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**Quantifying uncertainty due to fission-fusion dynamics as a
component of social complexity**

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Quantifying uncertainty due to fission-fusion dynamics as a component of social complexity

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Abstract

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Groups of animals (including humans) may show flexible grouping patterns, in which temporary aggregations or subgroups come together and split, changing composition over short temporal scales, (*i.e.* fission and fusion). A high degree of fission-fusion dynamics may constrain the regulation of social relationships, introducing uncertainty in interactions between group members. Here we use Shannon's entropy to quantify the predictability of subgroup composition for three species known to differ in the way their subgroups come together and split over time: spider monkeys (*Ateles geoffroyi*), chimpanzees (*Pan troglodytes*) and geladas (*Theropithecus gelada*). We formulate a random expectation of entropy that considers subgroup size variation and sample size, against which the observed entropy in subgroup composition can be compared. Using the theory of set partitioning, we also develop

12 a method to estimate the number of subgroups that the group is likely to be divided into,
13 based on the composition and size of single focal subgroups. Our results indicate that
14 Shannon's entropy and the estimated number of subgroups present at a given time provide
15 quantitative metrics of uncertainty in the social environment (within which social relation-
16 ships must be regulated) for groups with different degrees of fission-fusion dynamics. These
17 metrics also represent an indirect quantification of the cognitive challenges posed by socially
18 dynamic environments. Overall, our novel methodological approach provides new insight
19 for understanding the evolution of social complexity and the mechanisms to cope with the
20 uncertainty that results from fission-fusion dynamics.

21 *Keywords:* fission-fusion dynamics, social complexity, social uncertainty, social cognition,
22 social intelligence, Shannon's entropy

23 **1 Introduction**

24 Fission-fusion dynamics are a property of any social system that displays temporal variation in
25 cohesion, subgroup size and composition [1]. These dynamics have been shown to be adaptive,
26 especially for species that forage on heterogenous resources, since they afford individuals the
27 opportunity to adjust subgroups to current and local resource abundance [2–5]. The fluid nature
28 of subgroup composition due to a high degree of fission-fusion dynamics generates a complex
29 environment within which social relationships must be regulated and consequently, constitutes
30 a potential selective pressure for cognitive abilities required to keep track of interactions in
31 frequently changing social settings [1, 6].

32 Given the relevance and widespread occurrence of fission-fusion dynamics across taxa, it is nec-
33 essary to have metrics which can capture the variability in fission-fusion dynamics within and
34 across species and environments [1]. A high degree of fission-fusion dynamics, where subgroup
35 composition is frequently changing, increases the diversity of contexts in which the same indi-
36 viduals interact, making it more difficult to track social information in species where individual
37 recognition exists [7]. While several studies quantifying social complexity deal with the diversity
38 of relationships that individuals hold [8–10], quantifying the diversity of contexts in which these

39 relationships are established and maintained can also be useful as a measure of social complex-
40 ity [11]. To our knowledge there are no quantitative measures of this diversity of contexts for
41 social interaction [12]. Here we propose such a measure based on information theory.

42 When fission-fusion dynamics occur within the boundaries of a larger, stable group, subgroups
43 can be thought of as subsets of individuals taken from a finite set. Thus, information entropy
44 or information content (hereafter Shannon's entropy; [13]) is an ideal measure for the extent
45 to which subgroup composition is predictable, because the measure was derived precisely for a
46 process in which discrete symbols are selected from a finite set. Suppose that a group of $n = 10$
47 individuals can be found divided in subgroups. The total number of different subgroups that
48 can be formed, S , is $2^n - 1 = 1023$. If, for instance, all subgroups are equally likely, we would
49 have a $1/1023$ chance of guessing the correct composition of a subgroup chosen at random. For
50 such a set of possible subgroup compositions, the information content is equal to $\log_2(S) \simeq 10$
51 (in bits), which is the average minimal number of yes/no questions needed to figure out the
52 composition of a randomly chosen subgroup. When all the S subgroup compositions are equally
53 likely, the dataset's information content is maximal. More generally, knowing the probability p_i
54 of observing a subgroup with composition i (with i an index ranging from 1 to S), the Shannon's
55 entropy or information content H , for all possible subgroups S with associated probabilities p_i
56 is:

$$H = - \sum_{i=1}^S p_i \log_2 p_i \quad (1)$$

57 If all possible subgroup compositions are observed with similar frequencies, H will be near max-
58 imal, implying that each observed composition carries a high information content. In contrast,
59 if some subgroup compositions become more likely than others, our uncertainty will decrease
60 (and so will H), i.e. on average, the observation of a particular subgroup composition will reveal
61 less information.

62 Shannon's entropy is therefore directly related to the uncertainty one would have about the
63 composition of a subgroup chosen at random. Thus, we can use the entropy of subgroup com-
64 position to compare different species or situations. Moreover, this degree of uncertainty may
65 be a relevant feature not only for the researchers but for the animals themselves. Intuitively,

66 individuals in a group with a high degree of fission-fusion dynamics would face more uncertainty
67 about the composition of the subgroups they can form than individuals of species with less
68 flexible grouping patterns. The more uncertainty in the identity of group-mates, the greater the
69 uncertainty in social interactions [14]. Dealing with such uncertainty is thought to present a
70 cognitive challenge [7, 12, 15].

