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The Navigation Map-Based Cognitive Architecture—A New Class of Artificial Intelligence

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Abstract

A navigation map-based cognitive architecture uses versions of navigation maps as a store of procedural memories, semantic memories, episodic memories, as well as for working memories. Perceptual inputs are mapped to navigation maps and motor outputs are prepared on navigation maps. The brain-inspired Causal Cognitive Architecture 3 (CCA3) is an example of a navigation map-based cognitive architecture. In the CCA3, objects detected in the streams of sensory features are segmented, and visual, auditory, and other sensory features of each segmented object are spatially mapped onto navigation maps dedicated to one sensory system. These newly created or updated single-sensory navigation maps are then mapped onto a best matching multi-sensory navigation map. Instinctive and learned primitives, which act as small rules or productions, and which also are stored in modified navigation maps, then operate on the working navigation map, producing an action signal which can be outputted. If there is no actionable output from the Navigation Module, then intermediate results can be stored and fed back the next cognitive cycle. By feeding back and re-operating on the intermediate results, the architecture can formulate and explore possible cause and effect of actions, i.e., generate causal behavior as well as allow induction by analogy. The list of core operations and properties of the architecture are compared with the basic operations and properties of other approaches towards achieving artificial intelligence. This comparison shows that the navigation map-based cognitive architecture, as represented for example, by the CCA3, represents a new class of an approach towards artificial intelligence.

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1. Introduction—A Myriad of Approaches to Achieving “Artificial Intelligence” Exist

Given a mathematical universe [1–3], many approaches have been developed and will continue to be developed to allow an agent to act or think rationally (or human-like) in environments within such a universe [4]. These approaches represent “artificial intelligence” (AI) at varying levels of capabilities, from specialized narrow applications to broader applications including those that

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reach levels of human-level AI (HLAI), artificial general intelligence (AGI) or artificial superintelligence (ASI) [5–7]. In this paper we use the term "artificial intelligence" (AI) to refer to this wide spectrum of possible levels of artificial intelligence capability.

Darwiche [8] distinguishes model-based and function-based approaches to AI solutions to problems. In a model-based approach, one must represent knowledge about a problem in a model, and then apply logical reasoning to such knowledge. The function-based approach essentially curve-fits a problem, for example, image pixel inputs with a function output indicating recognition of a certain object. Artificial neural networks are typically used to achieve a function-based approach to AI solutions. Modern neural networks used in deep learning are powerful systems of parametrized functions that can learn to recognize most relationships between inputs and outputs. It is often claimed that deep learning is "representation learning" since the architectures of deep learning networks often need to be adjusted to better perform their task. However, Darwiche views this a function engineering, not representation learning.

Darwiche notes that over the last decade it seems that almost all human behaviors can be reproduced via the curve fitting abilities of artificial neural networks. However, he argues that artificial neural networks may not be able to handle broader applications that require model-based approaches for true understanding of the problem. While Darwiche recognizes the substantial accomplishments of deep learning over the last decade, he bemoans that its success is suppressing research in the many other approaches, particularly the model-based approaches, towards AI solutions. He calls this the "bullied-by-success" phenomenon where an academic community is "subdued" into pursing what is currently considered successful while unfortunately ignoring what might more genuinely be needed for success over the longer term. He gives an example where academic departments that in the recent past excelled in reasoning with symbolic logic, for example, have been forced to change so much because of the success of deep learning that symbolic logic now occupies almost no space in these departments' AI educational curricula.

To a large extent, much of the educated public at this point considers the term artificial intelligence (AI) as a synonym for deep learning. For example, a blog for technophiles despite trying to point out the differences in AI versus machine learning versus deep learning, concludes with "in practice artificial intelligence is often the same thing as a neural net capable of machine learning" [9]. Medical schools in North America are starting to form "Departments of Artificial Intelligence" [10]. While the public may think this will result in robotic medical systems that will function like physicians, in fact, most of the activity in these departments is the application of deep learning machine learning against traditional medical tasks with results that are considered by many experts as "overhyped" [11, 12].

