

Agents with four categories of understanding abilities and their role in two-stage (deep) emotional intelligence simulation

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Understanding is the essence of any intelligent system. We revise our four machine understanding paradigms which are: (i) basic understanding, (ii) rich understanding, (iii) exploratory understanding, and (iv) theory-based understanding; and we elaborate on the first two of them. We then introduce the concept of two-stage (or deep) machine understanding which provides descriptive understandings, as well as evaluations of these understandings. After a brief systematization of emotions, we cover the following paradigms for agents with two-stage (deep) understanding abilities for emotional intelligence simulation: (i) basic understanding, (ii) rich-understanding, and (iii) switchable understanding.

Keywords: Intelligent agents; two-stage (deep) understanding; emotion understanding; emotional intelligence simulation; semantic memory; episodic memory; basic understanding; rich understanding; switchable understanding; descriptive understanding; evaluation of understanding.

1. Introduction and Background

“Emotional intelligence is the ability to process information about one’s own emotions and the emotions of others”.¹ Perception and processing of emotions are influenced by the emotional status of an emotion understanding system. Ever more sophisticated emotional agents are required to keep pace with developing

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technologies that increasingly interact with humans and other artificial agents on an emotional level. Emotion understanding in intelligent agents is an emerging research topic and it is a subset of machine understanding; hence, our suggestion is to use approaches and techniques of machine understanding to resolve emotion understanding problems as well as avoidance of misunderstanding. In this paper, we use a two-stage process to enhance emotion understanding ability. In this two-stage approach, first stage is to recognize the emotion(s) to generate a descriptive understanding and the second stage is the evaluation of this descriptive understanding.

Understanding is an important as well as a challenging feature of any advanced knowledge processing system. The interest of the senior author on machine understanding started in 1990 specifically on machine understanding of simulation software and software in general. In early 1990s, several articles and reports documented progress on this aspect of the interest of the research group at that time.^{2,3} Starting in 1997, the interest was generalized to understanding systems.⁴ In 2006, the interest was switched to systems with understanding ability and understanding agents.⁵ In 2009, the focus was established as agents with ability to understand emotions and switchable understanding.^{6,7} Since 2011, we are also interested in systematizing and avoidance of misunderstanding in machine understanding in general and in emotion understanding, in particular.⁸

Software agents are becoming more advanced. “Additional abilities of agents are needed to make them intelligent and trustworthy”.⁹ We consider that the ability of understanding is essential for any intelligent system. “Two desirable abilities for agents are understanding as well as perception and reacting to emotional inputs”.⁹ Researches showed that emotions have key roles in decision-making, perception, learning and many mechanisms of rational thinking.^{10,11} “If we want computers to be genuinely intelligent and to interact naturally with us, we must give computers the ability to recognize, understand, even to have and express emotions”.¹²

According to the theory of emotional intelligence,¹³ four psychological abilities that enable humans to relate emotionally to one another are: (i) emotion perception, (ii) thought facilitation using emotions, (iii) emotion understanding, and (iv) emotion management. The ability to understand emotions is a pivotal characteristic for intelligent agents generally, and in semantic agents particularly.^{6,13–15} Moreover, misunderstanding is another important aspects of machine understanding by intelligent agents and has two meanings for a given context: failure to understand at all or a failure to understand an entity correctly.¹⁵

To understand emotions correctly, we consider two types of memory: episodic memory and semantic memory. *Episodic memory* “learns by storing specific details of emotional events experienced firsthand or observed”¹ and allows an intelligent agent to remember events in its previous experience.¹⁶ Recently, “several models of episodic memory have emerged in the domain of intelligent virtual agents (IVA)”¹⁷ to increase believability by remembering past interactions. *Semantic memory* stores our basic knowledge of the world, such as word meanings, facts, and propositions.¹⁸ In a semantic memory, lookup table of emotion-related facts is combined with

semantic graphs that learn through abstraction of additional relationships among emotions and actions from episodic memory.¹

We implemented our emotionally intelligent agents in an agent system in which agents interact with each other with the aim of making the other agents experience target emotions. Agents interact only through actions. Agents do not have any experience at the beginning of the simulation, but some had general knowledge (as semantic memory) about emotions.¹

We organize the rest of the paper as follows: Sec. 2 describes machine understanding. Section 3 gives the highlights of emotions and Sec. 4 describes two-stage emotion understanding paradigms. Finally, Sec. 5 covers evaluation and Sec. 6 presents conclusions and directions for future work.

2. Machine Understanding

2.1. Basic paradigm

An essential feature of an intelligent agent, is the ability to understand. Understanding is also one of the prominent philosophical topics. For clarification of understanding and its philosophical roots, see Ören.⁴ Since intelligent agents are becoming more influential in advanced knowledge processing, it is imperative that they have understanding abilities.

