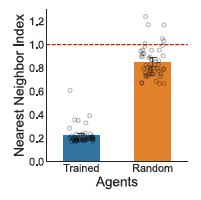
**TO DO LIST**

**1. Reference Section (Denizhan):** Feel free to use whatever paper reference system you’d like. I think Paperpile is a good option.

**2. Figure 2 (Samantha): Imprinting Graph:** **Figure 2a:** Bar graph showing final imprinting response during the test phase (one bar each for chicks, ICM, RND, & contrastive). Add a dot for each individual subject, so readers can see how the individual subjects performed (see below); **Figure 2b:** Line graphs showing imprinting performance across the training phase for the 4 rearing conditions.

**3. Figure 3 (Samantha): Object Recognition Graph:** **Figure 3.** Add bar charts showing the average performance (across all 12 viewpoint ranges) of the chicks and machines on the view-invariant recognition task (one bar each for chicks, ICM, RND, & contrastive) for each of the four rearing conditions (so ultimately, we want 4 bar graphs, each with 4 bars). Add a dot for each individual subject, so readers can see how the individual subjects performed (akin to this figure):



**4. Figure 4 (Denizhan + Samantha): t-SNE Graph:** To visualize the recognition differences between the chicks and machines across the 12 viewpoint ranges, let’s use t-SNE for visualization of the 12-dimensional space (with each dimensional corresponding to performance from one viewpoint). The t-SNE algorithm should map the chicks and machines to different parts of the embedding space, highlighting the considerable gap in object recognition performance across the two groups. Samantha, could you please send the chick data to Denizhan (binary performance for each chick across the 12 viewpoints for each of the 4 rearing conditions)? Then Denizhan can make the t-SNE graphs.

**Figure 5 (Samantha): Add chick-machine consistency score graph.** To quantify how well the machines could predict the object recognition behavior of the chicks, we quantified the similarity between chick and machine performance across the 12 viewpoint ranges, using a noise-adjusted correlation. The noise adjustment captures the idea that we should only judge prediction accuracy up to the level at which one population member (one chick) can predict another population member (another chick). This defines a clear noise ceiling with which to normalize prediction accuracy (Cao & Yamins, 2021). This means that if the machine-chick similarity is as good as the average chick-chick similarity, then the machine can be said to be predictively adequate of chick performance; in this case, the machine would have a “chick consistency score” of 1.0 (even if the machine has irreducible trial-by-trial stochasticity). As shown in Figure 5, the chick consistency scores were very low, indicating that there is a large gap in object recognition behavior across chicks and machines.

A newborn embodied Turing test for view-invariant object recognition

Anonymous CogSci submission

Abstract

Recent progress in artificial intelligence has renewed interest in building machines that learn like animals. Almost all of the work comparing learning across biological and artificial systems comes from studies where animals and machines received different training data, obscuring whether differences between animals and machines emerged from differences in learning mechanisms versus training data. We present an experimental platform—a “newborn embodied Turing Test”—that allows newborn animals and machines to be raised in the same environments and tested with the same tasks, enabling direct comparisons between the learning abilities of animals and machines. To make this platform, we performed controlled-rearing experiments on newborn chicks, then created “digital twin” experiments in which machines were raised in virtual environments that mimicked the rearing chambers of the chicks. We found that 1) machines (deep reinforcement learning agents with intrinsic reward) can self-organize visually-guided preference behavior, akin to imprinting in newborn chicks, and 2) machines are still far from newborn-level performance on object recognition tasks. Specifically, all of the chicks developed view-invariant object recognition, whereas the machines largely developed view-dependent recognition. We anticipate that this platform will empower researchers to develop embodied AI systems that learn like newborn animals.

**Keywords:** newborn; object recognition; Turing test; controlled rearing; chicks; reverse engineering

# Introduction

Since the birth of artificial intelligence (AI), scientists have attempted to build machines that can learn like biological systems. Early AI research laid the foundation for biologically inspired, neurally mechanistic models, and recent progress in deep learning has renewed interest in building scalable AI systems that learn like animals. For instance, a new “reverse engineering” approach in computational neuroscience involves comparing neural and behavioral measurements in animals to artificial systems performing the same tasks. Reverse engineering has revolutionized our algorithmic understanding of vision (Yamins et al., 2014), audition (Kell et al., 2018), olfaction (Wang et al., 2021), and visually-guided action (Michaels et al., 2021), while also informing our understanding of higher-level cognitive abilities—including language (Schrimpf et al., 2021), navigation (Whittington et al., 2022), and memory (Nayebi et al., 2022).

