

Ontological challenges to Cohabitation with Self-taught Robots

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Abstract. When you meet a delivery robot in a narrow street it stops to let you pass. It was built to give you precedence. What happens if you run into a robot that was not trained by or for humans? The existence in our environment of robots which do not abide by human behavioral rules and social systems might sound odd, but is a case we may encounter in the near future. In this paper, self-taught robots are artificial embodied agents that, thanks for instance to AI learning techniques, manage to survive in the environment without embracing behavioral or judgment rules given and used by humans. The paper argues that our ontological systems are not suitable to cope with artificial agents. The arguments are speculative rather than empirical, and the goal is to drive attention to new ontological challenges.

Keywords: Ontology, Robotics, Interaction, Multi-agent systems, Heterogeneous agents

1. Introduction

The marriage between robotics, even when enriched with Artificial Intelligence (AI) techniques, and semantic approaches has not worked well in the past. For long time roboticists have been concerned with hardware limitations and search problems in core areas like kinematics control, navigation, object recognition, obstacle avoidance and so on [1, 2] At that time, the information stored in the robot used to be carefully selected, and encoded in *ad hoc* fashion, to optimize reasoning for those tasks. The use of knowledge as a (conceptual) tool along with actuators, like a gripper, and sensors, like a camera, was a luxury limited to envisioned future scenarios.

Now things have changed. In the last 10 years the continuous improvement of hardware and information processing capabilities has led roboticists to imagine general purpose agents acting in open environments. This vision requires to develop planning techniques for multiple coexisting goals that go beyond traditional robot's control and navigation, and to build

robots that can reason in terms of actions, plans, expectations, other agents' intentions and possible collaborations. Important technical and conceptual consequences were brought up by this change like, e.g., the distinction between geometric planning and task planning [3], and the distinction between behavior (roughly, how the agent interacts with the environment) and function (that is, how that behavior contributes to the achievement of a goal) [4].

Once the need to enrich the robot with models for environment, goals, actions, functions and behaviors became clear, the community started to investigate suitable semantic approaches, e.g., [5, 6]. Today semantic techniques and applied ontology methodologies are largely exploited for a variety of tasks like decision making, belief update, situation assessment, interaction and communication. Interest in ontological modeling is further witnessed by the release of a dedicated standard in the area of robotics and automation [7].

1 When the aim is to develop general purpose au-
 2 tonomous robots, the information system of the robot
 3 must be able to process, integrate, store, recall and
 4 update information coming from a variety of sources
 5 (e.g., different kinds of sensors as well as different
 6 types of collaborators) and deliver dedicated informa-
 7 tion based on goals, detected environment and decision
 8 making processes. Furthermore, the knowledge model,
 9 which uses this information to build a view of the en-
 10 vironment, must also elaborate possible outcomes, de-
 11 tect the presence of other agents and relevant objects,
 12 predict other agents' goals and future actions. Ideally,
 13 such a system takes advantage of techniques in infor-
 14 mation science and uses ontology as pivot to ensure
 15 the reliability of the information management. This
 16 view looks very promising today since important lim-
 17 itations, like memory capacity and processing speed,
 18 have been largely removed.

19 What is the role of applied ontology in this set-
 20 ting? Applied ontology has been introduced to over-
 21 come interoperability problems, primarily at the se-
 22 mantic level, caused by the existence of different per-
 23 spectives, e.g., databases developed by different orga-
 24 nizations or interpretation mismatches by agents with
 25 different roles. What pushed the ontologists to believe
 26 in the possibility of information integration was the
 27 simple observation that all information is about reality
 28 or about human views of reality, since information (via
 29 human perception or human designed sensors) as well
 30 as its interpretation is human-based and since "real-
 31 ity cannot be (self-) contradictory", as the motto goes,
 32 as long as each agent is locally consistent, everything
 33 can be managed to fit. Of course, we have general on-
 34 tologies that make incompatible choices and are mutu-
 35 ally inconsistent. Yet, it is assumed that humans can,
 36 at least in principle, understand each other's ontolog-
 37 ical system, and even switch from one system to an-
 38 other as needed. Practically, two human agents relying
 39 on different ontologies may need to go through an in-
 40 teraction phase to understand each other's viewpoint
 41 but at the end they can correctly interpret the informa-
 42 tion they exchange. Or so it is believed. How to for-
 43 mally model this from the logical viewpoint remains
 44 a problem due, so the assumption goes, to the limita-
 45 tions of today's formal ontology understanding and of
 46 the adopted logical systems.

