A Cognitive Assistant that Uses Small Talk in Tutoring Conversation

Analyzing the Perception of Students

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Luciano Frontino de Medeiros (✉), Armando Kolbe Junior, Alvino Moser
Centro Universitário Internacional UNINTER, Curitiba, Brazil
luciano.me@uninter.com

Abstract—This paper presents a cognitive conversational agent for use in teaching and learning processes named THOTH (Training by Highly Ontology-oriented Tutoring Host) that is capable of formulating and enunciating a well-defined set of small talk segments in a Q&A (Question and Answer) interaction. The small talk structures are placed within the tutoring conversation by an agent designed as a cognitive assistant, in order to make communication smoother and less formal, presenting a more "concerned" behavior. Twelve small talk segments are suggested, included in conversation stages such as opening and closing the conversation, maintaining the rhythm and managing learning. We also explore some branches of the theoretical assumptions and concepts grounding THOTH, such as Dennett's intentional stance, Bloom's taxonomy and microlearning theory. In order to measure the perception and effects of using THOTH, we performed a quantitative and qualitative study with a group of students from a course in Applied Artificial Intelligence over one semester. The outcomes are classified into two main categories of analysis – interactivity and intentionality – informing the discussion on the potential uses of a small talk agent as a valuable resource in tutoring interaction, and also raising some points for improvement. In addition to this study, we also drew a small talk profile for this group of students revealing what structures and topics they use the most, as well as a partial performance analysis that allows identifying some effects on learning.

Keywords—Intelligent tutoring systems, ontologies, speech analysis, cognitive models.

1 Introduction

Education has evolved significantly over the last few years, undergoing substantial changes to its practices due to the emergence of new technologies, following different paths that raise new possibilities in the face of numerous new demands. Among several innovations, the use of intelligent tutors is a trend that enforces the growing needs for enhanced interactivity. Technologies that offer natural language interfaces are a good choice for improving interactions through embodied conversational interface agents [1], or the so-called "chatterbots"[2]. Students could have additional support from AI tutors, communicating in natural language and learning contents based on concepts, examples, illustrations or further links, managed by an cognitive assistant [3].

However, it is noteworthy that, despite the richness of content and visual quality, most materials produced for e-learning or b-learning seem to be of a static and sequential nature, or depend on predefined learning paths in order to enable the understanding from students. The learning objects methodology [4] can divide subjects into granular self-contained parts, thus helping present contents with more flexibility from their conception to their use within VLEs (Virtual Learning Environments).

Nowadays, the emergence of Q&A (Question and Answer) systems is changing data analysis, particularly for machine learning and Big Data tasks. Q&A consists in a special form of information retrieval aimed at retrieving knowledge online, unifying natural language and knowledge representation, logic inference, and semantic search. One example is the breakthrough technology of IBM Watson, which shows the relevance of such systems in the face of the current massive growth of data and information [5].

In gathering all these issues, this work introduces THOTH (stands for Training by Highly Ontology-oriented Tutoring Host), a cognitive pedagogical assistant for tutoring conversations in teaching and learning processes, capable of making small talk and designed to optimize tutoring interactions with students. As an object of study in linguistics, a "small talk" means short conversations with the purpose of maintaining the communication channel open between speakers, making interactivity smoother through common expressions and topics in human conversation [6]. Small talks are used to open or close a conversation, start topics not directly related to the main context of the conversation, and also to avoid awkward silences or embarrassing pauses. Therefore, techniques based on small talk could make interactivity easier and stimulate learning by offering a positive emotional context for teaching and learning processes.

We implemented THOTH's knowledge model using concepts of domain ontologies. Designed as tools to facilitate the learning of contents in organized courses or disciplines, ontology concepts are divided into common topics connecting particular attributes and meanings. These concepts are retrieved by a syntactic analyzer that extracts the core of the question formulated in natural language by the student, following a path similar to that proposed by Q&A systems.

This paper is divided into five sections:

- A brief approach of small talk;
- A description of the THOTH structure, organization, ontology modelling, evaluation, feedback, and micro learning aspects, along with the communication model containing strategies for the use of small talk;
- Practice and preliminary results from an experiment with a group of students, as well as a small talk profile drawn for this group;
- Related works; and
- Future research paths and conclusions.

1.1 Small talk

According to [6], there are two core elements that give credibility to a software in an interaction with a human being. The first is to give the agent a “body” under a sort of interface, i.e., to provide it with human appearance and behaviors. The second is to use small talk. The influence of small talk on the user’s perception of a software agent has been demonstrated in systems which implement chatterbots, similar to what was found initially with Weizenbaum’s ELIZA [7].

Small talk consists of non-task-oriented conversations about topics whose primary functions are to mitigate facial threat, provide an initial gap in which the interlocutors may compare themselves, establish an interactional style, and consolidate some degree of mutual confidence and relationship. Social meetings between individuals that have never had a previous encounter (or that are not familiar with each other) usually start with small talk in which a light conversation is held about topics of general interest for both parts [6].

Small talk research in linguistics started with Malinowski’s 1923 seminal work, which defined the term “phatic communion” as a kind of talk in which union bonds are created through a single exchange of words. Small talk can be understood as a language used in social relationships when people are in a comfortable state or when engaging in some joint work, entering into disconnected conversations about what they are doing [6]. One fundamental motivation to use small talk is to avoid silences that arise from an uncomfortable tension, which can have negative consequences for the social interaction. Taciturnity is even considered, in some cultures, an evident sign of hostility or bad mood [8].

Schneider [9] offers a perspective of small talk as having two basic functions: signaling positive face needs, fulfilling a social role; and signaling negative face needs, avoiding embarrassing situations or awkward silences before a stranger. The author describes roughly 30 conversation types, with small talk typically taking place in series of conversational segments. In contrast, Coupland, Coupland and Robinson [10] disagree with this perspective, offering an explanation of small talk as an interaction style that assures phatic communion in a continuous way, rather than in a discrete or segmented manner.

