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Musical improvisation reveals the fine-grained foraging dynamics of collective innovation

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Abstract

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Collective innovation is key to the global success of the human species. However, the moment-to-moment details of how creative innovation is accomplished by a collective remain unclear. One challenge is that while creative products (e.g., scientific breakthroughs, technological inventions, rehearsed performances) may be public, the creative processes that generated those products are often private. Here we introduce collective musical improvisation as a model system for the fine-grained study of *in vivo* collective innovation. In free jazz improvisation, the creative product *is* the creative process, offering a unique real-time window into the creative process. Using a corpus of free jazz recordings, we embedded each track as a trajectory through a high-dimensional “sonic space” and then analyzed the strategies by which musicians moved collectively through this space of sonic possibility. Despite the cognitive sophistication and cultural richness of musical improvisation, we find that musical ensembles spontaneously adopt a search strategy, Area Restricted Search, with deep evolutionary roots, previously identified in animal foraging. This convergence between behavioral ecology, cognition, and culture suggests deep evolutionary origins of the human capacity for collective innovation.

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20 **Introduction**

21 Collective innovation is a cornerstone of our species' global success [1, 2]. This capacity is man-
22 ifest in activities as varied as technological invention [3], crisis problem solving [4], scientific
23 collaboration [5], and even interpersonal conversation [6], all of which require the coordination
24 of creative behaviors distributed among multiple actors. Understanding the moment-to-moment
25 dynamics of collective innovation remains a grand challenge. One major stumbling block to the
26 scientific study of collective innovation is the inherent opacity of the creative process: while
27 creative products like scientific publications or rehearsed musical performances are visible as
28 the public "frontstage" of innovation, the crucial "backstage" of real-time collaborative cre-
29 ation often remains hidden [7]. The opacity of the creative process has severely limited our
30 understanding of the fine-grained dynamics of real-world collective innovation.

31 To penetrate this observational barrier, we turned to a unusual group of creative profes-
32 sionals notorious for engaging publicly in the process of collective innovation: free jazz musicians.
33 Improvising musicians must coordinate continuously, make constant decisions on the timescale
34 of milliseconds, and select their moment-to-moment activity from a huge space of acoustic pos-
35 sibility [9]. In stark contrast to domains where the creative process is hidden behind its product,
36 in musical improvisation the process of creation *is* the publicly observable product. This im-
37 mediacy distinguishes it from, say, musical composition or scientific research, where creative
38 products like musical scores or scientific publications are the polished outcomes of often pro-
39 tracted and private generative processes. Crucially, among improvisational practices, free jazz
40 is especially well suited for studying truly *collective* creativity. Unlike genres that focus on
41 individual soloists with harmonic or rhythmic accompaniment, in free jazz all ensemble mem-
42 bers participate simultaneously in the improvisational process [10, 11]. Free jazz ensembles
43 perform without established leaders, preexisting musical scores, predetermined chord changes,
44 planned solo intervals, established harmonies, or canonical musical phrases. Instead, they make
45 it up on the fly, collectively creating novel sounds as they navigate a space of possible sounds
46 that is largely unconstrained [12]. Likewise, collaboratively improvising musicians rapidly and
47 mutually adapt to their improvising partners to create optimal musical performances [13, 14].
48 Collective free jazz improvisation thus provides a unique real-world laboratory for studying the
49 unscripted, fine-grained, moment-to-moment dynamics of collective innovation *in vivo*.

50 Here, to quantify the fine-grained dynamics of collective innovation, we analyze the impro-
51 visational process as a kind of *foraging*, a search for rewards in an uncertain landscape. More
52 mundane forms of individual creativity have been characterized as foraging processes, includ-
53 ing searching through semantic memory [15], creating interesting visual patterns [16, 17, 18],
54 and solving insight puzzles [19]. Similarly, free improvisation can be thought of as a *collective*
55 foraging process, in which musical ensembles must move through an abstract space of sonic
56 possibility with the goal of discovering sounds that are novel, interesting, or otherwise reward-
57 ing. From this perspective, locations within the sonic space correspond to complex sounds
58 produced by the musical ensemble, which could be sounds that the musicians have produced
59 before (analogous to locations that a foraging organism has visited previously) or entirely novel