71 We thus propose that Shannon's entropy can be used to quantify social uncertainty due to fission-
72 fusion dynamics at the group and individual levels. At the group level, Shannon's entropy has
73 been used for characterising the overall degree of variation and uncertainty in social networks
74 [14, 16, 17]. Accordingly, we propose that the entropy of subgroup composition can be used as a
75 general metric of this particular dimension of fission-fusion dynamics [1]. At the individual level,
76 Shannon's entropy could also reflect the uncertainty actually faced by individuals in these groups.
77 Shannon's entropy has been used to quantify how evenly an individual distributes its grooming
78 interactions amongst the rest of the individuals in its group [8]. Our proposal is analogous
79 to this use of Shannon's entropy, but applies to the spatiotemporal associations between an
80 individual and the rest of its group mates. When subgroup composition is highly variable,
81 individuals do not repeat their interactions with the same individuals often. A lower frequency
82 of repeated interactions may lead to a higher uncertainty about social relationships, which in
83 turn may require alternate ways of reducing such uncertainty and predicting the outcome of
84 social interactions and others' behavior [7, 14]. Our approach to quantifying this uncertainty
85 should be relevant to any species exhibiting some degree of fission-fusion dynamics, where group
86 members repeat interactions with others, finding themselves associated with others at different
87 frequencies and individually recognizing one another (or at least classifying other group members
88 in broad categories) [1, 18].

89 We develop a proof of concept by measuring Shannon's entropies at the group and individual
90 levels in three species that show different degrees of fission-fusion dynamics: spider monkeys
91 (*Ateles geoffroyi*), chimpanzees (*Pan troglodytes*) and gelada monkeys (or geladas, *Theropithecus*
92 *gelada*), although our approach should be applicable to any species where the composition of
93 subgroups can be reliably observed and quantified. Although these three primates are known
94 for their high variability in subgroup size and cohesion, they differ in the degree of variation

95 in subgroup composition. Spider monkey and chimpanzee subgroups are highly variable in
96 composition with group members fissioning and fusing independently from one another [19]. In
97 contrast, geladas have a multi-level social system with highly stable one-male units that fission
98 and fuse with one another in predictable ways, creating a higher order “band” structure [20–22].
99 Because of this, we predict geladas to have lower entropy values than spider monkeys and
100 chimpanzees, despite the fact that they live in larger groups. We quantify social uncertainty at
101 the group and individual levels using Shannon’s entropy and a randomized expectation of entropy
102 that considers subgroup size variation and sample size, against which the observed entropy can
103 be compared. We complement the estimation of social uncertainty with an estimation of the
104 number of subgroups that the group is likely to be divided into at any given time, based on the
105 observed composition and size of single focal subgroups.

106 **2 Methods**

107 **2.1 Data collection**

108 Spider monkey data were collected from August 2009 to July 2010 and from January 2013
109 to September 2014 in the *Otoch Ma’ax yetel Kooh* protected area, in the Yucatan peninsula,
110 Mexico. The study group has been monitored continuously since 1997, and all group mem-
111 bers are identified and habituated to human presence. Observations consisted of instantaneous
112 scan samples performed every 20 minutes between 0600 and 1800 hours on subgroups chosen
113 according to criteria for homogenizing sample size across individuals. A total of 3916 scan sam-
114 ples, equivalent to 1305 h of observation, were collected in the 2009-2010 period and a total of
115 7917 scan samples, equivalent to 2639 h of observation, were collected in the 2013-2014 period.
116 During each scan sample, the identities of all subgroup members were recorded. A subgroup
117 was defined using a chain rule of 30m, such that individuals 30m or closer to any other were
118 considered as part of the same subgroup [23, 24]. Only adult individuals were included in the
119 analysis: 10 females and 7 males in 2009-2010 and 18 females and 7 males in 2013-2014.

120 Chimpanzee data were collected from January 2008 to December 2009 from the Sonso commu-

121 nity in the Budongo Forest, Uganda. The study group has been monitored continuously since
122 1990 [25]. All group members are identified and habituated to human presence. Observations
123 consisted of instantaneous scan samples performed every 15 minutes during focal follows be-
124 tween 0600 and 1800 hours, recording the identities of all subgroup members. A subgroup was
125 defined as all individuals visible or known to be present within 35-50m of the focal animal [25].
126 Subgroups were chosen each day according to criteria for homogenizing sample size across in-
127 dividuals. The 2008 period contained a total of 10616 scan samples, equivalent to 2654 h of
128 observation, while the 2009 period contained a total of 12935 scan samples, equivalent to 3234
129 h of observation. Only adult individuals that were present throughout each of the two entire
130 years were included in the analysis: a total of 20 (in 2008) and 21 (in 2009) females and 9 males
131 (both years).

132 Gelada data were collected from January 2014 to December 2015 in a population that has been
133 continuously monitored since 2006 in the Simien Mountains National Park, Ethiopia [22]. Each
134 morning, observers recorded the identity of all known individuals in a gelada subgroup (defined
135 using a chain rule of 50m) and then followed it for 1-8 hours. During follows, the observers
136 collected a scan sample every 30 minutes, recording the identity of all known individuals cur-
137 rently in the subgroup. The 2014 period consisted of 1420 scan samples, equivalent to 473 h of
138 observation, and the 2015 period consisted of a total of 1168 scan samples, equivalent to 389 h
139 of observation. Only adult individuals were included in the analysis: 21 males and 82 females
140 in 2014 and 29 males and 97 females in 2015.

141 2.2 Entropy calculation

142 To quantify social uncertainty at the group level, we calculated Shannon's entropy of subgroup
143 composition as follows. Imagine that a large number of observations allows the accurate esti-
144 mation of the probability of occurrence of any particular subgroup (or subset) with composition
145 $\{a\}$:

$$p_{\{a\}} \equiv \frac{\text{number of observed subsets} = \{a\}}{\text{total number of observed subsets}} \quad (2)$$

146 in a group (set) of n elements. The composition entropy H of the group stems from the definition
 147 (1):

$$H = - \sum_{\{a\}} p_{\{a\}} \log_2 p_{\{a\}}, \quad (3)$$

148 where the sum runs over all the observed compositions, i.e. those with $p_{\{a\}} \neq 0$.

149 To quantify social uncertainty at the individual level, we applied a similar entropy formula, but
 150 from the perspective of each individual. For those subgroups in which a given individual i was
 151 present, we measured i 's entropy by considering the different compositions of the subgroup in
 152 terms of the remaining $n - 1$ individuals (see Figure 1).

