Integration of Semantic and Episodic Memories

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***Abstract*— This paper describes the integration of semantic and episodic memory (EM) models and the benefits of such integration. Semantic memory (SM) is used as a foundation of knowledge and concept learning, and is needed for the operation of any cognitive system. EM retains personal experiences stored based on their significance—it is supported by the SM, and in return, it supports SM operations. Integrated declarative memories are critical for cognitive system development, yet very little research has been done to develop their computational models. We considered structural self-organization of both semantic and episodic memories with a symbolic representation of input events. Sequences of events are stored in EM and are used to build associations in SM. We demonstrated that integration of semantic and episodic memories improves the native operation of both types of memories. Experimental results are presented to illustrate how the two memories complement each other by improving recognition, prediction, and context-based generalization of individual memories.**

***Index Terms*— Cognitive system, episodic memory (EM), event significance, motivated and reinforcement learning, semantic memory (SM).**

I. Introduction

SEMANTIC and episodic memories belong to the category of declarative memories, where the past, consciously experienced events and knowledge are stored and can be recalled or declared [1]. Thus, they are critical components of any cognitive system. The two memories differ in their organization and use. Semantic memory (SM) integrates sensory experiences and is responsible for the creation and recognition of concepts. It is grounded, and as such, integrates unconscious sensory inputs to recognizable objects and ideas. Episodic memory (EM) uses the concepts represented by the SM to record the personal history of events located in time and space. While SM is developed incrementally over time, EM is developed immediately upon consciously recognized events.

The two memories are interdependent since episodes can only be consciously experienced after the SM recognizes them, while past episodes help to develop new knowledge stored in the SM, help to build associations between various objects and actions, and help to anticipate future events [2]. Until now, there has been no study of artificial neural networks implementing integrated architectures of semantic and episodic memories. This paper does it.

Tulving [3] in his seminal paper defined the original concept of EM and contrasted it with SM. Both memories are essential for the retrieval of past experiences, learning, planning, and anticipation [4], [5]. Tulving [6] reiterated the distinction between EM and SM by taking into account required operations and awareness involved in retrieving information stored in each type of memory. In addition to episodic events containing what, where, and when information, EM accumulates one's own past existence. This allows one to mentally revisit the past experiences while being aware that the recollection is related to earlier time [7]. In contrast, SM involves classification and recognition of objects without referring to where or when the event regarding them occurred. It refers to an individual's knowledge and perception of its environment at the present time. SM provides a cognitive interpretation of the perceived objects and events, and is critical to having a conscious experience.

EM plays an important role in support of cognitive functions such as: 1) representation of events in the spatio-temporal domain; 2) formation of concepts in SM; and 3) supervision of tasks in the implementation of goals [8]. Research on the hippocampus (the part of the brain where episodic memories are stored) indicates its importance for providing the context of the observed events. It plays a critical role in reinforcement learning, representing relationships between stimuli [9]. Using an SM, we can model some of the associative processes observed in biological nervous systems. An SM can bind together neuronal representations of trained data, so the relations between data could be expressed through connections and changing the sensitivity of neurons that specialize in recognizing various classes of objects. The major role of SM is to link objects that often occur in the same or similar context, and enable them to be recalled associatively [41].

Declarative memory benefits from the interaction between episodic and SM. Its critical neural circuitry involves bidirectional connections between the neocortex and the hippocampus [10]. A replay of episodes stored in the hippocampus is obtained without disturbing the semantic storage [11] and provides a mechanism for memory consolidation and learning of the knowledge structures [12], [38], [39]. Such memory consolidation transforms initially fragile memory traces into more stable representations [13] in SM. Semantic learning is gradual and yields knowledge about experienced

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episodes [14]. Norman and O'Reilly [15] presented a model of declarative memory and used it to show the relationship between recall and familiarity and the effects of hippocampal lesions on recognition.

Considering the importance of declarative memories, cognitive architectures try to include them in their design. One of the best-known cognitive architectures Soar [16], consists of several functional blocks such as semantic, procedural, EM, working memory, and symbolic and subsymbolic processing of sensory input data. All memories interact in Soar during each cognitive decision cycle, searching for knowledge relevant to current goals and expected rewards. In LIDA architecture [17], based on the global workspace theory [18], sensory data activates SM, and the local workspace is used to generate associations between semantic and episodic memories. We aim to develop and use declarative memories in our own cognitive architecture [19].

In this paper, we present an integrated system of semantic and episodic memories and demonstrate how these two memories can benefit from working in tandem.

We studied various aspects of such an integrated memory in the context of cognitive system architecture and its functional organization.

We demonstrated that an integrated memory system works better than its two individualized components. EM helps SM to resolve ambiguities and recall exact training sequences, while SM helps to recall proper episodes through learned associations.

Our aim is to propose an engineering model of declarative memory, not to describe its biological counterpart. We show memory as an integral part of our cognitive learning system: in Section II we describe semantic and episodic memories integrated with other functional blocks within a cognitive architecture. This is followed by a description of the role and organization of SM created by a self-organizing network of associative neurons presented in Section III. Section IV gives an overview of the organization of an EM based on sequential memory cells. Section V presents memory integration, and Section VI illustrates this with several tests of predictive responses obtained from the integrated memories. Section VII contains conclusions.

II. Semantic and Episodic Memories in MLECOG

In [19], we proposed a motivated learning (ML) cognitive architecture (MLECOG) that included such functionalities as learning, planning, prediction, and reasoning, as well as motivations, intrinsic rewards, goal creation, attention focus, attention switching, semantic, episodic, and working memory. MLECOG implements our ML approach [20] where the machine uses designer specified goals to create new motivations and goals it finds useful for its operation. The MLECOG architecture is used as an example in order to situate both episodic and semantic memories and describe their role in a cognitive system architecture. It helps to justify the properties we want to develop and explore in experiments with the integrated memory system.

The mutual interdependencies of episodic and semantic memories are well recognized in neurological and psychological studies [2]. While there are many research works on episodic and SM architectures, there has been no study testing their integration and online real-time operation. Early implementation of the MLECOG architecture in a simulated environment using NeoAxis [21] did not include EM, and SM was implemented using simple neural networks to learn goal-oriented behavior. This paper tries to remedy these deficiencies.

