Exploring Ontologies to Improve the Empathy of Interactive Bots

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***Abstract*—Bots are virtual agents that people can interact with text messages. They are mostly made with the aim of mimicking a person in conversations. Although several studies have devised natural language processing techniques for the creation of bots, few studies explore the use of ontologies in the development of novel context-aware interactive bots. In this article, we propose a software architecture that allows ontology-based interpretation of several types of data (audio, video, and text) from the bot's environment. We define formal concept-based rules to express affective behavior aiming to improve the empathy of bots. The proposed technique relies on Semantic technologies such as OWL and SWRL languages. This technique is illustrated in an interaction scenario.**

***Index Terms*—Interactive bots; Affectivity; Ontologies; SWRL**

I. Introduction

Various attempts in the literature aim to turn computer-based systems more human-friendly. Nowadays, there is a growth of the use of artificial entities who hold conversations with people as a virtual software creature [1]. Usually, text-based conversations take place with the commonly known chat-bots. These entities often appear as animated characters standing for a virtual real-life person. Their key feature is the ability of answering questions and performing tasks via conversational dialogues. This kind of human-like virtual assistants have the potential to represent brands, assist users in complex tasks as well as support teaching and learning.

Other researches have investigated means of designing systems that consider human-like behavior and their emotions [2], [3]. Bots as virtual assistants can play a central role in this context. However, the development of such virtual assistants requires further investigations to examine alternatives to approximate humans and machines. This demands understanding several types of inputs captured from the environment. The inputs might inform the virtual assistant to create correct decisions and to respond to humans in a way to generate empathy between artificial and human agents. In addition to free-text natural language questions, the bots could, for instance, interpret voice and visual signs so that communication becomes closer to people's conversations.

A virtual assistant can be valuable in teaching and learning in classroom activities. We describe a motivating scenario to illustrate the kind of interactive bots we aim to develop, which entails several research challenges in our investigation. Suppose that an interactive bot can explain a given subject to the class, for example, a history class about Renaissance art. The bot interprets students' affective states by analyzing their facial expressions, listening to their questions, and interpreting concepts in conversations. It is able to analyze if students are interested in the subject (or not) by searching for boredom expressions such as a yawning or sleeping.

A key research challenge to achieve interactive bots as presented in such scenario refers mostly to the difficulties of capturing, modeling, and interpreting human social environment. To this end, we need to take into account the interaction and social context when modeling the bots' knowledge and actions. The use of ontologies stands for an alternative to achieve this goal, once they represent semantics in computational systems, by describing concepts and interrelationships among them. These artifacts have the potential to support the representation of bots' behavioral and interpretation capacities. However, studies in literature aiming the exploration of ontologies for the development of bots are still preliminary [4]–[6].

In this article, we aim to understand how the use of ontologies can improve the bots' interpretation capacities, as well as their behaviors and actions. We aim to further support non-verbal conversations in a way to provide the bot context-awareness based on interpretation of emotional states from people. For this purpose, we contribute with the definition of a software architecture to deal with several types of input data and their interpretation with ontologies. The architecture

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organizes relevant system components to provide in this context. Furthermore, we defined a set of formal rules in an emotion ontology to express a series of behaviors for an interactive bot.

In this research, first we defined the architecture to accommodate the software components required. We investigated ontologies to represent emotional states. Afterwards, the formal rules were defined with the use of SWRL language and relying on the mirror neuron theory [7]. We then discussed the benefits and limitations of our proposal in an illustrative scenario and highlighted the open challenges to guide future researches.

The remaining of this article is organized as follows: Section II presents a literature review. Section III reports on our proposed architecture. Whereas Section IV illustrates the use of our solution in a scenario, Section V discusses the findings. Section VI wraps up the paper with conclusion remarks.

II. Background

Bradesko & Mladenic [8] studied chatbot development by including the use of keywords, pattern match, AIML and ChatScript. AIML is a mark-up language in which specific tags are defined to interpret meaningful elements within texts [9]. Their obtained results presented improvements over ELIZA [10], a famous chat-bot proposal, but the adopted approach still requires a huge knowledge database to develop a human-like bot behavior. Recently, proposals have explored discourse trees [11] to reinforce chatbot learning.

