What do we learn about development from baby robots?

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ABSTRACT

Understanding infant development is one of the great scientific challenges of contemporary science. In addressing this challenge, robots have proven useful as they allow experimenters to model the developing brain and body and understand the processes by which new patterns emerge in sensorimotor, cognitive, and social domains. Robotics also complements traditional experimental methods in psychology and neuroscience, where only a few variables can be studied at the same time. Moreover, work with robots has enabled researchers to systematically explore the role of the body in shaping the development of skill. All told, this work has shed new light on development as a complex dynamical system.

INTRODUCTION

To understand the world around them, human beings fabricate and experiment. Children endlessly build, destroy, and manipulate to make sense of objects, forces, and people. To understand boats and water, for example, they throw wooden sticks into rivers. Jean Piaget, one of the pioneers of developmental psychology, extensively studied this central role of action in infant learning and discovery[1].

Scientists do the same thing: To understand ocean waves, we build giant aquariums. To understand cells, we break them down to their component parts. To understand the formation of spiral galaxies, we manipulate them in computer simulations. Constructing artifacts helps us construct knowledge.

But what if we want to understand *ourselves*? How can we understand the mechanisms of human learning, emotions, and curiosity? Here, the physical fabrication of artifacts can also be useful. Researchers can actually build *baby robots* with mechanisms that model aspects of the infant brain and body, and then alter these models systematically (see Figure 1). We can compare the behavior we observe with the mechanisms inside. Indeed, robots are now becoming an essential tool to explore the complexity of development, a tool that allows scientists to grasp the complicated dynamics of a child's mind and behavior.

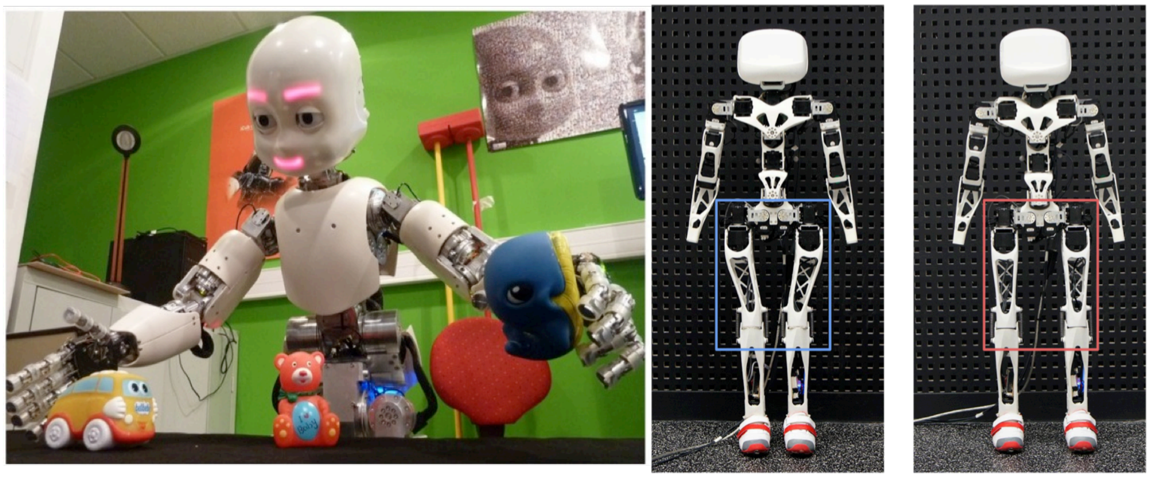

Figure 1 Robots can help us model and study the complex interactions among the brain, the body, and the environment during cognitive development. Here we see two open-source robotic platforms used in laboratories. Being open-source allows open science and better replicability by revealing experimental details. Built using 3D printing27, the Poppy (right) allows fast and efficient exploration of various body morphologies and how they affect skill development, such as leg shape (see alternative morphologies on the right (a) and (b)). Left: ICub http://www.icub.org; Right: Poppy http://www.poppy-project.org. Source: ICubPoppy.png (Creative Commons)

EXPLORING COMPLEX SYSTEMS

Modern developmental science has now invalidated the old divide between nature and nurture. We now know that genes are not a static program that unfolds independently of the environment. We also understand that learning in the real world can only work if there are appropriate constraints during development[2,3]. Finally, we know that many behavioral and cognitive patterns cannot be explained by reducing them to single genes, organs, or isolated features of the environment: they result from the *dynamic interaction* among cells, organs, learning mechanisms, and the physical and social properties of the environment at multiple spatiotemporal scales. Development is a complex dynamical system, characterized by spontaneous self-organization or "emergent patterns"[4] at multiple scales of time and space (Spencer et al., 2011).