As Russell and Norvig point out, there are many approaches to viable artificial intelligence [4]. In this paper, we discuss the navigation map-based cognitive architecture as a new type of approach towards artificial intelligence (AI).

2. The Causal Cognitive Architecture 3 (CCA3)—A Navigation Map-Based Cognitive Architecture

A navigation map-based cognitive architecture uses navigation maps (i.e., assist in navigation, for example, similar in many respects to the paper maps used in the pre-GPS era by hikers and motorists) as its main data element. A navigation map-based cognitive architecture uses versions of navigation maps as a store of procedural memories, semantic memories, episodic memories, as well as for working memories. Perceptual inputs are mapped to navigation maps and motor outputs are prepared on navigation maps.

The Causal Cognitive Architecture 3 (CCA3) is a navigation map-based cognitive architecture. The CCA3 is a brain-inspired cognitive architecture [13]. The main components of the CCA3 are shown in Figure 1. The CCA3 is inspired by the mammalian brain, in particular the mammalian hippocampus, and it uses navigation maps (i.e., maps whose principal purpose is to represent spatial locations) as its main data structure. Neuroscience research in the last few decades has shown the key role of navigation maps in the hippocampal structures and potentially elsewhere in the mammalian brain [14–20].

The navigation maps in the simulated version of the CCA3 [13] are (arbitrarily sized) 6 x 6 x 6 arrays holding spatial navigation information about the external environment. For example, Figure 2 shows the 6x6x0 dimensions of a navigation map based on sensed features of an area of land with a body of water in the middle of it. The navigation maps also include and number of nonspatial dimensions and are also coopted for the data storage and representational needs of the architecture, as well as for the various small algorithms, termed "primitives" which can operate on information in the navigation map currently in attention, termed the working navigation map represented in the equations below as **WNM'**.

Various perceptual sensors provide a stream of sensory features to the architecture. Objects detected in the streams of sensory features are segmented, and visual, auditory, and other sensory features of each segmented object are spatially mapped onto navigation maps dedicated to one sensory system. These newly created or updated single-sensory navigation maps are then mapped onto a best matching multi-sensory navigation map taken from the Causal Memory Module and moved to the Navigation Module (which can be virtually by way of activating the navigation map in place). Instinctive and learned primitives, which act as small rules or productions, and which also are stored in modified navigation maps, then operate on the working navigation map. This causes the Navigation Module to produce and send a signal to the Output Vector Association Module and then to the external embodiment.

The Causal Cognitive Architecture 3 heavily makes use of feedback pathways—states of a downstream module can influence the recognition and processing of more upstream sensory inputs. In the CCA3 the feedback pathways between the Input Sensory Vectors

Association Modules and the Navigation Module/ Object Segmentation Gateway Module are enhanced so that they allow intermediate results from the Navigation Module to be stored in the Input Sensory Vectors Association Modules (Figure 1). A cognitive cycle is a cycle of sensory inputs into and through the architecture usually resulting in an output from the Navigation Module to the output modules. However, as just mentioned, in certain states (such as no actionable output from the Navigation Module) the information in the Navigation Module can be fed back and stored in the Input Sensory Vectors Association Modules. When this happens then in the next cognitive cycle these intermediate results will automatically be considered as the input sensory information and propagated to the Navigation Module and operated on again. By feeding back and re-operating on the intermediate results, the Causal Cognitive Architecture is able to formulate and explore possible cause and effect of actions, i.e., generate causal behavior [13].

