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Current Opinion in Behavioral Sciences

Using robots to investigate the evolution of adaptive behavior

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In the field of evolutionary robotics, investigators evolve populations of autonomous machines to exhibit some desired behavior. The neurology, morphology, or both may be placed under evolutionary control, and different behaviors can be selected for. Results from this approach can generate unique and surprising hypotheses about why certain behaviors evolve, regardless of whether they emerge in organisms or machines. To illustrate this approach, I describe recent work on the evolution of modularity, morphological computation, and prospection.

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Current Opinion in Behavioral Sciences 2015, **6**:168–173

This review comes from a themed issue on **Integrated study of animal behavior**

Edited by **Dustin Rubenstein** and **Hans Hofmann**

http://dx.doi.org/10.1016/j.cobeha.2015.11.008

Introduction

The beginnings of robotics and computers can both be traced back to the late 1940s: W. Grey Walter demonstrated autonomous robot tortoises in 1948 and 1949 [1], while war efforts led to the first computers in the United States and England [2]. Yet, despite their cogenesis, computers have advanced much more rapidly than robotics. The reason for this is that, in retrospect, it has proved relatively easy to build machines that repeat the same actions indefinitely; building machines that continuously adapt to their surroundings remains difficult.

Evolutionary robotics (ER) [3,4•,5–7] is a subdiscipline within the larger study of robots, and began as an attempt to overcome the difficulty of manually constructing both adaptive and autonomous machines. Instead, in ER, computers are tasked with evolving such machines: the investigator provides the computer with a way to measure the quality of any given robot; the computer then creates populations of randomly generated robots and measures each robot's ability using the investigator-provided metric; deletes those with poor ability; and makes randomly modified copies of those that survive. If this process is repeated over a sufficient period of time, it is possible to automatically evolve robots that exhibit some desired behavior (Figure 1).

This approach to robotics has two major advantages over other approaches. First, it promises an automated method for yielding robots. A modern robot is composed of two main subsystems: its sensors, motors, and mechanical layout, roughly equivalent to an organism's body plan; and its controller, which transforms sensor signals into motor commands. In all other approaches in robotics, most of the architecture of a robot's body plan and controller is designed by hand. In ER, the evolutionary simulation may be tasked with sculpting as many details of the body plan and controller as desired.

The second advantage of ER is that it can generate hypotheses about the ultimate mechanisms of adaptive behavior observed in nature. If a particular trait evolves in a robot, it is possible to trace back through the robot 'fossil record' to study what selective forces and/or historical accidents led to that trait. Although such traces do not prove that similar forces led to the evolution of that trait in organisms, such studies can place explanatory lower bounds on hypotheses regarding adaptive advantages of traits: what is the simplest evolutionary system that will, if replayed with different starting conditions, consistently yield the emergence of that trait? Indeed, how consistently (if at all) do traits evolve, given such an iterative system?