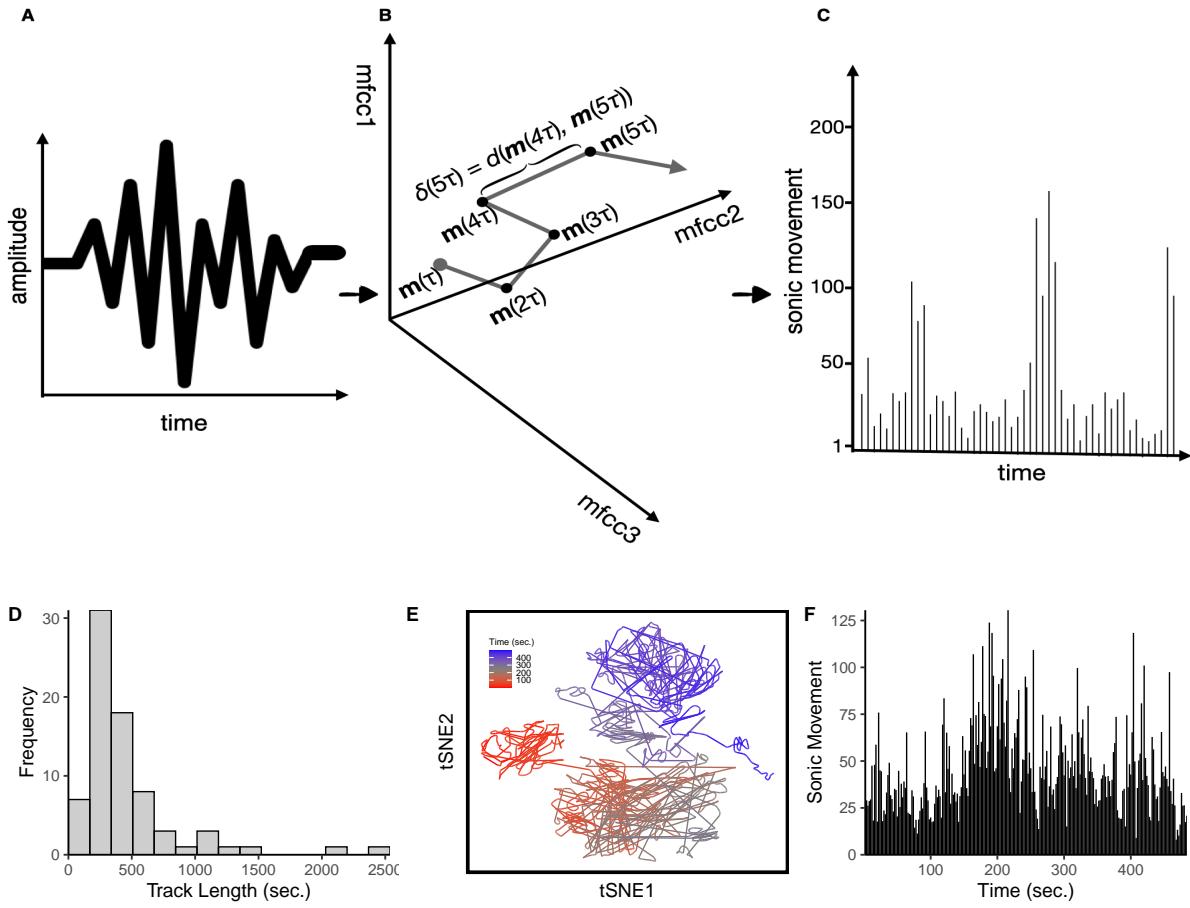


Figure 1: Quantifying the sonic trajectories of improvised musical performances. (A-C) Graphical illustration of the analysis pipeline. Single-track audio recordings of improvised free jazz, illustrated in (A), were transformed into trajectories through a ‘sonic space,’ illustrated in (B), that captured timbral features using Mel Frequency Cepstral Coefficients (MFCC). The trajectory for each recording consisted of consecutive sonic embeddings, $m(t)$, of brief, non-overlapping “moments” of duration τ . To quantify the moment-to-moment dynamics of these trajectories, we calculated the sonic movement at time t as the Euclidean distance between consecutive sonic embeddings, $\delta(t) = d(m(t - \tau), m(t))$. This generated a time series of moment-to-moment sonic movements, illustrated in (C). (D) Empirical distribution of track durations in the corpus of free jazz recordings. (E) Trajectory through sonic space of one illustrative track. For visualization, the trajectory’s 20 dimensions were reduced to 2 using t-SNE, a dimension-reduction technique [8]. Color indicates time within the recording, from start (red) to end (blue). (F) Time series of moment-to-moment sonic movements for the track in (E).

60 sounds that have never been created (analogous to locations that a foraging organism has yet to
 61 visit). Below, we explain how computational methods can formalize this foraging perspective

62 on musical improvisation (Fig. 1, A-C).

63 What foraging strategies might musical ensembles use to improvise? Across a wide range
64 of environmental conditions where resources cluster together in patches, a highly effective for-
65 aging strategy is to move through the space using a Lévy flight random walk [20]. In a Lévy
66 flight, the length of each step is drawn randomly from a heavy-tailed distribution, with frequent
67 small steps and infrequent large steps [21]. Despite their randomness and lack of any plan or
68 memory, Lévy flights can generate search trajectories that appear patchy, with extended periods
69 spent within local regions, interspersed with large jumps to new regions. The spatial foraging
70 behavior of a wide variety of organisms has been characterized as Lévy flights, including alba-
71 trosses [22], sharks [23], mussels [24], deer [25], humans [26, 27, 28], and even entire sports
72 teams [29], although subsequent reanalyses have cast doubt on some of these claims [30, 31].
73 While a random walk may seem an overly simplistic account of collective innovation, random
74 walks have been used to model a range of high-level cognitive processes, including decision
75 making [32, 33], memory retrieval [34], individual creativity [35], curiosity [36], and even
76 scientific productivity [37], and some have argued that they are optimal in a wide range of con-
77 ditions [20]. In the context of improvised music, novel and interesting sounds are distributed
78 unevenly and unpredictably throughout the space of sonic possibility, so musicians could per-
79 form an abstract form of a Lévy flight to increase their odds of encountering particularly novel
80 or interesting sounds.