Other studies have emphasized that ontologies present the potential of contributing to the development of bots. Kaisser *et al.* [12] explained the importance of the ontologies to expand the understanding over user's questions. In virtual assistants, ontologies can be used before machine learning algorithms start predicting the best suited answers from the available knowledge base.

Augello *et al.* [9] proposed to integrate ontologies with other existing technologies, like AIML, for building bots. Their ontologies are extracted from Cyc knowledge database [13], AIML and *Wordnet* [14]. This integration aimed to boost the understanding of synonyms, relationships between words and the analysis of the language without relying in a question-answering database.

Further recent researches have explored ontologies in the context of bots development [4]–[6]. Al-Zubaide & Issa [2] proposed the *OntBot*, which transforms knowledge described in ontologies into relational databases, explored to operate chatbots. According to the authors, their approach avoids the use of specific language such as AIML, as they consider this a central drawback of existing chatbots.

Social context plays a key role in conversations. A social context is an environment where an agent acts according to a situation based on his roles and norms given by the environment. Such agent has his own cultural norms [15]. Recently, Augello *et al.* [16] proposed a technique to construct dialogue plans using a model that considers both individual and social process.

Interactive bots can have several applications, including those related to learning in classrooms. For instance, Matsuura & Ishimura [3] studied the effects of visual presentation in lectures. They constructed and applied a chatbot to support the explanation of questions in student classes. Their results showed that the use of such humanoid agents for verbal presentation can benefit the learning activities.

Our approach is specially interested in modeling bot applications that use ontologies to understand users' emotional states, because it is an intrinsic part of human communication [17]. The user's affective expressions are interpreted to infer their emotional state. They are then used to interpret incoming information in a way to decide which expressive actions should be taken by the interactive bot. This decision is based on expected emotions to be caused. For this purpose, this work originally defines a software architecture and a set of rules to handle affective aspects. In the following, we present the explored technology, artifacts and theories to reach our goals.

We defined rules to express affective states exploring concepts already existing in ontologies. To this end, we have used the *Emotion Ontology* [18]. This ontology aims to provide an extensive representation of affective phenomena. It defines several classes to describe and relate emotions, moods, appraisals and subjective feelings. This representation formalizes the types of emotional states, relevant to be used in virtual agents. In this sense, the *Emotion Ontology* allows us to have a formal representation for reasoning purpose in a way to provide decisions on the bot's affective response. The *Emotion Ontology* is available in OWL language.

Our defined rules rely on the *Semantic Web Rule Language* (SWRL). SWRL refers to a language useful to express logical rules using OWL ontology concepts [19]. The logical rules are used to infer knowledge within an ontology. In the context of bots, we explore SWRL rules in conjunction with ontologies to define behaviors being observed from the environment. Our proposal infers reactions and possible behaviors resulting from the reactions. We assume that this can be useful in an attempt to maintain engagement and to promote the empathy between bots and humans. In the developed architecture, the bot interprets affective expressions to determine the emotional state from the person. The bot then predicts the possible behavioral/emotional changes related to its actions. The goal is to allow the bot to choose appropriate behaviors to maintain a context-aware, comfortable and enjoyable engagement based on human interaction features.

In this work, the rules for the modeling of bot's reactions is based on the mirror neuron theory [7]. This theory brings forth the mirror neuron, a kind of neuron whose its function is activated when the observer performs an action or when an action is observed.

III. OnInterBot: Software infrastructure for ontology-based expressive bots

A. Architecture conception

Figure 1 presents our conceived architecture. The main goal is to provide means of interpreting data monitored from the environment, based on bot's knowledge represented as ontologies. Also, our goal is to enable means to act properly based on this interpretation.

