Causal Cognitive Architecture 2: A Solution to the Binding Problem

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Abstract. The binding problem is considered in terms of how the brain or another cognitive system can recognize multiple sensory features from an object which may be among many objects, process those features individually and then bind the multiple features to the object they belong to. The Causal Cognitive Architecture 2 (CCA2) builds upon its predecessor with the Navigation Module now consisting of an Object Segmentation Gateway Module allowing segmentation of a sensory scene, the core Navigation Module where the navigation maps are operated on, and the Causal Memory Module storing navigation maps the CCA2 has made in the course of its experiences. Objects within an input sensory scene are segmented, and sensory features (i.e., visual, auditory, etc.) of each segmented object are spatially mapped onto a navigation map in addition to a mapping of all objects on another navigation map.

Keywords: binding problem, cognitive architecture, spatial navigation, artificial general intelligence

1 Introduction

1.1 The Binding Problem

Different sensory features, both between and within sensory systems, are often processed by different assemblies in the mammalian brain. For example, it is known that visual motion and color sensory inputs are processed in different brain regions with only sparse connections between them [1]. The "binding problem" considers how the brain can recognize and then essentially "bind" these separately processed pieces of data [2]. The binding problem has been considered key to explaining the unity of one's experience of consciousness [3,4] and the obvious extension to creating more general forms of artificial intelligence. However, in this paper, we consider only a narrow mechanistic aspect of the binding problem, i.e., what is a possible mechanism to segment objects and in particular combine back sensory features so that a single object is recognized.

A number of solutions to the binding problem have been described in the literature. Olshausen and colleagues [5] proposed that attention is focused on a particular region in a visual scene for example, with particular features fed forward to higher visual processing areas. A longstanding proposed solution to the binding problem has been temporal synchronization of the firing of neurons in different cortical areas with sensory features associated with a given object. For example, work by Engel and colleagues [6] showed neuronal oscillations in the cat visual cortex at separate sites can transiently synchronize and were affected by features of the visual input data. Shadlen and Movshon [7] considered the experimental evidence which was not fully supportive of this hypothesis. Merker [8] suggested that the synchronized gamma range neuronal oscillations, thought to be important in binding sensory input features, may simply be reflecting activation of cortical areas, and have little other function.

Kahneman, Treisman and Gibbs [9] proposed an "object-file theory" that different input features of an object are bound by their location. If in a visual scene there are three different objects, then three location tags are created to bind to various features. Goldfarb and Treisman [10] suggested that the ability of the brain to represent temporary object files as such, gives rise to an arithmetic system in humans as well as in animals. As well, Goldfarb and Treisman suggested how the above neural synchronization hypothesis can successfully work with the object-file theory discussed above. A location tag for each object exists, but the features for a particular object are bound by neuronal oscillation synchronization of features with a particular location. Thus, the features of different objects are not erroneously bound to each other.

Isbister and colleagues [11] described polychronous neuronal groups which contain binding neurons that with training learn to bind features of objects between lower and higher visual cortical levels. As such Isbister and colleagues believed this to be a solution to the binding problem in the primate visual system. However, at the time of this writing, a well-proven mechanism for the binding of input sensory features to various real-world objects sensed in the brain, remains unresolved.

1.2 The Neural-Symbolic Gap

Artificial neural networks (ANNs) can recognize patterns and perform reinforcement learning at a human-like proficiency [12, 13]. However, compared to a four-year old child, in terms of logically and causally making sense of their environment or a problem at hand, especially if training examples are limited, they perform poorly [14, 15]. This is sometimes referred to as the neural-symbolic gap [16].

A number of cognitive architectures integrate subsymbolic and symbolic processing to varying degrees [17, 18]. A review of the field by Langley [19] noted that while early models were mainly symbolic, many of the modern architectures are more hybrid. Lake and colleagues [20] proposed that thinking machines should build causal models of the world and discussed intuitive physics and psychology present in infants. Epstein [21] discussed cognitive and robotic modeling of spatial navigation. Hawkins and others [22, 23] described how abstract concepts can be represented in a spatial framework.

Despite many of the above designs and implementations combining ANNs and symbolic elements, they do not approach the causal abilities seen in human children.