81 Alternatively, instead of moving randomly as in a Lévy flight, foragers may respond strate-
82 gically to resource encounters [38]. In Area Restricted Search, for instance, resource encounters
83 prompt the forager to search nearby, thus ‘exploiting’ the local region. As resource encounters
84 become less frequent, the organism becomes more likely to abandon that region to ‘explore’
85 widely for a new patch of clustered rewards. Much like Lévy flights, Area-Restricted Search
86 has been documented widely in the natural world [38], including in ladybugs foraging for aphids
87 [39], seabirds foraging for fish [40], and humans foraging for mushrooms [41]. Since resources
88 are often clustered spatially, Area Restricted Search can generate patchy trajectories that resem-
89 ble those of a Lévy flight. After encountering an interesting sound, for instance, improvising
90 musicians may decide collectively to persist in exploiting the similar sounds within a sonic patch
91 or “soundworld,” only switching to explore for a new soundworld when they have exhausted
92 the current soundworld’s novelty or interest.

93 As accounts of foraging, Lévy flights and Area Restricted Search are difficult to distinguish
94 because both can generate search patterns that are patchy, with periods of sustained search
95 within a focal region punctuated by leaps to a new region. A key difference, however, is the
96 role of memory in the transition between patches [42, 43]. In a Lévy flight, the organism
97 does not adjust its behavior on the basis of recent resource encounters; it just draws randomly
98 from a heavy-tailed distribution of steps. An organism engaged in Area Restricted Search, by
99 contrast, will transition from exploring to exploiting when it encounters a new resource, and
100 it may then persist in exploiting that region based on the memory of that resource encounter.
101 Area-Restricted Search and Lévy flights are thus distinguished by whether or not the organism
102 adjusts its foraging behavior before and after a resource encounter. As a consequence, when an

103 organism uses Area Restricted Search to forage in a patchy landscape, large exploratory steps
104 should cluster together temporally within periods of sustained exploration; in a Lévy flight, by
105 contrast, the temporal distribution of large steps is random.

106 Using a corpus of audio recordings of professional musicians engaged in collective impro-
107 visation — a model system for the fine-grained study of *in vivo* collective innovation — we
108 investigated the foraging strategies adopted collectively as the ensembles engaged in free im-
109 provisation (Fig. 1, A, D). We converted each track ($N = 75$, ranging from 1 min. to over
110 40 min.) into a trajectory through a space of sonic possibility by embedding consecutive mo-
111 ments in a high-dimensional "sonic space" (Fig. 1B, E). We quantified the dynamics of these
112 trajectories by analyzing the moment-to-moment movements through this sonic space (Fig. 1C,
113 F). We then asked whether the dynamics of collective improvisation instantiate classic foraging
114 strategies from behavioral ecology.

115 Results

116 Sonic foraging exploits local patches of sound

117 We first characterized the overall dynamics of musicians' sonic foraging. We calculated the
118 pairwise distance between sounds produced throughout each track, using Euclidean distance
119 between sonic embeddings (see Methods). In more structured genres of music, including so-
120 called "straight-ahead" jazz in which improvised solos are interleaved with composed sections,
121 songs will often return repeatedly to the same region of sonic space (e.g., the refrain or chorus
122 in a pop song). In free improvised music, on the other hand, the sound may wander without
123 returning. (In Figure S1, we visualize this difference between a more structured jazz standard
124 and a free jazz performance.) As a result, freely improvised music should gradually diverge
125 from past sounds. As expected, in the corpus, sounds that were performed around the same time
126 in a track were highly similar, and mean sonic distance increased monotonically for sounds that
127 were produced at increasingly distant moments (Fig. 2A). On the long timescale of the entire
128 track, therefore, musicians explored widely in the the sonic space.

129 On the short timescale of moment-to-moment playing, however, the ensembles engaged
130 primarily in *exploitation* of local regions of sonic space, as revealed by the size and direction
131 of moment-to-moment sonic change. Musicians primarily made smaller adjustments to their
132 sound, but infrequently made unusually large changes, generating a heavy-tailed distribution of
133 sonic movements (i.e., sonic distannces between consecutive moments; Fig. 2B). This is con-
134 sistent with both Area Restricted Search and Lévy flight foraging strategies. In the Supporting
135 Information, we show that these sonic movements are well characterized by a log-normal dis-
136 tribution, which is typically generated by multiplicative processes [44], suggesting (unsurpris-
137 ingly) that musical improvisation reflects complex interactions among the musicians rather than
138 independent, additive contributions. (For context, in the Supporting Information we also plot
139 the distribution of sonic movements for a structured jazz standard; movements in this track are

