1	Animal minds: from computation to evolution
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6 In the great Darwinian struggle for existence, all animals must tackle the problems posed by 7 variable environments, be it finding and processing food, recognising and attracting potential mates, avoiding predators, outcompeting rivals or navigating back to nesting sites. Though the 8 mental processes by which different species deal with such challenges are varied, all animals 9 10 share the fundamental problem of having to cope with the sheer abundance of information in the 11 environment, much of which is likely to be irrelevant to the task at hand. The first step, therefore, is to attempt to sift through the mass of data and attend to that which may inform adaptive 12 13 decision making. Having acquired the relevant data, animals may then benefit from establishing how the different pieces of information relate to one another. Do yellow flowers reliably indicate 14 the presence of nectar? Does the presence of a dominant silverback male signal impending 15 danger? In complex environments, it may be advantageous not only to take into account 16 statistical co-occurrence of different stimuli, but to also extract general rules, making it possible 17 to act flexibly and solve a wide variety of problems across different contexts [1,2]. Certain 18 animal species might also form mental representations or models of the way the world works. 19 20 These internal representations may be used to reason about the desirability of alternative actions 21 or scenarios, based on expectations of their likely outcome, thus guiding the individual's 22 behaviour [3,4]. Thus, for instance, an animal with a mental representation of the action of gravity on objects could use it to reason that a food item will fall out of its reach if pushed 23 24 towards a precipice [5,6]. The possibility that animals may employ such human-like reasoning

has intrigued observers throughout the centuries, from Aesop's fables to Romanes's anthropomorphic anecdotes. However, careful scientific exploration of the mental faculties of other animals, and their relation to our own, did not commence in earnest until the last century, with the rise of comparative psychology and ethology. Contemporary comparative cognition, which grew from these two disciplines, aims to determine the mental processes underpinning animal behaviour, and to understand how these processes have evolved over the generations and develop over an animal's lifetime.

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33 Recent years have seen a great burgeoning of studies of comparative cognition, building on earlier advances in our understanding of basic processes of perception, attention, associative 34 learning and memory [4,7]. Elegant experimental work is generating insights into disparate 35 cognitive abilities across a wide range of taxa, from path integration in ants and spatial memory 36 in rats [8,9] to mental faculties that were considered uniquely human, such as mental state 37 attribution and mental time travel in apes and corvids [10–13]. Nevertheless, despite these 38 important empirical advances, the field suffers from a lack of theoretical underpinning, and 39 conceptual debates abound. For example, how might we discriminate between alternative 40 cognitive mechanisms underpinning behaviour? Do the abilities seen in cognitive experiments 41 reflect domain-specific 'adaptive specialisations' or domain-general problem solving capacities? 42 How and why do humans differ cognitively from other animals? This special issue brings 43 44 together a variety of developmental, mechanistic and functional approaches to the study of cognition with the goal of synthesizing this emerging body of work, and beginning to build a 45 theoretical framework to facilitate further progress towards our understanding of animal minds. 46

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48 1. DELVING INTO ANIMAL MINDS: DETERMINING MECHANISMS OF ANIMAL49 COGNITION

The range of possible mental processes through which animals may interact with their 50 environments poses a major challenge to students of animal minds. We can observe a non-verbal 51 creature solving a problem, but how can we infer the processes by which it does so? This issue is 52 particularly problematic given that seemingly complex behaviour may often be generated 53 through relatively simple mechanisms. Meerkats, for instance, teach their young to hunt by 54 responding to age-related changes in pups' begging calls, provisioning dead or disabled prey to 55 56 young pups and live prey to older pups. A simple stimulus-response mechanism thus allows adults to provide pups with prey-handling opportunities appropriate for the pups' age and 57 competence, without needing Theory of Mind to attribute ignorance to their pupils [14]. 58 Similarly, reflexive responses coupled with associative learning processes enable many animals, 59 from insects to primates, to use tools effectively without understanding their physical properties. 60 For example, larval antlions (*Myrmeleon* spp.), insects of the order Neuroptera, knock passing 61 prey into their pit-traps by flinging grains of sand in response to vibrational cues [15]. How 62 might we discriminate between such low-level mechanisms and other, more complex cognitive 63 64 processes? It may be tempting to assume that species that are more closely related to us may share more "human-like" cognitive faculties. However, numerous examples of evolutionary 65 convergence in unrelated taxa, along with abundant evidence of the importance of relatively 66 67 simple, evolutionarily ancient mental processes in human behaviour [16–18] caution against this archaic view of a mental scala naturae. Instead, the contributors to this volume urge a more 68 69 careful, bottom-up approach to determine the minimal computational requirements needed to

generate particular behavioural outcomes and to use careful experimentation to tease apartalternative explanations.