47 In other domains do not need to make these assump-
 48 tions. For instance, in the semantic web view ontolo-
 49 gies model circumscribed interests, and do not make
 50 fundamental claims about reality. If some form of in-
 51 formation integration is needed, alignment, extension

1 and mapping are the actual targets, anything more be-
 2 ing a plus. Unfortunately, this latter approach is not
 3 sufficient if the goal is to integrate the views of hu-
 4 mans and robots for day-to-day cohabitation, possi-
 5 bly enhancing collaborations and social relationships.
 6 To be reliable, the ontology has to model how these
 7 agents understand reality.¹ Standard arguments in de-
 8 fence of the existence of a unifying ontology or of the
 9 mutual understandability across ontologies rely on the
 10 assumption that understanding is human-based. In a
 11 world where human and artificial agents coexist and
 12 are independent, understanding ceases to be human-
 13 based and human-centred. In such a world, can we still
 14 defend the existence of a unifying ontological system?
 15 Can we still believe in the possibility of mutual under-
 16 standing at the ontological level? I doubt it.

17 Clearly, the environment is the same, and so is the
 18 material world. Or not? An embodied agent learns
 19 how the material world is by establishing relationships
 20 with the outside world: it learns and explores the en-
 21 vironment via its body, cognitive capabilities, sensors.
 22 Robots lack cognition as humans know it, and their
 23 body is not only equipped with different sensors, it
 24 is not even biological. This makes robots' experience
 25 of space, time and matter much different from that of
 26 humans. If the understanding of reality (whatever that
 27 means) depends on sensing and information process-
 28 ing, as we argue, different types of agent very likely
 29 develop different understandings of reality. How much
 30 different? That depends on the type of robot we are
 31 talking about and is, generally speaking, a complex
 32 question since it is unclear how to set up a possible
 33 comparison. Indeed, the initial claim that humans and
 34 robots are part of the same and only reality now sounds
 35 less reassuring.

36 What we are suggesting is that distinct agents (bi-
 37 ological, artificial, cyborg) naturally develop distinct
 38 ontologies about what reality is, and that the belief that
 39 different agents may agree on a unifying view, or even
 40 understand each other's system, is not supported by
 41 solid arguments. We should take seriously the possi-
 42 bility that humans and robots act according to views of
 43 reality that are not only incompatible but also largely
 44 incommunicable. The paper posits this as a problem
 45 for the future of our species and societies, and indicates
 46 directions where ontological investigation is needed.

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 52 ¹In the paper the term 'understanding' has a broad sense as it de-
 53 pends on the agent type. It covers notions like 'building a model',
 54 'attributing a behavior' as well as 'giving meaning' to something.

The rest of the paper is organized as follows: section 2 introduces the distinction between situation and scenario, and characterizes the expression ‘self-taught robot’; section 3 focuses on the change of perspective brought into applied ontology by the coexistence of highly heterogeneous robots; section 4 shows the need to discuss interaction in a broader setting; and the concluding section, section 5, points to a variety of related problems addressing briefly the world of non-human animals.

2. Situations, Scenarios and Self-taught Robots

Due to the ongoing development of robotics, humans need to learn how to cope with robots. This is having an impact on human social behavior, and in particular on conventions [8], that at the moment seem discussed in terms of heteromation [9]. The norms that determine the organization of the human community and of human everyday interactions will adapt to emerging forms of robotics. However, AI methodologies like deep learning and hybrid knowledge-neuronal systems, make possible the creation of robots which achieve autonomy independently of human intervention, and this pushes one to imagine a variety of hypothetical situations. In this paper we are interested in situations that arise in a state of coexistence between humans and robots, the latter understood as embodied artificial agents. In particular, we look at situations in which humans and robots maintain their substantial independence and face the need to share space and resources to achieve their goals (survival, satisfaction of desires, ensuring safety conditions, adapting the environment to special needs).

Let us call (*material*) *situation* the layout of the world in which the agent(s) is. The situation is essentially the spatio-temporal fragment of the world in which an agent can use its sensors to perceive and its actuators to act. We make a distinction between the situation, which we take to be a state of affairs (actual or possible), and the interpretation of the situation, which depends on the agent, and call the latter *scenario*. For instance, a situation could be an enclosed area with several acting objects sitting in front of another, the latter emitting loud sounds in their direction for some time. This situation can be interpreted in different ways, each identifying a different scenario. One scenario is that an academic seminar is taking place in the room, another that the group is doing a rehearsal of a theatre piece, a third that these are zombies con-

trolled by aliens, etc. Given a situation, humans use several types of information to choose a coherent and socially acceptable interpretation [10]. With the full development of robots we can imagine that this interpretation agreement should include robots, at least those involved in collaborations, and the achievement of a shared interpretation among humans and robots in general is clearly more complex.