153 For each entropy, it is useful to determine an upper bound value, denoted as H^* , through a
 154 null model neglecting preferential associations: The subsets of size k appear with the same
 155 size frequency distribution f_k as in observations, where $\sum_{k=1}^n f_k = 1$ by normalization, but all
 156 the compositions of same size k are assumed to be equiprobable. Given a particular subgroup
 157 composition $\{a\}$ of k_a individuals, there are $C_{k_a}^n$ different ways of choosing k_a elements from
 158 n , where $C_k^n = n! / [(n - k)! k!]$ stands for “ n choose k ”. The null conditional probability of $\{a\}$
 159 given k_a , $p^*(\{a\} | k_a)$, takes the form $p^*(\{a\} | k_a) = 1 / C_{k_a}^n$. One deduces:

$$p_{\{a\}}^* = p^*(\{a\} | k_a) f_{k_a} = \frac{f_{k_a}}{C_{k_a}^n}, \quad (4)$$

160 for the null composition probability $p_{\{a\}}^*$. The null maximal entropy follows:

$$H^* = - \sum_{\{a\}} p_{\{a\}}^* \log_2 p_{\{a\}}^* = - \sum_{k=1}^n f_k \ln_2 \left(\frac{f_k}{C_k^n} \right), \quad (5)$$

161 where, in the last equality, one has used the fact that in the sum over all compositions the terms
 162 can be re-arranged by size: each size k as a fixed factor $p_{\{a\}}^* \ln_2 p_{\{a\}}^*$, which appears C_k^n times
 163 in the sum.

164 2.3 Bootstrap entropy

165 The number of observations being finite in any empirical data set, it is often problematic to
 166 evaluate the probabilities $p_{\{a\}}$ by using Eq. (2), since many compositions of low probability
 167 may not be observed and are thus replaced by zero in the sum (3). Therefore the empirical H
 168 resulting from N_o observations *a priori* underestimates the real entropy. For a fair comparison
 169 of H with a randomized model, it is thus necessary to calculate the entropy of the randomized
 170 model given N_o observations as well, instead of Eq. (5). This can be done numerically with a
 171 bootstrap, or analytically as follows.

172 Let us denote $N(k) = N_o f_k$ as the number of times subgroups of size k have been observed in the
 173 data, with $\sum_{k=1}^n N(k) = N_o$. Let us denote $n_{\{a\}}$ as the number of times a given composition $\{a\}$
 174 (of size k_a) is observed from a sampling of size N_o of the null model. The probability that $\{a\}$
 175 appears exactly i times [$i = 0, \dots, N(k_a)$] in this sampling is given by the binomial distribution:

$$\text{Prob}[n_{\{a\}} = i] = p^*(\{a\}|k_a)^i [1 - p^*(\{a\}|k_a)]^{N(k_a)-i} C_i^{N(k_a)}, \quad (6)$$

176 where $p^*(\{a\}|k_a) = 1/C_{k_a}^n$. The bootstrap entropy H^b is obtained by replacing $p_{\{a\}}$ by $n_{\{a\}}/N_o$
 177 in Eq. (3) and taking the average over all the possible values of $n_{\{a\}}$:

$$H^b = - \sum_{\{a\}} \left\langle \frac{n_{\{a\}}}{N_o} \ln_2 \left(\frac{n_{\{a\}}}{N_o} \right) \right\rangle = - \sum_{\{a\}} \sum_{i=1}^{N(k_a)} \frac{i}{N_o} \ln_2 \left(\frac{i}{N_o} \right) \times \text{Prob}[n_{\{a\}} = i]. \quad (7)$$

178 (The term $i = 0$ contributes to 0.) Making the substitution $\sum_{\{a\}} \rightarrow \sum_{k=1}^n C_k^n$ as in (5) and
 179 using Eq. (6), one obtains the bootstrap entropy:

$$H^b = - \sum_{k=1}^n C_k^n \sum_{i=1}^{N(k)} \frac{1}{[C_k^n]^i} \left[1 - \frac{1}{C_k^n} \right]^{N(k)-i} C_i^{N(k)} \frac{i}{N_o} \ln_2 \left(\frac{i}{N_o} \right). \quad (8)$$

180 One recovers Eq. (5) by taking the limit $N_o \rightarrow \infty$ and $N(k) \rightarrow \infty$, keeping $N(k)/N_o = f_k$ fixed.
 181 This entropy is a more useful point of comparison with the observed data, because in contrast
 182 with the null maximal entropy H^* , where all combinations are equally likely regardless of the
 183 sample size, H^b is computed with the sample size of the observed data, the composition of the

184 subgroups being randomised. It is also equal to the mean entropy for a set of bootstrapped
 185 original data, in which the 1s and 0s in Figure 1 have been randomly shuffled within rows, thus
 186 keeping subgroup size and the number of observations for each individual unchanged.

187 2.4 Entropy comparisons

188 The Kullback-Leibler (KL) divergence is commonly used to quantify how much an empiri-
 189 cal distribution $p_{\{a\}}$ differs from an expectation $p_{\{a\}}^*$, thus providing a way of comparing
 190 the observed entropy H to the null maximal entropy H^* [26]. It is defined as $KL(p|p^*) =$
 191 $\sum_{\{a\}} p_{\{a\}} \ln_2(p_{\{a\}}/p_{\{a\}}^*)$ and represents, in the present context, the average additional amount
 192 of information (in bits) needed to identify a subgroup randomly drawn from $p_{\{a\}}$, when assuming
 193 that the distribution is $p_{\{a\}}^*$. For the null maximal model, it reads:

$$KL(p|p^*) = \sum_{\{a\}} p_{\{a\}} \ln_2 \left(\frac{p_{\{a\}} C_{k_a}^n}{f_{k_a}} \right), \quad (9)$$

194 where, once again, k_a represents the size of $\{a\}$, $p_{\{a\}}$ is given by Eq. (2), and the sum is over
 195 observed compositions.