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73 1.1 Bottom-up approaches: building models and robots

It is common in comparative cognition to use folk psychological intuitions of how humans solve 74 75 certain problems when designing experiments to test the cognitive abilities of other animals. While this approach has clear value in helping to derive hypotheses, it suffers from two major 76 weaknesses. First, our intuitions of how we solve problems have repeatedly been shown not to 77 78 reflect psychological reality (e.g. [19,20]). Secondly, a reliance on folk psychological intuitions may detract from considering other, arguably more "killjoy" explanations based on simpler 79 mechanisms [17,18]. A fundamentally different approach advocated by some of the contributors 80 to this issue is to build models of simple neural networks to determine the minimal necessary 81 requirements to solve a specific task. These models often yield rather surprising results, 82 suggesting that abilities that are commonly considered to be complex may in fact be 83 implemented by very simple networks (see [21], this issue). A circuit of only a few hundred 84 neurons, for example, has been shown to suffice for reliable face recognition [22]. This approach 85 86 is clearly of great value in quantifying basic computational complexity, undermining the assumption that many cognitive feats require big brains [21,23]. Indeed, recent studies have 87 revealed a number of striking cognitive feats in small-brained animals such as insects and, as 88 89 Webb discusses in this issue [3], there is evidence that insects may employ internal mental representations of the outside world. However, given that even miniscule invertebrate brains 90 contain more neurons than the theoretical neural thresholds predicted by computational models 91 92 for many tasks, this 'minimal cognition' approach may be limited in explaining observed

93 cognitive differences between species. Moreover, the computational requirements for solving a specific, isolated problem may underestimate those needed to solve the same task in the real 94 world, let alone solve multiple different tasks using the same network. One way to build up 95 96 complexity towards that faced by an animal in the physical world is to build a robot that must replicate the animal's behaviour using the hypothesised neural mechanism to solve a given task. 97 As Webb points out, robotics thus forces us to face real world difficulties such as perceiving and 98 attending to relevant stimuli in addition to the abstract computational aspects of a problem, thus 99 generating more realistic demonstrations of minimal sufficiency. For example, a robotic female 100 101 cricket may be able to discriminate between male songs and approach only those who sound like members of a given species without needing to rely on an internal computational mechanism for 102 evaluating and comparing songs [3]. Unlike a real cricket, however, it cannot deal with the 103 104 additional complexities involved in finding food and avoiding predators. The development of ever more complex robots, capable of computing solutions to multiple problems, may generate 105 important insights into the computational requirements needed for biological systems to respond 106 107 adaptively to the multitude of challenges they face in their natural environments. A related challenge is to determine how organisms may integrate currently available information with 108 previously acquired knowledge of how the world works, bringing all the necessary cognitive 109 resources to bear when faced with a novel problem. How are parallel processing units in the 110 brain integrated to create a coherent, structured system capable of responding appropriately when 111 112 encountering a problem for the first time? How might a New Caledonian crow (Corvus moneduloides) or a rook (Corvus frugilegus), for example, have the wherewithal to 113 spontaneously manufacture a hook to pull up a bucket containing food [24,25]? In this issue, 114 115 Shanahan takes a bottom-up approach, drawing on recent advances in brain connectivity to

116 propose a cognitive architecture that can generate such seemingly insightful solutions to novel 117 problems in the physical world [26]. This consists of a number of discrete modules with extensive internal connectivity (a "modular small-world network"), which are in turn connected 118 119 to one another through nodes known as connector hubs to form a "connective core". Such a system may enable the unanticipated integration of mental processes to produce a coherent 120 121 sequence of actions to achieve a goal. This theoretical approach thus holds the great promise of allowing us to move beyond current vague conceptions of insight as a sudden, magical "Eureka 122 moment", to a tangible computational process that is amenable to research. An important 123 124 question arising from this work is how and why, given that the brains of humans, macaques, cats and pigeons are all known to possess a connective core, these species may nevertheless differ 125 radically in their ability to plan their actions when solving a task. Answers to this question will 126 emerge from a more detailed understanding of differences in neural connectivity in the brains of 127 different species and their resulting computational power, coupled with behavioural tests of what 128 different animals are capable of. 129