Our view of “machine understanding” is founded on a definition by Zeigler: “... if a system knows about X , a class of objects or relations on objects, it is able to use an (internal) representation of the class in at least the following ways: receive information about the class, generate elements in the class, recognize members of the class and discriminate them from other class members, answer questions about the class, and take into account information about changes in the class members”.¹⁹

As depicted in Fig. 1 — adapted from Ören,⁴ — a system A can understand an entity B if three conditions are met:

1. System A has background knowledge about B s, i.e., A can access a meta-model about B s. (This condition implies that a system A cannot understand an entity B , if it has no readily available background knowledge about it, or if it cannot find and access, or generate background knowledge about it.)
2. System A can perceive B , i.e., A can generate $P(B/A:C)$, a Perception of B by A , with respect to C .
3. System A can compare its perception $P(B/A:C)$, with C to generate an understanding $U(B/A:C, P)$ or $U(B/A:C, P(B/A:C))$ of B by A with respect to C and P .

This implies that an understanding (as a result of an understanding process) of an entity B by an understanding system A depends on the meta-knowledge C , the perception P , and the interpretation of the perception with respect to the meta-model. By changing the point of view of an understanding system (i.e., its meta-model, its perception, and/or its evaluation of its perception with respect to

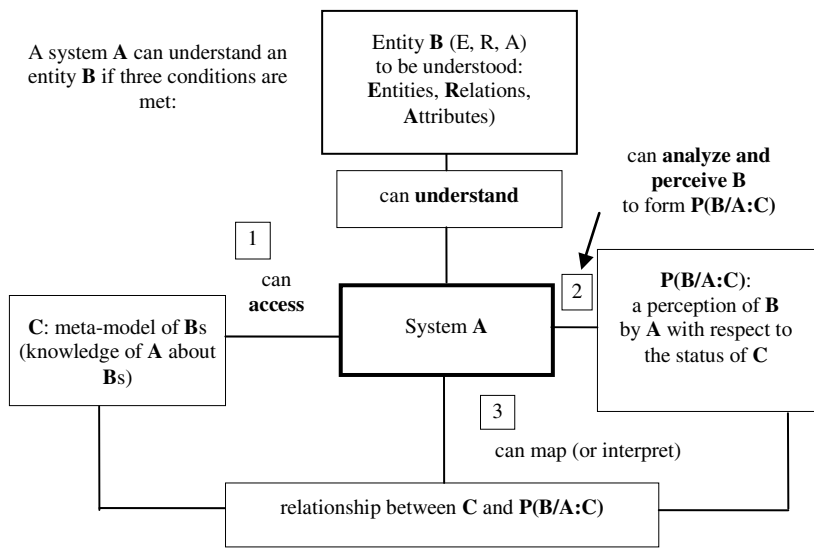


Fig. 1. Elements of an understanding system.

Note: Adapted from Ören *et al.* (Ref. 4).

its meta-model, or by changing the understanding system one may have different understandings of a given entity.

To be specific, an understanding (as an outcome of an understanding process of an understanding system) can be represented as $U(B/A:C)$ or more specifically, $U(B/A:C, P(B/A:C))$ to mean that an understanding of an entity B , by an understanding system A depends on the status of the meta-model C at the time of the understanding, the perception P , and the interpretation of the perception with respect to the meta-model.

Hence, an understanding of an entity is relative to the capabilities and limitations of the system which understands it, i.e., to its meta-model as well as to its perception and interpretation (or comparison) elements. These aspects of understanding are important since all elements which are essential in the understanding process may also be factors in the misunderstanding of an entity.

As represented in Fig. 2, a functional decomposition of an understanding system shows that to understand some entities, a system needs to have: a *meta-model*, an *analyzer*, and a *comparator*.

2.2. Four paradigms (or categories) of machine understanding

Four machine understanding paradigms can be distinguished as: (i) basic understanding, (ii) rich understanding, (iii) exploratory understanding, and (iv) theory-based understanding.⁸ These four categories of machine understandings can also be called one-stage understandings as follows: (i) one-stage basic understanding, (ii)

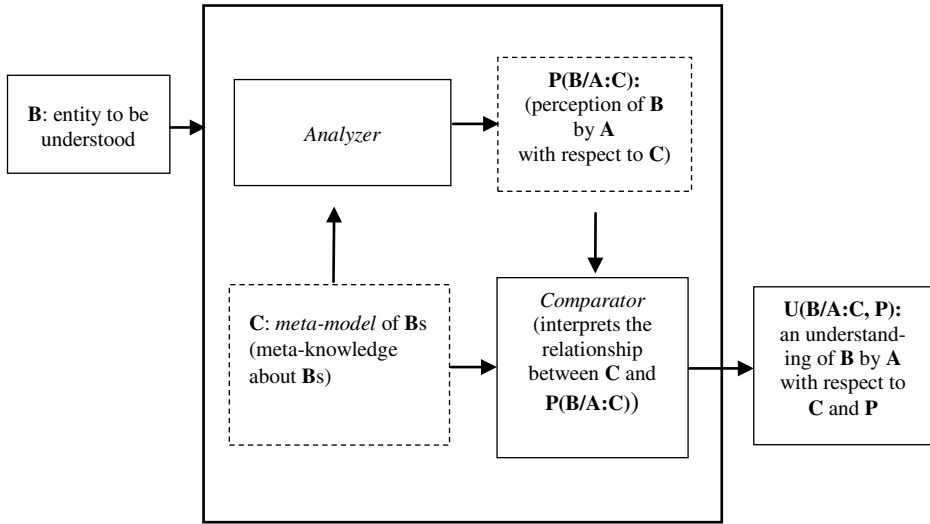


Fig. 2. Functional decomposition of an understanding system. Arrows indicate information flow.

