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Collective Decision-Making

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Abstract:

Collective decision-making is the subfield of collective behaviour concerned with how groups reach decisions. Almost all aspects of behaviour can be considered in a decision-making context, but here we focus primarily on how groups should optimally reach consensus, what criteria decision-makers should optimise, and how individuals and groups should forage to optimise their nutrition. We argue for deep parallels between understanding decisions made by individuals and by groups, such as the decision-guiding principle of *value-sensitivity*. We also review relevant theory and empirical development for the study of collective decision making, including the use of robots.

Introduction

We consider collective decision-making to be the subfield of collective behaviour concerned with how groups reach decisions without centralised leadership. Examples include nestsite selection by honeybees [1] and ants [2], and consensus selection of food sources in shoaling fish [3]. Individuals in a group can prefer to participate in a consensus decision, in which all individuals seek to agree on the same outcome, either because the group is tightly functionally integrated, as is the case with a social insect swarm or colony containing a single queen [1,2], or because group members prefer to remain within an unrelated group, for example to avoid predation risk [3]. Within high-

34 relatedness groups under appropriate conditions, selection on the group can
35 lead to group-level adaptations [4] , so group members' behaviour is shaped as
36 part of a group-level decision-making mechanism. Within unrelated groups,
37 individuals' behaviour should maximise their own expected fitness, within the
38 context of the group [5]. Indeed inferring 'group cognition' abilities for unrelated
39 groups may be harder than previously appreciated; alternative explanations for
40 improved decision performance in fish shoals are that fish in larger groups have
41 improved individual-level abilities, and that larger groups are more likely to
42 contain better decision-makers who dominate collective decisions [6].

43 In this review we focus primarily on functionally-integrated decision-
44 making systems for two reasons; first, as mentioned above, functional group
45 integration makes it appropriate to apply *optimality theory* at the level of the
46 group [7]. Second, parallels can be drawn between the behavioural rules of a
47 'superorganismal' group, and the behavioural rules of unitary individuals. We
48 consider such parallels to be illuminating. Our review can thus be read as
49 primarily presenting an 'economic' view of the behaviour of groups making
50 decisions, where decision outcomes result in gains or losses of quantities that co-
51 vary with reproductive fitness. We place particular emphasis on the links
52 between collective decision-making, perceptual decision making and value-
53 based decision-making, and on nutritional decision-making. We review
54 applicable theory, as well as the emerging use of robotics, for understanding
55 such systems.

56

57 ***Quorums and Confidence***

58 Groups can realise superior decision performance to individuals for a
59 variety of reasons. The simplest argument is based on the 'wisdom of the
60 crowds', recognised since the early 20th Century; for example a group decision
61 realised by pooling independent individual assessments will be more accurate
62 than an individual group member, under certain reasonable assumptions [8].
63 Inevitably, further refinements of group decision-making are possible; here we
64 mention two recent developments.

65 *Signal detection theory*, developed to understand optimal psychophysical
66 decision-making by individuals, shows that there is an inherent decision-making

67 trade-off between true positive rate and false positive rate; a decision-maker
68 cannot improve the rate at which they detect events of interest, without also
69 increasing the rate at which they incorrectly detect those events when they have
70 not happened. Yet in the group situation, Max Wolf and colleagues show how
71 introducing a quorum decision rule, typical of social insect colonies, allows the
72 group to simultaneously improve both rates [9]. Understanding how to correctly
73 set quorums, which may be sub-majority or super-majority according to the
74 accuracy of individuals, also shows that in fact group decisions are *always* more
75 accurate than individual decisions [10].

76 Still further improvement is possible on group decision-making, by
77 accounting for the unavoidable variation in individual decision accuracy.
78 Decision theory shows how to optimally weight individuals' contributions to
79 group decisions according to their accuracy, or 'confidence'; this theory has been
80 applied successfully to human groups and may be fruitfully applied to other
81 animal groups [11].

82

83 ***Value-Based Decisions***

84 In the preceding section group decision performance was considered in
85 terms of decision accuracy, or probability of making the correct response. Yet
86 consider the decision problem faced by a honeybee swarm selecting a new nest
87 site [12]. Obviously, it is advantageous for the collective of bees to choose the site
88 of highest possible quality. Imagine, for example, that there are two potential
89 nestsites available, both of equal but low quality. In this case it is best to wait and
90 postpone the decision until another option will be discovered. In contrast, if
91 there are two alternatives having equal but high qualities, then the honeybees
92 should choose as quickly as possible, as a long decision making process is
93 accompanied by the consumption of resources and a prolonged absence of
94 shelter, and does not lead to any further advantage.

