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The accelerated path of technological development, particularly at the interface between hardware and biology has been suggested as evidence for future major technological breakthroughs associated to our potential to overcome biological constraints. This includes the potential of becoming immortal, having expanded cognitive capacities thanks to hardware implants or the creation of intelligent machines. Here I argue that several relevant evolutionary and structural constraints might prevent achieving most (if not all) these innovations. Instead, the coming future will bring novelties that will challenge many other aspects of our life and that can be seen as other feasible singularities. One particularly important one has to do with the evolving interactions between humans and non-intelligent robots capable of learning and communication. Here I argue that a long term interaction can lead to a new class of “agent” (the humanbot). The way shared memories get tangled over time will inevitably have important consequences for both sides of the pair, whose identity as separated entities might become blurred and ultimately vanish. Understanding such hybrid systems requires a second-order neuroscience approach while posing serious conceptual challenges, including the definition of consciousness.

Keywords: Singularity, evolution, social interacting robots, major transitions, mind, memory, ageing

Can a machine think? Could it have pain?
Ludwing Wittgenstein

I. INTRODUCTION

The beginnings of the 21-st century have been marked by a rapid increase in our understanding of brain organisation and a parallel improvement of robots as embodied cognitive agents (Steels 2003; Cangelosi 2010; Nolfi and Mirolli 2009; Vershure et al 2014). This has taken place along with the development of enormously powerful connectionist systems, particularly within the domain of convolutional neural networks (Lecun et al 2015; Kock 2015). Two hundred years after the rise of mechanical automata, that became the technological marvels of the Enlightenment (Woods 2003) new kinds of automata are emerging, capable of interacting with humans in adaptive ways. The requirements for building an intelligent or a conscious machine are likely to be still ahead in the future, but some advances and new perceptions of the problem are placing the possibility at the forefront of "what-if" questions (Vershure 2016). To a large extent, today’s discussion on what separates humans from their artificial counterparts is deeply tied to the problem of how to properly define mind and consciousness (Zarkadakis 2015).

In the 1950s, the development of cybernetics by Norbert Wiener and others along with the beginning of theoretical neuroscience and Turing’s proposal for an intelligence test (Turing 1950) were received with a similar interest, triggering a philosophical debate on the limits and potential of man-made imitations of life (Nourbakhsh 2013). The study of the first “cybernetic machines” made by a few pioneers such as Gray Walter generated a great expectation. For the first time “behaviour” emerged as a word associated to mechanical machines, this time empowered by the rising technology that allowed to combine hardware and a new form of engineering inspired -to some extent- by natural devices (Water 1950, 1951; see also Brahenbog 1984). Those early experiments provided some interesting insights into the patterns of exploration of simple agents that where able to detect edges, respond to light and modify their movements according to some simple feedback mechanisms. Although their simple behaviour was essentially predictable, it was not completely free from surprise (Holland 1997). Later work in the 1990s and afterwards incorporated artificial neural systems as an explicit form of introducing learning and behaviour largely inspired in biology (Vershure et al 1992; Edelman 1992; Sporns and Alexander, 2002; Prescott et al 2006).

Nowadays we are rapidly moving towards a new generation of domestic, human-friendly robots that will probably trigger a new technological revolution, similar in some ways to the one proposed by the first personal computers. There is a great promise in this revolution. The promise of robots helping us, playing with us or simply having some basic support functions is pushing forward software and hardware companies towards designing cheap robotic systems. For the general public the fascination remains in the humanoids, those who really look like us. We are actually witnessing a rehearsal of the mechanical automata mania of the 18th century, except that the new automata will be much more autonomous and perhaps closer to us than ever. Not surprisingly, the rise of the new robots has come about with a parallel growth of new fields associated to human-robot interactions (Breazeal 2003; Fong et al 2003; Dautenhahn 2007) and the exploration of learning, cognition and evolution potentials of artificial agents (Clark and Grush 1999; Schaal 1999;
FIG. 1 Humans and robots have been interacting in increasingly more complex ways, most of them limited to simple tasks. However, communicating robots (a) could in the future interact in deeper ways both among them and with humans (image courtesy of Luc Steels -the human in the picture- and the Neurocybernetics group at Osnabruck). Fictional stories on future human-robot interactions, including (b) the movie *Robot and Frank* or (c) TV series *Humans* have started to consider the relevance of strong emotional ties established between elderly or impaired human beings and (possibly non-intelligent) robots capable of learning and communicating through natural language. Evolving connectomes will inevitably result from HRI (d). The long-term association between a human and a robotic agent, when the later is equipped with both communication skills and learning capacities implies the creation of an association network $\Gamma$ linking both "brains" through a number of shared memories. The relative importance of this shared connectome will be a function of the cognitive apparatus of each partner and the depth of emotional engagement.