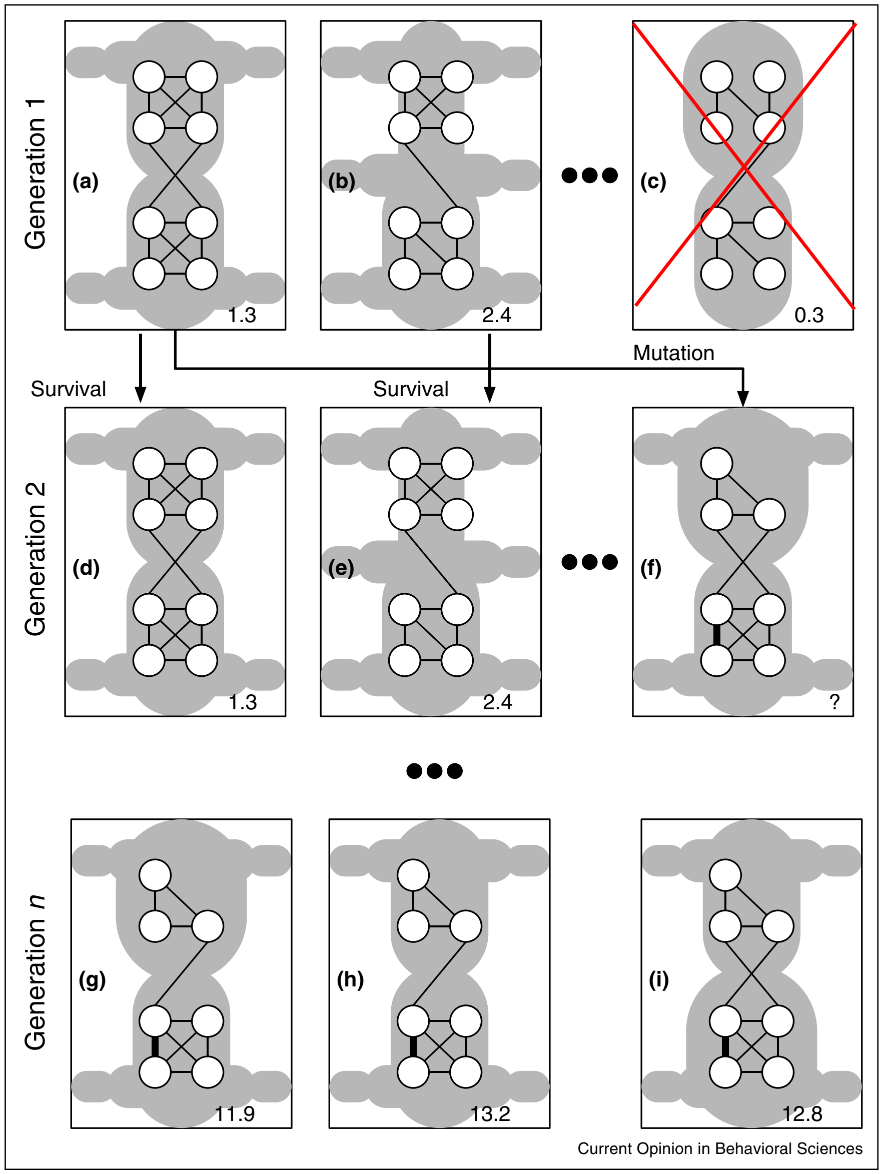
In the next three sections I survey the study of three such traits: modularity, morphological computation, and prospection.

The evolution of modularity

Modules are ubiquitous at all levels of biological organization, from discrete genes up to distinct ecosystems [8]. Modularity is also prevalent in most human-built structures, for the simple reason that it is only possible to extend or improve a complex machine if it is modular [9]. Otherwise, any change to a system with global integration will lead to large-effects and thus most probably undesired-effects.

Despite this obvious advantage of modular over non-modular systems, hypotheses regarding how modularity