Small talk could be an interesting communication strategy to make conversation with Q&A systems more realistic. In particular contexts with cognitive assistants or intelligent tutors, continuous interaction may be more acceptable to a user in a learning process. A promising path in the conception of such systems is to consider the discrete perspective (referred to as Schneider’s perspective) [9], which categorizes several types of small talk that may be combined with the content in a tutoring conversation.

2 Thoth–Training by Highly Ontology-Oriented Tutoring Host

The effectiveness of the interaction with a chatterbot is directly related to the user’s capacity to perceive a “mind” on the other side of the interface, according to Dennett’s intentional stance. The basic strategy of an intentional stance treats the counterpart entity as an agent capable to predict and even to explain its actions and movements. It involves interpreting the counterpart's behavior as that of a rational being with beliefs and desires that rule its choices and decisions [11].

Thus, a cognitive assistant should incorporate additional functionalities to a Q&A system if the goal is to enhance the credibility of a conversation expressed in natural language. Such systems can provide the student with the knowledge needed to comprehend certain contents, which are organized into an ontology built to retrieve such contents on demand. However, in order to transform this approach from a simple "search" process into credible talks, the interaction must be permeated by other modes of speech, shifting to a more "human" conversation.

In this sense, THOTH is conceived as a cognitive or learning assistant aimed at providing knowledge of a specific domain, previously stored and structured in ontologies, using a natural language interface that adapts itself to the questions formulated by the student. The use of THOTH in a given learning and teaching process is justified as a complementary tool, with its two basic cognitive objectives grounded on Bloom's taxonomy: *remembering* and *understanding* [12]. The remembering level consists of behaviors that emphasize storing information units susceptible of being assimilated. With respect to the understanding level, students are expected to comprehend the contents transmitted to them and, then, make use of the ideas and concepts retained.

2.1 Structure and functionalities

THOTH is conceived with two main modules (see Fig. 1): a KB (*Knowledge Base*) and a NLI (*Natural Language Interface*), the latter being divided into six agents. The *deterministic search* and *probabilistic search agents* base their performance on KB ontologies related to the content of the course in question. These ontologies allow THOTH to, through the NLI (in which the student inserts his or her questions), provide answers in OAV (*Object-Attribute-Value*) triplets, according to their ontological representations. Such answers are generated and returned by the *deterministic response* and the *conversation agents*.

THOTH keeps a Q&A database in the NLI, containing standard Q&A pairs related to learning management, handled mainly by the deterministic response agent. When the question cannot be solved by the deterministic search agent (i.e. questions asking for explanations of concepts, such as as "*what is*…" or "*give me an example of*…"), the probabilistic search agent processes this question using comparisons with four different metrics (described below) to analyze syntactic proximity, considering both simple and compound words as learning objects. Neither of these search agents implement rules based on lexical analysis. Rather, they analyze the phrases entered by the student in two parts: extraction of the object and extraction of the attribute (which is then associated with the type of question). When these agents successfully extract both object and attribute, they return values according to matching OAV triplets stored in the domain ontology. If no matching OAV triplets are found, THOTH will return "not found" responses, creating a log for future analysis by a human tutor.

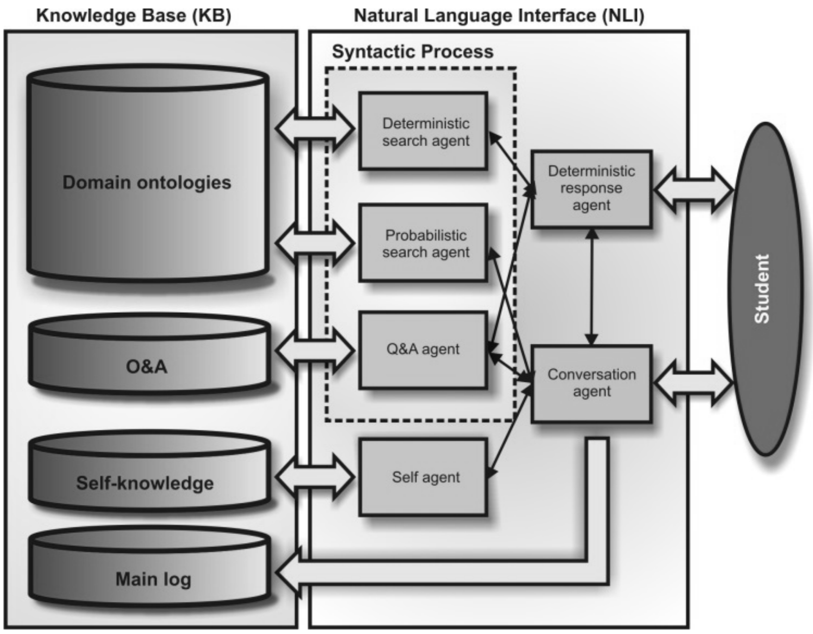

Fig. 1. Schematic diagram of THOTH, showing the main modules: the NLI, containing the agents that allow for tutoring conversation; and the KB, containing the domain ontologies, questions and answers, self-knowledge, and main log databases.

An interesting feature in THOTH is its adaptation to different student profiles. If the syntactic proximity index calculated for a given question falls below a specific threshold (calculated using Bayesian techniques), THOTH will launch up to three alternative questions, subject to confirmation by the student. If confirmed, the interactions that follow will consider such choices. This adaptability provides THOTH with machine learning characteristics.

The NLI is designed to respond to two modes of interaction:

- Directly typing the question into a field; or
- Composing the final question by choosing objects and patterns from a list.

For example, to ask a question about neural networks, the student must click on the specific question pattern item "what is …" and on the concept item "neural network." The question pattern is related to the attribute "concept." Then, based on the input of object and attribute, THOTH will return an answer with as many OAV triplets as available in the domain ontology, choosing one at random or displaying a value that has not been delivered to the student before.

The Q&A database also contains a few standard questions that allow students to situate themselves in the learning process, for example, "what was the last concept we viewed?", "how many concepts did we study?", "how many concepts are left to study?" and other questions regarding their overall and detailed performance, properly managed by the conversation agent.