196 The above quantity cannot be applied to compare H to the bootstrap entropy H^b , however,
 197 since a finite sample of $p_{\{a\}}^*$ can contain vanishing entries, thus making KL infinite. A useful
 198 alternate measure is the Jensen-Shannon distance between two distributions p and q , defined
 199 by $J(p|q) = H(m) - \frac{1}{2}[H(p) + H(q)]$, where the entries of m are $m_{\{a\}} = (p_{\{a\}} + q_{\{a\}})/2$ [26].
 200 Unlike the KL divergence, J can deal with vanishing entries (i.e., $\{a\}$ such that $q_{\{a\}} = 0$), it
 201 is symmetric and satisfies the triangle inequality. Another interesting property is that J is 0 if
 202 $p = q$ and 1 if the distributions have completely disjoint supports. In other words, if we do not
 203 know from which distribution we are choosing a random variable (i.e. if we are choosing from
 204 a mixture of p and q), J provides a measure of how much our uncertainty would be reduced by
 205 knowing from which distribution, p or q , we are choosing the random variable. This distance
 206 is thus adimensional, making comparisons across systems easier *a priori*. Here, q is a sampling
 207 of size N_o of the null model, and we calculate the average of $J(p|q)$, denoted as J^b , over all
 208 possible samplings. Following the same steps leading to Eq. (8), the mean distance between

209 observations and the bootstrap reads:

$$J^b = 1 - \frac{1}{2} \sum_{\{a\}} \sum_{i=1}^{N(k_a)} \frac{1}{[C_{k_a}^n]_i} \left[1 - \frac{1}{C_{k_a}^n} \right]^{N(k_a)-i} C_i^{N(k_a)} \left[p_{\{a\}} \ln_2 \left(1 + \frac{i}{N_o p_{\{a\}}} \right) + \frac{i}{N_o} \ln_2 \left(1 + \frac{N_o p_{\{a\}}}{i} \right) \right]. \quad (10)$$

210 where the sum runs over observed compositions.

211 The methods for the partition analysis are included in the ESM. All analyses were implemented

212 in R [27] and the code is shared in the ESM.

213 3 Results

214 3.1 Social uncertainty at the group level

215 The values of entropy (H) at the group level were highly consistent: 8 - 8.5 for spider monkeys,
 216 close to 10 for chimpanzees and close to 5 for geladas (Figure 2) and significantly lower than
 217 the calculated and bootstrap entropies (H^b) in each case; which is confirmed by KL divergences
 218 and JS distances (Figure 2), which were especially large for geladas.

219 When considering male-only data for geladas, entropy was relatively unchanged (2014: observed
 220 5.76 bits, bootstrap 10.12 bits; 2015: observed 6.19 bits, bootstrap 10.16 bits) but the KL
 221 divergence was lower (2014: KL divergence 9.67; 2015: 16.9; compare to values in Figure 2,
 222 which are around 70 and 90, for 2014 and 2015, respectively). On the contrary, the JS distance
 223 is still close to the maximal value of 1 when considering only the males (2014: 0.95; 2015: 0.99;
 224 compare to similar values in Figure 2).

225 3.2 Social uncertainty at the individual level

226 Figure 3 shows summaries of the entropy from the perspective of different individuals. For spider
 227 monkeys (Figure 3a-b), individual entropy varied from 4 to 8 bits in the case of females and
 228 tends to be lower and more consistent in the case of males. While the majority of individuals in

229 2009 show H values that are clearly lower than the bootstrap entropy H^b values, in 2013 there
230 are several females that show H values that are very close to H^b . When comparing these values
231 using the JS distance (Figure S4), there are indeed some females in the 2013 dataset for whom
232 the JS distance between the observed and the bootstrap entropy is relatively low (< 0.85), and
233 who could be considered to show a particularly high entropy compared to other females. Their
234 subgroups, thus, seem to show a maximum level of variability in composition.

235 In the case of chimpanzees, we found an opposite effect of sex on the individual entropy values:
236 males tend to have a higher and less variable observed entropy than females (Figure 3c-d). The
237 H values for females ranged from 0.88-9.56 bits and those of males ranged from 8.2-9-9 bits.
238 In all individuals, H was clearly lower than H^b in both periods, as can be confirmed by the
239 JS distance values (Figure S5). The values of JS distance (Figure S5) show more variability
240 amongst individual females than amongst the males.

241 Gelada individual entropy is aligned to the one-male unit to which individuals belong (Figure
242 3e-f), resulting in females sharing the same individual entropy values as the male. As in the
243 case of the group entropy values (Figure 2), individual entropy values were farther from the
244 bootstrap expectation than in the case of the other two species. Comparing these values using
245 the JS distance is not very useful, as most values lie very close to 1 (data not shown). However,
246 limiting the analysis to the one-male units yielded variability in the JS distances, particularly
247 in the 2013 dataset (Figure S6). Here, some one-male units have a JS that is farther away from
248 the maximum number, indicating that they have a higher degree of variability in their subgroup
249 compositions.

250 The results of the partition analysis, aimed at establishing the probability that a group is split
251 into different numbers of subgroups, can be found in the Electronic Supplementary Material.

252 4 Discussion

253 We used Shannon's entropy to quantify temporal variation in subgroup composition across
254 three primate species and provide a measure of "social uncertainty" at the group and individual
255 levels. As predicted, spider monkeys and chimpanzees, considered as species with a high degree

256 of fission-fusion dynamics [1, 19], have a higher entropy of subgroup composition than geladas,
257 which show variation in subgroup size and spatial cohesion between group members, but also
258 have indivisible one-male units and a higher order band structure [20]. This latter characteristic
259 constrains the flexibility in subgroup composition of geladas compared to spider monkeys and
260 chimpanzees, and explains why geladas have a lower observed entropy.

