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Contents – Part II

Posters

Ontology-Based Domain Diversity Profiling of User Comments	3
<i>Entisar Abolkasim, Lydia Lau, Antonija Mitrovic, and Vania Dimitrova</i>	
ROBIN: Using a Programmable Robot to Provide Feedback and Encouragement on Programming Tasks	9
<i>Ishrat Ahmed, Nichola Lubold, and Erin Walker</i>	
Conversational Support for Education	14
<i>Damla Ezgi Akcora, Andrea Belli, Marina Berardi, Stella Casola, Nicoletta Di Blas, Stefano Falletta, Alessandro Faraotti, Luca Lodi, Daniela Nossa Diaz, Paolo Paolini, Fabrizio Renzi, and Filippo Vannella</i>	
Providing Proactive Scaffolding During Tutorial Dialogue Using Guidance from Student Model Predictions	20
<i>Patricia Albacete, Pamela Jordan, Dennis Lusetich, Irene Angelica Chounta, Sandra Katz, and Bruce M. McLaren</i>	
Ella Me Ayudó (She Helped Me): Supporting Hispanic and English Language Learners in a Math ITS	26
<i>Danielle Alessio, Beverly Woolf, Naomi Wixon, Florence R. Sullivan, Minghui Tai, and Ivon Arroyo</i>	
VERA: Popularizing Science Through AI	31
<i>Sungeun An, Robert Bates, Jennifer Hammock, Spencer Rugaber, and Ashok Goel</i>	
Modelling Math Learning on an Open Access Intelligent Tutor.	36
<i>David Azcona, I-Han Hsiao, and Alan F. Smeaton</i>	
Learner Behavioral Feature Refinement and Augmentation Using GANs	41
<i>Da Cao, Andrew S. Lan, Weiyu Chen, Christopher G. Brinton, and Mung Chiang</i>	
Learning Content Recommender System for Instructors of Programming Courses	47
<i>Hung Chau, Jordan Barria-Pineda, and Peter Brusilovsky</i>	



Conversational Support for Education

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Abstract. This paper describes the development of chatbots that can help learners make the most appropriate use of a large body of content. The purpose of a Content-based Learning Assistant, COLA, is to suggest optimal educational paths, along with a persuasive and empathic coaching. COLAs are supported by a novel technology, iCHAT, based on the cognitive engine Watson (by IBM).

Keywords: Chatbots · Education · Virtual teaching assistant
Virtual learning assistant · Learning companion · Interactive tutoring system
Knowledge representation and reasoning

1 Introduction

In recent years, several bodies of digital content have been developed, for all school grades and higher education: libraries of learning objects, online courses, MOOCs, etc. Despite the fact that millions of users are actively using them, we can still observe that millions of potential users are lost. This is due, in part, to the difficulties for a user to find an (effective) way across several content items. Most libraries either provide predefined pathways or something equivalent to a traditional index or an analytical index where the user has to choose what she wants: a difficult operation for a learner who may not know the subject, let alone that specific body of content.

Our proposal is to build a conversational Content-based Learning Assistant (COLA), not as an expert on a subject, but *on a body of content* covering that subject, so that it can suggest optimal paths across the content items. Conversations, if properly designed, can combine guidance (across the various items), with adaptivity (to the learner's profile) and flexibility (dynamically steering paths).

2 The Case-Studies

The approach is developed through 2 case-studies. The first is about an online course on equations; the second is about a MOOC on “Recommender systems” to be offered on Coursera (in July 2018). The equations’ course had a twofold goal: to support struggling students in the 9th grade, or well-performing students in the 8th grade. The 4-weeks course was created by harvesting learning objects from the web (educational videos, interactive resources, PDFs, eBooks, ...), with other resources created on purpose. The whole body of content included more than 150 “learning objects”.

The second case is about a MOOC (“Recommender Systems” by prof. Paolo Cremonesi of Politecnico di Milano), developed with an innovative methodology, “iMOOC” (Casola et al, 2018), for designing customizable MOOCs that support different kinds of learners. iMOOC acknowledges that many users of MOOCs may have goals that do not imply going through the whole set of materials, in the sense that some learners may want to get an overview of a topic, others may already have a good background and therefore aim at accessing only advanced materials, etc. The chatbot is meant to support the learner in choosing the most appropriate path.

