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A Computational Mechanism for Encoding, Recalling and Forgetting of Real-Life Episodic Events

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Abstract
Episodic memory is one of the crucial dimensions of a human memory system; by imitating them, an agent can achieve human intelligence. A memory of a particular occurrence is referred to as an episodic memory. Due to the fact that every individual has a unique perspective and experience of a certain event, the episodic memories that they have of that event are also unique to each individual. It contains your recollections of individual occurrences, as well as personal information, generic occurrences and pictures of precise times in time you have experienced. To achieve human cognitive abilities, this paper presents a computational mechanism that encodes and forgets the real-life episodic events. The proposed model is based on role entity bindings that encode the real-life conceptual events. Furthermore, the model incorporates a computational gradual forgetting mechanism to achieve higher performance while controlling memory consumption over time. According to the findings of our assessments of the agents, forgetfulness lessens the impact of out-of-date information and states that are not frequently visited on the policies that are generated by the episodic control system. To validate the proposed model, an experimental study is conducted, where the evaluation is done based on event recalling's hit ratio. The model produces robust performance and got an enhanced hit ratio in event recalling concerning prior methods.
Keywords: *Episodic Memory, Recalling in Episodic Memory, Forgetting in Episodic Memory, Episodic Event Encoding.*

1. Introduction
The episodic memory is one of the crucial dimensions of a human long-term memory that are primarily responsible for human cognition and intelligence [1]. Episodic memory (EM) is the memory of one's personal experiences [1-3]. Episodic experience stores the detailed activities of events, the place where the event occurred [4,5], and the time of happening [6]. Today's generation society requires episodic memory enabled intelligent agents that can replace humans in performing those tasks where decisions are to be taken concerning the past episodic event memories and acquired related knowledge. In Episodic memory modeling, the event encoding, recalling, forgetting, and consolidation is a big issue [7,8]. In the past decade, several abstract EM and SM models have been devised as an agent architecture to enhance the performance of the agent. Right from the beginning, the prior models have considered event activities as a real-valued feature vector that cannot represent the abstract concepts of real-life events. The family of ART-based episodic models makes use of real-valued feature vectors in an adaption that is limited to only game applications [9-13]. Furthermore, the prior works do not support the consolidation that is an essential practice for knowledge building i.e. building facts of semantic memory [7]. To fill the aforementioned gaps, the article proposes a role entity binding based computational episodic event encoding and forgetting mechanism. The proposed work is a part of the episodic module of CLTMA Computational long-term memory Architecture). The detailed description of the CLTMA is given in the literature review section. The proposed model encodes activities as roles entity bindings, where roles are defined as object verb agreement for natural language sentence interpretation. Furthermore, the proposed mechanism is incorporated with a forgetting mechanism where

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memory strength gets modified with a dynamic decay rate. Compared with existing models of episodic memory, the experiment results show that the model is one of the best models in terms of hit ratio of event recalling while controlling the memory consumption. Experiments show that the model produces a robust level of performance in event recalling. The rest of this paper is organized as follows. Section II presents the literature review. Section III presents the algorithms and processes for event encoding, recalling, and forgetting. Section IV investigates the performance and robustness of the proposed model. The final section concludes and highlights future work.