Note: Adapted from Kazemifard *et al.* (Ref. 1).

one-stage rich understanding, (iii) one-stage exploratory understanding, and (iv) one-stage theory-based understanding. The reason of adding “one-stage” will be clear after the discussions in Sec. 4. We focus on basic and rich understandings in this paper. An ontology-based dictionary of about 60 types of machine understanding is given by Ören *et al.*⁵

2.2.1. Basic understanding

A *Basic understanding system* has background knowledge (i.e., a meta-model) to understand. A functional decomposition of basic understanding system is given in Fig. 2. The most common understanding type is *single vision understanding* where understanding is based on a single meta-model as well as a single perception and a single interpretation.²⁰ Single vision understanding is *dogmatic understanding* if the meta-model is not fully questioned and rationally justified and one single perception is interpreted only in one way.

2.2.2. Rich understanding

As given in Fig. 3, a *rich understanding system* is similar to Fig. 1, except all or some of the understanding elements may have more than one version. For example, more than one meta-model can exist to focus on different aspects of the entities to understand. Additionally, “rich understanding can allow multi-understanding and switchable understanding”.⁸ If an understanding system can have more than one understanding of an entity, it is a *multi-understanding system*.⁷ Recent researches

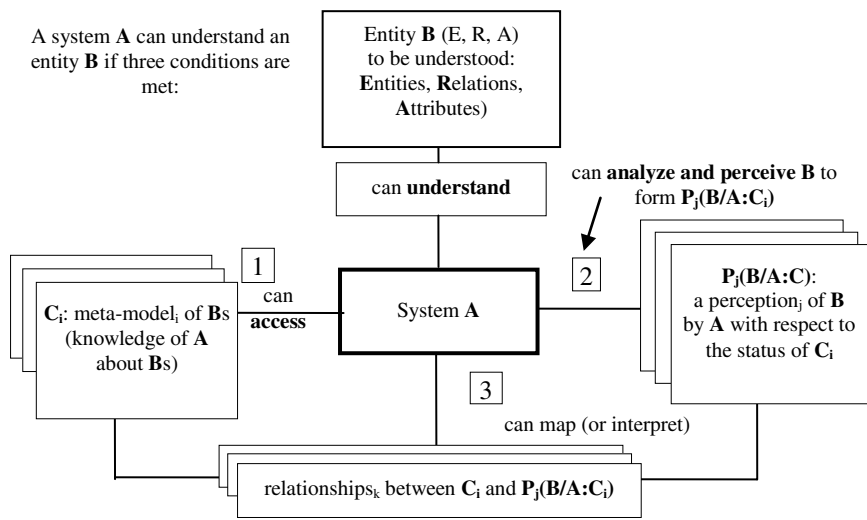


Fig. 3. A typical rich-understanding system.
Note: Adapted from Ören *et al.* (Ref. 8).

in program comprehension move to program comprehension with multiple information sources (i.e., documents, flow charts, comments).²¹ *Switchable understanding systems* can switch to an appropriate meta-model, or can have more than one perception and/or interpretation to understand characteristics of different sets or aspects of entities. Additionally, a switchable understanding system is a special case of a multi-understanding system which can explore different possibilities to generate different understandings of an entity and select the most appropriate one fit for the context.^{7,15} In program comprehension, integrated model²² is a sample of switchable understanding in which the programmer builds understanding by switching between several approaches.

2.2.3. *Exploratory understanding*

Exploratory understanding is similar to Fig. 1, except the understanding process starts with a perception. According to Fig. 1, the ordering of stages are (2), (1) and (3), respectively. In other words, background knowledge (or a meta-model) is to be found or developed to process the perception.

2.2.4. *Theory-based understanding*

Theory-based understanding “starts with hypothesis (or theory); then necessary technology would be developed to perceive (detect) relevant phenomena that would be tested later”.⁸ The gravitation wave and models to explain elementary particles are two examples for this type of understanding.

Table 1. Basic emotions.

Source of emotion		Nature of emotion		Emotion
Event-based	One step	Occurrence of	A desirable event	Joy
			An undesirable event	Distress
		Prospect of	A future desirable event	Hope
	Two steps	Confirmation of the prospect of	A future undesirable event	Fear
			A desirable event	Satisfaction
			An undesirable event	Fear-confirmed
Action-based	One step	Disconfirmation of the prospect of	A desirable event	Disappointment
			An undesirable event	Relief
			Action done by an agent is	
Compound			Consistent with the standards of the agent	Admiration
			Inconsistent with the standards of the agent	Reproach
			Joy + Admiration	Gratitude
			Distress + Reproach	Anger

3. Emotions

We used GEmA for generation of emotion of agents. GEmA is an appraisal model for software agents that can map observed events and actions to emotions.²³ GEmA uses the Ortony, Clore, and Collins (OCC) model of emotions²⁴ for the elicitation of emotions. We used the 12 emotions shown in Table 1. In this study, basic characteristics of the following emotions are reviewed: Admiration, Anger, Disappointment, Distress, Fear, Fear-confirmed, Gratitude, Hope, Joy, Relief, Reproach, and Satisfaction. Emotions can be classified according to whether they are event-based (one step or two steps), action based, or whether they are compound emotions. Table 1 summarizes characteristics of basic emotions.