The Causal Cognitive Architecture 1 (CCA1) and its predecessors combined connectionist and symbolic elements in a biologically plausible manner in which sensory input vectors were processed causally [24 – 27]. A collection of intuitive and learned logic, physics, psychology and goal planning procedural vectors (essentially acting as small algorithms) are applied against inputs, and intermediate causal results can be fed back to the sensory input stages and processed over and over again. An overview of the CCA1 is shown in Figure 1. As will be discussed below, in toy examples, the CCA1 seemed to narrow the neural-symbolic gap, i.e., it offered connectionist pattern recognition along with the ability to *generate* causal behavior, i.e., to take actions from exploration of possible cause and effect of the actions.

1.3 The Binding Problem and the Causal Cognitive Architecture

An issue relevant to both cognitive science and artificial intelligence is the binding problem—how can the brain or another cognitive system recognize multiple sensory features from an object which may be among many objects, process those features individually and then bind the multiple features to the object they belong to?

In work to enhance the abilities of the CCA1, particularly with regard to the neuro-symbolic gap, it is shown below how removing the Sensory Vectors Binding Module (Figure 1) in the CCA1 led to the development of the CCA2, and improved its abilities to bind sensory input features to an object.

2 Functioning of the Causal Cognitive Architecture (CCA1)

2.1 Sensory Processing in the CCA1

We start with an overview of the CCA1 before moving onto the CCA2. A summary of the architecture of the CCA1 is shown in Figure 1. Sensory Inputs 1..n from different sensory systems 1..n, propagate to the Input Sensory Vectors Association Modules 1..n, with a module dedicated for each sensory system. Each such module contains a conventional neural network [12] or a hierarchy of Hopfield-like Network units (HLNs) [24], or other similar mechanism that can robustly associate an input sensory vector with other vectors (previously learned ones, instinctive pre-programmed ones, as well as other recent sensory input vectors) within the CCA1. Further binding of the processed input sensory vectors, via straightforward temporal mechanisms, or more complex global feedback mechanisms, occurs within the Sensory Vectors Binding Module.

2.2 Pre-Causal Cognitive Processing and Output

Cognition in the CCA1 is fundamentally movement-based. At the simplest level, the CCA2's embodiment navigates through physical space, although at higher cognitive levels navigation occurs through a space of concepts and analogies. This is discussed more in Schneider [27].

In the CCA1 the Navigation Module holds a current navigation map of a small part of the inferred physical world. Represented on this modest map are objects from the Sensory Vectors Binding Module, an object representing the CCA2 embodiment itself, and possible objects from the Instinctive Primitives Module and the Learned Primitives Module.

The Instinctive Primitives Module and the Learned Primitives Module are triggered by processed vectors from the Input Sensory Vectors Association Module, the Sensory Vectors Binding Module, as well as by the Goal/Emotion Module and the Autonomic Module. The Instinctive Primitives Module and the Learned Primitives Module can manipulate the representations of the objects in the current navigation map and produce an output signal. This output signal from the Navigation Module causes the

Output Vector Association Module to produce the desired movement of the embodiment of the CCA1.

2.3 Causal Cognitive Processing and Output

In pre-causal operation of the CCA1, associations are made in the Input Sensory Vectors Association Modules and other modules described above. The Navigation Module effectively allows pre-causal processing since objects and rules are being applied by the Instinctive and Learned Primitives Modules onto the current navigation map. Then the Navigation Module makes a navigation decision which becomes the output of the CCA1.

In causal operation, a more significant feedback pathway from the Navigation Module to the Input Sensory Vectors Association Modules allows the intermediate results of a problem or a causal situation to be fed back to the sensory input stages, and processed again in the next processing cycle. This is described in more detail in Schneider [27]. Essentially, intermediate results can be fed back to the sensory input stages and then processed by the Navigation Module, then repeated as needed. As shown in the simulation example below, in this manner, causal processing of the inputs often results.

The navigation maps are stored in the Causal Memory Module. When similar events occur again, the most relevant navigation map(s) are activated and recalled into the Navigation Module, and thus provide the CCA1 with an instant possible model of the world and actions it took previously.

