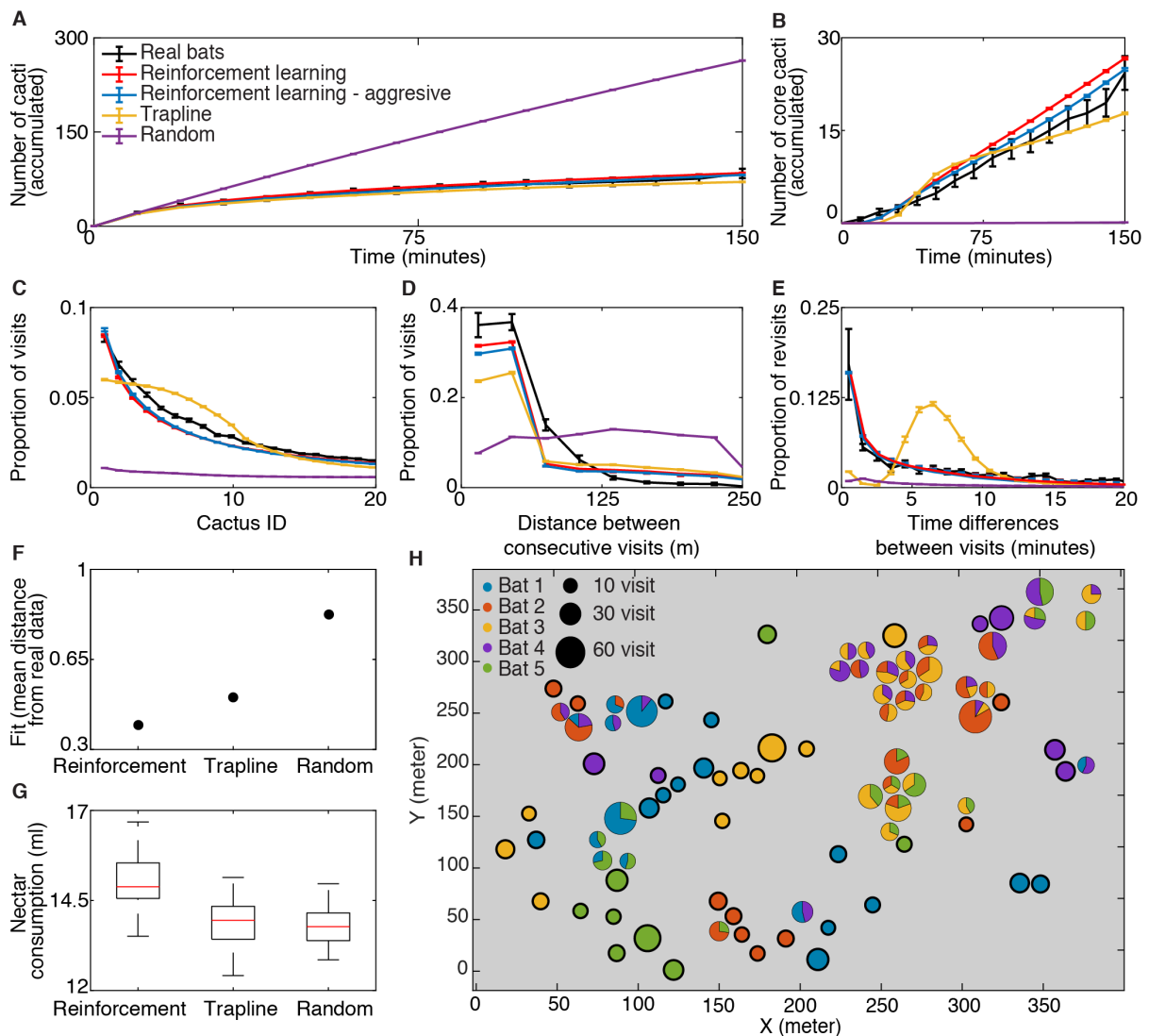
127 Similar to the real bats, the simulated bats showed a strong preference for specific core cacti,  
128 but they also continued exploring other cacti (Figure 2B-C). The simulated bats increased the  
129 exploitation to exploration ratio in a similar rate as the real bats and they showed a similar  
130 preference for cacti with more flowers (Figures S1I and S1M, respectively). The simulated  
131 bats hopped between cacti with a similar distance distribution as the real bats (Figure 2E),  
132 and they revisited cacti after similar time-intervals (Figure 2F). Our model was also able to  
133 predict the nectar consumption per visit of the actual bats, as we observed in the video  
134 (Figure S1N). All the above suggests that our simple model, which assumes little memory  
135 and a single free parameter can well-approximate the bats' behavior.

136 We also compared our model to two other models. The first, had no learning and bats visited  
137 the cacti uniformly at random. The second model, a version of a trapline-model, is similar to  
138 our model, except that cacti at the core are visited in an ordered manner that minimizes the  
139 distance to the next cactus (Figure 3A-E, and STAR Methods). Both of these alternative  
140 models performed worse in terms of their fit to the actual data (Figure 3F), and were also  
141 significantly less efficient in terms of nectar consumption (One-way ANOVA:  $F(2)=28.5$ ,  
142  $P<0.001$ , Figure 3G).

143 We conclude that learning is a key feature of the bats' behavior. Because bats rarely  
144 encounter conspecifics at the cacti (see below), the main way in which a bat experiences  
145 competition is through depletion of cacti. We thus hypothesized that learning is particularly  
146 useful in the face of competition. To examine this, we ran another simulation comparing the  
147 model, in which cacti are visited uniformly at random in each step, to our reinforcement  
148 algorithm strategy, under two circumstances: (1) when the forager is alone in the field and (2)



149 when it forages with conspecifics - unlike the simulations above, here we tested a situation  
 150 where half of the bats use the first strategy (i.e., random) and the other half use the second  
 151 strategy (i.e., learning). In the case of a sole forager, a purely random model was as good as  
 152 the learning model (Permutation-based t-test:  $P=0.3$ ,  $n=10,000$  simulations). This  
 153 phenomenon was reversed in the case of many competing bats, where the simulated bats that  
 154 used reinforcement learning consumed 43% more nectar than the randomly-visiting bats  
 155 (17.2 ml vs 11.9 ml in the learning and random models respectively, Permutation-based t-  
 156 test:  $P<0.0001$ ,  $n=10,000$ ).



157

158

159

160 **Individual foraging cores with little overlap emerge from reinforcement learning**

161 A prominent feature of our model is the formation of foraging cores with little overlap  
162 between individuals (Figure 3H, we prefer the term “core” to “home range” [26] because  
163 their important feature is the set of cacti they are composed of and not their area). The  
164 sharing of core cacti by multiple bats in our simulations was significantly lower than  
165 expected if the bats randomly visited the cacti (see STAR Methods, Permutation-based t-test:  
166  $P=0.0001$ ,  $n=10,000$  simulations). Data suggests that in reality bats also form disjoint cores  
167 with little overlap - video analysis revealed an estimated overlap of 1.3 bats per cactus, while  
168 in the simulations it was 1.5 bats per cactus, (Figure S2A-B).

