An Emotion Understanding Framework for Intelligent Agents based on Episodic and Semantic Memories[1]

Mohammad Kazemifard[2,a], Nasser Ghasem-Aghaee[b], Bryan L. Koenig[c,d], Tuncer I. Ören[e]

[a] Department of Computer Engineering, Razi University, Kermanshah, Iran

[b] Department of Computer Engineering, Sheikh Bahaei University and University of Isfahan, Isfahan, Iran

[c] Computational Social Cognition, Institute of High Performance Computing, Agency for Science, Technology, and Research, Singapore

[d] Department of Psychology, National University of Singapore

[e] School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, On, Canada

Email addresses: m.kazemifard@appliedemotion.com, aghaee@eng.ui.ac.ir, koenigbl@ihpc.a-star.edu.sg, oren@eecs.uottawa.ca

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[1] This work is based on the Ph.D. dissertation of the first author developed at the Department of Computer Engineering, University of Isfahan, Isfahan, Iran.

[2] Corresponding author. Email: m.kazemifard@appliedemotion.com

Abstract

Emotional intelligence is the ability to process information about one's own emotions and the emotions of others. It involves perceiving emotions, understanding emotions, managing emotions and using emotions in thought processes and in other activities. Emotion understanding is the cognitive activity of using emotions to infer why an agent is in an emotional state and which actions are associated with the emotional state. For humans, knowledge about emotions includes, in part, emotional experiences (episodic memory) and abstract knowledge about emotions (semantic memory). In accordance with the need for more sophisticated agents, the current research aims to increase the emotional intelligence of software agents by introducing and evaluating an emotion understanding framework for intelligent agents. The framework organizes the knowledge about emotions using episodic memory and semantic memory. Its episodic memory learns by storing specific details of emotional events experienced firsthand or observed. Its semantic memory is a lookup table of emotion-related facts combined with semantic graphs that learn through abstraction of additional relationships among emotions and actions from episodic memory. The framework is simulated in a multi-agent system in which agents attempt to elicit target emotions in other agents. They learn what events elicit emotions in other agents through interaction and observation. To evaluate the importance of different memory components, we ran simulations with components "lesioned". We show that our framework outperformed Q-learning, a standard method for machine learning.

Keywords: Artificial Intelligence, Emotion understanding ability, Episodic memory, Semantic memory, Intelligent agents, Multi-agent simulation.

1 INTRODUCTION

"*Agents* are autonomous software modules with perception and social ability to perform goal-directed knowledge processing, over time, on behalf of humans or other agents in software and physical environments" [1]. The widespread use of software agents requires them to have more advanced features [2,3]. "Additional abilities of agents are needed to make them intelligent and trustworthy. Abilities to make agents intelligent include anticipation, understanding, learning, and communication in natural language" [1] and emotional intelligence [4,5]. The breadth of applications developed with agents suggests the importance of emotion-level interaction. Indeed, applications using emotional agents include software cost estimators [6], tutoring systems [7-9], virtual classmates [10], estimators of emotions from text and annotation of emotions [11], story tellers and other gaming agents [12], and domestic robots [13]. In accordance with the need for more sophisticated emotional agents, there is a need to enhance the emotional intelligence of agents.

In humans, emotional intelligence involves four abilities that contribute equally, and evidence suggests that they have positive, moderate-sized inter-correlations [14,15]: (1) emotion perception, (2) thought facilitation using emotions, (3) emotion understanding, and (4) emotion management. Previous researches focused on the ability (1), (2), and (4) [16]. The current research focuses on a framework for emotion understanding in order to improve the emotional intelligence of software agents.

As far as we know, there is little research on emotion understanding for agents. Dias and Paiva [16] proposed a model on top of FAtiMA, an architecture for emotional agents, by looking at emotion understanding and emotion management abilities. Their model performs interpersonal emotion regulation in order to dynamically create relations with others [17]. The main focus of this model is emotion regulation and it did not have an explicit model for emotion understanding ability. Kazemifard, et al. [18] proposed use of a model with three levels of information processing as part of systems able to understand emotions. Our previous research introduced a framework that tailored a general model of machine understanding to emotion understanding and implemented it in a Virtual Tutor domain [4]. Such research provides guidance on implementing emotion understanding, but it does not identify learning mechanisms that enable agents to understand emotions based on their experience with other emotional agents—for this we turned to models inspired by theories of memory.

We consider two types of memory that might enable agents to learn from their experience how to understand emotions. The first is episodic memory. Episodic memory allows people to remember events in their previous experience [19]. Recently, "several models of episodic memory have emerged in the domain of intelligent virtual agents (IVA)" [20] to increase believability by remembering past interactions with users. Some applications with episodic memory include serious games [21], the creation of virtual agents with coherent life stories [22], long-term interactions with human-like robots [23], reconstruction of IVAs' personal histories [24], the Conscious Tutoring System [25], a model that integrates many facets of episodic memory in intelligent agents [26], episodic memory in Soar [27-29], a model of the relationship between reinforcement learning and episodic memory retrieval [30], in addition to many other studies that address the modeling of episodic memory in IVA [31-33] and in cognitive science [34,35]. The intensity of an emotion that a person feels has been found to influence episodic memory [36], but few models of episodic memory consider intensity [26,22,23] and others left it as future work [24,25,21,37]. Our framework encodes intensity into episodic memories of emotional events and uses intensity as part of its understanding of emotions.

The other kind of memory that we consider is semantic memory. Semantic memory stores people's basic knowledge of the world, such as word meanings, facts, and propositions [38]. As was the case for episodic memory, researchers are still fleshing out how to computationally model semantic memory. Semantic memory has been implemented in Soar [39], in avatars [40], and as a synthetic neural network model [41]. Despite its importance, the interaction between episodic memory and semantic memory has been deferred to future work in many models of episodic memory [26,32,27].

We built our implementation atop Soar, a general cognitive architecture for both modeling cognitive systems and implementing systems that exhibit intelligent behavior. Episodic memory in Soar encodes and stores the entire contents of the top state of Working Memory with a time stamp, which can be used in retrieval. These aspects of Soar were incorporated into our framework, but we also made some modifications. For humans, abstracting from personal experience is a part of semantic memory. We modeled this using semantic graphs to organize and represent these abstractions. We implemented semantic memory as learned semantic graphs and an unlearned emotion-knowledge lookup table. Our framework also differed from other implementations of Soar in that the intensity of emotions influences the encoding and retrieving of episodic memories, and episodic memory and semantic memory interact during recall.

To recap, the main contribution of this paper is the elaboration and evaluation of a framework for emotion understanding in agents. Inspired by how humans develop understanding of emotions through their experiences with others (or by introspection), we asked how such learning in humans could inform our framework to enable agents to understand emotions. Our emotion understanding framework combines psychology theories of episodic and semantic memories with the paradigm of machine understanding.

Since emotion understanding is useful for the other abilities that underlie emotional intelligence and could improve their performance, we evaluate our framework's emotion understanding in the context of emotion management; that is, our agents try to elicit specific emotions in other agents. This research does not focus on developing agents that have emotions themselves, but rather on agents that understand the emotions of others. Our agents are similar to a child who has innate and preliminary knowledge about emotions at birth (the semantic memory). We used the idea that "individuals use others' emotions to make sense of ambiguous situations" [42]. Hence, an agent gets emotional knowledge by observing the emotional reactions of other agents. We note that although the agent can use its knowledge about the emotional reactions of others to make inferences about goals or character [43,44], our agents could not do these things. The main concentration of the current research is on developing emotion understanding in agents; hence, our agents use their emotional knowledge to generate new emotional knowledge and increase their emotion understanding. In other words, our agents' emotional knowledge grows through their lives.

This paper reviews the related theoretical work and then presents our framework and its implementation and evaluation. Specifically, Section 2 describes the theoretical and implementation background, including emotional intelligence, machine understanding, episodic memory and semantic memory. Section 3 presents our simulation environment. Section 4 presents our framework for emotion. Section 5 presents the evaluation of emotion understanding components. Finally, Section 6 presents conclusions, limitations, and directions for future work.

2 BACKGROUND

2.1 Emotional Intelligence

For guidance on how to enable our agents to relate emotionally with other agents, we drew inspiration from the theory of emotional intelligence [14]. On the basis of this theory, emotional intelligence in humans involves four abilities. Here we consider these four abilities in relation to agents.

- *Perceiving emotions accurately in oneself and others* – agents have been developed with abilities to perceive emotions by processing emotional speech, recognizing facial expressions [45], and using general knowledge about affect [46].
- *Using emotions to facilitate thought process* – agents have used emotional states to guide their cognition and redirect their attention, for example through an alarm mechanism [47] or interruption [18].
- *Understanding and analyzing emotions, emotional language, signals and meanings conveyed by emotions* – in humans this ability concerns understanding emotions and using emotional knowledge [14]. With this ability a person can label emotions, perceive relations among emotions, and learn what emotions mean in terms of their inter-relationships [14]. Emotional knowledge grows throughout life, with increasing understanding of emotions such as the existence of complex emotions. For agents, by emotion understanding we mean the cognitive activity of making inferences using knowledge about emotions regarding why an agent (self or others) is in an emotional state (e.g., unfair treatment makes an individual angry) and which actions are associated with the emotional state (e.g., an angry individual attacks others). Emotion understanding for agents is an emerging research topic. A key point regarding the ability to understand emotion is that agents need knowledge about emotions to enable them to make inferences about emotions. This knowledge about emotions enables agents: (1) to interpret the meanings of emotions (e.g., loss is accompanied by distress), (2) to recognize relationships among emotions (e.g., being similar or opposite), and (3) to interpret complex emotions (e.g., compound and two-step emotions).
- *Managing and regulating emotion reflectively in order to attain specific aims* – agents might use perceived and understood emotions to manage their own emotions or the emotions of others , for example, by enacting coping strategies [48-50] to promote social goals [17]. Coping strategies are processes for dealing with emotions, either by acting externally on the environment (problem-focused coping), or by acting internally to alter one's attention or interpretation of circumstances (emotion-focused coping) [49,48].