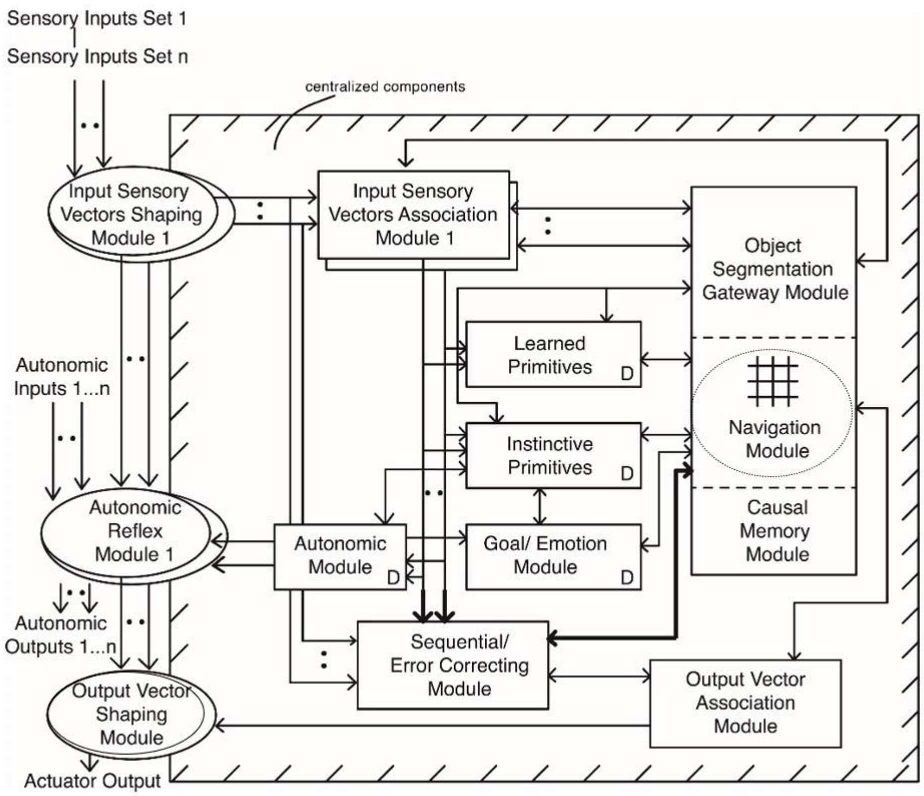

Fig. 1. Causal Cognitive Architecture 3 (CCA3)

LAND	LAND	WATER	LAND	LAND	LAND
LAND	WATER	WATER	LAND	LAND	LAND
LAND	WATER	WATER	LAND	LAND	LAND
LAND	WATER	WATER	LAND	LAND	LAND
LAND	WATER	LAND	LAND	LAND	LAND
LAND	WATER	LAND	LAND	LAND	LAND

Fig. 2. Example of a Navigation Map (6x6x0 spatial dimensions shown; non-spatial dimensions not shown)

Schneider [21] discusses how a small modification of the feedback algorithm from the Navigation Module to the Input Sensory Vectors Association Modules generates analogical results that may be more useful than simply feeding back and returning the intermediate results unchanged in the next cognitive cycle. Equations (101) – (107) below are presented in Schneider [21]. These equations are actually a continuation of the equations (1) – (92) in Schneider [13].

If the working navigation map **WNM’** that was produced from the sensory inputs did not result in any actionable result in the Navigation Module, then by default these results are as part of an analogical inductive process fed back to the Input Sensory Vectors Association Modules, where they will be temporally stored (101). (The symbol **WPR** in (101) represents the working primitive, i.e., the instinctive or learned primitive which is applied against the working navigation map **WNM'** in order to try to produce an action.) The procedure `feedback_intermediate` in (101) takes the working navigation map **WNM'** and breaks it up into local navigation maps **LNM**s representing its sensory components and stores the **LNM**s in their respective sensory modules in the Input Sensory Vectors Association Modules. The actual working navigation map **WNM'** still remains in the Navigation Module.

In (102) the working navigation map **WNM'** is matched against the various navigation maps stored in the Causal Memory Module and the best matching navigation map becomes the new working navigation map **WNM'**. The procedure `match_best_multisensory_navmap` in (102) is the same as the one in (61) in [13] and is described in more detail in this reference. (The variables in (101) – (107) have a "t" subscript indicating that they change with time. The symbol $\mathbf{WPR}_{t-1}$ in (107) represents the working primitive at time "t minus 1" cognitive cycle, i.e., the working primitive in the previous cognitive cycle. Similarly, $\mathbf{action}_{t-1}$ represents the action produced in the previous cognitive cycle.)