Florenano and Mattiusi 2008; Takeno 2013).

Along with the science and engineering of these human-like agents, science fiction is also exploring some relevant (and sometimes unexpected) consequences of these near futures. Most early works on robots have been centered on the possibility of intelligent, or even self-aware machines. Isaac Asimov published the Sci-Fi classic *I robot* three years before Turing’s landmark paper on intelligence, picturing a would-be society where robots become a central part of our lives (Asimov 1947). Perhaps the most interesting reflection of Asimov’s tales is the unexpected, the unforeseen consequences of robotic actions while interacting with their most complex part of the environment: us, the humans. The robots incorporate a set of hardwired rules (the "laws" of robotics) preventing the machines from harming humans and harming themselves but in special contexts, when a conflict among the laws emerges, the unexpected should be expected.

The scientific progress made in the field of human-robot interactions (HRI) and artificial intelligence (AI) have renewed the interest in the potential consequences of advanced cognitive robots (Wallach and Allen, 2009; Bradshaw et al., 2004; Murphy and Woods, 2009) and in particular the role played by embodiment in communicating agents (figure 1a) which is known to play a key role in the development of complex behavioural traits (Steels 2003, 2015). The plots in new Sci-Fi stories have become more subtle, and much more interesting. In the movie *Robot and Frank*, for example, we have a moving story of a declining man (Frank) facing the initial phases of Alzheimer’s and a robot companion which, despite a lack of real intelligence, shares experiences and memories with his human partner (fig 1b). At some point, the robot asks Frank to wipe out his memories. Frank rejects the idea, while the robot tells him "I am not a person, I am just an advanced simulation" but afterwards he uses a number of very personal (Frank-like) sentences to make his argument, resulting from previous learned
II. THE SPACE OF HUMAN-ROBOT INTERACTIONS

Here we are interested in the problem of how a socially interacting robot can trigger emotional and even cognitive changes in the human partner. In order to do so we need to take into account several components of this interaction, which is mediated by a complex network of exchanges and could be described in the context of distributed adaptive control theory (see Lallee and Vershure 2015). Two major groups of HRI interactions can be defined here. This first involves those scenarios where interactions are short-lived (the robot companion exchanges take place over a small time window) or predictable (the robot is programmed for simple tasks). The second instead incorporates robotic agents that can learn from experience and interact through long time spans. A major difference between the two cases, in terms of the HRI is the absence and presence of emotional engagement (EE). The choice of EE as a key axis in our approach is grounded in previous studies on second-person neuroscience (Schlibach et al 2013). In this field, the key assumption is that an active social engagement between two (or more) individuals is fundamentally different from a mere observation of subjects. Within our context, we will distinguish between a situation of low EE where the two partners in a HRI are essentially independent from another one where each agent shapes others cognition.

The space of HRI proposed here is summarised in figure 2a, where three axes have been used to locate different classes of robotic agents. In a way, this can be seen as the landscape of human-robot interactions. It provides a tentative picture of the diverse array of qualitative classes of HRI. Three axes are introduced, namely: the degree of cognitive complexity of robots and humans and a third axis linked to the emotional engagement, resulting from both a long-term interaction and the potential for learning and adaptation displayed by the robot. As shown in figure 2b and 2c, we can decompose this space, which we have partitioned in eight arbitrary combinations, in two main layers including low and high emotional ties. Below we present and discuss these two layers separately.