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131 **1.2 Top-down approaches: inferring cognitive mechanisms from behaviour**

132 *(a) Associative learning as a candidate explanation*

For behavioural researchers, a principal challenge is to devise experiments capable of discriminating between alternative mechanistic explanations for observed behaviour. The bottom-up approach exemplified by neural network models using computer simulations and robotics cannot yet provide testable predictions for the range of behaviours examined in contemporary comparative cognition research. Learning theory, in contrast, is grounded in behavioural research and provides concrete hypotheses that can be readily examined by 139 empiricists. Indeed, associative learning is found throughout the animal kingdom and is known 140 to play a role in generating even seemingly complex behaviour in both non-human animals and in our own species. Nevertheless, associative explanations are sometimes overlooked, perhaps as 141 142 a result of knee-jerk reactions to the overambitious claims of behaviourism, leading to a focus on what Heyes [17] calls "super-cognitive" explanations derived from folk psychological intuitions. 143 In fact, modern learning theory is considerably more nuanced than the caricature of 144 behaviourism would suggest. Unlike behaviourism, it does not claim that anything can be 145 learned (or that all behaviour is learned), but instead incorporates constraints that limit learning 146 of coincidental associations and promote learning of biologically relevant associations. 147 Moreover, learning theory has the distinct advantage over folk psychology in that it rests on 148 well-described, general theories such as the Rescorla-Wagner [27] and Mackintosh [28] models. 149 150 One interesting development discussed by Dickinson [29] is his 'associative-cybernetic' theory [30,31] which postulates that, if embedded in a constraining processing architecture, associative 151 learning may give rise to rational goal-directed action. That is, rather than simply learning that a 152 153 certain action is rewarded, an animal may also learn that its action causes a specific beneficial outcome. This theoretical prediction has considerable empirical support. For example, rats 154 155 trained to obtain a reward by pressing a lever will reduce their lever pressing if the value of the reward is reduced, indicating that they represent the causal relation between their own lever-156 pressing actions and the outcome (reviewed in [29]). Thus, associative learning theory provides a 157 powerful and tractable framework for research on animal (including human) minds. Indeed, 158 rigorous research in comparative cognition often uses associative learning as a null hypothesis, 159 making considerable efforts to derive candidate explanations from learning theory to be tested 160 161 through behavioural experiments (e.g. [32]). There will, of course, be instances when behaviour

cannot be understood purely in terms of associative processes. Human behaviour, for instance, is guided to a large extent by reasoning and inference about abstract causal relations in the physical and social worlds [33–35]. The possibility that animals may employ similar cognitive processes has attracted great interest from students of animal minds, but lacks the theoretical grounding of associative theory and so is more difficult to pin down. If associative processes are found to be lacking as explanations of animal behaviour, how might we make progress in determining alternatives?

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170 (b) Beyond associative learning: individual-level approaches

One common and powerful experimental approach is to use a series of training trials in which 171 subjects learn the basic requirements of the task, followed by transfer tests in which the causal 172 properties of the problem are kept constant, but arbitrary visible stimuli are changed. Thus, in 173 theory, subjects that have learned a simple rule based on visible features will fail transfers, while 174 those that have abstracted a generalizable understanding of the causal structure of the task should 175 176 apply it to solve the transfer [36, 37]. However, as Thornton & Lukas point out, the fact that transfer tests typically involve the same binary choice over multiple trials means that a subject 177 might learn a rule based on the visible properties of the transfer test itself [38]. Thus, subjects 178 may reach a given criterion (say nine correct trials out of ten) using nothing but associatively 179 learned rules. Conversely, reliance on crude binary criteria of success or failure leads us to 180 ignore potentially valuable data. Instead, several of the contributors to this issue advocate a more 181 fine-grained analytical approach that focuses specifically on individual differences in 182 performance on a trial by trial basis to shed light on the cognitive mechanisms employed when 183 184 solving tasks [33,38,39]. Seed and colleagues, drawing on insights from developmental

