Using A Parameterized Memory Model to Modulate NPC AI

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Abstract. While there continues to be exciting developments in research related to virtual characters, improvements are still needed to create plausibly human-like behaviors. In this paper, we present a synthetic parameterized memory model which includes sensory, working, and long-term memories and mechanisms for acquiring and retrieving memories. With the aid of this model, autonomous virtual humans are able to perform more reasonable interactions with objects and agents in their environment. The memory model also facilitates emergent behaviors, enhances behavioral animation, and assists in creating heterogeneous populations. To demonstrate the effectiveness of the memory model, we also provide an example in a 3D game environment and have conducted a user study in which we found general guidance in determining parameter values for the memory model, resulting in NPCs with more human-like game playing performances.

Keywords: Virtual Humans, Memory Model, Behavioral Animation

1 Introduction

Non-Player Characters (NPCs) have become vital assets in games and simulations. They allow game authors to add depth to the world by providing valuable enemies, allies, and neutral characters. Over the past three decades, there has been a great deal of work on improving NPCs. However, while a majority of it has gone into creating more visually appealing and animated characters, development of the underlying intelligence for these characters has remained fairly stagnant, creating strange and undesirable phenomenon such as repetitive behaviors and a lack of learning and knowledge understanding. A character may appear as a photo-realistic knight in shining armor, but can only greet the player or fight with the player monotonously. This lack of depth diminishes NPC believability and creates a less enjoyable gaming experience for the player.

There are many different forms and functions that NPCs need to fulfill, and these commonly correspond to their roles, relevance and importance to a player. In many of these cases, when the purpose of agents is to stay transiently and blend into the environment, it's less likely a player would spend a great deal of time examining each one of them. For example, if there is a squad of enemy soldiers the player must fight, it is doubtful that the player will spend considerable time monitoring each individual soldier's behaviors. In these contexts, there is not a great need for strong AI techniques, and it is generally impractical to implement and execute such techniques for a large group of agents. However, for those agents meant to serve as companions or enemies that are central to the game story and thus exist for longer periods of time, the player will most likely spend a lot of time interacting with them and also observing their behaviors. For these characters, techniques that create more believable agents are needed, and these types of NPCs are the focus of this work.

While there are many ways of improving the believability of virtual agents, in particular we see a human-like memory model helping to achieve this goal in two ways. First, given that information storage is inevitably needed for agents to reason and interact with their environments, a human-like memory model that include false memory and memory distortion can result in more human-like performances. These human-level abilities (i.e. not sub-human nor super-human) will provide more plausible interactions with the player, including more reasonable competition. Secondly, an event-independent memory model can make longer simulation more plausible and allow agents to carry their knowledge to other scenarios without massive editing. To realize such a system, certain aspects of human memory are necessary such as learning, forgetting and false memories. While there are many techniques, such as scripting and behavior trees, that can be used to simulate an agent's memory model and can create the illusion of false memories and forgetful agents, these techniques usually require a great deal of crafting by a game play author in order to create some form of believability. A memory model that causes an agent to forget or create hazy memories provides the virtual character some variability in its understanding of the world and what has taken place. This variability is inherent within a reasonable human-like memory model, and these differences do not have to be enumerated and explicitly written by the game author, as they would with prior techniques.

Toward this end, we have developed a memory model that includes components for *Sensory Memory*, *Working Memory* and *Long-term Memory* and have designed it to contain features such as forgetting and false memories. We also provided multiple parameters related to various memory capabilities. These parameters can be set by level designers or game systems to vary the difficulty level of games. To determine a reasonable range of values for these parameters, we conducted a user study in a 3D game environment and carried out a performance analysis. To summarize, our contributions include:

- A memory model that supports a variety of psychological activities such as forgetting and false memories and aims to bring the memory model for NPCs one step closer to a human-like memory system.
- A memory model that offers flexibility to users by providing several tunable parameters. A user study has been conducted to further provide general guidance and possible ranges for the model parameters.

- A memory model grounded in a 3D game environment, where agents are capable of demonstrating complex, emergent, and social behaviors, making longer duration simulations and games more believable.