169 Importantly, foraging cores are unlikely to be a result of territorial behavior: bats’ core cacti  
170 spread over  $0.04 \text{ km}^2$ , an area far too large for a bat to defend - flying from one side to the  
171 other would require  $\sim 40$  seconds while a visit of a conspecific to one of the bat’s cacti  
172 requires less than a second (Video S1). Moreover, the range from which a bat could detect a  
173 conspecific based on its echolocation is limited [27], and visual detection range is even more  
174 limited, reaching only  $\sim 50 \text{ m}$  [27,28].

175 To further understand the potential impact of interference competition, we added to the  
176 simulation a component of aggressive defense where a bat deters conspecifics it encounters at  
177 its core cacti (Figure 3A-E, blue lines, see STAR Methods). Consistent with our hypothesis  
178 that core formation is not a result of territorial defense, this aggressive model did not differ  
179 from the previous non-aggressive model.

180 Moreover, the formation of foraging cores was also not a result of the limited memory of the  
181 simulated bats (10 remembered cacti). We ran the model with unlimited memory where the  
182 bats remember the positions and weights of all cacti in the field, and the same type of core  
183 cacti evolved (Figure S2C-F). In fact, what appears to determine the size of a foraging core is  
184 the learning rate  $\alpha$ , where a larger  $\alpha$  generates smaller cores (Figure S2G-J). This is intuitive

185 as a larger  $\alpha$  drives more exploitation of previous profitable cacti at the expense of exploring  
186 new cacti.

187 The little overlap between neighboring cores in the simulation appears to result from a  
188 combination of two factors. First, bats initially visit cacti randomly, and then a positive  
189 feedback effect enhances the profitable initial discoveries through reinforcement learning.  
190 Second, the nectar-weights of profitable cacti are reinforced accumulatively, increasing their  
191 weight in the eyes of the owner bat and, at the same time, decreasing their nectar-weights in  
192 the eyes of occasional visitors that are likely to find the cacti empty. When this reinforcement  
193 learning strategy is employed in parallel by many bats, it enables the partitioning of the  
194 resources in the field without active communication and reduces the number of conflicts.  
195 Indeed, very few social agonistics interactions were observed - only in 5% of the 1123 visits  
196 documented on video.

### 197 **The efficiency of core formation**

198 Despite its simplicity, the proposed reinforcement learning strategy results in highly efficient  
199 foraging: as a group, the simulated bats consumed 91% of the total amount of nectar that was  
200 accumulated in the field during the night ( $14.9 \pm 0.8$  ml per bat). This means, in particular, that  
201 *any* other foraging algorithm could not improve nectar consumption by more than 10% on  
202 average.

203 In principle, one might expect that a more sophisticated (non-realistic) algorithm, that, e.g.,  
204 maintains a complete memory of the qualities of all cacti and visits them accordingly, would  
205 perform significantly better than one that only selects a small subset of core-cacti. However,  
206 an analytic analysis of a simplified model suggests that this intuition is wrong (see [29]). We  
207 mathematically analyzed a simplified setting in which a (single) bat aims to exploit a set of  $n$   
208 cacti with different refill rates ( $r_i$  is the rate of the  $i$ 'th cactus). Competition is modeled as  
209 uncertainty, i.e., a cactus  $i$  is emptied at each round with some “depleting probability”  $0 < s_i$

210 <1. Furthermore, distances between cacti are neglected, and in each round a new cactus can  
211 be visited. We restrict attention to purely-stochastic strategies that are characterized by a  
212 probability vector  $p = (p_1, \dots, p_n)$ , determining the probability  $p_i$  that the bat visits cactus  $i$  in  
213 each round. We prove analytically that when cacti are visited often by other bats (modeled by  
214 higher depleting probabilities) a purely-stochastic strategy based on exploiting a relatively  
215 small core will be almost as good as the best strategy. In our simulations, smaller cores can  
216 be achieved by increasing  $\alpha$ . Indeed, the reinforcement learning literature shows that  $\alpha$  can be  
217 tuned by an animal, based on the environment [30].

218 Another interesting result of our analytical analysis (mentioned above) is that the cacti bats  
219 should choose for the core are those that have higher refill rates  $r_i$  relative to low depletion  
220 probabilities  $s_i$ . In the analytical model, those cacti with higher  $r_i/s_i$  ratios are expected to  
221 accumulate larger amounts of nectar. This nicely corresponds to the reinforcement learning  
222 algorithm in our simulations, that assigns a large weight to a cactus that contains much nectar  
223 upon our bat's visit.

## 224 **Conclusions**

225 Foraging is a fundamental task which entails many decisions. In this study, we used  
226 comprehensive continuous tracking of lesser long-nosed bats in parallel to estimating their  
227 available resource to study their foraging decisions as they explore and exploit food resources  
228 in their natural environment. Interestingly, a single parameter model based on reinforcement  
229 learning was able to closely reproduce the bats' behavior.

230 This model has three main characteristics: 1. The emergence of individuals foraging cores  
231 through reinforcement learning and competition. 2. Exploitation of the cores through  
232 stochastic sampling that is dependent on the cacti quality and distances. 3. Exploration of the  
233 field in search of new profitable cacti and update of the core accordingly, in parallel to  
234 exploitation.

235 Another foraging strategy that is adopted by many species including insects and birds is  
236 trapline [31]. In our system, however, we do not see evidence for trapline. In principle, the  
237 bats could have used a reinforcement-learning component to identify a core with high quality  
238 cacti and then exploit the core using a trapline. However, as we show, it turns out that this  
239 combined strategy is inferior to the reinforcement-learning strategy (Figure 3G). Perhaps the  
240 reason for this, is that distances between cacti in a core are small and their qualities still vary.  
241 Hence, a strategy that specializes in minimizing traversal lengths such as trapline would be  
242 less effective than the reinforcement-learning strategy that effectively incorporates both  
243 qualities and distances despite being memoryless.  
244 Due to the simplicity and effectiveness of the reinforcement-based strategy, we hypothesize  
245 that other species facing similar foraging tasks also adopt a similar strategy. A key  
246 characteristic of which would be dividing the resources between individuals without direct  
247 communication and without a need for aggressive territoriality.