($\mathbf{action_t}$ ≠" move*" and $\mathbf{WPR_t}$ ≠ ["discard*"] and $\mathbf{WPR_t}$ ≠ ["feedback*"])
or $\mathbf{WPR_t}$ = ["analogical*"],
⇒Navigation_Module.`feedback_intermediate`($\mathbf{WNM'_t}$) (101)
⇒ $\mathbf{WNM'_t}$ = Causal_Memory_Module.`match_best_multisensory_navmap`($\mathbf{WNM'_t}$) (102)
⇒ **short_term_memory** $\in \mathrm{R}^{mxnxo}$ (103)
⇒ **short_term_memory** = $\mathbf{WNM'_t}$ (104)
⇒ $\mathbf{WNM'_t}$ = Navigation_Module.`next_map`($\mathbf{WNM'_t}$) (105)
⇒ $\mathbf{WNM'_t}$ = $\mathbf{WNM'_t}$ **– short_term_memory** (106)
($\mathbf{action_{t-1}}$ ≠ "move*" and $\mathbf{WPR_{t-1}}$ ≠ ["discard*"]) or $\mathbf{WPR_{t-1}}$ = ["analogical*"],
⇒ $\mathbf{WNM'_t}$ = Navigation_Module.`retrieve_and_add_intermediates` (107)

In (105) the navigation map which the new working navigation map **WNM'** linked to in the past, now is stored as the current working navigation map **WNM'**. The procedure `next_map` in (105) via the link addresses of the working navigation map **WNM'** loads the most recent navigation map which this **WNM'** linked to. This map now becomes the new **WNM'**. In (106) the difference between these two navigation maps, which essentially represents what happened in the past, is now stored as the working navigation map **WNM'**.

In the next cognitive cycle, in the procedure in (107) `retrieve_and_add_intermediates`, the Input Sensory Vectors Association Modules holding the intermediate results from (101) propagates these intermediate results back to the Navigation Module where they are added to (rather than replacing) the working navigation map, creating the new working navigation map **WNM'**. Now the working navigation map **WNM'** in the Navigation Module contains the action that occurred in the past of a similar working navigation map in a possible analogical situation. Schneider [21] gives a demonstration example going through these equations, revealing the utility of the analogical inductive solution in response to new situations.

3. Properties of the CCA3 Navigation Map-Based Cognitive Architecture

Many ways exist to compare artificial intelligence systems. Harel [22] gives a more conventional computer science approach in comparing different paradigms in algorithms and data usage. As noted above, Darwiche [8] distinguishes model-based and function-based approaches to AI solutions to problems. Russell and Norvig [4] classify AI systems in a variety of ways, but start off their book with the classification of artificial intelligence in terms of systems that act humanly, systems that think humanly, systems that think rationally, and systems that act rationally. Rosenbloom and colleagues [23, 24] have classified their common model of cognition as well as a vast range of AI approaches in terms of a sub/symbolic x a/symmetric x non/combinatory three-dimensional classification scheme. For example, a system that used first-order logic would be considered [combinatory, symbolic, symmetric] while a probabilistic graphical system would also be symmetric and symbolic but noncombinatory, i.e., [noncombinatory, symbolic, symmetric]. For example, a recurrent neural network would be considered [noncombinatory, subsymbolic and asymmetric].

While any of these and other schemes could be used to distinguish a navigation map-based cognitive architecture such as the CCA3 from other approaches towards artificial intelligence, we take a different but perhaps more relevant approach in this paper in its classification. We ask, what are the typical operations that a navigation map-based cognitive architecture uses in contrast to the typical operations used by other approaches to AI?

In Table 1 we list the typical, basic operations executed and properties possessed by a navigation map-based cognitive architecture, as represented by the CCA3 version described above that is enhanced with analogical core operations. Although under the Church/Turing thesis [22] the operations of the CCA3 can in that sense be performed by most other artificial intelligence systems, and vice versa, given current hardware capabilities, certain approaches to AI solutions for particular problems may be intractable compared to other approaches.

We will then compare the typical, basic operations performed and properties possessed by other approaches to artificial intelligence, as well as other cognitive architectures, against the list in Table 1. The typical, basic operations performed, and properties possessed could be quantified and thus allow numerical comparisons. However, at this point in our exploration of the navigation map-based cognitive architecture, it would not significantly increase our understanding.