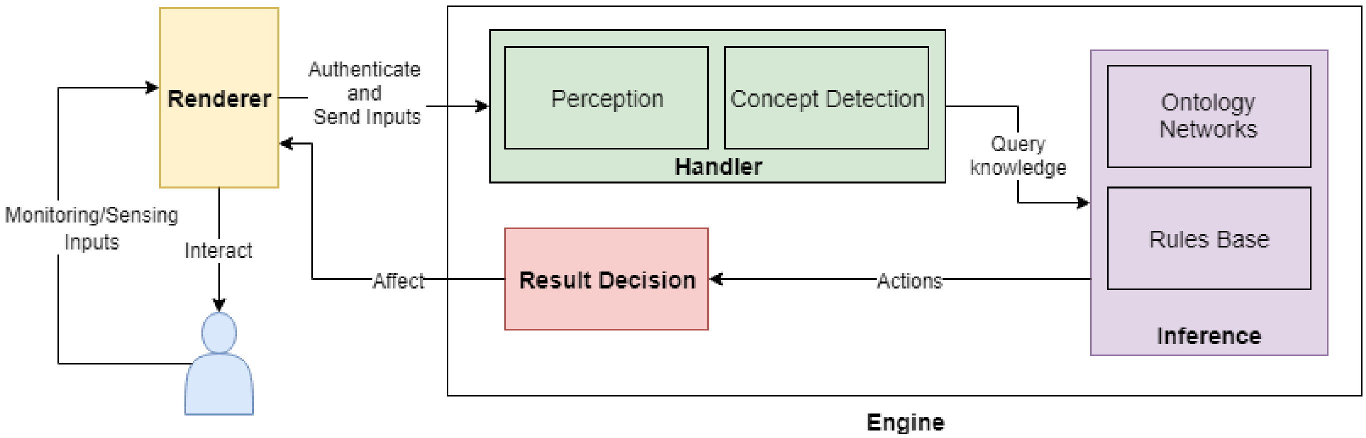

Fig. 1. ***OnInterBot*** architecture proposal

Typical environment data in conversation with bots includes free-texts or spoken audio. Our architecture considers various sources for bots' sensory input, including video streams and images with users' gestures and face expression. All these data are gathered to provide environment information to the bot's perception.

The data received is pre-processed in the *Handler* component to enable querying ontology classes and instances. We defined two modules to handle the environment data from users (Perception and Concept Detection). The *Perception* module analyzes all the indicators of emotional states presented in the input data. At this stage, speech recognition techniques transform voice into text. For this purpose, we have investigated state-of-the-art tools such as *Wit.AI*. In addition, computer vision features are used to recognize facial expressions from the user (*e.g.*, detection of emotional states). In the perception module, we have explored techniques such as [15] to address it. Our initial investigation have implemented the detection of users' face emotions relying on the *Face API*[1] from Microsoft cognitive services. The information from the perception is used into the inference architecture module to infer and act upon the situation by means of the interpretation regarding people's aspects.

Concept Detection module develops functions for the entity recognition and semantic linking to make explicit the semantic interpretation of the topics under discussion in the conversation. To this end, we investigate techniques of text analysis for the adequate identification of concept mentions in text [20]. In addition, this module concerns the detection of user's intentions as a way to further interpret intents from users' NL texts. For this purpose, we have considered a technique based on the matching with representative key phrases and semantic extension of terms to detect instances of intention classes in NL sentences [21]. We have experimented the service *Wit.AI* in this module.

We propose the use of *Ontology Networks* [22] so that we can interact with several knowledge domains in a variety of ways. The use of ontology networks opens up the possibility of mixing up traditional hierarchical ontologies with the advantages of other kind of ontologies like soft ontologies. Soft ontologies are flexible set of meta-data [23], which are useful to represent dynamically evolving information domains. These ontologies have individual elements associated with values in a non-structured *a priori* hierarchy, defining shared m-dimensional *ontospace*. We have devised a meta-model to describe mappings with *fuzzy* based relationships between the models.

In addition, the process of obtaining bot's decisions is backed up by the *Rules Base* module (*cf.* subsection III-B). This component focuses on the understanding of the effects caused on who the bot is interacting with. The rules play a fundamental role in the decision of the bot's action. For instance, the rules aim to ensure the bot's objective is achieved. At this stage, we consider these objectives as a way of improving the empathy between people and bot. Such interaction needs to be deliberated considering what type of affection the bot captured and what kind of affection it wants to cause by its actions. The *Inference* is responsible for interpret the ontologies' axioms and associated rules for inferring actions that fulfill the bots' objectives. We explored a semantic reasoner (rule engine), *Pellet*[2], as a OWL+SWRL reasoner.