2 Related Work

Memory systems, appearing to be an inevitable component in intelligent agent architectures, have been studied and developed from a variety of points-of-view. In animated, autonomous agents research, several groups have combined vision and memory systems to allow virtual characters to perform navigation and path planning tasks [21, 29]. Others have used memory to facilitate and enhance agent-object interactions [13, 24], crowd simulations [23], believability and intelligence in synthetic characters [4, 16], and virtual actors in dramas [18]. In these efforts, memory was not the main focus. It was a part of larger agent architectures that also included other components such as perceptual units, dialogue units, action selection modules, and goal and plan generation systems. Given the overall complexity, the memory model is often treated simply as permanent or temporary information storage with relatively simple structure, and is not intended to be scrutinizingly designed as a counterpart to achieve human-like performances in games and other applications.

More specifically, a great deal of work has explored using certain types of memory found in psychology literature. Episodic and autobiographical memory [30, 31] collect individual experiences that occurred at particular times and locations. Examples include, a pedagogical agent named Steve [25] who is equipped with episodic memory and can explain its decision-making process for a short time; Brom et al [3] exploited it to achieve longer duration storytelling activity in a gaming environment; Gomes et al [11] implemented an episodic memory model for emotion appraisal. Similar to episodic memory but with broader scope, autobiographical memory has also been incorporated into many applications. To name a few, Dias et al [7] has utilized it to enable synthetic agents reporting their past experiences. Similarly to the previously mentioned figure Steve, actors in [12] can tell stories for limited time period based on their autobiographical memory. While significant results were achieved, these efforts focused primarily on retrieving episodic knowledge and had memory modules crafted for specific tasks such as storytelling, communicating, and social companionship [17].

Another set of related work is in cognitive computing research. To list a few task-dependent applications, a memory model has been implemented for cognitive robots [8], and autonomous and virtual agents [6, 10, 5]. In addition, a large group of work has been associated with cognitive architectures such as SOAR [14], ACT-R [1], and CLARION [28]. These architectures generally have relatively comprehensive memory models in their large software infrastructures and are capable of simulating many psychological activities. Additionally, a shared goal of these architectures is to achieve task-independence including a standalone memory fragment. For example, Nuxoll [22] has attempted to build an event-independent episodic memory system integrated with SOAR. However, there are some issues with these cognitive architectures. First of all, generality is pursued, at the loss of some specific elements. Take, for example, SOAR, one of the virtual and gaming environment friendly cognitive architectures [15, 14]. While its usage has been demonstrated in several gaming applications, most of them are taken place in simple environments while agents are capable of conducting limited number of behaviors and interactions with environmental objects. Secondly, using these architectures requires considerable effort and seasoned programming skills. In contrast, a parameterized model with tunable values could be easily adopted by users to endow virtual characters with heterogeneous features.

To summarize, while strides have been made, improvements are still needed. In particular, animated, autonomous agents have limited memory model functionality, storytelling agents rely mainly on episodic or autobiographical memory, and general cognitive architectures are not yet mature for use in rich 3D environments. The work presented in this paper attempts to fill in gaps in these research efforts. Toward that end, we create a synthetic parameterized memory model based on several theories of memory and lessons learned in the cognitive computing and agents developing research communities. The model is grounded in a game world with autonomous virtual humans conducting life-like interactions with objects and each other.

3 Memory System

In this section, we will first explain the memory representation and then detail components of our memory model which includes *Sensory Memory*, *Working Memory* and *Long-term Memory*, and most importantly why our design choices could benefit NPCs in enhancing their believability and achieving human-like performances.

3.1 Memory Representation

For representing memory, we have chosen a directed graph with nodes representing concepts and edges enacting links between concepts. We chose a directed edge following observation that humans generally archive memories in a certain order, and this order does not necessarily work in reverse sequence. This representation can benefit NPCs, such as in a scenario where a NPC has been given a formula of a medicine which can be made only by adding its forming elements in a certain sequence. While some elements of this formula may be forgotten, the agent should still be able to create and preserve a sense of sequence in order to facilitate resolving the missing elements. An example of this would be an agent thinking, "I remember that in order to make this medicine I need one more item after I use the purple potion, but I forgot which item that is. I should search in this ancient book to determine what the item after the purple potion is". Without directions between concepts, this activity is harder to capture.