2. Literature Review

The term episodic memory (EM) is introduced by E Tulving in the year 1972 [1,2]. He has defined episodic memory as a memory of personal events in which place of the event, time, and activities gets stored [3,4]. Episodic memory stores one's own experiences and allows one to recall their own experiences in doing several-variety of tasks. The episodic memory provides several crucial functionalities, including learning the conceptual detail of an event, gradual forgetting for memory management, representation of events in the Spatio-temporal dimension [1-4,6-8]. Moreover, the episodic memory works in collaboration with the semantic memory (SM) in event consolidation for learning facts in terms of general events [7]. The biological brain researchers also support the theory of episodic memory. In several brain research, it has been found that the hippocampal region is primarily responsible for performing the functionalities of episodic memory. Since then several computational models have been published on episodic memory that follows the structural detail of the hippocampus and mimics the behavior that has been found in biological research. Although many of the biologically inspired models are based on the fourth-generation spiking neural network that mimics the behavior in spike pattern generation [20]. Till now, no significance of SNN has been proven in machine learning intelligence, therefore models have no significance in computational agents. In EM modeling, the event encoding, recalling, and consolidation is a big issue over which several efforts have been taken place. The very popular approach proposed for episodic memory is EM ART [9-13]. The model encodes the activities of an event as a vector of real-valued numeric features, and thus, it is not able to encode real-life concepts. However, some models like MINERVA [14], MINERVA2 [15] used binary vectors, where correspond to every value of a feature either 0 or 1 get stored. To store real-life conceptual activities such type of encoding is infeasible to use as it is highly space inefficient. Furthermore, the scope of the model is limited to recalling feature vectors where several other crucial functionalities are not addressed, like forgetting, and consolidation. Moreover, in encoding, models have used relational tuples where each event follows the same structure thus it can store limited type of events [16,17,18]. The biological plausible model SMRITI has shown the use of role entity bindings in capturing the activities of a real-life event [19,20]. The model's objective is to find the erroneous cues correctly and confined to the neural structure of the hippocampus, thus it lacks to cover several other crucial functionalities. Many other pre-established computational models of episodic memory have been capable of the use of emotion in maintaining the strength of event memory [13]. However, the model does not claim emotion detection from the event activities that is still an uncovered issue. Furthermore, the models [9-12] incorporated the forgetting mechanism for memory space management. The static decay rate in forgetting makes the model ineffective in maintaining a higher hit ratio of event recall, thus dynamic decay rate is required as explained in Ebinghaus forgetting [8]. Several biological research claims that episodic memory possesses a consolidation mechanism by which an episodic event gradually transformed into a semantic fact [7]. Thus, episodic memory actively participates in knowledge formation. However, the prior works have tried to mimic the functionality of consolidation in which the model stabilizes the memory strength instead of generating new facts [9,10]. Furthermore, in consolidation, the CARD model has given a recalling and occurrence frequency-based associative graph building mechanism of learning facts [21]. However, the

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consolidation mechanism of the model cannot learn hierarchical organization and general sequencing of events. In this article, forgetting and encoding have been taken care of in the above-mentioned problems of episodic memory modeling. The work is the part of the episodic memory module of the computational long-term memory modeling architecture (CLTMA). The detailed description of the CLTMA is described in below given subsection. For encoding, the proposed mechanism supports the role entity based binding mechanism that can encodes the real-life events activities. To support the Ebbinghaus like forgetting, a computational formula is given that consider the recalling rate, emotion factor while calculating memory strength for an episodic event.

2.1. CLTMA (Computational Long-Term Memory Architecture)

The architecture is designed to computationally mimic the functionalities of a human's long-term memory. The architecture embodies three computational modules, where each module corresponds to one of the long-term memories (i.e. episodic, semantic, and procedural memory). Modules in the architecture work collaboratively by disseminating their processed information from one module to another like human long-term memory does. Each module is designed to computationally mimic the functionalities of its respective long-term memory, shown in Figure 1.