The *Result Decision* derives the result created by the inference verifying all candidate decisions. This module chooses the way of affecting the environment: (a) the best action (according to a ranking); (b) send a set of actions; or (c) even randomly picking one action. For example, send a audio response to a participant and also change the bot's visual aspect, like sending a smile through an avatar. At the final stage, the bot delivers the decisions to the environment. We devised the *Renderer* component to treat it. For instance, change its avatar's face, send a sound, modify its voice tone or even send a text message.

Our current bot implementation is based on a web platform using HTML 5 and Javascript frameworks to create an interface that handles NL free-text, video and audio. The data inputs are collected and delivered via WebSocket to a backend developed

[1]https://azure.microsoft.com/en-us/services/cognitive-services/face/

[2]https://github.com/stardog-union/pellet

in Java 8 with Spring-Boot, MongoDB and *RabbitMQ*[3]. Our noSQL database stores all conversations, messages and the bot's knowledge. In the architecture implementation, each conversation is separated by one route inside the *RabbitMQ* to allow scalability in message processing. Our current prototype is deployed in the *Heroku cloud service*[4] creating an entire framework to build chatbots based on ontologies.

B. Defined SWRL rules

The definition of rules is usually bound to the interaction domain. We have emphasized the modeling of rules to create reaction considering emotional states. For this purpose, we explored the *Emotion Ontology* [18]. The modeled SWRL rules link the interpreted affective gestures with emotional states modeled in the ontology aiming to increase the bot's empathy by generating a sequence of neutral, happiness, surprise, joy among other reactions.

The process to create our rule set was based on the *Emotion Ontology* and the mirror neuron theory [7] (*cf.* Section II). To this end, we analyzed the defined affective states in the ontology, and modeled according to the theory the reactions given by each type of the affective state. For instance, if the state of joy is detected as input, the modeled rule expresses that the bot's reaction must keep the joy state.

We modeled specific classes related to human-bots interaction. For instance, in the ontology, a class named "*Person*" represents people interacting with or being observed by the bot. We defined a base rule as a way to interpret and act upon a person's emotional states (captured from the *Perception* component and included as class instances in the ontology). Several rules were created based on the emotional states to represent the different actions relying on the frame of following base rule:

$$Person(?p), emotionClassName(?e), \\ personEmoState(?p, ?e) \rightarrow action(?p, \mathit{listOfActions}) \quad (1)$$

This base rule expresses that there is a Person "p" and an emotion state "e" *emotionClassName*. The types of *emotionClassName* are all modeled in the *Emotion Ontology* as explicit classes which include, but it is not limited to:

$$emotionClassName = \{Anger, Disgust, Surprise, \\ Sadness, Joy, Fear, Boredom\} \quad (2)$$

The Person "p" is in an emotional state caused by the emotion "e" (of input) defined by the *personEmoState*. The detection of a person's emotional state derives a list of actions that the bot might choose to execute in order to achieve a determined objective in the interaction context. The list of actions includes a set of emotions to be expressed. Formally:

$$listOfActions = \{emotionClassName_1, \\ emotionClassName_2, ..., emotionClassName_n\} \quad (3)$$

[3]https://www.rabbitmq.com/

[4]https://www.heroku.com

For instance, following the example of a person who is feeling sadness, a possible list of actions, that might try to alleviate the sorrow is: feeling *surprised* with the possible tragic situation, then sharing the state of *sadness* with the person, and then trying to cheer the person up with the *joy* of positive thoughts. This sequence of actions is explicitly modeled in the rule and represents the bot's output behavior. The following rule formally expresses this example:

$$Person(?p), Sadness(?e), personEmoState(?p, ?e) \\ \rightarrow action(?p, \{``Surprise'', ``Sadness'', ``Joy''\}) \quad (4)$$