III. Semantic Memory

Object representation is obtained in the SM by associating different sensory data with action and reward information experienced by the system. Full awareness of such objects invokes qualia, responsible for the cognitive understanding of the observed input. Perception in MLECOG is accomplished through the active use of sensors in coordination with motor actions, following the ideas presented in [23]. A full treatment of building object representations and symbol grounding [23] is beyond the scope of this paper, thus in our further discussions, we assume symbolic representations of the perceived objects, actions, and goals.

In this paper, we use an active neuro-associative knowledge graph (ANAKG)—a special kind of SM devoted to consolidating representations of training sequences of objects or classes of objects [5], [24]. The SM aggregates representation of the training data. This is done by binding the semantic contexts for all trained objects and linking their neuronal representations together. The created connections are weighted, so each association has its own importance. The SM used in this research can associate distant time events in order to put them in a wider context. Moreover, the SM can trigger recalling processes automatically, taking into account the given context and semantic relations between objects represented in the neuronal graph structure. Finally, the SM can generalize knowledge gained during the adaptation process based on presented training data. The ANAKG SM can generate new responses according to the new contexts of recollection that were not previously taught. The SM explicitly demonstrates that memories can be changed if new data is added or existing data is repeated several times.

The ANAKG SM is constructed from associative neurons (called **As-neurons**), defined as neurons that incorporate ideas of spiking and artificial neurons together with new ideas about neuron modeling and plasticity. As-neurons model some functional aspects of biological neurons, not a biological computational platform or electrochemical processes. They represent various associations between objects and their parts defined as time-spread combinations of inputs. This new neuron model is time-dependent and can be charged, relaxed, and refracted after spikes, however, it does not reproduce biochemical processes as spiking neurons do. In contrast to spiking neurons, this model conditionally creates connections to other neurons that are activated in similar time. It enables the reproduction of biological connection plasticity processes and automatically creates a neuronal structure of ANAKG networks. The As-neuron is activated when it reaches its activation threshold θ taking into account the relaxation process that gradually returns this neuron to its resting state. Each As-neuron represents all of the time-spread combinations of input stimuli that activate it. Input combinations that activate an As-neuron may differ, however, they represent the same class of objects. They work similar to neurons in nature, where various combinations of the input stimuli can identify the same mental class of objects.

Each activation of As-neurons is as follows.

1) Enables stimulation and sending a message to other connected As-neurons about the recognized class of objects represented by this neuron.
2) Makes it possible to automatically and conditionally connect As-neurons activated in similar time or change synaptic efficacy and weight of the existing connections accordingly to the time that elapsed between activations of presynaptic and postsynaptic neurons.
3) Automatically takes into account a context defined by the previously activated neurons that are connected to the neuron(s) defining the next object(s) in the observed sequence.

In contrast to spiking neurons, the As-neurons can be adapted easily and very fast to represent the training sequences of objects in a consolidated neural graph structure (Fig. 5). They demand only a single activation of a training sequence set to create such a structure and compute all necessary parameters. This approach yields the neural graph structure much faster than training routines of artificial neural networks. It is also easier to compute than spiking neural networks, which require solving several differential equations. The most important aspect of the adaptation process of the ANAKG is based on the so-called **synaptic efficacy** (1) computed accordingly to the time that elapsed between presynaptic and postsynaptic activities of As-neurons if both neurons were activated in a close time succession. The longer this period is, the smaller the impact is on the synaptic efficacy. The synaptic efficacy is also dependent on a frequency of the contribution of this synapsis stimulation to the postsynaptic neuron activity to emphasize the Hebbian rule. The synaptic efficacy significantly simplifies the adaptation process in comparison to other models of neurons both spiking and those that use nonlinear activation function.

Let $S^n = [S_1^n, \ldots, S_m^n, \ldots, S_{m+r}^n, \ldots, S_{K_n}^n]$ be a training sequence from training sequence set $\mathbb{S} = \{S^1, \ldots, S^N\}$. The synaptic efficacy is computed for each two connected As-neurons N_m and N_{m+r} representing two objects (or classes of objects) S_m and S_{m+r} in each training sequence S^n that contains them. Objects S_m and S_{m+r}, represented by As-neurons N_m and N_{m+r}, obviously do not have to be present in all training sequences. If they are present they can be separated in time by a number of other objects $(r-1)$, where $r \geq 1$. The time differences between observation of S_m and S_{m+r} objects represented by activations of As-neurons N_m and N_{m+r} affect the computation of various components of the sum (1). The final synaptic efficacy for this synapse takes into account all training sequences that contain time ordered succession of objects S_m and S_{m+r}. The synaptic connection between As-neurons representing objects S_m and S_{m+r} is denoted as $N_m \to N_{m+r}$

$$\delta_{S_m, S_{m+r}} = \sum_{\{(S_m, S_{m+r}) \in S^n \in \mathbb{S}\}} \left(\frac{1}{1 + \frac{\Delta t^A - \Delta t^C}{\theta_{N_{m+r}} \cdot \Delta t^R}} \right)^{\tau} \tag{1}$$

where

- Δt^A is the period of time that lapsed between stimulation of synapse between N_m and N_{m+r} neurons and activation of postsynaptic neuron N_{m+r} during training;
- Δt^C is the period of time necessary to charge and activate postsynaptic neuron N_{m+r} after stimulating synapse between N_m and N_{m+r} neurons (here $\Delta t^C = 20$ ms);
- Δt^R is the maximum period of time during which postsynaptic neuron N_{m+r} recovers and returns to its resting state after its charging that was not strong enough to activate this neuron (here $\Delta t^R = 300$ ms);
- $\theta_{N_{m+r}^n}$ is the activation threshold of postsynaptic neuron N_{m+r} (here $\theta_{N_{m+r}^n} = 1$);
- τ is a context influence factor changing the influence of the previously activated and connected neurons on the postsynaptic neuron N_{m+r} (usually equal to 2, 3, or 4, here equal to 4).

Synaptic efficacy (1) is a measure of how strong input stimulation influences the postsynaptic neuron activity due to the elapsed time between activations of pre- and postsynaptic As-neurons. Synaptic efficacy weights and sums up all related activities of the connected neurons during training.