A. Low emotional engagement

In this level of engagement, robots are typically associated to simple tasks with low (if any) of cognitive complexity and playing the role of decision-making systems exhibiting low communication skills (figure 3b). Most standard socially interacting robots (at least the first generations of them) fall in this domain. The typical scenario is a programmed artificial agent that can perform predictable tasks and is expected to operate in simple environments.

Humans (from toddlers to adults) interacting with sim-
ple robots (such as toys or automata following simple orders) would define a lower bound of low cognitive complexity for both agents. Cleaning robots such as Roomba and receptionist robots answering requests from clients (giving simple types of information) would be obvious examples, although even in this case the use of personalization toolkits triggers emotional connections (Sung et al 2009).

In this domain, robots with high cognitive skills interacting with cognitively impaired individuals over specific tasks give the last option in our list. Robots can help in providing support to the elderly or impaired in ways that do not require learning potential from the artificial agent side. Robots capable of identifying the needs of their human partners can be helpful even if not emotionally engaged, while robots with a large amount of available data sets can be interesting as expert systems with user-friendly (humanoid) interfaces. Instead we weight cognition in terms of (pre-programmed) diverse repertoires of responses.

Agents and operative systems exhibiting a rich repertoire of interactions, such as SIRI (which can assist blind people) or Alexa would fit the high-cognitive complexity corner. Here of course “cognition” does not have the meaning that can be attributed to a neural system. For some of these non-embodied systems, a very large repertoire of potential answers can be communicated with the help of a natural language interface. The success of some systems such as Watson, which was trained for a specific goal (answering questions on the Jeopardy quiz show) using hundreds of millions of webpages illustrate the potential for surpassing humans in searching and solving questions.

This layer and the next layer in our space, now allowing higher emotional engagement, are not clear cut. This is particularly relevant if we take into account the human tendency to extract behavioural or emotional clues from the interaction with even simple computer programs. It is worth remembering that even the earliest attempts to program machines (Weizenbaum 1966) capable for answering questions, such as ELIZA (which used pattern matching to simulate a conversation) led to rather unexpected reactions (Weizenbaum 1976). ELIZA was supposed to imitate a speaking psychiatrist, essentially creating simple responses triggered by key words that were then used to create simple questions. But in many cases, people failed to believe they were talking with a computer (which was far beyond in computer power from anything existing today). Similarly, some robots can be simple companions if their interactions span a short time scale but create a strong bond (from human to machine) with their owners if interactions occur over long, shared periods of time. To reach the second layer, we must allow artificial agents to learn and adapt in flexible ways, as well as be capable of exhibiting and detecting emotions.

### B. High emotional engagement

Long-term relationships in HRI can lead to a rather distinct set of patterns that strongly depart from the previous layer. Here we consider the possibility that the robotic agents have been interacting with a given individual in a flexible manner and over an extended period of time. Such interaction might occur at different levels and this too is strongly dependent on the relative cognitive complexity or each partner (the human and the robot) as well as the level and span of their emotional interaction. A healthy, adult human brain is a highly complex system that can nevertheless engage in an emotionally strong relationship with a pet. Humans and dogs (and other pets) have been co-evolving over hundreds of thousands of years until today, where our animal companions have limited cognition powers but a highly developed set of skills associated to emotion recognition (Hare et al 2002). One side effect of this process is our tendency to generate empathy for non-living objects resembling pets. These evolutionary responses have left a detectable cognitive signal (Stoeckel et al 2014). What has been the outcome of HRI between human and artificial pets? A first glimpse of the implications of long-term exchanges between humans and pet robots capable of learning was provided by AIBO dogs, used as companions in a broad range of conditions, from preschool children to elder patients (Kahn et al 2006, Melson et al 2009). In the future, these type of pets (as well as those emerging from the Virtual reality world) are likely to become the rule rather than the exception (Rault 2015).