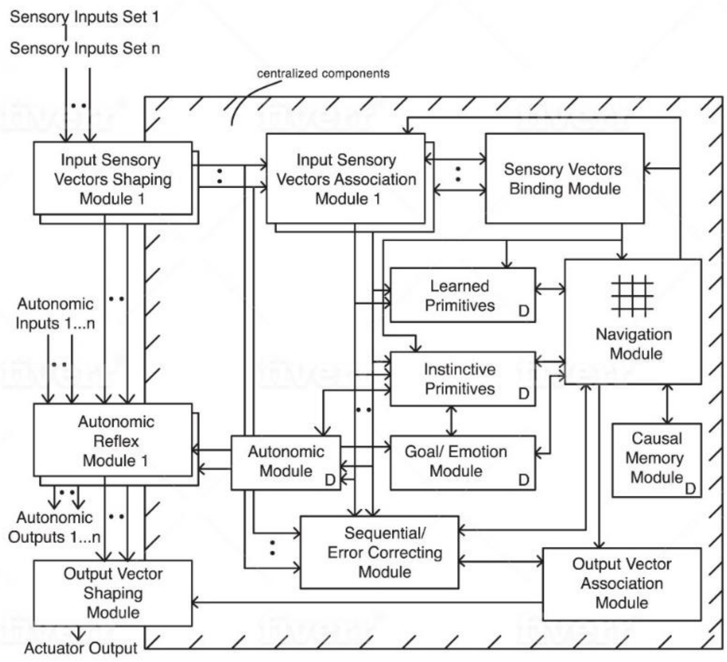

Fig. 1. Causal Cognitive Architecture 1 (CCA1)
(Not all connections shown. D – Internal Developmental Timer)

2.4 Pre-Causal Mode CCA1 Simulation Example

An embodiment of the CCA1 plus the CCA1 itself (both together informally referred to as "the CCA1") must enter a simulated grid world forest, and find and rescue a lost hiker. Figure 2 shows the starting position of the CCA1 in this grid world.

Consider a simulation example. After a number of moves, the CCA1 ends up in the square "forest" just north of the square "waterfall." (Note that "waterfall" is labeled in the map in Figure 2 for the convenience of the reader. The CCA1 does not know this square is a waterfall nor have access to this map's information—it must try to build up its own internal map.)

In the next few processing cycles the CCA1 recognizes a lake to the west (which the Instinctive Primitives Module signals to avoid movement to) and to the south a shallow river with fast flowing noisy water (the cliff part of the waterfall is not visible). A shallow river does not trigger any avoidance signals in the Instinctive Primitives Module and the CCA1 moves south to the square labeled "waterfall" in Figure 2. It is swept by the fast-moving river over the waterfall's cliff and is damaged.

Associative learning does occur. The next time the CCA1 recognizes a fast-flowing river with much noise, then this will trigger in the Goal/Emotion Module and the Learned Primitives Module a signal to the Navigation Module not to navigate to this square.

2.5 Causal Mode CCA1 Simulation Example

A brand new CCA1 starts off in a new simulation, again starting off as shown in Figure 2, and after a number of moves, it happens to navigate again to the square "forest" just north of the square which in Figure 2 (intended only for the reader) is labelled a "waterfall."

The CCA1 recognizes to the south a shallow river with fast flowing noisy water (the cliff part of the waterfall is not visible). This new CCA1 has never seen a waterfall before. However, {"water"} + {"fast flow" + "noise"} triggers in the Instinctive Primitives Module {"water"} + {"push"} which is sent to the Navigation Module.

The Navigation Module is unable to further process the vector representing {"water" + "push"}. Thus, it feeds it back to the Input Sensory Vectors Association Module. In the next processing cycle, the Input Sensory Vectors Association Module ignores the external sensory inputs, but instead forwards the intermediate result {"water" + "push"}, as if it is the new sensory input.

{"water" + "push"} triggers in the Instinctive Primitives Module a vector propagated to the Navigation Module which causes the Navigation Module to create a new current navigation map. On this new map is an object representing the CCA1 and objects representing water on much of the map. The Navigation Module feeds {"CCA1 under water"} back to the Input Sensory Vectors Association Module. In the next processing cycle, the Input Sensory Vectors Association Module ignores the external sensory inputs, but forwards the intermediate result {"CCA1 under water"} as the sensory input. This triggers in the Instinctive Primitives module a vector representing "do not go" which is propagated to the Navigation Module. This triggers the Navigation Module to load the previous current navigation map of the forest, and "do not go" applies to the square south, i.e., the "waterfall." The CCA1 recognizes the square to the east as forest and moves instead there.

