Experience-Specific AGI Paradigms

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Abstract. This position paper suggests the existence of a plurality of "general-purpose" AGI paradigms, each specific to a domain of experience. These paradigms are studied to answer the question of which AGI will be developed first. Finally, in order to make the case for AGI based on symbolic experience, preliminary results from Semiotic AI are discussed.

Keywords: Paths to AGI · Symbolic experience · Semiotic AI

1 Introduction

The term "Artificial General Intelligence" (AGI) conveys the idea that general AI is true AI, i.e. an artifact really reproducing natural intelligence (and not just mimicking an intelligent behaviour). However, the modifier "general" has at least two different uses and can therefore originate at least two different perspectives on AGI. AGI could either denote an artifact that has generalised from one or more special cases and can solve a full range of problems (a perspective of "universal" AGI [1]). Alternatively, it could denote an artifact that is a generalist over specific problems and is not restricted in its application (a perspective of "general-purpose" AGI [2]).

There may exist a plurality of "general-purpose" AGI paradigms, as there exists a plurality of general-purpose program paradigms (i.e. word processor, spreadsheet, etc). In this view, any AGI paradigm is still *specific* to a given domain of experience, definable as a class of input/output (or, in some cases, input/action), so that an artifact in that paradigm can solve all (most) problems in that domain.

Moreover, artifacts of our interests are not just machines, but programs. There may be problems that are *special* to programs, since programs are special in several senses: (i) they can be input symbols (e.g., text and numbers); (ii) they are given (hard coded) their goals; (iii) they can access their own code. Because of property (i), programs can have types of experience which no agent in nature can have. It follows from property (ii) that programs are very efficient problem solvers, so efficient that there is no need for them to understand the goals given to them. Finally, property (iii) carries major consequences on grounding and self-improvement.

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2 AGI Paradigms

While humans have the five senses and proprioception, an artifact can have a potentially unbounded number of sensors, each enabling a different type of experience. Robots can have actuators too. This would account for an unbounded number of experience-specific AGI paradigms. However, it seems reasonable that the first AGI will be developed in one of the following three domains (such that other types of AGI may benefit from the creation of this first AGI):

– AGI based on visual experience (VIS-AGI) of images, videos and live cameras;
– AGI based on sensorimotor experience (SEMO-AGI) of homogeneous or heterogeneous robots, partly operated under human control;
– AGI based on symbolic experience (SYM-AGI) of electronic texts (digitalised books, webpages, source codes) and i/o interfaces.

VIS-AGI will develop intuitive physics, make predictions potentially involving human behavior and detect anomalies. It may or may not take sound into account, but does not have to understand speech. VIS-AGI will be controlled via pre-loaded commands to produce simulations and virtual reality.

SEMO-AGI will develop purposeful behaviour and navigation for autonomous robots or cars, learning from logs of human operations of these robots or cars. It will be controlled via pre-loaded commands to perform tasks.

The experience on which SEMO-AGI builds is also called situated experience, or agency. While natural intelligence can take the form of agency without vision, cameras are the most typical artificial sensor. VIS-AGI would correspond to passive vision, which has no equivalent in nature. It may be the case that SEMO-AGI is a superset of VIS-AGI and that developing VIS-AGI is a prerequisite for developing SEMO-AGI. Yet, SEMO-AGI was listed as a possible first type of AGI, in case it may be developed independently from VIS-AGI, when not all the capabilities of VIS-AGI are necessary for it (SEMO-AGI needing only representational abilities for its action [3] may prove easier to develop than VIS-AGI needing to account for all possible aspects of image formation [4]).

In the list of first types of AGI that can be developed there is not a type of AGI based on linkage experience of being embedded simultaneously in the physical world and in a virtual world made of symbols [5] (let us call it LINK-AGI). Disbelief in SYM-AGI, since disembodied AI cannot solve the "symbol grounding problem" [6], has been cited as a motivation for investigating LINK-AGI. However, LINK-AGI cannot be the first AGI to be developed as it appears that one between VIS-AGI and SEMO-AGI must be a prerequisite for developing LINK-AGI. Let us distinguish between "passive linkage" and "active linkage". AGI based on passive linkage will experience image tagging and video captions, will have no equivalent in nature and will be a superset of VIS-AGI. AGI based on active linkage will have a human-like experience and will be a superset of SEMO-AGI. This type of AGI has been referred to as "human-like AI", although "based on human-like experience" would be more appropriate. As no synergy can be proved for basing AGI on a combined experience of the physical world and of symbols, research focusing on linkage and human-like experience appears more a speculation on the path of development from VIS-AGI or SEMO-AGI to LINK-AGI. Finally, research into this path cannot disprove that a path of developing SYM-AGI as the first AGI is possible. Let us then consider SYM-AGI.