1.	The existence of navigation map-like structures with the representation of the physical dimensions as well as the utilization of non-spatial dimensions, and their use as the core data and processing elements of the system
2.	The ability to match navigation map-like structures and determine closest matches, and compare same and different navigation map-like structures
3.	The ability to read and write cells of the navigation map-like structures and compare and perform simple manipulations on the cells of the navigation map-like structures
4.	The ability of navigation map-like structures and their cells to have links to other navigation map-like structures and their cells
5.	Mapping of input sensory data onto closest matching navigation map-like structures or create a new navigation map-like structure if needed
6.	Binding of the temporal features of the input sensory data as physical features onto the same or related closest matching navigation map-like structures
7.	Recognition of different continuous objects in the input sensory data and binding of object recognition onto the same or related closest matching navigation map-like structures
8.	Binding of multiple initial sensory data navigation map-like structures onto higher order navigation map-like structures
9.	The ability of the cells in the navigation map-like structures to hold data representative of features, and/or to hold links to other cells, and/or to hold simple operations which can be performed on another cell
10.	Simple operations which can be performed on other cells of the same or different navigation map-like structure including operations similar to: adding the contents of cells, subtracting the contents of cells, if one cell is larger than another cell make the other cell zero, if one cell is larger than another cell then add a value to the larger cell, if one cell is larger than another cell then operate on the cells linking to that cell
11.	The ability to learn new sequences of simple operations or to learn new sequences of compounded operations made up in turn by simple operations
12.	The ability of incoming sensory data to trigger the best matching built in or learned sequences of operations to operate on the incoming sensory data
13.	The ability to feed back the results of simple operations so as to be able to reprocess the intermediate results in the next cognitive cycle
14.	The ability to feed back the results of simple operations so as to be able to reprocess the intermediate results in the next cognitive cycle, looking for cause and effect of objects in the navigation map-like structure
15.	The ability to feed back the results of simple operations so as to be able to reprocess by analogic induction the intermediate results in the next cognitive cycle
16.	The ability to take an action signal produced, and convert it into an actual physical signal which can cause real world actuators to take action
17.	The ability to store the cause-and-effect results, the analogical induction results, the output actions, and provide an explanation for an output action in terms of the history of these results

Table 1. Basic Operations and Properties of a Navigation Map-based Cognitive Architecture

4. Differences between the Navigation Map-Based Cognitive Architecture and other Approaches to AI

Russell and Norvig [4] provide a comprehensive overview of existing approaches towards achieving artificial intelligence. We will compare what are essentially the different classes of artificial intelligence reviewed by Russell and Norvig with the navigation map-based cognitive architecture as represented by the CCA3 implementation above. These comparisons are summarized in Table 2.

Problems can be solved by agents that can search, and a number of search algorithms and heuristics are presented. The CCA3 also makes very extensive use of search and use of elements of search strategies described by Russell and Norvig, but it is a very specific search of navigation maps embedded as a very specific part of an overall architecture. Adversial search strategies and games as described by Russell and Norvig can be very advantageous to AI agents, but such strategies are not a part of the core operations of the CCA3, and need to be implemented through a combination of instinctive primitives and learned primitives.

Logic and knowledge-based agents as described by Russell and Norvig are an important approach towards AI. However, the CCA3 uses a very minor subset of first-order logic in its core operations, and again, embedded as a very specific part of an overall architecture. In order to exhibit the more complete first-order logic, or even propositional logic, described by Russell and Norvig, a combination of additional instinctive primitives and learned primitives are required. The core inference operation performed by the CCA3 is via the analogical inductive mechanism described above as well the feedback and repeated operations on intermediate results in order to tease out a cause-and-effect solution [13].