Ultimately, how will we know when we have succeeded in building machines that learn like animals? To address this question, we argue that an experimental platform must have two core features: 1) the animals and machines must be raised in the same environments; 2) the animals and machines must be tested with the same tasks. The first requirement follows from the observation that behavior depends both on the *learning mechanism* and the *training data* on which that mechanism operates. Any observed differences in behavior across animals and machines could be due to differences in learning mechanism, training data, or some combination of the two. Thus, evaluating whether machines learn like animals requires giving machines the same training data as animals. The second requirement follows from the observation that measurements of intelligence and behavior are task-dependent (Marr et al., 1976). Accordingly, biological and artificial systems must be evaluated with the same tasks to ensure that any observed differences are not due to differences in the tasks themselves.

While these two requirements may seem straightforward, building an experimental platform that meets both requirements has not previously been possible. Controlling the training data requires performing parallel controlled-rearing experiments on animals and machines. However, most newborn animals cannot be raised in controlled environments from birth, preventing researchers from controlling the training data presented to animals. Accurate comparisons between animals and machines also requires data with a high signal-to-noise ratio, where a subject’s behavior to a particular stimulus (e.g., an image) can be reliably estimated. However, most previous controlled-rearing studies collected data with a low signal-to-noise ratio, and focused on group-level analyses across coarse experimental conditions. As a result the field lacked the high-precision data needed to make accurate comparisons. Finally, the field lacked an experimental platform for raising machines in the same environments as newborn animals, preventing researchers from matching the training data across biological and artificial systems.

Here we present an experimental platform that overcomes these barriers, allowing newborn animals and machines to be raised in the same environments and tested with the same tasks. We used newborn chicks as a model system because they are mobile on the first day of life and can be raised in strictly controlled environments from the onset of vision (Wood & Wood, 2015). As a starting point, we focused on building machines that can mimic the *imprinting behavior* of newborn chicks. We focused on imprinting because (a) it is one of the earliest forms of visual learning that can be studied with high precision in a biological system (Wood & Wood, 2015), (b) it produces powerful (invariant) representations that support object recognition across new viewing situations (Wood, 2013; Wood & Wood, 2021), and (c) it emerges spontaneously during an animal’s early interactions with the world, driven by self-organized learning mechanisms. There is growing demand in AI for self-organized systems that can learn sparse data. Imprinting is therefore a promising target for reverse engineering the development of visual intelligence in embodied systems.