Let us call *self-taught robots*, self-robots for short, robots that learn to cope with the environment without human help, that is, without humans having the capability or even the opportunity to control how they learn or how they evolve.² In the rest of the paper we focus on self-robots since they are particularly challenging to ontological modeling. Note, however, that self-taught robots, or even self-engineered robots, are extreme cases that we use for exemplification. Our observations are more general and apply also to robots that, while built and trained by humans, are not completely transparent to them, like today’s robots based on neural network architectures. The behavior and goals of self-robots is likely neutral with respect to human behavior and interests, and thus far from our usual way to interpret situations. On top of this, for humans self-robots’ behavior can be largely unexpected since humans and robots lack even common biological needs (an important source of clues in animal studies). It is reasonable to think that a self-robot, since driven by its sensors, actuators, reasoning capabilities, body organization, and learning experiences, may focus on different elements in attempting to interpret a situation. Any interaction from the side of the self-robot will be based on its own scenarios, and the rules and expectations it has developed with them.

Let us further constrain our focus by concentrating on self-robots that develop similar understanding of the environment, similar behavior and comparable goals provided their hardware is similar and, with respect to this, they live in comparable environments. Let us assume also that these self-robots are fairly coherent in matching behavior, scenarios, goals and actions. In different words, let us restrict our attention on self-robots that manifest regularities in dealing with the environment. This does not go as far as implying that, given a situation and the type of self-robot, they are predictable. The assumptions aim to ensure

²This should not be surprising since artificial agents have already the capability to learn how to cooperate via coordination in simple unsupervised settings [11].

1 that it should be possible to develop some kind of
 2 shared set of rules and expectations among humans
 3 and self-robots, a set that can be the core for a system
 4 of norms [8] with which to regulate cohabiting and,
 5 perhaps, sustenance and cooperation among humans
 6 and self-robots.

7 8 9 **3. Ontologies vs. Agent's Ontologies**

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11 Compared to humans, which have very similar bod-
 12 ies and capabilities, robots can be very heterogeneous:
 13 they can comprise different sensors and actuators,
 14 some even tailored to specific information or actions,
 15 can have central or distributed processing units, can
 16 process information locally, at the central level or in
 17 dedicated subsystems, can reason with different com-
 18 putability and memory resources, and apply deduction
 19 rules, default rules, optimisation evaluations, proba-
 20 bilistic assignments, learned associations and so on,
 21 perhaps mixing several of these. As we saw, this vari-
 22 ety suggests that self-robots can understand a situation
 23 in unique ways, but since they show regularity in their
 24 behavior, it is reasonable to ask what kind of ontology
 25 may such robots develop.

26 This question is not new. It rephrases the classi-
 27 cal interoperability problem for which applied ontol-
 28 ogy has been introduced, that is, (a) to make interop-
 29 erability possible at the semantic level, and (b) to se-
 30 mantically integrate information of different kinds and
 31 from different sources. But is ontology engineering,
 32 as known today, suitable to model ontological systems
 33 not developed by humans?

34 To cohabit with self-robots and perhaps interact with
 35 them for information exchange, collaboration, or sim-
 36 ply to avoid ending up in dangerous situations, one
 37 needs to build a model of how robots understand real-
 38 ity and what needs they have, and possibly vice versa.
 39 The issue is not about merging or aligning ontolo-
 40 gies in abstraction, for which there are different tech-
 41 niques in ontology engineering. The issue is whether
 42 today's state-of-the-art in ontology engineering can
 43 make sense of ontological systems that self-robots
 44 could develop (leaving aside the related problem of
 45 how to elicit such ontologies).

46 To understand a self-robot which is physically and
 47 conceptually different from humans, that collects and
 48 classifies things in the environment according to view-
 49 points humans do not use or even consider, do humans
 50 need broader top-level ontologies (TLO) and a larger
 51 spectrum of agent-level ontologies (ALO)? While a

1 TLO can be understood as a foundational ontology in
 2 the usual sense, a ALO is here seen as an agent's spe-
 3 cialization of a TLO. Thus, if the TLO is primarily in-
 4 fluenced by the robot's capabilities (e.g., to sense, rea-
 5 son and act), the ALO is the consequence on the ontol-
 6 ogy needs that the agent develops because of its
 7 history of interactions with the outside world.

