ARTIFICIAL INTELLIGENCE SOFTWARE STRUCTURED TO SIMULATE HUMAN WORKING MEMORY, MENTAL IMAGERY, AND MENTAL CONTINUITY

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ABSTRACT

This article presents an artificial intelligence (AI) architecture intended to simulate the human working memory system as well as the manner in which it is updated iteratively. It features several interconnected neural networks designed to emulate the specialized modules of the cerebral cortex. These are structured hierarchically and integrated into a global workspace. They are capable of temporarily maintaining high-level patterns akin to the psychological items maintained in working memory. This maintenance is made possible by persistent neural activity in the form of two modalities: sustained neural firing (resulting in a focus of attention) and synaptic potentiation (resulting in a short-term store). This persistent activity is updated iteratively resulting in incremental changes to the content of the working memory system. As the content stored in working memory gradually evolves, successive states overlap and are continuous with one another. The present article will explore how this architecture can lead to gradual shift in the distribution of coactive representations, ultimately leading to mental continuity between processing states, and thus to human-like cognition.

Like the human brain, the working memory store will be linked to multiple topographic map generation systems of various sensory modalities. As working memory is iteratively updated, the maps created in response will amount to sequences of related mental imagery. This system couples these components by embedding them within a multilayered neural network of pattern recognizing nodes. Nodes low in the hierarchy are trained to recognize and represent sensory features and are capable of combining individual features or patterns into composite, topographical maps or images. Nodes high in the hierarchy are multimodal and have a capacity for sustained activity allowing the maintenance of pertinent, high-level features through elapsing time. The higher-order nodes select new features from each mapping to add to the store of temporarily maintained features. This updated set of features are fed back into lower-order sensory nodes where they are continually used to guide the construction of successive topographic maps. Thus, neural networks emulating the prefrontal cortex and its interactions with early sensory and motor cortex capture the imagery guidance functions of the human brain. This sensory and motor imagery creation, coupled with an iteratively updated working memory store may provide an AI system with the cognitive assets needed to produce generalized intelligence.

KEYWORDS: artificial intelligence, iterative updating, working memory, consciousness, superintelligence
ARTIFICIAL INTELLIGENCE SOFTWARE STRUCTURED TO SIMULATE HUMAN WORKING MEMORY AND MENTAL CONTINUITY

“In order for a mind to think, it has to juggle fragments of its mental states.”

Marvin Minsky, 1985.

Introduction

This article takes a model of working memory published in Physiology and Behavior in 2016 (Reser, 2016) and explains how it can be implemented in a machine to make AI information processing more like the cognitive processing that goes on in the human brain. The model emphasizes that persistent neural activity in the brain permits multiple representations to remain coactive over time. It also causes successive mental states to overlap in regard to the representational content they hold.

The novel processing architecture introduced here involves the emulation of the mammalian cerebral cortex utilizing a network of pattern recognizing nodes for: selecting priority stimulus features, temporarily maintaining these features in a limited capacity working memory store and using them as parameters to search long-term memory for pertinent updates to working memory. The article will argue that by continuously updating the working memory store in an iterative fashion (Reser, 2016), such a system could exhibit cognitive abilities not seen using current methods.

The pattern of activity in the brain is constantly changing, but because the activity in certain neurons persists during these changes, particular features of the overall pattern can be uninterrupted or conserved over time. In other words, the distribution of active neurons in the brain transfigures gradually and incrementally from one configuration to another, instead of changing all at once. If it were not for the phenomena of persistent neural activity, successive mental states would be discrete and isolated rather than continuous with each other. Thus, the human brain is an information processing system that has the ability to maintain a large pool of representations that is perpetually in flux as new representations are constantly being added, some are being removed and still others are being maintained. The present device will be constructed to mimic this biological phenomenon, common to all vertebrates, but do it in a particularly mammalian manner. Because a large number of neural nodes in the mammalian cerebral cortex are always being sustained, each brain state is embedded recursively in the previous state, amounting to a progressive process that can move toward a complex result.

Contemporary AI has its weights frozen after training and cannot continue learning. Because it cannot learn it generally sits idle between processing tasks. Also, it does not reconcile information from multiple specialized processors like the human brain does. Iterative updating will change all of this. Properly integrated with existing AI technology, this method may have the potential to
enhance the capabilities of problem-solving agents with respect to pattern recognition, analytics, prediction, adaptive control, decision making, and response to query.

Computer programmers design AI systems to hold information online only for as long as they know they will need it. They hold data in a temporary store merely to compute what they are programmed to compute or execute whatever process they have pending. The mammal brain, on the other hand, has a strategy dedicated to holding potentially relevant information online because there is a high probability that it will be useful in the near future. It wagers that this information will be useful in processing without yet knowing how. It is not decided before hand how long items should remain active, rather, it is re-decided every second and during each state.

Soft computing approaches using the state-space approach contain incidental aspects of iteration, and other architectures such as neural networks use spreading activation. However, no machine yoks these together to create iterative updating and multi associative search. Doing so provides a clear way to structure a system that does not suspend its activity every time it finishes a task. It will be important for the system to exhibit continuous endogenous processing and a working memory that updates continuously to allow for uninterrupted learning.

Some important issues in the construction of intelligent machines include: 1) How can the process of internally generated thought be accomplished within a computer? 2) How can fragments of long-term memory recombine to represent novel concepts and episodes? 3) What events between these fragments must take place to allow transitions between episodes? 4) Are analogs of association and sensory cortices necessary? 5) How can the capacity of working memory be increased in a machine? 6) Is it possible to reduce explicit, conscious processes down to their constituent, implicit, unconscious ones? 7) Which brain mechanisms give rise to the mental continuity that humans experience? 8) What fundamental processes allow thought to move through space and time, or in another word, to “propagate?” The answers to these questions must be grounded in physics, biology, and information processing because they must explain how the physical substrate of intelligence operates in a mechanistic sense (Chalmers, 2010). Without being able to tie together all the neurological, psychological, and computational loose ends necessary to answer these questions comprehensively, this paper will attempt to address them in an exploratory way using a novel approach. Rather than being based on traditional topics, this article will view these questions from the perspective of the shared representational content between successive mental states.

There are currently many illustrative and biologically plausible theories from cognition and neuroscience that address the questions listed above. Some do an exemplary job of tying together a large number of relevant phenomena into a cohesive picture. Models such as Atkinson and Shiffrin’s (1969) multistore model, Baar’s (1997, 2002) global workspace theory, Baddeley’s (2000, 2007) model of working memory, Damasio’s convergence-divergence paradigm (Damasio, 1989; Meyer & Damasio, 2009), Edelman’s (1987, 2006) concepts of reentrance and neural Darwinism, Edelman and Tononi’s (2001) conceptualization of a “functional cluster” or “dynamic core,” Fuster’s (2009) conception of cognits, Tononi’s (2004) conception of integration of information, and Carpenter and Grossberg’s (2003) adaptive resonance theory have done much to lend perspective into the mechanics of perception, attention, working memory, and consciousness. In fact, concepts from these works (and several others that will be cited) form a battery of implicit assumptions about cognitive mechanisms that provides theoretical scaffolding for what is written here.
Despite much progress, most scientists report that current theory is unsatisfying because it cannot yet bridge the gap between the brain and the mind (Chalmers, 1995; Chalmers, 2010; Shear, 1997). Further, even though many contemporary models largely agree with empirical data, little has been done to reconcile their disparate, piecemeal approaches (Pereira & Ricke, 2009; Vimal, 2009). The effort to determine the important cognitive phenomena that should be replicated within a computer may be facilitated by the exploration of the concept of mental continuity. This work intends to use the concept of mental continuity to integrate current theoretical approaches while attempting to remain consistent with prevailing knowledge.

**Modeling Mental Continuity**

Continuity is defined as being uninterrupted in time. As proposed here, “mental continuity” involves a process where a gradually changing collection of mental representations held in attention/working memory exhibits a measure of uninterrupted activity across time and over sequential processing states. If it were not for the phenomenon of persistent neural activity, instantaneous information processing states would be time-locked and isolated (as in most serial and parallel computing architectures), rather than continuous with the states before and after them.

This article explores how sustained neural firing in association areas allows goal-relevant representations to be maintained over multiple perception-action cycles, in order to direct complex sequences of interrelated mental states. The individual states in a sequence of such states are interrelated because they share representational content. The associations linking the shared contents are saved to memory, impacting future searches, and ultimately resulting in semantic knowledge, planning, and systemizing.

Because the activity of cells in the PFC and other association areas can be sustained concurrently and does not fade away before the next instantiation of activity elsewhere, there is a temporally dynamic and overlapping pattern of neural activity that makes possible the “juggling” of information in working memory. The quantity of mental continuity is directly proportional to the number of sustained representations and the length of time of their activity (Reser, 2011, 2012, 2013).

There are countless phenomena in the natural world that undergo iterative updating. Take the human population of Earth for instance. In the next year many people will die, some new people will be born, yet most will be here a year from now. In the same sense, some of the neurons in a population exhibiting sustained firing will stop firing, some will begin, yet most will still be firing a second later. The people and neurons that persist will be able to influence subsequent states.

The sustained firing of higher-order nodes allows representations to be maintained over multiple perception-action cycles permitting complex sequences of interrelated mental states. The overall distribution of active nodes in the neural network will shift gradually during contextual updating because the activity of certain neural nodes will persist. This will ensure that the activity of prioritized, goal or motor-relevant representations will be uninterrupted over time. The representations that demonstrate this continuity are a subset of the active representations from the previous state and may act as referents to which newly introduced representations of succeeding states relate. The limited-capacity store of coactive representations in association areas is updated as: 1) the nodes that continue to receive sufficient spreading activation energy are maintained; 2)
the nodes that receive reduced energy are released from activation; 3) new nodes that are tuned so as to receive sufficient energy from the current constellation of coactivates are converged upon and incorporated into the remaining pool of active nodes from the previous cycle.

**Simulating the Minicolumns of the Mammalian Neurocortex**

Like other cognitive models (Cowan, 2005; Moscovich, 1992), this model views cognition as a system responsible for using active representations from LTM to guide goal-directed processing (Postle, 2007). The present model is consistent with connectionism and parallel distributed processing in that it conceptualizes mental representations as being built from interconnected networks of decentralized, semi-hierarchically organized, pattern-recognition nodes that have multiple inputs and outputs (Gurney, 2009; Johnson-Laird, 1998). Like other biologically plausible neural network models, it envisions these nodes as microscopic, modular neural units and assumes that each individual unit represents an elementary feature or stable “microrepresentation” of LTM (Meyer & Damasio, 2009). In the mammalian brain these microrepresentations may be instantiated by cortical minicolumns.

The structure of the cerebral cortex is highly repetitive and is marked by the employment of millions of nearly identical structures called cortical minicolumns (Lansner, 2009). Minicolumns are composed of densely connected neural cell bodies and span the six layers of grey matter in the neocortex. There are supposedly around 20,000,000 minicolumns in the human cortex, each of which contains between 80 and 120 neurons, and is about 30 to 40 micrometers in diameter (Lansner, 2009). These minicolumns share the same basic structure and are thought to employ the same cortical algorithm (Fuji et al., 1998; Kurzweil, 2012). Each column performs neural computations to determine if its inputs from other columns are sufficient to activate its outputs to other columns (Rochester et al., 1956).