Another example could be given in the instantiation of the disgust emotion. By observing someone hurling emotions of disgust, one in an attempt to revoke this emotion bringing the portrayer to a state of joy could present *surprise* feeling. The expectations are the person to start acting surprised and realize that his/her disgust is somewhat awkward. If no changes are perceived, the feeling of *sadness* could be presented to convince that his/her attitude can make people around sad. Another emotion that would revoke disgust is *anger*. This emotion could intimidate the person with the distasteful feeling in a manner that he/she would feel apprehensive to continue exposing such emotion. At the final stage, *joy* is presented to try to make the person forget about his/her disgusted state and come back to enjoy other good things. The following rule express this example:

$$Person(?p), Disgust(?e), personEmoState(?p, ?e) \\ \rightarrow action(?p, ``Surprise", ``Sadness", ``Anger", ``Joy") \quad (5)$$

IV. Application scenario

We present one interactive scenario to illustrate the potentiality of use from our proposal. This scenario explores the use of bots in a history class about Renaissance art (Figure 2). Giving a bot whose its objectives include: (1) improve students' learning opportunities by boosting the interaction between the students and the subject of the class (*e.g.,* virtual objects of Renaissance art); and (2) perceive and interpret the different kinds of student's reactions in relation to the class, so the bot can suggest new ways to approach the subject improving the student's engagement in the class.

The bot uses various types of data input (#2 of Figure 2). The gathering of environment information consists in the students' voice in the classroom, video stream of the state of the classroom, which includes student's gesture and message text sent to the bot system from students.

The *Handler* organizes the gathered information as follows (#3 of Figure 2): concerning the voice, the captured data is split in (i) noise level in the classroom, (ii) what the noise is about, and (iii) voice tones; with respect to the video input, the captured data consists of students' facial expressions, actions and gestures during the lecture time; the captured message texts are used to interact more directly with the bot, and they are split into their conceptual meaning and detected emotions.

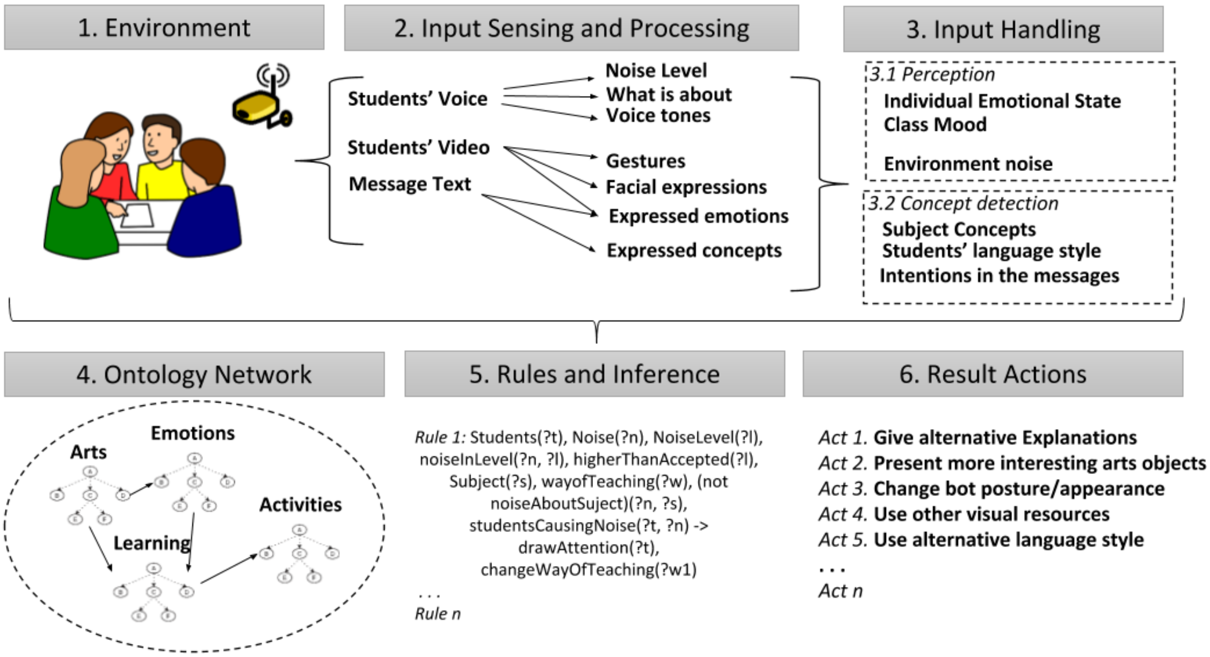

Fig. 2. Classroom Scenario Overview

In the *Perception* module, the bot detects if a sense of boredom appears in students based on gestures captured by video, indicating if students are paying attention, executing activities or just playing (#3.1 of Figure 2). The detection relies on the use of students' facial expressions, combined with voice tone and detected emotion entities in texts. In addition, the bot detects if students have passed long periods of time paying attention to other things, like the outside or smartphones. Also, the system can query how much noise and what kind of noise appears in the room to state what is going on in the classroom checking if it is related to the subject.