Figure 1



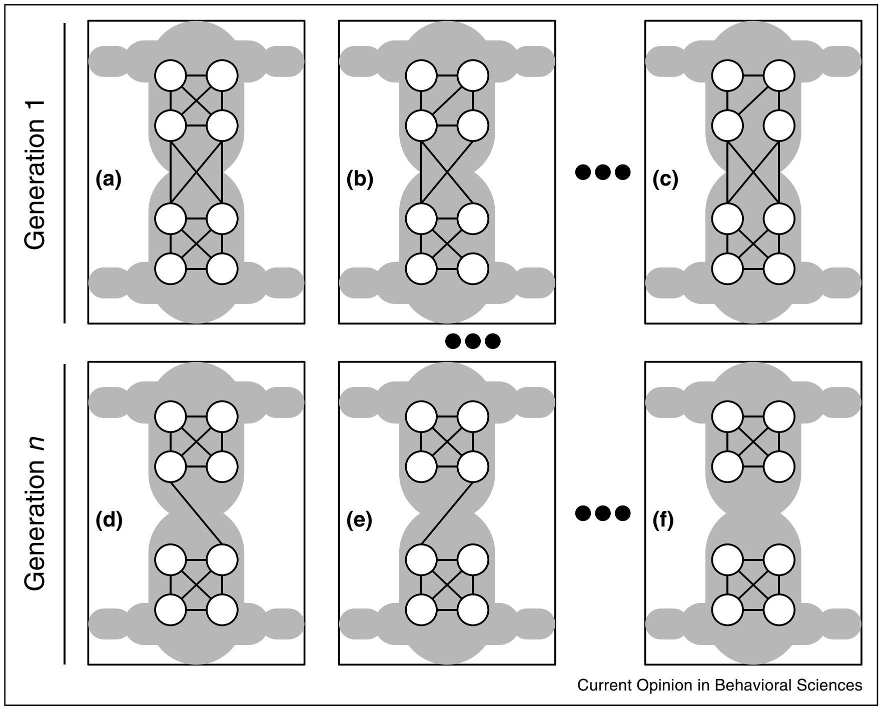
The evolution of robots. In a typical evolutionary robotics experiment, a population of robots, each with randomly generated body plans (gray shapes), neurons (circles), and synapses (lines), is created **(a–c)**. The ability of each robot to perform some task is evaluated and assigned a numerical score (numbers embedded in each panel). Robots with low 'fitness' are deleted (c), and robots that survive **(d,e)** produce offspring (robot a begets robot f). This cycle of evaluation, culling, and reproduction is repeated for several generations and gradually yields robots better able to perform the desired task **(g–i)**.

might evolve remained elusive until Wagner [10•] forwarded a theoretical argument that a combination of directional and stabilizing selection acting on a population would simultaneously decrease pleiotropic effects between emerging groups of traits and increase pleiotropic effects within emerging groups of traits.

This was followed by work by Kashtan and Alon [11], which provided computational validation for this account. They evolved populations of neural models and observed increasing modularity only when directional and stabilizing selection acted on different computations required of the neural models. Another study [12] demonstrated the same effect in gene network models, while others [13] demonstrated that a metabolic cost on the number of connections is an additional requirement for the evolution of neural modularity.

Despite these advances, it was not clear how such selective pressures could be brought to bear on robots.

Figure 2



The evolution of modularity in robots. Under the right conditions, robots with non-modular nervous systems **(a–c)** may gradually evolve into robots with modular nervous systems **(d–f)**, in which there is dense connectivity within neural circuits and little or no connectivity between circuits (following [19]).

Currently, the field of ER suffers from a lack of scalability: the ability to evolve ever more complex and adaptive machines [14,15]. Importing insights regarding the evolution of modularity could help to overcome this challenge. In recent work [16] we showed that this may be possible. We demonstrated that if both the body plan and nervous system is placed under evolutionary control, body plans can be found that cause the right combination of stabilizing and directional selection to act on different parts of the robots' controller, yielding the evolution of modular controllers. Because modularity is known to increase evolvability [17], we observed that such robots outcompeted non-modular robots in the population, leading to the evolution of neural modularity in robots (Figure 2).

The above work focuses on structural modularity: dense connectivity within modules and sparse connectivity across modules. Yamashita and Tani [18] demonstrated the utility of functional modularity — the ability of a continuous system such as a neural network to exhibit discrete functional states — for robotics. A neural model controlling a humanoid robot was able to learn and then combine simple actions into increasingly complex motor sequences.