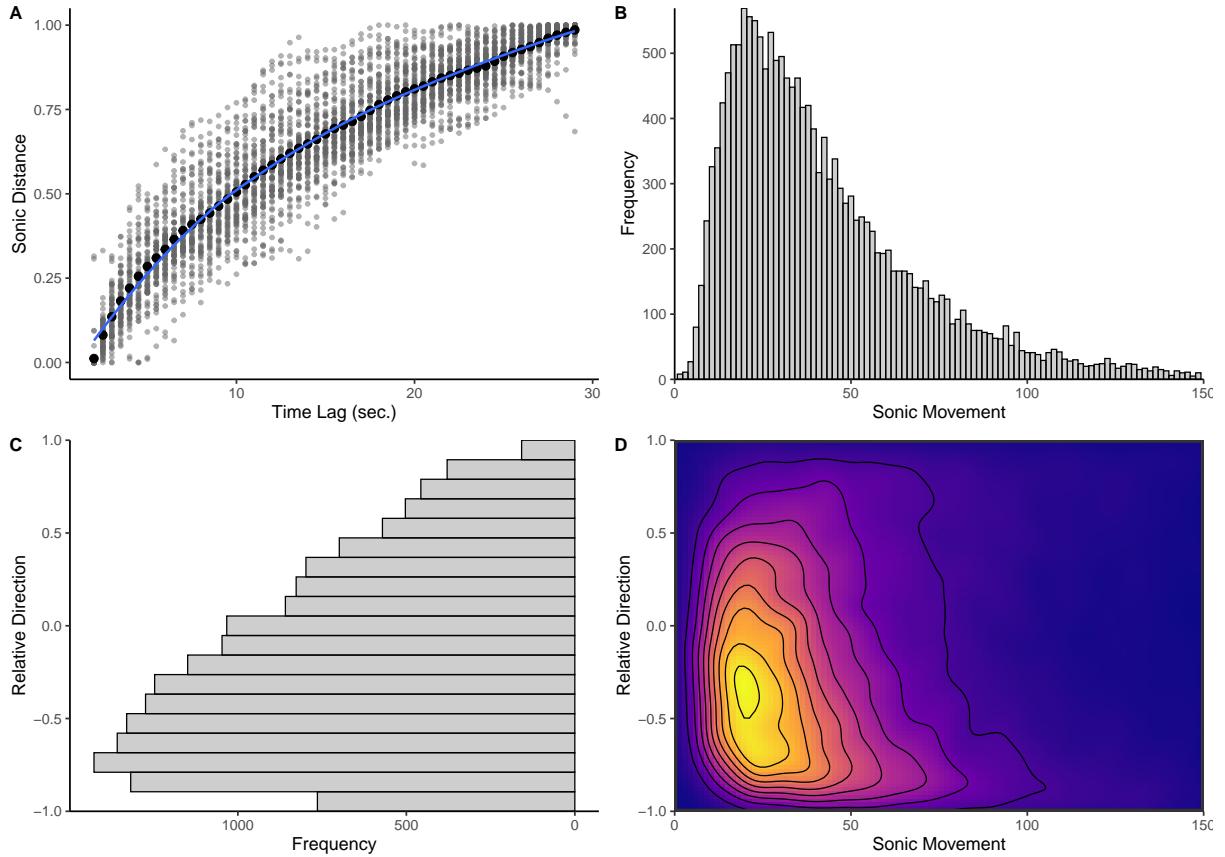


Figure 2: Free improvised music consisted primarily of local exploitation of the sonic space.

(A) Temporal decay of sonic similarity. Within each track, sounds were more dissimilar (vertical axis) if they were produced further apart temporally (horizontal axis). Smaller grey dots show the mean sonic distance between all pairs of moments within a particular track that were produced at a given temporal lag. Large black dots show means across all tracks. Sonic distance was rescaled within each track to range from 0 (maximally similar sounds) to 1 (maximally dissimilar sounds). (B) Heavy-tailed distribution of sonic movements (i.e., sonic distance between consecutive moments). (C) Distribution of relative directions across all tracks. Relative direction was measured using cosine similarity and thus ranges from +1 (continuing in the same direction), to 0 (moving in an orthogonal direction), to -1 (reversing direction). Moment-to-moment movements more frequently involved reversing the direction of the previous movement (i.e., more negative relative direction). (D) Kernel density heatmap of moment-to-moment sonic movement (distance between consecutive moments) and relative direction. Most movements involved a smaller step that reversed the direction of the previous step, consistent with local exploitation of a limited region of sonic space. (Color indicates relative density: lighter yellow = higher density; darker purple = lower density)

140 considerably smaller, with fewer larger steps.) Notably, the relative direction of sonic change,
141 which characterizes whether sonic movements continued or reversed direction, was less skewed
142 and primarily negative ($M = -0.11$, $SD = 0.50$; Fig. 2C), indicating a tendency to turn back
143 rather than continue in the same direction. This pattern of smaller sonic movements that tended
144 to turn back on themselves is indicative of local exploitation, which is characteristic of both the
145 ‘exploit’ phase of Area Restricted Search and the dominance of small steps in a Lévy flight.