Note that all these processing cycles were triggered from one to another, with no central controlling stored program, other than the basic architecture of the CCA1.

EDGE	*EDGE*	*EDGE*	*EDGE*	*EDGE*	*EDGE*
EDGE	CCA1 *	forest	shallow river	forest	*EDGE*
EDGE	lake	forest **	forest	forest	*EDGE*
EDGE	forest	water-fall	forest	forest	*EDGE*
EDGE	forest	HIKER	forest	forest	*EDGE*
EDGE	*EDGE*	*EDGE*	*EDGE*	*EDGE*	*EDGE*

Fig. 2. Birds-Eye View of the Starting Positions of the CCA1 and the Lost Hiker
(Note: For the reader. The CCA1 does not possess this information but must construct its own internal current navigation map)

3 The evolution of the CCA2 from the CCA1

3.1 Problems Arising in Attempts to Enhance the CCA1

The Causal Cognitive Architecture 1 (CCA1) appears to be able to narrow the neural-symbolic gap. However, the examples described above are toy problems—very simplified problems without the complexity found in real world examples. Thus, further development work began on the CCA2 which was to be a more robust version of the CCA1.

The CCA2, like the CCA1, incorporated several sensory input systems, and received visual, auditory, and olfactory features of objects and the environments in the direction in front of itself. An issue which arose in attempting to create a more robust system, i.e., the CCA2, is that Sensory Vectors Binding Module must output some vector which represents the object/environment it has detected by fusing the sensory features together and then using neural network-like pattern recognition to identify the objects and the sensory scene. (We will use the term “sensory scene” or just “scene” for short to refer to the sensory stimuli being presented to the CCA1 or CCA2—visual, auditory, olfactory, etc.) The output vector from the Sensory Vectors Binding Module then goes to the Navigation Module, the Instinctive and Learned Primitives Module, and several other modules, as shown in Figure 1.

Once examples become even modestly larger than the toy problems of the lost hiker in the simulated forest (or the three gears in Schneider [27]), it becomes extremely difficult for the other modules to understand what it is exactly that the Sensory Vectors Binding Module is recognizing. Is a sensory scene with a few trees, some large rocks, the sound of fast flowing water and the algae-like water odor identified the same as a scene with no trees at all but containing rocks, the fast-flowing water sound, and algae-like water odor, or the same as a scene of no trees but containing some large rocks and sounds of fast-flowing water, but with the distant smell of pine needles?

In the toy examples above we can use a convolutional neural network (CNN) or equivalent to crudely classify the sights, sounds, and smells to a forest square, an edge square or a waterfall/fast river square. However, once we allow even a slightly larger combination of features to be classified and reported to the Navigation Module, the conundrum arises of how to label different combinations detected by the Sensory Vectors Binding Module.

Even if we devise a training scheme to produce a variety of different labels for different combinations of sensory input features in the Sensory Vectors Binding Module, how does the Navigation Module, the Instinctive Primitives Module, the Learned Primitives Module and so on (Figure 1), process particular labels, i.e., the output vectors from the Sensory Vectors Binding Module? There is also another issue of how the system handles the addition or loss of a sensory system. For example, if vision inputs are occluded and the CCA1 only receives auditory and olfactory inputs for a scene, how does the Sensory Vectors Binding Module use this reduced information to make a decision?

3.2 Elimination of the Sensory Vectors Binding Module and the Emergence of the CCA2

Over the last decade many techniques have been developed to avoid brittleness in deep learning networks, i.e., not being able to recognize even slightly out-of distribution sensory representations of an object [12]. For example, Chidester and colleagues [28] discuss using CNNs to automatically analyze high volumes of microscope slide images. A problem is that different microscopic images of the same classification category may be somewhat rotated to each other. If a large variety of rotated versions of the microscopic images are available for training, then the CNN can become somewhat rotation-invariant. However, Chidester and colleagues note that biological data is often limited or costly to obtain, and thus they use various schemes (e.g., group convolution, conic convolution) to obtain the rotation-invariance so that their deep learning network will more accurately classify microscopic images that may have different rotations.