8 What would be an ontology that is not already cov-
 9 ered by today's TLO? A simple one, compatible with a
 10 robot that senses the environment at regular intervals,
 11 would claim that no event exists. There are only sce-
 12 narios in which knowledge of objects and their proper-
 13 ties, like relative position, is regularly override by the
 14 next sensing activity of the robot. This robot can de-
 15 velop a notion of causality, e.g., out of regularities in
 16 experienced sequences of scenarios. A notion of con-
 17 tinuous change might be unaccessible to it (this de-
 18 pends on the relationship between sensing frequency
 19 and stimuli processing speed, compare the case of
 20 movie frames and vision processing in humans).

21 In another case the robot's ontology may concen-
 22 trate on material properties (density, thermal energy
 23 storage, chemical stability, etc.) disregarding features
 24 usually relevant in human TLOs like shape or even re-
 25 lations like connection. For instance, a robot that has
 26 sensors to detect compounds of fluorides, chlorides,
 27 nitrates, hydrates and so on, could develop an ontol-
 28 ogy based on these distinctions becoming a sophisti-
 29 cated version of the biological substances that behave
 30 depending on the chemical concentrations in their en-
 31 vironment.

32 These two cases are not really challenging. The
 33 first ontology, which to the best of my knowledge has
 34 not been formalized as a TLO in applied ontology,
 35 presents a reasonable view which is not seriously con-
 36 sidered in our culture but is nonetheless at the core of
 37 some engineering devices. The second TLO is more
 38 likely a fragment of several existing TLOs. For in-
 39 stance, the DOLCE ontology [12] could be extended
 40 to include such an approach as an extension module of
 41 the Amount of Matter class.

42 More challenging for today's TLOs are the context-
 43 dependent ontologies. Here is an example. Assume
 44 a self-robot uses its sensors to check if the environ-
 45 ment is as desired. Whenever it discovers a difference,
 46 deemed relevant, between the sensor data and the de-
 47 sired state, it solves the problem by building whatever
 48 is missing and dismantling whatever is not matching
 49 the goal state. The point is that the behavior of this
 50 robot is centred on a contextual classification of what
 51 it detects. The agent's ALO has at least three classes: a

1 class of goals, a class of things to destroy, and a class
 2 of things to create. These classes are not ontological
 3 in our usual sense as they all depend on the state of
 4 the robot: situation interpretation and goals can change
 5 over time while what to destroy and what to create may
 6 depend on how the robot checks the environment and
 7 even on its position. This ALO is orthogonal to hu-
 8 man TLO since no ontological class is admitted, ev-
 9 erything is based on interpretation. For instance, the
 10 class of things to create could collect entities that in
 11 human TLO are in disjoint classes like physical ob-
 12 jects, individual qualities, relationships across objects
 13 and even arbitrary combinations of these. Note that the
 14 robot may not be able to make sense of our basic on-
 15 tological distinctions since its actions are very strict:
 16 to build from scratch and to dismantle. Note also that
 17 the data collected in a situation could correspond to
 18 the goal or not depending on the quality of the sensors
 19 and on the robot's position at that moment. In short,
 20 this robot may behave rationally but its view of reality
 21 would not be compatible with a TLO in today's terms.

22 These examples of self-robot ontologies are quite
 23 simple and only aim to show unusual cases. The ex-
 24 tent of human TLOs is challenged when investigat-
 25 ing robots based on neural network approaches since
 26 they may understand reality by detecting regularities in
 27 flows of information that overcome human capacities.

28 It might turn out that applied ontology, as we know it
 29 today, is fitted to develop TLOs suitable for self-robots,
 30 perhaps leaving out only some extreme cases, but most
 31 likely this is not so. We need to investigate method-
 32 ologies that enable understanding of different ALOs,
 33 to integrate them within a larger class of TLOs, and
 34 to develop interfaces for information exchanges across
 35 these TLOs. The results of this line of research help
 36 to model the interaction between heterogenous agents
 37 like humans and robots, the focus of this paper, but also
 38 between different robot types and, to stretch it even
 39 further, between humans and aliens.

4. Interaction

41 This paper started with a practical motivation, ex-
 42 pressed via hypothetical situations and scenarios, aim-
 43 ing to drive attention to the new ontological issues we
 44 are likely to face. The motivation, to foster possible
 45 interactions among human and artificial agents, points
 46 to another ontological problem: how should we under-
 47 stand the ontological notion of interaction?
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1 The social systems that humans have experienced
 2 so far are either systems that evolved with humans,
 3 like cities, or are largely controlled by humans, like
 4 farms and hunting scenarios (with or without the sup-
 5 port of non-human animals). These social systems are
 6 thus human-centred, and humans have been by far the
 7 most powerful agent in them. In the hypothetical world
 8 we are considering, humans may not have this special
 9 position. And this has important consequences.