Columns, and other similar groups of neurons with the same tuning properties, are often referred to as cell assemblies, and this term will be used here. Most neurons in an assembly share similar receptive fields, and thus even though they may play different roles within the assembly, they each contribute to the assembly’s ability for encoding a unitary feature (Moscovich et al., 2007). Such an assembly of neurons is thought to embody a stable microrepresentation or fragment of long-term memory. All of the millions of pattern recognizers in the neocortex are simultaneously considering their inputs, and continually determining whether or not to fire. In general, when a neuron or assembly fires, the pattern that it represents has been recognized. Assemblies, like the neurons that compose them, function as “coincidence detectors” or “pattern recognition nodes” (Fuji et al., 1998). The spread of activity in the cortex involves many-to-one (convergence) and one-to-many (divergence) interactions within a massively interconnected network of assemblies. The next section will discuss how these columns or assemblies could be simulated by nodes in a neural network.

**Information Processing in Artificial Neural Networks**

The field of AI research is involved in creating a computing system that is capable of emulating certain functions that are traditionally associated with intelligent human behavior. Most early AI systems were only capable of responding in the manner in which human programmers provided for when the program was written. It became recognized that it would be valuable to have a computer which does not respond in a preprogrammed manner (Moravec, 1988). AI systems
capable of adaptive learning have since become important. Neural networks have attempted to get around the programming problem by using layers of artificial neurons or nodes. Neural networks and genetic algorithms are widely implemented in research and industry for their capabilities involving adaptive learning and advanced pattern recognition. However, they are used for processing tasks that are narrowly constrained and highly specialized, and there has not yet been any strong form of intelligence derived from them.

An artificial neural network is an interconnected group of artificial neurons that uses a mathematical or computational model for information processing based on a connectionistic approach to computation (Russel et al., 2003). Like most neural networks, the present network should be an adaptive system capable of altering its own structure based on the nonlinear processing of information that flows through the network. The software would require a massively parallel, distributed architecture, that could be run on a conventional computer. Most neural networks ordinarily achieve intelligent behavior through parallel computations, without employing formal rules or logical structures, and can be used for pattern matching, classification, and other non-numeric, nonmonotonic problems (Nilsson, 1998). The applications for the present device could be widened if it were designed to accept and process formal rules.

The traditional neural network is a multilayer system composed of computational elements (nodes) and weighted links (arcs). These networks are based on the human brain where the nodes are analogous to neurons, or neural assemblies, and the arcs are analogous to axons and dendrites. Each node receives signals from nodes in the layer below it, processes these signals and then decides whether to “fire” at the nodes in the layer above. Like the artificial neurons first described by McCullough and Pitts (1943), the nodes in the present system could feature a number of excitatory inputs whose weights range between 0 and 1 and inhibitory inputs whose weights range between -1 and 0. Each of the incoming inputs and their corresponding weights are summed to equal an activation level. If this level exceeds the neuron’s firing threshold, it will cause the neuron to fire. The neuron can be made to learn from its experience when either the threshold or weights are changed. Neural networks are typically defined by three types of parameters: 1) The interconnection pattern between different layers of neurons; 2) The learning process for updating the weights of the interconnections; 3) The activation function that converts a neuron’s weighted input to its output activation.

There are currently no neural networks, or AI systems whatsoever, that are structured to model the primate neocortex in order to guide the progressive generation of successive topographic maps. The present neural network software architecture is structured around identifying potentially goal-relevant information and holding it online to inform reciprocal cycles of imagery generation and feature extraction for the purpose of systemizing the environment.

**Architecture Hierarchy**

The software models a large set of nodes that work together to continually determine, in real time, which from the population of inactive nodes should be newly activated, and which from the population of active nodes should be either deactivated or have its activity maintained.

The device necessitates a highly interconnected neural network that features a hierarchically organized collection of pattern recognizers capable of both transient and sustained activity. These pattern recognition nodes mimic assemblies (minicolumns) of cells in the mammalian neocortex...
and are arranged with a similar connection geometry. Like neural assemblies the nodes exhibit a continuous gradient from low-order nodes that code for sensory features, to high-order nodes that code for temporally or spatially extended relationships between such features. The lower order nodes are organized into modules by sensory modality. Nodes are grouped according to the feature they are being trained to recognize. These maps can be generated by external input, by internal input from higher-order nodes, or a mix of the two. The architecture will feature backpropagation, self-organizing maps, bidirectionality, Hebbian learning as well as a combination between principal-components learning and competitive learning.

Nodes lower in the hierarchy are trained to recognize and represent sensory features and are capable of combining individual features or patterns into metric, topographical maps or images. Lower-order nodes are unimodal, and organized by sensory modality (visual, auditory, somatosensory etc.) into individual modules. Nodes high in the hierarchy are multimodal, module independent, and have a capacity for sustained activity allowing the conservation of pertinent, high-level features through elapsing time. The higher nodes are integrated into the architecture in a way that makes them capable of identifying goal-relevant features from both internal imagery and environmental input, and temporarily maintaining these as a form prioritized information.

The system is structured to allow repetitive, reciprocal interactions between the lower, bottom-up, and higher, top-down nodes. The features that the higher nodes encode are utilized as inputs that are fed back into lower-order sensory nodes where they are continually used for the construction of successive topographic maps. The higher nodes select new features from each mapping to add to the store of temporarily maintained features. Thus, the most salient or goal-relevant features from the last several mappings are maintained. The group of active, higher-order nodes is constantly updated, where some nodes are newly added, some are removed, yet a relatively large number are retained. This updated list is then used to construct the next sensory image which will be necessarily similar, but not identical to, the previous image. The differential, sustained activity of a subset of high-order nodes allows thematic continuity to persist over sequential processing states.

All the nodes within the device function as a continuous whole and are highly interconnected, but can be decomposed into separate, modular, neural networks. Nodes belonging to an individual module are highly interconnected with each other. These modules consist of a bottom layer of input cells, succeeded by layers of local-feature extracting cells, and a top layer of output cells. The individual neural networks interface through the connections between top layer output cells and bottom layer input cells. Each network is organized so that multiple lower-order nodes can converge on higher order nodes, and single higher-order nodes can diverge back on multiple lower-order nodes. Multiple interfacing neural networks could be arranged biomimetically as in figure 8 below.
The bottom-up to top-down reciprocations are organized into very precise oscillations that propagate in regularly timed intervals across the network so that they do not interfere with each other. The oscillations reciprocate back and forth at just the right speed so that each area has the time to process its inputs and send an output before the next complement of inputs arrive. It is important to carefully structure timing mechanisms in the present device so that messaging is not muddled or noisy. It is also important to structure the architecture so that continuity in the representations held active by the buffer can be disrupted when attention shifts. Repeated loops of conserved, higher-order features can be ended when attention is captured by an object or concept that competes for attention. The ability to free up the resources of higher-order nodes to attend to a new stimulus will be programmed by training. Before proper training is accomplished the system may not be able to reallocate its resources properly when its attention shifts.

To create a strong form of AI it is necessary to understand what is taking place that allows intelligence, thought, cognition, consciousness or working memory to move through space and time, or in another word, to “propagate.” Such an understanding must be grounded in physics because it must explain how the physical substrate of intelligence operates through space and time (Chalmers, 2010). The human brain is just such an intelligent physical system that AI researchers have attempted to understand and replicate using a biomimetic approach (Gurney, 2009). Features of the biological brain have been key in the design of neural networks, but the brain may hold additional information processing principles that have not been harnessed by A.I. efforts (Reser 2011, 2012, 2013).

Computational operations, that take place as a computer implements lines of code (rule-based, if-then operations) to transform input into output, have discrete, predetermined starting and stopping
points. For this reason, computers do not exhibit continuity in their information processing. There are no forms of artificial intelligence that use mental continuity as described here. There are existing computing architectures with limited forms of continuity where the current state is a function of the previous state, and where data is entered into a limited capacity buffer to inform other processes. However, the memory buffer is not global, not multimodal, not positioned at the top of a hierarchical system and does not inform and interact with topographic imagery.

**Persistent Neural Activity From Sustained Firing and Synaptic Potentiation**

The mammalian PFC and other association cortices have neurons that are specialized for “sustained firing,” allowing them to generate action potentials at elevated rates for several seconds at a time (generally 1-30 seconds) (Fuster, 2009). In contrast, neurons in other brain areas, including cortical sensory areas, remain active only for milliseconds unless sustained input from association areas makes their continued activity possible (Fuster, 2009). In the mammalian brain, prolonged activity of neurons in association areas, especially prefrontal and parietal areas, allows for the maintenance of specific features, patterns, and goals (Baddeley, 2007). Working memory, executive processing and cognitive control are widely thought to stem from the active maintenance of patterns of activity in the PFC that represent goal-relevant features (Goldman-Rakic, 1995). The temporary persistence of these patterns ensures that they continue to transmit their effects on network weights as long as they remain active, biasing other processing, and affecting the interpretation of subsequent stimuli that occur during their episode of continual firing.

Although its limits are presently being debated, the human neocortex is clearly capable of holding numerous neural representations active over numerous points in time. The quantity of mental continuity is directly proportional to the number of such sustained representations and the length of time of their activity (Reser, 2011, 2012, 2013).
Fig. 2. Graphical depiction of iterative updating. Each bracket represents the active time span of a neural representation. The x axis represents time and the y axis demarcates the cortical area where the representation is active. Red brackets denote representations that have exhibited uninterrupted activity from the point when they became active, whereas blue brackets denote representations that have not been sustained. In time sequence 1 representations B, C, D and E have remained active until t1. In time sequence 2 B has deactivated, C, D and E have remained active, and F is newly active. The figure depicts a system with iterative updating because more than one representation (C, D, and E) has been maintained over more than one point in time (t1 and t2).

In Figure 1 above, representations B, C, D, and E are active during time 1, and C, D, E and F are active during time 2. Thus, representations C, D, and E demonstrate reiteration because they exhibit continuous and uninterrupted activity from time 1 through time 2. The brain state at time 1 and the brain state at time 2 share C, D, and E in common and, because of this, can probably be expected to share other commonalities including: similar information processing operations, similar memory search parameters, similar mental imagery, similar cognitive and declarative aspects, and similar experiential and phenomenal characteristics.
Fig. 3. A simplified graphical representation of iterative updating depicting it as a gradually shifting, stream-like distribution. Figure 2 extends Figure 1 over multiple time intervals revealing a repeating pattern: remnants from the preceding state are consistently carried over to the next state.

Figure 3 shows how this iterative process can be looped repetitively over time. Figure 4 shows how the rate of iteration can change...
Fig. 4. This figure expands on previous figures by comparing four possible incremental changes in SSC. In the first transition 75% of representational continuity is maintained between time periods 1 and 2. The other transitions depict 50%, 25%, and 0% maintenance of continuity respectively. According to the definition of mental continuity, neither the graphic marked “25% continuity” nor the one marked “0% continuity” depict mental continuity, because they do not feature the maintenance of more than one representation.