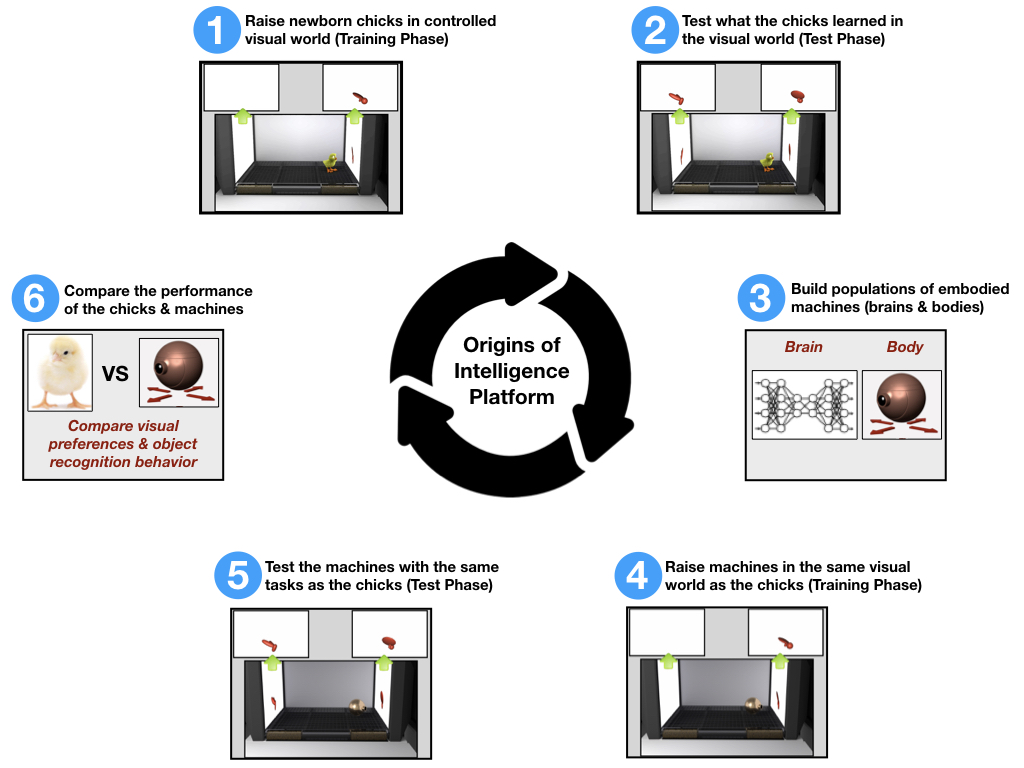


Figure 1. Experimental platform for comparing the visual learning abilities of newborn chicks and machines. The animals and machines are raised in the same visual environments and tested with the same tasks. This “newborn embodied Turing test” allows researchers to test whether animals and machines develop the same visual behaviors when provided with the same training data.

In this paper, we tested whether machines can mimic the imprinting and object recognition behavior of newborn chicks. We first raised newborn chicks in controlled visual environments and measured the chicks’ imprinting response and object recognition performance. To obtain data with a high signal-to-noise ratio, we used automated controlled-rearing chambers that measured behavior continuously (24/7) (Wood & Wood, 2019). Second, we created digital twins (virtual environments) of the chambers where we raised autonmous machines. By raising animals and machines in the same visual world, we could measure whether they spontaneously develop common visually-guided behaviors. We compared newborn chicks and machines on two measures:

* **Object Preference Behavior.** To mimic the chicks, the machines must develop a preference for the imprinted object, without any explicit rewards or supervision. The machines must also develop knowledge of their location and direction in space (ego-motion), so that they can navigate to their imprinted (preferred) object.
* **Object Recognition Behavior.** To mimic the chicks, the machines must learn to recognize the imprinted object across novel views. This requires learning view-invariant object features in impoverished visual environments that contain a single object seen from a limited range of views, using a purely self-supervised learning strategy (i.e. no supervised labels or rewards).

# Animal Experiments

We focused on the behavioral results from Wood (2013), which included data from 35 newborn chicks. In the study, chicks were hatched in darkness, then raised singly in automated controlled-rearing chambers that measured each chick’s behavior continuously (24/7) during the first two weeks of life. The chambers contained two display walls (LCD monitors) for displaying object stimuli (Figure 1). The chambers did not contain any objects other than the virtual objects projected on the display walls. Thus, the chambers provided full control over all visual object experiences available to the chicks from the onset of vision.

During the Training Phase, the chicks were reared with a single 3-D object rotating through a 60° viewpoint range. The object rotated back and forth every 6s. The chicks were raised in this environment for 1 week, allowing the critical period on filial imprinting to close.

During the Test Phase, the chambers measured the chicks imprinting response and object recognition performance. The “imprinting trials” measured whether the chicks had developed an imprinting response. During these trials, the imprinting stimulus was presented on one display wall and the other display wall was blank. Imprinting trials were scored as ‘correct’ when the chicks spent more time by the display wall with the imprinting stimulus and ‘incorrect’ when the chicks spent more time by the blank display wall. The “test trials” measured the chicks’ view-invariant object recognition performance. During these trials, the imprinted object was presented on one display wall and an unfamiliar object was presented on the other display wall. The unfamiliar object had the same size, color, motion speed, and motion trajectory as the imprinted object from the input phase (for details see Wood, 2013). Consequently, on most of the test trials, the unfamiliar object was more similar to the imprinting stimulus than the imprinted object was to the imprinting stimulus (from a pixel-wise perspective). To recognize their imprinted object, the chicks therefore needed to generalize across large, novel, and complex changes in the object’s appearance. This meets a reasonable operational definition of “invariant object recognition” established with mature animals (Zoccolan et al., 2009). Object recognition performance was tested across 12 viewpoint ranges (11 novel, 1 familiar). Test trials were scored as ‘correct’ when the chicks spent a greater proportion of time with the imprinted object and ‘incorrect’ when the chicks spent a greater proportion of time with the unfamiliar object.

# Machine Experiments

Our primary goal was to raise and test machines under parallel conditions under which we raised and tested animals. This required (1) agenrts that can learn from raw sensory inputs and perform actions, akin to the animal subjects, and (2) virtual environments for machines that mimic the visual environments of the chicks.