Applying various regularization techniques to reduce generalization errors within a particular sensory system in the CCA1 is advantageous. However, they do not adequately deal with the issues which arise when, for example, a complete sensory system or several sensory system inputs are not available. Although various engineering workarounds were considered to allow the Sensory Vectors Binding Module to better handle varying levels of sensor fusion, the conundrum raised above still remains—how to label different combinations detected by the Sensory Vectors Binding Module and feed this signal to the Navigation Module and other Modules. If through various sensor fusion techniques, the Sensory Vectors Binding Module classifies the input object and thus produces a symbolic output (e.g., forest or edge or fast-moving river, etc) this can be fed to the Navigation and other modules (and in fact is what occurs in the CCA1 toy models). However, the problem is that if there are a number of possible sensory systems, each with a number of possible sensory features, and there are a number of possible objects in the scene to be analyzed, there is an explosion of combinations possible, making processing a particular symbol for each possible combination unwieldly to handle.

The decision was thus made in the CCA2 to eliminate the Sensory Vectors Binding Module. Binding of the various sensory inputs will thus take place directly in the Navigation Module. The Input Sensory Vectors Association Modules still remain in the CCA2 for the various sensory modalities, although they function largely to preprocess sensory input signals, providing some classifications to help with segmentation, which will be discussed in the next session, and to help trigger more rapidly various Learned and Instinctive Primitives. Binding of the input sensory features no longer occurs in a “Binding Module” but in the Navigation Module.

4 Mechanism of Sensory Binding in the CCA2

4.1 Multiple Objects in a Scene

An overview of the architecture of the CCA2 is shown in Figure 3. While it is similar to the CCA1, the Sensory Vectors Binding Module is no longer present. As well, the Navigation Module has an Object Segmentation Gateway Module leading into it. In addition, the Causal Memory Module is more of an integral part of the Navigation Module now.

The function of the Object Segmentation Gateway Module is to segment a sensory scene into objects of interest. (As noted above we use the term “sensory scene” to refer to the sensory stimuli being presented to the CCA2—visual, auditory, olfactory, etc.) The individual objects segmented in the sensory scene, as well as the entire scene itself treated as one composite object, will then trigger navigation maps in the Causal Memory Module to be retrieved and moved to the Navigation Module.

A limited generative process is used in combination with an assembly of recognition units (e.g., CNN or other neural network). If a particular segmentation of the sensory scene better matches one stored navigation map (for example, a particular river) than another stored map, then that particular navigation map (for example, a particular river) in the Causal Memory Module will be transferred to the Navigation Module. (Actually, data is not transferred as in a typical computer architecture, but instead that navigation map is activated.)

4.2 Binding Sensory Features of a Sensory Scene to an Object

For simplicity and to better explain binding in the Navigation Module, we will assume there is a single object (or single collection of objects representing a composite object) in the sensory scene. The Object Segmentation Gateway Module (Figure 3) propagates the sensory features of this object to the Navigation Module. For example, as shown in Figure 4, the CCA2, looking for the lost hiker in the simulated forest grid world, is presented with a sensory scene of what *we* call a “river.” However, to the

CCA2 there are emerging out of the Input Sensory Vectors Association modules olfactory, auditory and visual sensory features.

These sensory features propagate to the Object Segmentation Gateway Module. As noted above, for simplicity we consider a single object here. These sensory features are then propagated to the Navigation Module. (Actually, they are already within the Navigation Module since in the CCA2 the Object Segmentation Gateway Module, the Navigation Module and the Causal Memory Module are all tightly integrated. It is often not necessary to transfer data from one part to another of the module, but simply activate data structures of interest.)