261 That variation in sample size and group size within a species does not influence the estimation
262 of entropy suggests that our method is robust and could be used to compare social uncertainty
263 across different species and datasets with different characteristics. The bootstrap entropy H^b ,
264 corresponding to the maximum entropy that could be expected in a dataset of the same size and
265 subgroup size distribution if all subgroup compositions were equally likely, serves as a reference
266 to evaluate whether the observed entropy is relatively high or low. In all three species, that
267 the observed entropy is lower than the bootstrap entropy implies that preferential associations
268 between individuals make some compositions more likely than others among the full set of
269 potential compositions. Together, the observed and bootstrap entropies serve as a measure of
270 how much of the potential variation in subgroup composition is actually observed.

271 We propose that our method can be used to compare the degree of fission-fusion dynamics
272 between species, particularly in terms of the temporal variation in subgroup composition. In
273 particular, Jensen-Shannon (JS) distances serve as a quantification of how far the observed
274 entropy is from the bootstrap entropy and can be used as for comparative purposes. A species
275 with a high JS distance (close to unity) would have a variation in subgroup composition that is
276 far from the maximum expected by the bootstrap entropy, and would have a relatively low degree
277 of temporal variation in subgroup composition. Conversely, a species with a low JS distance
278 would have a variation in subgroup composition that is close to the maximum expected, and
279 thus would have a relatively high degree of temporal variation in dimension of fission-fusion
280 dynamics. In our analysis, geladas stood out as having the highest JS distance relative to the
281 bootstrap entropy and thus would be the species with the lowest degree of variation in subgroup
282 composition. The implication is that there are more constraints to the flexibility of association,
283 and thus a lower uncertainty in subgroup composition, in geladas than in the other two species.
284 The difference in JS distances between spider monkeys and chimpanzees, although not as high

285 as between these two species and the geladas, is still detectable and suggests that chimpanzees
286 have the highest degree of temporal variation in this dimension of fission-fusion dynamics of the
287 three analyzed species. JS distances can also be used to explore within-species differences in the
288 temporal variation in subgroup composition. As Figure 2 shows, for spider monkeys JS distance
289 is larger in 2009 than in 2013, whereas JS distances of the two chimpanzee data sets are rather
290 similar.

291 The level of analysis of social uncertainty for geladas deserves special attention. The existence
292 of indivisible, one-male units decreases the number of potential subgroup compositions and thus
293 the observed entropy when considering all individuals. We also ran the analysis considering
294 only males, thus estimating the degree of flexibility of association between one-male units.
295 We obtained similar values of entropy at both levels, with an observed entropy around 4 bits
296 lower than the bootstrap expectation. This result is what would be expected if one-male units
297 associated preferentially with a few of the other one-male units, as opposed to associating freely
298 with all units. In other words, a low value of entropy in the association of one-male units into
299 bands (i.e. the clearest, more consistently observed level above the one-male units; [22]) implies
300 that the composition of these bands is relatively predictable. The JS distances between observed
301 and bootstrap entropies when considering only males were close to 1, suggesting that there is
302 much less variation than could be expected if there were no preferential associations between
303 one-male units. However, the fact that there are many more males in 2014 apparently leads to
304 much more predictable patterns (i.e. JS distances close to unity in all cases). It is as if the one-
305 male units responded by becoming less fluid, perhaps as a way of maintaining a low uncertainty
306 in the face of an increase in group size and all the potential disorder (i.e. higher entropy)
307 this could cause. The nonrandom association of one-male units in this population of geladas
308 has been demonstrated using both social network analysis [21] and hierarchical clustering [22].
309 Thus, our results are consistent with what we know about gelada multilevel society, but they
310 go a step further by quantifying a component of social complexity that is closely related to
311 social uncertainty due to fission-fusion dynamics and that can be compared between and within
312 species.

313 We also extended our analysis to the entropy of subgroup composition from the point of view

314 of each group member. Overall, we obtained values similar to those for the whole group, but
315 some differences between individual values of entropy were revealing. In spider monkeys and
316 chimpanzees, the two sexes differed in their individual entropy values. Higher values in female
317 spider monkeys compared to males are consistent with the females' lower rates of preferential
318 association compared to males [28]. By contrast, lower values in female chimpanzees compared
319 to males could be due to their known tendency to form strong and lasting bonds with particular
320 females [29], as well as to the opportunistic nature of associations between males [30]. In spider
321 monkeys, the females with a lowest JS distance had recently immigrated into the group (i.e.
322 females AE, HI, PC and TG in Figure S4b). This result suggests that is consistent with previous
323 studies [28] that found that during their first year in the group, immigrant females' preference
324 for particular others is low. This is an example of the utility of comparing the observed and
325 bootstrap entropy values using the JS distance. In the case of chimpanzees, the 2009 data
326 contained a newly immigrating female (TJ), which also had a relatively high JS distance value
327 compared to other individuals (Figure 5Sb). Other females with particularly high JS distances
328 include BC, KG and FL, who had severe snare injuries (entire hand or foot missing), and
329 thus limited their movements to the core area of the home range and were observed in smaller
330 subgroups than the rest of the females. This is an example of the usefulness of comparing
331 observed entropy values between individuals.

332 An individual's entropy value can be interpreted as the degree of uncertainty it has about its
333 particular set of associations [14]. It has long been established that several social interactions are
334 aimed at reducing the stress caused by uncertainty in social relationships [31,32]. A reduction
335 in uncertainty has been proposed to lie at the core of emerging features of social structure
336 such as dominance hierarchies [14,33,34]. In species where repeated social interactions occur
337 amongst group members that form subgroups, our measures of entropy at the individual level
338 are a promising metric for quantifying social uncertainty due to fission-fusion dynamics and for
339 comparing this component of social complexity across individuals, situations, groups and species.
340 Individuals with a lower observed entropy relative to the bootstrap entropy would face less
341 uncertainty than individuals with similar values of observed and bootstrap entropy. Analysing
342 these individual differences may help researchers understand the role played by individuals in

343 their groups and the extent to which they could predict the interactions amongst others in the
344 group [35].