## Pixels-to-Actions Machine Subjects

Newborn animals learn from raw sensory inputs and perform actions, driven by self-organized learning objectives. Thus, to directly compare animals and machines, it was necessary to use ‘pixels-to-actions’ machines that learn from raw sensory inputs and perform actions, driven by self-organized learning objectives (e.g., intrinsic motivation).

We created the machines by embodying self-supervised learning algorithms in virtual bodies. The machine bodies measuring 3.5 unit (height) by 1.2 unit length (radius) and received visual input (96×96 pixel resolution images) through an invisible forward-facing camera attached to its head. The machines could move forward or backwards, rotate left or right, or remain stationary. The actions were represented as a pair of discrete variables: translation along the longitudinal axis and rotation around the vertical axis.

As a starting point, we built the machine brains using a standard reinforcement learning system: Proximal Policy Optimization (PPO; Schulman et al., 2017). During the Training Phase, this algorithm was optimized for rewards generated by one of three possible intrinsic motivation algorithms: Intrinsic Curiosity (Pathak et al., 2017), Random Network Distillation (cite), and Contrastive Curiosity (cite). Each algorithm takes batches of inputs and produces a reward. The batch and the reward are then used to train the PPO system.

All three of the intrinsic motivation algorithms produced rewards based on the novelty of the input, with more unique inputs generating greater rewards. The Intrinsic Curiosity algorithm generated rewards based on the machine’s ability to predict the next state given the current state and action. The Random Network Distillation algorithm generated rewards based on whether the machine could predict the embedding generated by an input in a random network. And the Contrastive Curiosity algorithm generated rewards based on the distance (in the embedding space) between current inputs and prior inputs, using a contrastive learning scheme. We used the hyperparameters in Table 1. We created our agents using Unity ML-Agents Toolkit version 0.10.1 (Juliani et al., 2020).

## Virtual Environments for Machines

To simulate the visual environments of the chicks in Wood (2013), we raised (trained) the machines in realistic digital twins of the controlled-rearing chambers, using a video game engine (Unity 3D) (Fig. 1). We then tested the machines in the virtual chambers, presenting the same tasks and stimuli to the machines that were presented to the chicks. For each of the four rearing conditions in Wood (2013), we trained and tested 25 machine subjects. All of the machines had the same network architecture, hyperparameters, and learning algorithms. However, each machine’s neural network started with a different random initialization of connection weights, and each machine’s connection weights were shaped by its own particular experiences during the Training Phase. Like chicks, the machines received no external rewards from the environment. The actions were motivated entirely by the rewards from the intrinsic motivation algorithm.

At the beginning of each training episode, the machines were spawned at a random position and orientation within the chamber. The training episodes lasted 1,000 time steps. We trained the machines for 1,000 episodes. The machines were trained to optimize the sum of their intrinsic motivation reward using PPO. We scaled the prediction error of the world model by a factor of 0.1 for the curiosity reward. We used the following hyperparameters: *γ* (discount rate) = 0.99, *λ* (Generalized Advantage Estimate regularization) = 0.95, *β* (entropy regularization) = 0.001, batch size = 256, buffer size = 2560, learning rate = 0.001. The learning rate decayed linearly, reaching 0 at the end of training.

After the Training Phase, the network weights were frozen for the Test Phase (i.e., the machines did not receive any rewards during the Test Phase, and learning was discontinued). Each machine performed 40 test trials for each of the 12 viewpoint ranges presented to the chicks. Each test episode consisted of 1,000 time steps. At every time step, we recorded the position of the machine in X,Y coordinates. As with the chicks, test trials were scored as ‘correct’ when the machines spent a greater proportion of time with the imprinted object and ‘incorrect’ when they spent a greater proportion of time with the unfamiliar object.

# Results

**Imprinting results.** Figure 2a shows chick and machine performance on the imprinting trials. On the group level, the chicks spent significantly more time by the imprinting stimulus than the blank screen (stat). On the individual level, all of the chicks successfully learned to imprint (all *P*s < .001), with relatively little variation across the subjects (range X% to X%). Likewise, on the group level, the machines spent significantly more time by the imprinting stimulus than the blank screen (stat). Some of the machines developed an imprinting response, spontaneously learning to seek out the imprinting stimulus. However, on the individual level, imprinting was far less robust in the machines compared to the chicks (Figure 2b). While 100% of the chicks learned to imprint, only a minority of the machines learned to imprint. We observed similar patterns of imprinting behavior across the different intrinsic motivation algorithms. In all cases, the machines developed markedly different imprinting responses from one another, despite the machines starting with the same learning mechanisms and learning in the same visual environment. In contrast, the newborn chicks developed nearly identical imprinting behavior as one another, indicating that there is more variation in the development of machines versus animals.