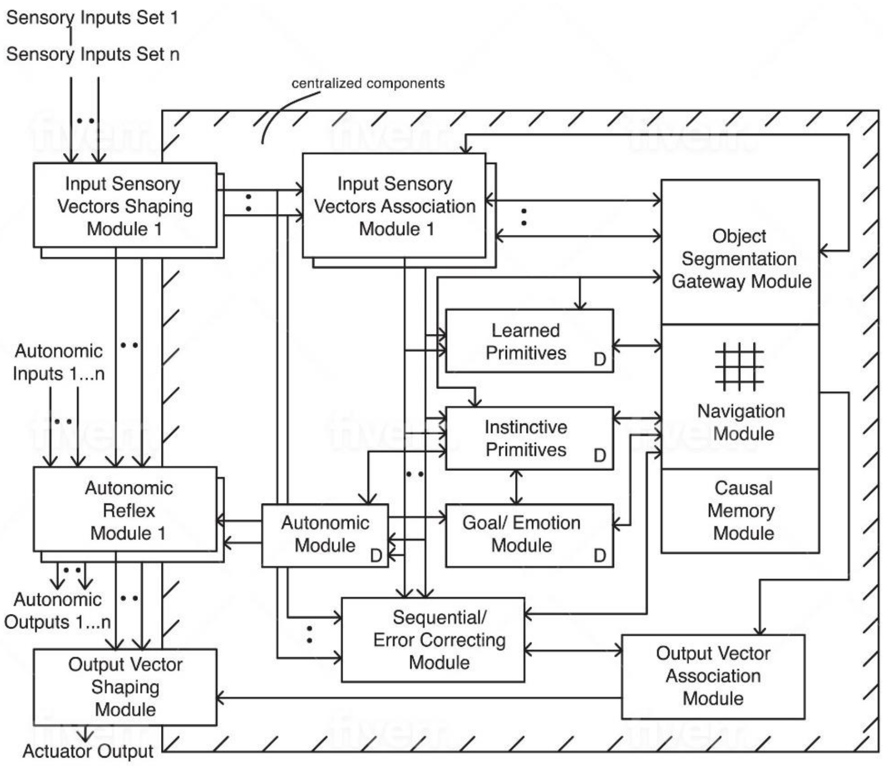

Fig. 3. Causal Cognitive Architecture 2 (CCA2)
(Not all connections shown. D - Internal Developmental Timer)

An existing navigation map that has similar sensory features of the sensory scene is recalled from the Causal Memory Module, e.g., a map of a previous "river" that the CCA2 had seen. (Actually, a number of navigation maps are recalled and are operated on in parallel allowing a generative aspect to finding the most suitable navigation map to use, but for simplicity in the discussion here we consider a single navigation map.) The sensory features of the sensory scene that are being propagated to the Navigation Module are now mapped onto the recalled navigation map or a copy of it, thus changing this to a newer navigation map.

Sensory features are spatially bound onto the navigation map. As shown in Figure 4, lines demarcating water from land are stored onto the navigation map. It is not an artistic reproduction of the scene but rather a representation of how the CCA2 senses it. Bubbling sounds are mapped onto two places on this navigation map. An algae-like smell is also mapped onto a location on this navigation map. The CCA2 uses navigation maps as its main storage of data. Note that the binding of separate streams of sensory data occurs automatically in a spatially oriented fashion onto a navigation map.

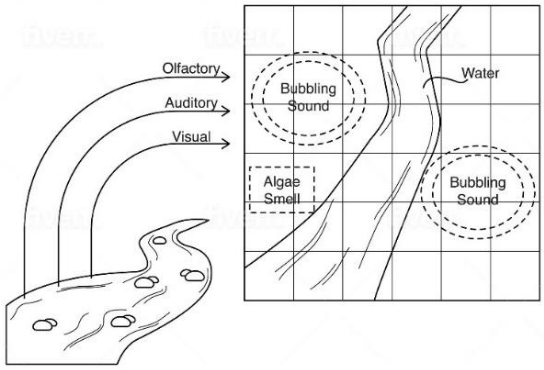

Fig. 4. Different sensory features are bound onto a navigation map representing the object, in this case a river

All the words and shapes on the map in Figure 4 are the lowest-level sensory primitives for the CCA2. “Water”, “bubbling sound”, “algae odor”, and the lines of the river are sensory primitives. While, of course, water, for example, requires even lower-level visual sensory features, it is considered a recognizable sensory feature and treated in the CCA2 as a lowest-level sensory primitive.

Not shown in Figure 4, and beyond the scope of this paper’s subject, are links between navigation maps. However, the operations on the navigation maps by the procedural vectors from the Instinctive and Learned Primitives Modules and other modules, and the connections between navigation maps are discussed in Schneider [27]. Figure 4 does not classify the sensory scene as a river, but there can be links between Figure 4 (and other navigation maps similar to it) to other navigation maps holding language words such as “river.”