248

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## 262 **Author Contributions**

263 A.G., Y.Y. and R.A.M., designed the experiments; A.G., M.H., O.E., A.B., T.S., S.C., S.G.  
264 and Y.Y. conducted the experiment; A.G. conducted the analysis, carried out drone imaging  
265 and analysis. A.K., S.C., Y.Y. and A.G. designed the model and A.G. implemented the  
266 model. A.K and Y.E conducted the analytic analysis of the simplified model. A.G, Y.Y. and  
267 A.K. wrote the manuscript.

## 268 **Declaration of Interests**

269 The authors declare no competing interests.

## 270 **Figure Legends**

271 **Figure 1. Typical movement of lactating nectar-feeding bats.** (A) Bats fly tens of  
272 kilometers from the cave to their foraging site (colors represent different individuals, n=11  
273 bats for which we had at least one full night). The bat that flew farthest (red) flew a one-way  
274 distance of ~104 km on her first night (depicted by a black arrow) to her foraging site (white  
275 circle). The zoomed in circle panel shows how the cacti quality - the number of open flowers  
276 - differ greatly within one of the Saguaro fields, with 0-4 open flowers on an average night (0  
277 flowers are presented as grey circles and 1-4 flowers are presented as blue to red circles). See  
278 also Figure S1. (B) Bats typically visited the same Saguaro field on consecutive nights  
279 (colors from blue to red depict different nights for each bat, three bats with a mean of  $4.3 \pm 2.0$   
280 nights per bat are shown). When returning to the same site, the bats visited ~75% of the cacti  
281 that they visited on the previous night (n=8 bats, see also STAR Methods and Table S1).

282 **Figure 2. Nectar-feeding bats foraging dynamics.** (A) Flight trajectory of one bat is shown  
283 (grey line) and the cacti it visited are colored according to the number of visits (unvisited

284 cacti are not presented). Top left insert shows hops between cacti, where the width of the  
285 black lines represents the number of hops between cacti and colored circles represent only the  
286 core cacti that were visited more than 5 times at different hours throughout the night. In all  
287 panels B-F colors are as follows: grey - real bats data; black - Mean $\pm$ SE of 8 real bats; red -  
288 Mean $\pm$ SE of 45 simulated bats (30 simulations). **(B)** The accumulated number of visited cacti  
289 and **(C)** core cacti throughout the night (see also Figure S1J). **(D)** The proportion of visits per  
290 cactus are sorted according to cactus ID, i.e., cactus 1 is the cactus that received most visits.  
291 **(E)** The distribution of distances between consecutive visited cacti. **(F)** The distribution of  
292 time lags between revisits to the same cactus. Core cacti were close to each other (25.1 $\pm$ 13.6  
293 m apart) and bats revisited them very often (consecutive visits to core cacti were on average  
294 8.9 $\pm$ 3.5 minutes apart, Figure 2E-F).

295 **Figure 3. Comparison of different models.** **(A-E)** Foraging behavior of real bats (black),  
296 and simulated bats using different foraging models: reinforcement learning (red),  
297 reinforcement learning with aggression (blue), trapline (yellow) and random (purple). **(A)**  
298 Accumulated number of visited cacti and **(B)** core cacti (first 2.5 hours). **(C)** Sorted  
299 proportion of visits per cactus (in the 20 most visited cacti). **(D)** The distribution of distances  
300 between consecutive visited cacti (30 meters bins). **(E)** The distribution of time lags between  
301 revisits to the same cactus (first 20 minutes). **(F)** The fit of different foraging models  
302 (normalized mean distance from real data, data was normalized to a max of 1 before fitting).  
303 **(G)** Bats' nectar consumption in different foraging models. **(H)** Core cacti of five simulated  
304 bats in the reinforcement learning model. Cacti of different individuals are depicted by  
305 different colors and circle size represents the number of visits (accumulated over a full night).  
306 Cacti that were in the core of more than one bat appear in multiple colors according to the  
307 relative number of visits of each bat; and cacti that were in the core of a single bat are circled  
308 by a black line. See also Figure S2.

309

310 **STAR Methods**

311 **Lead Contact**

312 Further information and requests for resources should be directed to and will be fulfilled by  
313 the Lead Contact, Yossi Yovel (yossiyovel@gmail.com).

314 **Materials Availability**

315 This study did not generate new unique reagents.

316 **Data and Code Availability**

317 The datasets and code generated during this study are available at Mendeley, doi:

318 10.17632/jxghjjsttw.1

319 **EXPERIMENTAL MODEL AND SUBJECT DETAILS**

320 All experiments were conducted under permit number 443 # 04019/15, 03946/15 14509/16  
321 from the Dirección General de Vida Silvestre (=Wildlife Service). All experiments on *L.*  
322 *yerbabuena* and *C. gigantea* has been conducted in El Pinacate Biosphere Reserve and in  
323 the surrounding Saguaro fields (in the Sonoran Desert in northwest Mexico).

324 **METHOD DETAILS**

325 **Tracking bats' movement**

326 During May-June 2015-2017, we successfully monitored the movement of a total of 17  
327 lactating female lesser long-nosed bats (*Leptonycteris yerbabuena*). We used miniature GPS  
328 data-loggers (Lucid Ltd., Israel) combined with a synchronized ultrasonic microphone (FG-  
329 23329, Knowles) [27] to tag bats roosting in a maternity colony with more than 50,000  
330 lactating bats in El Pinacate Mexico [32]. A telemetry unit (either LB-2X 0.3 g, Holohil  
331 Systems Ltd. Carp, Ontario, Canada or Pico pip Ag379 0.37 g, Biotrack Ltd, Dorset, UK)  
332 was attached to the GPS, to enable its recovery after falling off the bat. Tracking bats'



333 movement for up to eight days in a row revealed fundamental aspects of their foraging  
334 strategy.

335 The device's total weight was  $4.1 \pm 0.1$  g (mean $\pm$ SD), which accounted for less than 14% of  
336 the average body mass of the bats (the average mass of the bats was:  $30.0 \pm 2.7$  g, n=17). We  
337 have already mounted these tags on similar sized bats (e.g., *Rhinopoma microphyllum*,  
338 *Myotis vivesi* and *Myotis myotis*) for which we performed several control experiments to test  
339 the effect of the extra loading on their well-being and behavior (see detailed information in  
340 Cvikel et al. [27] and Egert-Berg et al. [33]). Here too, we made sure that this additional  
341 weight did not affect foraging: all tagged bats left the cave and flew to remote foraging sites,  
342 sometimes as far as ~100 km from their roost where they exhibited vast foraging. We also  
343 conducted several control experiments ensuring that flight and foraging abilities of the bats  
344 were maintained. To test bats' ability to forage, we captured three non-lactating females,  
345 mounted the same GPS tags on their backs, and recorded their behavior while feeding on  
346 flowers on a cut Saguaro branch placed inside a flight tent. All bats were able to approach the  
347 flowers, hover in front of them and drink (See Video S2). Bats were allowed to feed *ad-lib*  
348 and were released in good condition at the cave at the end of the experiment. To test the  
349 effect of the additional weight on the overall flight duration, we tagged 10 bats with  
350 lightweight (1g) telemetry unit (without GPS). The bats that were tagged with heavier GPS  
351 devices spent a similar amount of time outside the cave ( $6.3 \pm 1.4$  hours, n=9) as the bats that  
352 were tagged with light tags ( $5.9 \pm 1.3$  hours, n=10, Wilcoxon rank sum test, P=0.84).