Emotional intelligence abilities "are arranged from more basic psychological processes to higher, more psychologically integrated processes" [14]. For example, emotion perception concerns the relatively simple abilities of perceiving and expressing emotion but emotion management concerns the reflective regulation of emotion [14].

2.2 Machine understanding

The emotional intelligence of our agents is a special case of the general class of machine understanding. Elements of an understanding system as well as necessary conditions for understanding are given in Figure 1, from [3]. A system **A** can understand an entity **B**, if and only if three conditions are met:

1. System **A** has some knowledge about **B**s[1], namely **A** can access a meta-model **C** of **B**s.

[1] '**B**s' means multiple instances of B

2. System **A** can analyze **B** to form a perception **D** of **B** with respect to **C**.
3. System **A** can compare and interpret the relationship between perception **D** and meta-model **C**.

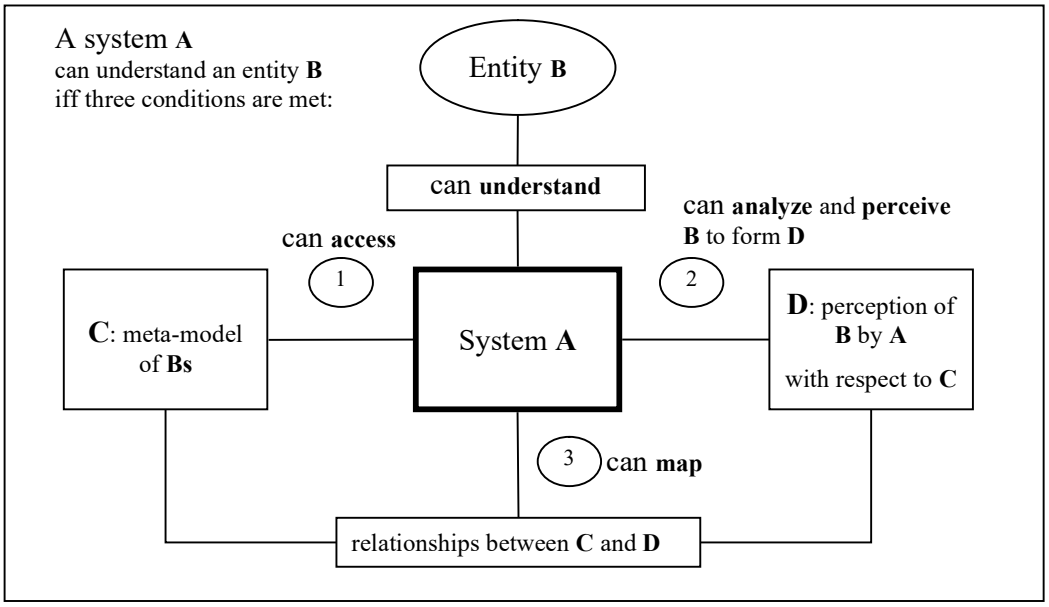

Figure 1: Elements of an understanding system [3]

Biermann [51, pp. 450-457] gives an example of how a system could understand that an object is a chair. Suppose a system has a knowledge structure of chairs. When it perceives an image of a chair, if it can link its chair knowledge to the lines and regions of the image, the system "would be able to identify the object, to name its parts, to explain connectedness relationships of the parts to each other, and to give the uses of this object. It could find all other details that may be stored in its knowledge base (e.g., owner, cost, materials, history). If these linkages can be made, we say that the system understands this image with respect to this knowledge" [51].

As shown in

Figure **2**, a functional decomposition reveals that an understanding system has a meta-model, an analyzer, and an evaluator. The meta-model stores knowledge about Bs. The analyzer analyzes inputs with respect to C to produce a perception of B. The evaluator can compare the perception of B with the meta-model to provide additional information about B, such as its non-observable characteristics and how this instance of B relates to other Bs. The product of the understanding process has the following characteristics:

- It depends on the understanding system; that is, another system may have a different understanding of the same entity.
- For a system **A**, understanding depends on: (1) its meta-model, (2) its analyzer, and (3) its evaluator; that is, with a different meta-model, analyzer, or evaluator, the understanding may differ.

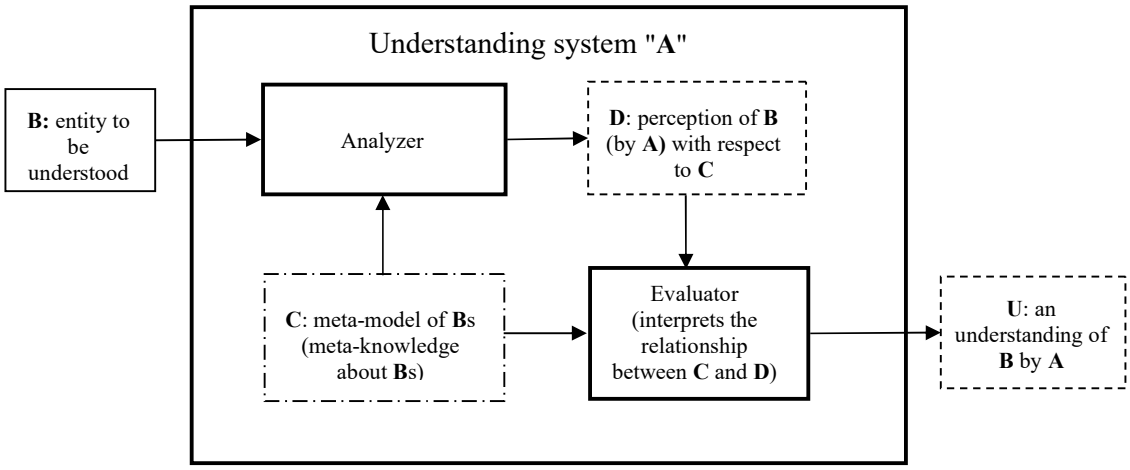

Figure 2: Functional decomposition of an understanding system.

Arrows indicate information flow.

2.3 Memory

The structure of our agents' meta-models of emotions is inspired by psychological theories of human memory. Table 1 overviews these types of memory. Three broad categories are very short-term memory, short-term memory and long-term memory. The very short-term memory is sensory memory, basically a sensory buffer, which was irrelevant for our goals so we excluded it. However, it could be important for research on visual inputs as in Ekman's work [45]. Short-term memory (also referred to as working memory) temporarily represents information about events that occurred up to about 30 seconds ago or information retrieved from long-term memory [52]. Long-term memory records experiences for longer time periods, potentially permanently, and can be separated into two kinds: declarative memory and procedural memory. Whereas declarative memory holds "explicit knowledge that we can report and of which we are consciously aware," procedural memory holds "knowledge of how to do things, and it is often implicit" [53]. Our framework uses only declarative memory, which can also be separated into two kinds: episodic memory and semantic memory. In short, an agent with episodic memory *remembers* experiences and an agent with semantic memory *knows* general information.

Table 1: Types of memory

Memory	**Very short-term memory**	**Sensory memory** (e.g., for visual and auditory inputs)	
	Short-term memory	**Working memory**	
	Long-term memory	**Declarative memory** (or **explicit memory**)	**Episodic memory** (for personal experiences)
			Semantic memory (for known facts)
		Procedural memory (**implicit memory**)	

2.3.1 Episodic Memory

Episodic memory allows an agent to remember personal experiences (some researchers use the term "autobiographical events") [19]. Episodic memory can be conceptualized as consisting of the following three stages [52]:

1. *Encoding* refers to transforming information of a salient event into a memory that can be stored [38]. Emotions may serve as a contextual cue (or marker) for event importance [54]. Hence, our framework encodes – in addition to other things – the

intensity of an observed agent's emotional reaction to an event for later use when it is trying to infer what event might elicit that emotion.

2. *Storage* refers to the preservation of memory over time [52]. Consolidation entrenches episodic memories over time, making them less likely to be forgotten [52].
3. *Retrieval* refers to recalling an experience into short-term memory for further use [52]. Retrieval can happen either spontaneously or deliberately [26]. Our framework uses deliberate retrieval only.

A person's emotional state has been found to influence episodic memory. For example, the intensity of an emotion that a person feels has been found to influence how long the person remembers the emotional experience, how vivid the memory is, and so on [36]; the neural mechanisms underlying these effects are being elucidated [55]. Our agents encode into episodic memory the intensity of the emotion that they observe in another agent, not the intensity of the emotion they themselves felt. Basically, during encoding and retrieval, our framework assumed that agents felt the observed emotions as intensely as the agents who experienced the emotions. We thought this was a reasonable simplifying assumption given that observers often take on aspects of the emotional states of those whom they observe [56].