146 Large-scale sonic exploration occurred in bursts

147 While the musicians engaged primarily in local exploitation — small steps that turned back on
148 themselves — the heavy-tailed distribution of sonic steps reveals that they occasionally engaged
149 in larger steps that allowed them to explore new sonic possibilities. In a Lévy flight these big
150 steps occur at random, while in Area Restricted Search they arrive in bursts while the collective
151 is engaged in sustained exploration for a new patch of interesting sounds. To quantify the
152 burstiness of large sonic steps, we identified sonic movements that were unusually large and
153 calculated whether these clustered together in bursts of sonic exploration (see Methods). In line
154 with Area Restricted Search, and unlike a Lévy flight, the temporal distribution of large sonic
155 steps was significantly bursty (Burstiness: $M = .15 \pm .02$ SE, $t(73) = 6.9$, $p < .001$, Fig. 3B).
156 Large sonic movements thus occurred in temporal clusters.

157 To determine the foraging strategy that could have generated this pattern, we implemented
158 minimal models of Lévy flight and Explore-Exploit foraging. The latter captures the outcome of
159 Area Restricted Search in a patchy landscape of sonic resources. To test whether these models
160 could recover the observed temporal distribution of sonic movements for each track, we fit
161 the models to the empirical distribution of sonic movements and then generated synthetic time
162 series of sonic movements.

163 First, the Lévy flight model was a memory-less, uncorrelated random walk. At each time
164 step, the musical ensemble takes a sonic step of length d , with d drawn from each track’s
165 empirical distribution of sonic movements (Fig. 3A, top). Note that here we use the heavy-
166 tailed empirical distributions of sonic movements rather than a true Lévy distribution, although
167 our results are robust to the choice of distribution.

168 Second, the Explore-Exploit model traded off between exploration and exploitation (Fig. 3A,
169 top), the behavior generated by Area Restricted Search in a patchy landscape. Like the Lévy
170 flight model, this minimal model generates sonic movements by drawing randomly from distri-
171 butions estimated from the tracks in the corpus. Unlike a memory-less Lévy flight, the musical
172 ensemble can be in one of two latent states, and the distribution from which the sonic movement
173 is drawn depends on the latent state: smaller movements while *exploiting*, larger movements
174 while *exploring*. For simplicity, we ignore the resource encounters that drive changes in be-
175 havior in Area Restricted Search, and instead allow the minimal model’s latent state to switch
176 stochastically. We implemented this process as a two-state Hidden Markov Model, fit to the
177 empirical time series of each track’s sonic movements. Since Hidden Markov Models estimate
178 the distribution of observations associated with each latent state, they can capture processes