ANAKG consolidates representations of many training sequences in such a way that repeated objects occurring in training sequences are represented by single As-neurons. It means that the representation of objects is not duplicated. Such neurons bind training sequences together and thanks to contextual connections between them it is possible to retrieve many of these sequences using a unique initial context for recalling them [5], [24], [38]. When new or nonunique contexts are used, the ANAKG retrieves the most frequent training sequences or new sequences that are built either from parts of the training sequences or their associated elements.

The synaptic efficacy is used to compute a **synaptic permeability** (also called connection **weight**). The synaptic permeability is computed after activity of the presynaptic neuron N_m by considering synaptic efficacy that contains its influence on the postsynaptic neuron activity using the following equation (see also [40]):

$$w = \theta \frac{\eta\delta}{\eta\delta + \eta^2 - \delta^2} \tag{2}$$

where

- η is a number of activations of a presynaptic neuron N_m during training for training sequence set $\mathbb{S}$;
- δ is a synaptic efficacy computed for this synapse.

The synaptic permeability values of each synapse are in the range between 0 and θ, where θ is a threshold value of the

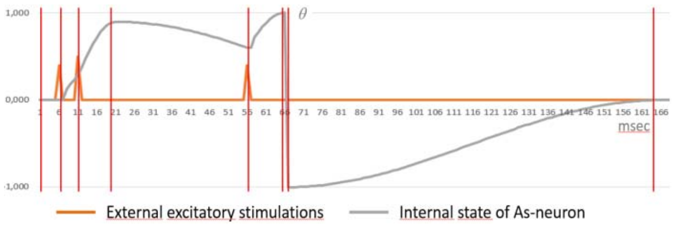

Fig. 1. Discrete moments of time when an internal As-neuron state is updated.

postsynaptic neuron N_{m+r}. The range of permeability values emphasizes the influence of the presynaptic neuron N_m on the postsynaptic neuron N_{m+r}.

The synaptic permeability equation should satisfy the **rule of associative stability**. This rule states that repeated training using the same training sequence set in the same timing order does not change the network structure or the connection weights of the neural network.

Lemma: Connection weights described by (2) satisfy the rule of associative stability.

Proof: The repetitions of training sequences λ times result in appropriate changes of $\lambda\eta \to \eta$ and $\lambda\delta \to \delta$. If the computed weights λw for λ repetitions of training sequences are the same as computed weights w^1 for a single presentation of training sequences then the equation is associatively stable

$$w^{\lambda} = \theta \frac{\lambda\eta\lambda\delta}{\lambda\eta\lambda\delta + (\lambda\eta)^2 - (\lambda\delta)^2} = \theta \frac{\eta\delta}{\eta\delta + \eta^2 - \delta^2} = w^1.$$

It is proven that weights do not change during the adaptation process for (2) with repetitions of all training sequences. Thus, they are associatively stable.

In our model each As-neuron is in one of four states: resting, charging, recovering and refraction according to its internal excitation level. Equations (3)–(5) model the As-neuron excitation level during charging (3), recovering (4), and refraction (5) periods

$$X_{N_i}^{t+\Delta t} = X_{N_i}^{t} + \left[\sum_{N_m \to N_i} \left(x_{N_m}^{t} \cdot w_{N_m,N_i} \right) \right] \cdot \sin\left(\frac{\pi \cdot \Delta t}{2 \cdot \Delta t^C} \right) \tag{3}$$

where $t < \Delta t \le t + \Delta t^C$

$$X_{N_i}^{t+\Delta t} = X_{N_i}^{t} \cdot \frac{1}{2} \cdot \left(1 + \cos\left(\frac{\pi \cdot \Delta t}{X_{N_i}^{t} \cdot \Delta t^R} \right) \right) \tag{4}$$

where $t < \Delta t \le t + \Delta t^R$

$$X_{N_i}^{t+\Delta t} = X_{N_i}^{t} \cdot \frac{1}{2} \cdot \left(1 + \cos\left(\frac{\pi \cdot \Delta t}{\left| X_{N_i}^{t} \right| \cdot \Delta t^F} \right) \right) \tag{5}$$

where $t < \Delta t \le t + \Delta t^F$, Δt^F is the maximum period of time during which neuron N_i finishes its refraction after activation and returns to its resting state (here $\Delta t^F = 60$ ms).

A given neuron charges when it is stimulated through excitatory synapses. During charging an As-neuron raises its internal excitation to the level defined by its previous state $X_{N_i}^t$ and the current external stimulation (3) (the rising curve between 6 and 20 msec in Fig. 1). The charging process continues if further input stimulus comes during the incomplete charging process (at 11 msec in Fig. 1).

The recovering process starts when the charging process is finished (after 20 msec in Fig. 1). If the neuron is no longer stimulated before reaching its activation threshold (at 20 msec in Fig. 1) it starts to recover (4) from its charged state $X_{N_i}^t$, gradually returning to its resting state. If the neuron reaches its activation threshold level (at 66 msec in Fig. 1) it is activated, starting stimulation of other connected neurons, and starts its refraction process (after 67 msec in Fig. 1).

IV. Episodic Memory

A. Memory Formation

Two basic elements of EM are events and episodes. An **event** is a snapshot of experience or the observed scene. It represents what was observed, where and when or what action was performed. An **episode** is a sequence of events. Significant events and their episodes are remembered for a longer period of time. To efficiently encode events and episodes, an EM model should differentiate distinct events and episodes with a well-defined matching scheme. The novelty detection should distinguish similar but semantically different events. However, it should tolerate minor differences for events within episodes, such as slight changes in the observed events or their temporal order. Some existing EM models have addressed many of these issues [25], [26].

We developed an efficient EM model based on long-term memory (LTM) cells described in [27]. The network proposed in [27] anticipates the next element of the input sequence using feedback connections to the SM neurons. Learning of an input sequence occurs only when the anticipation of the next elements is incorrect. The model performs chunking of input sequences into smaller subsequences, once the learning signal is triggered. The EM requires only a single presentation of a training sequence to learn. This is unlike other EM structures (e.g., memories based on the Markov model or neural network memories like the one presented in [28]) that require multiple sweeps or repetitions of the sequence.