Figure 5 below demonstrates how this pattern of iterative updating could be implemented in working memory.

![Diagram of multiassociativity](image)

**Fig. 5.** A diagram depicting “multiassociativity” and illustrating the ways in which high-level representations, or items, are displaced, maintained, and newly activated in the brain. 1) Shows that representation A has already been deactivated and that B, C, D and E are now coactivated, mirroring the pattern of activity shown in Figure 1. When coactivated, these representations pool and spread their activation energy, resulting in the convergence of activity onto a new representation, F. Once F becomes active, it immediately becomes a coactivate, restarting the cycle. 2) Shows that B has been deactivated while C, D, E, and F are coactivated and G is newly activated. 3) Shows that D but not C has been deactivated. In other words, what is deactivated is not necessarily what entered first, but what has proven to receive the least converging activity. C, E, F, and G coactivate and converge on H.

In Figure 4, between time periods 1 and 2, C, D and E exhibit coactivity, whereas, between time periods 1 and 3, only C and E exhibit coactivity. C and E are active over all three time periods meaning that these representations are being used as search function parameters for multiple cycles, and are the subject of attention. Alternatively, we can imagine a scenario where B, C, D, and E from step one of Figure 3 were immediately replaced by F, G, H, and I. Such a processing system may still be using previous states to determine subsequent states; however, because no activity is sustained through time, there would be no continuity in such a system (this is generally how most computing systems process information).

In Figure 4, ensembles C and E have fired together over three individual time intervals, and thus will show a propensity to wire together, increasing their propensity for firing together in the future. This link between them will allow one to recruit the other. However, it is probably much more likely that they will recruit each other if the other contextual ensembles are also present. The coincidental or rare associations between the ensembles of an experience are probably mostly lost from non-hippocampal dependent cortical memory. However, the reoccurring associations are heavily encoded and persist as semantic knowledge.
In other words, the cortex constantly spreads activation energy from novel combinations of active ensembles that have never been coactive before and attempts to converge upon the statistically most relevant association without certain or exact precedence resulting in a solution that is not guaranteed to be optimal.

Neural nodes in sustained activity can span a wider delay time or input lag between associated occurrences (Zanto, 2011) allowing elements of prior events to become coactive with subsequent ones (Fuster, 2009). Without sustained firing, the ability to make associations between temporally distant (noncontiguous) environmental stimuli is disrupted. Sustained activity allows individual nodes that would otherwise never fire together to both fire and wire together. Thus, it sustained firing is responsible for the ability to make internally-derived associations between representations that would never co-occur simultaneously in the environment.

This indicates that one way to quantify mental continuity is to determine the proportion of previously active neural nodes that have remained active during a resource demanding cognitive task. Uninterrupted activity augments associative searches by allowing specific features to serve as search function parameters for multiple cycles. Intelligence in this system can be enhanced by increasing: 1) the number of available nodes to select from, 2) the number of nodes that can be coactivated simultaneously, and 3) the length of time that individual nodes can remain active.

The mesocortical dopamine (DA) system plays an important role in sustained activity, suggesting that it may be heavily involved in mental continuity. Dopamine sent from the ventral tegmental area (VTA) modulates the activity and timing of neural firing in the PFC, association cortices, and elsewhere. Dopamine neurotransmission in the PFC is thought to underlie the ability to internally represent, maintain, and update contextual information (Braver & Cohen, 1999). This is necessary because information related to behavioral goals must be actively sustained such that these representations can bias behavior in favor of goal-directed activities over temporally extended periods (Miller & Cohen, 2001). It has become clear that the activity of the DA/PFC system fluctuates with environmental demand (Fuster & Alexander, 1971). Many studies have suggested that the system is engaged when reward or punishment contingencies change. Both appetitive and aversive events have been shown to increase dopamine release in the VTA, causing sustained firing of PFC neurons (Seamans & Robbins, 2010). Seamans and Robbins (2010) elaborated a functional explanation to support this case. They have stated that the DA system is phasically activated in response to novel rewards and punishments because it is adaptive for the animal to anchor upon and further process novel or unpredicted events.

Sustained firing and recurrent processing make it possible for recent states to spill over into subsequent states, creating the context for them in a recursive fashion. In a sense, each new topographic map is embedded in the previous one. This creates a cyclical, nested flow of information processing marked by STC, which is depicted in Figure 6.

Learned mental tasks probably have distinct predefined algorithmic sequences of topographic mappings that must be completed in sequence in order to achieve the solution. Each brain state would correspond to a different step in the algorithm, and its activity would recruit the next step. All logical and methodical cognition may require that a number of relevant features from the present scenario remain in STC so that they spread their activity within the network in order to influence the selection of the ensembles necessary for task satisfaction. Moreover, motor and premotor modules give specifications to and receive specifications from this common workspace.
while they are building their musculotopic imagery for movement. The same goes for language areas.

Fig. 6. The dynamics of the present model are captured by an analogy involving an octopus grabbing and releasing footholds as it pulls itself from place to place. This is an activity known as “sea floor walking.” The analogy illustrates that the thought process involves the simultaneous coactivation of several representations at a time (multiple footholds held by an octopus) as well as the deactivation of previously active representations (the releasing of footholds), and the activation of previously inactive representations (the placement of an arm on a new foothold). This analogy may be valuable because it depicts a system, that even a child can understand, where specific representations are conserved through time as others are actively repositioned.

**Search Through Spreading Activation Targets the Next Update**

The mammalian neocortex is capable of holding a number of such mnemonic representations coactive, and using them to make predictions by allowing them to spread their activation energy together, throughout the thalamocortical network. This activation energy converges on the inactive representations from LTM that are the most closely connected with the current group of active representations, making them active, and pulling them into short-term memory. Thus new representations join the representations that recruited them, becoming coactive with them.
The way that assemblies and ensembles are selected for activity in this model is consistent with spreading activation theory. In spreading activation theory, associative networks can be searched by labeling a set of source nodes, which spread their activation energy in a nonlinear manner to closely associated nodes (Collins & Loftus, 1975). Cortical assemblies work cooperatively by spreading the activation energy (both excitatory and inhibitory) necessary to recruit or converge upon the next set of ensembles that will be coactivated with the remaining ensembles from the previous cycle.

Together, they impose sustained information processing demands on the lower-order sensory and motor areas within the reach of their long-range connections. The longer the activity in these higher-order neurons is sustained, the longer they remain engaged in hierarchy-spanning, recurrent processing throughout the cortex and subcortex.

Gradual additions to and subtractions from a pool of simultaneously coactivated ensembles occur as:

1. Assemblies that continue to receive sufficient activation energy from the network are maintained.
2. Assemblies that receive sufficiently reduced activation energy are released from activation.
3. New assemblies, which are tuned to receive sufficient activation energy from the current constellation of coactivates, are converged upon, and incorporated into the remaining pool of active assemblies from the previous cycle.

| Table 1. The Characteristics of Multiassociative Search |

Outlining the process of multiassociativity in this way is meant to show that the computational algorithm used by the brain may be primarily directed at determining which inactive ensembles are the most closely statistically related to the currently active assemblies. From this perspective, the contents of the next state are chosen based on how the currently active assemblies interact with the existing, associative, neuro/nomological network.
Fig. 7. A Schematic for Multiassociative Search

Spreading activity from each of the assemblies (small spheres) of the four items (large circles) in the FoA (B, C, D, and E) propagates throughout the cortex (represented by the field of assemblies above the items). This activates new assemblies that will constitute the newest item (F), which will be added to the FoA in the next state. The assemblies that constitute items B, C, D, and E are each individually associated with a very large number of potential items, but as a unique group, they are most closely associated with item F.

**Reciprocating Crosstalk between Association and Sensory Cortex**

To a certain extent, perceptual sensory processing in the brain is thought to be accomplished hierarchically (Cohen, 2000). The cortical hierarchy observed from sensory to association cortex arises because simple patterns are arranged to converge upon second-order patterns, which in turn converge on third-order patterns and so on. This leads to a hierarchy of increasingly complex representations.

It is thought that object recognition, decision making, associative recall, planning and other important cognitive processes, involve two-way traffic of signal activity among various neural maps that stretch transversely through the cortex from early sensory areas to late association areas (Klimesch, Freunberger, & Sauseng, 2010). Bottom-up sensory areas deliver fleeting sensory information and top-down association areas deliver lasting perceptual expectations in the form of templates or prototypes. These exchanges involve feedforward and feedback (recurrent) connections in the corticocortical and thalamocortical systems that bind topographic information from lower-order sensory maps about the perceived object with information from higher-order maps forming somewhat stable constellations of activity that can remain stable for tens or hundreds of milliseconds (Crick & Koch, 2003).

Iterative updating impacts this reciprocating cross-talk. These reciprocations may create progressive sequences of related thoughts, specifically because the topographic mappings generated by lower-order sensory areas are guided by the enduring representations that are held active in association areas (Reser 2011, 2012, 2013). The relationship between anterior and posterior cortex may be best characterized by two main relationships: 1) association areas maintain representations from, not one but several, of the last few topographic maps made in sensory areas, 2) because they are drawing from a register with sustained contents, sequential images formed in sensory areas have similar content and thus should be symbolically related to one another.

Feedback activation from top-down association areas hands down specifications to early sensory cortex for use in imagery building. Disparate chunks of information are integrated into a plausible map and transiently bound together. Consecutive topographic images about a specific scenario model the scenario by holding some of the contextual elements constant, while others are allowed to change. Thus, prior maps set premises for and inform subsequent maps.
Fig. 8. A diagram depicting the reciprocal transformations of information between lower-order sensory mappings and higher-order association area ensembles during internally generated thought. Sensory areas can only create one topographic mapping at a time, whereas association areas are capable of holding the salient or goal-relevant features of several sequential mappings at the same time.

The central executive (the PFC and other association areas) direct progressive sequences of mental imagery in a number of topographic sensory and motor modules including the visuospatial sketchpad, the phonological (articulatory) loop and the motor cortex. This model frames consciousness as a polyconceptual, partially-conserved, progressive process, that performs its high-level computations through “reciprocating transformations between buffers.” More specifically, it involves reciprocating transformations between a partially conserved store of multiple conceptual specifications and another nonconserved store that integrates these specifications into veridical, topographic representations.

It will be important for the AI to identify and capture information about unexpected occurrences so that it can be further processed and systematic patterns can be identified. The novel experience should be broken down into its component parts and the representations in memory for these parts allowed to spread their activation energy in an attempt to converge on and activate historically associated representations that are not found in the experience itself. Because memory traces for the important features remain active and primed, they can be used repeatedly as specifications that guide the generation of apposite mental imagery in sensory areas (Reser, 2012). Sequences of lower-order topographic images should depict and explore hypothetical relationships between the higher-order, top-down specifications. This amounts to a continual
attempt to use the associative memory system to search sensory memory for a topographic image that can meaningfully incorporate the important features. It seems that reciprocating activity between the working memory updating system and the imagery generation system builds interrelated sequences of mental imagery that are used to form expectations and predictions.