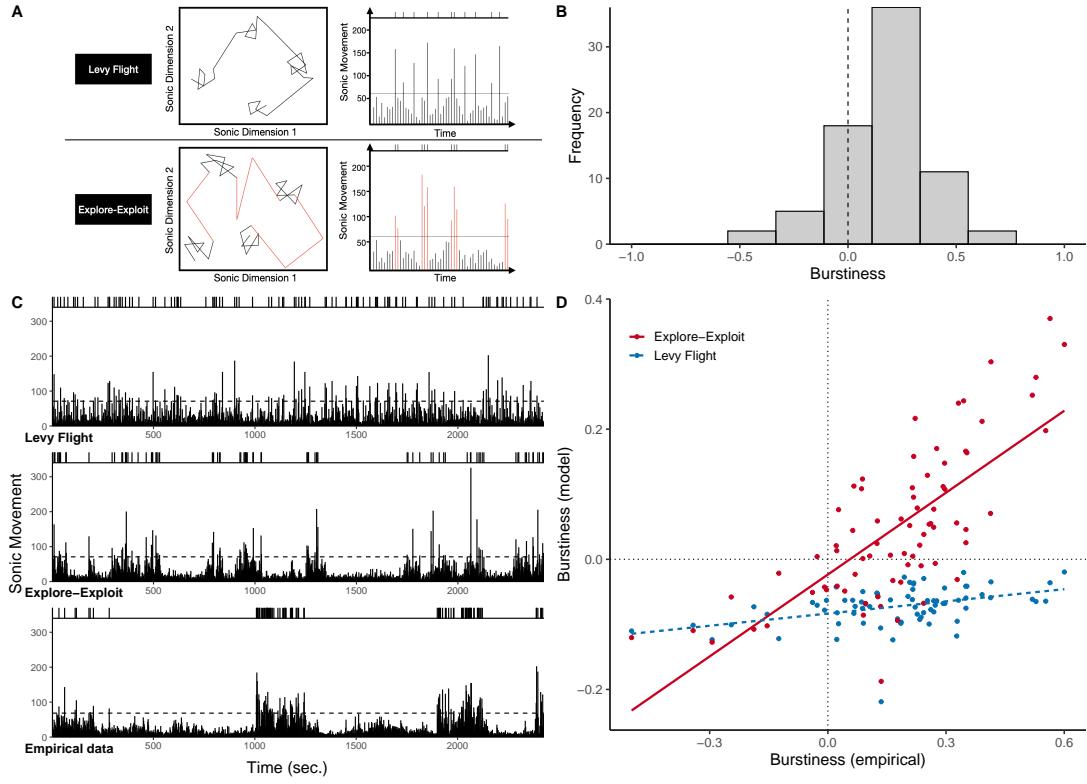


Figure 3: The burstiness of free improvisation was consistent with Explore-Exploit foraging, a pattern generated by Area Restricted Search in patchy environments. (A) Graphical illustration of minimal models of foraging: Lévy flight (top) and Explore-Exploit (bottom). Left panels illustrate hypothetical trajectories through sonic space. Explore-Exploit alternates between exploitation (black) and exploration (red). Right panels illustrate hypothetical time series of sonic movements (i.e., sonic distance between consecutive moments) derived from these trajectories, with movements considered ‘large’ if they passed a threshold (dashed line). Raster plots atop each time series show the timing of large movements: random in the Lévy flight and in clustered bursts in the Explore-Exploit process. (B) Empirical distribution of burstiness of large sonic movements. Large movements typically occurred in clustered bursts (i.e., burstiness > 0), consistent with an Explore-Exploit process. (C) Time series of sonic movements from one representative free jazz performance (bottom) and minimal models fit to that recording: Explore-Exploit (middle) and Lévy flight (top). Raster plots atop each time series show the timing of large movements. (D) Burstiness of recordings in the free jazz corpus (x-axis) compared to the burstiness generated by minimal models of those recordings (y-axis): Explore-Exploit (red) and Lévy flight (blue). Lines show linear regressions between empirical burstiness and model burstiness. Only the Explore-Exploit model recovered the burstiness of the empirical recordings.

179 where one latent state is associated with larger steps and the other with smaller steps, although
180 this is estimated from the empirical time series for each track. Moreover, since Hidden Markov
181 Models estimate the transition probabilities between latent states, they can capture persistent
182 latent dynamics (i.e., the tendency to persist in *exploit* or *explore* modes), although once again
183 this is estimated from the empirical time series. This model thus incrementally extends the Lévy
184 flight model by allowing the musical ensemble to toggle between two latent regimes of sonic
185 improvisation.

186 We used these minimal models to simulate time series of sonic movements. For each track,
187 we used each of the two models to generate 100 simulated time series, with duration equal to
188 the track's actual duration (Fig. 3C). Then, for each track, we calculated the mean burstiness of
189 these simulated time series. As predicted, large sonic movements generated by the Lévy flight
190 model were reliably anti-bursty (burstiness: $M = -0.07 \pm .00$ SE, $t(74) = -19.03$, $p < .01$).
191 Instead the temporal distribution of large steps ranged from random to periodic (Fig. 3D, blue
192 dots). Conversely, the large sonic movements generated by the Explore-Exploit model clustered
193 together in time and were thus consistently bursty ($M = .05 \pm .01$ SE, $t(74) = 3.47$, $p < .01$).
194 The improvised tracks' true empirical values of burstiness were strongly associated with the
195 burstiness values generated by the Explore-Exploit model (linear regression predicting empir-
196 ical burstiness: $b = 1.30 \pm 0.17$, $p < .001$; Fig. 3D, red dots and line) but not the burstiness
197 values generated by the Lévy flight model ($b = -0.03 \pm 0.66$, $p = .96$; Fig. 3D, blue dots and
198 line). Thus, the temporal clustering of large sonic movements in collectively improvised music
199 is explained by a minimal model of Explore-Exploit foraging, but not by a model of Lévy flight
200 foraging.

201 Ensembles explore before and exploit after encountering a new soundworld

202 Finally, we examined whether musicians changed their foraging behavior before and after en-
203 countered a novel patch of sonic space or 'soundworld,' as predicted by Area Restricted Search
204 but not Lévy flight foraging. We identified acoustic transitions between soundworlds as peaks
205 in Foote novelty, a measure of change between stable periods of a time series (see Methods).
206 These are moments when the musical ensemble changed its playing suddenly, going from one
207 stable soundworld to a novel one. In the period immediately before transitioning to a new
208 soundworld (i.e., the 10 second period before), musicians' sonic foraging was systematically
209 more exploratory than moments away from a transition (Fig. 4A), with moment-to-moment sonic
210 movements that were larger ($M = 53.5 \pm 2.4$ SEM; Fig. 4A) and changes in direction that were
211 more orthogonal (i.e., closer to 0; $M = -0.10 \pm 0.03$ SEM; Fig. 4B). A shift toward exploratory
212 foraging can thus serve as an early warning signal of an impending sonic transition. By con-
213 trast, in the period immediately after encountering a new soundworld (i.e., the 10 second period
214 after), musicians' sonic foraging rapidly shifted from exploration to exploitation, with a sudden
215 decrease in the size of sonic movements ($M = 47.4 \pm 2.3$ SEM) and relative directions that
216 turned back on themselves ($M = -0.19 \pm 0.03$ SEM). This pattern was confirmed by multi-
217 level Bayesian models of sonic movements and relative directions, with random effects by track

218 to account for between-track variation. These models confirmed that, compared to moments
219 away from a transition, sonic foraging immediately before a transition involved significantly
220 larger sonic movements ($\beta = 6.8$, 95% Bayesian Credible Interval = [1.2, 12.3]) and signifi-
221 cantly more orthogonal turns ($\beta = 0.10$, 95% CI = [0.03, 0.17]). By contrast, sonic foraging
222 immediately after a transition did not differ from baseline sonic exploitation (sonic movements:
223 $\beta = -0.4$, 95% CI = [-5.4, 4.5]; relative directions: $\beta = 0.00$, 95% CI = [-0.07, 0.07]). Thus,
224 transitions to a novel soundworld were prefigured by sonic exploration, while encounters with
225 novel soundworlds were associated with a shift back to exploitation (Fig. 4C), as predicted by
226 Area Restricted Search, but inconsistent with a memory-less Lévy flight process.

