
From Cephalopods to Large Language Models: Conceptions of Intelligence and Reasoning

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Abstract

1 This paper explores convergences and contrasts between conceptions of intelligence
2 and reasoning in three domains: cephalopods (principally octopus and cuttlefish),
3 other marine animals (notably cetaceans), and contemporary large language models
4 (LLMs). We use comparative biology and cognitive ethology to highlight different
5 embodiments of information processing, problem-solving, and flexible behaviour,
6 then draw instructive analogies for artificial intelligence research. We argue that
7 cephalopods and other marine animals instantiate forms of intelligence that em-
8 phasize embodied, distributed, and context-sensitive problem solving; by contrast,
9 current LLMs implement a disembodied, statistical-syntactic form of competence
10 that nonetheless achieves surprising forms of emergent reasoning. Examining
11 causal mechanisms, ecological pressures, and developmental trajectories that shape
12 these intelligences reveals lessons for designing AI systems that are robust, adapt-
13 able, and socially situated. We suggest that reasoning and intelligence lie on a
14 continuum from cephalopods to humans, and on to AI systems.

15 1 Introduction

16 How should we define intelligence and reasoning? Classical accounts emphasize problem solving,
17 abstraction, and rule-based manipulation. Contemporary approaches in cognitive science emphasize
18 adaptation to ecological niches, embodied sensorimotor loops, and the role of social interaction.
19 Recently, engineered systems, especially large language models (LLMs), have challenged traditional
20 demarcations by exhibiting capabilities (e.g., in-context learning, chain-of-thought-like behaviour)
21 that are functionally similar to human reasoning in some tasks despite radical differences in substrate
22 and training.

23 This paper juxtaposes three perspectives: cephalopods and other marine animals (as products of
24 natural evolution and ecological pressures) and LLMs (as products of large-scale statistical optimiza-
25 tion on text). We seek to (1) characterise the forms of reasoning manifested in each, (2) identify
26 structural and functional parallels, and (3) propose a conceptual framework to guide future empirical
27 and engineering work.

28 Current conceptions of intelligence, cognition and reasoning are very anthropocentric [1, 2].

29 Studying cognitive abilities between species can help AI researchers more accurately assess whether
30 artificial systems possess, exceed, or lack cognitive capabilities [3]. *We suggest that reasoning and*
31 *intelligence lie on a continuum from cephalopods to primates, and on to AI systems* [4].

32 Understanding cognition, intelligence and consciousness in understudied species and taxa such as
33 cephalopods may also give us insights into how intelligence and correlates of intelligence (such
34 as tool use) can evolve in diverse computational substrates such as potentially even large language
35 models.

36 **2 Background: Three kinds of intelligence**

37 **2.1 Cephalopods and embodied cognition**

38 Cephalopods, particularly octopuses, cuttlefish, and squid, display rich repertoire of flexible behaviour:
39 problem solving (e.g., opening jars), tool use, camouflage and dynamic body patterning, and rapid
40 reconfiguration of body morphology [5]. Anatomically, a large proportion of cephalopod neurons are
41 located in peripheral ganglia (arms) rather than centralized in a single brain, producing a distributed
42 architecture [6, 7].

43 **2.2 Other marine animals: social and distributed cognition**

44 Marine mammals such as dolphins and whales demonstrate social intelligence: cooperative hunting,
45 cultural transmission of behavioural traditions, and complex vocal communication. These phenomena
46 have been extensively reviewed by Rendell and Whitehead [8] and others.

47 **2.3 Large language models: statistical and emergent reasoning**

48 Large language models are trained by optimising predictive objectives over massive corpora. They
49 lack direct sensorimotor embodiment (with exceptions in multi-modal agents) and are typically
50 deployed as disembodied text-processing systems; nevertheless, LLMs achieve surprising capabilities
51 such as coherent long-form generation, few-shot generalisation [9], and chain-of-thought style multi-
52 step reasoning when prompted appropriately [10]. Critical reflections on the limits and risks of
53 language models are provided by [11].

54 **3 Comparative analysis**

55 We compare domains across several axes: substrate and architecture, representation and memory,
56 learning and development, embodied constraints, sociality, and ecological functions.

57 **3.1 Substrate and architecture**

58 Cephalopods: neural tissue distributed between central and peripheral ganglia; high parallelism and
59 local autonomy (arms) [6].