353 Additionally, one bat that we tagged and was caught a week later (at the same time of the  
354 night), was found in a very good condition and gained 1.3g during this period when it carried  
355 the extra tag-weight.

### 356 **Movement analysis**

357 GPS positions were sampled every 2, 5, 15 or 30 seconds for different bats (Table S1  
358 summarizes which bats were used in which of the analyses). GPS positioning standard  
359 deviation was estimated to be 8 m in the horizontal plane and 11 m in height [27]. Bats'  
360 ground speed was estimated as the derivative of distance over time between GPS points that  
361 were 15s apart, and outliers with ground speed above 30 m/s were removed. Bats' airspeed  
362 was calculated by subtracting the estimated wind speed in the direction of the flight from the  
363 bat's ground speed. Wind data was collected from a weather station located between the cave  
364 and the foraging sites (31.679985, -113.304831). The bats' height above the surface was  
365 estimated by subtracting the geoid and the elevation above the surface from the altitude  
366 above the ellipsoid (provided by the GPS). The geoid height was estimated to an accuracy of  
367 0.001 m using the EGM2008 Geopotential Model and surface elevation was extracted using  
368 Google Maps Elevation API. The height over-time was smoothed using the 'LOESS' local  
369 regression smoothing filter [34]. Bats' movement was divided to commute and foraging using  
370 the straightness index that measures the ratio between the actual path length and the direct  
371 distance between two points [35]. The straightness index was calculated for segments of five  
372 minutes and revealed a bimodal distribution with a trough at 0.4 separating the two modes.  
373 hence, GPS positions with a straightness index lower than 0.4 were considered as foraging  
374 and GPS positions with straightness index greater than 0.4 were considered as commute  
375 (Figure S2K-L). Short flights inside the foraging sites were considered as foraging even if  
376 their straightness index was higher than the threshold (0.4).

### 377 **Foraging behavior analysis**

378 Some of the bats briefly visited secondary foraging sites on the way to the main one  
379 (spending no more than 10 minutes in these sites). We restrict our analyses to foraging in the  
380 main site.

381 *A visit.* A visit to a cactus was defined as flying at a distance of less than 15 meters from a  
382 cactus, in an altitude of less than 20 meters. The video analysis revealed that bats typically  
383 lingered in the area of a cactus for a few seconds before visiting it which made GPS-based  
384 visit recognition easier. We also validated our visit detection method using the video  
385 recordings (See Video S1 and Figure S2M). Notably, all of our analyses are based on the  
386 proportions of visits and not the absolute number of visits, so even if our method for  
387 detecting visits under- or over-estimated their number, this should not have affected our  
388 results.

389 Consecutive visits to the same cactus less than 60 seconds apart were considered as one visit  
390 since the video recordings (below) showed that bats tend to fly around the cacti and approach  
391 it repeatedly during a visit. In cases where a bat visited a patch with several cacti less than 15  
392 m apart, one of the cacti in the patch was chosen randomly and considered as the visited  
393 cactus. For every visited cactus, number of visits, visits duration, distance and time past  
394 between consecutive visits were calculated.

395 We examined the influence of the lower GPS sampling rates on the results, by reducing the  
396 sample rate of bats that were sampled every two seconds to five, 15 and 30 seconds. We  
397 found no difference between the bats' behavior using sample rates of every two and five  
398 seconds, and corrected the results for only three bats that were sampled at a lower rate (one  
399 bat that was sampled every 30 seconds and two bats that were sampled every 15 seconds).

400 *The definition of core cacti.* Cacti that were visited more than five times during the night by  
401 a specific bat were defined as the bat's core cacti. We used a criterion of five revisits to the  
402 same cactus because the distribution of revisits drops rapidly above five visits (Figure S1G-  
403 H).

404 **Cacti locations and number of open flowers**

405 Several approaches were used to assess cactus and flower distribution: (1) cacti locations in  
406 specific areas where the tagged bats foraged were identified using (a) drone-imaging (using a  
407 DJI Phantom 3 advanced drone with its built-in camera 12.4M pixel, DJI Science and  
408 Technology Co. Ltd., Guangdong, China); (b) Google Earth satellite and aerial images (in  
409 cases where flying a drone in the area was prohibited). In total, we managed to map the cacti  
410 in the foraging sites of eight bats. (2) The flowering of 414 cacti from three cacti fields  
411 around El Pinacate biosphere reserve were characterized: 327 cacti (121 flowering cacti) in  
412 an area of  $\sim 84 \text{ m}^2$  were monitored over  $8.3 \pm 2.8$  days per cactus (22/5/2016-7/6/2016) by  
413 remote-imaging using the same drone and camera as above. The drone was flown above the  
414 field early in the morning when the flowers are still open. A 3D model of the field was  
415 created using Pix4Dmapper Pro version 2.2.25 allowing to count the number of open flowers.  
416 Additional cacti were monitored every morning in a manual census during  $10.7 \pm 3.4$  days per  
417 cactus (26/5/2015-11/6/2015 n=48 cacti, 6/5/2016-28/5/2016 n=23 cacti, 25/4/2017-2/5/2017  
418 n=6 cacti, 13/5/2017-27/5/2017 n=10 cacti).

#### 419 **Video observations**

420 33 saguaro cacti were videoed for an average of  $1.8 \pm 1.2$  nights (n=62 nights in total) during  
421 the flowering season (11/5-1/6/2016, 12/5-18/6/2017) using IR video cameras (Full Spectrum  
422 POV Cam, GhostStop, Florida, USA or Panasonic Action Cam HX-A1, H.264 1920x1080,  
423 30fps). Each camera was placed on a two m pole at a distance of two m from the cactus for a  
424 period of nine hours (starting at sunset). Bats' echolocation and social calls were recorded in  
425 45% of these observations using Ultrasonic recorders (Song meters SM4BAT, Wildlife  
426 Acoustics Inc., Massachusetts, USA) that were placed  $< 50$  cm below the flowers. In cases  
427 where the cactus had more than one branch with flowers, we used a separate camera for each  
428 branch, so that all approaching bats to all of the cactus flowers could be observed. The videos  
429 were fully analyzed and all visits of all pollinators (bats, moths and birds) were denoted.