227 Discussion

228 By analyzing the moment-to-moment creative decisions of free jazz musicians, we have shown
229 that their collective improvisation reflects a process of collective foraging through sonic space.
230 Their sonic movements were heavy-tailed, with many small sonic movements and few large
231 ones. Large sonic movements tended to cluster together in time, a bursty pattern that is con-
232 sistent with the regime switching of Area Restricted Search but not the random draws of a
233 Lévy flight. To further distinguish between these two foraging strategies, we examined the
234 musicians' behavior before and after they encountered a novel 'patch' of the sonic space. Ten
235 seconds before transitioning to a new patch, the musicians' playing became more exploratory,
236 with larger sonic movements in more orthogonal directions. After arriving in the new sonic
237 region, their playing reverted to more exploitative foraging, with smaller sonic movements and
238 more reversals. This responsiveness to new sonic encounters is consistent with Area Restricted
239 Search but not a memory-less Lévy flight. Thus, despite the cognitive sophistication and cul-
240 tural richness of musical improvisation, we find that musical ensembles spontaneously adopted
241 a search strategy, Area Restricted Search, with deep evolutionary roots, previously identified in
242 animals foraging for food [38, 39, 40, 41, 42, 43]. This suggests that collective improvisation
243 — a model system for studying collective innovation — involves the kind of distributed sensing
244 and collective memory that is required for Area Restricted Search.

245 The collective sonic dynamics analyzed here complement accounts of the individual-level
246 cognitive and physical processes involved in musical improvisation. One model of the cognitive
247 processes underlying individual musical creativity, for instance, posits that musicians improvise
248 in clusters of events that are either associated or interrupted [45]. Associated clusters seek con-
249 tinuity, consistent with the periods of collective sonic exploitation described here. Interrupted
250 clusters differ from the preceding sound, consistent with bursts collective sonic exploration.
251 Here we've shown quantitatively that the fine-grained dynamics of collective improvisation fol-
252 low a similar pattern of stasis and transformation, association and interruption, exploitation and
253 exploration. Other approaches have focused on the microdynamics of musician-musician inter-
254 action. Musicians are known to couple both their high-level playing (e.g., harmony, [13, 14])
255 and their low-level physical movements (e.g., swaying to and fro; [46, 47]). Dyadic coupling