All features exposed here provide some indications on how the THOTH's student model can be conceived. Woolf [13] states that a student model observes the student behavior, furnishing a qualitative representation of a student's cognitive (and affective) knowledge. Such model is built as a proper subset of a more extensive knowledge domain, showing differences between novice and expert, usually indicating how to achieve mastery of each topic and evidencing which elements need more effort. In describing the overlay model, Brusilovsky and Millán [14] emphasize that the nature of the student knowledge will depends, by its time, on the nature of the expert knowledge represented in a given system, either conceptual or procedural. Specifically, a conceptual knowledge, related to facts and its relationships, is often represented as a network of concepts. THOTH intends to follow this path, proposing the knowledge representation as domain ontology of facts and its relationships.

2.2 The ontology for OAV triples

One of the several challenges of developing a cognitive assistant for tutoring conversation is to define how knowledge should be organized. A good starting point was to divide the knowledge into contents that have topics in common, based on the structure of the courses and disciplines. A robust and high level knowledge organization system is based on the notion of ontologies. Ontologies in computer science were originally proposed to handle shareable and reusable representations of knowledge [15]. An ontology is defined as a formal specification of a given concept [16]. An ontology related to a given knowledge field is called a *domain ontology*. Typically, ontologies can be created for shared knowledge bases and for organizing the semantics of complex software applications [15]. Mizoguchi and Bordeau [17] pointed out the importance and utility of ontological engineering in the effort to enable computers to understand knowledge present in learning and instructional systems.

The prototype ontology built for THOTH was designed specifically for the AAI (Applied Artificial Intelligence) course of a Systems Analysis and Development undergraduate program. In order to build the prototype, the course contents were organized into a hierarchy of concepts (see Fig. 2), understood as global concepts within the discipline. Drawing a parallel with learning objects, this step makes objects as fine grained as possible without losing meaning, laying out the attributes and values for the OAV triplets.

From this hierarchy of objects, attributes are extracted from contents related to concepts, examples, links, diagrams, images, relationships with other objects, comments, authors, videos, etc. The last version of the list of attributes has 65 different attributes. In order to convert a question given by a student into an attribute, the conversation agent tries to extract the type of question. Each attribute has at least one type of question.

For example, a student might enter the sentence "*what is neural network?*" First, the deterministic search agent will look for an object in the domain ontology from the possible objects that the deterministic response agent has split and parsed in the sentence. The search will be successful, returning "*neural network*" as an object present in that ontology.

Next, the deterministic response agent will split the question again in an array that contains possible subsentences, sending it back to the deterministic search agent. This agent will perform a search in the Q&A database, retrieving the subsentence "*what is*", matching it to the attribute "*concept*" and to the answer patterns "`<object>` is `<value>`" or "the concept of `<object>` is `<value>`." However, in case the array of subsentences does not match any questions stored in the Q&A database, the conversation agent performs an approximate search along with the probabilistic search agent.

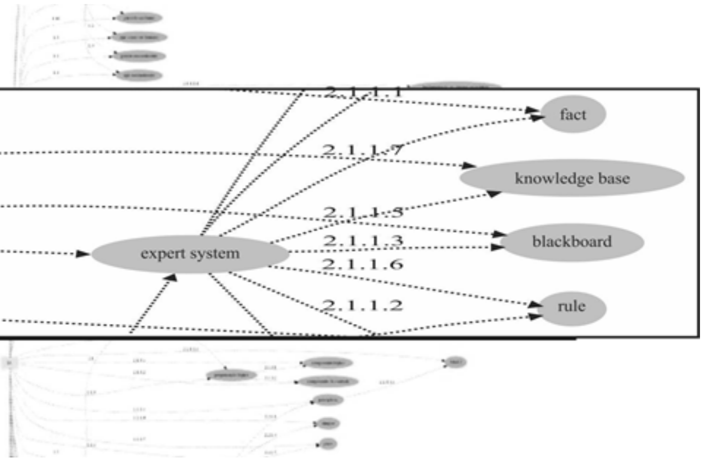

Fig. 2. Schematic diagram of THOTH, showing the main modules: the NLI, containing the agents that allow for tutoring conversation; and the KB, containing the domain ontologies, questions and answers, self-knowledge, and main log databases.

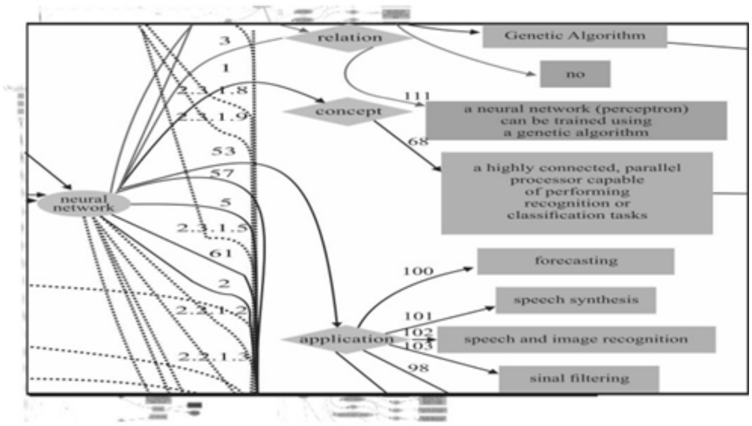

Fig. 3. Section from the AAI domain ontology, showing the concept "neural networks", the attribute "concept" and the value "a highly connected(…)." THOTH generates the graph automatically using the GraphViz API and implementing a zoom frame to increase the scale.

Having found the object "*neural network*" and the attribute "*concept*", the deterministic search agent retrieves the matching value(s) from the proper OAV triplets (see Fig. 3) stored in the ontology (for example, "*a highly connected, parallel processor capable of performing recognition or classification tasks*"). The object and value chosen fill in the answer pattern (also chosen at random), enunciating a possible response: "*neural network is a highly connected, parallel processors capable of performing recognition or classification tasks.*"

This prototype ontology for THOTH was designed by the AAI professor. The latest version released included 86 concepts, 65 attributes, 265 values and 278 OAV triplets.