2.3.2 Semantic Memory

Although the existence of semantic memory and its distinction from episodic memory have been debated [57,19,58], semantic memory is generally considered as separate from episodic memory and to consist of "a network of associations and concepts that underlies our basic knowledge of the world-word meanings, categories, facts, and propositions, and the like" [38]. In contrast to episodic memory, semantic memory does not represent personal experiences [52]. It contains facts such as "Tehran is the capital of Iran." Semantic memory includes general knowledge *abstracted* from personal experiences [59], which involves "deletion of many of the perceptual details and retention of the important relationships among" them [53]. Semantic memory does not need episodic memory for encoding and storage but many operations of episodic memory depend on semantic memory [58]. "It has been suggested that episodic and semantic long-term memory systems interact during retrieval" [60] as they do in our framework.

3 SIMULATION

In our simulation where agents interact, the agents had to develop an understanding of emotions in order to manage their emotions with respect of the emotions of other agents. This can be seen as a case of problem-focused coping. This simulation enabled us to test our framework components. Although human-agent interaction would have had some advantages, agent-agent simulation allowed us to sidestep some difficulties that arise when agents interact with humans, such as detecting human emotions. We note that this research was about emotion understanding. We used emotion management only to evaluate our suggested emotion understanding framework; hence, to simplify implementation for now we set aside key issues related to emotion management (e.g., social relationships, theory of mind, and social behavior) [17]. As our agents had neither sensory systems nor theory of mind with which to model others' mental states, we gave our agents direct access to other agents' goals.

For each round the aim of each agent was to elicit a randomly assigned target emotion in other agents. Agents interacted only through actions, which were interpreted by the receiving agent as both an action and an event. An action has a time (i.e., *now* or *future*). When the value of the time variable is now or future, agents perceive that the action is occurring now or will occur in the future. In this simulation, only hope and fear were elicited by future actions.

Actions and events, in turn, could elicit emotions in the receiving agent depending upon its goals and standards[1]. Goals and standards differed across agents and were determined randomly at the start of the simulation. Agents did not have any experience at the beginning of the simulation, but they had general knowledge (as semantic memory) about emotions (see below). The agents thus had to learn the mapping of emotions with goals and standards by trial and error, in addition to using their understanding abilities, to achieve their aim of eliciting target emotions in other agents. In the simulation environment each agent could observe all other agents and their interactions, and they could learn from such observations.

The agent system included two kinds of agent: (1) a *simulator agent*, who managed the simulation, and (2) *emotional agents*, which followed the simulation scenario and interacted with other emotional agents and the simulator agent. At the beginning of the simulation, the simulator agent initialized the internal variables of each emotional agent: assigned an "id", randomly assigned importance values ranging from 0 to 1 to goals and standards, and set simulation parameters regarding the number of agents and the total number of simulation cycles[2]. Throughout the simulation, the simulator agent collected the score (representing successful emotion management) of each agent for use in evaluation of the memory abilities. Since these variables did not change during simulation, the simulation was deterministic.

In our simulation, each agent used GEmA to generate its emotions. GEmA is an appraisal model for software agents that can map observed events and actions to emotions [62]. GEmA uses the Ortony, Clore, and Collins (OCC[3]) [61] model of emotions for the elicitation of emotions by the appraisal of events and actions with regard to goals and standards, respectively. In this study, emotions were characterized by a type (e.g., joy) and intensity (a value between 0 and 100). We used the 12 emotions shown in Table 2. When an emotional agent had no emotion, the emotional state was "neutral" with zero intensity. For each goal, agents had a corresponded standard. Corresponding goals and standards had the same (random) importance values (a simplifying assumption). Hence, in the rest of the paper, we use only goals for emotional agents.

Table 2: Selected emotions from GEmA's output to an agent

Emotion type	Eliciting conditions
	Event-based emotions (One step):
Joy	Occurrence of a desirable **event**
Distress	Occurrence of an undesirable **event**
Hope	Prospect of a future desirable **event**
Fear	Prospect of a future undesirable **event**
	Event-based emotions (Two-steps):
Satisfaction	**Confirmation** of the prospect of a desirable **event**
Fear-confirmed	**Confirmation** of the prospect of an undesirable **event**
Disappointment	**Disconfirmation** of the prospect of a desirable **event**
Relief	**Disconfirmation** of the prospect of an undesirable **event**
	Action-based emotions (One step):
Admiration	**Action** is done by another agent and is **consistent with** the standards of the agent
Reproach	**Action** is done by another agent and is **inconsistent with** the standards of the agent
	Compound emotions (One step):
Gratitude	Joy + Admiration
Anger	Distress + Reproach

[1] The concept of "standard" refers to value that agents use to evaluate a manner of behaving [61].

[2] To fix the number of interactions for all the simulations, we set the number of agents and number of simulation cycles per run such that their multiplication product is equal. For example, the number of interactions of a run with 10 agents and 80 cycles was equal to another run with 20 agents and 40 cycles.

[3] This model was restricted in that it did not incorporate embodied, automatic, and associative accounts of emotion generation. This clearly is a limitation when modeling emotional intelligence.

4 THE EMOTION UNDERSTANDING FRAMEWORK

We tailored a general model of machine understanding [3] into a framework of machine understanding of emotion. A functional decomposition of this model is depicted in

Figure 3. It consists of a meta-model, analyzer, evaluator, and memory modulator. The meta-model C contains knowledge about Bs, agents and emotions. It consists of three modules. First is an episodic memory module that stores observed details of specific, experienced events. Second is a semantic memory implemented as a lookup table of general knowledge about emotions, such as their similarities. Third is a semantic memory implemented as semantic graphs which are semantic networks that represent observed relationships among emotions and actions stored in episodic memory.

The analyzer with agent and emotion analyzers analyzes **B** to form a perception **D** of **B** in which agents with similar goals are assigned to a group (e.g. group_j) and the emotional states of agents perceived. In this simulation, the emotion analyzer automatically receives the emotional states of agents without any additional processing. We have considered the aim of agents to elicit a target emotion in other agents as a part of **D**, perceptions.

The evaluator interprets **D** (i.e. the perceived agent and the target emotion) with respect to the meta-model **C** (i.e., the current state of episodic and semantic memories). Evaluation results an understanding that enables the system to select an action that might achieve the agent's aim of eliciting the target emotion in the observed agent.

To update meta-model based on observed emotional reactions of agents to actions, we added another module that we call the "memory modulator".

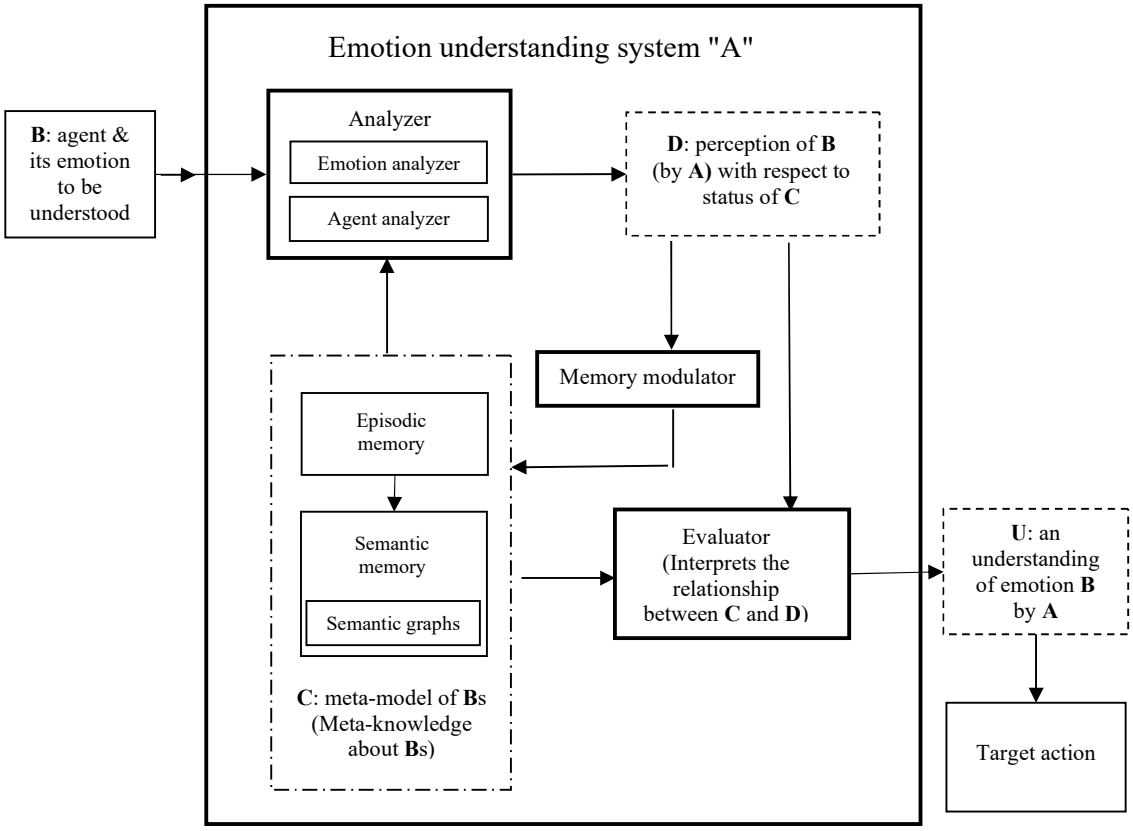

Figure 3: Functional decomposition of the framework of emotion understanding

4.1 Meta-model

The meta-model consists of episodic memory, semantic memory, and two kinds of semantic graphs, one that represents observations of what elicits emotions for each group of agent and another that represents common patterns in what elicits emotions across agents. They will be discussed in the following sections.