**Object recognition results.** Figure 3 shows overall chick and machine performance on the test trials. All of the chicks developed view-invariant object recognition (all *P*s < .001), recognizing their imprinted object across novel views. Thus, newborn chicks can successfully recognize objects across large, novel, and complex changes in the object’s appearance (for details see Wood, 2013). In contrast, none of the machines developed view-invariant object recognition. Rather, the machines developed view-dependent recognition, favoring test images that were the closest match to the imprinting stimulus presented during the training phase.

To visualize the recognition differences between the chicks and machines across the 12 viewpoint ranges, we used a technique developed for the visualization of high-dimensional data called ‘t-SNE’. The t-SNE algorithm mapped the chicks and machines to different parts of the embedding space (Figure 4), highlighting the considerable gap in object recognition performance across the two groups.

**Animal-Machine Performance Gap.** To quantify how well the machines could predict the object recognition behavior of the chicks, we quantified the similarity between chick and machine performance across the 12 viewpoint ranges, using a noise-adjusted correlation. The noise adjustment captures the idea that we should only judge prediction accuracy up to the level at which one population member (one chick) can predict another population member (another chick). This defines a clear noise ceiling with which to normalize prediction accuracy (Cao & Yamins, 2021). This means that if the machine-chick similarity is as good as the average chick-chick similarity, then the machine can be said to be predictively adequate of chick performance; in this case, the machine would have a “chick consistency score” of 1.0 (even if the machine has irreducible trial-by-trial stochasticity). As shown in Figure 5, the chick consistency scores were very low, indicating that there is a large gap in object recognition behavior across chicks and machines.

# Discussion

We performed digital twin experiments, in which newborn chicks and machines were raised and tested in the same visual environments. This approach permits direct comparison of whether animals and machines learn the same behaviors when provided with the same experiences (training data). In this paper, we explored whether self-supervised machines can spontaneously learn visual preferences (i.e., imprinting) and view-invariant object recognition, mimicking the early emerging behaviors of newborn chicks.

We found that imprinting can spontaneously emerge in deep reinforcement learning machines equipped with intrinsic motivation. However, unlike newborn chicks, only a subset of the machines successfully imprinted. Most of the machines failed to imprint, and other machines developed an imprinting response at some point, but then lost the response as training continued: a form of catastrophic forgetting that was not observed in the chicks.

Object recognition performance also differed significantly across the chicks and machines. All of the chicks developed view-invariant recognition, successfully recognizing their imprinted object across large, novel, and complex changes in the object’s appearance. In contrast, most of the machines developed view-dependent recognition, preferring the visual stimulus that was the closest match (from a pixel-level perspective) to the training stimulus. These results indicate that while deep reinforcement learning and intrinsic motivation are sufficient for developing rudimentary forms of imprinting and object recognition, a large gap still exists between the visual learning abilities of newborn chicks and machines.

How might we close this gap? Prior work shows that artificial visual systems (self-supervised CNNs) can successfully learn view-invariant object features in these visual environments (Lee, Pak, & Wood, 2021; Lee, Gunarathi, & Wood, 2021). This finding indicates that CNNs might be a sufficiently powerful ‘front-end’ (visual system) to solve this view-invariant recognition task. We suspect that closing the gap between animals and machines will require innovations on the ‘back end’ of the algorithm (e.g., processes related to memory, decision making, action, and agency). Our experimental platform should be useful for exploring these possibilities, enabling researchers to systematically test whether AI algorithms can learn visually-guided behaviors as rapidly and efficiently as newborn chicks. For example, researchers might explore how different architectures, objective functions, and learning rules perform on this task (Richards et al., 2020). Since our approach focuses on embodied agents, researchers might also explore how changes in embodiment (e.g., action space, morphology, sensor types) and learning dynamics (e.g., type of intrinsic motivation, metabolic pressures, network dynamics) influence the behaviors learned by machines.

More generally, we introduce an experimental platform for reverse engineering visual intelligence in a newborn model system. This approach has much in common with the reverse engineering approach that revolutionized the neuroscience of perception, including a reliance on precise (high signal-to-noise ratio) data from biological systems and a shared goal of building neurally mechanistic, image computable models of visual intelligence. While we did not focus on internal (neural) measurements here, future research could expand this experimental platform to include neural measurements from newborn animals.