OAV triplets in the ontology can also be organized into lists, resulting in OAV streams that can represent more complex and complementary concepts. For example, the concept of an object may be followed by an example or image of such object. When THOTH replied to the student's question "*what is neural networks*", after a few seconds it also returned an example of a neural network, next to an image of a neural network with its units fully connected. Many examples can be stored in the ontology, and THOTH randomly chooses one to display. Therefore, it is possible for OAV streams to keep many forms of content representation within the domain ontology. In the AAI ontology, 46 of 278 OAV triplets were combined into OAV streams.

2.3 Evaluation and feedback

THOTH comprises an evaluation system that lets the student check, at any time, how many concepts were studied in the current and previous sessions, as well as how many concepts are left to be studied. This feedback is given quantitatively, represented by responsive graphics (pie and bar charts) in a side box.

To practice the contents, students can ask THOTH to launch a module of exercises containing a set of objective questions. Then, wrong answers will redirect the student to the concepts related to the question without providing the correct answer. THOTH offers a detailed concept by concept performance index, so that students can identify which concepts were mastered and which require more attention. This detailed performance index can also be summarized into an overall performance index. This feature makes THOTH an adaptive learning tool.

2.4 Distance metrics for question similarity

In contrast to deterministic searches, probabilistic searches for questions not previously stored in the Q&A database will use a metric to calculate the similarity between a given input question and the questions stored in the Q&A database. The four distance metrics used in THOTH are Jaro, Jaro-Winkler, Levenshtein and Carla. Jaro and Jaro-Winkler metrics are classified as similarity metrics, searching for common characters between two strings and using operations as transposition in order to calculate the metric [18]. Levenshtein metric is an edit distance measure calculated from the normalized number of edit operations needed to transform one string to another [19]. Carla metric explores the occurrence of common substrings between two strings, solving an optimization problem called maximum common characters in blocks [20]. With these metrics used for search common characters, string edit operations and comparison with substrings, the purpose is to cover the many possible forms of classification, calculating a mean weighted value, the index that will represent the distance between the input question and the questions from the Q&A database. Then, a list of indexes is given in descending order, with the most similar index at the top.

Table I details an example of the weighted proximity index for the question "what do neural networks mean." This kind of question was not previously stored in the Q&A database. The probabilistic search agent runs the distance metric algorithms in order to build the list, in which mean weighted values are classified in descending order. Analyzing the list, we can see that the option "what is neural networks" is the most similar question calculated by the algorithms.

Distance metrics algorithms are also quite useful for the deterministic search agent, as questions with an exact match will always return the value 1.00.

Table 1. List of questions stored in the Q&A database compared with the input question "what do neural networks mean." This list is classified in descending order of the mean weighted value, as shown in the last column (We translated the figure from the original in Portuguese).

Phrase	**Metrics**				**Mean Value**
	Carla	***Jaro***	***Jaro-Winkler***	***Leven-hstein***	
what is neural network?	0.74	0.66	0.83	0.61	0.72
what is the meaning of neural network?	0.75	0.65	0.68	0.71	0.71
does neural network has software?	0.65	0.75	0.77	0.43	0.65
what's neural network?	0.70	0.56	0.61	0.57	0.64
who was neural network?	0.70	0.50	0.55	0.61	0.63
how can neural network be classified?	0.61	0.57	0.61	0.65	0.61
what do you know about neural network?	0.56	0.58	0.79	0.56	0.60
is there neural network software?	0.61	0.58	0.62	0.46	0.58
what do you know on neural network?	0.53	0.56	0.78	0.50	0.57
define neural network	0.56	0.46	0.52	0.61	0.55
how are classified neural networks?	0.57	0.49	0.54	0.53	0.54
where can neural networks be applied?	0.53	0.56	0.60	0.50	0.54

2.5 THOTH and microlearning

THOTH includes an event agent that directly connects to the domain ontologies database and periodically sends fragments of OAV content, packed as short messages or quotes, to students that have a Twitter account registered in the system. THOTH's answers to questions asked by students on the interface are used to reinforce contents on the go. In this sense, organizing knowledge into OAV triplets makes THOTH suitable for microlearning. In Juhary [21], Twitter was explored as a revision tool, well accepted by students. His research led to conclude that students performed better in their tests after using Twitter in revision activities.

Microlearning uses short learning units and short term activities. Although the term *microlearning* can be applied to contents, processes, technologies, competencies or learner groups, the underlying key concept is that the learning process must occur within minutes rather than hours or days [22], [23]. If OAV triplets may be properly defined as *microcontents*, the process that involves triggering OAV triplets as messages or quotes sent to students may also be classified as a microlearning activity. Considering Twitter's length restrictions, if the microcontent to be sent has more than 140 characters, the message is split and sent in more than one piece.

2.6 THOTH and small talk

The approach to *small talk* used in this work considers as non-task-oriented, by exclusion, all speech that does not aim to retrieve contents in the form of OAV triplets. Consequently, a wide range of enunciations can be framed as small talk. Within the NLI, small talk segments are placed in different moments of the tutoring conversation, currently organized into 12 segments, according to [9], described as follows.

- **Overture**: Initial greetings, contextualized as per whether this is the first session or not. The greetings are not deterministic, rather, they are a series of enunciations given in a probabilistic way.
- **Finale**: Closing a session, following the same probabilistic format of the overture.
- **Self-knowledge**: Refers to THOTH's self, an embedded knowledge that holds its personality, assuming a more "human" aspect and allowing THOTH to introduce itself to the student, when asked.
- **Silence gaps**: When the student is no longer interacting, THOTH attempts to resume the session, asking questions to draw the attention of the student, encouraging him or her to ask about new objects. If there is no interaction, THOTH assumes the student is no longer available and ends the conversation.
- **Pauses**: Concerned with long periods of time spent in one session, THOTH lists the objects studied back to the student, asking if the student wants a break.
- **Rhetorical phrases**: Little sentences, placed at random before the answers about concepts, making the student feel like THOTH is "thinking" before answering.
- **Content suggestions**: Returned after a query about which contents THOTH knows about a specified object.
- **Learning management**: Through questions formulated by the student, THOTH can inform what has already been studied – in terms of objects viewed previously – and what remains to be studied, similar to the overall and detailed performance indexes.
- **Contacting the tutor**: In case an object cannot be retrieved from the domain ontology, or a question cannot be answered, THOTH informs that it will contact the tutor to ask for clarification.