In the *Concept Detection* component, questions about the subject being taught are detected in the midst of the available data (#3.2 of Figure 2). For instance, if the message texts are doubts about the subject or just attempts to chit-chat.

We consider a *Network Ontology* (#4 of Figure 2) that: (1) models accepted noise levels in a classroom that are unrelated to the subject under study; and, (2) models emotions and moods recognized by facial expressions, voice tones and text input. The rules associated with theses concepts are interpreted and the *Inference* infers bot's reactions (#5 of Figure 2).

V. Discussion

Our literature review points out that virtual assistants as interactive bots fail in further explore other types of media like data sensors, images, audio, and video streams to improve interactions with people. In particular, they do not consider neither react to the users' emotional states. Usually, existing solutions only use free-text resources. Our approach goes towards a new way of building systems that explore interaction with virtual agents based on a combination of media.

We contributed with a software architecture and prototype for the creation of ontology-based bots. We defined an architecture that implements components for monitoring the environment and providing result decisions based on the semantic interpretation. In the rules base component, we found that it is possible to implement and execute SWRL rules that specify means for the system to interpret the input affective data. The system infers the bot's behavior considering affective states as a list of actions, and it determines the bot's actions using rules based on mirror neuron theory. Our aim was to provide means of improving the bot's empathy in the interaction with human people.

Our proposal opens directions to deal with various research challenges. Based on the raw input data, we explored computer vision features to detect affective states from people's face. This information was combined with the annotation of semantic concepts and intentions in the *Concept Detection* module.

We proposed ontology-based bots relying on a network of ontologies. This network enables the bot to understand data and provides the capability of retrieving useful information for its actions. In the network, it must coexist domain-related ontologies, upper-level ontologies, and models that formally represent the bot's actions. However, this entails several research challenges.

The use of interconnected ontologies requires an alignment process to create correspondences between equivalent concepts from different ontologies described in various languages using different background theories. The creation of semantic mappings in this network can be very beneficial, but the management of such heterogeneous artifacts is a difficult problem. This is further aggravated when considering networks that contain soft ontologies as well as rigid and formal structured ontologies. Another challenge to be undertook is the specification of SWRL rules in conjunction with soft ontologies and other less structured ontologies. This may require "soft rules" in which logical relations and consequences are not rigidly constructed, but defined by changes in ontological spaces. Fuzzy extensions of SWRL rules (*e.g.*, [24]) can be considered as one alternative to deal with this problem.

Our defined SWRL base rule does not include the bot's objective neither other constraints that might affect the list of actions, such as known user's personal characteristics, history of emotions, history of conversation, *etc*. However, these additional elements of the rule set are dependent upon each interaction domain. In addition, the modeling of the bot's intentions/objectives will be further explored in future studies.

VI. Conclusion

Interactive bots can be relevant in several contexts to support user's activities and guide complex tasks. However, chatbots are still limited in relying mostly on NL free-text and delimited plans of answers. In this paper, we argued that further data streams like audio, video and sensors from the environment must be considered. We defined an architecture to enable interpretation of affective expressions and semantic concepts from user's data input. Our proposal was based on a network of ontologies to represent the meanings of input data semantics. In particular, we addressed the interpretation of affective states to improve the bot's empathy in the interaction based on the *Emotion Ontology*. This investigation provided a set of SWRL rules to model the bot's reaction behaviors and presented a case study scenario. Future work involves to explore additional ontologies with distinct modeling approaches and refine the set of rules to consider others bot's aspects. Furthermore, we aim to develop a complete system and conduct long-term user studies to examine the interaction with the bot.

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