Tables 2(a) and 2(b) show the symmetries in the relationships. Table 3 shows general emotional knowledge about emotions extracted from Tables 1–3.

Table 2. Event-based emotions (One step).

	Desirable event	Undesirable event
Occurrence of a(n)	Joy	Distress
Prospect of a future	Hope	Fear

Table 3. Event-based emotions (Two-steps).

Of the prospect of		
	A desirable event	An undesirable event
Confirmation	Satisfaction	Fear-confirmed
Disconfirmation	Disappointment	Relief

Table 4. Emotional knowledge of an intelligent agent stored in semantic memory as lookup table. “NO” means that the item does not exist, e.g., joy does not have evaluation or a previous emotion.

Emotion type	Class	Valence	Previous emotion	Consequence	Evaluation	Time
Joy	Well-being	Positive	NO	Desirable	NO	Now
Distress	Well-being	Negative	NO	Undesirable	NO	Now
Hope	Prospect-based	Positive	NO	Desirable	NO	Future
Fear	Prospect-based	Negative	NO	Undesirable	NO	Future
Satisfaction	Two-step	Positive	Hope	Desirable	NO	Now
Disappointment	Two-step	Negative	Hope	Undesirable	NO	Now
Relief	Two-step	Positive	Fear	Desirable	NO	Now
Fear-confirmed	Two-step	Negative	Fear	Undesirable	NO	Now
Admiration	Attribution	Positive	NO	NO	Standard-consistent	Now
Reproach	Attribution	Negative	NO	NO	Standard-inconsistent	Now
Gratitude	Compound	Positive	NO	Desirable	Standard-consistent	Now
Anger	Compound	Negative	NO	Undesirable	Standard-inconsistent	Now

Note: Adapted from Kazemifard *et al.* (Ref. 1).

4. Agents with Two-Stage (Deep) Understanding Abilities for Emotional Intelligence Simulation

4.1. Emotion understanding

“Emotion understanding is a cognitive activity of making inferences using knowledge about emotions about why an agent 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)”.¹

An understanding system (1) may be limited to generate a one-stage descriptive understanding of the emotion of an agent or (2) can generate two-stage descriptive as well as evaluated understandings for all four types of understandings. Also an understanding system can generate only one single understanding or may generate several understandings to select one of them. The first case is single vision understanding. The second case corresponds to multi-understanding and switchable understanding.

4.2. One-stage basic emotion understanding

Figure 4 shows the functional decomposition of a general framework for agents with one-stage basic emotion understanding abilities. The system is to understand emotions of others as well as its own emotions. Furthermore, while understanding emotions, the system may alter its own emotion(s). An emotion understanding system may consists of the following components: an analyzer, a meta-model, a memory modulator, and a comparator.