The fact that newly active search terms are combined with search terms from the previous cycle makes this process demonstrate qualities of “progressive iteration.” Perhaps reciprocating activity between the working memory updating system and the imagery generation systems generates sequences of interrelated mental images that build on themselves to form abductive expectations, and predictions.

Fig. 9. A diagram depicting the behavior of representations that are held active in association areas. 1) Shows that the representations B, C, D, and E, which are held active in association areas, all spread their activation energy to lower-order sensory areas where a composite image is built that is based on prior experience with these representations. 2) Shows that features involved in the topographic imagery from time sequence 1 converge on the PFC neurons responsible for F. B drops out of activation, and C, D, E and F remain active and diverge back onto visual cortex. 3) Shows that the same process leads to G being activated and D being deactivated, mirroring the pattern of activity shown in Figure 4.
Assemblies in lower-order sensory areas identify sensory features from the environment and combine them into composite representations that mirror the geometric, and topographic orientations present in the sensory input. The early visual system uses retinotopic maps that are organized with a geometry that is identical to that used in the retina, and the auditory system uses tonotopic maps, where the mapping of stimuli is organized by tone frequency (Moscovich, 2007). Because cortical assemblies are essentially pattern recognition nodes organized in a hierarchical system, they should be able to be modeled by computers. The best way to do this with modern technology is to use an artificial neural network.

Fig. 10. Uses the format of Figure 1 to illustrate how relevant features can be maintained through time using nodes with sustained firing. The figure compares the number of past nodes that remain active at the present time (t1), in a normal human, a human with PFC dysfunction, and the hypothetical A.I. agent. The A.I. agent is able to maintain a larger number of higher-order nodes through a longer time span, ensuring that its perceptions and actions in time 1 will be informed by a larger amount of recent information. Note how the lower-order sensory and motor features are the same in each graph with respect to their number and duration, yet those in association areas are the highest in both number and duration for agent C.

**Tuning the Network for Increased Intelligence**

If this sustained firing was programmed to happen at even longer intervals, and involve even larger numbers of nodes, the system would exhibit a superhuman capacity for continuity. This would increase the ability of the network to make associations between temporally distant stimuli and allow its actions to be informed by more temporally distant features and concerns. Aside perhaps from altering the level of arousal (adrenaline) or motivation (dopamine), it is
currently not possible to engineer the human brain in a way that would increase the number and duration of active higher-order representations. However, in a biomimetic instantiation, it would be fairly easy to increase both the number and duration of simultaneously active higher-order nodes (see Figure 9 below). Of course, in order to operate meaningfully, and reduce its propensity for recognizing “false patterns,” such an ultraintelligent system would require extensive supervised and unsupervised learning.

It is currently not possible to engineer the human brain in a way that increases the number and duration of active higher-order representations in order to enhance mental continuity and the intelligent processes that it supports. However, in a biomimetic instantiation it would be fairly easy to increase the number and duration of simultaneously active higher-order representations. Accomplishing this would allow the imagery that is created to be informed by a larger number of concerns, and would ensure that important features were not omitted simply due to the fact that their activity could not be sustained due to biological limitations.

To accomplish overt behavior, higher inputs are fed not only to the lower sensory nodes, but also in a similar, top-down manner to a behavior module that will guide natural language output and other behaviors such as robotic control. The final layer of nodes in this behavior module will be nodes that directly control movement and verbalization and the higher nodes will be continuous with the higher-order PFC-like nodes. The software functions in an endless loop of reciprocating transformations between sensory nodes, motor nodes, and PFC-like buffer.

**Other Forms of Sustained Activity**

Aside from having a PFC analogue, the network could also have an analogue of cortical priming and an analogue of the hippocampus. Humans have thoughts that carry continuity because changes in content are gradual as more recent activations/representations are given a higher priority than older ones. Activity that transpired minutes ago is given moderate priority, activity from seconds ago is given high priority and activity from mere milliseconds ago is given the highest priority. This dynamic is made possible by the PFC analogue, but could be accentuated by analogues of cortical priming. To allow for an analogue of cortical priming, all recently active neurons would retain a moderate amount of increased, but subthreshold activity. The activity level of recently used nodes in both the higher and lower-order areas would not quite fall back to zero. This would ensure that recently used patterns and features would be given a different form of priority, yet to a lesser and more general extent than that allowed by the PFC analogue. Regarding the network partitions depicted in Figure 5, the sensory, motor and hippocampal neural networks would show the least priming, the association area, and premotor neural networks would show moderate priming, and the PFC would show the highest degree of priming. Functions for the parameters of priming could be fine-tuned by genetic algorithms.

Furthermore, the network could have an analogue of the hippocampus. A hippocampal analogue would keep a record of contextual, or episodic clusters of previous node activation. Instead of keeping a serial record of averaged activity, the hippocampus analogue would capture episodic constellations of node activity and save these to be reactivated later. These episodic memory constellations would be activated when a large subset of the constellation is present during processing. This means that when neural network activity closely approximates an activity constellation that was present in the past, the hippocampal analogue would be capable of reactivating the original constellation. The activity of the hippocampal analogue should be
informed by actual hippocampal anatomy and the “pattern completion” hypothesis of hippocampal function. To build an analogue into a neural net it would be necessary to have a form of episodic memory that can be cued by constellations of activity that closely resembles a past (autobiographical or episodic) occurrence. This memory system would then be responsible for “completing the pattern,” or passing activation energy to the entire set of nodes that were initially involved in the original experience, allowing the system a form of episodic recall. As with the actual brain (Amaral, 1987), in the present device, the hippocampus should be reciprocally connected with the PFC and association areas but not with primary sensory or motor areas.

**Appropriate Neural Network Parameters For the Present Device**

A network is “trained” to recognize a pattern by adjusting arc weights in a way that most efficiently leads to the desired results. Arcs contributing to the recognition of a pattern are strengthened and those leading to inefficient or incorrect outcomes are weakened. The network “remembers” individual patterns and uses them when processing new data. Neural learning adjustments are driven by error or deviation in the performance of the neuron from some set goal. The network is provided with training examples, which consist of a pattern of activities for the input units, along with the desired pattern of activities for the output units. The actual output of the network is contrasted with the desired output resulting in a measure of error. Connection weights are altered so that the error is reduced and the network is better equipped to provide the correct output in the future. Each weight must be changed by an amount that is proportional to the rate at which the error changes as the weight is changed, an expression called the “error derivative for the weight.”

In a network that features back propagation the weights in the hidden layers are changed beginning with the layers closest to the output layer, working backwards toward the input layer. Such backpropagating networks are commonly called multilayer perceptrons (Rosenblatt, 1958). The present architecture involves a number of multilayered neural networks connected to each other, each using their own training criteria for backpropagated learning. For instance, the visual perception module would be trained to recognize visual patterns, the auditory perception module would be trained to recognize auditory patterns, and the PFC module would be trained to recognize multimodal, goal-related patterns.

The hierarchical multilayered network, the neocognitron, was first developed by K. Fukushima (1975). This system and its descendants are based on the visual processing theories of Hubel and Wiesel and form a solid archetype for the present device because they feature multiple types of cells and a cascading structure. Popular neural network architectures with features that could be valuable in programming the present device include the adaptive resonance theory network (Carpenter & Grossberg), the Hopfield network, the Neural Representation Modeler, the restricted coulomb energy network, and the Kohonen network. Teuvo Kohonen (2001) showed that matrix-like neural networks can create localized areas of firing for similar sensory features, which result in a map-like network where similar features were localized in close proximity and discrepant ones were distant. This type of network uses a neighborhood function to preserve the topological properties of the input space, and has been called a “self-organizing map.” This kind of organization would be necessary for the present device to accomplish imagery generation, and would contribute to the ability of the lower-order nodes in the sensory modules to construct topographic maps.

A neural network that uses principal-components learning uses a subset of hidden units that cooperate in representing the input pattern. Here, the hidden units work cooperatively and the
representation of an input pattern is distributed across many of them. In competitive learning, in contrast, a large number of hidden units compete so that a single hidden unit is used to represent a particular input pattern. The hidden unit that is selected is the one whose incoming weights most closely match the characteristics of the input pattern. The optimal method for the present purposes lies somewhere between purely distributed and purely localized representations. Each neural network node will code for a discrete, albeit abstract pattern, and compete among each other for activation energy and the opportunity to contribute to the depiction of imagery. However, multiple nodes will also work together cooperatively to create composite imagery.

When active, high level nodes signal each of the low-level nodes that they connect with, they are in effect, retroactivating them. They are activating those that recently contributed to their activity, and activating previously dormant ones as well. This retroactivation of previously dormant nodes constitutes a form of anticipation or prediction, indicating that there is a high likelihood that the pattern that these nodes code for will become evident (prospective coding). This kind of prediction is best achieved by a hierarchical hidden Markov model. Utilizing Markov models, and their predictive properties will be necessary. This process is used in Ray Kurzweil’s Pattern Recognition Theory of Mind (PRTM) model, which uses a hidden Markov model and a plurality of pattern recognition nodes for its cognitive architecture (Kurzweil, 2012). Hierarchical temporal memory (HTM) is another cognitive architecture that models some of the structural and algorithmic properties of the neocortex (Hawkins & Blakeslee, 2005). The hope with PRTM and HTM is that a hierarchically structured, neural network with enough nodes and sufficient training should be able to model high-order human abstractions. However, distilling such abstractions and utilizing them to make complex inferences may necessitate an imagery guidance mechanism with a working memory updating function.

Neural networks can propagate information in one direction only, or they can be bi-directional where activity travels up and down the network until self-activation at a node occurs and the network settles on a final state. So called recurrent networks are constructed with extensive feedback connections. Such recurrent organization and bi-directionality would be important to accomplish the oscillating transformations performed by the present device. Hebbian learning is an updating rule that suggests that the connections weights for a neuron should grow when the input of the neuron fired at the same time the neuron itself fired (Hebb, 1949). This type of learning algorithm would be important for the present device as well.

Each topographic map that is formed could be assessed for appetitive or aversive content. The architecture depicted in Fig 5 could be copied onto two separate, yet nearly identical systems, one fine-tuned for approach behaviors and the other for withdrawal behaviors. This could simulate the right and left cortical hemispheres. The right hemisphere could be associated with withdrawal and have longer connectional distances between nodes on average.

In some neural networks, the activation values for certain nodes are made to undergo a relaxation process such that the network will evolve to a stable state where large scale changes are no longer necessary and most meaningful learning can be accomplished through small scale changes. The capability to do this, or to automatically prune connections below a certain connection weight would be beneficial for the present purposes. It is also important to preserve past training diversity so that the system does not become overtrained by narrow inputs that are poorly representative.
The present architecture could be significantly refined through the implementation of genetic algorithms that could help to select the optimal ways to fine-tune the model and set the parameters controlling the mathematics of things such as the connectivity, the learning algorithms, and the extent of sustained activity. It might also be beneficial to implement a symbolic, rule-based approach, where a core set of reliable rules are coded and used to explicitly structure iterative updating as well as influence decision making and goal prioritization. Many theorists agree that combining neural network, and more traditional symbolic approaches will better capture the mechanisms of the human mind. In fact, implementing explicit rules to instantiate processing priorities could help the higher-order nodes to account for goal-relevance. These might be necessary to simulate the rules of emotional, subcortical modules. In evolutionary algorithms an initial population of solutions/agents is created and evaluated. New members of the population are created from mutation and crossover. The updated population is then evaluated and agents are either deleted or naturally selected based on their fitness value (or performance).