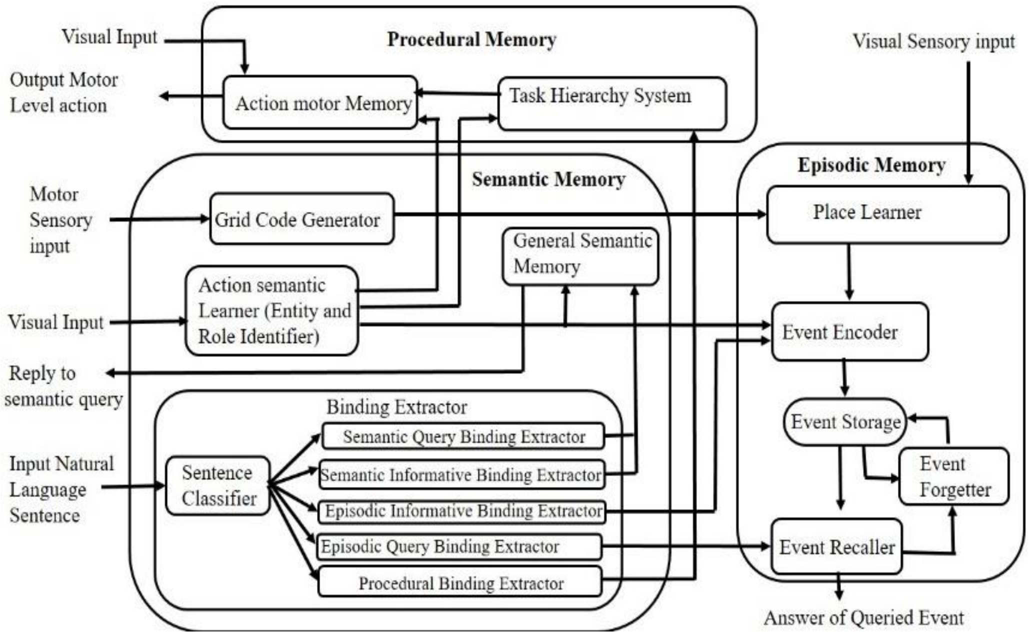

Figure 1 CLTMA: Computational Long-Term Memory Architecture

2.1.1. Semantic Memory Module

The module consists of several functional blocks that mimics the functionalities of human semantic memory. The detailed description of functional blocks is given below: Grid code generator (GCG): It mimics the functionality of biological grid neuron that takes the sensory input and generate the grid code for the place neuron to learn a place. Action semantic learner (ASL): It learns the semantics of body action from visual input so that the agent can determine roles of each individual present in the event. For example, in an event, a person X gives book to person Y, then the extracted role of X will be “giver”, and the extracted role of Y will be ‘taker’. The module sends the extracted entity and their role to the episodic module for event encoding. Furthermore, the module sends the extracted role entity binding to the GSM functional to update knowledge of the agent. Binding Extractor: This functional block is responsible for appropriate communication with the agent. The module possesses a sentence classifier that determines the category of the input sentence so that the sentence can be transmitted to the correct memory for the communication. For example; if the sentence is “what has been given to Sita”, the given input sentence is asking about an activity of an episodic event, therefore the sentence classifier would transmit this sentence to the recaller functional block of the episodic memory to recall the episodic event. Before transmission of the sentence, the sentence needs to be converted into the format of the destination memory so that the memory can process the sentence. Five classes are defined for the sentences which are semantic query, episodic query, semantic informative, episodic informative and the procedural. For each class there is a corresponding binding extractor for preprocessing the sentence. The semantic query extractor converts the sentence to the format of GSM that stores semantic facts and returns the queried fact. Semantic informative extractor adds the knowledge in the GSM. Episodic query extractor processes the sentence to send to the recaller of the episodic module. Episodic informative extractor processes the sentence to store the event details in the episodic store of episodic module. Procedural extractor processes the sentence to send the details of tasks to task hierarchy system of procedural module.

2.1.2. Episodic Module

It mimics the functionalities of human episodic memory. The module is divided into the several functional blocks. The detailed description of each functional block is given below.

- Encoder: Its task is to receive the information of event activities and encodes event activities in an episodic store.
- Recaller: The task of the recaller is to recall the appropriate event based on the receive information from the episodic query extractor of the semantic module.
- Forgetter: The task of this functional block is to manipulate the strength of events. A memory strength value of an event decides how long an event would remain in the episodic store.
- Place neuron: this functional block takes the grid code for a place and learns to localize in an environment.

2.1.3. Procedural Module

The module mimics the functionalities of the human procedural memory. The module consists of two functional blocks. One is the task hierarchy system that learns a task as a sequence of actions, where each action is further divisible into another sequence of some other actions. An action will be not divisible if motor level signals are present correspond to the action. Another functional block is the action motor memory, the block takes the information of action ID and current working memory parameters through visual input and generates the signals for the motors to perform tasks.

3. Proposed Work

The proposed computational mechanism is proposed for the episodic module of the CLTMA, which is shown in Figure 2. The episodic module is devised with three interdependent computational processes: encoding, retrieval, and forgetting. An episodic event gets stored into a memory storage and retrieved by the method event encoder and event recaller respectively. Whereas, event forgetter method manages memory consumption through the removal of insignificant events. The computational principles and algorithms are described in detail in the following sections.