95 Precisely such an adaptive value-sensitive decision making mechanism
96 has been analysed in a model of the stop-signalling behaviour of honeybees [12],
97 whose decision dynamics change adaptively as a function of quality of available
98 options [13,14]. In case of equal, high quality options a lower cross-inhibition
99 strength is sufficient to break decision deadlock compared to higher cross-

100 inhibition strengths required for lower quality options [13]. This has led to the
101 proposal of a *speed-value tradeoff* [15] that underlies value-based decisions,
102 rather than a *speed-accuracy tradeoff* as discussed in the preceding section, and
103 considered in conventional two-alternative choice perceptual decisions [16].

104 Conceptualising value-based decisions shows, however, that there are
105 similarities between perceptual and value-based decision making [17,18],
106 although the usage of the term ‘value’ may vary with context [19]; value may
107 refer to stimulus intensity, or to reward magnitude. In fact, recent studies
108 demonstrate that for primates value-sensitivity represents an important feature
109 of perceptual decision making, underlining the significance of absolute values
110 (magnitudes) of input signals [20]. Teodorescu et al. showed in experiments with
111 human participants that increasing the magnitudes of two input signals while
112 keeping their difference or ratio constant leads to faster responses; this effect is
113 not predicted by influential decision models that optimise the speed-accuracy
114 trade-off. Using data from humans and monkeys, similar observations are
115 reported by Pirrone et al. [21] for the case of equal alternatives for both
116 perceptual decisions where ‘value’ represents the magnitude of an input signal,
117 and value-based decisions where ‘value’ denotes a reward. These results provide
118 evidence for a speed-value tradeoff in decision making and, given the suggested
119 similarities between decision making in the brain and collective decision making
120 in social insects (e.g. see [7,22]) may provide new insights into the underlying
121 principles of collective decision making in social groups. Speed-value trade-offs
122 should be as fundamental for groups as they are for individuals.

123 A speed-value tradeoff should play a key role in decision making that is
124 not about ‘correct’ or ‘false’ but rather requires a strategy to choose the best
125 alternative among available options. Therefore, it would be interesting to
126 investigate the link between speed-value tradeoffs and a recently published
127 model describing the optimal decision making strategy for value-based decisions
128 [23], which may reflect the ultimate goal of maximising fitness and reproductive
129 success in realistic natural decision making scenarios, including collective
130 decision making of insect societies.

131

132

133 ***Nutrition and Decision Making***

134 Individuals on their own or within social groups frequently make foraging
135 decisions. Those decisions often aim at balancing the intake of different nutrients
136 rather than maximising the gain in energy [24], as described by the *Geometric*
137 *Framework* — a graphical approach pioneered by Stephen Simpson and David
138 Raubenheimer [24,25]. In this framework, the performances of animals or insect
139 colonies are evaluated by considering their actions in *nutrient space*. The
140 geometric framework is important for functionally-integrated social insects
141 colonies as for single animals, as satisfying nutritional needs is crucial for both.
142 Thus, nutritional deficits may bias or shape decision making for both in a similar
143 way. The nutrient space is an N-dimensional space, which is spanned by N axes
144 each of which represents one nutrient required in the diet. Imagine, for example,
145 an animal or social insect colony that needs to consume proteins and
146 carbohydrates. Then, the nutrient space is two-dimensional. The performance of
147 the animal or social insects can then be evaluated by plotting the deficits in
148 proteins and in carbohydrates on the axes of a two-dimensional Cartesian
149 coordinate plane. As the aim of the (super)organism is to reach a nutritional
150 target [25], a measure of distance between current state (a point in the diagram)
151 and target (another point) quantifies the effectiveness of their foraging
152 behaviour. When nutrients do not interact this required distance measure is
153 simply Euclidean distance [25].