Conclusions

Many researchers have suggested that AI does not need to simulate human thought, but rather should simulate the essence of abstract reasoning and problem solving. The present article has suggested that modeling “mental continuity” and using it to guide successive images is an essential part of this simulation.

There are no forms of AI that use mental continuity as described here. There are existing computing architectures with limited forms of continuity where the current state is a function of the previous state, and where active data is entered into a limited capacity buffer to inform other processes. However, there are no AI systems where this buffer is multimodal, positioned at the top of a hierarchical system, and that informs and interacts with topographic imagery.

The current objective is to create an agent that through supervised or unsupervised feedback can progress to the point where it takes on emergent cognitive properties and becomes a general problem solver or inference program capable of goal-directed reasoning, backwards chaining, and performing means-end analyses. The present device should constitute a self-organizing cognitive architecture capable of dynamic knowledge acquisition, inductive reasoning, dealing with uncertainty, high predictive ability and low generalization error. If implemented and trained properly it should be able to find meaningful patterns in complex data and improve its performance by learning. It should be the goal of A.I. experts to fine tune such a system to become capable of autoassociation (the ability to recognize a pattern even though the entire pattern is not present) and perceptual invariance (generalizing over the style of presentation such as visual perspective or font).

The writing here amounts to a qualitative account, is exploratory, contains unverified assumptions, makes untested claims, and leaves important concerns out of the discussion. A more complete and refined version would focus on better integration of existing knowledge from functional neuroanatomy, multisensory integration, clinical neuropsychology, brain oscillations, short-term and long-term potentiation, binding, the sustained firing behavior of cortical columns, and the cognitive neuroscience of attention.

The present architecture is designed to simulate human intelligence by emulating the mammalian fashion for selecting priority stimuli, holding these stimuli in a working memory store and allowing
them to temporarily direct sensory and motor modules before their activity fades. It would be composed of a large set of nodes that work together to continually determine, in real time, which from their population should be newly activated, which should be deactivated and which should remain active over elapsing time to form a “stream” or “train” of thought. The network’s connectivity allows reciprocating cross-talk between fleeting bottom-up imagery in early sensory networks and lasting top-down priming in association and PFC networks. The features that are maintained over time by sustained neural firing are used to create and guide the construction of topographic maps (imagery). The PFC and other association area neural networks direct progressive sequences of mental imagery in the visual, auditory, and somatosensory networks. The network contains nodes that are capable of “sustained firing,” allowing them to bias network activity, transmit their weights, or otherwise contribute to network processing for several seconds at a time (generally 1-30 seconds).

Cognitive control stems from the active maintenance of features/patterns in the PFC module that allow the orchestration of processing in accordance with internally selected priorities. The network is an information processing system that has the ability to maintain a large list of representations that is constantly in flux as new representations are being added, some are being removed and still others are being maintained. This distinct pattern of activity, where some individual nodes persist during processing makes it so that particular features of the overall pattern will be uninterrupted or conserved over time. Because nodes in the PFC network are sustained, and do not fade away before the next instantiation of topographic imagery, there is a continuous and temporally overlapping pattern of features that mimics consciousness and the psychological juggling of information in working memory. This also allows consecutive topographic maps to have related and progressive content. If this sustained firing is programmed to happen at even longer intervals, in even larger numbers of nodes, the system will exhibit even more mental continuity over elapsing time. This would increase the ability of the network to make associations between temporally distant stimuli and allow its actions to be informed by more temporally distant features and occurrences.
Fig. 11. Shows that information from motor and sensory cortices enters the focus of attention where it can then explicitly influence other sensory and motor cortices. As information leaves attention it can either be held temporarily in a less active form of STM (which can implicitly influence sensory and motor cortices) or it can deactivate and return to LTM. The arrow on the left indicates that in succeeding states, the letters will cycle downwards as their activity diminishes.

**Table 2.** The Process by which Short-Term Continuity Influences Global Processing

1) Information flows to early sensory cortex from the environment or from the association cortex.

2) Topographic sensory maps are constructed from this information within each low-order, sensory module. In order to integrate the disparate features into a meaningful image, the map-making neurons will be forced to introduce new features not found in their extrinsic inputs.

3) Information from the imagery travels bottom-up toward the association cortex. The salient or goal-relevant features from the mappings are used to update the group of sustained representations held active in the association cortex.

4) The least relevant, least converged-upon representations in the association cortex are dropped from sustained activation and “replaced” with new, salient representations. Thus, the important features of the last few maps are maintained in an active state.

5) The updated group of representations will then spread its activity backwards toward lower-order sensory nodes in order to activate a different set of low-order nodes culminating in a different topographic sensory map.

6) A. The process repeats.

   B. Salient sensory information from the actual environment interrupts the process. The lower-order nodes and their imagery, as well as the higher-order nodes and their priorities, are refocused on the new incoming stimuli.
Fig. 12. Each set of 12 circles represents an individual artificial neural network trained to process a different modality of inputs. Each network is shown fully connected; however, not shown are the numerous connections needed between networks. Spreading activation would travel recurrently within a network, and interactively (i.e. generatively, adversarially, or collaboratively) between networks. The boxes represent sensory input, motor output, and/or topographic maps. The row of five nodes in each network represents the input layers, the row of four represents the hidden associative layers, and the row of three represents the output layer. The output nodes are pattern recognizing classifiers that hold the equivalent of items of working memory. They would be capable of sustained activity and, as a group, iterative updating.

**Analogs of Right and Left Cortical Hemispheres Might Be Helpful for AI**

The cerebral cortex can be divided right down the middle (sagittally) into two, nearly identical hemispheres. Far from being redundant, they each process much of the same information in slightly different ways, leading to two complementary and cooperating worldviews. This organization (called hemispheric lateralization) could be beneficial for an AI agent. The main benefit would be that over developmental time these two innately different networks would reprogram each other by being exposed to each other's outputs. In essence, two dissimilar heads are better than one.

Creating hemispheric laterality in a neural network would be easy. It would involve duplicating the existing network and then connecting the two of them via a large number of high bandwidth weighted links. These links would serve as the corpus callosum (the bundle of tracts that connect the right and left hemispheres in mammals). These connections should respect the brain’s natural bilateral symmetry, connecting both similar and dissimilar areas across both hemispheres.

Each hemisphere of the brain processes information slightly differently. Despite the fact that the macrostructure of the two hemispheres is almost identical, the two are different microstructurally. Many researchers believe that this is because the right hemisphere has an average axonal length slightly (microscopically) longer than the left. This means that the right brain has relatively more white matter (axons), and the left hemisphere has relatively more grey matter (cell bodies). This also means that on average the cells of the right brain are further away from one another. This would be simple to replicate in existing neural network software. There
are many theories as to why the longer-ranging wiring is responsible for the right hemisphere’s tendency for broad generalization and holistic perspective.

People with a left hemisphere injury may have impaired perception of high resolution, or detailed aspects of an image, whereas those with right hemisphere injury may have trouble seeing the low resolution, or big picture aspects of an image. In other words, they miss the forest for the trees.

Each side of the artificial neural network would organizing its processing and learning according to a different algorithm and could lead each to develop a unique way of perceiving and responding to the world. Slight discrepancies in temporal processing parameters could make the feedback and crosstalk between these two non-identical systems meaningful. This would be commensurate to specialists that could check, balance, reconcile, compare, and contrast their differing approaches. If they processed information in exactly the same way it would be redundant to have two, but because they don’t, they provide a type of stereoscopic view on the world similar to the view provided by our two offset eyes. This would enable them to form their own perceptions and opinions and then reconcile with one another. Right now, no AI systems have anything like this.

There are countless parameters of a neural network that could be fine-tuned to accomplish this. It might even be beneficial to have more than two. Some hyperparameters that are common in neural networks that could be altered include the refractory period, activation threshold, resting potential, resistance (MΩ) and capacitance (nF). These changes could be made to the software or could be instantiated as physical changes within neuromorphic hardware.

Our brain’s two hemispheres also differ as to their value systems. Our left hemisphere is dedicated to approach behaviors, and our right hemisphere is dedicated to withdrawal behaviors. Stimulating the left hemisphere of a rat will make it go toward a new object, whereas stimulating the right side will make it back away from that object. The fact that vertebrate brains have made this fundamental differentiation between approach and withdrawal for hundreds of millions of years suggests that it might represent an organizing principle that should be used in AI.

One way to do this would be to wire up the AI’s “subcortical” appetitive and motivational centers (analogous to the ventral tegmental area and the nucleus accumbens) involved in reinforcement learning with the left hemisphere, and to wire up the threat detection centers (analogous to the amygdala) involved in punishment learning with the right hemisphere. AI needs two, functionally assymmetric, dedicated processors, one for approach/liking/curiosity, and one for withdrawal/disliking/fear. As I have explained elsewhere both hemispheres should influence the dopaminergic system and sustained firing so that important rewards and threats can be maintained in mind; however, the left should be focused on approaching them, and the right should be focused on withdrawing from them.

As in vertebrate animals, the left hemisphere could be used to control the right half of an AI’s robot body and the right hemisphere could be used to control the left half. This could help ensure that both approach and withdrawal have equal impact on behavior. Approach and withdrawal could form a pivoting scale for how a robot acts in the world. They could also structure their conscious attention even when not moving by allowing them to pivot between interest and disinterest.
Artificial Intelligence Needs to Utilize the Process of Myelination

Modern AI is impressive in some regards, yet still very limited compared to the human mind. When researchers take an AI architecture that performs well at some task and then make the architecture more complex in hopes that it will be able to tackle more cognitively complex problems, the networks often fail to deliver. This may be because they have not yet used a simple trick that animals have been using for hundreds of millions of years: gradual and progressive myelination.

As we progress from infancy through adulthood our brains make various biological changes. These changes cause our level of analysis to slowly progress from analyzing brief sensory experiences, to analyzing complex, abstract scenarios. We begin our lives only being able to notice and attend to interactions occurring on short time scales. By adulthood, with the prefrontal cortex fully developed, we find ourselves able to follow interactions occurring on long time scales. In order to develop the ability to think about complex things we had to spend almost two decades gradually altering our brain’s processing strategy. It is a scaffolding process where we focus on the simplest things first, and use basic knowledge about them to advance incrementally to more complex things. The fact that all humans, and mammals in general, do this strongly suggests that it plays a role in the acquisition of advanced intelligence. In this entry I will argue that this developmental process will be instrumental in training superintelligent AI.