4.1.1 Episodic Memory

Episodic memory encodes five aspects of each experience (time, action_i, group_j, emotion_k, intensity), which means at a certain time an agent performed action_i towards another agent in group_j who, in response, has an emotion_k with an intensity between 0 and 100. The five aspects subsequently help an agent to determine which action is appropriate in a given context. *In other words, the experiences enable the agent to interpret the meanings of emotions.* To do so, the agent retrieves from episodic memory its previous experiences of which actions resulted in which emotions for the given agent group. Episodic memory covered all possible cases that could occur for an agent (e.g., agent_1) when encoding an experience: agent_1's action eliciting the emotions of another agent, another agent's action eliciting agent_1's emotions, or observing another agent's action eliciting the emotions of a different agent.

Episodic memory could store only actions that elicited joy, distress, hope, fear, admiration, and reproach. We named theses emotions primary emotions by which other emotions, two step and compound, can be represented. However, there are considerations for primary emotions [63,64], we ignored them in this paper.

4.1.2 Semantic memory as a lookup table

In this study, semantic memory refers to general knowledge about emotions. Agents used this knowledge to guide their retrieval of episodic memories. Table 3 shows the knowledge about emotions stored in a lookup table that represented a part of the semantic memory of our agents. This knowledge is based on the OCC model of emotions [61]. For illustration we describe one emotion from each class. Joy is an emotion with *positive* ***valence*** in the ***class*** of emotions elicited from the *occurrence* of an event whose ***consequence*** is *desirable* and whose ***time*** is *now.* Hope is similar to joy but whose ***time*** is *future*. Satisfaction is an emotion with *positive* ***valence*** in the ***class*** of emotions elicited in an agent that previously felt hope (a **previous emotion),** when it has *confirmation* of an event whose ***consequence*** is and whose ***time*** is *now.* For example, an agent who felt hope and then an event elicited joy would have feel both joy and satisfaction (and depending upon temporal decay, perhaps hope as well). Admiration is an emotion with *positive* ***valence*** in the ***class*** of emotions elicited from an action whose ***evaluation*** is *consistent with* the standards of the agent and whose ***time*** is *now.* Gratitude is an emotion with *positive* ***valence*** in the ***class*** of emotions elicited by *confirmation* of an event whose ***consequence*** is *desirable* and an action whose ***evaluation*** is *consistent with* the standards of the agent, and whose ***time*** is *now.*

Our simulated agents did not learn this semantic knowledge about emotions; they received it at initiation. In this sense our framework made an assumption analogous to the idea that animals, including people, might have inborn knowledge related to emotions (see, e.g., [65,66]). Note that in our simulation this general knowledge of emotions does not include which events or actions elicit what emotions. That information had to be learned by experiences encoded into episodic memory.

Table 3: Knowledge of an agent with emotion understanding ability stored in semantic memory (based on Table 2) "NA" means not applicable, e.g., joy does not have ac action evaluation or a previous emotion.

Emotion type	Class	Valence	Previous emotion	Event Consequence	Action Evaluation	Time
Joy	Occurrence-based	Positive	NA	Desirable	NA	Now
Distress	Occurrence-based	Negative	NA	Undesirable	NA	Now
Hope	Prospect-based	Positive	NA	Desirable	NA	Future
Fear	Prospect-based	Negative	NA	Undesirable	NA	Future
Satisfaction	Confirmation-based	Positive	Hope	Desirable	NA	Now
Disappointment	Confirmation-based	Negative	Hope	Undesirable	NA	Now
Relief	Disconfirmation-based	Positive	Fear	Desirable	NA	Now
Fear-confirmed	Disconfirmation-based	Negative	Fear	Undesirable	NA	Now
Admiration	Action-based	Positive	NA	NA	Standard-consistent	Now
Reproach	Action-based	Negative	NA	NA	Standard-inconsistent	Now
Gratitude	Compound	Positive	NA	Desirable	Standard-consistent	Now
Anger	Compound	Negative	NA	Undesirable	Standard-inconsistent	Now

4.1.2.1 Exploring episodic memory with the lookup table

When episodic memory lacks experience with a target emotion (e.g., joy) for a given group of target agent (e.g., group_8), agents with the lookup table of semantic memory use it to further explore episodic memory in order to make informed guesses with respect to what action might elicit the target emotion for the target group of the agent. They can do so using five mechanisms.

1. The first mechanism is viable for joy, distress, hope, or fear. Agents check the lookup table for an emotion similar to the target emotion but differs only on the time dimension. As shown in Table 3, joy is similar to hope and distress is similar to fear. So, for example, if episodic memory lacks an action to elicit joy, the agent searches the lookup table for hope, which is similar to joy. The agent tries to retrieve an action for hope. If successful, the agent selects that action but changes the time to now, the time for the original target emotion.

2. Second, for any target emotion the agent could find an emotion that is identical but with the opposite valence, and then try to retrieve an action that elicits that emotion for an agent of an opposite group of the target agent. As shown in Table 3, the following emotion pairs differ only in their valence: joy/distress, hope/fear, satisfaction/disappointment, relief/fear-confirmed, admiration/reproach, and gratitude/anger. The opposite group for a target agent has a goal-importance value equal to 1 minus the target agent's goal-importance value (for the target emotion, not its opposite). So, for example, if episodic memory has no instances of a group_8 agent experiencing joy, the agent can use the lookup table to determine the emotion of opposite valence (i.e., distress) and then try to retrieve an action that elicits distress for an agent of a opposite group of the target agent (e.g., group_13). The selected action *might* elicit joy in the target agent.

3. The third mechanism combines the first and second. The agent tries to find an experience for the emotion whose valence is the opposite of the emotion that is similar to the target emotion. Here, as discussed in the first mechanism, the agent finds a similar emotion (hope) to the target emotion (joy). Then, as discussed in the second

mechanism, the agent selects an action previously observed to elicit the opposite emotion (fear) of the emotion similar to the target emotion (hope) in an agent of the opposite group of the target agent's group, and then changes the time to match the target emotion. The selected action *might* elicit joy in the target agent.

4. The fourth mechanism enables the agent to find sequences for the two-step emotions: satisfaction, disappointment, relief, and fear-confirmed (see Table 3). Normal episodic memory cannot do alone (as it records only the observed action and emotion). Two-step emotions have an emotion, hope or fear, as a prior condition. The second step is an emotion with a desirable or undesirable consequence, joy or distress. If an agent wants to elicit a two-step emotion in another agent, it needs to perform two actions, an action for each step. For example, suppose agent_1 wants to elicit satisfaction in agent_2. As a first step, agent_1 performs an action to elicit hope in agent_2. As the second step, agent_1 performs another action to elicit joy in agent_2. Performing the second action elicits satisfaction in agent_2. The agent had to refer to the episodic memory twice because information about satisfaction itself was not stored in episodic memory, as was information about its two building blocks, hope and joy.
5. The fifth mechanism enables agents to find actions to elicit the compound emotions of gratitude and anger (see Table 3). Gratitude is elicited by a standard-consistent action coupled with a desirable event. Anger is elicited by a standard-inconsistent action with an undesirable event. If an agent wants to elicit a compound emotion in another agent, it needs to perform an action that fits both conditions since compound emotions were not stored in episodic memory. For example, to elicit anger in agent_2, an agent performs one action that elicits both distress and reproach in agent_2. Identifying this action is computationally problematic for large numbers of experiences since episodic memory records only the observed action and emotion. Hence, first the agent needed to find an action that matched the first condition and then search the rest of experiences to see whether the action matched the second condition. If the second condition is not matched, the agent should find another action and check the conditions again. This could be a problem for applications that store large numbers of experiences.

4.1.3 Semantic memory as semantic graphs

In addition to the lookup table, we used semantic graphs to represent the abstraction of episodic memory into semantic memory. Semantic graphs provide some compensation for limitations of Soar's basic implementation of episodic memory, which simply retrieves only the most recent relevant experience. When an agent's episodic memory had multiple relevant experiences indicating how to elicit the target emotion in the target agent, one of these experiences may indicate a more effective way to elicit the target emotion than the most recent experience. Also, older experiences may also have been informative when target agents have unpredicted emotional responses due either to being categorized inaccurately or nondeterministic behaviors (see below).