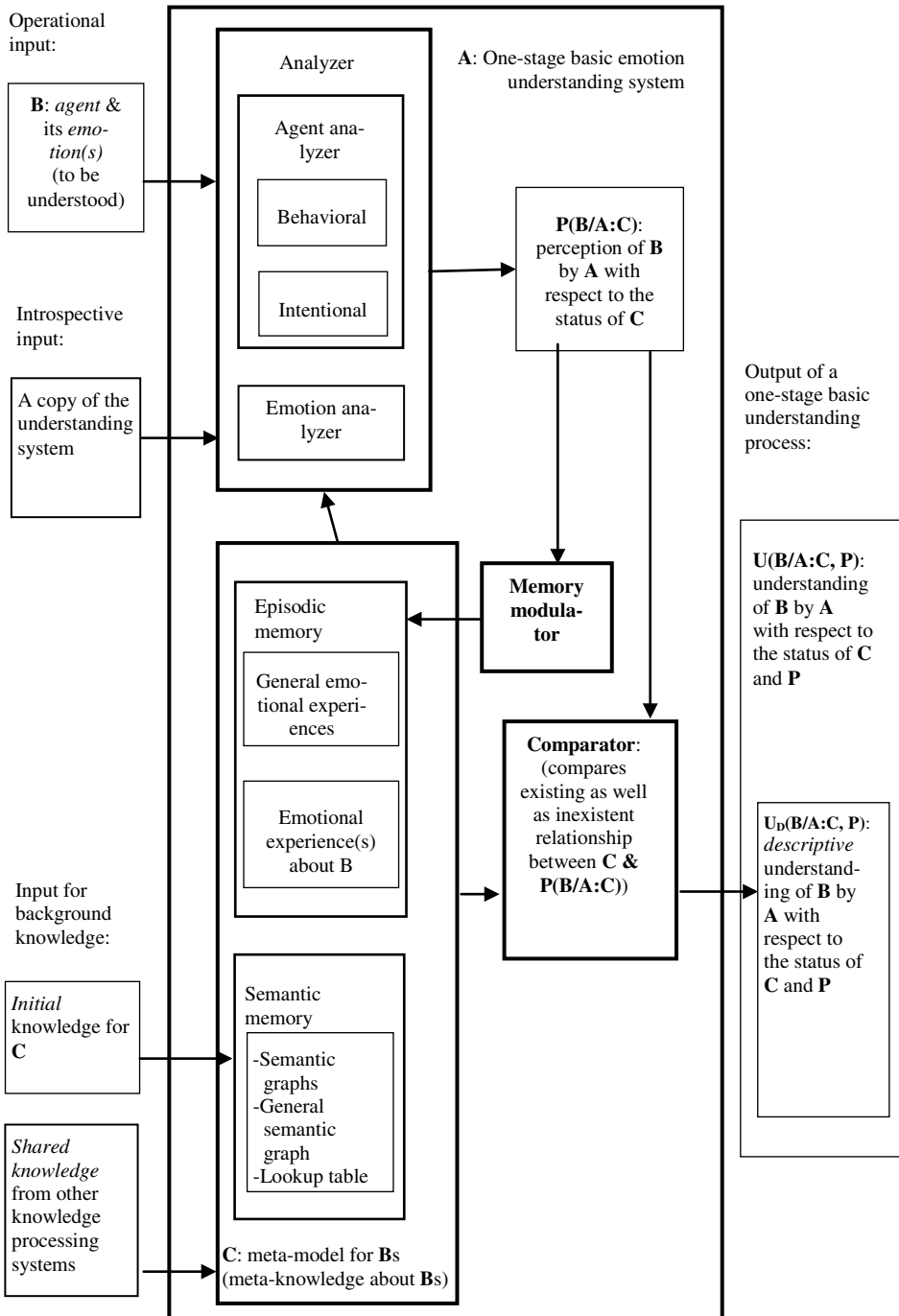


Fig. 4. Functional decomposition of the framework for agents with *one-stage basic emotion understanding* abilities for emotional intelligence simulation.

The **analyzer** consists of an *agent analyzer* to analyze agent's behavior and/or its intention as well as an *emotion analyzer* to analyze the behavior of an agent or its own emotion(s). Analyzer's output is a perception of **B** by **A** with respect to the status of **C**, i.e., $P(B/A:C)$.

The **meta-model** consists of two types of dynamic memories: episodic and semantic memories.

Episodic memory consists of the knowledge distilled from the experiences of the understanding system which can include knowledge about previous experience(s) about a specific as well as several agents.

Semantic memory holds general knowledge of **A** about **Bs**. There are three versions of semantic memory, semantic graphs, a general semantic graph, and a lookup table of general information about emotions. 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. Second, semantic graphs helped to find actions for eliciting compound emotions. 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. Agents used semantic memory to guide their retrieval of episodic memories. General emotional knowledge of semantic memory is represented in Table 3 and it does not include which events or actions elicit what emotions. Both memories hold three types of knowledge: (i) general knowledge which might be useful to understand, (ii) knowledge about the entities to be understood, and (iii) self-knowledge of the understanding system.

Memory modulator is the learning component of an understanding system. It can distill knowledge about its experience and can store the acquired knowledge in episodic memory.

The *comparator* examines and reports similarities and differences of the status of the meta-knowledge **C** and the perception of **B** by **A** with respect to the status of **C**, i.e., $P(B/A:C)$. The *comparator* switches between memories to result 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. In the one-stage basic emotion understanding when an agent cannot find an action eliciting a target emotion (e.g., joy) for a given type of target agent, it gets stuck and selects one randomly. The agent uses semantic memory to further explore episodic memory in order to make informed guesses. Although the selected actions based on semantic memory may elicit joy in the target agent, it is better than randomly selected action of single vision understanding. The agent can use the following processes:

- (i) The agent checks the semantic memory for an emotion similar to the target emotion that differs only on the time dimension.
- (ii) For any target emotion, the agent could find an emotion identical other than having the opposite valence, and then try to retrieve an action that elicits that emotion for an agent of a type opposite of the target agent.
- (iii) 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.
- (iv) The fourth mechanism enables the agent to find sequences for two-step emotions: satisfaction, disappointment, relief, and fear-confirmed, which its normal episodic memory cannot do alone (as it records only the observed action and emotion). Two-step emotions have a previous emotion, hope or fear, as a prior condition.
- (v) Semantic memory using semantic graph can find parts for compound emotions: gratitude and anger. Compound emotions have two emotion parts. Whereas gratitude is elicited by a standard-consistent action coupled with a desirable event. If an agent wants to elicit a compound emotion in another agent, it needs to perform an action that fits both conditions.
- (vi) A general semantic graph is used if the memory systems fails to identify an action (perhaps the agent has not yet observed an agent of the given group experience the target emotion).

The outcome of the comparator (as well as the *output* of a one-stage basic emotional understanding system) is $U_D(B/A:C, P)$, namely, *descriptive understanding* of **B** by **A** with respect to the status of **C** and the perception **P**.

A one-stage basic emotional understanding system has several types of inputs: operational input, introspective input, and input for background knowledge.

Operational input is an agent and its emotion(s) to be analyzed to generate a descriptive understanding.

