

# Curious and Creative Machines

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## 1 Introduction

I recently gave a robot demonstration to a class of 1<sup>st</sup>-grade elementary school children. In the school's gymnasium hall, a few dozen 6-year-olds gathered enthusiastically around a few shiny machines with plenty of sensors and actuators, demonstrating patterns of locomotion. "These robots learned how to move by themselves" – I explained. "Some even developed their own shape", I said, pointing at a set of 3D-printed plastic robots whose morphology and control evolved in simulation.

The kids were not impressed.

One courageous child finally asked the question that was probably on everyone's mind: "But what can they *do*?" I delved into an elaborate discussion of locomotion and manipulation, morphology and control, and machine learning. "But what can they do?" the child persisted. The Emperor's new clothes, I thought, were not that shiny after all. But before long, another child came to my rescue: "Aha! The robot is jogging!" he realized. Yes, that's what the robot was doing. It learned how to exercise, an activity that took western civilization centuries to discover. Perhaps in the not-so-distant future, robots will one day be able to jog an exercise for us. The gymnastics teacher was pleased.

When it comes to intelligence, people are difficult to impress. Children have seen robots that talk, walk, fight and perform a myriad of complex tasks in movies such as Star Wars™ and Terminator™, but they know very well that robots in movies are not real. Artificial Intelligence is almost an oxymoron: Whenever breakthroughs are achieved – from Deep Blue's mastery of chess to Stanley's autonomous traversal of the Mojave desert – something is still missing. If it is just doing what it was *designed* to do, is it *truly* intelligent?

It is fascinating to watch how teachers and parents, when asked about signs of intelligence, quickly point out: Curiosity and creativity are hallmarks of a gifted child. Can we make such curious and creative machines? Will we relinquish some control over what they discover and create?<sup>1</sup> Are we ready to give up on our human-centric claim to curiosity and creativity?

## 2 The Second Half of AI

One of the hallmarks of human intelligence is the ability to design: To synthesize a set of elementary building blocks in order to achieve some novel, high-level and

open-ended functionality. Imagine a Lego set at your disposal: Bricks, rods, wheels, motors, sensors and logic components are your “atomic” building blocks, and you must find a way to put them together to achieve a given high-level functionality: A machine that can move<sup>2</sup>, say. You know the physics of the individual components’ behaviors; you know the repertoire of pieces available, and you know how they are allowed to connect. But how do you determine the combination that gives you the desired functionality? This is the problem of *Synthesis*.

In the last two centuries, engineering sciences have made remarkable progress in their ability to analyze and predict physical phenomena. We understand the governing equations of thermodynamics, electromagnetics, and fluid flow, to name but a few. Numerical methods such as finite elements allow us to solve these constitutive equations with good approximation for many practical situation. We can use these methods to investigate and explain observations, as well as to predict the behavior of products and systems long before they are ever physically realized.

But progress in systematic *synthesis* has been frustratingly slow. Robert Willis, a professor of natural and experimental philosophy at Cambridge, wrote back in 1841:

*[A rational approach is needed] to obtain, by direct and certain methods, all the forms and arrangements that are applicable to the desired purpose. At present, questions of this kind can only be solved by that species of intuition that which long familiarity with the subject usually confers upon experienced persons, but which they are totally unable to communicate to others. When the mind of a mechanic is occupied with the contrivance of a machine, he must wait until, in the midst of his meditations, some happy combination presents itself to his mind which may answer his purpose.”*<sup>3</sup>

Almost two centuries later, a rational method for general open-ended synthesis is still not at hand. Design is still taught today largely through apprenticeship: Engineering students learn about existing solutions and techniques for well-defined, relatively simple problems, and then – through practice – are expected to improve and combine these to create larger, more complex systems.

How is this synthesis process done? We do not know, but we cloak it with the term “creativity”. Fields such as humanities and arts, share the same conundrum: You can learn to appreciate good poetry, music, and sculpture, but how do you systematically create it?

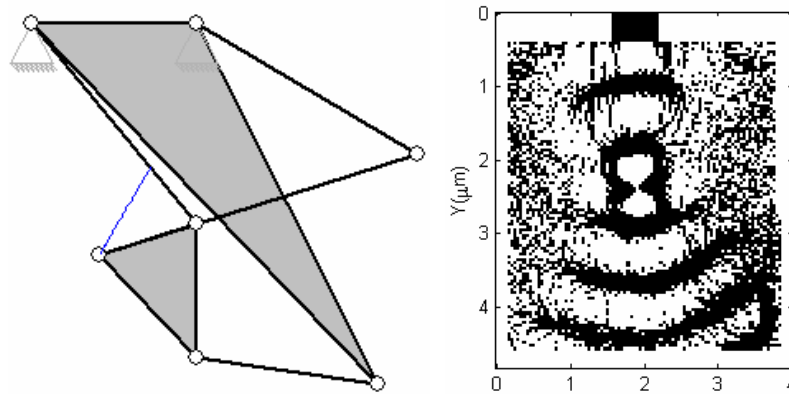
The field of Artificial Intelligence has not escaped this inevitable course either. Over the last fifty years, AI – and its modern incarnation as machine learning in particular – has been primarily occupied with deduction, modeling and prediction, but not synthesis of *new things*. Learning from examples, combining logical facts, and propagating constraints, leave us interpolating inside the convex hull of our existing knowledge. I am not claiming that this is either easy or that it is not useful, nor that it has been fully mastered. But it is a fundamentally different direction than the quest for open-ended creativity, where the results are unbounded in their complexity and performance.