In addition, we have implemented a strength factor for both nodes and edges, hereby denoted $Node_{strength}$ and $Edge_{strength}$ accordingly. $Node_{strength}$

indicates how strongly a concept is encoded within the memory model while $Edge_{strength}$ denotes the degree of ease going from one node to another. These strength factors add believability to characters. To be specific, while many objects afford many different actions, an agent should select not a random object, but the most familiar object for a particular task. For example, if a NPC is trying to build a birdhouse, it is more believable that the NPC uses its frequently used hammer over a nail gun. While both items can perform the same tasks, the NPC is more accustom to using his hammer, and so should be more likely to do so. Currently, both $Node_{strength}$ and $Edge_{strength}$ share the same integer range, 1 to 10, and this range is further divided into two stages, a strong and a weak stage. By creating this division, our model is able to support memory distortion. The division between the two stages is chosen by the user, who does so by choosing the threshold values $Node_{threshold}$ and $Edge_{threshold}$. Therefore, if someone has chosen $Node_{threshold}$ to be 5, then a value of 1 to 4 would create a weak stage node and values between 5 to 10 would be the node's strong stage. While the threshold may be different, the same logic applies to edge values. When nodes and edges are in weak stage, the phenomenon known as false memory can occurs with probability $P_{false} = 1 - \frac{Node/Edge_{strength}}{Node/Edge_{threshold}}$. So, if $Node_{threshold}$ has been set as 5, then nodes in the weak stage with values from 1 to 4 have corresponding probabilities from 80% to 20% to be forgotten. This simple design allows us to simulate partial human fuzziness. Currently instead of having a sophisticated mechanism for selecting an incorrect node and edge to replace the correct ones during the course of false memory generation, the false concept will be picked among neighboring concepts based on an object ontology of the environment.

3.2 Sensory Memory

One module of our memory model is called *Sensory Memory*. This component maintains transient information captured by the sensory system. In our current work we only address vision. There are several reasons for us to design and develop this component including psychology research studies that have shown that information coming from environment does not contact memory directly. Instead, these studies show that information will spend a short time in a system that serves as an interface between the perception and memory [26, 2]. This interface is always present in real humans, and can be seen in simple phenomenon such as the light curve observed by swinging an illuminating object swiftly in the dark. We believe this module is also necessary due to the fact that, unlike electronic devices, humans never record complete events, as noted in [20]. Instead, physical humans record key elements and later on with the aid of environmental cues, use these elements to reconstruct past scenarios and events. In this work, we use $SM_{capacity}$ to indicate how many cues will be potentially maintained in the sensory memory module. Inspired by findings in [19], which state a human can process 5 to 9 items at once, and considering that design choice that all elements from sensory memory will transit to working memory with various strength factors, we have chosen the range of $SM_{capacity}$ being 1 to 10. This implementation helps preserving *Sensory Honesty* which has been argued plays vital role for synthetic characters [4]. Essentially, we believe a player would not want to compete with a NPC for a task in a place where a lot of object exists and he can process everything while the player is bound by the human limitation of only processing 5 to 9 items at a time.

3.3 Working Memory

We have also included a *Working Memory* module which is seen in many virtual agent architectures. This is a module that stores information currently being used by the agent for a variety of cognitive activities such as reasoning, thinking and comprehending. Studies have shown that in order to use declarative long-term memory elements, one has to extract the material into working memory first. The working memory has been documented to have much smaller size and information maintaining time compared to long-term memory [2]. From this, we decide that only one graph structure could exist in the working memory at a time and this feature is adopted by several architectures as well such as SOAR. In addition, while one graph could contain multiple nodes and edges, the actual reinforcement rate on each node and edge depends on the total number of nodes/edges and the information linger time. The equation for calculating the reinforcement rate is: $Node/Edge_{rate} = \frac{Information\, linger\, time(secs)}{Total\, number\, of\, nodes/edges} \times \frac{WM_{scale}}{10}$ where WM_{scale} sharing the same range (i.e. 1 to 10) with the strength factor. Therefore, if the working memory currently contains 4 nodes and 3 edges and this information resides for 12 seconds while WM_{scale} equals to 10, then each node and edge will get its strength factor increased by 3 and 4 accordingly. This procedure can be interpreted as: a few items lingering for a long time in working memory would have their strength factor values higher than those of many items lingering for a short time. This design decision is inspired by findings in [27] in which the author found that memory reactive time increases in a linear fashion when the number of items in the memory increases. Though here we don't have a reactive time associated with each node and edge, we believe the strength factor can act as an indicator manifesting memory retrieving difficulties. Through this approach, a user can control the amount of information being processed in the working memory, achieving a similar effect to setting a working memory duration and processing strategy without concerns about individual memory differences and the graphical complexity of specific scenarios.