430 Social interactions between conspecifics were also noted (based on the video or based on the  
431 detection of social calls in the audio recordings).

### 432 **Nectar refill rate and nectar consumption**

433 To estimate the nectar refilling rate throughout the night, the upper part of eight cacti were  
434 covered with mesh (20D nylon tulle) to prevent access to their flowers. During two  
435 consecutive nights (20-21/5/2017), nectar was extracted from the flowers every 90 minutes  
436 (from 21:00 at least until 03:00, during the bats' presence in the field) using a 1 ml syringe,  
437 and the amount of nectar was measured (n=17 flowers, 1.4±0.8 flowers per cactus per night).  
438 Sugar concentration was measured using Bellingham-Stanley low-volume Eclipse  
439 refractometers (0–50 Brix). We found little variation in sugar concentration (24.5±2.7%), in  
440 nectar rate and in the accumulative nectar quantity (0.73±0.13 ml) at the end of the night, and  
441 no correlation between the accumulative nectar quantity at the end of the night and the  
442 number of open flowers (Pearson correlation test:  $r=0.1$ ,  $P=0.6$ ). The amount of nectar in a  
443 flower (ml) can thus be predicted according to the time passed since 21:00 (~1.5 hours post-  
444 sunset) using a linear equation:  $0.13 + 0.102 \times \text{time (hours)}$ ,  $R^2=0.89$ ,  $P<0.001$ ,  $n=40$  flowers  
445 (Figure S1A). To assure that repeated nectar depletion does not affect nectar secretion, we  
446 conducted another experiment where we measured the nectar quantity throughout the night in  
447 different flowers (each flower was depleted and measured only once). When comparing the  
448 two experiments, with and without repeated depletion, we found that nectar secretion rate  
449 throughout the night is not affected by repeated nectar depletion (Generalized linear mixed-  
450 effects model:  $P=0.381$ ,  $n=202$  flowers that were measured once, 20 flowers that were  
451 repeatedly depleted throughout the night, and depletion status as fixed effect).

452 To examine how much nectar a bat drinks in a visit, five bats were released in a flight tent for  
453 four nights (21:00-03:00), and video-recorded while feeding ad libitum on 25% sugar water  
454 from 1-ml tubes which were placed inside 10 Saguaro flowers that were mounted on the top

455 of two 20 liter water bottles (mimicking the cylinder structure of a Saguaro cactus). After  
456 every feeding event, the amount of nectar was measured, and the tube was refilled. Drinking  
457 duration of each drinking event was measured from the tube. We found that drinking amount  
458 per feeding event could be predicted by the feeding duration, according to a linear equation:  
459 nectar feeding amount (ml)=0.052 + 0.44 × feeding duration (s)  $R^2=0.36$ ,  $P<0.001$ ,  $n=187$ ,  
460 Figure S2N-O). Based on this equation, we concluded that a bat in the field drinks  $0.04\pm 0.04$   
461 ml (mean $\pm$ SD,  $n=2492$  observations) in an average visit.

#### 462 **Estimating the bats' energy consumption**

463 In order to examine whether the nectar consumed by our bats is enough to cover their  
464 energetic demands, we used literature estimates of their energetics. According to Horner et al.  
465 [36], a 23g non-reproductive lesser long-nosed bat spends 1.05, 0.97, 0.32 Watts during  
466 commute, foraging and day roosting, respectively. Converting these values to kJ according to  
467 the average duration our bats spent in each activity (commuting for  $3.1\pm 1.2$  hours, foraging  
468 for  $2.2\pm 1.0$  hours and day roosting for  $18.7\pm 1.5$  hours,  $n=11$ ) results in a mean energy  
469 demand of 40.9 kJ per day. Kunz & Nagy [37] estimated the energy consumption of lactating  
470 bats as 50-100% higher than non-reproductive individuals, hence we estimate the energy  
471 consumption of a lactating lesser long-nosed bats as 61.4-81.8 kJ. Since 0.1 ml of Saguaro  
472 nectar provides 0.43 kJ [36], lactating bats need to drink between ~14-19 ml of nectar and  
473 non-reproductive bats need to drink ~9.5 ml of nectar per night.

474 Based on our GPS monitoring and video analysis, the lactating bats conducted ~450 feeding  
475 visits on average throughout the night, drinking 0.04 ml on an average visit (according to our  
476 video observation and nectar model, Figure S1N). That accumulates to drinking 18 ml of  
477 nectar during a full night, nicely corresponding to the calculation above.

478

#### 479 **The foraging model**

480 In order to unravel the bats' visitation strategy, we developed a mathematical model that  
481 simulates a single night of foraging under competition in a space with multiple replenishing  
482 food-sources. At each step, each agent (bat) in our model decides which cactus to visit next  
483 based on its previous experience and current location. To capture the fact that bats visited  
484 profitable cacti more often (Figure S1M), we modeled this decision process using a rule  
485 inspired by reinforcement learning [25], in which the agent learns to prefer rewarded stimuli.  
486 In the simulation, each bat associates each cactus with two parameters: a 'nectar-weight' and  
487 a 'score'. The nectar-weight of a cactus depends on the cactus' nectar yield as experienced by  
488 the bat in previous visits, and the score of a cactus depends on both the nectar-weight and the  
489 distance of the cactus from the current location of the bat. After every visit to a cactus, the bat  
490 updates its nectar-weight (see below) and it then visits the next cactus with probability that is  
491 proportional to its score. If higher nectar is found in a cactus, it will have more nectar-weight  
492 and hence a higher score, which means that the probability of returning to it can only  
493 increase.

494 In the simulations, the bats start without prior knowledge on cacti quality. At any point in  
495 time, bats remember the nectar-weights and positions of only 10 cacti (we chose this number  
496 because this is the number of cacti we observed in the core in time slots of 30 minutes (see  
497 Figure S1J). Moreover, nectar feeding bats have been shown to have an immense spatial  
498 working memory [24]). "In the eyes" of a bat, the nectar-weights of all other cacti are set to  
499 1. Cacti scores are proportional to their nectar-weights and inversely proportional to their  
500 distance, that is, the score  $S_b(c,t)$  that a bat ' $b$ ' associates with cactus ' $c$ ' at time ' $t$ ' is:

501 Eq 1. 
$$S_b(c,t) = \frac{W_b(c,t)}{T_b(c,t) + \tau},$$

502 where  $W_b(c,t)$  is the nectar-weight that bat ' $b$ ' gives to cactus ' $c$ ' at time ' $t$ ' (see below),  
503  $T_b(c,t)$  is the duration of flight to cactus ' $c$ ' from the current location of bat ' $b$ ' (which is  
504 proportional to the corresponding distance) and  $\tau$  is the time duration of a visit.