Our next model [29] introduced a flexible matching mechanism that gives a real-valued measure of similarity between the learned sequence and the testing sequence. It addressed the error tolerance problem of the neural network to order distortion, time delay, and imperfect segmentation. The improved LTM algorithm [30] was tested in continuous learning on the Australian sign language data set [31] that was recorded by a high-quality hand position tracker from a native signer expressing various signs, and in mobile robotic navigations using sequences of the observed scenes [32]. The model introduced error tolerance within an LTM cell, incorporated the significance of elements in sequential memories, and used a novel activation decay mechanism.

In this paper, we adopted a simpler version of the LTM cell structure to organize the EM integrated with the SM. One reason for this simplification was to highlight the interdependence of the two memories and to provide easier interpretation of the obtained results.

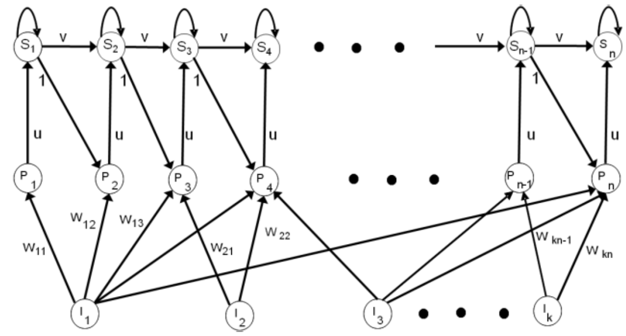

Fig. 2. Simplified parallel model of an LTM cell.

B. Episodic Memory Organization

A crucial element of EM is the encoding of the sequential or temporal order between events. Each event activates primary neurons P_i in the SM. Each episode that contains a sequence of events can be stored in a simplified LTM cell shown in Fig. 2.

During episode learning, primary neurons are linked to the corresponding secondary neurons with constant links u. Secondary neurons are linked to primary neurons using weights equal to 1, and are also connected to neurons representing the next element of a sequence using constant weights υ. Thus, learning of an episode involves only the selection of neurons that need to be linked.

All links from the primary to the secondary neurons (also known as the **primary links**) are normalized to $u = (1 - \gamma\upsilon)$, where γ is a decay factor of the secondary neuron activations. This normalization limits the maximum activation of the secondary neurons to be less than or equal to 1.

The activation of the first secondary neuron is obtained with

$$S_1^t = \max\left((1-\gamma\upsilon) * P_1^t, \gamma S_1^{t-1}\right). \tag{6}$$

At each time step t, the activation of all other secondary neurons is obtained with

$$S_j^t = \max\left((1-\gamma\upsilon) * P_j^t + \gamma\upsilon * S_{j-1}^{t-1}, \gamma S_j^{t-1}\right). \tag{7}$$

Prediction can be obtained in the same way as chunking and prediction in the modified LTM model shown in Fig. 3. In Fig. 3, neurons PN_i are prediction neurons. A PMN_i prediction matching neuron is connected to corresponding PN_i and P_i neurons using links with interconnection weights equal to 0.5, so this neuron is activated when both of its inputs are activated. Activation of any *PMN* neuron activates a prediction checking neuron *PCN*. If a *PCN* is active this means that the prediction was correct and there is nothing to learn, so the learning flag neuron *LFN* is inhibited and there is no activation of the learning neuron *LN*. The Multiple winner detection neuron *MWDN* can be activated by two or more secondary neurons that are activated above the threshold. If this happens, all PN_i neurons are inhibited and no prediction is possible, which typically means the introduction of a new LTM cell is needed. In Fig. 3, dashed lines represent a connection to a preceding chunk of LTM memory, and S_{co} stands for a preceding chunk output (last) neuron.

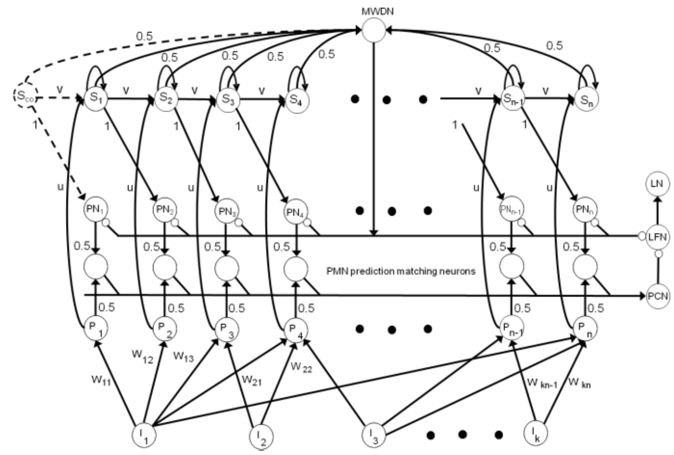

Fig. 3. Prediction in a simplified parallel model of LTM cell.

C. Memory Retrieval

EM retrieval involves three stages: event detection, episode recognition, and episode recall, described as follows. During event detection, activation of primary neurons is used to activate events stored in various LTM cells. This event-driven operation is performed in parallel on all activated cells. Episode recognition is a result of competition between partially activated LTM cells. If the winning cell is activated above the threshold, the episode is recognized. Episode recall is used to predict the subsequent events in the order in which they were stored in the EM. Correct predictions indicate familiarity with the observed scenes, while incorrect prediction may indicate a new situation, and may trigger additional learning depending on the significance of the observed events.

In an LTM cell memory retrieval is organized as in the following Algorithm 1.

Algorithm 1 (Memory Retrieval)

1. Upon presentation of a new input, the corresponding primary neurons P_j^t are activated.
2. Existing secondary neuron activations are shifted by one location to obtain S_{j-1}^{t-1}.
3. Primary neurons' activation is multiplied by $(1 - \gamma\upsilon)$ to obtain $(1 - \gamma\upsilon) * P_j^t$.
4. Previous time secondary neuron activation is used to obtain γS_1^{t-1}.
5. Activation of secondary neurons S_j^t is computed using (6) and (7).
6. Activation of each LTM cell is on the level of the strongest activation of its secondary neurons S_j^t.
7. Secondary neuron S_j^t of the winning LTM cell predicts the next episode.

D. Forgetting

Many studies have observed that episodic memories in the hippocampus are not permanent, they may quickly be forgotten, and occasionally are transferred to neocortical areas in the brain through consolidation processes [22]. This memory consolidation makes important or frequently recalled episodes less prone to being forgotten [6]. According to [25], sleep periods are used for memory consolidation and active forgetting of less useful events and knowledge consolidation.