Our semantic graphs are weighted graphs in which weights represent certainty factors. As discussed above, each instance of episodic memory has five parts (time, action_i, group_j, emotion_k, intensity). In the semantic graphs, nodes connect to a central node via edges, but nodes do not connect to one another. Semantic graphs allow multiple candidate actions to be compared using certainty factors. Prior work has used certainty factors for inexact reasoning in expert systems [67]. For our agents, a certainty factor represents their degree of belief that an action will elicit a target emotion for the given agent group. Our computation of certainty factors incorporates the recency of storage and the intensity of emotion. We limited our

recency values to a maximum value of *100*, so older experiences had a recency value of *100* and "time of storage" was changed accordingly. Computing an overall certainty factor for whether an action will elicit a target emotion for the given group of agent requires preliminary calculations (with Eq. (1)) of a separate certainty factor, CF(action), for each experience of every action in episodic memory that results any emotion for the given group of agent. Certainty factors are positive for experiences if the action elicited the target emotion, negative if the action elicited an opposite emotion, or *neutral* if the action elicited another emotion. Table 4 presents examples for nine chronologically organized experiences. Here is an example calculation for Experience 1 in Table 4: CF(action_1, joy) = ((50/100) + (70/100)) / 2 = .60.

$$CF(action, emotion) = \frac{\frac{\text{time of storage}}{\text{time of most recent experience}} + \frac{\text{intensity of emotion}}{100}}{2} \qquad (1)$$

Table 4: Example excerpt from episodic memory and certainty factors (CF) based on each experience that the action will elicit joy as computed with Eq.(1)**.**

Experience	Time	Action	Group	Emotion	Intensity	CF(action, joy)
1	50	1	2	joy	70	.60
2	60	1	2	joy	80	.70
3	65	1	2	joy	70	.67
4	70	3	2	distress	100	-.85
5	74	1	2	distress	40	-.57
6	80	1	2	admiration	40	0
7	90	2	2	joy	30	.60
8	96	2	2	joy	30	.63
9	100	3	2	joy	60	.80

Eq. (2) (adopted from [68]) computes an overall certainty factor by combining of all the certainty factors computed by Eq. (1). Eq. (2) works recursively in that it can combine the certainty factors of two experiences whose resultant value is a certainty factor that can itself be combined with other experiences by Eq. (2). For an agent group, its overall certainty factor for an action-emotion pair represented belief that the action will cause the target emotion for that agent group. For example, by using Eq. (2), the overall certainty factor that action_1 elicits joy in agents with group_2 is CF(action_1, joy) = 0.91; for action_2, CF(action_2, joy) = 0.85; and for action_3, CF(action_3, joy) = - 0.25. These certainty factors are included in the semantic graphs. Figure 4 visualizes a semantic graph of an agent, based on the experiences in Table 4, of its certainty regarding which emotions are elicited by what actions for agents of group_2. Each agent has a distinct semantic graph for each agent group. In Figure 5, the CF of action_1 with respect to joy is 0.75, whereas it is -0.95 with respect to distress. Although joy and distress are described as opposite emotions, the CF values are not each other's opposite (e.g., 0.75 and -0.75). This is because CF values are computed based on experiences not on emotion relations. As Table 4 shows, for three experiences *action_1* elicited *joy*, but for one experience *action_1* elicited *distress*. Hence *action_1* had different CF values for *joy* and *distress*.

$$CF_{combine}(action, emotion) = \begin{cases} CF_1 + CF_2 * (1 - CF_1) & CF_1 \geq 0 \quad and \quad CF_2 \geq 0 \\ \dfrac{CF_1 + CF_2}{1 - \min\{|CF_1|, |CF_2|\}} & \begin{matrix} CF_1 < 0 \quad and \quad CF_2 > 0 \\ CF_1 > 0 \quad and \quad CF_2 < 0 \end{matrix} \quad or \\ CF_1 + CF_2 * (1 + CF_1) & CF_1 \leq 0 \quad and \quad CF_2 \leq 0 \end{cases} \tag{2}$$

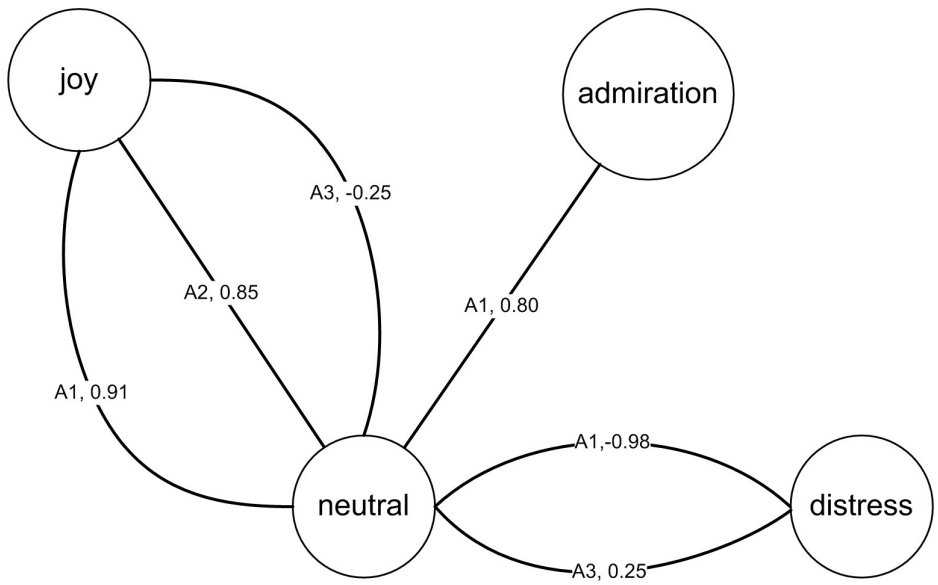

Figure 4: A semantic graph of certainty factors for action_1 (A1), action_2 (A2), and action_3 (A3), for agents with group_2, with respect to the experiences in Table 4

As mentioned earlier, if an agent wants to elicit a compound emotion such as gratitude in another agent, it needs to perform an action that elicits both joy and admiration. Semantic graphs can identify such actions simply by identifying intersections of relevant edges. By this process, the edges of action_1 (i.e., A1 in Figure 4) intersect for joy and admiration, indicating that action_1 might elicit gratitude.

4.1.4 Semantic memory as a general semantic graph

We used a general semantic graph – a semantic graph abstracted from the semantic graphs of agent groups – to encompass general knowledge about all agent groups. Our rules for this abstraction were inspired by Anderson [53], who described the organization of general abstraction in semantic memory as follows: "If a fact about a concept is frequently encountered, it will be stored with that concept even if it could be inferred from a more superordinate concept. The more frequently encountered a fact about a concept is, the more strongly that fact will be associated with the concept". Our abstraction rule for general semantic graphs is that experiences with consistent action-emotion elicitation are included in the general semantic graph if they are in over half of the semantic graphs specific to different agent groups. For example, if over half of semantic graphs included an experience in which action_1 elicited joy, then the belief that action_1 elicits joy would be in the general semantic graph. It suggests that action_1 might elicit joy in agents of other groups who have not yet experienced action_1. Since the general semantic graph is a semantic graph for all agent groups, its visualization is similar to Figure 4.

4.2 Analyzing (perceptually categorizing) agents

Agents categorized other agents with whom they interacted into different groups depending upon differences in those agents' goals. This categorization helped agents to organize their experiences based on perceived agent groups. Hence, an experience with an agent of a given group could be informative about other agents of the same group. Note that the groups were perceived and not real; that is, agents were not generated to be similar depending on grouping.

We did a pilot evaluation of three candidate methods for categorizing agents into groups that are applicable for our framework of emotion understanding. After describing ideal characteristics for such methods, we describe three candidate methods and then report evaluations of them. The first ideal characteristic is that the method is *accurate*, which means that two agents in the same group have the same emotion in response to given actions. The second is that it is *dynamic*, which means that each agent is categorized when it is selected as a target agent instead of all agents being categorized at once. The total number of groups is unknown and the categorization method must be capable of adding new groups, updating old groups by joining or splitting them, and by moving an agent from one group to another. The final ideal characteristic is that the categorization method *retains previous knowledge*, which means that it keeps a record of an agent's experiences under a previously assigned group when it changes the assigned group, as is relevant when two groups join or one group splits. This characteristic has a trade-off with dynamic categorization because dynamic methods lose previous experiences.

We now describe and evaluate three categorization methods. In Method 1, two agents have the same group if their goals match based on the criteria of whether their goals have importance values of zero or not. For example, consider agents with three goals: A, B, and C. If *agent_1* has goal importance values of $A = 0.6$, $B = 0$, and $C = 1$, and *agent_2* has values of $A = 0.1$, $B = 0$, and $C = 0.7$, then this categorization method will assign *agent_1* and *agent_2* to the same group (e.g., *group_5*) because they matched with goals A and C having non-zero values, and goal B having zero values. This method considers all possible groups of agents (making the number of groups fixed): with n goals there are 2^n groups, corresponding to combinations of n goals with cutoff of zero and non-zero values. Although this method can dynamically add new agents, the number of groups and group assigned to an agent is fixed to retain previous knowledge. This method may have some empty groups.

Method 2 uses *ISODATA* [69], a clustering algorithm method that works with an estimated number of groups (for a review of clustering algorithms, see [70]). ISODATA dynamically adjusts the number of groups by merging and splitting groups. Since merging and splitting may change the group assigned to an agent, this categorization method fails to retain previous knowledge. To evaluate this categorization method, we consider the best case for this method in which all the agents are categorized at initialization, avoiding the need for them to change group and therefore Method 2 retains previous knowledge during evaluation.