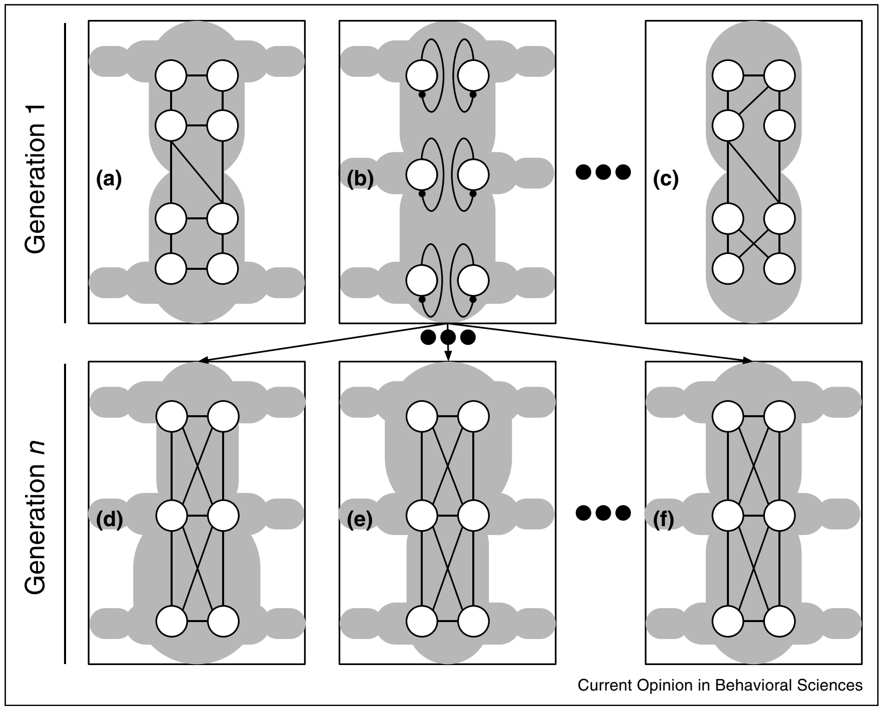
Such work suggests that morphology and action may need to be incorporated into future explanations of the evolution of modularity in biological systems.

The evolution of morphological computation

Modularity is just one domain in which it is advantageous to consider interactions between morphology and neural control of movement. Practitioners in the field of embodied cognition [20–23] have long argued that the body of an animal or robot can provide an appropriate response to external stimuli, without recourse to explicit neural control (because they lack such control, plants provide excellent examples of how this can be accomplished). This concept is often referred to as 'morphological computation' [24,25]. However, it is difficult to quantify how much the morphological or neural subsystems of an animal or robot contribute to a given adaptive response [26]. Such a quantification could prove useful for the study of adaptive behavior: not only might the relative contributions of body and brain to behavior be quantified in biological organisms, but how the ratio of this contribution changes in response to selection would also be of interest. Such detailed tracking of morphological and neural evolution could provide a more detailed account for the evolution of cognition (Figure 3).

Progress in quantifying morphological computation has been reported in [27]: concepts from information theory were used to establish a link between the complexity of a robot's environment and the complexity of the geometry of its body plan. Advances in materials science has recently made it feasible to construct robots from soft

Figure 3



The role of morphological computation in evolution. If a robot exhibits more morphological computation **(b)** than its conspecifics **(a,c)**, it may possess a selective advantage: It may be easier for evolution to shift the burden of an adaptive response from the ancestor's morphology (b) to the more complex nervous systems of its offspring **(d–f)** than it is to enrich an adaptive response already controlled by relatively complex nervous systems (a,c).

materials [28,29••,30–32], and a number of projects have now demonstrated that the complex dynamics inherent in soft materials can provide complex and appropriate responses in soft robots, even though such robots are equipped with simple controllers [33,34•,35–37]. Such robotics experiments are now being utilized to test biological hypotheses regarding how, whether, and why organisms perform morphological computation [38,39].