Introspective input to an understanding system is a copy of itself provided to be analyzed by itself with respect to its own its emotional experiences and emotional background knowledge.

Input for background knowledge is needed to provide several types of working knowledge to an emotional understanding system. It consists of (i) *initial knowledge* for **C** and (ii) possible *shared knowledge* from other cognitive knowledge processing systems.

4.3. Two-stage (deep) basic emotion understanding paradigm

Deep emotion understanding necessitates a two-stage process: (i) understanding the emotion(s) and (ii) evaluate it (them). We call this, a two-stage emotion understanding (or deep understanding) process.

Figure 5 shows the functional decomposition of the framework of a two-stage basic understanding system for emotional intelligence. It is similar to the one-stage

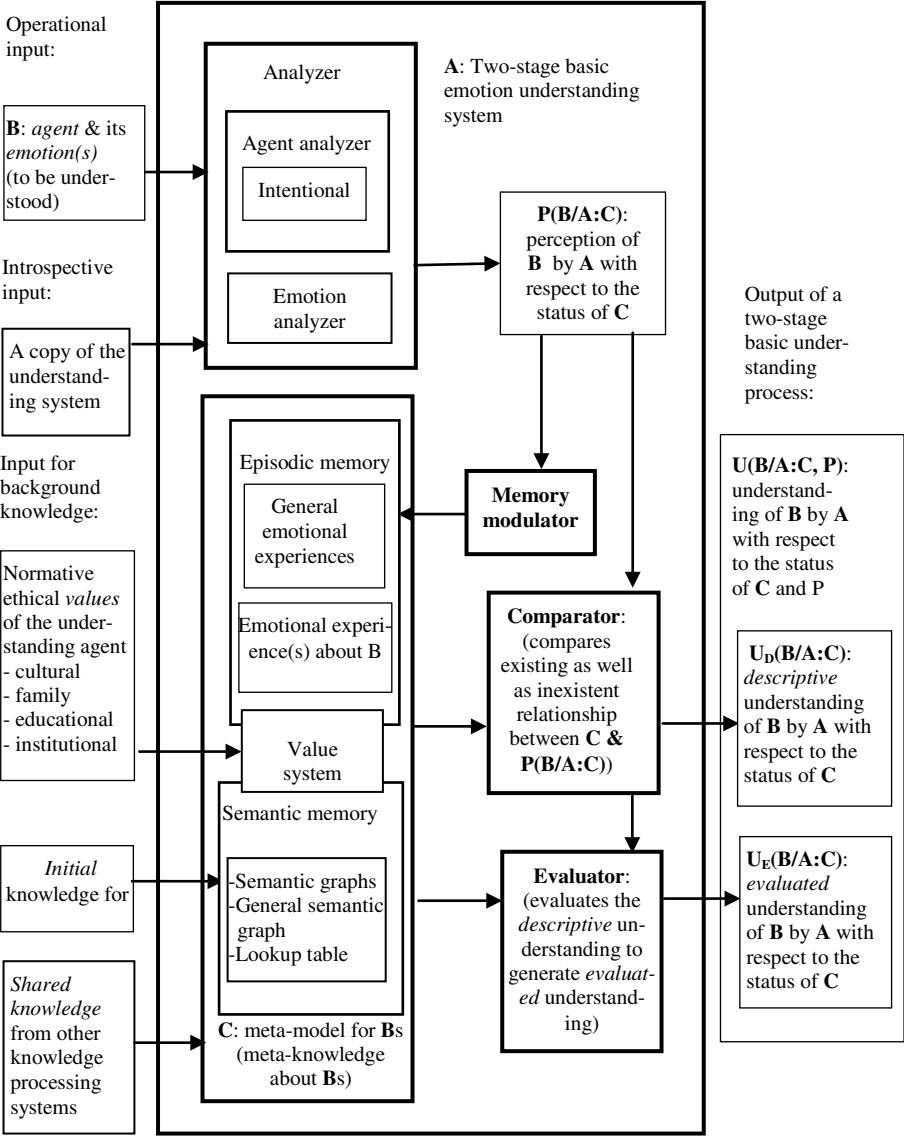


Fig. 5. Functional decomposition of the framework for agents with *two-stage basic understanding* abilities for emotional intelligence simulation.

basic understanding system (as depicted in Fig. 4), except the following components are different: meta-model, comparator and inputs; furthermore there is an evaluator module.

Meta-model: An important component of the meta-model is the *value system*. It can contain several layers of values: (i) learned values such as cultural values, family values, educational values, and institutional values as well as (ii) individually

acquired values. An understanding system's understanding is filtered (or tinted) by its own value system. An *advanced understanding system* needs to have knowledge about the value system of the entities it is designed to understand. Such an understanding system may understand the target entities; however, it may not necessarily accept the value system of the target entities. A *mature understanding system* may realize that its understanding of an entity depends on its own value system; hence may need to use different value systems to assure balanced emotional understanding.

The *comparator* provides input to the evaluator module in addition to generate a descriptive understanding.

The *evaluator* determines the value of the *descriptive* understanding to generate an *evaluated* understanding $U_E(B/A:C, P)$, i.e., *evaluated* understanding of B by A with respect to the status of C and the perception P .