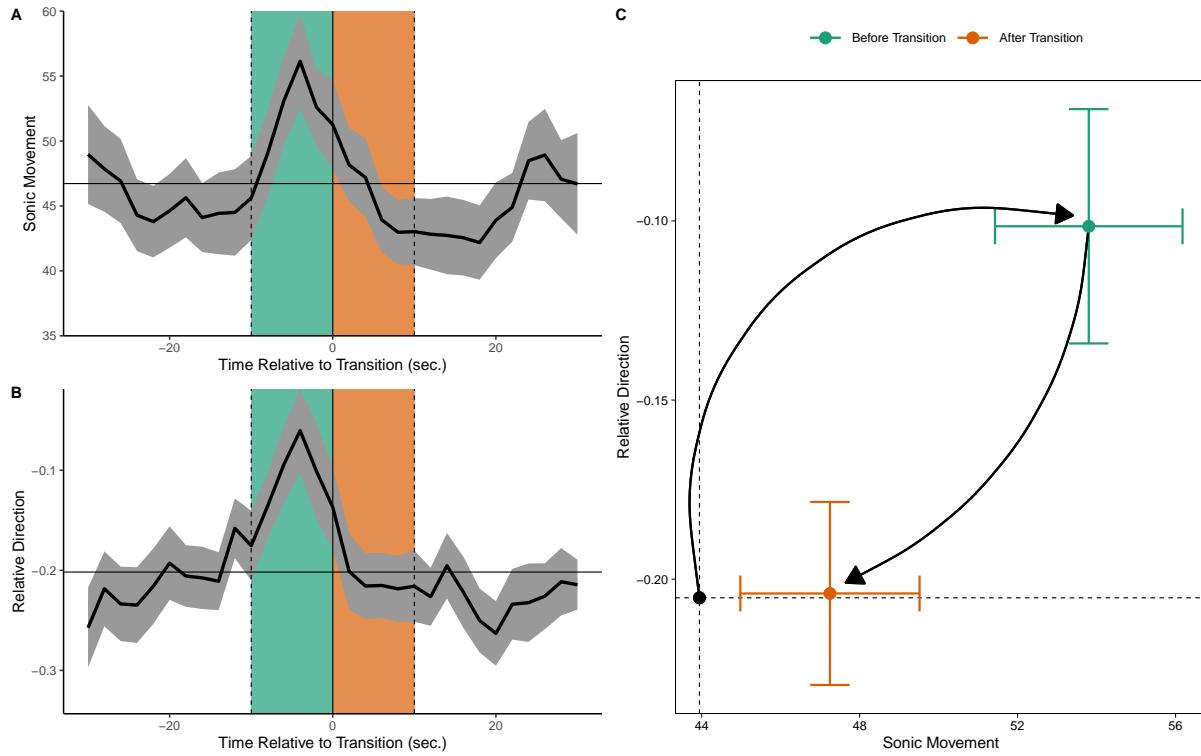


Figure 4: Sonic foraging was more exploratory before sonic transitions. (A) Time series of sonic movements in the period around major sonic transitions. In the 10 seconds before a transition (green), sonic movements became systematically larger than average (solid horizontal line), consistent with exploration. Sonic movements dipped rapidly in the 10 seconds following a transition (orange), consistent with a return to exploitation. (thick black line = mean; grey ribbon = standard error) (B) Time series of relative direction in the period around major sonic transitions. In the 10 seconds before a transition, relative direction approached 0, indicating that consecutive movements were in orthogonal directions, consistent with exploration. In the 10 seconds following a transition, relative direction become more negative, indicating consecutive movements that reversed direction, consistent with a return to exploitation. (thick black line = mean; grey ribbon = standard error) (C) Phase plot of relative direction and sonic movement before and after major sonic transitions. Arrows illustrate the transition from baseline foraging (all moments away from a major transition; black dot) to foraging in the 10 seconds before a major transition (green dot), to foraging in the 10 seconds after a major transition (orange dot). Before a transition, sonic foraging became more exploratory, with larger sonic movements in more orthogonal directions. Immediately after the transition, sonic foraging returned to a baseline of exploitation, with smaller sonic movements that turned back on themselves to stay in the same patch of sonic space. (points = means; error bars = standard errors.)

256 among musicians is one simple, local mechanism that could give rise to the sophisticated col-
257 lective coordination analyzed here, similar to the collective synchronization that can emerge in
258 coupled non-linear oscillators [48, 49].

259 Analyses similar to the ones performed here may shed light on other forms of collective
260 search through acoustic, semantic, or physical space. Collectively improvised dance, for in-
261 stance, could be analyzed as a search through “movement space” using motion tracking hard-
262 ware [50] or pose estimation models from computer vision [51], while collective conversation
263 could be analyzed as a search through semantic space [52]. We suspect that an unscripted free-
264 wheeling conversation, for example, may resemble an Area Restricted Search for juicy topics in
265 semantic space. And while we have focused on the short-timescale dynamics of improvisation
266 within a single musical track, this rapid process of mutual adaptation and coordination is nested
267 within much slower processes of lifelong learning and rehearsal [53]. Since the short-timescale
268 dynamics of engagement and struggle can give rise to qualitatively different long-timescale dy-
269 namics of learning [53], it remains unclear how the short-timescale foraging dynamics analyzed
270 here might develop and change over the course of a sustained creative collaboration or an entire
271 musical career.

272 In seeking to understand collective innovation, Area Restricted Search can serve as metaphor,
273 model, or mechanism. As a metaphor, Area Restricted Search can offer a framework — strate-
274 gic (non-random) foraging — for thinking qualitatively about the patterns of behavior exhibited
275 by innovative groups. As a model, Area Restricted Search can offer formal tools to quantify
276 those patterns. And as a mechanism, Area Restricted Search can designate an evolutionarily
277 conserved capacity, exapted to navigate figurative rather than literal spaces. We think Area
278 Restricted Search is undeniably a fruitful metaphor. And the current results add to a larger
279 movement to use Area Restricted Search as a model for analyzing a range of foraging-like cog-
280 nitive phenomena in individuals [54, 16, 17, 18, 55, 19]. Finally, in terms of mechanism, the
281 spontaneous emergence of Area Restricted Search in improvising musicians suggests a deep
282 evolutionary origin of the human capacity for collective innovation. For instance, varied for-
283 aging processes — from searching for food to collective improvisation — may rely on con-
284 served, evolutionarily-ancient mechanisms for goal-directed behavior [56]. But we hesitate to
285 conclude that Area Restricted Search as a foraging strategy is innately specified. In addition to
286 evolutionarily-conserved neural mechanisms, the repeated emergence of Area Restricted Search
287 may reflect a recurring solution to a common problem — namely, searching for exhaustible re-
288 sources in patchy environments. More speculatively, the ubiquity of Area Restricted Search
289 may reflect a kind of universality [57], wherein systems that differ in their microscale details
290 exhibit the same qualitative behavior at a more coarse-grained scale. Strategic tradeoffs between
291 local, intensive exploitation and global, extensive exploration may emerge in a wide range of
292 systems that differ radically in size, timescale, and content.

293 **Open data and analyses**

Data and analysis scripts required to reproduce all results are available through the Open Science Framework: https://osf.io/6krg8/?view_only=14701b4bf32647d6ab354397c25588a9

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