Method 3 utilizes an adjusted version of *k-means*. Similar to Method 1, *k-means* considered 2^n groups ($k = 2^n$), for which n is the number of goals. Each agent is represented by its goals' value as an n elements vector. In *k-means,* when adding a new agent to a group, the center of the group (means of the vector of agents' goals in the group) may change and consequently the group assigned to some agents may change; hence, *k-means* may fail to retain previous knowledge. To avoid this problem, the center is fixed for each group and a pilot simulation indicated that goals corresponding to combinations of n goals with cutoff of zero and non-zero values, the center value should be 1 for the values of non-zero, for example a center for *group_1* can be *(1, 0, 0)* and a center for *group_5* can be *(1, 0, 1)*. *k-means* uses Euclidean distance to categorize a new agent. For the example given for Method 1, *agent_1*

would be in a group with a center *(1, 0, 1)* and of a group (e.g., *group_5*), but now *agent_2* would be in a group with a different center *(0, 0, 1)* and therefore be of a different group (e.g., *group_1*). The main difference between Method 1 and Method 3 is that Method 3 utilizes a similarity measure for categorization.

The accuracy of the three categorization methods is compared in Table 5. Overall, Method 3 had the best results. Method 2 had the best result only when the number of goals was 2 and the diversity of agents is low. The accuracy of Method 1 and Method 3 increased with increasing numbers of goals from 2 to 4 as well as increase in the diversity of agents. We used Method 3 in the rest of this paper for computing the group of agents.

Table 5: Mean percent categorization accuracy of the three methods, for different numbers of goals, over 20 runs (with 14 actions). The pairs are (number of agents, number of simulation cycles per run). Bold numbers are the maximums in each column.

Categorization method	2 goals			3 goals			4 goals		
	(10,20)	(20,10)	(40,5)	(10,20)	(20,10)	(40,5)	(10,20)	(20,10)	(40,5)
Method 1	74.5	73.4	69.1	80.6	74.4	74.2	**93.5**	**89.6**	84.3
Method 2	72.0	68.7	**74.0**	80.5	76.8	73.0	83.1	77.1	76.0
Method 3	**77.5**	**73.5**	69.2	**83.8**	**79.3**	**81.4**	**93.5**	88.9	**85.3**

4.3 Evaluator element

The evaluator element allowed agents to produce an understanding of what actions might elicit the target emotion for the agent with whom they interacted. They did so by comparing their perception of the target agent's group to their meta-model about agents and emotions. Since the content of these memory systems is dynamic, the evaluator could produce different understandings of an identical input at different times.

In the selection of target action, when more than one action is a candidate for activating the target emotion, an agent using semantic graphs selects the action with the highest overall certainty factor. An agent using basic implementation of episodic memory selects the most recent action. With respect to Figure 4, three actions (*A1*, *A2*, and *A3*) have been observed to elicit joy in an agent of *group_2*. An agent using semantic graphs selects the action with the highest overall certainty factor. Hence, using semantic graphs the agent selects *action_2* (*A2*). In contrast, an agent using the basic implementation of episodic memory selects *action_3*, the most recent action to have elicited joy in an agent of *group_2* based on Table 4.

4.4 Memory modulator

This module updates the contents of the episodic and semantic memories based on observed emotional reactions of agents to actions. When an agent performs an action toward another agent, the other agent may have emotional reactions, which the agent perceives. The memory modulator adds this new experience to episodic memory. Then, it updates the semantic graphs by processing the content of episodic memory.

5 EVALUATION OF EMOTION UNDERSTANDING COMPONENTS

We selectively lesioned (disable) memory components in order to evaluate the role of each in the emotion understanding framework. The evaluation measure is how well our simulated agents achieve their aim of managing the emotions of other agents. We first have to

find constraints due to our configuration of memory components. All the memory components depend on episodic memory, so all configurations have this memory component. Many abilities of the lookup table version of semantic memory depend on semantic graphs. The general semantic graph depends on semantic graphs. Given these constraints, we have five configurations of memory components. Configuration 1 used Soar's basic episodic memory. It retrieved only the most recent experience, making time the only parameter of retrieval. Configuration 2 added semantic graphs to Soar's basic episodic memory to represent the abstraction of experiences into semantic memory. In this configuration, the semantic graphs generated the outputs instead of using the most recent experience. The semantic graphs were updated with new experiences when episodic memory encoded them. Configuration 3 added a general semantic graph to Configuration 2. If the memory systems of Configuration 2 failed to identify an action (perhaps the agent has not yet observed an agent of the given group experience the target emotion), the general semantic graph attempted to find an output. Configuration 4 added the lookup table version of semantic memory to Configuration 3. If the memory systems of Configuration 3 failed to identify an action, the evaluator element used the lookup table (see Table 3) as described above. Configuration 5 is similar to configuration 4, but it excludes the general semantic graph.

In order to provide a robust evaluation of the emotion understanding systems, different simulations included 3, 7, 14, or 28 types of actions and 2, 3, or 4 types of goals[1]. This set of simulations allowed us to evaluate the emotion understanding framework with a small and large number of action types and agent groups. For criteria to compare the configurations, we used recall, precision, and F-scores as developed in the field of information retrieval [71]. The following sections discuss them sequentially.

5.1 Recall

Recall is the ratio of the number of relevant actions retrieved to the total number of selected actions [71]. Relevant actions are those that elicit the target emotions in other agents. Selected actions include those selected randomly and those retrieved from episodic memory, semantic graphs, general semantic graphs, or the semantic memory lookup table. Since recall includes all selections it provides the most direct measure of the overall accuracy of the agents' emotion understanding framework.

As Figure 5 shows, across all memory configurations the recall increased as the number of actions increased. When there were fewer actions than emotions, agents often fail to elicit the target emotion since *no* action could do so. With larger numbers of actions, more than one action can elicit an emotion; hence, recall is higher.

As Figure 5 shows, comparison across memory configurations indicates that adding memory abilities – especially the lookup table – tended to increase recall. In general, Configurations 4, 5, 3, 2, and 1 had higher recall, respectively. For example, considering simulations with 14 actions, Soar's basic episodic memory (Configuration 1) performed fairly well, selecting an appropriate behavior on average 36% of the time. Adding semantic graphs and general semantic graphs (Configurations 2 & 3) provided only slight improvements of up to 2 percent compared to Soar's basic episodic memory. The semantic memory lookup table (Configurations 4 & 5) substantially enhanced recall, improving it an average of 13% as compared to Soar's basic episodic memory.

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[1] Since goal hierarchies in many applications, such as [62], use a small number of goals with large number of sub-goals and to make our implementation easier, we used only 2, 3, or 4 goals for each agent.

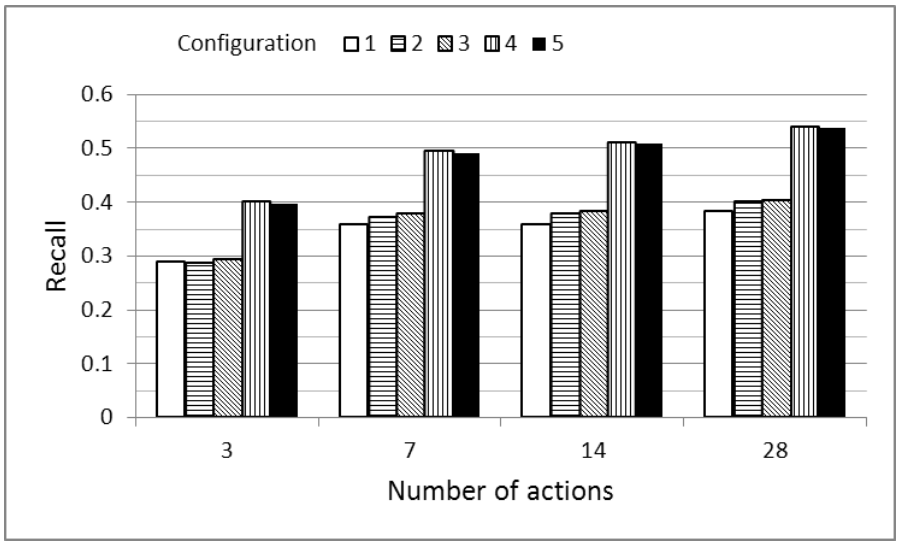

Figure 5: Recall of all configurations for agents that can perform 3, 7, 14, or 28 types of actions (s[1] = 0.05)

Figure 6 shows that for different number of goals adding memory components – especially the lookup table – again improved recall. When comparing across the number of goals, recall tended to decrease as the number of goals increased since agents' groups increase and the number of similar agents decrease.