The *output* of a two-stage basic emotional understanding system is $U(B/A:C, P)$, i.e., understanding of B by A with respect to the status of C and perception P . It consists of $U_D(B/A:C, P)$ and $U_E(B/A:C, P)$. $U_D(B/A:C, P)$ is the *descriptive* understanding of B by A with respect to the status of C and perception P . $U_E(B/A:C, P)$ is the *evaluated* understanding of B by A with respect to the status of C and perception P .

A two-stage basic emotional understanding system has some additional inputs which consist of input for background knowledge, operational input, and introspective input.

Input for background knowledge includes initial normative values for the understanding system such as cultural, family, educational, and institutional values. *Shared knowledge* from other knowledge processing systems may also include normative values.

Introspection may alter normative values of a system.

4.4. Two-stage rich understanding paradigm

The differences between a basic and rich understanding systems are the following: In a rich understanding system, multiple meta-models and more than one perception as well as several comparisons and evaluations may exist. In two-stage rich understanding systems, different values may be considered in the evaluation of descriptive understandings. However, ethical principles should be given priority in evaluations and selection of understandings as bases of decisions and actions in fully automated systems.

4.5. Switchable understanding

Switchable understanding²⁵ may apply to both one-stage and two-stage understandings. A system capable of generating more than one understanding of an entity (or a multi-understanding system) may have the additional ability to select one of the

understandings. It is desirable that the understanding system be able to provide the justification of the selection.

5. Evaluation

Similar to Kazemifard *et al.*,¹ we used the precision, recall, and F-score in information retrieval science for comparing one-stage and two-stage (deep) basic emotion understanding. Here, *precision* is the ratio of the number of relevant actions retrieved to the total number of retrieved actions. *Relevancy* means the actions elicit targeted emotions in other agents. *Recall* is the ratio of the number of relevant actions retrieved to total number of selected actions (randomly or non-randomly selected). F-score considers both the precision and the recall to compute a score. It is a weighted average of the precision and recall. Range of F-score is between zero and one, in which the best score is one and the worst score is zero. The general formula of F-scores is given in (1).

$$F_{\beta} = (1 + \beta^2) * \frac{\text{precision} * \text{recall}}{\beta^2 * \text{precision} + \text{recall}}. \quad (1)$$

The example in (2), an F_1 score gives even weighting to recall and precision.

$$F_1 = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}}. \quad (2)$$

We used the standard concept in OCC to simulate the value system. The concept of “standard” refers to values that agents use to evaluate manners of behaving. “Standards of behavior include conventions, norms, and other kind of accepted regularity governing or characteristic of social interaction”.²⁴ As represented in Table 1, elicitation of four emotions, reproach, admiration, anger, and gratitude, are related to the standards. In Fig. 6, $F_{0.5}$, F_1 , and F_2 scores of: (i) one-stage basic emotion understanding and (ii) two-stage (deep) basic emotion understanding are

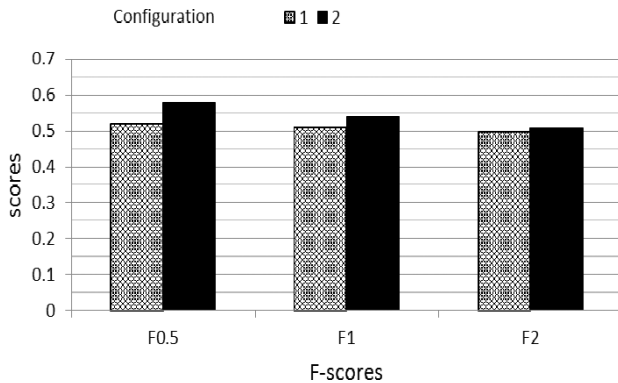


Fig. 6. Comparing $F_{0.5}$, F_1 , and F_2 scores of (i) one-stage basic emotion understanding and (ii) two-stage (deep) basic emotion understanding.

showed. Two-stage (deep) basic emotion understanding is better in all Fs. In the $F_{0.5}$ and F_1 the difference is more meaningful. It shows that the precision of two-stage (deep) basic emotion understanding are better than one-stage basic emotion understanding since it has value system to evaluate the results as well as the four standard-based emotions.

6. Conclusion and Future Works

In this paper, we revise our four categories of machine understanding paradigms which are: (i) basic understanding, (ii) rich understanding, (iii) exploratory understanding, and (iv) theory-based understanding.⁸ After this brief background, we introduce the concept of two-stage (or deep) machine understanding. Based on the concept of two-stage understanding, we then extend our recent work titled: “An emotion understanding framework for intelligent agents based on episodic and semantic memories”.²⁵ We cover the following paradigms for agents with two-stage (or deep) emotion understanding for emotional intelligence simulation: (i) basic understanding, (ii) rich-understanding, and (iii) switchable understanding.

In a sequel article, we are going to extend our systematization of the sources of misunderstanding in machine understanding in general,^{15,8} and in emotional intelligence in particular. We will then explore switchable understanding ability as an appropriate paradigm for understanding in general, as well as in emotional intelligence, in particular. Our work will continue to implement our models and explore emulation of emotional intelligence based on our work on emotional intelligence simulation.

