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## Higher-level Knowledge, Rational and Social Levels Constraints of the Common Model of the Mind

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### Abstract

We present the input to the discussion about the computational framework known as Common Model of Cognition (CMC) from the working group dealing with the knowledge/rational/social levels. In particular, we present a list of the higher level constraints that should be addressed within such a general framework.

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**Keywords:** Unified Cognitive Architectures; Computational Models of Cognition; Common Model of the Mind; Cognitive Constraints; Knowledge Level; Rational Level; Social Level.

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### 1. Introduction

In his famous 1982 paper, Allen Newell [23, 24] introduced the notion of knowledge level to indicate a level of analysis, and prediction, of the rational behavior of a cognitive artificial agent. This analysis concerns the investigation about the availability of the agent knowledge, in order to pursue its own goals, and is based on the so-called Rationality Principle (an assumption according to which “an agent will use the knowledge it has of its environment to achieve its goals” [23, p. 17]). By using the Newell’s own words: “To treat a system at the knowledge level is to treat it as having

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some knowledge, some goals, and believing it will do whatever is within its power to attain its goals, in so far as its knowledge indicates” [23, p. 13].

In the last decades, the importance of the knowledge level has been historically and systematically downsized by the research area in cognitive architectures (CAs), whose interests have been mainly focused on the analysis and the development of mechanisms and the processes governing human and (artificial) cognition. The knowledge level in CAs, however, represents a crucial level of analysis for the development of such artificial general systems and therefore deserves greater research attention [18]. In the following, we will discuss areas of broad agreement and outline the main problematic aspects that should be faced within a Common Model of Cognition [13]. Such aspects, departing from an analysis at the knowledge level, also clearly impact both lower (e.g. representational) and higher (e.g. social) levels.

## 2. Areas of Agreement

The analysis at the knowledge level is directly involved in, at least, three of the four dimensions considered within the Standard Model of the Mind [13] (later renamed Common Model of Cognition – CMC). In particular, it concerns the issues related to: i) the Structure and Processing mechanisms, ii) the Memory and Content of the CMC, as well as iii) its Learning processes. Concerning the first element, there is an agreement about the architectural necessity regarding the distinction between a Long-Term Declarative Memory and a Procedural one, as well as the necessity of a working memory module operating as a control interface between the Procedural module and other modules such as Declarative Memory and the Perception/Motor modules. Also, the cognitive cycle assumption [13] (with both serial and parallel information processing mechanisms between/within modules), seems perfectly compatible with the above mentioned Rationality Principle through which it is possible to evaluate the agent intelligent behavior.

For what concerns the Memory and Content issues, the integration of hybrid symbolic-subsymbolic representations and processing - and the inclusion of relevant metadata like frequency, recency, similarity, activation etc - represents the main element of difference with respect to the classical early symbolic CAs. The fact that such integration is necessary, in order to build integrated intelligent agents able to interact in the real world, is widely accepted. Some issues concern the way in which such integration can be obtained and novel solutions to address some representational problems of the Declarative Memories have been proposed and will be discussed in the sections below.

Finally, for what concerns the learning part, the facts that: i) all types of long-term knowledge are learnable, ii) learning is an incremental processes typically based on some form of a backward flow of information through internal representations of past experiences and, iii) learning over longer time scales is assumed to arise from the accumulation of learning over short-term experiences, also seem to be accepted constraint elements. These elements are also explicitly grounded in, and compliant with, the Anderson’s Decomposition Thesis [1]<sup>1</sup> based on the schema between different time-scales, types of operations and bands of cognition proposed by Allen Newell.

Figure 1 reproduces an extended version of the original four bands of cognition schema proposed by Newell [24] including the Biological, the Cognitive, the Rational, and the Social band. In the Newell framework, each band captures different types of human experience and represents different types of information processing mechanisms required to describe the levels within them. In particular: the neural band is described in terms of cellular biology, the cognitive band in terms of symbolic information processing, the rational band in terms of knowledge, reasoning and goals, and the social band in terms of distributed, multi-agent processing. The elements discussed so far in the CMC are, as for the entire enterprise of the cognitive architectures, mainly focused on the deliberate act level of the Cognitive band. In the following we provide additional elements of discussion for what concern both the Rational and the Social Band. Discussions about the lower band (e.g. the Biological one) are out of the scope of the present contribution.