Preventing accumulation of events in the EM is a crucial aspect when dealing with continuous real-time operations. Thus, a forgetting mechanism should update the durability of events based on their significance and frequencies of use.

One important requirement for EM is to relate the strength of episodes saved in the machine's memory to their relevance to the machine's mission. Human EM preserves lifetime experiences with various intensities and related storage time. Routine actions (like where I parked my car today) are preserved for a limited duration, after which they may be cleared to make room for new memories. Also, episodes with stronger emotional context are recalled easier and with more detail than those of weaker importance.

When episodes are initially stored in the memory, their relevance is often not determined. The duration for storing such undetermined episodes is limited, and if they are found to be useful, it can be reevaluated. The initial signal activation strength of recalled memories y_{i0} is modulated (over time or the number of recorded episodes t) as follows:

$$y_i = \gamma^{|\alpha|} y_{i0} \exp\left(-\frac{t}{T_0 \beta^{|\alpha|}}\right) \tag{8}$$

where $\gamma > 1$, $\beta > 1$ are selected to indicate how strongly event significance and emotional context affect the duration and strength of the EM for the selected episode, and

$$\alpha = \sum_k r_k. \tag{9}$$

In this equation, α stands for the total reward received for all actions that involved the selected episode. Since rewards can be positive or negative, their effects may cancel each other out, however, if the episode is strongly related either to rewards or punishments they will return a significant value $|\alpha|$ and will result in stronger and more durable memory. T_0 is a nominal time constant that determines memory preservation time (for instance $T_0 = 1000$ will decay the memory e times after each 1000 episodes). If no reward or punishment is associated with this episode, the episode is removed from the EM once its strongest signal y_i falls below a specified threshold. According to (9), episodes that are related to a significant reward or punishment will be remembered longer, and their signal strength may increase.

Notice that since signal strength is also used to indicate sequential order, it is possible that part of the sequence will fall below the threshold and, thus, only the most important or recent part of this episode can be restored.

Using this approach, the EM retains storage of all the relevant episodes and remove less useful ones. This mechanism protects the memory from storing irrelevant information and reduces the memory access time. Both features are needed for EM in continuous, real-time operation of autonomous agents.

V. Memory Integration

The integrated system of semantic and episodic memories is a hetero-hierarchy of LTM cells that collaborate with activations of neurons in the short-term (working) memory and underlying SM.

The concept of integrated declarative memory is in accord with neuropsychological studies on inner workings of the brain. The brain imaging research reported in [33] led to finding a brain default network that participates in cognitive processes when individuals are not involved in interaction with their environment. This network is responsible for planning and thinking, as well as extraction of episodic memories, and corresponds to multiple interacting subsystems including medial temporal lobe (MTL), medial prefrontal cortex, and posterior cingulated cortex. In addition, reenacting the past and planning for future involve interactions with episodic memories as described in [34] and [35].

Although both EM and SM are an integral component of long-term declarative memory, most works in the literature study them in isolation. Only one prior research [37], discussed the interaction and co-evolution of episodic and semantic memories. In [37], EM traces are vectors of feature values relevant to the represented event. Semantic knowledge in [37] is represented by a matrix that shows activations of these features. Each element of this matrix stands for the frequency of co-occurrence of the two features represented by rows and columns of this matrix.

A. Integrated Declarative Memory Organization

The Integrated Memory organization includes two major parts. First, an input pattern is processed by hierarchically organized SM to activate the short-term memory. Input processing on lower levels is responsible for feature selection and early representation building. The evidence of such preprocessing exists in V1, V2, and V4 layers of the human visual cortex [36]. The second major part of this memory organization is a hierarchically organized array of LTM cells. Primary inputs to LTM cells are obtained from the short-term working memory triggered by attention focus on activities in the SM.

Event-driven signals are used to control the recall of a sequence stored in a selected LTM cell.

The Integrated Declarative Memory works by passing information to and from both memory structures. The ANAKG network is stimulated by test questions and generates the subsequent neuron responses as input to the LTM structures. The EM accepts input from the ANAKG network and provides predictions back to the ANAKG network via LTMsensor. All ANAKG neurons have two sensors, a regular input sensor, which activates a neuron, and an LTMsensor, which increases a neuron charge in the range from 0.6–1. Algorithm 2 describes dynamics of the Integrated Declarative Memory.

B. Complexity Analysis

Consider the effort of encoding m episodes with e events each. In order to estimate hardware requirements and computational complexity of the integrated memory, we perform a hardware and time complexity analyses.

Algorithm 2 (Operation of Integrated Declarative Memory)

1. Initialize memories by passing training sets to both memories. The training sets can be identical or specific to each memory. This:
   a. Creates initial LTM based episodic memory
   b. Generates initial associations in the ANAKG semantic memory.
2. After the initial training phase, the ANAKG memory is stimulated via a "question" presented to the sensory neurons S_m through S_n.
3. The ANAKG network passes its neuron activations to the LTM network (in the form of sequential activations of LTM cells via I_1-I_k).
4. The LTM attempts to recognize the sequence via the process discussed in *Algorithm 1*.
5. The episodic network's prediction is passed back to the semantic network to influence its activation via LTMsensor inputs S_{L1}-S_{LK}.

1) Hardware Complexity: SM requires p category nodes and k synaptic connections depending on the number of associations between events. Assuming that the average number of associations is a, we need $p \cdot a$ synaptic connections in the SM. Each LTM memory cell requires s secondary neurons, and each such neuron needs four synaptic connections, so to store e episodes we need $e \cdot s$ secondary neurons and $4 \cdot e \cdot s$ synaptic connections. Thus, the integrated declarative memory system requires $p + e \cdot s$ neurons and $p \cdot a + 4 \cdot e \cdot s$ synaptic connections.

