SUPPLEMENTARY MATERIAL

A. Choice of the task

Building with modular bricks is based on visuo-spatial constructive play objects [12] used for engaging learners into tangible programming brick games [7], [11] with modular educational robots [9], [18]. The task is considered based on the cognitive science literature regarding problem solving tasks [13], [20], with the addition of considerations regarding ill-defined problems. In the context of an ill-defined problem solving task [20], the affordances of the robotic elements will influence the actions of the participant [6] towards the object (observing, grasping, assembling).

B. Neuro-cognitive model of the learner

1) Different types of memory: Our team Mnemosyne (Mnemonic Synergy) holds a special interest in studying the role of memory in learning, and more precisely the interactions between all different types of memory.

Three types of memory are generally considered to represent and describe how individuals' knowledge and memories are stored in the long term. [1] They are classified with regard to how they store memory traces and where they are localized in the brain. They may be *declarative* (or explicit), that is to say translatable into words, or *non-declarative* (implicit). An implicit type of memory is **procedural memory**, which corresponds to motor skills and know-how: it allows to remember how to make a gesture or a sequence of gestures, without having to think about it consciously. Among declarative memories, we distinguish semantic and episodic memories. On the one hand, **semantic memory** stores general knowledge about the world (i.e. facts, concepts, word definitions, functions and characteristics of objects, etc.), "objective" facts in the sense that they do not refer to the individual's self. On the other hand, **episodic memory**, localized in the hippocampus, regards the storage of contextualized traces of events the individual has experienced in their past. These memories remain situated, i.e. associated with temporal data (e.g. a precise date, a period), spatial data (e.g. a clearly defined place, a setting), emotional data (i.e. what they were experiencing at the time: it may be a precise emotion or just a diffuse sensation). An interesting property of episodic memory is that it allows to "replay" episodes (i.e. sequences of events) forwards and even backwards, thus providing a way to "rearrange" memories. Some pieces of these episodes can eventually be consolidated into more definitive traces in semantic memory or procedural memory. Episodic memory is therefore believed to play a crucial role in human learning [3].

As for short-term memory, the notion was gradually swapped for that of **working memory** from the 1970s onwards, the latter being considered not simply as a system for the transitory storage of information, but also as a processing system. After being filtered through the attentional focus, incoming stimuli are encoded in the sensory areas as long as they are present (as a kind of "buffer", that is called "immediate sensory memory" by some authors). If they retain the focus of the learner, they can be temporarily stored in working memory for future use and manipulation. When an individual tries to solve a problem, working memory makes it possible to store traces useful to the processes involved in carrying out the task, by updating them as the task progresses. Working memory is also the stage for retrieving information stored in longer-term memories.

2) Four cognitive queries involved in goals: In order to progress in a problem-solving task, the learner sets goals. His general goal is to complete the task, which, after listening to the instructions and discovering the cubes, translates concretely into the realization, using four cubes, of a vehicle that moves autonomously from the red point to the black point. This goal can then be broken down into several sub-goals, which, in order to be achieved, will themselves require the definition of new sub-goals. The goals and their sub-goals thus unfold into trees that take shape through stimuli and experiences, which will always have to be reassembled in order to achieve the final goals. These goals are linked to the learner's cognitive functions, combined through associative circuits: in carrying out his task, the learner is always concerned by goals, and for each one, its importance, the way used to reach it, and its location: they all enable decisions to be made in the context of problem solving and are constantly mobilized to organize behavior. For example, wanting to find out what the blue cube is for, is in itself a goal, yielding a new sub-goal which is manipulating a cube. The learner knows that they will have to grasp it beforehand; this is another sub-goal. They start by looking for it: locating it on the table is yet another sub-goal, etc. As explained in the main paper, we rely on [2] to decompose the goals pursued by the learner into four queries: what and why refer to the main object of the goal and the motivation undelying it, in link with high-level executive functions. These high-level goals yield new questionings, inducing (*Where*, *How*) behavior mechanisms thus resulting in sub-goals at a more local level, in link with sensori-motor behavior.

3) Link with the ontology design choices: The Learner model of the ontology defines several concepts in link with the previous models:

- the learner **prior knowledge** refer to what is stored in their long-term memory, mainly declarative (episodic and semantic).
- the learner **hypotheses** are the temporary representations used by the learner to make sense of their environment. They are issued from a combination of prior knowledge of the learner (retrieved in semantic and episodic memory) with the stimuli received from the environment, and may therefore be localized in working memory. When they have been verified (thus believed by the learner as true), they are maintained in the working memory as **contextual knowledge**, but they are not questioned anymore by the learner, unless a new stimulus raises a contradiction.
- the learner **goals** are broken into the four questionings described earlier, but also considering goal orientation [16] distinguishing mastery goals and performance goals. Par-

ticipants concerned with *mastery* are oriented to develop task-related self-improvement [17] while those focusing on *performance* aim to achieve the task objective using "known ways to quickly implement knowledge and skills that have already been mastered" [21].