The evolution of prospection

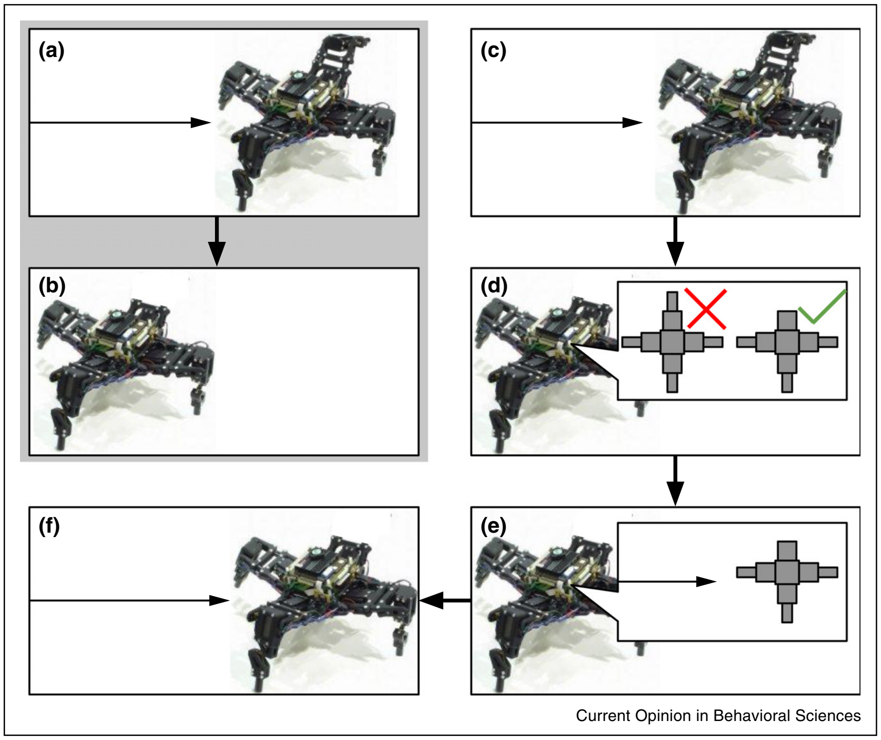
For some, the ability to predict is synonymous with intelligence [40,41]. More specifically, the hallmark of human cognition may be prospection: the ability to mentally simulate the consequences of future events that have never been encountered before [42,43]. The advantage of such ability is clear for animals and robots alike: it allows for rapid responses to novel situations without the need for physical trial and error. Indeed in past work [44] we demonstrated how a robot can accomplish this feat in simple settings. A physical robot mentally simulates itself in two different ways (Figure 4). It uses one evolutionary simulation to continuously improve its understanding of itself, which can enable it to diagnose any unexpected situations such as injury (Figure 4d). It uses a second evolutionary simulation to mentally rehearse novel motor programs that will enable it to recover function, despite its injury.

More recently this method has been adapted to study how robots (and, by extension, animals and humans) may predict the future actions of others [45]. In another project [46••], a robot stored a large portfolio of diverse actions and successfully predicted which of those actions would be useful in the face of unanticipated events.

This body of work, along with recent advances in pattern recognition in the related field of machine learning [47], has been implicated as a possible source for studying the selective advantage of dreaming [48,49] and creativity [50]. Such approaches may eventually allow for the creation of not just adaptive and autonomous machines, but cognitive machines: machines that can predict which actions will help usher in desired future outcomes, all the while navigating increasingly challenging physical environments and complex social situations.

But such machines may act as more than useful tools. They may also serve as unique scientific instruments for studying, in new ways, the most prolific yet mysterious engine of adaptive behavior: cognition.

Figure 4



Robot prospection. A robot incapable of prospection **(a)** is unable to move once it suffers physical damage, such as the loss of part of a leg **(b)**. Another robot that can move and can predict **(c)**, once damaged, mentally simulates its situation and deduces that it has been damaged **(d)**. It then mentally rehearses a motor program that will enable it to regain the ability to move despite its injury **(e)**. Finally, it executes that motor program and thus autonomous recovers from the injury **(f)**.

Conflict of interest statement

Nothing declared.

Acknowledgements

NSF awards PECASE-0953837 and INSPIRE-1344227 provided support for the preparation of this manuscript.

References and recommended reading

Papers of particular interest, published within the period of review, have been highlighted as:

- • of special interest
- •• of outstanding interest

1. Walter WG: **An imitation of life**. *Sci Am* 1950, **182**:42-45.

2. Dyson G: **Turing's cathedral: the origins of the digital universe**. *Vintage* 2012.

3. Cliff D, Husbands P, Harvey I: **Explorations in evolutionary robotics**. *Adapt Behav* 1993, **2**:73-110.

4. • Bongard J: **Evolutionary robotics**. *Commun ACM* 2013, **56**: 74-83.

This paper provides a more in-depth review of the field of the evolutionary robotics than is possible here.