2) Time Complexity: The concurrent version of LTM cells requires constant processing time since each new event only activates the secondary neurons. A response is immediate if the cells are implemented in parallel processing hardware. (Only a single multiplication and comparison is needed.) If the processing is simulated on a sequential computer, then processing time depends on the number of LTM cells in memory and the number of secondary neurons activated by the input event. If on average, a single event activates c synaptic connections, then processing time per each event is proportional to $O(c + e)$ multiplication and comparison operations to select the winning LTM cell. Thus, the processing time for all events is proportional to $O((c + e) \cdot e)$. SM requires processing time proportional to number of events multiplied by the average number of activations in the neural network graph. Since the number of connections per neuron stored in the SM grows with the logarithm of events, we can estimate time complexity to build the SM as $O(e \cdot \log_2(e))$. We verified this estimate by performing simulation on a large data set of all words in all of Grimm's Fairy Tales. In our simulation, each individual word is treated as an object, and unique words are individual neurons in the associative memory graph. The results are presented in Fig. 4.

The average number of objects represented by a neuron [Fig. 4(a)] grows during the adaptation process (here: up to 44 objects per neuron), because the same neurons represent the recurring objects. The average number of connections per

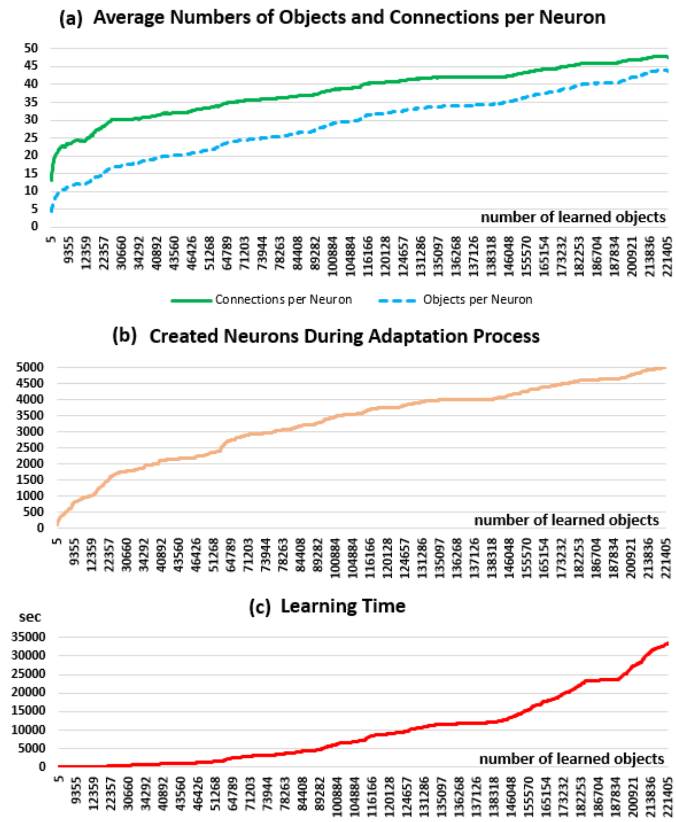

Fig. 4. Performance results for a large data set. (a) Average numbers of objects and connections per neuron. (b) Created neurons during adaptation process. (c) Learning time.

neuron [Fig. 4(a)] is slowly growing (here: up to 48 connections per neuron) for similar reasons. The total computational complexity of this construction and adaptation process on a sequential machine is $O(o \cdot s \cdot \log_2(n))$, where o is the number of objects, s is the average number of synapses per neuron, and n is the number of neurons (or sensors). Fortunately, n is usually much smaller than o, due to the aggregated representation of the same objects (here: 221405 of objects have been represented by 5022 neurons) [Fig. 4(b)].

In the sequential simulation, sensors are processed using a binary search algorithm. In parallel computation, the computational complexity is O(o), because there is no need to use binary search to find out an appropriate sensor representing an input object. Since in story telling each sentence is an event, and an average event has a constant number of objects (words), and each neuron has a small number of synapses, we estimate time complexity to build this SM is $O(e \cdot \log_2(e))$.

Simulation has shown that sequence learning and self-organization of SM is scalable to large sets of data. Construction and adaptation of thousands of training sequences consisting of 221405 words requiring 5022 neurons and 241211 connections took less than 10 h [Fig. 4(c)] on an average laptop (i7-3612QM CPU, 2.10 GHz, 12 GB RAM).

VI. Simulation Results

In this section, we demonstrate the capabilities of individual memories, point out their limitations, and indicate the benefits of the integrated declarative memory system.

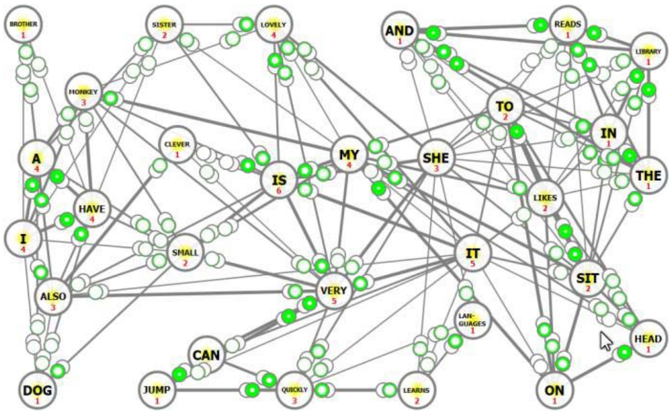

Fig. 5. View of the training sample sequences described in Example 1.

A. Context-Based Prediction

One of the roles of the memory is a context-based recall and prediction. Typically, context is provided by the SM, although some priming in the SM is also obtained from predictions based on the EM. We illustrate this with an example session of questions and answers provided by the semantic and episodic memories.

Example 1: The training input file contains the following sentences.

1) I have a monkey.
2) My monkey is very small.
3) It is very lovely.
4) It likes to sit on my head.
5) It can jump very quickly.
6) It is also very clever.
7) It learns quickly.
8) My monkey is lovely.
9) I also have a small dog.
10) I have a sister.
11) My sister is lovely.
12) She is very lovely.
13) She likes to sit in the library and reads.
14) She quickly learns languages.
15) I also have a brother.

First, we create an SM (Fig. 5) that activates the secondary neurons. After the memory was trained, the following questions were asked.

1) What is my monkey like?
2) What is my sister like?
3) Monkey is what?
4) Sister is what?
5) Is my sister actually my brother?
6) What does she do at the library?
7) What does she like to do at the library?

Knowledge in the ANAKG memory is created through the consolidation of training sequences. The consolidations are context dependent, i.e., the predecessors stimulate the successors to reflect the frequency of their near or far incidence in the training sequences. This SM is able to consolidate subsequences of training sequences that match a context provided by training sequences.