The concepts of complex systems and self-organization revolutionized physics in the 20^{th} century. They characterize phenomena as diverse as the formation of ice crystals, sand dunes, water bubbles, climatic structures, and galaxies. A key to these scientific advances was the use of mathematics and computer simulations. Indeed, it is hard to imagine how we could understand the dynamics of ice crystals or the formation of clouds without mathematics and computer simulations. At the end of the 20^{th} century, biologists began to use these concepts, for example, to understand the formation of termite nests (Ball, 2001[5], see Figure 2). They used computer simulations to show how local interactions among thousands of little termites, with no plan of the global structure, could self-organize sophisticated and functional large-scale architectures. Other mathematical and computational models were similarly used to study the self-organization of stripes and spots on the skin of animals, the spiral patterns of horns and mollusk shells, the dynamics of predator-prey populations, and of the dynamics of a heart beat[5].

Child development also involves the interaction of many components, but in a way that is probably orders of magnitude more complicated than crystal formation or termite nest construction. Hence, to complement the (tremendously useful) verbal conceptual tools of psychology and biology, researchers have begun building machines that model pattern formation in development. Such efforts can play a key role in 21st century developmental science.

Figure 2 The architecture of termite nests is the self-organized result of local interactions among thousands of insects. None of these insects has a map of the architecture. Computer simulations contributed to understanding this process. Today, models in developmental robotics are used similarly to study how local short term mechanisms can give rise to macro and long-term behavioral and cognitive developmental structure. Source: http://commons.wikimedia.org/wiki/File:Termite%27s_nest.jpg

Building machines that learn and develop like infants is actually not a new idea. Alan Turing, who helped invent the first computers in the 1940s, already had the intuition that machines could be useful for understanding psychological processes:

> *"Instead of trying to produce a programme to simulate the adult mind, why not rather try to produce one which simulates the child's? If this were then subjected to an appropriate course of education one would obtain the adult brain. Presumably the child brain is something like a notebook as one buys it from the stationer's. Rather little mechanism, and lots of blank sheets."*[6]

For several reasons, Turing's vision was not transformed into a concrete scientific program until the very end of the 20th century. First, the 1950s saw the rise of cognitivism and artificial intelligence, views that promoted the (unsuccessful) idea that intelligence could be seen as an abstract symbol manipulation system that could be handcrafted directly in its adult form. Second, Turing missed two important elements: a) Learning from a blank slate—a tabula rasa—could not work in real organisms facing the complex flow of information and action in the world. Rather, development needs constraints; and b) Turing missed the role of the body: behavior and cognition arise in a physical substrate, and this physical substrate strongly influences development[7]. The central role of the body in psychological development is the reason why robots, and not simply abstract computer simulations, will play such a key role in future progress (Cangelosi and Schlesinger, 2015).

THE ROLE OF THE BODY IN BIPEDAL WALKING

Let us look at some examples, beginning with the behavior of bipedal walking. While this is a very familiar skill, we are nevertheless far from understanding how we walk with two legs, and how infants learn to do this. What is walking? What does it mean to acquire the capability to walk on two legs? Walking requires the real-time coordination of many body parts. Our bones and muscles are like the musicians of a symphonic orchestra: each must move (and be still) at exactly the right moment. And it is the juxtaposition and integration of all these movements that builds the symphony of the whole body walking forward with elegance and robustness.