5. Vargas PA, Di Paolo EA, Harvey I, Husbands P: *The Horizons of Evolutionary Robotics*. MIT Press; 2013.

6. Eiben AE, Smith J: **From evolutionary computation to the evolution of things**. *Nature* 2015, **521**:476-482.

7. Bongard J, Lipson H: **Evolved machines shed light on robustness and resilience**. *Proc IEEE* 2014, **102**: 899-914.

8. Callebaut W, Rasskin-Gutman D: *Modularity: Understanding the Development and Evolution of Natural Complex Systems*. MIT Press; 2015.

9. Suh NP: *The Principles of Design*. Oxford University Press; 1990.

10. • Wagner GP: **Homologues, natural kinds and the evolution of modularity**. *Am Zool* 1996, **36**:36-43.

Although a theoretical paper that does not include robotics, this paper describes the necessary conditions for the evolution of modularity. These conditions are now being incorporated into a growing number of computational and robot studies.

11. Kashtan N, Alon U: **Spontaneous evolution of modularity and network motifs**. *PNAS* 2005, **102**:13773-13778.

12. Espinosa-Soto C, Wagner A: **Specialization can drive the evolution of modularity**. *PLoS Comput Biol* 2010, **6**:e1000719.

13. Clune J, Mouret J-B, Lipson H: **The evolutionary origins of modularity**. *Proc R Soc B* 2013, **1755** http://dx.doi.org/10.1098/rspb.2012.2863.

14. Matarić M, Cliff D: **Challenges in evolving controllers for physical robots**. *Robot Auton Syst* 1996, **19**:67-83.

15. Eiben AE: **Grand challenges for evolutionary robotics**. *Front Robot AI* 2014 http://dx.doi.org/10.3389/frobt.2014.00004.

16. Bongard JC, Bernatskiy A, Livingston K, Livingston N, Long J, Smith M: **Evolving robot morphology facilitates the evolution of neural modularity and evolvability**. *Procs of the Genetic and Evolutionary Computation Conference*. 2015:129-136.

17. Wagner GP, Altenberg L: **Complex adaptations and the evolution of evolvability**. *Evolution* 1996, **50**: 967-976.

18. Yamashita Y, Tani J: **Emergence of functional hierarchy in a multiple timescale neural network model: a humanoid robot experiment**. *PLoS Comput Biol* 2008, **4**:e1000220.

19. Newman MEJ: **Modularity and community structure in networks**. *PNAS* 2006, **103**:8577-8582.

20. Brooks RA: **Elephants don't play chess**. *Robot Auton Syst* 1990, **6**:3-15.

21. Pfeifer R, Bongard J: *How the Body Shapes the Way We Think: a New View of Intelligence*. MIT Press; 2006.

22. Davis JI, Markman AB: **Embodied cognition as a practical paradigm: introduction to the topic, the future of embodied cognition**. *Top Cogn Sci* 2012, **4**:685-691.

23. Shapiro L: **The Routledge Handbook of Embodied Cognition**. *Routledge* 2014.

24. Pfeifer R, Iida F: **Morphological computation: connecting body, brain and environment**. *Jpn Sci Mon* 2005, **58**:48-54.

25. Paul C: **Morphological computation: a basis for the analysis of morphology and control requirements**. *Robot Auton Syst* 2006, **54**:619-630.

26. Zahedi K, Ay N: **Quantifying morphological computation**. *Entropy* 2013, **15**:1887-1915.

27. Auerbach JE, Bongard JC: **Environmental influence on the evolution of morphological complexity in machines**. *PLoS Comput Biol* 2014:e1003399.

28. Shepherd RF, Ilievski F, Choi W, Morin SA, Stokes AA, Mazzeo AD, Chen X, Wang M, Whitesides GM: **Multigait soft robot**. *Proceedings of the National Academy of Sciences United States of America* 2011, **108**:20400-20403.

29. •• Kim S, Laschi C, Trimmer B: **Soft robotics: a bioinspired evolution in robotics**. *Trends Biotechnol* 2013, **31**:287-294.
This overview paper of the new field of soft robots makes clear that there are many opportunities for insights from biological organisms to inform this rapidly growing field.