TABLE I
SM RESPONSE TO INPUT QUESTIONS

Question	ANAKG Answer
What is my monkey like?	Is very my lovely sister is very lovely
What is my sister like?	Is very my lovely sister is very lovely
Monkey is what?	Is very lovely
Sister is what?	Sister is very lovely
Is my sister actually my brother?	Is very my lovely sister is very lovely my sister brother is very lovely
What does she do at the library?	She the library
What does she like to do at the library?	She to sit in the library the library

B. Context-Based Prediction in Semantic Memory

Fig. 5 shows the ANAKG graph topology created for the training sequences described in Example 1. Each neuron stands for a single word. The numbers under the names of neurons tell us about the number of activations of these neurons (η) during a training phase. Synaptic permeability values (w) are represented by the amount of filling in the small circles representing postsynaptic elements of the synapses.

If there is a dot inside the circle representing a postsynaptic element, it means that the value of the synaptic weight is equal the value of threshold θ of a postsynaptic neuron, i.e., the stimulation of this synapse is sufficient to activate the postsynaptic neuron. If the value is smaller than the threshold, it is necessary to stimulate more synapses to activate a postsynaptic neuron. The presynaptic elements are denoted using a crescent shape. In Fig. 5, none of the synapses are stimulated, and all neurons are in their resting states.

As a result of external stimulation of As-neurons in the ANAKG network, we activate As-neurons according to the time of their activations. The resulting sequences of objects represented by the activated neurons are treated as an answer obtained by the ANAKG network in response to the external stimulation. If the context of the external stimuli to ANAKG is sufficiently rich, we will get one of the training sequences. If the context is new or not sufficiently rich, then the output from ANAKG is the most frequent training sequence containing this context or a new sequence of objects that is a generalization of training sequences for the given context. The ANAKG networks can represent and retrieve the semantic relations between objects and reveal their time associations.

When the created SM (represented by the graph on Fig. 5) was stimulated using questions from Example 1 we obtained the results presented in Table I.

As we can see the ANAKG memory activates rich semantic context that helps to answer questions about past experiences.

C. Context-Based Prediction in Episodic Memory

To provide context-based stimulation of the EM, we consider activations of the primary neurons as time events, for LTM cells. Each secondary neuron in EM represents a single occurrence of a word, such that from 71 words used in the training input file, we used 29 unique words to activate various LTM cells. Subsequently, 15 LTM cells are used to store all of the sentences.

TABLE II
EM RESPONSE TO INPUT QUESTIONS

Time	Question	LTM Answer	Winning LTM activation level	Winning activation level with forgetting
1	What is my monkey like?	'My monkey is very small ' and 'My monkey is lovely '	0.7051	.7051
2	What is my sister like?	'My sister is lovely '	0.7051	.6707
3	Monkey is what?	'My monkey is very small ' and 'My monkey is lovely '	0.6864	.6211
4	Sister is what?	'My sister is lovely '	0.6864	0.5317
5	Is my sister actually my brother?	'My sister is lovely '	0.7051	0.4676
6	What does she do at the library?	'She likes to sit in the library and reads'	0.7321	0.5702
7	What does she like to do at the library?	'She likes to sit in the library and reads'	0.7657	0.5828

After training of EM, different questions were presented on the input, activating various primary and secondary neurons. After each question, a winning LTM cell with the most activated secondary neuron is selected to represent the answer to the question. First, we show simulation results where we do not use associations in the SM, to focus on the role of feedback from the EM. The EM response to each question is shown in Table II. In the case when two or more of the LTMs' activations are equal, all of them provide the answer.

Additionally, we provide a second result column with the forgetting mechanism (from Section IV-D) enabled. Note that this is a simplified implementation of the forgetting mechanism with $\alpha = 1$, since we do not yet have our memory system tied with a motivated agent that can provide the reward information to calculate α. (Other parameters γ , β, and T_o are set to 1, 2, and 10, respectively.) While this leads to a relatively quick decay of the episodic memories, these settings are good for showing how forgetting works, particularly since values below 0.6 are considered below the recall threshold in our current implementation.)

The pseudo code of the **episodic prediction algorithm** is shown in Algorithm 3.

In step 5 of the episodic prediction algorithm, all primary neurons activated by the SM are fully restored (to 1), while activation levels of all other primary neurons gradually decline (the decay parameter beta multiplies previous activations).

SM may activate several primary neurons. Also, the primary neurons may be activated by predictions made by a winning LTM cell in the EM. This can be used to recall an entire episode or to support an existing association in the SM.

The activation level of a winning neuron from the EM will be multiplied by the feedback link to SM to influence activation of the linked secondary neuron in the SM. The link weight is adjusted according to the synaptic learning rule of the SM.

Only those secondary neurons that are updated are processed, triggering events both in the semantic and episodic memories. Since we know which primary neurons are updated, only the LTM cells connected to these neurons and feedback

Algorithm 3 (Episodic Prediction)

1. For each input question repeat 2-10.
2. Reset primary and secondary neurons activation levels.
3. Reset the winner flag to 0.
4. After each word of a question is read perform steps 5-10.
5. Update primary neurons' activations.
6. For each memory cell in the episodic memory that is linked to updated primary neurons repeat 7-10.
7. Update activations of the secondary neurons.
8. Update episode activations to account for forgetting (if enabled).
9. Find the winning episodic memory cell.
10. If the winner's activation is larger than the prediction threshold then
    a. Set the winner flag to 1.
    b. Predict a primary neuron to be activated next.
    c. At the end of the episodic memory sequence, no prediction can be made, in such case the winner flag is reset to 0.
11. If the winner's activation is smaller than the prediction threshold, then the winner flag is reset to 0.

from those cells need to be processed. However, all LTM cells activations decay in time.

D. Integration With the Semantic Memory

The EM benefits from integration with the SM and vice versa—the SM works better if it is supported by events recalled from the EM. At each sensory observation that activates the EM, there is an exchange of signals between the semantic and episodic memories. We illustrate this with two examples.

Example 2: Assume that an input sequence "What does she do at the reading room?" is presented to the SM. If the SM made an association between a library and a reading room, then the EM can recall the episode: "she likes to sit in the library." Without such association, only a question "What does she do at the library?" could correctly be answered based on the training data.