AI Approach (Russell, Norvig [4])	**CCA3 Significantly Different?**	**Summary of Explanation**
Search algorithms	Yes	Embedded, related to navigation maps
Adversial search, games	Yes	Not part of core operations; requires primitives
Logic-based agent	Yes	Repeated feedback and reprocessing of intermediate results to obtain cause-and-effect behavior and induction by analogy; emulation of first order logic requires primitives
Knowledge representation system	Yes	Simple, automatic organization of navigation maps at the core level; higher knowledge representation requires primitives
Automated planning system	Yes	Not part of core operations; emulation of any particular planning system requires primitives
Probabilistic-based system	Yes	Core operations use elements of probabilistic theory, but higher level of probabilistic-based system as described by Russell, Norvig requires primitives
Decision trees (and similar)	Yes	Not part of core operations although some elements present in relationships between navigation maps
Deep learning	Yes	CCA3 is a completely different architecture although elements of deep learning can be used on an individual navigation map
Reinforcement learning	Yes	CCA3 at present makes little use of RL; expect future versions to incorporate more but will be different, embedded application compared to RL described by Russell, Norvig
Recurrent neural networks, Transformers	Yes	CCA3 usage of feedback is very different

Table 2. Comparing properties of a Navigation Map-based Cognitive Architecture as represented by the CCA3 with AI Approaches Reviewed by Russell, Norvig [4]

While the CCA3 exhibits many aspects of ontological engineering in creating knowledge representation AI systems, note that the organization of navigation maps at the core operation level is a very simple and automatic mechanism in terms of binding of information onto navigation maps. At a higher level of organizing knowledge in the CCA3, this requires an interaction of the instinctive primitives and learned primitives in a fashion very different than the operations that occur in the knowledge representations systems reviewed by Russell and Norvig.

Automated planning systems are an important class of AI systems. However, the CCA3 does not perform any planning operations at the core operation levels other than dealing with certain signals from the autonomic module and the goal/emotion module (Figure 1). Different levels of planning in the CCA3 require interactions of the instinctive primitives and learned primitives, which of course, can duplicate the automated planning described by Russell and Norvig. However, such planning is occurring by a very different mechanism than would be used by typical systems to implement planning systems.

Probabilistic-based systems are reviewed by Russell and Norvig and form an important approach to artificial intelligence. At a core operation level, the CCA3 utilizes elements of probabilistic reasoning in terms of the strength of links and the frequency certain data is bound via one navigation map to another navigation map. However, the higher level probabilistic reasoning described by Russell and Norvig can be duplicated in the CCA3 but via the interactions of the instinctive primitives and learned primitives, using a very different underlying mechanism.

Machine learning of decision trees and of parametric models form important approaches that an agent can use to approach artificial intelligence. Developing this topic Russell and Norvig then move on to the contemporary dominant approach to artificial intelligence of deep learning. While the CCA3 can use elements of deep learning within a given navigation map, the architecture of the CCA3 is vastly different than typical deep learning networks. The different navigation maps of the CCA3 are interconnected sparsely, and in fact, can exhibit continual learning which is not easily possible with deep learning networks [13].

Reinforcement learning is an important approach towards artificial intelligence. At present, the CCA3 makes little use of reinforcement learning other than the frequency of some events and outcomes in binding of the input sensory data and the usage of certain instinctive primitives. It is expected that future versions of the CCA3 will more extensively make use of reinforcement learning. However, as before, the usage of this approach to artificial intelligence will be embedded and particular to the architecture of the CCA3. There are elements of recurrent neural networks and transformers in the CCA3 given the latter's heavy usage of feedback pathways, but as before, the usage of these elements is very different than as used in a typical recurrent neural network.

5. Discussion

As described above, a navigation map-based cognitive architecture uses versions of navigation maps as a store of procedural memories, semantic memories, episodic memories, as well as for working memories. Perceptual inputs are mapped to navigation maps and motor outputs are prepared on navigation maps. The Causal Cognitive Architecture 3 (CCA3) [13] is an example of navigation map-based cognitive architecture. In the CCA3, objects detected in the streams of sensory features are segmented, and visual, auditory, and other sensory features of each segmented object are spatially mapped onto navigation maps dedicated to one sensory system. These newly created or updated single-sensory navigation maps are then mapped onto a best matching multi-sensory navigation map taken from the Causal Memory Module (Figure 1) and moved to the Navigation Module. Instinctive and learned primitives, which act as small rules or productions, and which also are stored in modified navigation maps, then operate on the working navigation map. This causes the Navigation Module to produce and send a signal to the Output Vector Association Module and then to the external embodiment (Figure 1).