154 Although based mostly on laboratory experiments, considering two-
155 dimensional problems such as choosing between proteins and carbohydrates, or
156 food and water, has led to important insights into how animals and social groups
157 forage and is empirically well motivated [24,26–29]. Given a target intake the
158 animal or the insect colony has to fulfil an ongoing decision task by selecting
159 repeatedly among two alternatives, to bring their internal state as close as
160 possible to their target intake. Hence, behaviour that is guided by multiple
161 decisions can be tracked in nutrient space. Deficits in one or more nutrients
162 drive the motivations for deciding for or against an action that reduces a deficit.
163 Houston et al. analyse the optimal strategy for reducing expected deficit in
164 simple scenarios where food types contain differing ratios of required nutrients
165 [30]; the optimal strategy requires decision-makers to reach a switching line and

166 then move along this by ingesting food items in the required ratio. This is hard
167 for animals to do without incurring switching costs, which change the optimal
168 strategy [29], but could be more readily achieved by a social insect colony, or
169 similar, regulating nutrient intake via a population of foragers.

170 The geometric framework has been studied in decentralised decision-
171 making systems such as ant colonies [27] and slime molds [26]. Nutrition in ants
172 is particularly well studied and emphasises the insect group's cognitive ability to
173 integrate the different nutritional needs of workers and larvae [27], and the
174 flexibility to make decisions in dynamic environments [31], whilst also
175 highlighting the vulnerability to extreme nutritional imbalances [32].
176 Considering the foraging decisions of ant colonies illustrates the social
177 dimension of nutrition [33] and has been related to social immunity [34]. This
178 link between nutrition and immunocompetence has also been observed in
179 honeybees [35].

180 Being central to all social groups, nutritional interactions may have
181 contributed to the evolution of social behaviour [36]. In this light, recent
182 observations in wasps [37] showing reductions in mushroom body investments
183 from solitary to social species indicate the intriguing connection between
184 'distributed cognition' [37], sociality and nutritional decision making by social
185 insect colonies in evolutionary contexts. It could be interesting to see what
186 effects imbalanced nutrition has on non-foraging decisions of social insects, such
187 as in the house hunting of honeybees. Here, the geometric framework could be
188 used to characterise the nutritional state of the colony, providing the link
189 between nutrient regulation at multiple organisation levels, social immunity,
190 cognitive abilities in general and collective decision making in particular.

191

192 ***Robots and Collective Behaviour***

193 For several decades, solutions from nature have been taken as a source of
194 inspiration for the design of robotic systems. This is particularly true for the field
195 of *swarm robotics*, where a large number of autonomous robots coordinate with
196 each other to perform a common task. In these decentralised systems, each
197 individual gathers and exchanges information with the environment and peers in
198 a local range; the large number of individuals and nonlinear interactions lead to

199 a coordinated collective response of the swarm. Given the difficulties in
200 identifying the rules that each agent should follow in order to obtain the desired
201 collective behaviour, a widespread approach has been to look at natural
202 processes that display the desired behaviour and adapt such processes to
203 implement multirobot systems.

204 While most works have an engineering scope a few robotics studies,
205 instead, aim at replicating the actual animal behaviour to investigate the veracity
206 of different assumptions, or validate the correctness of biological models (e.g.,
207 [38,39]). Usually, to understand collective processes biologists use analytical and
208 computational models such as multiagent simulations, in order to identify
209 individual rules that lead to the observed group response. Through models, the
210 individual behaviour can be varied systematically to identify which are the
211 relevant components or model parameters. In collective behaviour, the process
212 dynamics are principally determined by how information is acquired, processed
213 and transferred between individuals. In some cases, all relevant components and
214 realistic assumptions can be included in the mathematical model. However,
215 when space, situatedness¹ and the physical environment are determining factors
216 in the process, implementing collective behaviour models on robots presents
217 advantages which should not be overlooked [38,40,41]. Working with a physical
218 device imposes constraints that force the designer to consider the limited
219 capabilities of each individual (in terms of sensors and actuators), the effect of
220 noise, and the mechanistic process of information transfer. As a result, a robot
221 implementation reduces the possibility of oversimplifying the model and can
222 provide insights into biological mechanisms. In particular, the embodiment and
223 situatedness of a physical device influence group motion and alter the
224 environmental perceptions of groupmates. As a consequence the dynamics of the
225 communication topology are affected, and this can have a bearing on the
226 collective dynamics (e.g. [42]).

227 Finally, a research area that is receiving growing attention is
228 experimentation in *mixed societies*, composed of animals and robots that interact

¹ In robotics, situatedness refers to the extent to which a robot is embedded in the environment that can be sensed and modified through the robot's sensors and actuators [41].