This illustrates the use of associations to recall associated events, and it is an example of when the SM helps the EM.

Example 3: This example illustrates how the prediction by EM triggers proper sequence in the SM. The EM helps to remove ambiguity from identical responses by the SM to questions. "What is my monkey like?" and "What is my sister like?"

Without feedback from the EM, both of these questions activated a sequence of primary neurons that yields: "is very my lovely sister is very lovely."

When the SM is integrated with the EM, EM can either recall the entire sequence associated with the observed events, support recognition by suggesting what should be present in the observed scene, or simply remove ambiguity from multiple likely solutions, by suggesting the one observed in the past. A machine is more likely to choose a solution that it is more

TABLE III
REAL-TIME PREDICTION BY EM

Question	LTM Answer	Winner LTM secondary	Winning LTM activation level	LTM prediction
What	-	-	0.44	-
is	-	-	0.44	-
my	-	-	0.44	-
monkey	'My monkey is very small '	monkey	0.6864	is
like?	'My monkey is very small '	is	0.6562	very
	'My monkey is very small '	very	0.6273	small
	-	-	0.44	-

TABLE IV
SM RESPONSE IN REAL-TIME INTERACTION

Question	ANAKG only	ANAKG with LTM feedback
What is this monkey like?	Is monkey	Is monkey
Monkey is what?	Monkey is	Monkey is very lovely small
Sister is what?	Sister is	Sister is lovely
Who is very clever?	Is very lovely clever	Is very lovely clever small
Who is very clever?	Is very clever	It is also very clever
What my brother like?	My brother	My brother
What she likes to do in the reading room?	She likes to in the reading library room in the	She likes to sit in the library reading room the in library

familiar with. This can change the train of thoughts described as mental saccades in the full cognitive model [18] and affect the outcome of using associations and past memories.

A prediction made by the EM is performed in real time, influencing the neuron's activities in the SM and vice versa. Each new observation reflected in the activities of primary neurons in the SM or each result of attention focus on an associated concept or action will affect the EM.

This is illustrated in Table III that shows simulation results of the LTM cells in response to activations of primary neurons in the question "What is my monkey like?"

In Table III, after the winning LTM reached the prediction threshold (after the first 4 words "What is my monkey") the prediction word was "is" and after the whole question was asked, the prediction word was "very." This was followed by the prediction "small" played by the EM without further input from the SM.

E. Real-Time Interaction of the Two Memories

After an event was detected in either memory, we have real-time interaction of the two memories. We consider that this type of interface may happen in the subconscious mind before the attention focus triggers exact recall of an episode or leads to the formulation of a grammatically correct response based on the knowledge stored and retrieved from the SM. In this experiment we tested the responses of both memories, observing their activation levels and output events. In order to create associations needed to answer the question: "What does she likes to do in the reading room?"

We complemented the training set presented in Example 1 with the following statement: "The reading room is in the library."

Table IV shows the results of activations in the SM only.

As we can see from the last row in Table IV the response

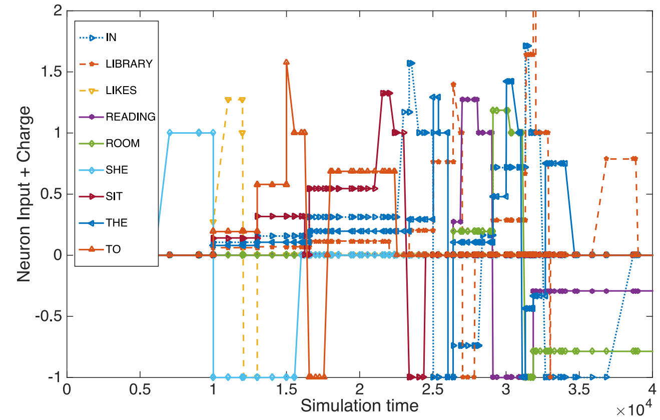

Fig. 6. Charges accumulated in As-neurons over event time.

TABLE V
SM RESPONSE WITH EM INPUT

Question	ANAKG only	ANAKG with LTM answer
She likes to sit alone?	She likes to sit	She likes to sit in the library
What does she learns?	She learns	She quickly learns languages
Where does monkey likes to sit?	Monkey likes to sit	It likes to sit on my head
Who is very clever?	Is very clever	It is also very clever
What my brother likes?	My brother likes	--
What she likes to do in the reading room?	She likes to in the reading room library room in the	She likes to sit in the library

from the integrated system sometimes triggers additional spurious activations of the SM neurons. Fig. 6 shows waveforms that represent charges accumulated in various neurons [computed using (3)–(5)] in the SM during real-time interaction with the EM in response to the last question in Table IV.

While the spurious activations support cognitive associations, they may distort the expected correct response. To obtain correct episodic recall while maintaining cognitive associations, we need to use attention focus when preparing a cognitive response. This is discussed in the next section.

F. Cognitive Support

In the cognitive system architecture described in [20], EM is not only integrated with SM, but its activation is also through the working memory mechanism of attention focus, scene building, and episodic management. This additional feedback to EM corresponds to understanding the full question before the answer is obtained from EM. We simulated this effect by testing the response from EM and its effect on SM. The sentences from Example 1 were used for training of both memories. Questions asked were not grammatically correct considering that networks were not trained to associate words like learn and learns. The results are illustrated in Table V. We can see that cognitive support provided by the EM improved the response obtained in the integrated declarative memory system.

VII. CONCLUSION

This paper proposed an integrated semantic and EM model. Integration improves recognition in EM by providing associated context that helps to trigger EM traces. EM influences activation of the SM neurons, removing ambiguities of sequential recall within a specific context. This is important in situations where the exact recall of an event is needed, rather than recall of all associated events.

An integrated declarative memory can efficiently store, consolidate, and retrieve information while considering event significance. It uses a forgetting mechanism to remove unimportant events. The model satisfies the functional requirements needed in cognitive systems and may be used to control autonomous robots using motivated reinforcement learning [18]. It is needed for symbol grounding, object recognition, concept development, cognitive understanding of perceptions, feelings, and emotions in motivated agents.

Our future work is to integrate this model with other functional blocks of the MLECOG architecture to make full use of the SM in machine learning, planning, anticipation, and thinking.

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