C. Using an ontology to model learning activities

1) Reviews about ontologies to model learning activities: Here we consider the ontology to model a very specific problem-solving task. A rather large literature is already available regarding the use of ontology in order to model e-learning systems, as reviewed in [5], especially learning analytics as developed e.g., in [14] in order to perform semantic inference on the observable [8]. Most approaches attempt to model the knowledge or the how-to to teach, i.e., model the learning contents, not the learner. More precisely, they model curricula, learning domain, learning data and e-learning service. Approaches that attempt to model the learner data are the closest to our approach. These approaches are very inspiring but differs from our in a few important aspects:

- They attempt to model the learner "in general", i.e., in rather large and very different learning tasks, whereas we want to study here how we benefit from such approach considering a specific learning task.
- A large majority of these tasks are well-defined (e.g., well defined knowledge or how-to acquisition), whereas we consider here a more open ill-defined problem solving task.
- The goal of such existing ontologies is to tune the learning adaptive resource behavior with the goal to improve the learner performances, which is on one hand less easy to define in our problem solving context (e.g., fast solving of the task does not mean that we learn a lot from it), and not our main purpose which is to better **understand** the learner behavior.

We can however cite the work of the Ludo Game Model Ontology (LUDO) [22] to describe serious games with activities: despite being not reusable here, it is inspiring for us because it includes both a model of the game (task) and a model of the player (learner) behavior. Furthermore, we introduce here computational and cognitive neuroscience knowledge in the modeling process which is does not seem a current practice.

2) Instantiation and methodology: The concepts defined in our ontology based on the theoretical justifications given in B. have been instantiated step by step, based on the design of the task itself, and preliminary observations on the first participants (videos) [19]:

1) Observe all the possible actions and break them down into elementary actions;
2) Associate these actions with the learners' goals, issued from the task observation, but also considering goal orientation and broken down into elementary goals corresponding to the four cognitive questions;
3) Specify the hypotheses and knowledge:
   - hypothese instances are issued from both preliminary observations of task resolution by different subjects and evaluation interviews after the tasks, as made explicit and discussed for instance in [9], [18];
   - hypotheses on the contextual knowledge are mainly driven by the qualitative analysis of preliminary experimental observations, while
   - hypotheses on the prior knowledge are mainly driven by the design and analysis of the task itself.
   - at this point, we also consider interdependencies, that is to say which pieces of knowledge are pre-requisite for others;
4) Determine what, in the material environment, could have been at the origin of the goal (a stimulus, sometimes associated with the "what", e.g.: it is because I see the wheels that my goal is to see if the cube rolls) and therefore of the action, and what the action modifies in the material environment;
5) Identify, from step 3 and step 4, the contexts in which each of them was accomplished, in order to determine which are the preconditions (necessary or optional) and in which state the system is after the action has been performed;
6) Trace all the possible paths, all broken down into different stages, in order to account for the progressive discovery of affordances, the construction of knowledge, hypotheses and beliefs, exploratory actions, actions aimed at testing the hypotheses, etc. This last point therefore consists of a detailed description of all the stages by linking all the concepts previously described and listed.

In any case it is clear that these are preliminary prior assumptions in order to bootstrap a first version of the ontology, with the perspective to adapt them top both the fact they will be really deductible from the observables, and further observation by learning sciences experts.

While this initial ontology has been drafted in a rather informal manner, we consider consolidating this work following and revisiting classical methodologies such as Methontology [4] or a more flexible approach such as [15].

3) Considering foundational ontology: A step further beyond this exploratory phase, we consider basing our ontology as much as possible on a "foundational ontology" (see, e.g., [10] for both an introduction and the description of the proposed design choice) in order to contribute in validating the proposed elements and easily interface with complementary initiatives of this kind. This aspect is not obvious to tackle because, up to our best knowledge and after domain specialist feedback, we are not aware of any ontology describing brain states other than medical ontology which are not of interest to this study. In addition, closely related ontology foundry like Basic Formal Ontology make the choice to avoid representing state of human knowledge (in the sense of what is present in human brain) but only real world related elements, while we take the risk to take this challenge. A more appropriate choice for us would likely be the Descriptive Ontology for Linguistic and Cognitive Engineering [10] which is general enough to link with both cognitive and learning sciences aspect of our formalization work, and which design choices are closed to our paradigm: In a nutshell, it is a descriptive ontology that "aims at capturing the ontological stands that shape natural language and human cognition, based on the assumption that the surface structure of natural language and the so-called commonsense have ontological relevance". It is also an ontology based on individuals and on a multiplicative approach (see [10] for precise definition), which may fit which our approach, and allow us to relate some of our concepts to well established formalize semantic concepts.

However, as reviewed in the previous sub-section, we did not find among ontologies that inspired us and are directly related to learning modeling as developed here (e.g., the LUDO ontology [22]) a derivation from a foundational ontology. This may come from the fact that the underlying concepts, such as cognitive notions like attention, motivation or curiosity, or neuro-computational objects such as the hippocampus mechanisms of fast learning and episodic memory are not yet formalized at the general and abstract level of existing foundational ontology. This also the case for learning science concepts. As a consequence, we are only going to consider deriving our ontology from foundational ontology as a perspective task, while we indeed are going to take such possibility into account when designing our specification.

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