

1 The Animal AI Olympics

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4 A new competition presents AI agents with cognition challenges to test their
5 animal intelligence

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7 The last decade has seen great progress in artificial intelligence (AI). Machines can now categorise
8 and generate images, make complex physical and social inferences, and reach, or exceed, human
9 performance in many games. However, the long-term goal of recreating human-like general
10 intelligence remains out of reach and some argue that a radical change in approach is needed [1].

11 Animal-level intelligence provides a natural stepping stone on the path towards human-level AI.
12 Tests in animal cognition research normally involve presenting an animal with a problem or
13 environment that it would not naturally encounter and seeing if it can ‘work out’ how to obtain a
14 reward—typically food. These tasks are carefully designed to probe for a particular cognitive
15 capacity, such that successful performance on the task provides evidence that the animal has the
16 capacity in question. Researchers have used this approach to test for capacities such as episodic
17 memory, planning, spatial reasoning and social cognition in animals as varied as dogs, goats,
18 chimpanzees and spiders.

19 In contrast to most animals, modern AI systems cannot just be placed in new environments and be
20 expected to perform intelligently. Consider AlphaZero, a general algorithm that can be trained to
21 better-than-human levels at a wide range of perfect information games. Without extensive
22 retraining, however, it cannot adapt to never-seen-before games on the fly, and different games
23 may require different input spaces, fundamentally preventing transfer between them. While
24 AlphaZero is an impressive feat of AI, this case illustrates the large difference between current
25 generalisation capabilities of state-of-the-art AI systems and animals.

26 In animal cognition research a wide range of species with different types of embodiment and
27 (biological) actuators have been tested using a variety of experimental paradigms. These paradigms
28 typically abstract away from interspecies differences by focusing on intelligent behaviour mediated
29 by the shared sensory modality of vision. At the same time, we have seen rapid progress in the
30 ability to train AI systems through visual inputs alone [2]. Thus, it is an ideal time for making direct
31 comparisons between animals and AI. This is the aim of the [Animal-AI Olympics](#), a new AI
32 competition that translates vision-based animal cognition tasks into a testbed for cognitive AI. To
33 keep the comparison to the animal case as close as possible, the participants (like the animals) will
34 not know the exact tasks in advance. Participants will instead have to submit an agent that they
35 believe will display robust food retrieval behaviour in tasks unknown to the developer.

36 We will be releasing a ‘playground’, a simple simulation environment for intelligent agents based on
37 the Unity platform [3]. This environment has basic physics rules and a set of objects such as food,
38 walls, negative-reward zones, pushable blocks and more. The ‘playground’ can be configured by the

39 participants and they can spawn any combination of objects in preset or random positions, as
40 depicted in Figure 1. It will be important for the participants to design good environments for their
41 agents to learn in. Configuration files for the playground can also be exchanged between
42 participants should they wish to collaborate. The competition tasks will include ten cognitive
43 categories each with ten subtasks. This gives us one hundred distinct tasks, each of which will be run
44 multiple times with minor variations for testing purposes. The categories will range from basic food
45 retrieval—where only food is in the environment—to tasks that require capacities such as object
46 permanence, object manipulation and an understanding of the basic physics of the environment to
47 solve.

48 We expect this to be a hard challenge for modern AI systems, and want to give publicity to
49 interesting approaches that make even small advancements in this area. We also hope that this will
50 be a good testbed for approaches that use continual, transfer, and one-shot learning as well as non
51 goal-directed learning methods such as curiosity and intrinsic motivation and intuitive physics
52 modelling (see e.g. [4, 5]). Being able to solve all the tasks in a category would demonstrate real
53 cognitive capacities comparable to those found in animals.

54 We will release the playground at the end of April so that there is time for community feedback to
55 be incorporated before the full release of the competition at the end of June. The competition itself
56 will run from June to November with participants able to submit to a live leaderboard throughout.
57 The results will be announced at NeurIPS 2019 in December.

58 We hope this competition sparks further research in cognitive AI and that it becomes a useful
59 ongoing testbed. We expect it to help pinpoint the current challenges and limitations of AI for large-
60 scale real-world application involving interaction with unknown environments. We have made great
61 progress on the hard problems, it is now time to tackle the easy ones.

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67 **Competing interests**

68 The authors declare no competing interests.

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70 **References**

- 71 1. Lake, B. M., Ullman, T. D., Tenenbaum, J. B. & Gershman, S. J. Building machines that learn and
72 think like people. *Behavioral and Brain Sciences* **40**, (2017).
- 73 2. Mnih, V. et al. Human-level control through deep reinforcement learning. *Nature* **518**, 529 (2015).
- 74 3. Juliani, A. et al. Unity: A general platform for intelligent agents. arXiv preprint arXiv:1809.02627
75 (2018).

- 76 4. Haber, N., Mrowca, D., Fei-Fei, L. & Yamins, D. L. Emergence of structured behaviors from
77 curiosity-based intrinsic motivation. arXiv preprint arXiv:1802.07461 (2018).
- 78 5. Ullman, T. D., Spelke, E., Battaglia, P. & Tenenbaum, J. B. Mind games: Game engines as an
79 architecture for intuitive physics. *Trends in Cognitive Sciences* **21**, 649–665 (2017).