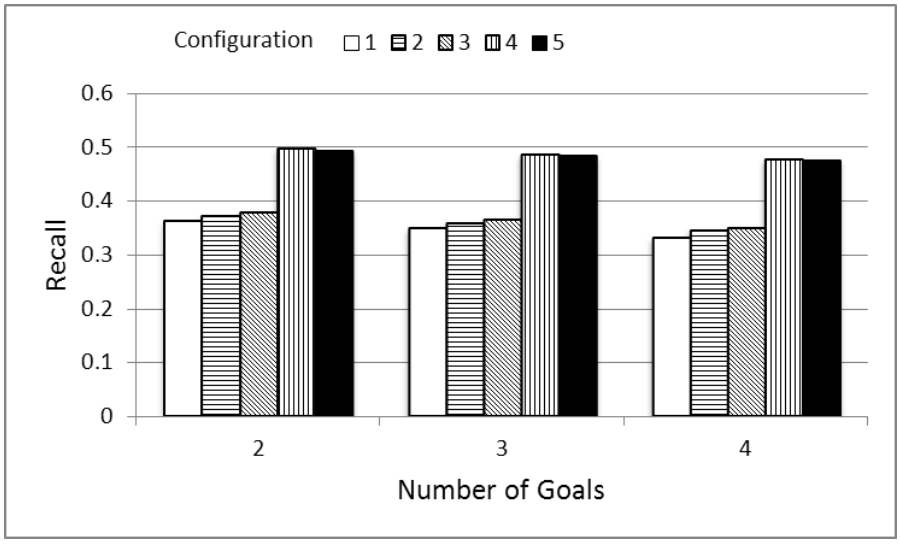

Figure 6: Recall of all configurations for agents with 2, 3, or 4 types of goals (s = 0.05)

5.2 Precision

Recall included instances in which agents were unable to retrieve an action from memory and therefore randomly selected an action – basically, when they guessed. However, agents could select incorrect actions even when they were not guessing: the selected action might be incorrect if they miscategorized the agent or some aspect of their semantic memory resulted in an incorrect inference. To distinguish between incorrect guesses and incorrect inferences we

[1] Standard deviation

looked at precision, the accuracy of selected actions when ignoring randomly selected actions [71]. We defined precision as the ratio of the number of relevant actions retrieved to the total number of retrieved actions.

As Figure 7 shows, despite Configurations 4 & 5 having the best recall, they had the worst precision. This suggests that Configurations 4 & 5 had the most fallible emotion understanding system in that they produced the most false positives. Configurations 4 & 5 achieved the highest recall because the other configurations had to guess randomly when they searched their memory and found no information available to inform action selection. Configurations 4 & 5, in contrast, could utilize the stored knowledge about emotions in more ways, by considering emotions similar or opposite to the target emotion. That is, Configurations 4 & 5 could make informed guesses. By doing so, Configurations 4 & 5 improved their recall by getting more hits when the other Configurations guessed randomly. The informed guessing resulted in more irrelevant selected actions.

As Figure 7 indicates, in almost all cases, Configurations 2, 3, 1, 4, and 5 have higher precision respectively. For simulations with few actions some of the emotions may not have actions associated with them, in which case the emotion understanding framework could not generate all emotions, thereby lowering precision. When the number of actions is higher, more than one action may elicit some emotions; hence, the probability that an action elicits a target emotion is higher, and so is precision. Across all simulation conditions, Configuration 2 had the best precision.

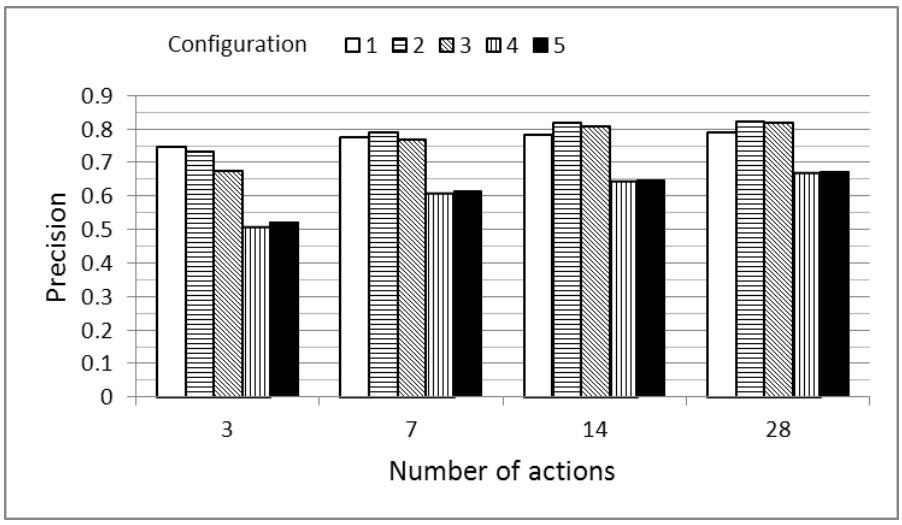

Figure 7: Comparing precision of all configurations when agents have 3, 7, 14, and 28 types of actions (s = 0.07)

In agent's categorization, two agents in the same group should have the same emotion reaction for an identical action. Simulations with more goals had more groups of agents, resulting in more fine grain categorization of agents and increasing accuracy of the categorization method. Hence, as Figure 8 shows, across all memory configurations the precision increased as the number of goals increased.

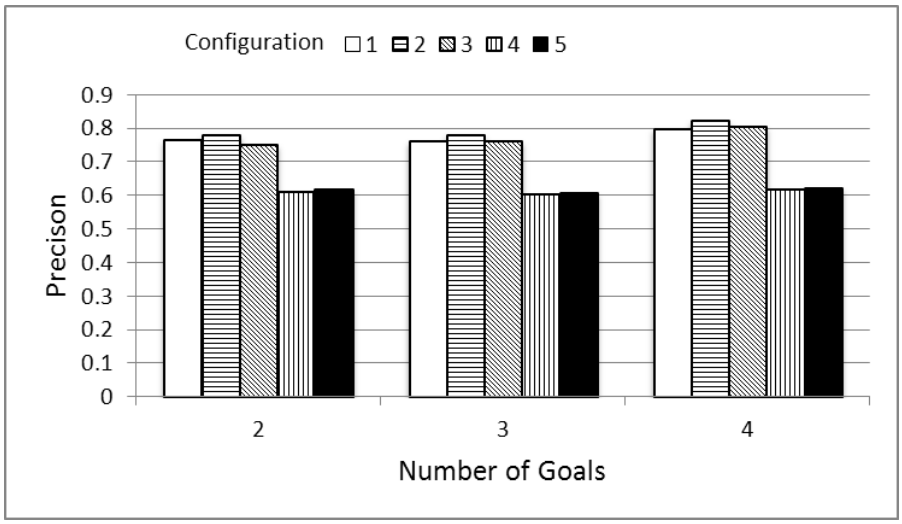

Figure 8: Comparing precision of all configurations when agents have 2, 3, and 4 types of goals (s=0.07)

5.3 F-scores

F-scores consider both precision and recall. They are weighted harmonic means of recall and precision based on Rijsbergen's [71] effectiveness measure. F-scores range between zero and one, with zero as the worst score and one as the best score. The general formula of F-scores is as follows (Eq. (3)):

$$F_{\alpha} = (1+\alpha^2) * \frac{precision * recall}{\alpha^2 * precision + recall} \tag{3}$$

For example, an F_1 score gives even weighting to recall and precision (Eq. (4)).

$$F_1 = 2 * \frac{precision * recall}{precision + recall} \tag{4}$$

In Figure 9, $F_{0.5}$, F_1, and F_2 scores are compared across all configurations. Configurations 4 & 5 have the best F_1 and F_2 scores, but Configuration 2 has the best $F_{0.5}$ score.

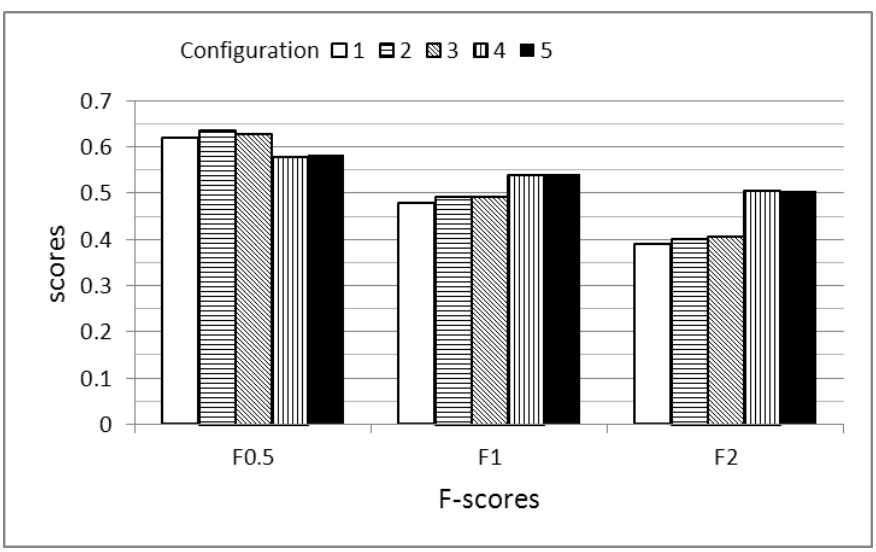

Figure 9: Three F-scores across all configurations

5.4 Comparing with Q-Learning

We also compared the success of our agents with that of agents that used Q-learning, a standard machine learning method. We selected Q-learning since it does not need training data and a model of the environment. Q-learning is a machine learning method in which an agent can learn to select optimal actions to achieve its goals [72]. An agent performs an action to change its state and then receives a reward or punishment. In this study, we have used emotions as states. Two variables of this algorithm are β and γ. β is learning rate and γ is the discount factor indicating the importance of future rewards.