3.4 Long-term Memory

The final module is the *Long-term Memory* module. Intuitively, this module maintains an extensive number of concepts and maintains them for a longer duration. Unlike working memory, this component can contain multiple rather than one graph structure. While both $Node_{strength}$ and $Edge_{strength}$ will only get strengthened in the working memory, in long-term memory they will suffer from decay. Currently, the decaying activity occurs every 5 minutes and the decaying percentage roughly follows the classic Ebbinghaus forgetting curve [9].

In addition, while there is a great debate within the scientific community on whether memory elements are completely forgotten, from the engineering perspective, we have decided to remove any node and edge with $Node/Edge_{strength}$ below 1 and consider any element with $Node/Edge_{strength}$ higher than 10 as a permanent encoded concept. Last but not least, in developing memory models for virtual agents, the distinction between two types of long-term memory: the episodic memory and semantic memory, is not rare. However, in this work, we will not differentiate them due to two reasons: firstly, we are targeting more general tasks in gaming environments rather than specific activities as discussed in the related work section. Secondly, in psychology studies, there exist evidence showing these two types of memories could transform to each other in certain forms. However, the process and detailed relationship between them have yet been resolved [2].

The general working pattern of above modules is as follows: firstly via perception, certain environmental cues are passed into the sensory memory. If the number of cues in a place are greater than $SM_{capacity}$, the cues will be random selected. These cues are then sent to the working memory, where they are formed into a strong connected graph with a minimum value of $Node/Edge_{strength}$. If a concept has additional properties such as color and material, only the concept and its properties would be linked together. Next, cues will be matched against long-term memory and elements (i.e. nodes and edges) above $Node_{threshold}$ and $Edge_{threshold}$ will be retrieved correctly while elements below this threshold would be subject to potential concept replacement. For example, if the correct concept "Coin_0" has a strength factor below $Node_{threshold}$, then it's possible it will be replaced by "Coin_1" under the meta-concept "Coin" (if "Coin_1" exists, otherwise it might be forgotten). In other words, a different coin might be incorrectly remembered. Currently, we only consider replacing concepts that are at the same level of the correct concept in our object ontology. This design decision is supported by the data we collected through a user study in which we found that most false memories involved players picking an object from under the same meta-concept instead of completely unrelated concepts. After successfully constructing a single graph structure in working memory, reinforcement will start according to the total number of nodes/edges, information linger time, and the value of WM_{scale}. Finally, memory material will transit to long-term memory with their various strength factors. The whole process is illustrated in Figure 1.

4 Example and Analysis

To further explore our memory model and its capabilities, we implemented a game (Seen in Figure 2). In this game, our heroes are tasked with saving their princess, who is locked away in a tower. The first person to find the magic gems to unlock the door and free her will win her everlasting love. Players (both human and a NPC we named Carl) begin by exploring the environment to find two magic gems (one red, one blue). As they explore different areas, they find many objects, but no magic gems. After a time, they encounter a villager NPC holding

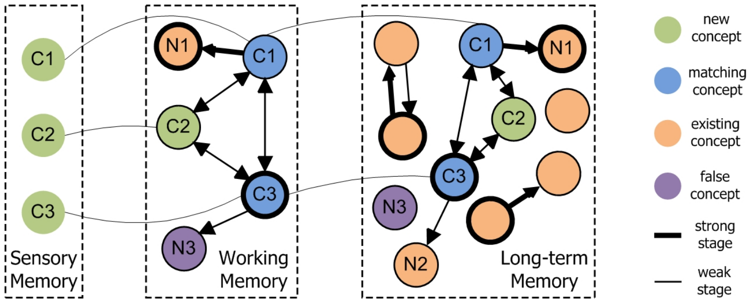


Fig. 1. The general working pattern of sensory memory, working memory and long-term memory. "C" stands for Cue and "N" stands for Node (not all nodes are labeled).

a red gem. Interacting with the villager, they discover he would be willing to trade the red gem for an iris. Players then have to try to remember where they might have seen an iris. If they cannot remember, they start looking around until they find it. While looking around, their memories of the environment are reinforced. A similar procedure is followed for the blue gem.