505 Similarly to the reinforcement learning framework [25], bats update nectar-weights at each  
506 visit based on how much nectar they drank (relative to an average expectation). At time ‘t’,  
507 the nectar-weight of the last visited cactus ‘c’ is updated:

508 Eq 2.  $W_b(c, t) = W_b(c, t - 1) + [N - Avg] \times \alpha$ ,

509 where  $W_b(c,t)$  is the nectar-weight of cactus ‘c’ at time ‘t’ in the eyes of bat ‘b’, N is the  
510 volume of nectar consumed during the visit, Avg is the average consumed volume (set to  
511 0.04ml based on field observations) and  $\alpha$  is a scaling parameter equivalent to the learning  
512 rate in reinforcement learning.

513 The list of remembered cacti is updated as follows: if the nectar-weight of a visited cactus  
514 exceeds the nectar-weight of at least one of the 10 remembered cacti, it will replace the  
515 remembered cactus with the lowest score. In turn, the latter cactus will go out of the list and  
516 its nectar-weight will be set to 1. In order to keep exploring, the bats can also visit  
517 unremembered cacti (i.e., with nectar weights = 1) but since they do not remember the  
518 location of these cacti, they will only visit unremembered cacti within their visual sensing  
519 range [28,38].

520 The fixed parameters of the model, namely, the numbers of bats and cacti (45 bats with a  
521 ratio of 1 bat per 12 flowering cacti), cacti locations, flower distribution and nectar filling  
522 rate, were all set based on our field measurements (see below).

523 The model thus has one free parameter,  $\alpha$  - the learning rate. We used an evolutionary  
524 algorithm [39] in order to predict the value of  $\alpha$  (an evolutionary algorithm searches for a  
525 solution that is at equilibrium under the modeled conditions). The value of  $\alpha$  in our  
526 evolutionary simulations converged to an average of 4.6, with all individuals converging to a  
527 range around it ( $4.6 \pm 4.8$  Mean  $\pm$  SD). Importantly, although we did not fit the data to the  
528 model ( $\alpha$  was determined evolutionary) the simulated bats with this  $\alpha$  behaved very similarly  
529 to the real bats (compare the red and black lines in Figure 2B-F).



530 ***The Fix factors of the model*** A bat in our simulation arrives at a field with a fixed number of  
531 cacti that are distributed over a plane according to an actual field whose cacti-positions have  
532 been reconstructed. The simulated field has 1125 cacti and 45 bats. This agrees with our  
533 observed bats-cacti ratio estimations: ~200,000 bats are estimated to roost in the El Pinacate  
534 cave using annual bats counting and ~5,700,000 cacti were estimated to be in a radius of 100  
535 km from the cave based on satellite imaging analysis, see sensitivity analysis for this parameter  
536 in Figure S3A-F). Each cactus has a certain number of open flowers that are sampled from a  
537 real distribution (Figure S1B) and it refills all of them in a constant rate according to our field  
538 measurements (Figure S1A).

539 ***Initial nectar weight*** Bats start at random positions in the field (real bats can fly from one  
540 side of the field to the other in ~40 seconds), without prior knowledge on cacti quality (all  
541 cacti receive initial equal nectar-weights = 1). We chose the value of 1, since if we choose  
542 any other positive constant instead of 1, say  $c$ , the system will behave the same by replacing  
543  $\alpha$  with  $c$  times  $\alpha$ . Since we are aiming to evolve and learn  $\alpha$ , we will get the same  
544 result, only named differently. At any point in time the bats remember the values (i.e., nectar-  
545 weights) and positions of only 10 cacti and can visit these remembered cacti and other cacti  
546 within their vision detection range. Because a bat always sees additional cacti in its range it  
547 will never hold in its memory a cactus with weight smaller than the default value (1),  
548 therefore we don't have to worry about negative weights.

549 ***Remembered cacti*** The number 10 was chosen because on average, the bats visited 10 core  
550 cacti at every moment throughout the night. We divided the night into time period of 30 min  
551 and during this period real and simulated bats visited  $9.6 \pm 0.5$  ( $n=8$ ) and  $10.2 \pm 1.1$  ( $n=45$ ) core  
552 cacti, respectively. Figure S1J). We also show that there is no advantage in remember more  
553 than 10 cacti, since even bats that remembering all cacti in the field perform very similar to  
554 bats that remember only 10 cacti (Figure S2C-F).

555 **Bats' detection range** In the simulation, we assumed that the bats' detection range of a cactus  
556 is 50 meters. There is very little behavioral data on bats' vision. In a previous study we found  
557 that the night vision of *Rousettus aegyptiacus* is similar to humans' [38]. Lesser long-nosed  
558 bats have smaller eyes (ca. 0.23 diameter of those of *Rousettus aegyptiacus*) and should thus  
559 be less sensitive. To estimate their visual detection range of a cactus, we first estimated  
560 humans' detection range and we used this as an over estimation for the bats' detection range.  
561 Four humans (adjusted to scotopic vision) were able to detect cacti (n=10) from a distance of  
562  $55\pm 9$  m. To estimate this, we had them move towards a cactus from a distance of 100 m and  
563 report when they first detected it. On the one hand, as explained above, the bats are less  
564 sensitive, but on the other hand, their task should have been easier since they observe the  
565 cacti from above (unlike the humans) and can search for white flowers. We thus estimated  
566 the bats' detection range to be within a range of 30-70 m. To validate that our results are not  
567 sensitive to an error of up to 40% in this parameter, we ran our model with cacti detection  
568 range of 30, 50 and 70 meters (Figure S3G-J).

569 **Maintaining core cacti on consecutive nights** Notably, our model assumes that bats are  
570 naïve at the beginning of the night, while in reality bats' foraging cores on consecutive nights  
571 heavily overlap (on a certain night, bats visited ~97% of the core cacti that they visited on  
572 previous nights, Figure S3K). This suggests that bats incorporate information gathered on  
573 previous nights when forming their foraging core on a given night. Relying on information  
574 over consecutive nights probably reduces the costs of finding and mapping the positions of  
575 flowering cacti. We also observed that bats reused the same flying pathway between cacti on  
576 consecutive nights (Figure S3L), a strategy which could ease navigation in the field. One of  
577 the bats that we tracked switched the field it visited while we were tracking it, allowing us to  
578 examine its movements in a new field over time. In contrast to all other bats we tracked, in its  
579 first nights in the field, this bat spent more time scanning the field and less time foraging, in

580 comparison to the other bats. Over several consecutive nights, it gradually increased the  
581 proportion of foraging (Figure S3M). In order to account for this knowledge, we allowed our  
582 simulated bats to scan quickly for a short period at the beginning of the night. Thus, at the  
583 beginning of the night, our simulated bats explored cacti with a detection range of 250 m.  
584 This exploration phase lasts ~10 minutes, until each bat acquires 10 remembered cacti.  
585 Despite the fact that we neglect this issue of information transfer across nights, our  
586 approximated model well captures the general characteristics of bat foraging dynamics.