3.1. Event Encoder

The episodic detail of an event apprises what, where, and when an event has occurred. The encoding mechanism stores all such characterizing details of an event. Theepisodic activities of an event are encoded as a set of role entity bindings. A binding tells which entity has played what role? Correspond to each role, a subject-verb agreement is present as a sequence of words, where each word can be verb, noun, adjective, and modals. An entity in binding is described as living or non-living things. For example, the event “Ram has given a book to Sita” will be encoded as a set of bindings <Ram- who has given>, <Sita–whom has been given>, <book–what has been given>. Here, Ram, Sita, and the Book are the entities, “who has given”, “What has given” and the “whom has been given” are the corresponding roles of the entities. Recognizing the entities and their roles is not the part of this work.

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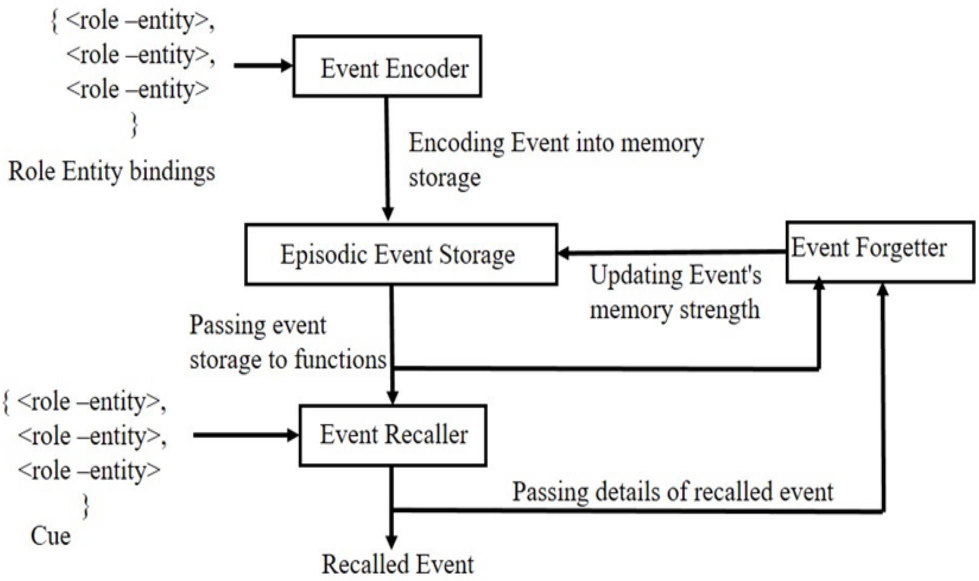

Figure 2 Proposed Episodic Module

An episodic event will be get stored in a relational tuple of an event table, as shown in Table 1. Each tuple of the table corresponds to an individual event. Since an event is attributed to its characterizing bindings, therefore multiple binding fields are present in a tuple. The value in a binding field is a reference number that refers to a tuple of the binding table i.e unique role entity binding. Moreover, a 'strength' field is present whose value lies between 0 and 1 and represents the memory strength of an event. The tuple in a binding table is having only two fields one is the entity field that represents the participated entities and another one is the role field that represents the roles played by the entity. Here instead of "Giver" our mechanism used "who has given" to make it more informative in a general format so that correct binding can be retrieved while talking or any kind of recall. Retrieving the role "giver" for a query "who has given" would require an explicit mapping between both, which is not possible for a large set of actions and allows possible queries related to an action, shown in Table 1 & Table 2.

Table 1 Event Table

Event	Strength	Binding1	Binding2
e1	0.5	33	31
e2	0.2	12	01
e3	0.9	13	24

Table 2 Binding Table

Binding	Entity	Role
33	Ram	Who has given
31	Book	What has been given

3.2. Event Recaller

The most obvious application of episodic memory is to recall the desired details from a target event that a retrieval method of the encoder module performs. The method chooses the most appropriate event as per the given cue/situations. The proposed recalling mechanism evaluates a score for each event and the event having the highest score will be chosen for the recalling. Before any evaluation, the mechanism first checks the consistency of each event concerning the input cue. If an event is found not consistent then the event will be out from the list of competitors. If an entity that is present in a cue is also present in an event, then the corresponding roles in both cue and the event must also be the same. If the role is found different then the event will be declared as inconsistent and its score will be set to zero. After the consistency checking, the score evaluation will be performed only on the consistent events according to Eq.1.

$$R^k = (1-\alpha)\frac{M}{T} + \alpha * ms^k \qquad (1)$$

Recalled _Event = max (E)

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Where R^k is the recalling score of a k^{th} event, M is the number of bindings matched, ms^k is the memory strength of a k^{th} event, T is the total number of bindings in a cue. The recalling score of any k^{th} event is the weighted summation of memory strength and the ratio of event bindings matched to the number of bindings present in the cue. The event having the highest recalling score i.e. R^k will be chosen for recalling.