345 One of the reasons a high degree of fission-fusion dynamics is considered to be cognitively chal-
346 lenging is that individuals face a high uncertainty about their social relationships [1]. For social
347 interactions to reduce the uncertainty about other group member's behavior and the quality of
348 relationships with them [31], specific mechanisms must be in place that can allow individuals to
349 update their information about these relationships with others, as well as to generalize across
350 different relationships that share similar features. Therefore, cognitive abilities that allow in-
351 dividuals to reduce their uncertainty with respect to social relationships, like abstraction (e.g.
352 using concepts such as "friend" or "potential mate" to classify relationships) and transitivity
353 (i.e. inferring a linear order of relationships using partial information), may be particularly
354 important in species with high levels of fission-fusion dynamics, where the understanding of
355 social relationships must be carried out using partial information in highly variable social con-
356 texts [6]. In addition, cognitive abilities to deal with uncertainty, such as inhibition of ongoing
357 responses until the social situation can be assessed when subgroup composition changes, are
358 also important in fission-fusion dynamics [36]. We predict that species with a high uncertainty
359 in subgroup composition are more likely to show these cognitive abilities than species with a
360 lower uncertainty.

361 Estimating the probability that the whole group would be partitioned, or split, in different
362 numbers of subgroups provides a further way to quantify social uncertainty. The probability
363 distributions that result from our partition analysis can be considered a measure of the uncer-
364 tainty with respect to the grouping patterns of unobserved group members. For example, it
365 might be easier for an individual to predict which group members not present in its current
366 subgroup could be close or associated with one another in a group that is potentially split in
367 2-6 subgroups than in a group that is split in 9-14 subgroups (e.g. compare Figures S9 a and
368 b). In addition to its usefulness for studying higher levels in multi-level societies, our partition
369 analysis could be more generally applied in any study in which only one subgroup can be fol-
370 lowed at one time (like in the majority of studies of species with a high degree of fission-fusion
371 dynamics). For example, research on topics like between-subgroup vocal interactions [23, 37] or

372 home ranges [38,39] could be aided by an estimation of how many subgroups there are likely to
373 be at a given time, even if only one subgroup has been monitored directly.

374 It is necessary to note that our method assumes that the distribution of observed subgroup size
375 f_k reflects the true distribution of subgroup size in which a group was found during a certain
376 study period. Under that assumption, the bootstrap entropy H^b reflects the maximum entropy
377 that could be observed given the observed distribution of subgroup size. Also, our estimation
378 of the most likely partition in which the group is found relies on a correctly estimated f_k .
379 However, when studying species with high degrees of fission-fusion dynamics, there are potential
380 biases which might make it more likely for researchers to observe the larger or more conspicuous
381 subgroups. Thus, in field studies, steps should be taken to ensure that the sample of subgroups
382 is representative of the true distribution.

383 Establishing metrics to estimate social complexity is not a trivial matter [12, 40, 41]. Crude
384 measures, such as group size, number of different interactions, presence of triadic interactions,
385 etc., have been used but have not been operationalized in such a way that different species with
386 different group size and degree of fission-fusion dynamics can be compared (but see [10]). As we
387 show, Shannon's entropy represents a relevant metric of social uncertainty as one component of
388 social complexity, but it is important to bear in mind the relationship between complexity and
389 uncertainty. While a completely random process, which in turn would have the highest entropy,
390 would be maximally uncertain, we would not necessarily consider it as a complex process. On
391 the opposite end, a fully predictable pattern, with minimal complexity, would also be minimally
392 uncertain, with a correspondingly low entropy. When considering complexity, including social
393 complexity, we need to take into account both the flexibility and the nonrandom structure of
394 a process [42, p. 353] [43]. Thus, maximally complex societies would not necessarily lie in any
395 of the two extremes of the uncertainty spectrum. A middle-ground, where relationships are
396 somewhat predictable, also corresponds to the greatest degree of relationship differentiation,
397 which is another way to characterize social complexity [10]. This is because random processes
398 would involve no relationship differentiation, while completely stable groups can emerge from
399 simple rules that involve only a categorical differentiation between in and out-group individuals.
400 We predict that, in terms of subgroup composition, higher social complexity would occur in

401 groups with high observed entropy that is, nonetheless, still lower than the bootstrap entropy.
402 In terms of JS distances, a species would have a higher social complexity at intermediate values.
403 In these groups, individuals would have to cope with a high degree of uncertainty about who
404 their associates would be at any one time, but at the same time maintain a diversity of social
405 relationships with preferred companions, in many different contexts [10,11,32,34]. It is possible
406 that the real complexity might lie in the cognitive and behavioral mechanisms used to deal with
407 social uncertainty in the face of an existing social structure.

408 Our approach to measuring social complexity through social uncertainty can be applied to
409 any species that interacts in temporary and variable subsets and may be particularly relevant
410 for taxa in which a known set of individuals can recognize one another through visual, vocal
411 or olfactory means. The proposed metrics should also be useful for future studies comparing
412 the degree of fission-fusion dynamics across species varying to different extent in subgroup
413 composition, together with subgroup size and spatial cohesion [1]. More generally, they can aid
414 our understanding of the influence of flexible social settings on the interactions between group
415 members and their implications for social cognition.

416 **5 Ethics**

417 All fieldwork was conducted under the Guidelines for the Use of Animals in Research of the
418 Association for the Study of Animal Behaviour / Animal Behavior Society and conformed to
419 the legal requirements of the respective countries where it was conducted.