References

1. Kazemifard M., Ghasem-Aghaee N., Koenig B., Ören T., An emotion understanding framework for intelligent agents based on episodic and semantic memories, *Autonomous Agents and Multi-Agent Systems*, **28**:126–153, 2014.
2. Ören T., Abou-Rabia O., King D. G., Birta L. G., Wendt R. N., Reverse engineering in simulation program understanding, in: Jávora A. (ed.), *Problem Solving by Simulation*, *Proc. IMACS European Simulation Meeting*, Esztergom, Hungary, 1990a.
3. Ören T., Abou-Rabia O., King D. G., Birta L. G., Wendt, R. N., A software understanding environment for SLAM II programs, *Proc. European Simulation Multiconference*, Erlangen-Nuremberg, Germany, SCS International, San Diego, CA, 1990b.
4. Ören T., Understanding systems: A taxonomy and performance factors, *Proc. FOOD-SIM*, SCS, San Diego, CA, pp. 3–10, 2000.
5. Ören T., Ghasem-Aghaee N., Yilmaz L., An ontology-based dictionary of understanding as a basis for software agents with understanding abilities, *Proc. 2007 Spring Simulation Multiconference — Volume 2*, Norfolk, Virginia, Society for Computer Simulation International, 2007a.
6. Kazemifard M., Ghasem-Aghaee N., Ören T., Agents with ability to understand emotions, *Proc. Summer Computer Simulation Conf.*, Istanbul, Turkey, SCS, San Diego, CA, pp. 254–260, 2009.

7. Ören T., Yilmaz L., Kazemifard M., Ghasem-Aghaee N., Multi-understanding, A basis for switchable understanding for agents, *Summer Computer Simulation Conf.* Istanbul, Turkey, SCS, San Diego, CA, pp. 395–402, 2009.
8. Ören T., Kazemifard M., Yilmaz L., Machine understanding and avoidance of misunderstanding in agent-directed simulation and in emotional intelligence, *3rd Int. Conf. Simulation and Modeling Methodologies, Technologies and Applications (SIMULTECH 2013)*, Iceland, 2013.
9. Ghasem-Aghaee N., Ören T., Towards fuzzy agents with dynamic personality for human behavior simulation, *Proc. Summer Computer Simulation Conf.*, Montreal, PQ, Canada, SCS, San Diego, CA, pp. 3–10, 2003.
10. Damasio A. R., *Descartes' Error: Emotion, Reason and the Human Brain*, G. P. Putnam, New York, 1994.
11. Ledoux J., *The Emotional Brain*, Simon & Schuster, New York, 1996.
12. Picard R., *Affective Computing*, MIT Press, Cambridge, MA, 1997.
13. Dias J., Paiva A., Agents with emotional intelligence for storytelling, *8th Int. Conf. Autonomous Agents and MultiAgent Systems, Doctoral Mentoring Program*, Budapest, Hungary, 2009.
14. Kazemifard M., Ghasem-Aghaee N., Ören T., Emotive and cognitive simulations by agents: Roles of three levels of information processing, *Cogn. Syst. Res.* **13**:24–38, 2012.
15. Ören T., Yilmaz L., Semantic agents with understanding abilities and factors affecting misunderstanding, in Elci A., Traore M. T., Organ M. A., *Semantic Agent Systems: Foundations and Applications*, Springer-Verlag, 2011.
16. Tulving E., *Elements of Episodic Memory*, Oxford University Press, New York, 1983.
17. Brom C., Lukavsky J., Kadlec R., Episodic memory for human-like agents and human-like agents for episodic memory, *International Journal of Machine Consciousness (IJMC)*, **2**:227–244, 2010.
18. Schacter D. L., *Searching for Memory: The Brain, the Mind, and the Past*, Basic Books, NewYork, 1996.
19. Zeigler B. P., Systems knowledge: A definition and its implications, in Elzas M. S., Ören T. I., Zeigler B. P., (eds.), *Modeling and Simulation Methodology in the Artificial Intelligence Era*, North Holland, Amsterdam, 1986.
20. Ören T., Ghasem-Aghaee N., Yilmaz L., An ontology-based dictionary of understanding as a basis for software agents with understanding abilities, *Proc. 2007 Spring Simulation Multiconference*, Norfolk, VA., Society for Computer Simulation International, pp. 19–27, 2007b.
21. Vinz B. L., Etzkorn L. H., Improving program comprehension by combining code understanding with comment understanding, *Knowledge-Based Syst.* **21**:813–825, 2008.
22. Mayrhauser A.V., Vans A. M., Program comprehension during software maintenance and evolution, *Computer* **28**:44–55, 1995.
23. Kazemifard M., Ghasem-Aghaee N., Ören T., Design and implementation of GEmA: A generic emotional agent, *Expert Syst. Appl.* **38**:2640–2652, 2011.
24. Ortony A., Clore G. L., Collins A., *The Cognitive Structure of Emotions*, Cambridge University Press, Cambridge, UK, 1988.
25. Kazemifard M., Ören T., Toward agents with switchable emotion understanding ability, *Proc. 5th Int. Conf. Cognitive Science (ICCS)*, Tehran, Iran, 2013.