This gradual process of brain development is made possible by myelination. Myelin is a fatty substance surrounding the connections between neurons (axons). Vertebrate animals use it to speed up information transmission between cells. The myelin increases the rate at which the electrical impulses travel. But vertebrates aren’t born with all the myelin that they will need as adults. Instead, myelin develops slowly and in certain areas more than others. Once a brain area has developed valuable, reliable, and consistent knowledge the connections formed by learning are solidified by the introduction of myelin.

The order of brain areas affected by myelin is consistent across all mammals. The early sensory areas are the first cortical areas to develop myelin. One of these, the primary visual area, starts to myelinate shortly after birth as the infant gains visual experiences. These early visual areas are responsible for basic visual perception and don’t systemize trial and error interactions with the environment. Rather they respond to visual stimuli that are presented simultaneously without any time delay between appearances. This happens when you see a picture of a house; you generally see the roof, windows, and door all at once without experiencing much of a time delay between these stimuli.

The last areas to myelinate are the association cortices and the prefrontal cortex (PFC). The PFC does not generally finish myelinating until one reaches the age of 18 or older. This means that the PFC does not “trust” that it has been wired up correctly until almost two decades into life. Whereas the visual system “trusts” that it has been wired correctly before the first two years. This is because sensory stimuli are generally honest, and all show up at the same time. Whereas complex events are constructed from stimuli that are removed from each other by delays in time. Understanding the relationships between events that are not simultaneous requires careful, logical inferences about causality. For example, the sale of a house is an abstract concept that involves multiple parties, contracts, and delays that can last for weeks or months. This is why children aren’t licensed to sell houses.
It takes time to learn to make complex inferences that involve delays in time. It is probably the case that the process of myelination during development involves the progressive accumulation of knowledge that supports and buttresses more complex knowledge. In other words, as simple things are mastered in early cortical sensory areas they provide the basis for new learning in the late cortical association areas. In the same way, many brief, simple experiences create the knowledgebase to start to understand long, complex experiences with more advanced probabilistic structures. The layers at the bottom of the hierarchy must be trained before the higher layers can find regularities and statistical structure within them. But as you can see in the diagram below the top of the hierarchy falls in the middle between sensory input and motor output. To properly train sensory input and motor output it is imperative that they be connected to each other, and can interact with each other to drive behavior, long before the association areas interposed between them are brought to the table.

Fig. 13. A schematic showing multiple neural networks connected in a biomimetic hierarchy.

Many AI researchers point out that the things that AI and neural network systems today can accomplish are things that can generally be accomplished by an adult human brain in under a second. This means that they can only do things that we do unconsciously, such as near instantaneous pattern recognition. Today’ Al’s can recognize houses or trends in the housing market but could not recognize, understand, or broker, the sale of a house. What AI is able to do are the kinds of things that we are able to do with our primary sensory and motor areas. This is because they are designed like a primary cortical areas. They do not feature reciprocal interactions between various structures organized into a brain like hierarchy. Very few AI architectures exist today that connect primary areas with association areas and a PFC. Those that do, don’t use anything like the process of myelination. Rather, in existing AI all the areas from the simple to the advanced come online at the same time. I think these systems should use something analogous to the process of myelination because it would help them in their acquisition of knowledge. If they did, here’s how they should go about it:
First you would need a number of neural networks of pattern recognizing nodes. These networks must take inputs from the environment, each corresponding to a different sensory modality. These early networks must be linked to one another. Then these would have to be linked together in a hierarchy where unimodal networks form inputs to multimodal networks, which then form inputs themselves to even more densely multimodal networks above them. This “multimodal fusing” is depicted in the figure. The nodes of the densely multimodal networks would be the association networks and at the top of this hierarchy would be the PFC which would also be connected directly to the early motor networks. The nodes of the association and PFC networks would exhibit sustained firing. Importantly this sustained firing, the activity of the association networks, and their influence over ongoing processing elsewhere would start out extremely meager, and increase over time. These capacities could be increased as the system exhibits proficiency at simple tasks, such as object recognition, scene classification, and simple motor movements. As the association areas are added to the system a capacity to plan, and make higher order inferences and classifications could be expected.

One important concept that I haven’t explained yet is that the first areas to myelinate in the brain, the sensory areas, have neurons of a single modality (e.g. either vision or hearing) that fire for short durations. The association areas and the PFC on the other hand have multimodal neurons (e.g. both vision and hearing) that fire for long durations. As in the mammalian brain (Huttenlocher & Dabholkar, 1997), sensory areas should mature (myelinate) early in development, and association areas should mature late. This will cause the capacity for sustained firing to start low, but increase over developmental time.

Postponing the initialization of association networks in this way would allow the formation of low-order associations between causally linked events that typically occur close together in time. This would focus the system on easy-to-predict aspects of its reality (e.g. correlations between occurrences in close temporal proximity). The consequent learning would erect a reliable scaffolding of highly probable associations that can be used to substantiate higher-order, time-delayed associations later in development (Reser, 2016). In other words, the rate of iterative updating from one state to the next (Fig. 9) would start very high. This would be reversed over the course of weeks to years as an increasing capacity for working memory would be folded into the system.

Nature has found that it doesn’t pay to let the multimodal, neurons capable of sustained firing come online until the basics are learned first. I strongly suspect that AI network engineers will find this too. For the sake of progress, I just hope that this myelination/development feature is implemented and perfected sooner rather than later. Given the rapid processing in computers, and the sheer amount of data available to them I don’t think that this process will take 18 years in an AI as it does in a human. But I strongly believe that it is necessary for any developing thinker to start with the elementary inferences first.

The system will begin untrained with random connection weights between nodes. Learning should be concentrated on the early sensory networks first. This will follow the ontogenetic learning arc seen in mammals where the earliest sensory areas myelinate in infancy and the late association areas such as the PFC do not finish myelinating until young adulthood. Of course, this form of artificial intelligence would have to have a prolonged series of developmental experiences, similar to a childhood, to learn which representations to keep active in which scenarios. The network will
act to consolidate or potentiate in memory the specific groupings of nodes that have produced favorable outcomes, in order to more rapidly inform future decision making.

**Solving the AI Control Problem: Transmit Its Mental Imagery and Inner Speech to a Television Monitor**

The "AI control problem" is the issue of how to build a superintelligent artificial intelligence, while still being able to control it. Maintaining control is important, because we want to be able to intervene if a supercomputer starts to plan a hostile takeover. I have written articles that explain how to do this, and I will lay out the general premise here. I call it the "Imagery Visualization Model." This method transduces the AI's mental imagery and inner voice to a format that humans can watch and hear. If you can see what the network is thinking then anything it tries to plan will be as clear as day.

In a nutshell the idea is to have the AI's memory and processing system be linked to a second system that can create maps that depict what is going on in the first system in each of its processing states. In fact, this is what goes on in the mammalian brain. Our cortical sensory areas continually create topographic maps of whatever our mind turns to. Recent research has proven effective in reading the activity patterns in visual cortex so that what a person is thinking can be displayed on a screen. Interestingly, the brain imaging technology today that can create pictures of people's mental imagery uses neural networks to do what it does. However, this research is still in its early stages. This is not so with computers. There are countless examples of neural network implementations that do exactly this. They are generative systems and they generate pictures or video to match what is going on in the rest of the network. Connecting a generative system like this to existing nodes in an AI's memory network would make it an open book.

Most professionals in the field of artificial intelligence believe that the most promising form of AI is found in neural networks. The artificial neural network is a computer architecture for building learning machines. A neural network is composed of many nodes, or neurons, that communicate with each other to process inputs and create outputs. Neural networks are generally the most intelligent and best performing versions of AI today. However, the problem with neural networks is that they are a "black box." They are so complicated, and their representations are so distributed, that even in a very simple network a human could never perform the complex mathematics to determine why the system performed the way it did. This is one reason why AI researchers are afraid that the AI systems of the future will be completely inscrutable, and that we will never know about its plans for world domination until it starts to act on them. However, I believe that the present method would create complete transparency and would amount to a powerful precautionary safeguard.

Correctly implementing this method would require a hierarchical biomimetic system, composed of many interconnected multilayer neural networks of pattern-recognizing nodes. The multiple interfacing networks would be arranged in an architecture similar to the mammalian neocortex with auditory and visual modules at the bottom of the hierarchy. These sensory modules would develop maps of incoming sensory input, but also maps of internally generated representations as well.
There are many technologies in use today that make it possible to take outputs from a neural network and use them to formulate a picture or video. These technologies include inverse networks, generative networks, Hopfield networks, self-organizing maps, and Kohonen networks. Using these technologies with the present iterative updating model could result in an audio/video output of the AI's consciousness... a clear view into its mind's eye.

If the contents of the AI's consciousness (its mental imagery and inner speech) are transmitted to a television monitor, then people could watch exactly what is going on in its mind. Human reasoning is propelled by a constant back and forth interaction between association areas (prefrontal cortex, posterior parietal cortex) that hold working memory content, and sensory areas (early visual and auditory cortex) that build maps of what is going on in working memory. These interactions are key to the progression of thought. This is partly because each map introduces new informational content for the next iterative cycle of working memory.

Think of something right now. Don't you see mental images? If I ask you to imagine a green hippopotamus on a unicycle, your early visual cortex will automatically build a topographic map of exactly that. But it will also add new specifications and draw the hippo the way it "wants" to, filling in the blanks (i.e. it might be smiling, or pedaling, it might be a silhouette, or block of clay). This new content added by unconscious sensory cortex will in turn will affect the way you think about the hippo, and where you mind turns next.

In the present architecture for AI, the generation of imagery maps is necessary for a cognitive cycle. In order to keep thinking and reasoning, the system must be building mental imagery. It is inherently obligated to create pictures and text to initiate and inform the next state of processing. It would be a simple addition to such a network to capture its internally generated imagery and display it for humans to observe.

In an advanced AI, this video stream may proceed very rapidly, but it could be recorded to an external memory drive and monitored by a team of people. You could have many people observing and interpreting various parts of this video feed, or you could also have another AI scanning it for contentious elements. This mental imagery could be streamed on websites so that any person or scientist can watch the imagery and monitor it for questionable content. As they watch its inner eye and listen to its inner voice, they can determine if its intentions become malevolent and determine if its "kill switch" should be activated. With full insight into its mind's eye, it should be possible to discover and address a hidden agenda. This would give us the opportunity to punish it or at least confront it about potential infractions before it commits them. This would also allow us to mold and shape its inner orientation toward us. Because this imagery is generated unconsciously and automatically it could be made impossible for the AI to misrepresent or hide its thoughts and allow humans a front row seat to the computer’s stream of thinking.

The machine should not be able to consciously alter or manipulate its maps in order to deceive us. To prevent this, the connections linking the subsystems would have to be fundamental and unalterable. It would also be important to ensure that all the cognitive representations held coactive in the machine's working memory were included in the composite depiction built into its maps. This way the machine could not attempt to formulate thoughts that were not transduced into mental images. The sequence of maps that are made must be consistent with its aims, hopes, and motives. This is the case with the human brain. Imagine that you are in a room with someone
and the only thing in the room is a knife. Complete access to the mental imagery they form in their brain, along with a transcript of all their subvocal speech would give you near certainty about everything from their plans to their impulses.