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<sup>1</sup> According to such thesis learning at the highest Band (the social one) can be reduced to learning occurring at lower bands. In general this thesis suggests that there is good evidence that high level tasks can be decomposed and understood at the micro-cognitive level, and that improvements at the micro-cognitive level can create improvements as measured at higher levels.

## Levels of “Cognition”

$t$ (sec)	Time Terms	Band	System
$10^{11-13}$	$10^4$ - $10^6$ years	Evolutionary	Archeology
$10^{10}$	Millennia	Historical	Written History
$10^9$	~50 years	Historical	Personal history
$10^8$	Years	Historical	(Expertise)
$10^7$	Months	Social	(Expertise)
$10^6$	Weeks	Social	Culture
$10^5$	Days	Social	Culture
$10^4$	Hours	Rational	Task
$10^3$	10 min	Rational	Task
$10^2$	Minutes	Rational	Task
$10^1$	10 sec	Cognitive	Unit task
$10^0$	1 sec	Cognitive	Operations
$10^{-1}$	100 ms	Cognitive	Deliberate act
$10^{-2}$	10 ms	Biological	Neural circuit
$10^{-3}$	1 ms	Biological	Neuron
$10^{-4}$	100 $\mu$ s	Biological	Organelle

Fig. 1. Extended version of the Newell’s Time Scales and the different Action Bands.(Green is Newell’s Figure 3.3, blue is Newell’s Figure 3.14, black added by W.G. Kennedy).

### 3. Rational Band

Newell equates the rational band with the knowledge level. The knowledge level refers to the level at which knowledge becomes abstract and can be treated largely independently from the physical systems that process it. Currently, the position according to which there is no need of including, in the CMC, specialized architectural modules to perform activities belonging to the rational band (e.g. planning, language processing and Theory of Mind) is majoritarian. The underlying assumption is that all such activities should arise based on the composition of processes executed during different cognitive cycles according to specific computational models. Despite this position, however, few cognitive architectures have formulated computational approaches to this effect, in particular to the Theory of Mind (ToM). Among these few works, there is that one by [27] where the SIGMA cognitive architecture [33] is used to demonstrate two distinct mechanisms (automatic processing vs. controlled reasoning) for ToM using as an example several single-stage simultaneous-move games, in particular, the well-known Prisoners Dilemma. Authors left open the possibility of using SIGMA’s learning capability to allow the agents to learn models of each other in a repeated game setting. ACT-R [2] has also been used to build several models of false belief and second-order false belief task (answering questions of the kind ‘Where does Ayla think Murat will look for chocolate?’) to assess whether children have a ToM [42]. Additionally, in [40] several scenarios were set up using ACT-R to show how ToM ability can improve the quality of interaction between a robot and a human by predicting what a person will do in different situations; e.g., that a person may forget something and may need to be reminded or that a person cannot see everything the robot sees.

Despite such efforts, however, the modeling attempts of such rational aspects remain still limited (while there are many more models developed for other phenomena concerning, for example, planning, or natural language processing etc.). An alternative proposal [44] to the view of creating specific computational models for cognitive phenomena occurring at the rational band, suggests to adopt additional schema to organize the activity at the higher bands to complement those proposed in Newell [24]. Such proposal will be discussed in more detail in the next sections since it also affects the modeling of phenomena occurring not only at the Rational band but also at the Social one and beyond.

In particular: in the section entitled “Knowledge Problems at the Rational Band”, we will focus on some current limitations of the knowledge level of CAs and will show how this level of analysis also suggests some reflections for the CMC concerning the underlying representational assumptions to adopt/integrate within the Declarative Memory of cognitive agents. In the following section, instead, we introduce some of the main issues concerning the Social Band.