229 with each other [41,43–45]. The first challenge of this research field concerns the
230 design of robots that are considered as groupmates by the animals. These studies
231 allow identification of the relevant perceptual components used by the animals
232 (e.g., robot-fish [46–48], robot-bee [49], robot-rat [50]). Once a robot is accepted
233 as a groupmate, controlling the robot’s behaviour allows investigation of social
234 interactions and how animals respond to specific behaviours. These studies help
235 to identify individuals’ cognitive abilities [45,51–53] as well as how (and what)
236 information is transferred within groups [54,55].

237

238 ***Conclusions***

239 As motivated in the Introduction, our review has focussed primarily on an
240 economic view on collective decision-making. The economic view is a staple of
241 behavioural ecology, and motivates the tools of optimal decision theory for the
242 study of animal behaviour. Here we argue that for decisions in functionally-
243 integrated groups, such as social insect colonies, optimality theory should also be
244 applied to collective behaviour. The economic, optimality theory, view is also
245 applied extensively to understanding animal behaviour in the various fields of
246 neuroscience and psychology. There, the additional focus on mechanisms
247 underlying behaviour opens up a new dimension of study. In studying individual
248 animal behaviour, behavioural ecology has traditionally ignored mechanism,
249 however there is a movement to integrate the study of mechanism with function
250 [56]. Collective behaviour is, of course, particularly amenable to observation of
251 mechanisms. Furthermore, through adopting modern robotics technology,
252 behavioural mechanisms can be elucidated through manipulation; this might be
253 of particular interest in functionally-integrated decision-making groups such as
254 social insect colonies. We argue that when drawing parallels between
255 mechanisms for collective behaviour and mechanisms for individual behaviour is
256 justified, doing so provides a particularly powerful research programme.

257

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414

415 **Reference Annotations**

- 416 • Wolf, Kurvers, Krause, Marshall (2016) - ** In this paper the authors
417 demonstrate how group decisions are always more accurate than
418 individual decisions, yet achieving this improvement requires that
419 quorum thresholds for decisions be set according to the accuracy of group
420 members, and optimal thresholds need not be simple majority rules.
- 421 • Marshall, Brown, Radford (2016) - ** In this review the authors note that
422 when group members vary in individual decision accuracy, decision
423 theory shows how contributions to group decisions should be weighted
424 by the accuracies, or confidences, of group members. The authors review
425 the application of such theory to human collective decision-making and
426 note the potential for application of the theory to non-human animal
427 groups.
- 428 • Teodorescu, Moran, Usher (2016) - ** This paper demonstrates the
429 presence of magnitude sensitivity in decision making by individuals. The
430 authors show that the absolute value of a stimulus does matter in decision
431 making, as an increase of the absolute value reduces decision times, in
432 agreement with theoretical arguments [13,15] . The authors emphasise
433 that theoretical frameworks explaining decisions only based on the
434 accumulation of relative evidence cannot explain experimental findings
435 and they propose two alternatives to resolve this issue, one being based
436 on a drift diffusion model with value-dependent multiplicative noise and
437 the other one being related to a leaky competing accumulator model with
438 lateral inhibition.
- 439 • Tajima, Drugowitsch, Pouget (2016) - ** This paper derives the optimal
440 strategy for decisions in which the decision-maker is rewarded by the
441 value of the option chosen. Interestingly, the optimal strategy is
442 equivalent to a process of integrating differences in evidence streams, but

443 with decision boundaries that collapse over time. Relating this optimal
444 strategy to behavioural observations and to models of collective decision-
445 making (*e.g.* [13]) should prove valuable.

- 446 • O'Donnell, Bulova, DeLeon, Khodak, Miller, Sulger (2015) - ** In this paper
447 the authors study a distributed cognition hypothesis, building on social
448 communication instead of individual cognition. One prediction of this
449 model is that brain investment in social species is reduced. The authors
450 present data from observations in wasps, which support the distributed
451 cognition hypothesis. They conclude that evolution of eusociality in wasps
452 was accompanied by the reduction of central processing brain areas,
453 which might be a significant feature of other types of social insects, too.
- 454 • Frohnweiser, Murray, Pike and Wilkinson (2016) - * In this review the
455 authors survey the use of robots for understanding animal cognition,
456 including examples mentioned above. The authors argue that robotics
457 could have an important impact on understanding of perception, spatial
458 cognition, social cognition, and early cognitive development. Their
459 highlighting of social interactions, such as between fish and honeybees, is
460 particularly relevant to the study of collective decision-making.