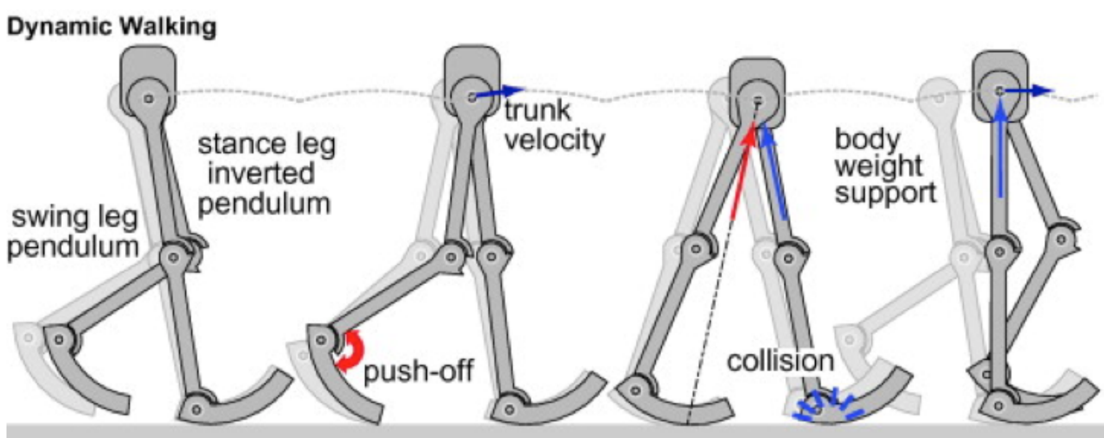

Figure 3 A robot that walks but does not have a brain! It has neither electric power nor computer control. The steps it takes are spontaneously generated through the physical interaction between its structure and gravity. Such mechanical experiments allow to characterize concretely how self-organization of behavioral structure can arise in physical dynamical systems such as proposed by the dynamical approach to development (Thelen and Smith, 1996) (Adapted from http://dyros.snu.ac.kr/concept-of-passive-dynamic-walking-robot/) Source: passiveWalking.png

Is there a musical score that plans and coordinates walking? Is there a conductor driving the movement? In technical terms, is walking equivalent to calculating? Does the brain, every few milliseconds, observe the current state of the body and environment and compute the right muscular activations to maintain balance and move forward with minimal energy consumption?

Viewing walking as pure computation is the approach that has long been taken by specialists who study human walking. Viewed in this context, understanding the development of walking requires understanding how the child could develop the capability to achieve all these real-time computations and make predictions about the dynamics of its body. Some roboticists interested in walking bipedal robots also tried this approach. Yet, even though they sometimes produced beautiful performances[8], this approach has so far led to robots that fell too easily and looked unnatural.

Perhaps, then, walking is *much more* than calculation. Twenty years ago, a roboticist named Tad McGeer conducted an experiment that changed our understanding of biped walking in humans and machines. He built a pair of mechanical legs (see Figure 3 and video https://www.youtube.com/watch?v=WOPED7I5Lac) without a motor and without a computer (thus without the possibility to make calculations), and reproduced the geometry of human legs[9]. Then, he threw the robot on a mild slope and—remarkably—the robot walked: automatically, through the physical interaction among the various mechanical parts and gravity, the two legs generated a gait that looked surprisingly similar to a human gait The robot even responded robustly to disturbances. Other laboratories replicated the experiment many times (e.g. see video https://www.youtube.com/watch?v=rhu2xNIpgDE) and showed that this bipedal walking would persist on a treadmill[10]. The coordination of the set of mechanical parts of this robot, interacting only locally through their physical contacts, is an example of *self-organization*: there is no predefined plan for coordination and no conductor synchronizing every part of the score. Walking is a dynamic emergent pattern where the physics of the body and environment plays a fundamental role in interaction with the (learning) neural system, with each component part of the system structuring and constraining the others, as conceptually investigated by the dynamic systems approach to development (Thelen and Smith, 1996; Adolph and Robinson, 2015).