10 The question that arises is not whether interaction in
 11 these hypothetical cases is possible, but in which sense
 12 it is. After all, one may doubt that humans and self-
 13 robots can make sense of each other's behavior and ex-
 14 pectations. Here the very use of the term 'interaction'
 15 may be challenged as it implicitly suggests some kind
 16 of purposefulness (at least from one of the interacting
 17 entities) combined with some form of reciprocity. In-
 18 deed, this is the standard understanding in robotics. In
 19 this sense, it brings to mind intentional agents. Even
 20 though agents capable of making decision and having
 21 goals may fit this view, it seems to me that such pur-
 22 posefulness and reciprocity is too restrictive.

23 I like to start from the notion of interaction as used
 24 in physics and engineering, essentially the way entities
 25 influence or affect each other's behavior. Roughly, an
 26 interaction described at the level of physical laws, say
 27 the interaction between a book and the table where it
 28 lays, states that the behavior of one entity is influenced
 29 by the presence of the other. This physical interaction
 30 can be the starting point for an ontological analysis. Of
 31 course, not all interactions apply to entities controlled
 32 by physical laws only. A cognitive agent detecting an
 33 object in its environment, e.g., perceiving a car on its
 34 path, moves its attention to it (manifesting an interac-
 35 tion at the cognitive level) and may change position
 36 (interaction at the planning, functional and acting lev-
 37 els) to avoid contact. Other types of interaction occur
 38 at the social and cultural levels when joining a queue at
 39 an office or singing 'Happy birthday' at a party. In the
 40 human-computer interaction (HCI) domain there has
 41 been attempts to develop a technical language for mod-
 42 eling interaction [13] followed by efforts to ontologi-
 43 cally generalize this view in other domains, e.g., [14],
 44 but the issue is clearly more general and of wider ap-
 45 plication.

46 The problem here is that the physical notion of in-
 47 teraction does not generalize well. Indeed, we have not
 48 developed a suitable framework for interaction beyond
 49 that of the physical laws. Without such framework we
 50 cannot establish how and to which extent an object
 51 may influence the behavior of another object. Yet, to

make ontology suitable to evaluate interaction across humans and self-robots, a robust ontology of interaction must be developed.

5. Problems ahead of us

In the novel “The Book of Days”, Robert Chambers tells about a sow and her piglets charged and tried for the murder of a small child in 1457 [15]. Indicting a pig for a crime seems ridiculous today since, we believe, animals lack awareness of their actions and of the outcomes (interestingly, the book reports that “The sow was found guilty and condemned to death; but the pigs were acquitted on account of their youth, the bad example of their mother, and the absence of direct proof as to their having been concerned in the eating of the child.”³). A trial in which an animal is charged of crime is today unthinkable for many people, and the same people would be willing to wink at the substitution of a robot for the animal.

From the point of view of modern animal studies as well as of robotics, the conclusion vary depending on the animal species, the robot system, and the theory of consciousness one takes [16, 17]. The problem of founding and running a social and equal system that can comprise humans and self-robots remains widely open: we lack the basic principles about how to understand and organize such systems, and to measure their ethical status.

The previous observation triggers a series of topics, from issues rooted in cognitive and educational sciences to socio-technical organization and individual responsibility. Leaving these apart, we can imagine a classification of conditions for which social systems cannot even develop or survive beyond contingent or fortuitous circumstances. Among the foreseeable cases we can also imagine social systems that would very likely arise as an evolution of our existing systems. There is a need to study these conditions and how they relate to each other. On the ontological side, we should develop dedicated methodologies to understand the parameters to evaluate reliable interactions across different agent types, and even sustainable full fledged social systems.

Finally, most of the scenarios that we may want to elaborate about humans and self-robots are not com-

pletely new in our world. There are plenty of interactions between humans and other non-human animals which already give the gist of the ontological problems we are called to study. Nonetheless, there are two substantial differences between non-human animals and self-robots that push the problem at a different level. First, in modeling interactions humans have always taken the anthropological viewpoint. We have attributed to animals a worldview which apes our own. This move is not possible now. Second, human experience is limited to interactions with biological agents. For sure we can start from what we know about our mixed societies where human and non-human animals cohabit (with human consent or not) but we have to move beyond this if we want to be ready to develop a general social system or, at least, to reliably interact with self-robots.

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