30. Tolley MT, Shepherd RF, Mosadegh B, Galloway KC, Wehner M, Karpelson M, Wood RJ, Whitesides GM: **A resilient, untethered soft robot**. *Soft Robot* 2014, **1**:213-223.

31. Lipson H: **Challenges and opportunities for design, simulation, and fabrication of soft robots**. *Soft Robot* 2014, **1**:21-27.

32. Majidi C: **Soft robotics: a perspective-current trends and prospects for the future**. *Soft Robot* 2014, **1**:5-11.

33. Shim Y, Husbands P: **Feathered flyer: integrating morphological computation and sensory reflexes into a physically simulated flapping-wing robot for robust flight manoeuvre**. *Advances in Artificial Life*. Springer; 2007:: 756-765.

34. • Hauser H, Ijspeert AJ, Füchslin RM, Pfeifer R, Maass W: **Towards a theoretical foundation for morphological computation with compliant bodies**. *Biol Cybernet* 2007, **105**:355-370.
This paper makes clear how morphological computation may be measured in soft organisms and robots alike. This may, in future, pave the way to understanding the conditions under which morphological computation evolves, and why.

35. Nakajima K, Li T, Hauser H, Pfeifer R: **Exploiting short-term memory in soft body dynamics as a computational resource**. *J R Soc Interface* 2014, **11**:20140437.

36. Cacucciolo V, Corucci F, Cianchetti M, Laschi C: **Evolving optimal swimming in different fluids: a study inspired by batoid fishes**. *Biomimetic and Biohybrid Systems*. Springer International Publishing; 2014:: 23-34.

37. Khazanov M, Jocque J, Rieffel J: **Evolution of locomotion on a physical tensegrity robot**. *ALIFE* 2014, **14**:232-238.

38. Ashley-Ross MA, Perlman BM, Gibb AC, Long JH: **Jumping sans legs: does elastic energy storage by the vertebral column power terrestrial jumps in bony fishes?** *Zoology* 2014, **117**:7-18.

39. Long J: *Darwin's Devices: What Evolving Robots Can Teach Us about the History of Life and the Future of Technology*. Basic Books; 2012.

40. Hawkins J, Blakeslee S: *On Intelligence*. Macmillan; 2007.

41. Wissner-Gross AD, Freer CE: **Causal entropic forces**. *Phys Rev Lett* 2013, **110**:168702.

42. Gilbert DT, Wilson TD: **Prospection: experiencing the future**. *Science* 2007, **317**:1351-1354.

43. Osman M: **What are the essential cognitive requirements for prospection (thinking about the future)?** *Front Psychol* 2014, **5**:626.

44. Bongard J, Zykov V, Lipson H: **Resilient machines through continuous self-modeling**. *Science* 2006, **314**:1118-1121.

45. Kim KJ, Lipson H: **Towards a theory of mind in simulated robots**. *Procs of the Genetic and Evolutionary Computation Conference*. ACM; 2009:2071-2076.

46. •• Cully A, Clune J, Tarapore D, Mouret JB: **Robots that can adapt like animals**. *Nature* 2015, **521**:503-507.
This paper presents the most adaptive autonomous machine yet demonstrated: this robot can very rapidly recover from a diverse range of unanticipated situations, including body damage and change to its environment.

47. Hinton GE, Salakhutdinov RR: **Reducing the dimensionality of data with neural networks**. *Science* 2006, **313**:504-507.

48. Conduit R: **To sleep, perchance to dream**. *Science* 2007, **315**:1219.

49. Svensson H, Thill S, Ziemke T: **Dreaming of electric sheep? Exploring the functions of dream-like mechanisms in the development of mental imagery simulations**. *Adapt Behav* 2013 http://dx.doi.org/10.1177/1059712313491295.

50. Kolodny O, Edelman S, Lotem A: **Evolved to adapt: a computational approach to animal innovation and creativity**. *Curr Zool* 2015, **61**:350-367.