420 **6 Data and code**

421 All datasets used to illustrate the methodology are shared in a data repository. We also share
422 the code in R [27] to calculate the entropy measures, both at the group and individual levels, the
423 comparison of entropies using the KL divergences and the JS distances, as well as the partition
424 analysis (see Electronic Supplementary Material).

425 **7 Competing interests**

426 We have no competing interests.

427 **8 Authors' contributions**

428 The study was conceived by GRF, AJK, FA and DB. The study was designed by GRF, AJK,
429 MCC, AD, JL, CMS, FA and DB. Field data were collated by JL, JCB, TCB, NSM and KS.
430 Data analysis was carried out by GRF and DB, with techniques developed by DB. The workshop
431 where ideas were first discussed was coordinated by FA and CMS. The manuscript was drafted
432 by all coauthors, who also gave final approval for publication.

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Figure 1: Dataset coding for the calculation of subgroup entropy, at group and individual levels. The data consist of observations at regular intervals (rows) on different individuals who can be present (filled circles) or absent (empty circles) in any given subgroup due to fissions and fusions. For calculating the group entropy, we code presences as 1 and absences as 0 and each subgroup composition would correspond to a particular sequence of 1 and 0. For calculating the individual entropy for an individual A, we do the same but only for those subgroups in which A was present and considering all other individuals except A (shaded area), thus capturing the variability in subgroup composition from A's perspective.

Figure 2: (a) entropy of subgroup composition for two data sets of each of three species: spider monkeys (blue; data from 2009 and 2013), chimpanzees (green; data from 2008 and 2009) and geladas (dark red; data from 2014 and 2015). Solid dots correspond to the observed entropy (H) and empty dots to the bootstrap entropy (H^b). Group size n is 17 and 25 for spider monkeys, 29 and 30 for chimpanzees and 103 and 126 for geladas. Sample size No is 3916 and 7917 for spider monkeys, 10616 and 12935 for chimpanzees and 1420 and 1168 for geladas. (b) KL divergence between the observed and the null maximal entropy; (c) JS distance between the observed and the bootstrap entropy, for the same datasets. The observed entropies for spider monkeys and chimpanzees are similar and higher than the geladas'. Also, while the difference between observed and bootstrap entropies is evident in all data sets, it is much larger in geladas than in spider monkeys and chimpanzees.