185 psychology, point out that a detailed focus on individual behaviour, taking into account failed 186 trials as well as successes, may provide valuable insights into why subjects may fail, and the precise mechanisms required for success. Using this approach, they show that chimpanzees (Pan 187 troglodytes) that failed a task requiring them to discriminate between a complete and a broken 188 tool failed not because of an inability to represent "connectedness" but rather because of 189 limitations in memory and attention [33]. Thus, an individual-based analytical approach may 190 allow us to determine the set of cognitive processes that must be employed together when 191 solving tasks. 192

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The individual-level approach may also benefit from using formal planning theory used in 194 artificial intelligence (AI) research. In this issue, Chappell & Hawes explored a four-trap variant 195 196 of the classic 'trap tube' test in which the precise characteristics of the task (e.g. which of the four traps was functional) varied systematically across a series of 64 trials. Using an AI planning 197 language, they generated a series of possible computational rules or "plans" an animal could 198 199 employ to solve the task. They then simulated how each of these plans would perform in each of the different trials, and compared these simulations to the actual trial-by-trial performance of 200 orangutans (Pongo pygmaeus) [39]. The advantage of this method is two-fold. First, 201 decomposing the problem into its constituent parts may be valuable in designing experiments. 202 Second, in common with Seed et al.'s approach, it forces us to move away from the simplistic 203 and statistically problematic [38] dichotomy of success and failure and instead to harness the rich 204 data emerging from all the actions of all individuals in all trials to assess how animals solve 205 problems. In the future, we hope that such individual-based approaches will be combined with 206 207 insights from learning theory to determine the role of associative processes in within-task

learning, and to discriminate between alternative mechanistic explanations. We also envisage great potential in linking this top-down approach of decomposing and simplifying specified problems with bottom-up approaches that specify the components and connectivity of the computational systems implementing the solutions. For instance, specifying the computational components and connectivity of a neural system (c.f. [26]) may allow us to constrain the possible range of plans the system might implement to solve a cognitively challenging task in a biologically realistic way.

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216 2. THE EVOLUTION OF ANIMAL MINDS

217 2.1 Fitness consequences of individual cognitive variation

Through a combination of experimental and theoretical approaches, comparative cognition is 218 219 beginning to provide important insights into the mental processes of different animals. However, existing approaches tend to place relatively little emphasis on the central goal of understanding 220 how these processes evolve. In this issue, Thornton & Lukas point out that researchers 221 222 commonly assume that the cognitive traits they find in laboratory animals are the adaptive products of natural selection, but they very seldom assess whether the basic tenets of Darwinian 223 224 theory apply to the trait in question [38]. For natural selection to act, there must be heritable variation in the trait, leading to variation in reproductive success [40]. Consequently, if we want 225 to understand how cognitive traits evolve, we must ask whether they vary between individuals, 226 227 are heritable and influence fitness. Laboratory studies commonly reveal substantial variation in individual performance, but rarely consider its causes. Thornton & Lukas's meta-analyses of 228 individual performance across a series of cognitive tasks suggest that much of this variation may 229 230 be explained by laboratory rearing conditions, with enculturated individuals with extensive

231 previous experience of laboratory tests typically outperforming the rest [38]. It is therefore 232 unclear to what extent this variation may be heritable, or indeed how cognitive traits may be manifested in the natural conditions in which they evolved. In some short-lived animals it may 233 234 be possible to explore cognitive evolution using selection experiments in the laboratory [41], but for many of the birds and mammals of interest to students of comparative cognition, such 235 experiments are less feasible. Laboratory studies must therefore be complemented by field 236 research to examine links between individual cognitive variation and reproductive fitness. 237 Unfortunately, the difficulties in examining cognition in the wild have led to a recent trend for 238 239 field researchers to assume that individuals that succeed in any experimentally presented "problem-solving task" possess elevated cognitive abilities, without testing the underlying 240 mechanisms. Given this trend, there is a danger that, for example, the action of a pigeon pecking 241 242 a key to obtain a reward in the field would be regarded as a measure of "cognition", while no one would consider the same action to be cognitive if done in a laboratory setting. If field studies are 243 to provide productive insights into cognitive evolution, it is therefore critical that they 244 incorporate the valuable lessons of psychological research concerning cognitive mechanisms into 245 the task design. For instance, Visalberghi and colleagues have used elegant experiments inspired 246 by laboratory tests of physical cognition to establish that capuchin monkeys recognise the 247 physical properties that render objects for use as hammers to crack nuts [42]. Similarly, studies 248 by Healy and colleagues have elegantly adapted laboratory tests of spatial memory and timing 249 for use in the field (reviewed in[43]), while Cheney & Seyfarth, McComb and others have 250 devised tests of social cognition incorporating expectation violation paradigms from 251 developmental psychology [44,45]. Such experimental approaches, as well as novel statistical 252 253 tools allowing mechanisms of learning and cognition to be inferred from natural behaviour [46]