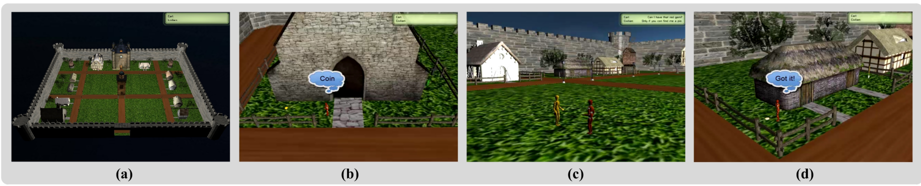


Fig. 2. (a) The game environment. (b) Carl is exploring the environment, trying to find the desired gems. (c) Carl talks to a civilian about trading his gem. (d) Carl uses his memory successfully to find the item for trading.

While our NPC Carl can certainly successfully complete his task, we are more interested in how his performance can approximate real human performance and what memory model parameters would be appropriate for different human player skill levels. In order to explore this, we conducted a user study. In total 31 subjects (15 female, 16 male) participated. Before playing, subjects took a simple memory test and completed a survey related to their experience with video games. Then each subject was asked to play the game solo eight times with different game level complexities. In the first four rounds, the game world contained only eight objects for the players to remember. The number of objects in a given area increased from a single object to four similar objects of different colors. In later rounds, more object models were included as opposed to differentiating by color. Results are shown in Figure 3 in which subjects are classified as having good, medium, or bad memories. We found game worlds containing more objects created more confusion, resulting in players forgetting or incorrectly remember object locations more often.

In particular, we have set Carl's $SM_{capacity} = 7$ and $Node/Edge_{threshold} = 5$. With gathered data, we were able to tune the parameters of our memory model to make our NPC achieve more human-like performances. By scaling WM_{scale}, which determines the reinforcement rate on nodes and edges in the working memory, we found when $WM_{scale} \geq 8$ Carl achieves similar performances to human player's with good memory; when $5 \leq WM_{scale} < 8$ medium memory performance is obtained and when $WM_{scale} < 5$ performance of human player with bad memory is reached. Furthermore, the data yielded some other interesting findings:

- Using all different object models has no significant improvement over using limited models with different colors (which was assumed to be more confusing) in terms of recalling their locations. This implies that creating more models in games may have limited function in helping players remember their locations.
- When the total number of objects in the environment was over 20, 90% of players forgot the desired item's location even when the item was among the last 6 items seen. This indicates that reinforcement is not strictly distributed to the latest concepts.
- People who play games more than 20 hours per week out-performed people who play games between 5 to 20 hours per week and those who play games less than 5 hours a week by 26% and 65% respectively, with no such increment in their memory capabilities (based on their self-reporting memory abilities and memory test results).

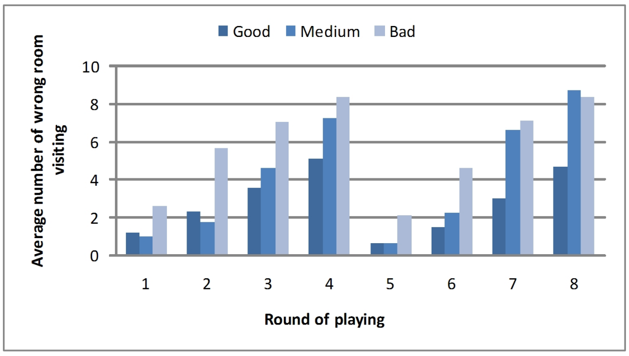
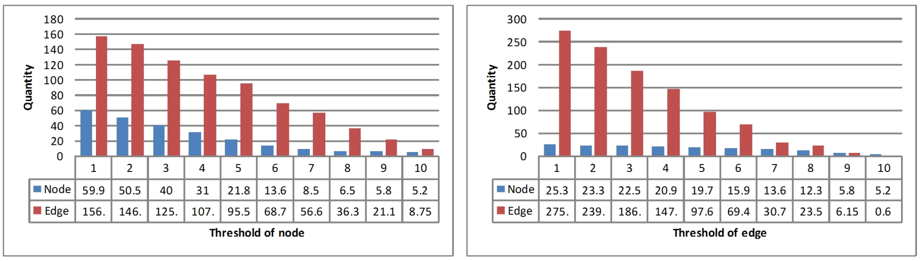


Fig. 3. Performance results of the user study: subjects are grouped as having good, medium, or bad memories according to the memory test. The first four (i.e. 1 to 4) rounds contain limited objects with different colors while the rest four (i.e. 5 to 8) contain more object models in which influence of the color factor was dropped.