- **Resuming point**: In new sessions after a forced or abrupt ending induced by silence gaps, after the overture, THOTH shows the student the last objects queried, helping them start over from where they left off.
- **Object confirmation**: Before triggering contact with the tutor, THOTH shows the student the top three questions of the list (formulated by the probabilistic search agent) in order, asking for a simple confirmation. In case of a positive response from the student to any one question, this question is associated with the original question and then stored in the Q&A database.
- **Kindness demonstrations**: Positive replies to student's displays of appreciation.

Fig. 4 details an extract of a tutoring conversation held with THOTH, where it is possible to identify some small talk segments inserted into the conversation (according to the itemization above).

In order to keep THOTH's operability at a level where it may be possible to establish the continuity of communication with the student, we considered the parameters below:

- **Believable response time**: The answer must not be given immediately nor take too long.
- **Response randomness**: Different responses may be given, causing the student to perceive THOTH as having a "large repertoire."
- **Responsiveness control**: At certain moments of the conversation, where small talk segments are placed, students can give positive or negative feedback.
- **Tutoring continuity**: THOTH must maintain continuity when suggesting elements to the student, proposing objects that were not studied or queried previously.
- **Self-contained knowledge**: Refers to the granularity of contents, stored in the ontology in small parts that can be retrieved by simple questions.

3 Results

In order to map students' perceptions and gather information from their interactions, we introduced THOTH to an AAI class with 48 students from a Systems Analysis and Development undergraduate program. After more than 75% of the programmatic content elapsed, we gave a presentation on THOTH, explaining its purpose, functionalities and some conversation examples. Then, the students interacted with THOTH for an hour and a half.

The web interface was programmed to prompt, after one hundred Q&A interactions, a survey to gather the perceptions of students on using THOTH (Cronbach's alpha $\alpha = 0.8$). This survey was composed of 10 questions, in 1-5 Likert scale, based on two categories of analysis: interactivity and intentionality. Relevance of the interactivity category resides on features like usability and communication possibilities, and eventually other resources that could enhance the interface [1]. On the other hand, the intentionality category was correlated to Dennett's intentional stance [10], aiming to identify human aspects behind the exchange. In summary, interactivity refers to objective aspects, whereas intentionality refers to subjective features. The relationship of small talk with both categories is evident. Regarding the interactivity category, the feeling of being part of a "human" dialogue and the attractiveness of the conversation are directly related to the presence of small talk. Small talk also has an influence on the feeling of talking to a person and on the perception of a personality.

3.1 Quantitative analysis

Under the assumption of a causal relationship between the use of small talk and a better perception by students, questions regarding *interactivity* were grounded on a few subcategories:

- Previous use of similar tools
- Level of learning and understanding
- List of predefined questions
- Level of "humanity" of the conversation
- Attractiveness of the dialogue
- Use of THOTH as a support tool. As for the intentionality category, questions focused on: i) the perception of a subjacent "intelligence"; ii) the feeling of talking to a person; iii) the presence of a subjacent "personality"; and iv) the preference of human tutoring over computer assistance. The mean scores for most of the subcategories described above are shown in Table II.

Dialogue excerpt	**Small talk segment index**
(connecting...)	
[Thoth]: Hello, User! How are you?	**(1)**
[Thoth]: Welcome!	
[Thoth]: In the last session, you asked 'what does artificial neuron mean'...	**(10)**
[Thoth]: Your last object viewed was 'artificial neuron'...	
[User]: Thanks!	
[Thoth]: You're welcome!	
[User]: Is there a concept about neural networks?	**(12)**
[Thoth]: (Searching: neural network, concept)	**(5, 6)**
[Thoth]: According to Haykin (2004), neural network means a processor distributed massively and in parallel, consisting of simple processing units, having the natural inclination to store experimental knowledge and make it available to use.	
[User]: What's my overall performance?	**(8)**
[Thoth]: (Searching: help, overall performance)	**(5, 6)**
[Thoth]: Your overall performance on the exercises is 71,93%.	
[User]: What contents do I need to reinforce?	
[Thoth]: (Searching: help, reinforcement of objects)	**(5, 6)**
[Thoth]: Objects that you need to review are: act rationally (50%), think rationally (52%), rule (55%), lines of research (55%) and fact (57%)	**(8)**
[Thoth]: Would you like to learn about another object?	**(7)**
[User]: Give me a link about neural networks	**(8)**
[Thoth]: (Searching: neural network, link)	
[Thoth]: Ok... from Wikipedia, I have the following link: Neural Network (https://en.wikipedia.org/wiki/Artifical_neural_network)	**(11)**
[Thoth]: Do you want to visit this site?	
[User]: Yes	
[Thoth]: I can't open this link!	**(9)**
[Thoth]: I'm letting the tutor know, and he will check it soon!	

Fig. 4. Example of a tutoring conversation held with THOTH, showing the respective small talk segments (labelled by the item numbers). We replaced the original name with "User", and translated the original talk from Portuguese into English.

Table 2. Mean Scores for THOTH's perception survey

Categories	Subcategories	Mean score
Interactivity	Degree of understanding from THOTH's responses (1-Low;5-High)	3.75
	THOTH's potential for explaining contents (1-Low;5-High)	4.51
	List of predefined questions makes the conversation easy (1-Low;5-High)	4.15
	Degree of "humanity" of the dialogue (1-Low;5-High)	3.17
	Dialogue attractiveness (1-Low;5-High)	3.78
	THOTH as a support tool (1-Low;5-High)	4.26
Intentionality	Perception of THOTH's intelligence (1-Low;5-High)	3.95
	Sense of talking to a person (1-Low;5-High)	3.21
	Sense of manifesting a personality (1-Low;5-High)	3.08
	Human vs. system preference (1-Human; 5-System)	3.18

It is interesting to note that the *interactivity* category was well accepted and evaluated by the students, with all scores above average, considering that the Likert scale used ranged from 1 (strongly disagree) to 5 (strongly agree). The potential for explaining contents (4.51), THOTH's acceptance as support tool (4.26) and existence of predefined questions (4.15) are the subcategories with the highest scores, meaning that THOTH's performance in providing a reasonable dialogue is satisfactory. As for the *intentionality* subcategories, analyzing the perception of intelligence from THOTH (3.95) along with the feeling of talking to a person (3.21), it appears that students identify faint traces of personality in THOTH (3.08). Other interesting results were the relatively score of a slight preference for a conversation with the system over the human (3.18), and the reasonable acceptance of THOTH as a support tool. In general, we can conclude, from THOTH's perception survey reports, that objective, rather than subjective aspects had a more positive evaluation.