Despite the lack of a complex communication, the domestication of dog’s cognition has lead to emotional ties that can be strong. All studies on HRI involving robotic pets reveal that human perception is markedly biased towards perceiving them as life-like entities and treated as such, instead as artifacts (Kahn et al 2006). This creates a number of interesting situations relevant for the problem addressed here, an in particular the blurring of lines between ontological categories. As a consequence, emotional ties and their consequent effects are likely to be shared. Such effects are enhanced by the development of some “personality” associated to robot learning capacities, which can strengthen emotional ties. These differential behaviours result from the historical sequence of HRI events: by tapping AIBO’s head sensor after a given behavioural display, it is possible to enforce or decrease a given response, but each case and how it relates with other responses will depend on each specific HRI. Among other things, the loss of a pet can trigger a strong reaction in the human, but also in the animal end of the tie. Perhaps not surprisingly a similar situation has been emerging in relation with AIBO owners who, unable to repair their old dog robots, have to accept their “death” and eventually organise funerals not different from those made for the living counterparts. In this case, the human and the robot are separated by a huge cognitive complexity gap, but the capacity of the robot for learn-
FIG. 2 The cognitive space of H-R interactions under the two-agent perspective taken here. Non-robotic systems (such as ELIZA, SIRI or Watson) are also included. The axes represent (in a qualitative ordering) emotional engagement as well as two dimensions associated to the complexity displayed by the human and the artificial agents, respectively. Here the relative location of each system needs to be taken as indicative. Some of these robots appear in the high human cognitive complexity domain, mainly because their full operational function is expected to take place here, although they could in principle be useful in the other side of the cognition space. The domain where humanbot systems would emerge is indicated by a blurred sphere. A broad array of possible HRI pairs could be expected here, involving strong cognitive dependences that could generate, particularly when the human side is impaired, a new class of cognitive agent.

The previous example would correspond to the possible interactions in the lower part of our space (figure 2c) associated with low robotic cognition. A relevant scenario is the interaction between elderly patients requiring care and therapy (the so called fourth age) and some robots, such as Paro: an artificial, seal-shaped agent. Paro is equipped with sensors detecting touch, light, sounds or movement, with motors and actuators and other standard robotic features but also with some additional features such as responses to cuddling and a constant seeking of eye contact. Additionally, several emotions have been programmed and it can respond to its own name as well as learn other names. Paro has been used in treatment of patients with dementia. The result of these interactions was a reduction of anxiety and helping recover from chronic ailments as well as improving communication with other patients and often creating strong attachments (Kidd et al 2006, Takayanagi et al 2014). Similar patterns have been found using AIBO (Melson et al 2009).

Most companion robots helping patients with dementia are programmed to respond to specific tasks in a more or less flexible way. On a basic level, the robot can be very useful by reminding the human the name and/or location of objects. This has been proposed as a memory prosthesis for elders (Ho et al 2013) where the robotic companion would be equipped with a visual episodic memory, but consider now a HRI capable of learning and using natural language. On another level, it can serve as a medium to communicate with other humans and preventing isolation. Similarly, if capable of moving in outdoors environments, it could greatly improve orientation. But what if the artificial agent is equipped with a powerful cognitive system beyond simple reactions and capable of dealing with daily living environments using multimodal integration learning? Here deep neural networks can play a fundamental role, including the use of natural language (Noda et al 2014).

Consider a robotic agent capable of maintaining a conversation, using natural language, and capable of gathering relevant information concerning past events related with the life of the patient, detecting goals and wishes as well as emotions and capable also of facial expression to share emotional states. This would also be a very de-
sirable form of interaction, since the loss of memories or -more generally- the difficulties to access stored recollections can be a great source of stress for elder people with mild cognitive impairment\textsuperscript{1} and Alzheimer’s patients in particular, specially in early phases of the disease. An artificial agent capable of coping with memory decay and disorientation by means of verbal communication would leverage the anxieties associated to cognitive decline and improve reasoning and judgement. If flexible enough, a neural agent can learn how to help the human in the most useful and personalised way. And here comes the problem.

The HRI involved here leads to a rather unique outcome. For example, if the artificial agent provides support to losses in episodic memory, a first paradoxical situation might emerge: it can occur that some events become absent from the impaired brain while they remain stored within the artificial agent. Such stored recollections can be easily over-interpreted by the artificial agent, in particular their relative value and potential correlations among different memories. On a general level, reminding the human subject where are the lost keys or a misplaced wallet are simple and yet important tasks that can easily counterbalance or alleviate early symptoms.