587 **Learning rate ( $\alpha$ )** We used an evolutionary algorithm (using Matlab's Global Optimization  
588 Toolbox) in order to predict the value of  $\alpha$ . We ran 30 simulations with 100 generations each  
589 and took the average  $\alpha$ . We used a population size of 45 bats, with initial values of  $\alpha$  that are  
590 randomly distributed between 0 and 100. At each generation, 20% of the bats best fitted  $\alpha$   
591 (i.e., bats) survived, out of the rest remaining 80%, 62% randomly survived and 18% were  
592 crossed with mutation. The values of  $\alpha$  always converged within 100 simulations. Nectar  
593 consumption was used to estimate fitness.

594 **Modeling aggressive response** A similar model with an aggressive response (aggressive  
595 model) provided us the ability to estimate whether social interactions play a role in shaping the  
596 foraging behavior of the bats. In this model, simulated bats foraged in the same manner as in  
597 the non-aggressive model, except for when two bats simultaneously chose the same cactus. In  
598 this case the dominant bat (the bat that has a higher nectar-weight for this cactus) drank from  
599 the cactus, and the subordinate bat drinks nothing and is moved near a random cactus 200-500  
600 m from its current location mimicking the result of a territorial agonistic interaction.

601 **Alternative models** We compared the real bats' behavior to two additional models (random and  
602 trapline) using the same fixed parameters as in the reinforcement learning model, except for  
603 the following changes: In the random model  $\alpha=0$ , and thus the bats did not learn from previous  
604 experience. In the trapline model, bats used reinforcement learning during ~10 minutes at the

605 beginning of each simulation to acquire the first 10 remembered cacti (with  $\alpha=6.1$  that was  
606 found using a genetic algorithm). Once the remembered set was established, the simulated bats  
607 exploited the core in an ordered manner – always flying to the next closest cactus (as in a  
608 trapline). They still occasionally explored additional cacti (according to the same rules of the  
609 original model). Finally, we also ran the exact same foraging model with a single bat (and 125  
610 cacti) to compare the nectar consumption of a learning ( $\alpha=4.6$ ) and a random ( $\alpha=0$ ) simulated  
611 bat.

612 *Estimating the overlap of cores* We used the results of 100 simulations to compute how  
613 many bats shared each of the core cacti. For each simulation, we collected the core cacti of all  
614 bats into one set S, and then randomly selected a core for each bat, while maintaining the  
615 number of core cacti per bat the same as in the specific simulation. That is, if a bat had x cacti  
616 in its core in the simulation, we now randomly select x cacti in S to be in its random core. We  
617 used a permutation test to compare the overlap in a typical core cactus in these two situations.

## 618 **QUANTIFICATION AND STATISTICAL ANALYSIS**

619 All statistical analysis conducted using MATLAB R2018a unless stated otherwise.

620 Comparison between groups were conducted using two tailed tests, unless stated otherwise.

621 Non-parametric Wilcoxon rank sum tests were used to examine the influence of the GPS  
622 weight on the time bats spent outside the cave because of the small sample size. One-Way  
623 ANOVA was used to compare bats' nectar consumption in different foraging models and all  
624 other comparisons between models were conducted using Permutation based t-test, to avoid  
625 influencing the power of our analysis by changing the sample size (i.e., the number of  
626 simulations). We used Linear regression to find the equation of nectar secretion throughout  
627 the night and nectar feeding quantity according to feeding duration, and GLM test used to  
628 estimate the influence of depletion status (as a fixed factor) on nectar secretion rate  
629 throughout the night. Monte-Carlo test conducted using R 3.6.1, ade4 package.

630 **Supplemental videos legends**

631 **Video S1. Bats foraging behavior. Related to STAR Methods.** Bats typically lingered in the  
632 area of a cactus for a few seconds: they fly near the cactus, approach it, approach a specific  
633 flower and drink from it. Most foraging behavior is solitary, and social interactions are seldom.

634 **Video S2. GPS weight control. Related to STAR Methods.** Bats successfully maneuver and  
635 feed on Saguaro's flowers in a flight tent – a comparison of feeding behavior of a bat with and  
636 without GPS device attached to its back. Related to Tracking bats' movement in STAR  
637 Methods.

638

639 **References**

- 640 1. Howell, D.J. (1974). Acoustic behavior and feeding in glossophagine bats. *J. Mammal.*  
641 55, 293–308.
- 642 2. Herrera M., L.G., and Martínez Del Río, C. (1998). Pollen digestion by New World  
643 bats: effects of processing time and feeding habits. *Ecology* 79, 2828–2838.
- 644 3. Arends, A., Bonaccorso, F.J., and Genoud, M. (1995). Basal Rates of Metabolism of  
645 Nectarivorous Bats (Phyllostomidae) from a Semiarid Thorn Forest in Venezuela. *J.*  
646 *Mammal.* 76, 947–956.
- 647 4. Sahley, C.T., Horner, M.A., and Fleming, T.H. (1993). Flight speeds and mechanical  
648 power outputs of the nectar-feedint bat, *Leptonycteris curasoae* (phyllostomidae:  
649 glossophaginae). *J. Mammal.* 74, 594–600.
- 650 5. Medellín, R.A., Rivero, M., Ibarra, A., Torre, J.A. de la, Gonzalez-Terrazas, T.P.,  
651 Torres-Knoop, L., and Tschapka, M. (2018). Follow me: foraging distances of  
652 *Leptonycteris yerbabuenae* (Chiroptera: Phyllostomidae) in Sonora determined by  
653 fluorescent powder. *J. Mammal.* 99, 306–311.
- 654 6. Zimmerman, M. (1979). Optimal foraging: A case for random movement. *Oecologia*  
655 43, 261–267.
- 656 7. Giuggioli, L., Potts, J.R., and Harris, S. (2011). Animal interactions and the emergence  
657 of territoriality. *PLoS Comput. Biol.* 7.
- 658 8. Stiles, F.G. (1971). Time, energy, and territoriality of the Anna Hummingbird (*Calypte*  
659 *anna*). *Science* (80-. ). 173, 818–821.
- 660 9. Wolf, L.L. (1970). The impact of seasonal flowering on the biology of some tropical  
661 hummingbirds. *Condor* 72, 1–14.
- 662 10. Feinsinger, P. (1976). Organization of a tropical guild of nectarivorous birds. *Ecol.*  
663 *Monogr.* 46, 257–291.
- 664 11. Linhart, Y.B. (1973). Ecological and behavioral determinants of pollen dispersal in  
665 hummingbird-pollinated *Heliconia*. *Am. Nat.* 107, 511–523.
- 666 12. Kadmon, R., and Shmida, A. (1992). Departure rules used by bees foraging for nectar:  
667 A field test. *Evol. Ecol.* 6, 142–151.
- 668 13. Gill, F.B. (1988). Trapline foraging by hermit hummingbirds: competition for an  
669 undefended, renewable resource. *Ecology* 69, 1933–1942.
- 670 14. Lihoreau, M., Raine, N.E., Reynolds, A.M., Stelzer, R.J., Lim, K.S., Smith, A.D.,  
671 Osborne, J.L., and Chittka, L. (2012). Radar tracking and motion-sensitive cameras on  
672 flowers reveal the development of pollinator multi-destination routes over large spatial  
673 scales. *PLoS Biol.* 10, 1001392.
- 674 15. Janzen, D.H. (1971). Euglossine bees as long-distance pollinators of tropical plants.