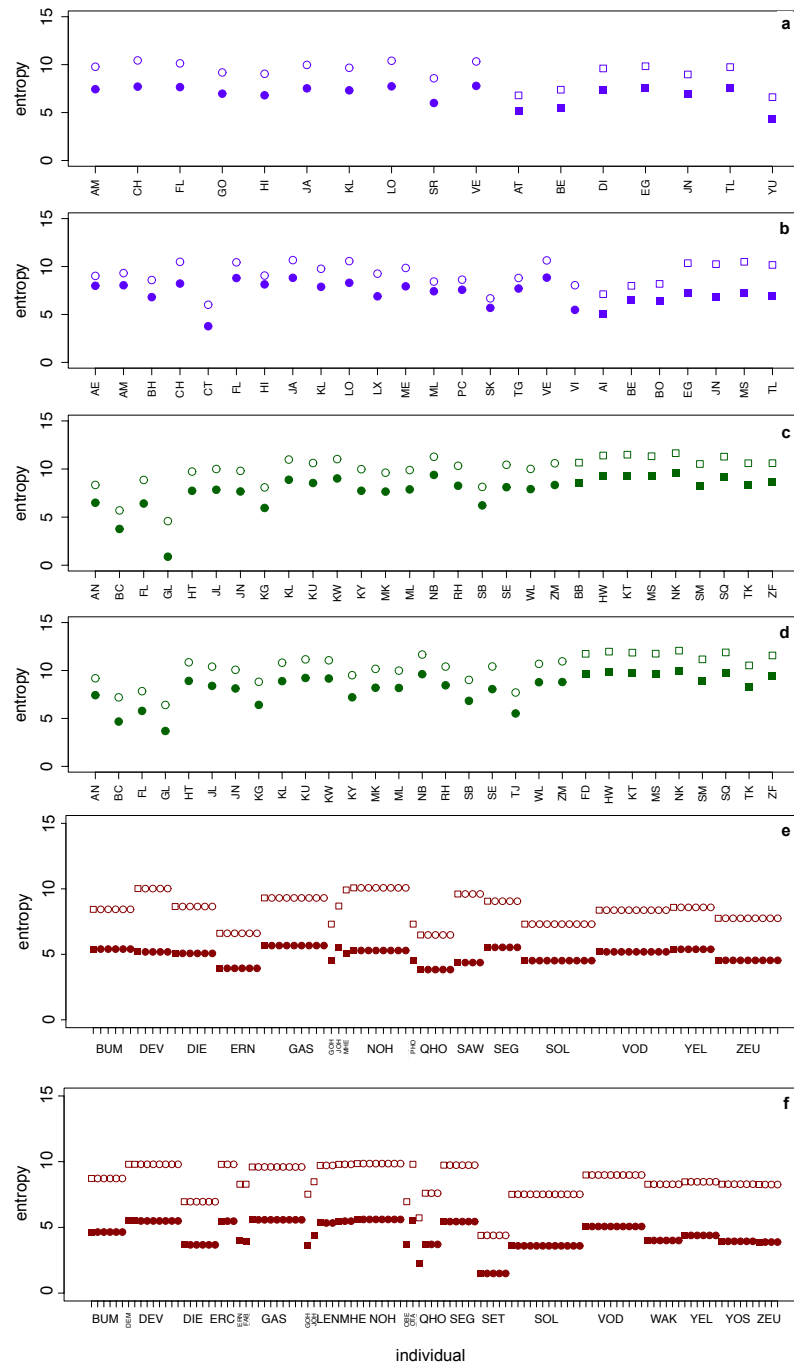
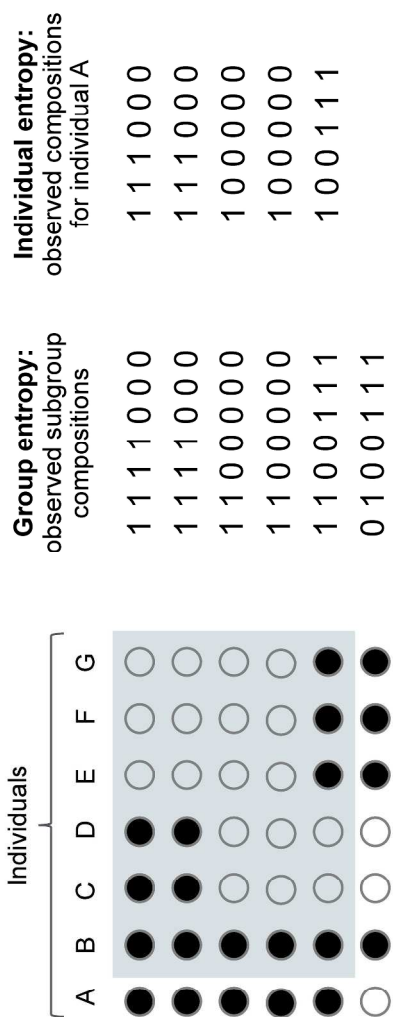
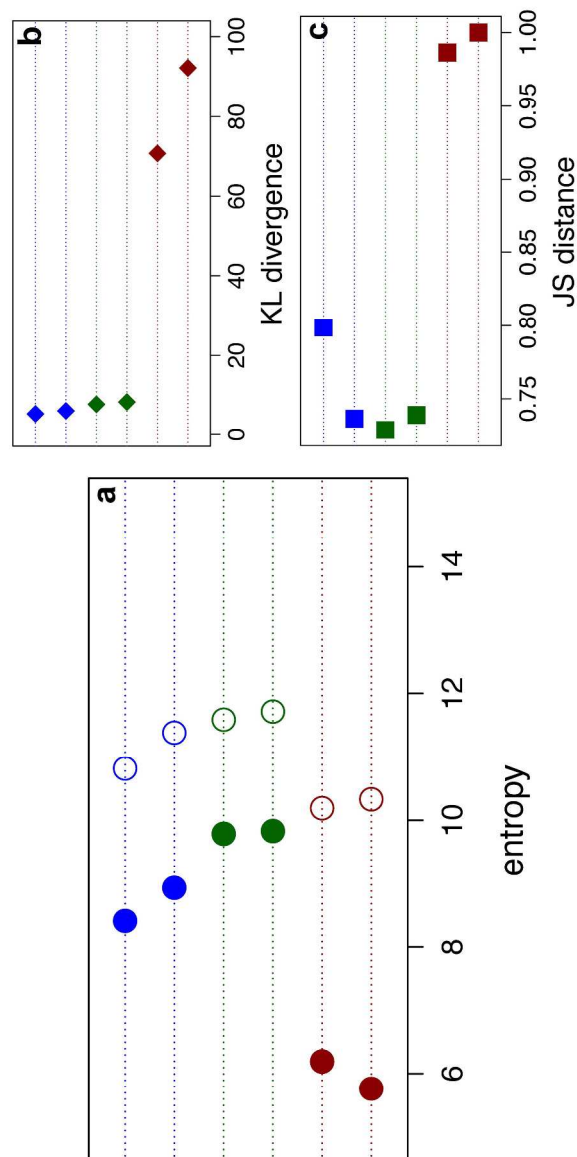


Figure 3: Individual entropy of subgroup composition for adult spider monkeys in the 2009 dataset (a) and 2013 dataset (b); chimpanzees in the 2008 dataset (c) and 2009 dataset (d); geladas in the 2014 dataset (e) and 2015 dataset (f). Circles and squares represent females and males, respectively. Solid symbols correspond to the observed entropy (H) and empty symbols to the bootstrap entropy (H^b). Labels for each individual (a-d) or one-male unit or lone male (e-f) in the horizontal axis. While all individuals have a lower observed entropy than the bootstrap, some have a smaller difference, implying that their subgroup composition is closed to the maximum, e.g. females AE, AM, ML, PC, SK and TG in (b).



Dataset coding for the calculation of subgroup entropy, at group and individual levels. The data consist of observations at regular intervals (rows) on different individuals who can be present (filled circles) or absent (empty circles) in any given subgroup due to fissions and fusions. For calculating the group entropy, we code presences as 1 and absences as 0 and each subgroup composition would correspond to a particular sequence of 1 and 0. For calculating the individual entropy for an individual A, we do the same but only for those subgroups in which A was present and considering all other individuals except A (shaded area), thus capturing the variability in subgroup composition from A's perspective.

279x361mm (300 x 300 DPI)



(a) entropy of subgroup composition for two data sets of each of three species: spider monkeys (blue; data from 2009 and 2013), chimpanzees (green; data from 2008 and 2009) and geladas (dark red; data from 2014 and 2015). Solid dots correspond to the observed entropy (H) and empty dots to the bootstrap entropy (H^b). Group size n is 17 and 25 for spider monkeys, 29 and 30 for chimpanzees and 103 and 126 for geladas. Sample size N is 3916 and 7917 for spider monkeys, 10616 and 12935 for chimpanzees and 1420 and 1168 for geladas. (b) KL divergence between the observed and the null maximal entropy; (c) JS distance between the observed and the bootstrap entropy, for the same datasets. The observed entropies for spider monkeys and chimpanzees are similar and higher than the geladas'. Also, while the difference between observed and bootstrap entropies is evident in all data sets, it is much larger in geladas than in spider monkeys and chimpanzees.

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