\\textsuperscript{1} This refers usually to a transition stage between a normal process of brain ageing and dementia, characterised by low performance in memory tasks

\begin{figure}
\centering
\includegraphics[width=\textwidth]{cognitive_space.png}
\caption{The cognitive space of H-R interactions (a-b) here the two layers associated to different emotional engagement (related to short/long term interactions) have been separated indicating potential examples within each discrete class. Several examples of robotic agents engaged in HRI are shown in d-k, including programmed systems with little or no emotional responses nor learning capabilities to robots capable of simulating emotions, seeking eye contact and other features that enhance human emotional and social responses. Here we show: (d) Roomba cleaning robot, (e) REEM, from PAL robotics, (f) ASIMO, (g) Pepper, (h) Aibo, (i) Paro the seal, (j) Nao and (k) Milo.}
\end{figure}
But it can also have a major impact on autobiographical memory. This class of memory, associated to the left prefrontal cortex, provides the basis for putting together a timeline of past events connected to visual and sensory-perceptual features. We should have in mind that a major limitation of robotic agents (and a crucial component of the human mind, Suddendorf 2013) is their lack of understanding or representation of time.

The agent, if properly equipped with visual recognition systems, can have seen pictures of family members (alive or not) and learned about their stories from the patient. These stories can be true or not, but in both cases the agent will contribute to store and recover them. A great advantage of any neural-based system capable of pattern recognition and generalisation (as deep learning networks, see LeCun et al 2015, and references therein) is that the robot can extract correlations required to help in more complex tasks, particularly in relation to episodic, semantic and working memory as well as language and executive functioning. But these correlations rely on both the (possibly faulty) input provided by the human and the emotional weight given to each memory by both partners within the HRI. Because correlations are likely to be generated from biased perceptions, the resulting internal correlation matrix created by the robot (and returned to the human through HRI events) can depart from the original correlations generated in the brain.

If we take into account that memories themselves are not reliable (this in particular affects priming) the long-term HRI inevitably leads to considerable deviations from the original memory web. In this respect, we have a first glimpse of an anomalous pattern: potential memory deficits are compensated by the reliable storage of information residing in the artificial neural network, which can use false memories, create incorrect (but strong) correlations associated to emotional events and feed-back them into the mind of the human. Can this process lead to a runaway amplification phenomenon? What seems likely to occur is that mismatches between the relevance and emotional weight associated to different memory patterns and their interactions might promote deep distortions of the memory and behavioral landscapes. As the HRI proceeds, a new set of interactions will coalesce between the human connectome $\Gamma_h$ (figure 1d) and the network of neural correlations created within the robot brain ($\Gamma_r$). The whole cognitive map must be found in the merged structure $\Gamma$ that includes both networks along with all the human-robot correlations that have emerged and that we also indicate as links between areas.

The loss of plasticity that results from ageing or damage reinforces dependencies among human and robotic cognitive maps mediated by co-occurrence patterns. The view of a given object or image elicits a response in both sides that defines effectively an interaction between both, since these responses will immediately lead to an information exchange. Consider for example a picture of someone (or any other representation of it) that is identified by the human and also stored by the robotic companion. Previous exchanges will have weighted the relevance of this picture and the associated subnetwork of related objects, people or actions.

As cognitive impairment grows in time, the relative importance of the object representation within the artificial system might have been enhanced beyond its original relevance, while exciting and reinforcing other related subnetworks. If decisions or actions derive from this perception, the loss of proper decision making by the human might have been displaced towards the robot, thus shifting the deep correlates from one agent to the other and helping to preserve episodic and semantic memory. Alternatively, different perception and decision layers might become segregated between them. If the memory of this specific image is gone from the human, it can nevertheless remain accessible in the artificial side, which would now contain part of the autobiographical memory.