While in Figure 4 the features in the map are the lowest-level sensory primitives, it is possible, and indeed an important element of advantageous cognitive behavior, to hold higher-level complex objects and properties, on a navigation map, which link to other navigation maps and in turn to yet other navigation maps. For example, a tiny crude image of sorts of the lost hiker (not shown in Figure 4 but would exist in another square of the simulated grid world forest) could be part of a navigation map representing the CCA2’s internal map of the forest. However, the tiny crude image of sorts of the lost hiker would link to another navigation map(s) that contains more information about the lost hiker. The Causal Memory Module of the CCA2 contains navigation maps, all linked to a variety of other navigation maps.

4.3 A Solution to the Binding Problem

As shown in Figure 4, it does not really matter that sensory features are processed in distinct streams, since they are all mapped onto a common navigation map. The various visual features—edges, colors, and so on, are mapped onto the map. The auditory features are also mapped onto the map, as best as the location of the sounds can be determined. The olfactory features are mapped onto the map. As shown in Figure 4 the purpose of this navigation map is not to classify the river as a "river" but to spatially map the sensory features onto a navigation map, which is the common data structure used by the CCA2.

The binding problem was described above as how the brain or other cognitive system can recognize multiple sensory features from an object which may be among many objects, process those features individually and then bind the multiple features to the object they belong to. The Object Segmentation Gateway Module described in the section above, allows segmenting a number of objects in a sensory scene. Sensory features for each object are then spatially mapped onto a navigation map. Although not shown in Figure 4, since for simplicity we only have one object (i.e., the river), scenes containing multiple objects are also mapped onto another navigation map (i.e., providing a composite map of the whole scene) with links to their individual navigation maps.

The navigation map-based structure of the architecture requires data stored in and operated on in the form of navigation maps. Binding operations are implicit in the operation of the CCA2. Note that if a sensory system is unable to be used (for example, the visual sensors are blocked) and the other sensory systems available are reasonably functional, the same navigation maps can end up being used—the CCA2 still has almost the same representation of the world and can take similar operations on this navigation map-based representation of the world.

As discussed in Schneider [27] the causal cognitive architecture easily allows the emergence of pre-causal behavior for straightforward operation. It easily allows the emergence of full causal behavior as well the as the possibility of psychosis (both occurring in humans but weakly or rarely in other mammals) when the intermediate results from the Navigation Module are fed back to the sensory modules and operated on again in the next processing cycle. It easily allows the emergence of analogies. In this paper, we discuss how with modest modifications of the CCA1 to the CCA2, the causal cognitive architecture readily handles the binding of sensory features, even if these features are processed separately. The causal cognitive architecture is brain inspired. Given that a navigation map-based data structure is required for its operation, it is hypothesized that a similar functional requirement applies to mammalian including human brains, and that this map-based structure allows the brain to bind sensory features from an object, even if the sensory features have been processed separately.

5 Discussion

There are theoretically a myriad of different mechanisms which can produce a general intelligence (i.e., artificial general intelligence in the case of machines) but at the time of this writing there is only one which exists in practice—the human brain. Hence, it was worthwhile to consider the binding problem, an aspect of the brain which continues to intrigue neuroscientists, cognitive scientists as well as neurophilosophers.

The CCA1 and its predecessors [24, 26, 27] were originally designed to consider other questions of animal and human brain function: Why do humans but not other animals demonstrate robust causality? Why do humans but not other animals demonstrate psychosis with any significant frequency? Why does navigation appear to be a basic ability of most animals, and in mammals be a basic function of the hippocampal-entorhinal system? In this paper we consider another question of animal and human brain function: What is a solution to the binding problem?

While the CCA2 may only loosely (or even incorrectly) model the biological binding process, by attempting to answer this question the CCA2 is able to surpass the CCA1 in being able to better process sensory scenes involving multiple objects with multiple sensory features involving multiple different sensory systems.

As noted above, in this paper, the binding problem is considered in terms of how the brain or another cognitive system can recognize multiple sensory features from an object which may be among many objects, process those features individually and then bind the multiple features to the object they belong to. In order to do so, the Sensory Vectors Binding Module of the CCA1 is removed and instead binding now occurs within the Navigation Module. In the CCA2 the greater Navigation Module now consists of an Object Segmentation Gateway Module allowing segmentation of a sensory scene, the Navigation Module where the navigation maps are operated on, and the Causal Memory Module storing navigation maps the CCA2 has made in the course of its experiences.

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