(a) **(b)**

Fig. 4. An experiment of influences of $Node_{threshold}$ and $Edge_{threshold}$ on the total number of strong nodes and strong edges retrieved from the long-term memory into the working memory. (Quantity of nodes is 100, of edges is 2,500; $SM_{capacity} = 5$, $Edge_{threshold}$ in (a) and $Node_{threshold}$ in (b) are both 5).

Besides the user study, in order to further provide users some guidance in tuning the parameters of our memory model and also to evaluate the sensitivity of these parameters, we conduct several analyses. In our first analysis, we examine the impact changing values of $Node_{threshold}$ and $Edge_{threshold}$, how many nodes and edges in their strong stages will get retrieved from the long-term memory into the working memory. These values play a vital role in determining agent memory capability. To carry out the experiment, we have chosen 100 nodes and random 2,500 edges with randomly assigned strength factors residing in the long-term memory. The first result is shown in Figure 4(a). In this case, the $Edge_{threshold}$ and $SM_{capacity}$ have been set to 5 when $Node_{threshold}$ increases from 1 to 10. As we can see, as $Node_{threshold}$ grows which indicates the range of node strong stage shrinks, the number of retrieved strong nodes and strong edges decreases. The result shown in Figure 4(b) has enlarged the difference between the two values, in this setting, both the $Node_{threshold}$ and $SM_{capacity}$ have been set up to 5, while the $Edge_{threshold}$ increases from 1 to 10. This analysis manifests, given that in our memory model, concepts are represented by nodes, in terms of enhancing memory capability of the virtual characters, $Node_{threshold}$ has more influence over $Edge_{threshold}$ even though the later value decides how many possible links can be stretching out from a particular node during the memory retrieving process.

Based on the results of our first analysis, the second one was run testing the total number of retrieved strong nodes and edges in the working memory when the edges were increased from 500 to 2500. The result is shown in Figure 5. In this case, the $Node_{threshold}$, $Edge_{threshold}$ and $SM_{capacity}$ have been all set to 5 for a consistent experiment. When 500 edges exist in the graph and also with random strength factors that could spread with value equal or higher than 5, we can see basically only starting nodes and nearly no edges would be activated. After that, the difference between the two values enlarges. The last analysis is about $SM_{capacity}$. While the number of starting nodes controlled by $SM_{capacity}$ is assumed to have an impact on the number of strong nodes and strong edges retrieved into the working memory, we found that increasing the value of $SM_{capacity}$ from 5 to 9 has a trivial effect. This is because while $SM_{capacity}$ is increasing from 5 to 9, making the starting nodes in the activation process increase, this ratio compared to overall nodes (i.e. 100 in this experiment) is still quite small. In addition, the sparse nature of the graph limits the effects.

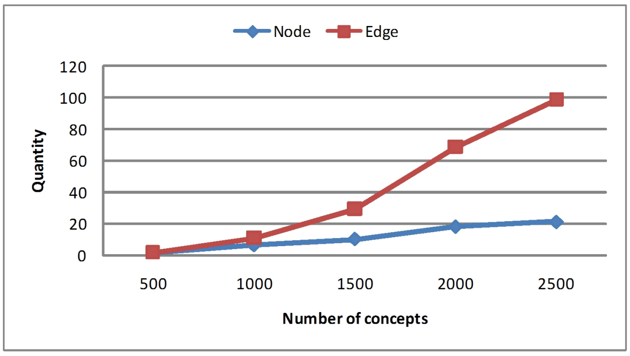


Fig. 5. An experiment of correlation between number of concepts and total number of nodes and edges in working memory ($SM_{capacity} = 5$, $Node/Edge_{threshold} = 5$).

5 Conclusion and Future Work

We designed and developed a synthetic, parameterizable memory model with the intent of creating more plausibly human NPCs. Our model embodies a sensory system, working memory model, and long-term memory model, which supports a variety of psychological activities such as forgetting concepts and creating false memories. This allows our virtual characters to perform complex, emergent, and believable behaviors. Additionally, our user study and analysis provide guidance and insights into potential uses for our memory model and it's effectiveness in setting up NPCs with skill levels comparable to human users.

Of course, our model is not complete. We would like to add a more refined perception model which includes modalities other than sight. Also, our future agenda includes extending the implementation of memory distortions to more than just a simple probability. This mechanism can potentially stimulate agent creativity and enable more spontaneous, emergent behaviors. Given our current detailed memory infrastructure, further development of an effective, plausible mental control module is also worth exploration. Finally, with some optimization, integration with an existing knowledge base could yield interesting results.

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