Since other related events connected to this memory might indirectly interact with the brain network, it is possible that novel forms of hybrid memory might emerge. However, despite the positive side of keeping otherwise erased memories, the dynamics associated to the formation of the HR network can easily shift the importance of events over time and even disrupt it. Unless under some external supervision by close relatives of the patient, the humanbot can lead to a shared mind that strongly departs from the organisation and coherence of the original subject. In other words, one outcome of this HRI is the conscious experience of a different subject, like living in the mind of someone else. The humanbot is a likely outcome of future HRI and its potential to become real is tied to the new generations of robots equipped with powerful learning systems and high memory capacities. These robots might be not yet here, but they are certainly much closer than the coming of intelligent machines.

III. DISCUSSION

The increasing frequency of dementias, being Alzheimer’s the most common one, will affect millions of human beings in the next decades (Reitz et al 2011). While prevention strategies are developed and new drugs are been tested, the need to caregivers helping these patients is becoming a major issue. Beyond the staggering economic costs, caregivers (often family members) are also affected by strong physical and emotional stress. In many cases, their health is also deteriorated. The possibility of using a robotic agent providing help seems a desirable option, although ethical issues need to be considered (Ienca et al 2016). Because cognitive decay is a central issue in most cases, the artificial agent should be equipped with a flexible, adaptive system capable of dealing with changing conditions and specific needs. But such plasticity and learning potential can generate new emergent phenomena. In this paper we have explored the potential outcomes of long-term HRI with artificial agents able to replace memory deficits and communicat-
ing through a natural language interface. As discussed above, the increasing replacement of faulty cognitive networks is likely to create a profound dependency of the human companion that can eventually end in a blurred boundary between the robot and the brain.

There are other implications derived from this class of long-term HRI:

(a) The theory of attractor neural networks (Amari and Maginu 1988; Amit 1992; Rojas 2013) has shown that the qualitative responses of neural networks concerning their responses to noise, memory potential and other properties can experience sharp changes as some parameters are tuned. One particular example is the rapid decline of associative memory as the neural network is damaged beyond a given threshold. Similarly, the qualitative changes associated to an mismatch between the memory requirements and the available cognitive power can lead to the emergence of spurious memory states that is decoupled from the real repertoire of original memories. In all these cases, neural networks display different phases separated by well defined phase transition points (Amit 1992). If these results, grounded in simple neural network models, can be extrapolated to our hybrid system, we would expect to observe tipping points in the cognitive organisation of memories and other key properties.

(b) human beings display awareness, while machines (so far) do not. A relevant problem concerning consciousness is how to define it and even how to measure it (Tononi and Edelman 1998). Some efforts in this direction suggest that a single parameter $\Phi$ could be defined that can capture the degree of consciousness (Tononi 2012). Using this parameter, obtained from an information theoretic approach, it has been argued that we can to the least order different case studies, from animals to impaired human brains or machines (Tononi and Koch 2015). An interesting outcome of this approach is the suggestion that machines (in particular those based on von Neumann architecture) are not conscious (Tononi et al. 2016). Without discussing this conclusion, it seems clear that the humanbot, by inhabiting the boundaries between human and machine will also incorporate some level of consciousness (as measured by $\Phi$). Under the conditions described above, we need to ask the impact of the cognitive replacement associated to the increasing interdependence and how is consciousness shared by both parts.

(c) Once the human is gone, we should seriously evaluate what is left behind within the robot. As long term interactions are likely to shape the robotic cognitive network, some key components of the human’s mind might remain there for inspection or preservation. Once deceased, what is left can keep changing as other inputs from the external world keep entering the system, thus modifying or even erasing the previous stored memories. What to do next? Should the capacity for inspecting the environment be put on hold? Would the robot be capable of interacting with friends and close people of the deceased in meaningful ways? Should the stored information be preserved as the only relevant remain of the gone mind?

One of the most interesting and puzzling components of Asimov’s vision of a future with robots playing a major role in our society was the existence of a novel research field: robopsychology. Experts in this area had to deal with the sometimes unexpected behavior of robots, emerging from the conflicts associated to the there rules of robotics and their inevitable interaction with a complex external world. In the picture presented here, a different (but related) class of robotic psychology might emerge in the future. The interaction, merging and blurring of behavioral patterns resulting from the HRI described above defines an uncharted territory. Long before machines might outsmart us or develop consciousness or intelligent behaviour (Barrat 2013) we will need to either face the rise of the humanbot or prevent it to happen.

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