3 Organizing Content

The first step to develop a COLA is to create “topologies”, i.e. colored graphs representing possible interconnections among content items, to build adaptive paths. A topology can take into account various aspects: (i) quality of the background of the learner, (ii) commitment of the learner (time to spend), (iii) goals of learning (e.g. concepts, skills, ...), etc. Table 1 is a (simplified) example of topology.

Each content item has a node ID and a DB ID (that univocally identifies the item); the length (in minutes) and the media (e.g. “video”) are also specified. The color of the item represents the level of difficulty (e.g. a red item is an “advanced” content); the color of the arrows instructs on the possible paths among the items taking into account the difference between first time visitors (blue) and second time visitor (violet). The strong/light hue of the arrows represents strong/low motivation.

4 Content-Based Learning Assistant

We can imagine 3 main directions for an application supporting learning:

- A. Helping by providing knowledge about **the specific subject matter**. Intelligent Tutoring Systems that are “experts” on the specific subject matter.
- B. Helping by providing a **predefined body of content** and **interaction mechanisms** to access it. Most (if not all) online courses or MOOCs or libraries of learning objects (e.g. Khan Academy, Brainpop) fall in this category.
- C. Helping by providing a **predefined body of content** (like A) and providing **intelligent mechanisms** to access it (like B). **This is the approach of COLAs.**

Table 1. Excerpt from a topology of content for a learner with a low background

Node ID	Item ID	Item title	Media	Minutes	Color	Arrows
1	cc1001	Course Overview	Video	05:00	Black	→ 2 blue → 2 light blue → 3 violet → 3 light violet
2	cc1002	Introduction	Video	03:32	Black	→ 3 blue → 3 light blue → - violet → - light violet
3	cc1003	Taxonomy of Recommender Systems	Interactive presentation	04:03	Black	→ 4 blue → 4 light blue → 4 violet → 4 light violet

Useful learning assistants can be developed using the approach “C”, i.e. providing a well-organized body of content and using modern AI to build conversations on it. Under which conditions can COLAs improve a learning process?

- (a) **The intrinsic quality of content**, i.e. quality of the learning objects.
- (b) **Optimal (dynamic, adaptive, flexible) paths across the content items**, that facilitate the learning process taking into account (i) the teacher’s plan, (ii) the learner’s static profile and (iii) the dynamic situation of the learner.
- (c) **Empathic, friendly and persuasive conversation**, not just offering the right items in the right sequence, but also generating a feeling of “being taken care of”.

B and C are the aspects where AI may help. In the next section, we describe iCHAT, the AI-based technology that supports the development of COLAs.

5 iCHAT: The Technology

iCHAT is an innovative technology being developed as a joint effort by Politecnico di Milano (HOC-LAB) and IBM (the Italian research division). iCHAT allows developing (at a reasonable cost/time) a chatbot that can support a user in her effort to access a body of content. The execution of an iCHAT application is supported by the architecture shown in Fig. 1. A user interacts with “iCHAT Conversation manager”; she can start several streams of conversations: at the end of the session, they can be saved to be resumed later (via the “iCHAT long-term memory manager”).

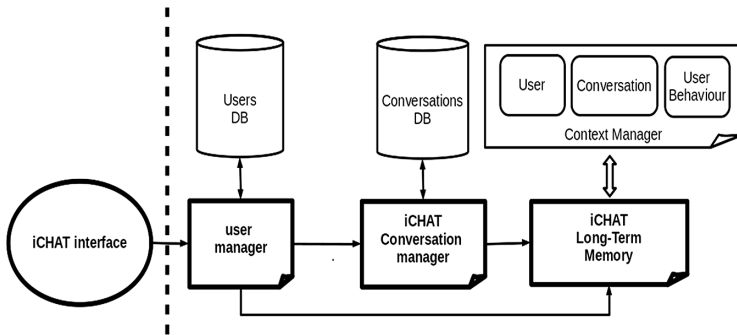


Fig. 1. Overall architecture of iCHAT

The user chats with the chatbot, alternating turns; sometimes (not always) a new content item is offered to the user, consisting of a variety of media: video, images, audio, text, etc. We use, at the moment, a combination of chat-line and multimedia player; in the future, we could add a text-to-speech or speech-to-text interface or house robots. The technology of the interface can be replaced with different interfaces. The conversation module of WATSON (Fig. 2) is used to implement the linguistic aspects of the conversation. One of the goals of the conversation is also to collect information about the user's situation (e.g., is she tired? Did she understand?). All the current information about the user and the "usage" of the topology define the **current context**. Whenever a user takes a turn, a "user intent" is detected (by the conversation module) and interpreted. The interpretation may lead to 3 possible situations: (i) the conversation does not need a new item of content and therefore it continues along a traditional line; (ii) the conversation (implicitly) needs a new item of content and the intent interpretation engine is activated; (iii) the user explicitly asks for a piece of content and the entity interpretation engine is activated.