We refer to agents that used Q-learning as having Configuration 0 (zero). The results of such agents were similar across different values of β and γ. For simplification, we evaluated simulations with only 3 and 28 (maximum and minimum) types of action. The results are shown in Figure 10 and Figure 11, can be summarized succinctly. In all cases and on all outcome measures, the agents with any emotion understanding configuration outperformed agents that used Q-learning. This shows that the emotion understanding framework performed better than a standard machine learning method.

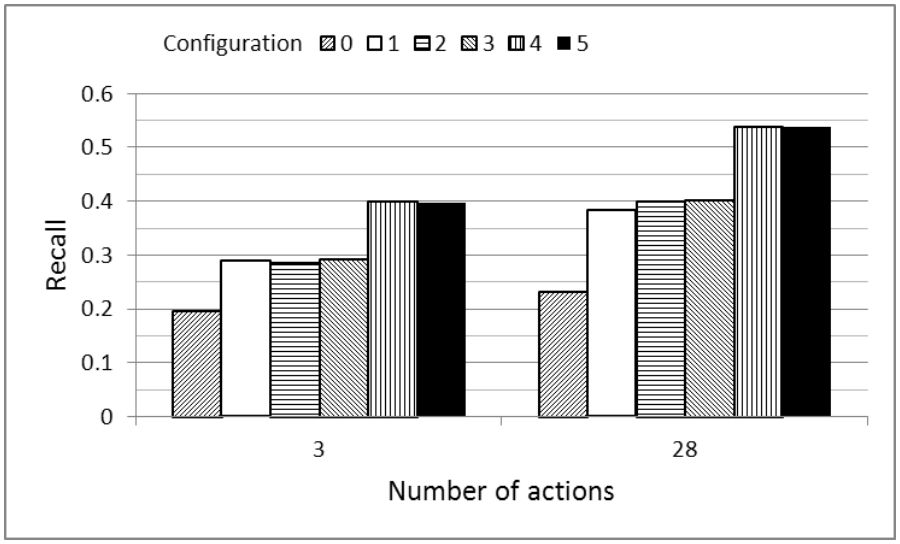

Figure 10: Comparing recall of all configurations, with Configuration 0 using Q-Learning (for β = 0.8 and γ = 0)

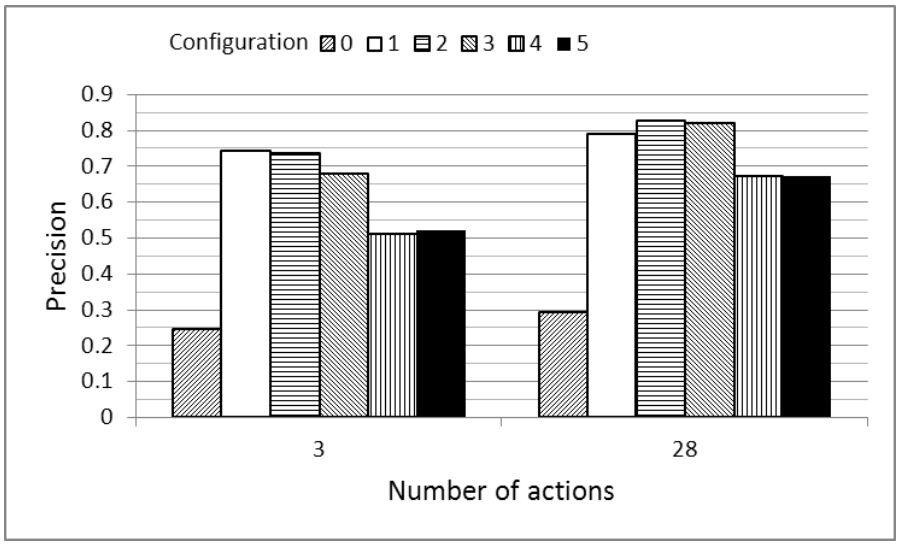

Figure 11: Comparing precision of all configurations, with Configuration 0 using Q-Learning (for β = 0.8 and γ = 0)

6 CONCLUSION

We presented a framework for emotion understanding to enable intelligent agents to improve their emotional intelligence when interacting with other agents. Our framework builds on a paradigm of machine understanding [3]. The framework includes (1) a meta-model, (2) an analyzer, (3) an evaluator, and (4) a memory modulator. The meta-model consists of episodic memory and three versions of semantic memory, semantic graphs, a general semantic graph, and a lookup table of general information about emotions. The analyzer is a perceptual categorization mechanism. The evaluator consists of an interpreter that provides an understanding of the perceived agent (analyzer output) with respect to the contents of the different kinds of memory (the meta-model). The memory modulator updates episodic memory and semantic graphs.

We evaluated three categorization methods. An adjusted version of *k-means* was the most accurate categorization method. Multi-agent simulations showed that the importance of each memory component in emotion understanding ability by enhancing emotion management success in the form of eliciting target emotions in other agents. We also evaluated five configurations of memory components: (1) agents with episodic memory, (2) agents with episodic memory and semantic graphs, (3) agents with episodic memory, semantic graphs, and a general semantic graph, (4) agents with episodic memory, semantic graphs, a general semantic graph, and semantic memory as a lookup table, and (5) agents with episodic memory, semantic graphs, and semantic memory as a lookup table. The evaluation results indicate that if precision is the key performance indicator for an application, basic episodic memory combined with semantic graphs, Configuration 2, works best. By contrast, when recall is more important or as important as precision, Configuration 4 and 5 are the best choices. Also, the evaluation results showed that in our simulation the role of the general semantic graph was not significant. The numbers in the results of evaluations only show the preference of a Configuration over the other Configurations and functionality of each memory component. These numbers are related to the data sets. Similar experiences can influence these numbers. Since in this paper we used a simulation environment with random variables, the number of similar experiences has an almost normal distribution. The final evaluation

compared Q-learning with the configurations of the framework of emotion understanding. It showed that our framework for emotion understanding performed better that a standard machine learning method.

In our system the interaction between episodic and semantic memories was critical for the performance of our agents. Episodic memory was abstracted into semantic graphs specific to groups of agents and into general semantic graphs for all groups of agents. Semantic graphs augmented our framework in three ways. First, they reduced its vulnerability to inconsistencies of episodic memory (increasing precision) so that Configuration 2 had the best precision and $F_{0.5}$ score. Second, semantic graphs helped find actions for eliciting compound emotions (increasing recall) in Configuration 4 and 5. Third, they represented a general knowledge learned about all agent groups when used as the general semantic graph.

Our agents used semantic memory in the form of a lookup table to identify emotions similar to a target emotion and episodic memory to identify what action might elicit a similar emotion. When agents could use semantic memory in the form of a lookup table, it provided information about inter-relationships among emotions, substantially improving performance. This was because the inter-relationships among emotions could inform guessing when no exact knowledge was available. The other memory configurations had to guess randomly in such cases. Hence, Configuration 4 and 5 had higher recall and F_1 and F_2 scores. We recognize that human memory may or may not work in an analogous fashion, but we articulated computational ways that semantic memory can help the retrieval of episodic memories.

Our framework for emotion understanding could be considered as a system able to learn associations between actions and emotions of other agents. With the regular machine learning methods such as Q-learning, agents only learn which action is the best in the current state (here current emotion) without considering other useful details, such as the time that the action occurs, the intensity of the emotion, and the subject and object of the action. In other words, Q-learning lost these details. In contrast, our framework is based on learning such details from experience and if an agent wants to elicit an emotion in other agents using an action, it can use a representation of its experiences to identify such an action.

On the basis of this paper and our previous studies [18], we can define a new type of intelligent agent named emotive agent. Emotive agents are intelligent agents that may:

(1) have cognitive knowledge processing abilities;

(2) have personalities and detect the personalities of others;

(3) are sensitive to emotional inputs;

(4) are able to understand their own emotions and the emotions of others, and

(5) use this understanding for further knowledge processing and action.

We note some limitations of the current work. It included how appraisals elicit emotions but not how emotional states influence or are influenced by other cognitive functions (e.g., perception, motivation, and cognition) [18]. Our agents had only reactive behaviors and they could generate only one output (an action). The episodic memory covered all possible perspectives among agents: the self-eliciting another agent's emotions, another agent eliciting one's own emotions, and observing another agent elicit a different agent's emotion. All the perspectives were given the same weight in retrieval, even though for real people such experiences are very different. Our computation of the certainty factor, Eq. (1), distinguished recency only within a window of the 100 most recent experiences. Also, in the general semantic graph, we arbitrarily used fifty percent of the semantic graphs as the threshold for

inclusion. Future work is needed to determine which values work best for both the window size and the threshold.

We also want to extend this study into human-agent interaction. For example, agents may use their understanding of emotions to manage the emotions of others, such as an agent in an interactive system attempting to change a human user's emotional state from distressed to joy. Perhaps it can use its knowledge that hearing pleasant music sometimes makes the user joyful. For systems intended to interact with humans, agents can access to the goals or personality of users via questionnaires [62,73,10]. Interactive systems are *dynamic* in that users interact with them sequentially and the agent does not know the total number of users. Our agents categorized other agents based only on goals and standards, but categorization of agents based on personality may be more accurate and natural, especially when a human user interacts with an emotive agent.

Finally, research has identified approximately sixty sources of agent misunderstanding [74]; our future work will explore ways to help emotive agents avoid misunderstanding emotions.

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