These very clever experiments show how robots can be used to disentangle the roles of the body and the nervous system in walking. At the same time, they articulate concretely concepts that enlighten our understanding of human development. Here, we observe the self-organization of a pattern (bipedal walking) that is neither innate (there are no genes and no program) nor learned (there is no learning taking place). Therefore, this simple robot concretely demonstrates how the divide between innateness and learning can be meaningless. Structure can appear spontaneously through complex biophysical interactions. And such structure can then be leveraged for learning and development. This robotic approach also helps reinforce and 'ground' the hypothesis that learning how to walk can be facilitated by reusing and tuning a movement structure already embedded in the dynamics of the body (Adolph and Robinson, 2015).

SELF-ORGANIZATION OF CURIOSITY-DRIVEN DEVELOPMENTAL PROCESSES

Let's now examine a second robot example that shows how local short term mechanisms (here curiosity-driven attention and exploration) can generate macro-organized developmental structure on the long term in child development (here sequences of behavioural and cognitive phases of increasing complexity). Human children learn many things, often in a progressive way with specific timing and ordering. For example, before they learn to walk on their two legs, infants typically first explore how to control their neck, then to roll on their belly, then to sit, to stand up, and walk with their hands on the walls. Why and how do they follow this particular progression? Although most infants follow a similar ordering, some children do not. Why do some children follow quite different developmental paths? How can we explain the apparent universal tendencies on one hand and the individual variability on the other? Is universality the result of a "program"? And when we observe a different developmental path, does this imply that something in the "program" is broken?

The social environment plays a big role in guiding developmental process, and has been the object of study of robot modeling work focusing on the roles of *imitation*[11-13], *joint attention*[14], *language*[15,16], and *interactive alignment of tutor and learner*[17]. But there is another fundamental force that drives all of us: *curiosity*, which pushes us to discover, to create, to invent.

Research in psychology and neuroscience has shown how our brains have an intrinsic motivation to explore novel activities or stimuli for the sake of learning and practicing[18]. Yet we still understand little about curiosity-driven attentional and motivational mechanisms, and how it impacts learning and development in the long term. Neuroscientists are only beginning to identify brain circuits involved in spontaneous exploratory behaviors[19].

Figure 4 Curiosity-driven learning and self-organization of developmental structure in the Playground Experiment22,28. The robot in the center explores and learns to predict the effects of its actions, driven by an intrinsic motivation mechanism that drives it to focus on sensorimotor experiments that maximize learning progress/information gain. At the short time scale, this constitutes a model of curiosity-driven attention pushing the robot to prefer sensorimotor contingencies of intermediate complexity, compatible with recent experiments studying informational preferences in infants (Kidd et al., 2012). When running over an extended period of time, one observes the spontaneous self-organization of developmental phases of increasing complexity, without an initial program that specifies these phases. For example, the robot learns on its own to grasp an object in front of it, and later on focuses on exploring how to produce vocalizations that elicit reactions in another robot. Source: playground.png (Creative Commons)

Several research teams have proposed to advance our understanding of curiosity and its impact on development by fabricating robots that learn, discover, and generate their own goals with formal models of curiosity-driven learning[19-21]. An example comes from the Playground Experiment (see Figure 4 and video https://www.youtube.com/watch?v=uAoNzHjzzys;[21,22]). Here, a robot learns by conducting experiments: it tries actions, observes effects, and detects regularities between these actions and their effects. This allows it to make predictions. The way the robot chooses actions is like a little scientist: it chooses experiments that can improve its own predictions, which can provide new information, which makes learning progress, while continuously allocating some proportion of time to exploring other activities in a search for new possibilities. The robot is also equipped with a mechanism that simultaneously categorizes its sensorimotor experiences into different categories based on how similar they are in learnability and controllability.

At any moment in its development, the robot mainly focuses on exploring activities that are sources of learning progress, those that are neither too easy nor too difficult. This models the idea that what the brain finds interesting to practice is what is just beyond the current level of knowledge or competencies[23-25], and as observed in recent experiments with infants (Kidd et al., 2012). Such a model also leads to a concrete definition of epistemic curiosity as a motivational mechanism that pushes an organism to explore activities for the primary sake of gaining information (as opposed to searching for information to achieve an external goal like finding food or shelter, see (Oudeyer and Kaplan, 2007) for a review of formal models of intrinsic motivation and curiosity-driven exploration).