### 3 On Creativity

While computers can compute – and now analyze – almost anything, open ended creativity is still the unconquered Holy Grail still seen as distinctively human. Human intelligence is ultimately a natural biological phenomenon, and like any other biological phenomenon, it is a product of evolution. Many theses have been written about the evolutionary origin of intelligence<sup>4</sup>, and one argument is that intelligence was driven by the need to create and use new tools. Not blindly execute an innate recipe for building a nest, a dam, or a hive – but a true *adaptive* ability to construct new things that rapidly exploit current resources, strengths and weaknesses of others.

Indeed the two standing examples of systematic synthesis we have to inspire us are both evolutionary: One is natural evolution, governed by Darwinian natural selection and variation. The other example is engineering design – not by the mythical maverick designer, but by a slow evolutionary progress, accumulating successive small variations and recombination of exiting technologies made by millions of ordinary designers, subject to the natural selection of the market<sup>5</sup>. These evolutionary processes are admittedly slow, inefficient, and provide no guarantees of optimality or even success, but perhaps there are fundamental limits on the conversion of energy into new information – a kind of thermodynamic law<sup>6</sup>.

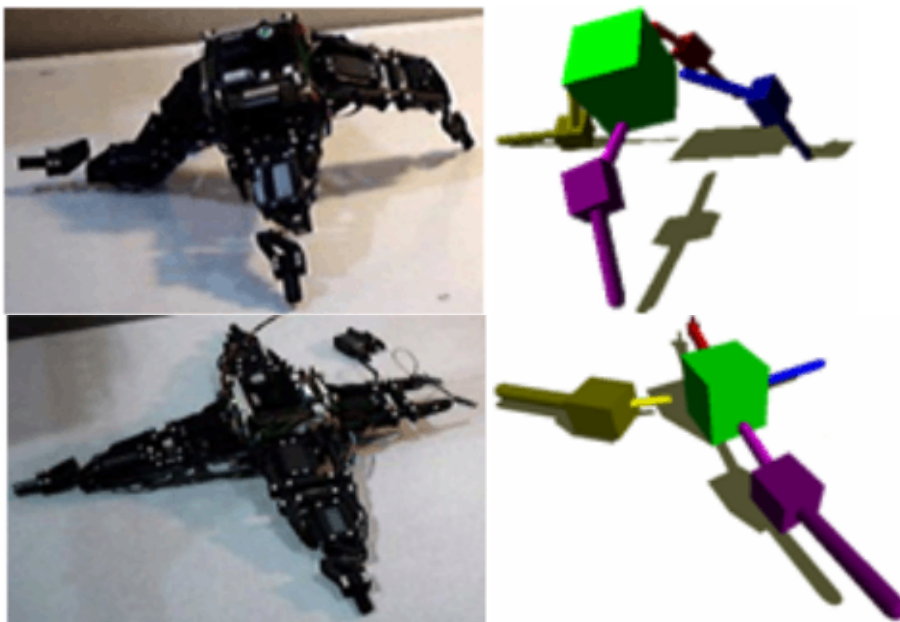
Over the last few decades, a number of results have appeared showing how evolutionary search is able to generate new solutions to open-ended synthesis problems. Whether or not these solutions are deemed “creative” is a matter of opinion, but they certainly satisfy some objective criteria of innovation such as patentability and publishability in their own right. The number of such inventions is growing, and Fig 1 shows two examples.



**Fig. 1. Machine Creativity.** Two examples of open-ended synthesis. Left: A kinematic machine automatically designed to trace a straight line without requiring any straight line in the mechanisms<sup>7</sup>. Right: An automatically designed light-confining nanophotonic structure with a novel hourglass-shaped element<sup>8</sup>.

## 4 On Curiosity

Perhaps the most fascinating form of intelligence is the one that combines open-ended synthesis with open-ended analysis. *Curiosity* is the pursuit of new knowledge: Not only passively searching for patterns in data, but actively probing and perturbing the world to extract new information – like a child asking questions. Asking the right question is again an open-ended synthesis problem, involving creation of new predictive hypotheses and generation of actions to best test their consequence<sup>9</sup>. Though the field of artificial curiosity is in its infancy, it is rooted in the principles of active learning. Fig 2 shows one recent examples.



**Fig. 2. Machine Curiosity:** Through a series of self-directed actions, a robot explores itself and creates an explicit internal model of its topology. The self-model is then adapted after damage. Left: Physical machine; Right: Emerged internal abstraction of that morphology, that the robot has developed to explain its actuation-sensation relationships. Top: Intact; Bottom: Damaged (from Bongard *et al*<sup>10</sup>).

## 5 Conclusion

I am not alone in this quest for a new AI that can creatively generate new things<sup>11</sup> and ask new questions<sup>12</sup>, nor am I unique in my view that nature's evolutionary processes provide the key; but *open-ended* evolutionary computation and active learning<sup>13</sup> have existed on the periphery of mainstream AI for decades. In this fiftieth anniversary of AI, I seek a new thrust – from analysis to synthesis, and from learning machines, to curious and creative machines.

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