SYM-AGI does not fall into the definition of “human-like AI”. Humans cannot have symbolic experience [7], because they have no equivalent of an i/o channel for exchanging symbols, but rather interpret analogue stimuli from the senses in order to create symbols and act upon them. However, it is possible to imagine such a type of experience (for example, abstracting from a process of reading and writing, such as in Searle’s Chinese room [8]). The fact that there is no equivalent to SYM-AGI in nature [9] is no decisive argument against the feasibility of SYM-AGI. Symbolic experience does not have to be only passive, as i/o channels enable interactions. SYM-AGI will interact successfully with humans through language (any language) and other games, develop science through mathematics and self-improve through machine programming. Obviously, there will also be a path of development from SYM-AGI to LINK-AGI.

A program interacting with human inventions such as mathematics and language cannot constitute SYM-AGI - even if it learns (through inference, trial and error, optimisation) to prove theorems or to answer queries from texts - if it cannot learn by *purposefully* interacting with mathematics and language. Consider the example of a program that cannot learn that performing a certain operation a given number of times or outputting a given string can be related, respectively, to “summing” and to somebody “saying” something as represented in a certain input: there will be so many mathematical and linguistic problems and games, legitimate in the symbolic domain, that the program cannot solve. Therefore, the requirement of generality is not met.

Yet, it is still possible for a learning program to constitute VIS-AGI or SEMO-AGI, if it can learn to solve all problems in the domain of visual or sensorimotor experience that can be given it as goals (hard coded) without the (purposeful) use of language. Recently, neuro-symbolic integration has been proposed to guide learning in visual query answering [10]. Tasks of vision (and control) can be also addressed through reasoning, e.g. by processing a semiotic network [11].

Possible paths of development for the AGI paradigms discussed are shown in Fig. 1.

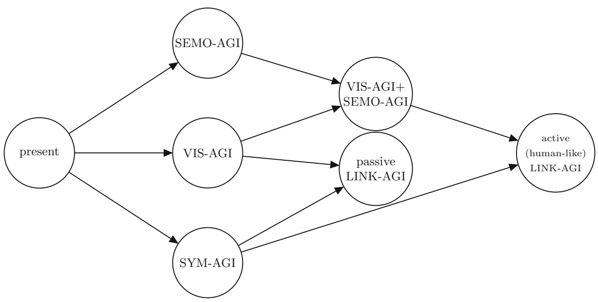

Fig. 1. Paths to AGI. Nodes represent different AGI paradigms, each specific to a domain of experience. Arrows represent possible (alternative) development paths of the considered AGI paradigms: only some of them can be developed first, i.e. directly

3 Semiotic AI

SYM-AGI grounds symbols in its program structure and in i/o interactions history, rather than in sensorimotor interactions history. It may be the case that it is possible to develop SYM-AGI by operating entirely in a high-dimensional continuous space, into which discrete symbols are to be transformed. Yet, evidence exists for a design of SYM-AGI involving (at least some) reasoning iterations on discrete symbols.

Targon [12,13] reported how *Semiotic AI* can form, respectively, a meaning for "summing" and a meaning for someone "saying" something, solely by acting on discrete symbols. Said meanings, even if differing from the usual meanings for humans, are interpretations of first-order symbols (the character `+`, the string `say`) as second-order information (a command for Peano successor, a write command). Semiotic AI reproduces human semiosis, in the sense that if a human were to execute its algorithms we would describe what done by the human as understanding.

The working hypothesis of Semiotic AI is that symbols which cannot form a (direct) second-order interpretation will still have (complex) higher-order interpretations thanks to i/o interactions history. Let me take a twist: why should an AGI, in order to form a meaning for the string `hamburger`, need to watch videos of how hamburgers are made or even need to actually mince meat?

In order to build higher-order interpretations, it will be necessary for Semiotic AI to avoid combinatorial explosions, especially in reasoning, which is a problem common to other designs of AGI [14]. An interesting question is whether the grounding of discrete symbols in the structure of the program itself and in i/o interactions history could act as a control mechanism able to keep the size of inference manageable. If this were not the case, one could consider - in order to speed up learning - transforming the task of building interpretations into a continuous embedding.

4 Conclusion

This paper suggests using experience-specific AGI paradigms to facilitate the study of paths to AGI. The requirement of generality has been interpreted as the ability to solve all (most) problems in a domain. An artifact that can speak English, but cannot (learn to - given access to linguistic resources -) speak Spanish cannot be general. However, such an artifact should not be required by generality to master computer vision or to drive a car. Similarly, one could deploy artifacts able to produce any visual simulation, and to perform an unrestricted class of tasks, but without the ability to understand language (independently from the fact of being controlled through natural language).

The first types of AGI that can be deployed, as well as development paths to extend the capabilities of these first types of AGI, have been identified. It has been argued that AGI linking sensory and symbolic experience cannot be created directly, but rather through extension of another AGI. A possible design to achieve AGI based on symbolic experience, i.e. Semiotic AI, has been discussed.

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