#### 4. Social Band

Events happening at the Social Band can take place over longer time scales (days, weeks, and months). However, they are composed of social events happening at much shorter time scales (seconds, minutes, and hours) and, as evidenced by Anderson [1] may be supported by cognitive and rational processing in individuals at lower time scales. To discuss the potentially controversial topic of motivations, some of our needs, such as physiological needs, come from the bottom up and may explain why we developed high level cognition, i.e., the ability to solve those problems. The social level can also result in goals that people are intrinsically motivated to pursue and our cognition needs to be able to account for that. Our biological and social needs provide goals and may have resulted in innate cognitive capabilities. For example, we seem to have some innate capabilities associated with social cognition, such as perceiving other people, processing direction of gaze, determining intentions of others, limitations on knowing others as individuals (Dunbar’s Number), and the topic of Theory of Mind. Related areas such as cooperation, trust, collective action are tasks or behaviors that arise at the social level. These social interactions may influence the CMC at the lower levels, not simply above the rational level.

Concerning the modeling of macro-scale or macro-cognition events there are, as mentioned, two different perspectives currently debated in the literature. On the one hand such elements are seen as too high level to be included within the minimal information processing mechanisms of a general cognitive architecture and, as such, are left to specific computational models to be developed on the top of such architectures. ACT-R, for example, has been used to study social behaviors and distributed collective decision-making processes which must balance diverse individual preferences with an expectation for collective unity. Romero and Lebiere [30, 31] proposed a multi-agent approach where cognitive agents have to reach global consensus while opposing tensions are generated by conflicting incentives, so agents have to decide whether to follow the most influential agent, follow the majority, negotiate with others, come to an agreement when conflicting interests are present, or keep a stubborn position.

Alternatively, the PolyScheme cognitive architecture [6] applies ToM to perspective taking in the human-robot interaction scenario, that is, the robot can model the scene from the human’s perspective and use this information to disambiguate the command when moving in a scenario with multiple occluding elements [41]. However, although there are computational models of social interactions in a practical sense, there are no current CAs supporting research in social cognition, at best there are frameworks (as examples, BDI [28, 29] and PECS [43, 38]). An alternative position with respect to the current majoritarian view is proposed in [44] and [26]. These authors suggest the inclusion of macro-cognitive architectural elements that should specify the information processing mechanisms allowing to determine complex behavior at both the rational and social level bands and other constraints from the social band. These elements will be discussed in the section ‘Problems for Macro-Cognition’.

#### 5. Higher Bands

As Newell observed: “It is not clear that there actually are any higher bands”. We agree that currently there is not evidence for a system level above the social level for cognition of individuals or for the cognition of groups of people/agents. For additional discussion on this point, we remind to the section 3.11 of Newell’s Unified Theories of Cognition [24].

#### 6. Knowledge Problems at the Rational Band

From a knowledge processing perspective, one of the main problem concerning the knowledge level of CAs is that, currently, the CAs are not able to deal with wide and complex knowledge bases that can be, even slightly, comparable

(for what concerns both the size and heterogeneity of the handled knowledge<sup>2</sup>) to the amount of knowledge heuristically managed by humans. The limited size of the knowledge bases processed by the cognitive architectures was already acknowledged by Newell as a functional problem to address [24]. More recently, the content limit has been newly pointed out in literature [25] and some solutions for filling this “knowledge gap” have been proposed.

The ACT-R architecture, for example, has been semantically extended with an external ontological content coming from three integrated semantic resources composed by the lexical databases WordNet [21], FrameNet [23] and by a branch of the top level ontology DOLCE [20] related to the event modeling. In this case (see [25]), the amount of semantic knowledge selected to extend the ACT-R declarative memory only concerned the ontological knowledge about the events. While this is a reasonable approach in an applied context, it still does not allow to test the general cognitive mechanisms of a CA on general, multi faceted and multi-domain, knowledge. Therefore it does not allow to evaluate, *strictu sensu*, to what extent the designed heuristics allowing to retrieve and process, from a massive and composite knowledge base, conceptual knowledge can be considered satisfactory with respect to the human performances.