3.3. Event Forgetter

The task of this method is to maintain a higher hit ratio of event recalling while controlling the memory consumption. With this objective, the module has added an extra parameter with the memory of events called memory strength. The parameter value decides whether the event would remain in the memory or not. At the moment of event occurrence, the memory strength value for the event will be initialized to a predefined value which is taken 0.5. If the occurred event interfered with other events means, then the memory strength of the past interfered events will be decayed by a factor. In the case of recalling an event. Moreover, if the recalled event gets interfered with other events, then again, the memory strength of the interfered events will be decayed. Instead of a fixed, a dynamic decay factor is used that derives from the recent recalling's, elapsed time, and the current memory strength. The forgetting scheme gives more chances to those events that are having higher recent recalling's and vice versa. The calculation for the memory strength is given in Eq.2.

$$MS_i(new) =$$
$$MS_{initial}, Created$$
$$MS_i^{(old)} + (1 - MS_i^{(old)})r, Reactivated$$
$$\left\{ \begin{matrix} MS_i^{(old)} + MS_i^{(old)\left(1-MS_i^{(old)}/\beta\right)}(1-e), MS_i^{(old)} < 1 \\ MS_i^{(old)}, MS_i^{(old)} == 1 \end{matrix} \right\},$$
$$\text{Otherwise}$$
$$MS_{initial}$$
$$= 0.5, \beta = 10, e \text{ belongs to } [0,1]$$

Where, $MS_i^{(new)}$ is the updated memory strength of i^{th} event. At the time of event creation, the memory strength will be initialized to a default value of $MS_{initial}$. 'r' is the reinforcement rate. The strength of an event decreases when the activity of the event becomes active and the event is not activated.

4. Experimental Work and Results

To assess the performance of the proposed mechanism, several experimental works have been performed, furthermore, a comparative analysis is done with the previous models that are as follows.

4.1. Recalling Accuracy Concerning the Cue Length

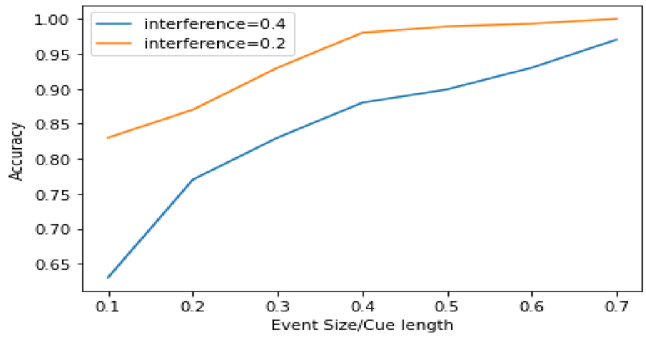

Figure 3 Recalling Accuracy Concerning Cue Length

As the proposed encoder module is incorporated with a recalling mechanism that can take a partial clue as input and recall the appropriate event. To assess the performance of the recalling mechanism, the mechanism has been tested on several test cues of different lengths. The testing cues are chosen randomly from the set of stored events. The length of a cue lies between 0 and 1. The length will be equal to one when all activities of a chosen program are taken as a cue, and no activity will be taken when the length is zero. The cue length affects the recalling accuracy more when sharing of activities is high among past events and vice versa. As shown in Figure 3, varying the length of cue affected the recalling accuracy of target events more in the case of higher interference.

4.2. Effect of Proposed Forgetting Mechanism on Event Recalling

The dynamic forgetting mechanism gives more chances to emotional salience events or events having a previous history of higher recalling by keeping the low decay rate. The dynamic nature of forgetting makes it different from the models that possess constant decay rates like EM ART and Deep ART. The proposed forgetting mechanism is explained using the forgetting curves of different events (shown in Figure 4).