hold great promise in enabling us to understand the cognitive processes used by animals in their environments. A key challenge now is to determine whether individual animals in the wild vary in their cognitive abilities, to use advances in quantitative genetics to assess the heritability of this variation and to begin to examine its fitness consequences.

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It may be tempting to assume that elevated cognitive abilities ought always to confer fitness 259 benefits, and are therefore subject to positive selection. However, any benefits associated with 260 improvements in cognition will be balanced against the costs they may carry. In *Drosophila*, for 261 262 example, there is evidence that selection for improved associative learning abilities among adults comes at a cost of reduced ability to compete for food resources at the larval stage [47]. In 263 addition, at the individual level, the potential benefits of cognition will depend on behavioural 264 265 phenotypes. As Sih & del Giudice discuss in this issue, there is extensive evidence that individual animals differ consistently in their behaviour over time and across contexts, and this 266 behavioural consistency may place important constraints on the ways in which cognitive abilities 267 268 are manifested [48]. Consider, for example, two individuals that have equal cognitive abilities but differ in their behaviour, with one being very bold and exploratory while the other is shy and 269 270 slow to investigate unknown places or objects. While the bolder individual is likely to encounter novel stimuli more often, the shier individual may have a greater tendency to pause and attend to 271 changes in the environment and update its assessment of a given situation. Behavioural 272 273 differences may therefore generate a trade-off between speed and accuracy when dealing with novel problems, and influence the benefits that individuals can derive from their cognitive 274 abilities. 275

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277 Just as individuals commonly exhibit suites of inter-correlated behaviours (termed "behavioural 278 syndromes" [48]) they may also exhibit consistency in cognitive abilities across different contexts. Indeed, there is a longstanding debate as to whether animal behaviour is underpinned 279 280 by cognitive specialisations that have evolved to fulfil specific ecological functions (e.g. retrieving cached food [49-51]), or rather is governed by domain-general mechanisms that 281 operate across contexts. Herrmann and Call, using large datasets of the individual cognitive 282 performance of chimpanzees across a test battery of multiple different tasks, suggest that the 283 truth may lie somewhere in between the two views [50]. Their analyses reveal that while some 284 285 exceptional chimpanzees consistently outperformed their conspecifics across a range of tasks, there is no evidence for one single "general intelligence" factor, but neither were performances 286 entirely unrelated across different tasks. Rather, the data appear to support the existence of a 287 number of distinct clusters of abilities, such as spatial knowledge and discrimination learning 288 [52]. Further work is needed to determine whether the cognitive abilities of other organisms will 289 exhibit similar clustering, but the evidence from chimpanzees suggests that there may be 290 291 common mechanisms that animals apply to different tasks within particular clusters of abilities. An understanding of cognitive evolution will therefore benefit from explicit theoretical models to 292 293 consider not only how overt, measurable behavioural abilities evolve, but also how selection may act on the underlying mechanisms [53]. 294

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296 2.2 Modelling the evolution of cognitive mechanisms

As Lotem & Halpern discuss, rigorous theoretical analyses of cognitive evolution must consider how different components of cognitive processing interact and co-evolve [54]. For example, to understand how learning mechanisms evolve, we must also consider the evolution of the 300 attentional and motivational mechanisms. Whereas traditional learning models assume that data 301 are presented to the animal as discrete, distinguishable stimuli, Lotem & Halpern's model explicitly considers the fact that animals must sift through and obtain relevant information from 302 303 the morass of data in their environments. The model assumes that, when animals encounter biologically relevant stimuli such as food, they will also attend to other information in the 304 immediate environment. This array of data is then compared to previously encountered datasets. 305 Segments of data that are rarely encountered tend to be forgotten and decay, while links between 306 commonly encountered segments increase in weight and may become fixed in memory. Thus, by 307 308 segmenting and linking chunks of data according to encounter rates and allowing irrelevant data to decay, the animal may build up a structured representation of the environment without the 309 heavy computational burden of learning and remembering connections between all possible 310 segments of data. Natural selection may act to tweak the parameters of both the data acquisition 311 and learning mechanisms, resulting in organisms that are well adapted to handle the natural 312 distribution of biologically relevant data in their environment. Lotem & Halpern argue that this 313 process of co-evolution of data acquisition and learning may generate incremental cognitive 314 change, allowing organisms to extract relevant data even when faced with dynamic and complex 315 316 arrays of information such as those that characterise some social systems. In their view, this process might even facilitate key human cognitive characteristics such as theory of mind and 317 318 language acquisition [54–56].