- 675 Science (80-. ). *171*, 203–205.
- 676 16. Gilbert, L.E. (1975). Ecological consequences of a coevolved mutualism between  
677 butterflies and plants. *Coevol. Anim. plants*, 210–240.
- 678 17. Janson, C.H., Terborgh, J., and Emmons, L.H. (1981). Non-flying mammals as  
679 pollinating agents in the Amazonian forest. *Biotropica*, 1–6.
- 680 18. Garber, P.A. (1988). Foraging decisions during nectar feeding by tamarin monkeys  
681 (*Saguinus mystax* and *Saguinus fuscicollis*, Callitrichidae, Primates) in Amazonian  
682 Peru. *Biotropica*, 100–106.
- 683 19. Janson, C.H. (1998). Experimental evidence for spatial memory in foraging wild  
684 capuchin monkeys, *Cebus apella*. *Anim. Behav.* *55*, 1229–1243.
- 685 20. Watts, D.P. (1998). Long-term habitat use by mountain gorillas (*Gorilla gorilla*  
686 *beringei*). 2. Reuse of foraging areas in relation to resource abundance, quality, and  
687 depletion. *Int. J. Primatol.* *19*, 681–702.
- 688 21. Lihoreau, M., Chittka, L., and Raine, N.E. (2011). Trade-off between travel distance  
689 and prioritization of high-reward sites in traplining bumblebees. *Funct. Ecol.* *25*,  
690 1284–1292.
- 691 22. Thomson, J.D., Slatkin, M., and Thomson, B.A. (1997). Trapline foraging by bumble  
692 bees: II. Definition and detection from sequence data. *Behav. Ecol.* *8*, 199–210.
- 693 23. Schmidt, J.O., and Buchmann, S.L. (1986). Floral biology of the saguaro (*Cereus*  
694 *giganteus*) - I. Pollen harvest by *Apis mellifera*. *Oecologia* *69*, 491–498.
- 695 24. Winter, Y., and Stich, K.P. (2005). Foraging in a complex naturalistic environment:  
696 Capacity of spatial working memory in flower bats. *J. Exp. Biol.* *208*, 539–548.
- 697 25. Niv, Y., Joel, D., Meilijson, I., and Ruppin, E. (2002). Evolution of reinforcement  
698 learning in uncertain environments: A simple explanation for complex foraging  
699 behaviors. *Adapt. Behav.* *10*, 5–24.
- 700 26. Börger, L., Dalziel, B.D., and Fryxell, J.M. (2008). Are there general mechanisms of  
701 animal home range behaviour? A review and prospects for future research. *Ecol. Lett.*  
702 *11*, 637–650.
- 703 27. Cvikel, N., Levin, E., Hurme, E., Borrisov, I., Boonman, A., Amichai, E., and Yovel,  
704 Y. (2015). On-board recordings reveal no jamming avoidance in wild bats. *Proc. R.*  
705 *Soc. B Biol. Sci.* *282*.
- 706 28. Danilovich, S., Krishnan, A., Lee, W.J., Borrisov, I., Eitan, O., Kosa, G., Moss, C.F.,  
707 and Yovel, Y. (2015). Bats regulate biosonar based on the availability of visual  
708 information. *Curr. Biol.* *25*, R1124–R1125.
- 709 29. Korman, A., Emek, Y., Collet, S., Goldshtein, A., and Yovel, Y. (2020). Exploitation  
710 of multiple replenishing resources with uncertainty. <http://arxiv.org/abs/2007.09640>
- 711 30. Behrens, T.E.J., Woolrich, M.W., Walton, M.E., and Rushworth, M.F.S. (2007).

- 712 Learning the value of information in an uncertain world. *Nat. Neurosci.* *10*, 1214–  
713 1221.
- 714 31. Ohashi, K., and Thomson, J.D. (2009). Trapline foraging by pollinators: its ontogeny,  
715 economics and possible consequences for plants. *Ann. Bot.* *103*, 1365–1378.
- 716 32. Tellez, G., Medellín, R.A., Mora, C., and McCracken, G. (2000). Evidence of  
717 migration of *Leptonycteris curasoae* in the Mexican tropics. *Bat Res. News* *41*, 143.
- 718 33. Egert-Berg, K., Hurme, E.R., Greif, S., Goldstein, A., Harten, L., Herrera M., L.G.,  
719 Flores-Martínez, J.J., Valdés, A.T., Johnston, D.S., Eitan, O., *et al.* (2018). Resource  
720 Ephemerality Drives Social Foraging in Bats. *Curr. Biol.* *28*, 3667-3673.e5.
- 721 34. Hen, I., Sakov, A., Kafkafi, N., Golani, I., and Benjamini, Y. (2004). The dynamics of  
722 spatial behavior: How can robust smoothing techniques help? *J. Neurosci. Methods*  
723 *133*, 161–172.
- 724 35. Benhamou, S. (2004). How to reliably estimate the tortuosity of an animal's path:  
725 Straightness, sinuosity, or fractal dimension? *J. Theor. Biol.* *229*, 209–220.
- 726 36. Horner, M.A., Fleming, T.H., and Sahley, C.T. (1998). Foraging behaviour and  
727 energetics of a nectar-feeding bat, *Leptonycteris curasoae* (Chiroptera:  
728 Phyllostomidae). *J. Zool.* *244*, 575–586.
- 729 37. Kunz, T.H., and Nagy, K.A. (1988). *Methods of energy budget analysis* (Washington:  
730 Johns Hopkins University Press).
- 731 38. Boonman, A., Bar-On, Y., Yovel, Y., and Cvikel, N. (2013). It's not black or white—  
732 on the range of vision and echolocation in echolocating bats. *Front. Physiol.* *4*, 248.
- 733 39. Frenzel, J.F. (1993). Genetic algorithms. *IEEE Potentials* *12*, 21–24.
- 734