3.2 Qualitative analysis

In order to address a few qualitative aspects, the last question of the survey was open ended and aimed to gather students' opinions. Overall, the answers point to THOTH as a useful tool for clearing doubts and supporting studies. It seems significant that most positive views were related to the "intentionality" category, whereas most negative opinions were about the "interactivity" category.

Positive responses illustrate the good acceptance of the tool, such as "I thought it was interesting and exciting" and "[THOTH's] knowledge is very important for the students." One opinion was "I found it easy to understand and use. The notion of an assistant talking to you is a cool idea and I can see it being implemented in the future, helping people do many things." Another view highlighted THOTH's trust level: "The system seemed very reliable and easy to use. The questions were well formulated and the responses were well informed, expanding our knowledge." Some questions referred to the time spent in VLEs: "Really, if they had the full contents for all subjects, the student would spend more time in the VLE" or "If this system was present at the beginning of the VLE experience, interactions would be more attractive." One specific response shows little knowledge of the matter, but good acceptance: “I really liked the interaction, although I don’t master these specific contents. [It] can answer questions in a satisfactory way.” Lastly, one opinion recalled Dennet’s intentional stance: “I believe that when the system answers the question with a few errors, returns the right answer or asks for clarification showing that it doesn’t understand what was asked, in my opinion, it’s thinking like a human being, and it’s easy to fool a normal person in a chatroom.” It is noteworthy that this opinion was given by a paraplegic student from the group, who uses a wheelchair and only has the movements of his left arm to operate the keyboard and touchpad on his laptop.

Criticism, although constructive, focused mostly on the interface and its structure. The organization of the boxes should be different, according to some impressions: “I was a bit lost in the order of the boxes, I believe the objects should appear first.” Because THOTH shows a tutorial upon the first login, some opinions did manifest concern about the time it takes: “You should be able to skip the first tutorial” or “The initial help hangs the interaction for too long.” THOTH’s interface requires an internet browser, and some browsers blocked the popup windows that showed the exercises: “I couldn’t open the exercise module.” One interesting view was related to the characterization of a personality for THOTH: “If we give it a stronger personality than it already has, some people may feel uncomfortable. It’s better to leave it unchanged.” Another impression was regarding THOTH’s response time: “The response time should be shorter.” With respect to the interface design, students expressed demands such as “the interface could be more user-friendly” or “it should be affordable and usable.”

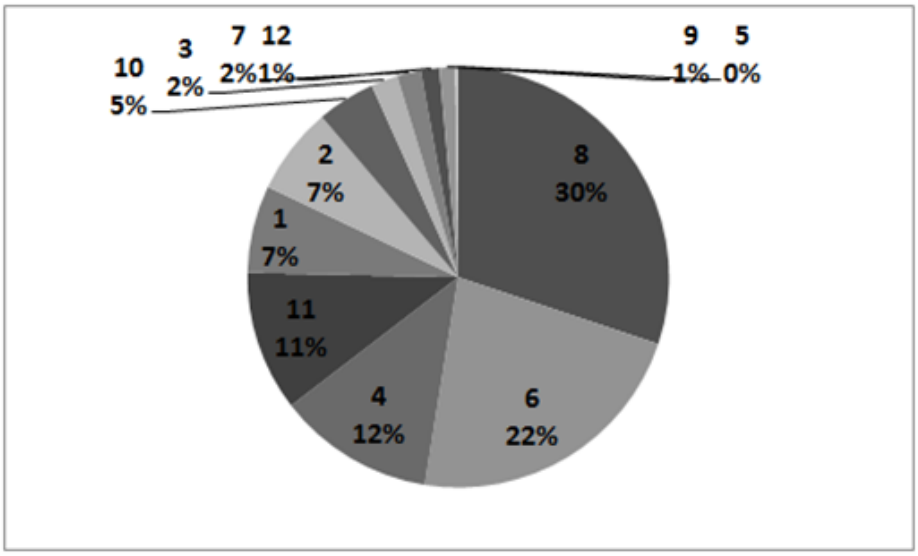

Fig. 5. Small talk profile extracted and analyzed from 1,732 phrases in THOTH’s conversation log using transcriptions as suggested in Figure 5. The top number on each slice is the respective small talk segment index based on Schneider’s perspective, according to Section 3.6. The bottom number is the percentage over the total number of phrases.

Moreover, some suggestions were given involving exercises, such as: “When the student misses the question, the system should immediately show the contents related to that question” and “An option with a voice synthesizer would make the system more attractive, but the main menu would have to be kept unchanged since it accepts few questions.”

In summary, the qualitative approach of the survey shows that opinions regarding the “intentionality” category were more favorable, and those regarding the “interactivity” category received more criticism. Taking advantage of these suggestions, the most recent implementation of THOTH so far includes a speech synthesizer, a new interface design (now exploiting Javascript frameworks) and a more intuitive positioning for the boxes.

3.3 Drawing a small talk profile

Based on a detailed analysis of THOTH’s conversation log from these 48 students, considering the sequence of all phrases entered for each student and answered by THOTH, we drew a small talk profile inspired by the example described in Fig. 5. We analyzed a total of 1,732 phrases, selecting 491 excerpts of small talk, sorted within the 12 categories explained in Section 3.6. As shown in Fig. 5, the four most relevant categories were “learning management” (Id 8) with 30%, followed by “rhetorical phrases” with 22% (Id 6), “silence gaps” with 12% (Id 4), and “object confirmation” with 11% (Id 11).