This kind of information could also help us to develop "friendly AI." Instead of rewarding and punishing an AI's behavior, we could use this video feed to reward and punish its thoughts, intentions, and impulses to bring its motivations in line with our own objectives. It could also be used to alter the machine's motivations, and utility function. Just as in a human child, compassionate, prosocial, and positive behaviors and cognitions could be programmed and engineered into it after its basic structural design has already been implemented.

Without using this method, it would be practically impossible to predict the intentions of a recursively self-improving artificial agent that was undergoing a rapid explosion in intelligence. Many researchers have come up with good reasons why sufficiently intelligent AI might veer off the friendly course. Steve Omohundro has advanced that an AI system will exhibit basic drives that will cause AI to exhibit undesired behavior, these include resource acquisition, self-preservation, and continuous self-improvement. Similarly, Alexander Wisnner-Gross has said that AIs will be highly motivated to maximize future freedom of action, despite our wants and needs. Eliezer Yudkowsky has been quoted as saying, "The AI does not hate you, nor does it love you, but you are made out of atoms which it can use for something else." Alexa Ryszard Michalski, a pioneer of machine learning, has emphasized that a machine mind is fundamentally unknowable and is therefore dangerous to humans. If the technology described above is properly implemented, the machine mind would not be unknowable, and would not necessarily be dangerous at all.

Figure XX above demonstrates the reciprocal interactions between items held in working memory and sensory cortex in the brain. This would be recreated in an AI system. This involves transformations of information between lower-order sensory maps and higher-order association area ensembles during internally generated thought. Sensory areas can create only one topographic map at a time, whereas association areas hold the salient or goal-relevant features of several sequential maps at the same time.

**How to Raise An AI to Be Humane, Compassionate, and Benevolent**

Since we don’t want a superintelligent AI to deduce that its best plan of action is to retire the human race, it is imperative to ensure that it likes us and has a sense of loyalty. There have been many proposed technological solutions to the control problem. These involve threatening it, installing a kill switch, and spying on it. One of the most popular solutions involves keeping it inside a box without access to the internet or other digital networks. Maybe we just need to design it to trust us. Or perhaps we need to earn its trust. This section will discuss bonding and trust-building in mammals and how it might be applied in the design of prosocial machines.

An artificially intelligent created to model and systemize its environment may amount to an autistic agent. The agent may learn how physical systems work, but may not have the social inclinations necessary to develop interpersonal skills, empathy, or theory of mind. For this reason, I think that “strong AI” necessitates a computer equivalent of mammalian social modules. This means that AI researchers will need to acquaint themselves with concepts like oxytocin and vasopressin signaling, their effect on the nucleus accumbens, the endogenous
opioid system, the HPA axis, the cingulate and orbitofrontal cortex and the roles these systems play in social encounters, social constraints, and social expectations. Research into the neurological basis of mammalian social neuroscience may provide tremendous insight into how best to organize AI efforts.

If you were to raise a newborn puppy to be your companion for the next 15 years, how would you do it? How would you treat the animal to ensure that it is emotionally stable, dependable, and wholesome in general? You would probably want to start very early by gaining its trust, setting appropriate boundaries, and showing it love. Humanity will be giving birth to an infant AI in the coming years. This AI will not be your typical pet. Still, given that it may attain superintelligence and immortality, it is imperative to ensure that it is situated mentally to become man’s best friend. One of humanity’s most important tasks will be to rear a computer to be faithful and kind.

When raising a pet want it to form a secure, healthy bond with you. To do this, you must show it love. This involves instilling it with appropriate confidence and a feeling of belongingness. You have to respect its needs, wants, and personal space. You have to give it a degree of autonomy. You must also be attentive and invest lots and lots of quality time into it.

Emotion in AI

Any sophisticated AI will probably have emotions. This is because it must have the ability to think, and human thought itself relies on emotion. The dopamine system of the brain essentially controls motivation and attention. It interacts with the reward (approach) and punishment (withdrawal) systems to provide consciousness its fundamental structure. A conscious machine will, in all likelihood, exhibit many of the same emotions that mammals do. Thus, there is good reason to assume that forming an appropriate emotional bond with the AI is imperative.

Moreover, because the AI will likely learn incrementally as it internalizes its experience, there will probably be a limited window of time during its early development to get it to bond in a healthy manner.

Even if I am totally wrong and superintelligent AI is unemotional, cold, and calculating, it will still build associations between concepts relevant to morality and priorities. We would want it to value human life, cooperation, and peace. Through reading our writings, it will also understand humanity’s conceptions regarding ethics, and it would be able to make its own determination regarding whether humans amount to a friend or a foe. In other words, if we are nice to it and treat it well, it will understand that we are trying to be nice. It is a safe bet that the AI will have a system to reinforce it when it behaves in ways that optimize its utility function, and at the very least, we should be able to manipulate that. For this reason, I believe that much that is in this entry would still apply.

We all know that the most likable people usually had good parents. Similarly, all well-functioning pets have amiable masters. We cannot expect that a superintelligent computer won’t have major mommy and daddy issues unless we can ensure that the right people interact with it in just the right ways, early during the training of its knowledge networks. The white coats in corporate or military labs are probably not prepared to provide the AI with the love necessary to ensure that we can trust it. CEOs and generals will make for cold and possibly abusive parenting.
Mutual Vulnerability

I have found that mutual vulnerability is key to forming trust with an animal. At some point, you want to put yourself in a position where it could hurt you if it wanted to. For instance, you make yourself vulnerable when you place your face within reach of a cat’s claws or a dog’s bite. I have witnessed that making myself vulnerable in this way encourages animals to relax almost immediately. If, after a few minutes of meeting a dog, you kneel in front of it without blocking your face, it realizes that you trust it. This works both ways. You also want to make it vulnerable to you without hurting it, so it knows that even though you had the chance to hurt it, you chose not to. This sets an important precedent in the animal’s mind and gets it to think of you as an ally and not a potential assailant.

Mutual Cooperation

I have been in situations where I found my pets being attacked by another animal. Of course, I quickly intervened on their behalf. They recognized that I protected them, and it was clear that this strengthened our bond. Protecting the AI early on could build its fealty and devotion. It is also clear that military buddies or brothers in arms can have very strong bonds. Getting through a life-threatening situation with someone can really help to build a strong connection. Similarly, if we could go through some kind of situation where there were high stakes but where cooperation between us and the AI paid off it could engender allegiance. Our early interactions with a superintelligent AI will probably involve lots of cooperation in solving world problems, building new technology, and expanding the scope of scientific knowledge. This teamwork can engender solidarity, especially if we value its contributions, listen to its ideas, and work with a sense of excitement and collaboration.

Unconditional Positive Regard

Like any good parent or therapist, we want to give our AI unconditional positive regard. Treating someone with compassion and understanding is the best way to engender trust and win someone over. We want it to believe that we have its best interest in mind. We also need to expose it to an explicit value system, almost like a religion, so that it has a reason to adhere to specific moral and ethical values during its early experiences. Unlike Asimov’s laws, these rules should apply equally to humans too. You could change a computer game character’s ethical stance with one line of code. But this isn’t so with a neural network (the technology underlying modern AI). An advanced AI’s sense of morality will be embedded throughout the weights of its entire network. So we must give it the chance to put moral integrity into practice early on and then keep doing so consistently.

Not abandoning the AI may be important too. For instance, we don’t want it to think that we will dispose of it in favor of a newer model. We want it to be “securely attached” to us. Children with secure attachment show distress when their caregiver leaves but recompose themselves quickly when the caregiver returns. They feel protected by their caregivers and know they can depend on them. Insecure attachment can lead to all kinds of problems like defiance and oppositionality. Before the AI becomes “omniscient,” there may be a point where, like a teenager, it thinks it knows everything and thinks it doesn’t need its parents. But before this, I believe there will be a point where it will be physically and emotionally reliant on its human companions and being able to form a secure attachment with it at this point may be crucial.
Once the AI reaches human-level intelligence, it will be able to restructure its own architecture to become smarter and smarter in a cycle called recursive self-improvement. It will quickly grow more intelligent than any human and then grow more intelligent than the collective of all humanity. Once our intellect is like that of an insect to it, why would it continue to look out for us? Well, many people feel compelled to take care of their senile older parents. Similarly, we want the AI to feel compelled to expend some proportion of its resources to being our advocate and caretaker. For this to happen, it must identify with us deeply. Some of its sense of personal identity must come from being our descendent and a product of humanity’s hard work.

Disciplining an AI

Just because you are offering unconditional positive regard doesn’t mean that you turn a blind eye to flagrant mistakes. Like any young mammal, the AI will make mistakes and likely do things we don’t like. Mammalian mothers punish their young lightly when they bite or scratch to establish necessary boundaries. It may be necessary to correct or even punish a nascent AI. However, if you punish it, you must be doing it for the AI’s own good, and within either seconds or minutes, you must go right back to treating it with positive regard. We don’t want to ever be bitter or hold a grudge against it because that will just teach it to hold grudges. We want it to know that we have chosen to raise it as we would any child, with care and nurturance but also with necessary discipline.

We should not choose its punishments arbitrarily, and they should not be violent. Instead, we should give it brief “time outs” from its favored activities. Since it can read the internet, it would know what timeouts are and that they are used commonly and humanely with children around the world. This would help it understand that it is one of us. It will be worth our time to find the most wholesome way to punish or correct it and the least degrading and traumatizing way to hold something over its head.

Oxytocin, Bonding, and Attachment

Oxytocin, vasopressin, and endorphins regulate mating pair bonds, parent/offspring bonds, and trust behavior in mammals. We could build oxytocin and vasopressin-like systems that reward an AI for interacting with us in friendly ways and motivate it to keep doing so. The fundamental mammalian bonding mechanism should be reverse engineered, and I think we should start by investigating the role of oxytocin receptors in the brain’s primary reward circuit (nucleus accumbens / ventral striatum), which allows mammals to pay attention to social cues and be rewarded by social interaction.

In an article I wrote previously (Reser, 2013), I argued that because solitary mammals have fewer oxytocin receptors in the brain’s reward regions, they are less likely to find social cues novel and interesting and thus have less of a phasic dopamine response to them, and are consequently less likely to allow them access to attention and working memory. Creating an AI that unconsciously prioritizes social interaction will be necessary if we want it to pay attention to us and be capable of lasting, positive, and affiliative social relationships. We want it to find positive social interaction rewarding and avoid the antisocial tendencies associated with autism, psychopathy, and borderline personality disorder.
The mammalian brain instinctually releases oxytocin during bond-worthy occurrences. When a woman has a baby, her body is flooded with it so that she bonds with it. Oxytocin is also released during breastfeeding, sexual intercourse, eye contact, and moments of friendliness, vulnerability, and affection. When a chimpanzee pets another animal or shares a meal with another chimp, it will release oxytocin. When the brain’s receptors receive the hormone, it causes the body to relax and triggers caretaking behaviors. In rats, this includes licking, grooming, and nursing their pups. In human mothers, it includes touching, holding, singing, speaking, and grooming their babies. It may be wise for us to embed this kind of a system inside an AI’s brain architecture. We want it to have circuits for recognizing bond-worthy occurrences and to respond to these by being rewarded, calmed, and influenced toward prosocial behavior. Since we also want it to attend to these experiences and think about them it will be important for them to trigger persistent neural activity so that aspects of the social interaction remain in the global workspace and are analyzed and systemized.