More recent works have tried to completely overcome the size problem of the knowledge level. To this class of works belongs one proposed by Salvucci [34] aimed at enriching the knowledge model of the Declarative Memory of ACT-R with a world-level knowledge base such as DBpedia (i.e. the semantic version of Wikipedia represented in terms of ontological formalisms) and a previous one proposed in [3] presenting an integration of the ACT-R Declarative and Procedural Memory with the Cyc ontology [15] (one of the widest ontological resources currently available). Both the wide-coverage integrated ontological resources, however, represents conceptual information in terms of classical symbolic structures and encounter the standard problems affecting this class of formalisms concerning the representation and reasoning on common-sense knowledge. (see [18] for a detailed treatment of this aspect). With respect to the size problem, the knowledge level is also problematic for the Soar [14] and the SIGMA [32, 33] CAs. Both architectures, in fact, do not currently allow to endow agents with general knowledge. For Soar, this problem is acknowledged in [14] but there is no available literature attesting progress in this respect<sup>3</sup>. A possible alternative solution that, in this perspective, is suitable to account for both the size problem and typicality (or common-sense) effects in conceptualization has been proposed in DUAL-PECCS [19]: a system that has been successfully employed to extend the Declarative Memory of diverse CAs and that combine, on a large scale, both common-sense representation and reasoning with standard ontological semantics. The main merit of such proposal lies in the adoption of the representational component of Conceptual Spaces [9] integrated with other neural-symbolic formalisms. The benefits coming from the integration of the Conceptual Spaces framework as an intercommunication layer between different types of representations in a general cognitive architecture has been recently pointed out in [17] and, with respect to the CMC, it has been acknowledged both in [7] and [11]. Recently, within the representation framework adopted in such system, it has been proposed a unifying categorization algorithm able to reconcile all the different theories of typicality about conceptual reasoning available in the psychological literature (i.e. prototypes, exemplars and the theory-theory, see [16]). Another interesting approach that aims at synchronizing beliefs and truth values among multiple domains to provide a unified treatment of these various forms of knowledge is described in [35]. In general, going towards unified representations and reasoning procedures seems to be a reasonable path to explore within the CMC research efforts.

Another important issue to consider in this dimension of analysis concerns whether the CMC should make a distinction between the knowledge about the ‘self’ and knowledge about ‘others’. If so, a plausible solution would be that knowledge about the self is maintained by specialized memory systems, for instance, autobiographical declarative memories (both semantic and episodic) while beliefs about others are maintained by separate declarative memories. Likewise, procedural memory would contain distinct knowledge about actions allowing the agent to pursue both individual and collective goals, and those actions would be competing against each other inside the cognitive agent’s

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<sup>2</sup> The heterogeneity issue concerns the problem of representing different types of conceptual knowledge in a cognitive agent, including the common-sense one. Handling common-sense knowledge representation and reasoning mechanisms, however, still represents an unsolved problem to deal with. This aspect is problematic not only for the rational band processes but also for the information processing mechanisms occurring at Cognitive Band (in particular those involving the operations and unit task levels, see Figure 1).

<sup>3</sup> There are, however, attempts to extend in a efficient way the Semantic Memory of Soar with external lexical resources such as, for example, Wordnet [8].



mind when there would be conflicting interests. Another concern to be addressed is the potential necessity of keeping a collective memory to store shared knowledge about the world, social behaviors and norms developed by agents. This would be a distributed knowledge system by nature, but also would reflect high levels of redundancy, that is, agents would have a partial copy of the knowledge system (constructed as a result of learning processes) which would allow them to communicate ideas efficiently with each other. One potential issue with this approach is the representational incompatibility between agents grounded in a different cognitive architecture and, therefore, in different representational and reasoning assumptions. A possible way out, as suggested above, is that one of exploiting the potential of representational and reasoning systems *à la* DUAL-PECCS that have shown a good level of compatibility with diverse architectures. More generally, this is the kind of capability that the CMC aims to enable.