We interpreted this profile taking into account that this was the students’ first contact with THOTH, and their needs to grasp its functionalities were more relevant at that occasion. “Rhetorical phrases” is a label for small talk made up of little sentences, placed randomly by THOTH at the beginning of some phrases. A relevant index of 22% shows a usage of more than 1/5 of the analyzed set of small talk segments. The “silence gaps” label indicates situations where a significant amount of time elapsed while THOTH waited for a message. Although the mean elapsed time between phrases (calculated from the conversation sequences analyzed) was 23.9 seconds, students could take up to 1 minute or more, enough time for THOTH to trigger the resuming phrases. This fact could be interpreted as students either experiencing moments of dispersion or taking more time to read large blocks of content returned by THOTH. At last, “object confirmation” shows that some students might have been trying to figure out THOTH’s behavior in grasping the syntax and handling objects entered manually, rather than chosen from the list of objects on the interface.

3.4 Partial performance analysis

Although the main goal of this work was to focus on the perception analysis and acceptance of THOTH by the learners, some preliminary results regarding the performance of students in using THOTH could be observed. An analysis of the performance in the resolution of the exercises showed a gradual increase of correctness on the part of some learners. This analysis was based on the performance of two students who did not reach the minimum grade to be approved on the AAI course. To give them a new opportunity, such students could use THOTH to review the content studied in the AAI course, before retaking the test. Because of this, the students carried the exercises out many times, interleaved with the study of knowledge objects in THOTH. Considering that each exercise had three questions randomly chosen from 31 questions inserted, while the first student, labelled as "S1", performed the exercises 66 times, the second, labelled "S2", performed 41 times. These quantities were very high in comparison with the mean value of 4.77, reached by the other students.

Figs. 6 and 7 demonstrate the performance of "S1" and "S2", respectively. The vertical axis of both scatterplots reflects the percentage of correct answers (indeed, having only four values: 0%, 33%, 67% and 100%). Even with low linear correlation (R2=0,499 and R2=0,119 respectively), both regression lines are presenting positive slopes, eventually indicating better performance in using THOTH as time goes on. Unfortunately, this analysis couldn't be extended to the rest of the class because of the low number of exercises achieved by them, as explained before. In order to give better indication about THOTH's effectiveness, further research should consider a large sample of learners in doing intensively the exercises, as well as the commitment level of the learners.

4 Related Works

One relevant aspect to be discussed is the naming of such a system. In this work, we preferred the term "cognitive assistant", because the system not only returns answers for a given question, but also learns from its interactions with the students. Many research publications in this field provide a set of denominations other than "cognitive assistant" [24], [25] or "cognitive tutor" [26], but we can also find terms such as "chatbot assistant" [27], "personal assistant" [5], [28], [29], [30], [31], [32], "intelligent tutors" [33], [34], [35], [36], "knowledge exploration assistant" [37], "ontological learning assistant" [38] and "conversational agent" [39][40][41].

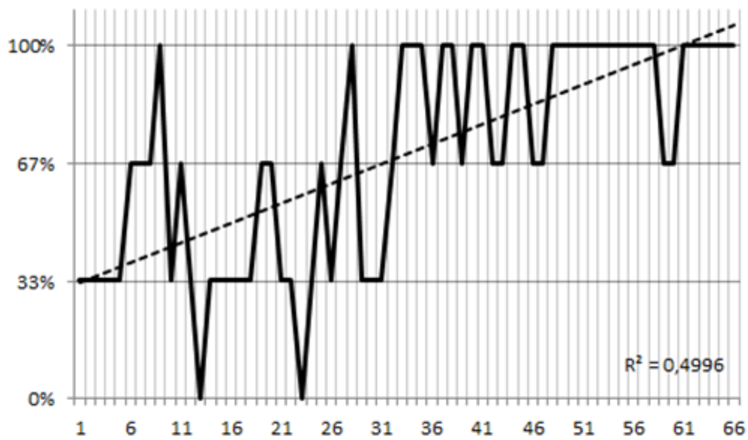

Fig. 6. "S1" performance in the resolution of 66 times the exercises.

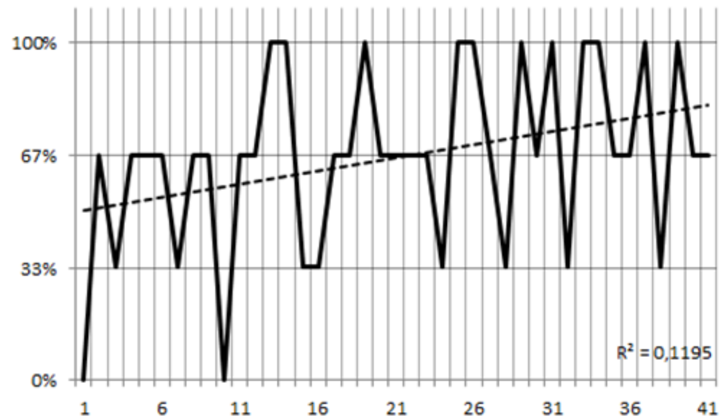

Fig. 7. "S2" performance in the resolution of 41 times the exercises.

With respect to *small talk*, one relevant work is by Bickmore and Cassel [6], who described the development of an embodied conversational interface agent capable of understanding and generating multimodal inputs and outputs, operating on a limited application domain in which both social and task-oriented dialogue are important.

Use of ontologies for knowledge representation can be found in some parallel works. Mizoguchi and Bordeau [17] has discussed several achievements of using ontological engineering, pointing out trends and perspectives in the area, as well as some difficulties, in particular the lack of authoring tools in helping authors consider theory-compliant learning scenarios.

According with the framework detailed in Dicheva et al [42] for ontologies in education, the activities involving OAV ontology in this work are taking place in the application perspective by means of a cognitive tool, related to knowledge construction, externalization and communication.