Also as described above, in a navigation map-based cognitive architecture such as the CCA3 the feedback pathways between the Input Sensory Vectors Association Modules and the Navigation Module/ Object Segmentation Gateway Module are enhanced so that they allow intermediate results from the Navigation Module to be stored in the Input Sensory Vectors Association Modules (Figure 1). If there is no actionable output from the Navigation Module, then the information in the Navigation Module can be fed back and stored in the Input Sensory Vectors Association Modules. When this happens then in the next cognitive cycle these intermediate results will automatically be considered as the input sensory information and propagated to the Navigation Module and operated on again. By feeding back and re-operating on the intermediate results, the Causal Cognitive Architecture can formulate and explore possible cause and effect of actions, i.e., generate causal behavior [13] as well as allow induction by analogy [21].

In Table 1 above we listed the core operations and properties of a navigation map-based cognitive architecture such as the CCA3. We then compared this list of core operations and properties with the basic operations and properties of other approaches towards achieving artificial intelligence, taken from Russell and Norvig's comprehensive review of the field [4]. In performing this comparison, we showed that the navigation map-based cognitive architecture, as represented for example, by the CCA3, represents a different class of an approach towards artificial intelligence.

As discussed above the analysis was a qualitative one. As well, note that we did not consider which approaches to artificial intelligence are more useful than others but simply compared what are the basic operations performed and properties possessed. Until there is a more robust set of instinctive primitives and learned primitives in the CCA3, it is hard to realistically assess its potential real-world performance.

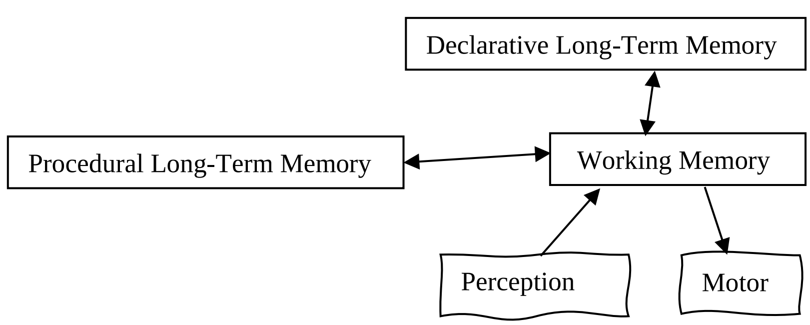

Fig. 3. Standard Model of the Mind

This paper considered the navigation map-based cognitive architecture as a different class of an approach towards artificial intelligence by comparing it to the approaches in Russell and Norvig's review of the field [4]. Unfortunately, Russell and Norvig only included a small single paragraph mentioning cognitive architectures. There is a large field of different cognitive architectures

[25, 26]. However, Laird, Lebiere and Rosenbloom [27] have proposed a standard model of the mind (Figure 3), which in an analogous fashion to the physics standard model, attempts to unify the various cognitive architectures modelling the mind. They show, for example, how this standard model unifies features from the popular ACT-R, Soar and Sigma cognitive architectures. As seen in Figure 3, the standard model of the mind would seem generic enough to accommodate most cognitive architectures. However, there are core operations in the navigation map-based cognitive architecture as represented by the CCA3, which are not easily feasible in the even this very generic model. For example, the declarative long-term memory and the procedural long-term memory in the CCA3 can link directly between each other, and actually can be stored within the same navigation map. For example, the mapping of data onto navigation maps which are then bound along with temporal features onto further navigation maps is a key feature of the CCA3 and is not really represented by the standard model of the mind. For example, the key ability to feedback intermediate results and obtain cause-and-effect results as well as analogous inductive inference from this process, is not really supported by the standard model of the mind.

The navigation map-based cognitive architecture is still at an early stage in its development. However, as shown above, it represents a new and a different class of artificial intelligence as well as cognitive architecture.

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