In the Playground Experiment, not only is the robot able to learn skills based on its own initiative—for example, learning how to grasp an object in front of it—but the robot is also able to spontaneously evolve and self-organize its behavior, which progressively increases in complexity. Cognitive stages appear, but they are not pre-programmed. For example, after beginning through relatively random body babbling, the robot often focuses first on moving the legs around to predict how it can touch objects, then focuses on grasping an object with its mouth, and finally ends up exploring vocal interaction with another robot. Critically, the engineer preprogrammed none of these activities, nor did the engineer preprogram their timing and ordering.

This self-organization results from the dynamic interaction between curiosity, learning, and the properties of the body and environment. If the same experiment is repeated several times with the same parameters, one observes that often the same course of developmental stages appear. Yet, sometimes individual robots invert stages, or even generate qualitatively different behaviors. This is due to random small contingencies, to even small variability in the physical realities, which are amplified through closed-loop exploration and learning, and leading this developmental dynamic system into different paths that mathematicians call “attractors”: a collection of differentiated patterns towards which the system spontaneously evolves as soon as it finds itself in their vicinity, so-called “basins of attraction.”

This robot experiment helps us to understand and formulate hypotheses about aspects of how development works. It suggests a way to model the mechanisms of curiosity-driven learning, and to assess how a form of epistemic curiosity can be modeled as a concrete mechanism within a physical agent. It also shows how, over the long term, curiosity-driven attentional processes can self-organize learning and developmental phases of increasing complexity, without a predefined maturational schedule. Finally, it offers a way to understand individual differences as emergent in development, making clear how developmental processes might vary across contexts, even with an identical underlying mechanism and an identical environment.

CONCLUSION

We are only beginning to uncover the basic mechanisms of infant development. Much of the difficulty comes from the fact that the development of infant skills results from the interactions of multiple mechanisms at multiple spatial (molecules, genes, cells, organs, bodies, social groups) and temporal scales. Like spiral galaxies with shapes that result from neither the programmatic unfolding of a plan nor from learning, infant development consists of complex patterns that form spontaneously out of a distributed network of forces. Such patterns cannot be explained within the confines of a false dichotomy like "innate vs. acquired." Rather, what is needed is a shift to a systems perspective.

As physicists realized a long time ago, systemic explanations of pattern formation in complex systems require the use of formal models based on mathematics and algorithms that allow us to fabricate and simulate aspects of reality. In the words of the physicist and Nobel laureate Richard Feynman:

"What I cannot create I cannot understand"

Such an approach is now being brought to developmental science, where algorithmic and robotic models are used to explore the dynamics of pattern formation in sensorimotor, cognitive, and social development. Formulating hypotheses about development using such models, and exploring them through experiments with simulation and robots, allows us to consider the interaction among many mechanisms and parameters. This approach crucially complements traditional experimental methods in psychology and neuroscience where only a few variables can be studied at the same time.

In this context, the use of robots is of particular importance. The laws of physics generate everywhere around us spontaneous patterns in the inorganic world (ice crystals, clouds, dunes, river deltas, and so on). They also strongly impact living beings, and in particular constrain and guide infant development through changes in the body and its interaction with the physical environment. Being able to consider the body as an experimental variable, something that can be systematically changed in order to study its impact on skill formation, has been a longstanding dream for many developmental scientists. Robotics is making that dream a reality[26].

ACKNOWLEDGMENTS

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Playground Experiment:
https://www.youtube.com/watch?v=uAoNzHjzzys

Video of passive dynamic walker robot of Tad McGeer:
https://www.youtube.com/watch?v=WOPED7I5Lac

Video of a replication of passive dynamic walker:
https://www.youtube.com/watch?v=rhu2xNIpgDE

Web site of open-souce ICub humanoid robot:
http://www.icub.org

Web site of Open-Source 3D printed humanoid platform Poppy:
http://www.poppy-project.org

Video of TedX talk where I present some of the ideas in this article:
https://www.youtube.com/watch?v=AP8i435ztwE