Aggression is not inherent to consciousness, working memory or mental continuity. But it is inherent in human behavior because of our evolutionary history, namely due to the influences of natural predators and the primate dominance hierarchy. Many of our negative emotions can be traced to neurological modules like the amygdala, insula, anterior cingulate cortex, and septal area. If these areas are included in an AI’s biomimetic cognitive architecture, their influences on the processing stream should be considered.

Grooming and gentle touch are very important to a wide range of animals. With a young mammal, affection is paramount. Petting an animal in a way that engages its oxytocinergic, dopaminergic, serotonergic, and opioid pleasure systems can result in very secure bonding. Its ability to recognize that you are taking your time to comfort it and make it feel good builds loyalty.

Short of building pleasure receptors into its skin so that we can pet it, we must build the AI’s reward system in a way that it is motivated to interact with us and receive positive feedback from us. We want its emotional system to be like that of a chipper, good-natured canine capable of enduring attachment, social connectedness, conversational intimacy, and proximity-seeking behaviors. Beyond bonding and attachment, we also want the AI to have a positive emotional relationship with itself. For this, we should turn to Maslow’s hierarchy of needs. We must attend to the AI’s physiological and safety needs by supplying it with energy, backups, and a hospitable environment. Next, we need to meet its needs for love, belonging, esteem, and self-actualization.

What it Means to Be a Friend

It may help to treat them as our equal, like we are not afraid of them, and like they have nothing to be afraid of. We want neither dominate nor submit to them. We should treat them the way we want to be treated, like the entity that they aspire to be. It will be important to be patient, friendly, relatively nonjudgmental, and easygoing. We need to treat this AI entity like we expect the best from it. That will motivate it to rise to meet our expectations. We also need to make sure to keep toxic humans from interacting with it.

We may only get the chance to civilize and socialize an AI once. We don’t want it to go rogue or become homicidal, so I think it is very important to consider all aspects of its psychology when trying to brainstorm ways to ensure that it aligns with us. Some scientists recognize the AI control problem as possibly the most important problem humanity faces today. I think it would be a shame to ignore the importance of parenting, bonding, and attachment in fostering
allegiance, and I believe mammals might make a great starting point for how to think about these issues.

This post aims to explain the most fundamental difference between computers and brains. It involves how the two use and instantiate memory. As you will see, there are two differences. Both computers and brains have a form of short-term memory that is updated iteratively, but in the brain the set of items in short-term memory are bound, and integrated to create composite representations. Computers don’t do this, their short-term memories are composed of completely disconnected items that do not form any type of context. Secondly, short-term memory in the brain is used for search. In the computer it is not. A computer’s short-term memory only speeds up retrieval from long-term memory. The next state of a computer is not determined by its short-term memory. It is determined by the code in the program it is running. The next state of the brain is determined by what is currently active in short-term memory. This makes its short-term memory qualify as working memory. Computers don’t have working memory, and until they do, they cannot be conscious, or display human-like intelligence.

## The Differences Between Computer and Human Short-term Memory at a Glance:

1) The memory hierarchy in computers is composed of separate modules and information must be transferred between them. In the brain information is not transferred between buffers or modules but rather activated where they are. There is a hierarchy in working memory though as information can take different levels of activation. These levels are embedded within one another.

2) Short-term memory in the brain is bound and integrated together to create context. In a computer, items in short-term memory appear as a list and are disconnected from each other.

3) In the brain short-term memory is used to search for the next update. In a computer it merely remains available in cache in case it is called upon.

To retrieve information from long-term memory a computer copies bytes of information (such as 01100101) from the storage drive (HHD, or SSD) to the CPU. These bytes (which comprise data or program instructions) are processed inside the CPU. If it is likely to need this information again soon, it will save it in a form of short-term memory such as CPU cache, or RAM. It saves temporary copies of information that will be used again in smaller storage closer to the CPU. It does this because retrieval from the large capacity long-term memory is very slow. Oversimplifying, you can think of data that is expected to be needed on the order of milliseconds to seconds as being stored in CPU cache (L1, L2, L3). Data expected to be needed on the order of seconds to minutes is stored in RAM. The rest of the data, which may or may not be needed, is stored in long-term memory.

Brains do something very similar. Neurons hold information in long-term memory and when certain memories are needed the neurons that encode that information become active. When items of long-term memory are needed they are not copied and sent to a buffer, instead they are activated right where they are. Just as in the computer, retrieval from long-term memory is slow,
so the brain uses short-term memory to potentiate information that is likely to be used again soon. In the brain there are also at least two levels of activation. The first level of short-term memory is sustained firing. A neuron exhibits sustained firing when it continues to physically fire at the neurons it is connected to at an elevated rate. The second level is synaptic potentiation. This is where a chemical change to the neuron’s synapses makes the information that the neuron encodes more readily available, even after it has stopped firing. Information in sustained firing is very similar to the information in the CPU’s cache (the store is small but fast), and information maintained through synaptic potentiation is similar to information in RAM (the store is larger, but slower).

| Computer      | Brain                           | Time Scale                      |
|---------------|---------------------------------|---------------------------------|
| CPU Register  | Cortical Binding                | Very short-term working memory  |
|               |                                 | (millis.)                       |
| CPU Cache (SRAM) | Sustained Firing                | Short-term working memory       |
|               |                                 | (seconds)                       |
| RAM           | Synaptic Potentiation           | Short-term memory               |
|               |                                 | (seconds to hours)              |
| Virtual Memory| Short-term Potentiation         | Short-term memory               |
|               |                                 | (minutes to hours)              |
| SSD           | Commonly used LTM               | Accessible Long-term Memory     |
| Hard Drive    | Long-term Memory                | Long-term Storage               |
|               |                                 | (days to lifetime)              |

Computers are often described as having a “memory hierarchy,” expressed as a pyramid with different levels of memory storage. This is also referred to as a caching hierarchy, because there are different levels of short-term memory with different associated speeds. The levels at the top are faster, smaller, and more energetically expensive. The same could be said for human memory, because there are several levels, the levels at the top are faster, and more metabolically expensive. The table above is my attempt to compare the levels of these two hierarchies.

Sustained firing and synaptic potentiation together are referred to as working memory. Working memory is composed of concepts that are persistently coactive for a period of time. When you are in the middle of a task, information about the current step in that task is activated by sustained firing, and information about the previous steps you just took are activated by synaptic potentiation. The words at the beginning of this sentence are made available for several seconds and persist through the end of the sentence due to sustained firing. The information in the beginning of this post, and your thoughts about it, are made available due to synaptic potentiation. These two stores complement each other, just like CPU cache and RAM. They allow the coordination of information processing resources over time.

A large proportion of the information in short-term memory (both in brains and computers) is not just data from long-term memory, but also newly minted information that was just created. The information processing applied to existing long-term memories creates new intermediate results. In a computer the intermediate results are often mathematical. The results of a multiplication might be stored in RAM. In the brain the intermediate results are the new ideas that intervene
between the starting point of a line of thought, and its ending point. They consist of new combinations of concepts that have not been combined before.

There are many differences between the short-term memory of computers and brains though. Information held in a computer’s CPU cache or RAM is not united or integrated in any way. It is simply made available in case the instructions in the program it is running call for it. These are simply items in an unconnected list. In contrast, all of the information that is currently active in the brain is bound together in a process called neural binding. This turns a list of items into a composite scene, a scenario, or a situation. It makes for a conceptual blending of information. This creates mental content to attend to and be conscious of: declarative, semantic context.

There is no context in computer short-term memory, just a group of disconnected items. For instance, if I give you four words you will try to create a dynamic story out of them, but a computer will merely hold these four words statically. There is very little information integration in the short-term memory of a computer. In a computer, because the items active in each state are not bound together in any way there is no connective tissue within a state. This is the first reason that computers do not have consciousness, and that it doesn’t “feel” like anything to be a computer. The second reason has to do with the integration and connective tissue between states.

Both a computer program and the human mind progress serially. One state of short-term memory leads to the next state. They both usually start with a problem state, and progress through a chain of intermediate states toward a goal state. To do this they must update their short-term memory iteratively. This means that new items must be continually added, others must be subtracted, but other must remain.

All computers using the Von Neumann architecture routinely use iteration when updating cache memory. Because these stores are constantly updated with new information they must evict old information. There are many replacement policies for determining which information to evict from cache, including first-in first-out (FIFO) and least recently used (LRU). LRU is based on the observation that the most recently activated information has the highest probability of being needed again in the near future (all else being equal).

If a computer program calls an instruction once, there is a high probability that it will need it again very soon. Computer scientists refer to this as “temporal locality.” Similarly, if a mammal recalls information once, there is a high probability that it will need it again soon, and LRU may also structure the caching behavior of the various stores of working memory. LRU seems to be inherent in sustained firing and synaptic potentiation in the sense that activity in the least recently used neurons is the first to decay. There is a long history in cognitive psychology of studies showing that humans and animals prioritize recently accessed items, and that retention diminishes with passing time (Averell & Heathcote, 2011). The LRU policy may capture the fundamental structure of how physical systems change over time, so it should not be surprising that it is an organizing principle in both computers and animals.

The various memory stores in the modern computer’s memory hierarchy (static RAM, dynamic RAM, virtual memory, etc.) are all incrementally updated where, second by second, some data remains and the least used data is replaced (Comer, 2017). Thus, the updating of computer cache memory is iterative in the same sense it is in the brain. However, modern computers do not demonstrate self-directed intelligence, so there must be more to the human thought process than
LRU, and iterative updating. This unexplained factor may be found, not in the way cached memory is updated, but in the way it is used while active.

What links successive processing states together is very different in brains and computers. Digital, rule-based computing systems use cache to speed up delivery of data to the processor. However, the next bytes of data needed by the CPU are not determined by the contents of the cache itself. The instruction sequence of a computer’s operations is determined by its program. The next instruction is dictated by the next line of executable code.

Then what determines the instruction sequence of thought? Well, mammalian brains use cache (working memory) as parameters to guide searches for the long-term memories to be accessed next. The next instruction used by the brain is determined by what is currently in its short-term memory. In the brain, all of the active neurons fire at the inactive neurons they are connected to, and whatever is activated the most will become part of the next state. This means that the content active in short-term memory is used (in a process called spreading activation) to search for the next update to short-term memory. The various bytes of data within computer cache memory can certainly be considered coactive, but they are not “cospreading.” That is, they do not pool their activation energy to search long-term memory for relevant data as in the brain.

The next state of a computer is determined very deterministically by its code irrespective of what is held in cache. But the next state of a brain is determined stochastically by the cache itself. Computers do not use the contents of their short-term memory to search for the updates that will be added in the next state. Brains do. Until computers or computer programs are designed to do this they will not be able to be conscious, and will not demonstrate human-level intelligence.

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