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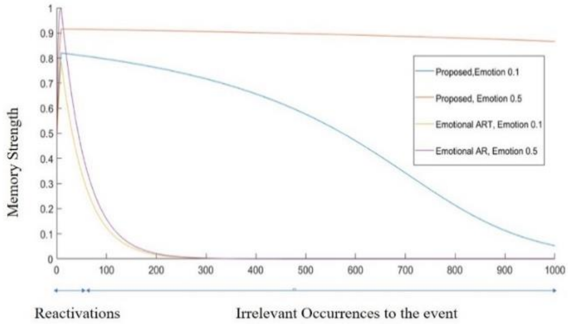

Figure 4 Decay of Memory Strength

The decay rate of the events having different emotions in the emotional ART (yellow and violet line) is almost similar. Although the highly emotional event has reached the higher memory strength comparatively fast to the non-emotional event. While consecutive occurring's of irrelevant events the decay rate is similar to both emotional and non-emotional events that is why the retention period does not elongate for the emotional events. The decay rate in the emotional ART will be higher at the initial of encoding and it slows down after several expositions, but not sufficient to give more chances of a recall to emotional salience events. Whereas in the proposed model the emotional events can achieve higher strength so fast compared to the non-emotional events and the decay rate can be slowed down if the emotional saliency of the event is high and vice versa. The proposed forgetting mechanism gives higher time for the retention in the initial, but after a period, if the event does not recall then the event's memory strength starts decreasing exponentially with time.

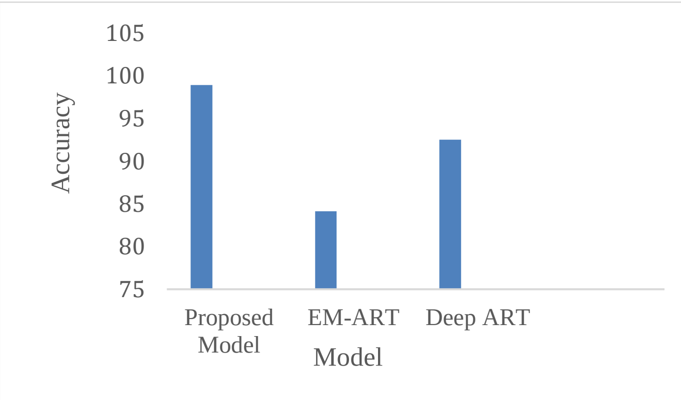

Figure 5 Results Comparison of Recalling Accuracy

To find the effect of the proposed forgetting mechanism on the performance of event recalling, experimental work is done. In the experiment, after every ten events, a cue is generated which can be related to any past event, but here the probability of the emotional salience and the local events of being chosen for the cue generation is high. To generate a cue random number of bindings are chosen then performed recalling. If the event which got the highest score on matching with the cue is the same as the target event, then the recalling will be considered successful. In case if the target event lost its memory strength, then the event will forget from the memory and the wrong event will win which can reduce the accuracy of event recalling. In Figure 4, the difference is observed in the forgetting rate of the proposed and the prior model of EM i.e. EM ART, Deep Emotional ART. The decay rate in the forgetting graph of the proposed mechanism gets lower in the initial which suddenly increased with the elapsed time. The model elongated the period of slower decay rate based on the emotional saliency, previous recalling, and memory strength. Therefore, the accuracy of the proposed mechanism which is shown in Figure 5 is very higher compared to the EMART and the Deep Emotional ART.

Conclusion

In this work, a computational mechanism is proposed that captures the real-life episodic details of an event in memory storage. Furthermore, a computational mechanism is given that controls the decay rate of events based on the previous frequency of recalling and the emotion factor. The given mechanism provides a higher hit ratio of events on recalling while controlling the space demand. Moreover, in the article, an empirical comparative study is present between the proposed and the prior works. In the study, compared to the prior works, it is observed that the proposed mechanism is far better in maintaining the relevant events in the memory. Since the emotion factor is one of the deriving components for controlling the decay rate, therefore, one immediate extension to the episodic memory is to explore the usage of a deep neural mechanism that can predict the emotional factor based on event activities so that a correct emotion factor can be used in the evaluation

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of memory strength of an event.

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