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320 **3. THE QUESTION OF HUMAN UNIQUENESS**

321 Of course, the quest to understand how and why the cognitive abilities of our own species may 322 differ from those of other animals has long been a central motivating force for much of comparative cognition. What cognitive processes make us unique, and what are the origins of 323 324 these processes? As Shettleworth discusses in her contribution to this issue, there have been a multitude of theories of human uniqueness throughout the years [57]. Some of these suggest that 325 326 the difference between humans and other animals lies in broad, domain-general processes that are manifested across a wide range of behavioural contexts [58,59]. In contrast, evolutionary 327 psychologists have tended to view human cognition as comprising a suite of discrete modules, 328 329 some of which may exist in our species alone [60]. Both of these approaches appear to emphasise dichotomous distinctions between "us and them". Is a given cognitive faculty (be it 330 domain-general or specific) uniquely human, or might it be found in other animals? Such human 331 vs. non-human comparisons suffer from two main problems. First, comparative studies have 332 tended to apply tests designed for adult, verbal humans and thus may often risk underestimating 333 the abilities of non-verbal creatures [61]. Second, an emphasis on the presence or absence of 334 335 particular cognitive capacities may detract attention from the possibility that, even if an animal fails a test of some human ability, some of the cognitive processes it applies may still be shared 336 337 with humans. Instead, Shettleworth [57] and Spelke [35] argue that important insights may lie in examining the development of cognitive abilities over individual lifetimes. Just as in 338 evolutionary biology it is recognised that seemingly different traits may share important 339 340 developmental commonalities [62], it is increasingly clear that considering developmental cognitive trajectories may reveal important elements of similarity and difference. For example, 341 experiments by Spelke and colleagues [35] suggest that human spatial cognition develops in two 342 distinct stages. From infancy, children exhibit two systems for representing objects and vectors. 343

344 These are largely shared with other animals and are thus likely to be evolutionarily ancient cognitive adaptations for navigation. Later in development, the acquisition of language and 345 culture enables children to combine the two systems in uniquely human ways to form abstract 346 geometrical concepts (reviewed in [35]). Tomasello, Call and colleagues place a similar 347 emphasis on developmental processes as being at the heart of human socio-cognitive uniqueness 348 349 (reviewed in [63]). Their extensive comparative experiments suggest that while human children and apes show similar performance on tests of physical, spatial and numerical cognition, children 350 typically outperform apes on social tasks. In particular, they argue that, unlike our closest 351 352 relatives, humans are endowed from an early age with the motivation to engage with others in joint activities involving shared goals and attention. Later in development, this tendency 353 facilitates the use of linguistic symbols and the creation of cultural norms [52,64,65]. As these 354 examples show, a continued emphasis on developmental processes in comparative cognition is 355 likely to yield further important insights into the similarities and differences between humans 356 and other species. To fully take advantage of this approach, it is important to extend the current 357 358 focus on comparing children with adult non-human animals to compare developmental 359 trajectories across species, acknowledging the fact that non-human cognition also develops. 360 Indeed, a common theme of this issue is that, as the field of comparative cognition matures, it must incorporate careful comparative analyses across all levels - within individual lifetimes, 361 between individuals and between species. Understanding animal cognition is a deeply 362 363 challenging endeavour, not least because it requires investigation of multiple layers, from genes and neurones to computational processes and the resulting behaviours to the developmental and 364 evolutionary processes shaping cognition over time. We hope that a synthesis of empirical and 365 366 theoretical tools from fields including robotics, neuroscience, psychology and biology, such as

those showcased in this issue, will help future research further unravel the mysteries of animalminds.

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