## 7. Problems for Macro-Cognition

As mentioned above, there is a majoritarian consensus that no additional specialized architectural modules are necessary for performing high-order capabilities of the social band. However, some specific architectural primitives may be still necessary for supporting social cognition such as visual imagery for visual-feature reasoning; pre-attentive and attentive vision sub-modules for the recognition of complex non-verbal signals of attention and emotional state, social-gaze following, face detection, etc. In the CMC, in fact, there is a real consensus over the ‘minimum’ number of high-level modules that are present in a cognitive architecture (e.g., perception and motor, working memory, declarative memory, and procedural memory); however, it still remains incomplete concerning other modules and mechanisms that can be useful for social cognition: emotion, direct communication, language, attention, metacognition, ethical/moral reasoning, among others [5, 36, 12, 37]. Thus, we envision that the main challenge is to identify which of these additional modules and mechanisms are completely necessary (and therefore should be included in the CMC) and what their level of involvement in social cognition is. For instance, it seems that at the lowest level, simple social interactions (such as gaze following) require at least the interplay of perception, attention and memory modules, whereas more complex social interactions (such as building rapport, negotiation, etc.) may require the interplay of additional modules such as emotion/motivations, metacognition, and language, just to name a few. So, it is necessary to define a well-structured hierarchy of a representative set of social interactions that help us identify which modules and mechanisms are strictly necessary at each level of the hierarchy and, from there, establish the architectural constraints that should be added to the CMC in order to allow social cognition to emerge.

Concerning the learning assumptions of the CMC connected the Social Band: the current version of the model [13] states that learning occurs mainly in two modules, procedural and declarative, where procedural learning involves at least reinforcement learning and procedural composition, and that more complex forms of learning involve combinations of the fixed set of simpler forms of learning. We know, however, from the Social Learning theory [4] that learning takes place in a social context and can occur purely through observation/imitation or direct instruction, even in the absence of motor reproduction or direct reinforcement. In addition to this, the field of robotics and multi-agent systems have reported [10] that learning by imitation can be supported not only by classical reinforcement learning but also by supervised learning (e.g., behavioral cloning, learning by demonstration), inverse reinforcement learning (e.g., apprenticeship learning) and transfer learning. Therefore, some questions to address at this point are: what other kind of learning, other than reinforcement learning, can be considered to model cognitively plausible social agents? What kind of architectural criteria should be taken into consideration in order to determine the ‘minimum’ requirements for procedural learning when modeling social cognition?

As mentioned earlier, an alternative proposal concerning the modeling of macro-cognitive phenomena has been recently pointed out by [44]. The authors applied to macro-cognition the same criticism raised by [22] as to the epistemological value of creating different models for each cognitive phenomena. In Newell’s view this praxis is of limited use because it leads to a multitude of unrelated micro models. Similarly, [44] noticed that the field studying macro-cognition currently produces a vast array of ad hoc models and pointed out that this is true even when well specified cognitive architectures are used to make the models. This is because there are multiple ways to implement complex tasks in a cognitive architecture since it does not restrict the knowledge content at the rational band (see above). The adoption of Macro-cognitive architectures may offer some resolution to this problem as they are based on the proposal that the knowledge level is constrained and tends to be organized in particular ways.

In terms of relating the common model architectural principles to macro-cognition, a pragmatic approach is to specify best practices and common solutions for supporting macro-cognitive functions, such as planning, dealing with unexpected interruptions, task switching, problem solving, and dealing with large knowledge bases. This could be thought of as constituting a proto common model of macro-architecture, but one doesn't need to buy into the macro-architecture concept in order to appreciate that this sort of approach would have practical advantages for facilitating applications of the common model to real world modeling projects. A starting point for this would be to gather all the models built in common model architectures that are related to macro cognition and look for commonalities. That is, use the same methodology that was used to conceptualize the common model [13]. Likewise this same approach could be used with knowledge level languages to see if there are any commonalities.

Alternatively, an approach can be chosen in which the higher level of abstraction is treated as a more independent modeling platform with its own representations and mechanisms, but one that can be reduced to the level of the Common Model (e.g., [39]). The possible interplay between these two contrasting views is not yet entirely clear and represents, for sure, an important element of discussion and elaboration to address within this working group and between diverse CMC working groups.

## 8. Conclusion

We have proposed an overview of some of the main constraints and open problems that should be addressed within the CMC concerning the knowledge/rational/social levels. In our analysis we also have specified, when possible, some plausible directions to follow in order to overcome, or partially address, such problems.

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