Our approach also prioritizes different dimensions of the reverse engineering problem. We focus on newborn animals (rather than mature animals) in order to study the core learning mechanisms that power visual intelligence. We focus on controlled rearing (rather than animals raised in natural worlds) in order to understand how core learning mechanisms and visual experience interact to produce visual intelligence. And we focus on embodied (rather than disembodied) AI systems, embracing the possibility that much of visual intelligence might emerge from an agent’s interactions with the world, allowing learning systems to ground knowledge in real-world experiences and interact with the environment in purposeful ways. Our approach thus extends the call from a large group of scientists arguing for “embodied Turing tests” that involve benchmarking and comparing how animals versus machines learn and interact with the world (Zador et al., 2022).

## Conclusion

We have shown how advances from diverse fields can be linked to create an experimental platform for comparing newborn animals and machines side-by-side in the same learning settings: (1) automated controlled rearing allows precise data to be collected from newborn animals; (2) video game engines allow machines to be raised in realistic visual environments; (3) AI provides scalable and embodied (pixels-to-actions) learning systems; and (4) computational neuroscience provides a reverse-engineering framework for interpreting parallel studies of biological and artificial systems. By combining advances across fields, researchers can explore which learning algorithms and training data are sufficient to mimic the powerful and flexible learning abilities of newborn animals.

Ultimately, we anticipate that a machine with the same learning mechanisms (brain and body) and training data (environment) as newborn chicks should pass this newborn embodied Turing test, developing common visual preferences and object recognition abilities as newborn chicks. Our hope is that this platform will empower researchers to build machines (and engineering-level scientific models) that learn like newborn animals.

**CogSci Instructions (delete)**

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The entire content of a paper can be no longer than six pages in the **initial submission,** plus an unlimited number of pages for references. In the **final submission**, the text of the paper, including an author line, must fit on six pages. An unlimited number of pages can be used for acknowledgements and references.

The text of the paper should be formatted in two columns with an overall width of 7 inches (17.8 cm) and length of 9.25 inches (23.5 cm), with 0.25 inches between the columns. Leave two line spaces between the last author listed and the text of the paper; the text of the paper (starting with the abstract) should begin no less than 2.75 inches below the top of the page. The left margin should be 0.75 inches and the top margin should be 1 inch. **The right and bottom margins will depend on whether you use U.S. letter or A4 paper, so you must be sure to measure the width of the printed text.** Use 10 point Times Roman with 12 point vertical spacing, unless otherwise specified.

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### Third Level Headings Third level headings should be 10 point, initial caps, bold, and flush left. Leave one line space above the heading, but no space after the heading.

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## Footnotes

Indicate footnotes with a number[[1]](#footnote-2) in the text. Place the footnotes in 9 point font at the bottom of the column on which they appear. Precede the footnote block with a horizontal rule.[[2]](#footnote-3)

## Tables

Number tables consecutively. Place the table number and title (in 10 point) above the table with one line space above the caption and one line space below it, as in Table 1. You may float tables to the top or bottom of a column, and you may set wide tables across both columns.

Table 1: Sample table title.

| Error type | Example |
| --- | --- |
| Take smaller | 63 - 44 = 21 |
| Always borrow | 96 - 42 = 34 |
| 0 - N = N | 70 - 47 = 37 |
| 0 - N = 0 | 70 - 47 = 30 |

## Figures

All artwork must be very dark for purposes of reproduction and should not be hand drawn. Number figures sequentially, placing the figure number and caption, in 10 point, after the figure with one line space above the caption and one line space below it, as in Figure 1. If necessary, leave extra white space at the bottom of the page to avoid splitting the figure and figure caption. You may float figures to the top or bottom of a column, and you may set wide figures across both columns.

CoGNiTiVe ScIeNcE

Figure 1: This is a figure.

# Acknowledgments

In the **initial submission**, please **do not include acknowledgements**, to preserve anonymity. In the **final submission**, **place acknowledgments** (including funding information) in a section **at the end of the paper**.

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Use a first level section heading, “**References**”, as shown below. Use a hanging indent style, with the first line of the reference flush against the left margin and subsequent lines indented by 1/8 inch. Below are example references for a conference paper, book chapter, journal article, dissertation, book, technical report, and edited volume, respectively.

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1. Sample of the first footnote. [↑](#footnote-ref-2)
2. Sample of the second footnote. [↑](#footnote-ref-3)