60 Marine mammals: highly centralised brains, large social networks and long lifespans [8].

61 LLMs: artificial neural networks, typically transformer-based architectures that implement attention
62 over token sequences [12].

63 **3.2 Representation and memory**

64 Biological systems encode memory across multiple timescales: synaptic modifications, neuromodula-
65 tory states, and behavioural traditions [13, 14]. Cephalopods exhibit rapid learning and contextual
66 memory including local motor learning in arms [15].

67 LLMs store statistical associations in high-dimensional parameter space; short-term “working mem-
68 ory” is implemented by context windows. Persistent episodic memory is typically absent unless
69 explicitly engineered (e.g., retrieval-augmented systems, memory-augmented agents) [9].

70 **4 What counts as reasoning?**

71 We propose a typology useful for cross-domain comparison: sensorimotor reasoning (fast perception-
72 action loops), algorithmic/symbolic reasoning (abstract manipulation), social and cultural reasoning
73 (prediction and manipulation of other agents), and statistical/associative reasoning (inductive general-
74 isation from patterns). These classes overlap and co-exist in complex systems [14, 13].

75 **5 Case studies**

76 **5.1 Octopus problem solving**

77 Octopuses show flexible motor tactics to retrieve food from novel enclosures, exemplifying embodied
78 problem solving where exploratory motor routines and local arm autonomy enable fast, context-
79 sensitive solutions [15, 6].

80 **5.2 Dolphin social coordination**

81 Dolphins coordinate complex foraging strategies and transmit learned behaviour culturally, highlight-
82 ing joint intention, shared attention, and long-term memory of social norms [8].

83 **5.3 Emergent multi-step behaviour in LLMs**

84 LLMs can be coaxed into multi-step reasoning via chain-of-thought prompting and in-context
85 examples, though such behaviours can be brittle and prone to hallucination without grounding or
86 external verification [10, 9, 11].

87 **6 A synthetic framework: ecological competence**

88 We propose *ecological competence* as a unifying lens: the degree to which a system achieves
89 functional goals within a specific niche given its embodiment and resources. We outline a functional
90 decomposition (perceptual front-end, short-term buffer, action generator, long-term store, social
91 interface) that can be used to map biological and artificial systems and identify missing components.

92 **7 Experimental proposals and benchmarks**

93 We propose several experiments: embodied imitation tasks for LLM-augmented agents, social
94 transmission simulations for multi-agent cultural emergence [16], modular-effectors robustness tests
95 to mimic octopus arm autonomy, and an integrated ecological competence benchmark combining
96 perception, manipulation and social coordination tasks.

97 **8 Implications and ethical considerations**

98 Design lessons include: embodiment matters; modularity and locality can improve robustness; social
99 scaffolding helps communicative competence; and multi-timescale memory supports cumulative
100 learning. Philosophically, cross-domain comparison supports a pluralistic, function-oriented con-
101 ception of intelligence. Ethical cautions include respecting animal welfare, avoiding over-extended
102 metaphors, and anticipating socio-technical impacts [11].

103 **9 Conclusion**

104 Cephalopods are unusual animals and offer a useful bridge. With three hearts and a highly distributed
105 nervous system that includes several centralized ganglia, octopuses and their kin embody neural
106 architectures radically different from ours; as Godfrey-Smith puts it, their minds are among the most
107 genuinely “other” [17].

108 This prompts a central question: what kinds of non-linguistic intelligence, reasoning and conscious-
109 ness could arise in novel computational substrates?

110 What kind of concepts might be engendered in novel computational substrates (such as LLMs)?
111 Recent debates about anti-representationalism bear on this problem [18].

112 Anti-representationalism is the view that cognition does not fundamentally depend on internal,
113 structured representations of the world: that thinking and intelligent behaviour can arise from
114 direct, dynamic coupling between an agent and its environment. The position challenges traditional

115 computationalist and representational accounts in cognitive science and AI by shifting explanatory
116 focus away from symbol manipulation

117 Reservoir Computer models can learn and predict extremely complex dynamical patterns while
118 apparently lacking rich, compositional internal representations from which parts of a target could
119 be selectively extracted [18]. If so, they offer concrete models of intelligent behaviour that function
120 without conventional concepts, raising the possibility that large language models and other systems
121 might likewise operate with very different, or even without, conceptual representations.

122 Comparing cephalopods, marine mammals, humans, and large language models highlights multiple
123 forms of intelligence. This pluralistic view can both improve our understanding of natural cognition.

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