The style/wording of the conversation is different for each family of applications (Education vs. Cultural Heritage) and within the same family for each "genus" (school education vs. higher education). Training the chatbot to a specific pair of <style, wording> is done (via WATSON) at family (or genus) level and does not need to be redone for each specific chatbot: this is one of the main advantages by iCHAT.

The Intent-Interpretation Engine is a new piece of SW. A user intent defines what the situation of the user is (e.g. is she understanding?); a "transition intent", instead, defines a more objective intent, that can be considered a requirement for identifying the next item of content to be offered to the user. The transition engine translates a user intent into a transition intent. When the chatbot replies to the user, the opposite translation occurs: the motivation of the chatbot for selecting that specific content item is translated into a motivation that makes sense for the user. The **Entity-Interpretation Engine** is activated when the user names a specific subject of interest, which must be translated into a proper entity that makes sense for the chatbot. The engine performs its job using Vocabulary_DB and the vocabulary-mapping developed using WATSON learning capabilities.

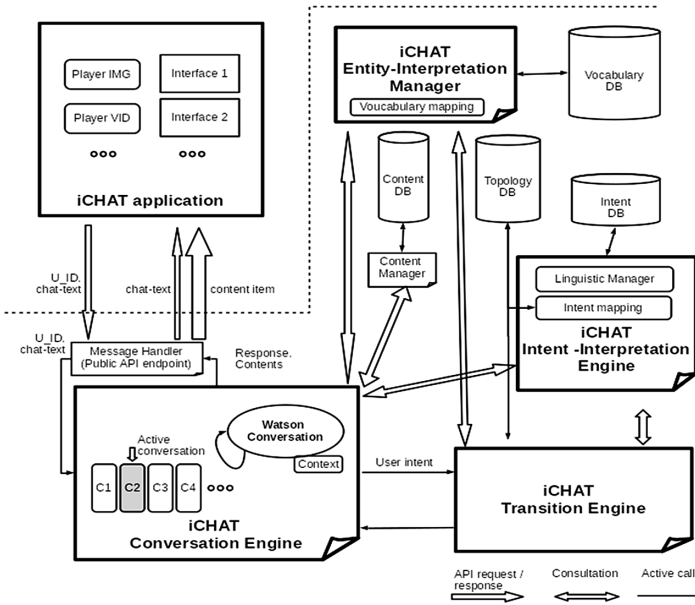


Fig. 2. iCHAT conversation manager

6 Conclusions and Future Work

We have discussed, in this paper, a number of issues:

- Introducing the idea of COLA: a COnTent-based Learning Assistant specialized in helping the user to make an “optimal use” of the items of a specific body of content. It is important to note again that, differently with respect to other AI applications, the expertise of a COLA is about a body a content, not a subject.
- The proposal of using the **semantic organization of content in order to drive the conversation** (see the example of topology in Sect. 3). This approach promises two advantages; to allow non-technical experts of the subject to optimize the conversation (via optimization of the organization of content), to make the effort of development and maintenance scalable and sustainable.
- Proposing that a valid learning assistant, besides reacting to the user’s interaction, should also reflect the **point of view of the teacher**. The teacher, defining metadata and topologies, implicitly determine which paths are offered to learners.
- Putting forward the idea that a **conversational interface** has several advantages over a more traditional point-and-click interface. First of all, it can establish a friendly and empathic relationship with the learner, secondly, it can be used to collect information about the current situation of the user.
- The proposal of a **novel architecture, ICHAT**, to support the development of COLAs.

We are currently improving the organization of content for the two real-life case-studies described in Sect. 2. Teams of teachers are involved in this effort and for the linguistic training of the conversation engine. The user testing of the COLAs should start in the late spring of 2018. Using control groups of students, we will verify if, how, and under which conditions COLAs effectively improve the quality of learning.

Reference

Casola, S., Di Blas, N., Paolini, P., Pelagatti, G.: Designing and delivering MOOCs that fit all sizes. In: Proceedings of Society for Information Technology and Teacher Education International Conference 2018 (2018), (accepted)