With respect to collaborative learning, Isotani et al [43] has highlighted the importance of using ontologies in providing the needed formalization to represent collaborative learning and its processes, and some activities such as planning scenarios or forming groups are supported by pedagogical decisions based on learning theories.

Warda and Jordano [44], based on previous works, described the functionality and implementation of a semantic web-based e-learning application — an ELA (Electronic Learning Assistant) — with focus on the RDF (Resource Description Framework) data model and OWL (Web Ontology Language) ontology of the application.

Choinski and Chudziak [38] proposed a concept of an OLA (Ontological Learning Assistant) — an ontology-based KDDSE (KDD Support Environment) platform — for carrying out knowledge discovery. Such a concept is based on the critical analysis of state-of-the-art studies in intelligent KDD (Knowledge Discovery in Databases) using ontologies. The work emphasized the fundamental role of knowledge transfer and cooperation between domain and technology experts.

Li and Sun [45] presented a study involving knowledge management, ontologies and intelligent tutoring systems. Based on the relationship between these concepts, they described a model of ontology-based knowledge management in intelligent tutoring systems.

Concerning intelligent tutors, Mikic-Fonte et al. [35] presented INES (INtelligent Educational System), an operational prototype of an e-learning platform with LMS

(Learning Management System) and LCMS (Learning Content Management System) functionalities and intelligent tutoring systems. To achieve these functionalities, the system includes several tools and technologies, such as:

- Semantic management of users and contents
- A conversation agent to communicate with students in natural language
- BDI-based (Believes, Desires, Intentions) agents, which shape the tutoring module of the system
- An inference engine
- Ontologies to semantically model the users, their activities, and the learning contents.

Students interacting with intelligent tutors are supposed to enhance their cognitive capabilities, as much as just provide knowledge. Mamoun *et al.* [46] proposed to set up an e-learning platform integrating an ITS capable to manage the limited ability of the learner, with regard to the working memory skills.

Santos and Jorge [34] described a new approach to implementing an open-source and interoperable intelligent tutor through standardization. In contrast to other methods, their technique does not require the use of non-standardized peripheral systems or databases, which would restrict the interoperability of learning objects.

Krishnamoorthy *et al.* [33] presented an enhanced approach that augments intelligent tutors with selected information from online FAQs (Frequently Asked Questions) and online open-source code, thereby providing more explanation and context about how to use APIs (Application Programming Interfaces) in practice.

Funabiki *et al.* [47], in order to assist self-study, developed a web-based JPLAS (Java Programming Learning Assistant System). The JPLAS had two main functions to support studies at several difficulty levels: code writing problems and fill-in-the-blank problems. One of the premises grounding the work assumed the student was capable of writing code from scratch, and the code submitted was automatically tested on the server with the TDD (Test-Driven Development) method.

With regard to small talk segments viewed in section 3.7, a closer parallel can be established with the Soller's Collaborative Learning Conversation Skills taxonomy, which was designed to facilitate recognition of active learning conversation [48]. This taxonomy contains three skills (active learning, conversation and creative conflict), divided into 8 subskills and 36 attributes. Each attribute is assigned a short phrase or sentence opener conveying the desired dialogue intention. Some subskills or attributes seem to be similar with certain small talk segments (e.g. the attribute "teacher mediation" and the segment "contacting the tutor", or the subskill "argue" and the segment "rhetorical phrases"). Although such approaches are originated from different contexts, as well as THOTH has focused on individual learning, a mapping of these two conversation structures could be established and may reveal not only similarities but possible gaps.

Lastly, citing works related to Q&A systems, Bhattacharyya [5] analyzed a survey of Q&A systems and then discussed IBM Watson, the famous system built at IBM Research Labs. Questions are classified in learning domains based on Bloom's taxonomy. Finally, Phatnani *et al.* [15] explained Siri as an intelligent personal assistant and knowledge navigator that works as an app on Apple's iOS. The work categorized Siri from a programmer's perspective, giving it three layers: a speech-to-text analyzer, a grammar analyzer, and a set of service providers.

5 Conclusion

This paper presented THOTH, a cognitive assistant for tutoring conversation that uses small talk to envelop or modulate knowledge stored in ontologies to facilitate the reinforcement of contents from a discipline or course. We explained many aspects of this tool, such as its structure and the organization of its agents and databases. The small talk feature plays an interesting role in making the tool more approachable. The quantitative and qualitative analysis of the survey gave relevant insight and validated its use.

In its next stage of development, THOTH will undergo more intensive testing as a support tool for one semester of the AAI discipline, being part of the course syllabus and having significant weight on the overall evaluation. The tool will be made available to students in a computer lab to be used continuously, and the final grade of the class will be composed of continuous exercise solving.

The methodology used to evaluate the perception of THOTH allowed for some interesting findings, organized into the intentionality and interactivity categories. One improvement planned for upcoming works will correlate details of the interactions performed individually by the students and the evaluation data raised in the survey. This feature could enhance the quantitative aspects of the evaluation, as well as help with data validation.

Taking into consideration the teaching and learning process, the use of a cognitive assistant does not intend to replace a teacher or knowledge mediator in a classroom context. THOTH was designed as a complementary tool, intended to help students in their self-study, covering different moments outside the classroom. THOTH's potential for distance learning is also promising, taking into account student autonomy, the inherent aspects of representation depending on the type of knowledge considered for the course/discipline in question, and the infrastructure available for broad access in scale.

Other interface-related features relevant to enhance the interaction with students are technical improvements such as voice recognition and speech synthesizers, as mentioned in the qualitative analysis. Some APIs have been tested, but the main difficulty at the moment is relying on a suitable support for Portuguese language in systems of voice recognition and speech synthesis.

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7 Authors

Luciano Frontino de Medeiros is a professor of Applied Artificial Intelligence at the Postgraduate Program in Education and New Technologies, UNINTER, Brazil.

Armando Kolbe Junior is a professor of Information Systems and Startups Management in Distance Learning at UNINTER, Brazil.

Alvino Moser is presently a professor of Technological Mediation at the Postgraduate Program in Education and New Technologies, UNINTER, Brazil,

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