Conversational AI for Corporate e-Learning

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ABSTRACT

Natural language tutors have been an active research topic for decades and the widespread use of chat interfaces lead to a high level of acceptance of chatbots. Despite that, conversational AI has not found its way into the practice of corporate e-learning yet. In this paper we present a novel approach to leverage the advances in the field of conversational AI for corporate e-learning. Following a design science approach, we identify the pivotal stakeholders and design objectives. We propose a service architecture and demonstrate its feasibility with a prototypical implementation. Finally, we conclude that the proposed approach has the potential to lower entry barriers for conversational AI for the practice of corporate e-learning.

CCS CONCEPTS

• **Applied computing → E-learning**; *Interactive learning environments*; *Collaborative learning*; *Learning management systems.*

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1 INTRODUCTION

Over the past decades natural language processing has made tremendous progress. But while we experience these progress in consumer electronics and even customer support, corporate e-learning remains largely unaffected. This may seem surprising since Natural Language Tutors have been an active research topic in the area of Intelligent Tutoring Systems (ITS) for many years. However, research typically focuses on how to improve learning or learner experience and neglects transferability and implementation costs. To address this gap we chose a design science approach [4, 9] to design an information system that allows to leverage the advances of conversational AI for corporate e-learning. In this paper we first present the most relevant related work in section 2, before reporting the identified key design objectives for the information system in section 3. Subsequently we present our preliminary information system design and our prototypical implementation in section 4, before concluding and providing an outlook on future work in section 5.

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2 RELATED WORK

In this section we will describe the most relevant related research for our work. We start with the more general work in the field before presenting e-learning specific research.

2.1 Task oriented dialog

When it comes to building intelligent dialog systems, a lot of research focuses on task oriented dialog systems. The main goal of these systems is to solve domain-specific tasks by deriving the intent and entities with Natural Language Processing (NLP) from a sentence of a user. Many strategies include statistical models like the Markov Decision Processes (MDPs) [6, 7] and Partially Observable Markov Decision Process (POMDP) models[16, 17]. A lot of the literature about these dialog systems also applies Reinforcement Learning (RL) to train the dialog policies [11, 14, 15]. There are many potential applications of task-oriented dialog systems in various business niches aiming to assist its customers via natural language conversation such as a hotel booking or a technical support service. Another application area for a task-oriented dialog systems is the field of Intelligent Tutoring Systems (ITS).

2.2 Intelligent tutoring systems

The term Intelligent Tutoring System (ITS) is a well established research area and is purposed to replace a human tutor with an intelligent system which is able to guide a user through a learning process by providing individual and customized feedback [10]. AutoTutor [8] is an ITS simulating the discourse patterns and pedagogical strategies of a typical human tutor. Designed to assist college students in learning the fundamentals of hardware, operating systems and the Internet, this system was on of the first to use natural language for their interactions. With today's availability of smartphones and their potential as messenger, the rise of chatbots in combination with conversational AI is huge. Schmulian and Coetzee [12] designed two messenger bots to fulfil the support role offered by a co-teacher in the context of a large class. Their evaluation showed that the education benefits of using the bots by increasing the engagement of the students. Although many students liked to experiment with new ways of learning online, a number of students thought the messenger bots are only suited for supplementing rather then replacing the face-to-face classroom. Another example of a chatbot as ITS was proposed by Kerly et al. [5] using an Open Learner Model, where the system's model of the user's knowledge is revealed to the user, allowing the user to enhance the system's adaptivity by improving the accuracy of the underlying learner model. Bots like these [5, 12] are often designed to work only in a specific domain by using rule-based decision making of the chatbot. In this paper we propose a chatbot able to understand different domains.

3 DESIGN OBJECTIVES

The aim of our research effort is to design an information system for corporate e-learning delivering learning resources through a chat interface. To assert a rigorous approach, we identify the key objectives for the design of an information system for productive use in that area. Corporate e-learning is typically used to deliver learning resources in a cost efficient way. Any information system in this area has to at least take into account two roles: provider and consumer. While the role assignments are sometimes dynamic, the needs and requirements of users typically relate to these roles. However, most research efforts focus on the role of the consumer (i.e. learner). We try to address this gap by proposing an information system including providers and consumers, and hence constructing our design objectives from both perspectives. Additionally, we also identify potential regulatory demands or restrictions.

3.1 Providers

The provider role is responsible for adapting, arranging, orchestrating and delivering learning resources. For e-learning delivery typically means to make content available online. Providers sometimes also act as producers, creating new learning resources. However, especially in the corporate context most learning resources are created by transforming existing material into learning resources. Learning Management Systems (LMS) are extremely popular for the flexibility they provide. They allow almost any form of digital content, reducing the transformation effort for the providers. For orchestration, most information systems in place use hierarchical structures (e.g. category, course, activity), as they are easy to maintain. However, certain aspects such as similarity or interconnections between learning resources cannot be modeled by hierarchies.

(1) easy authoring
(2) easy import and transformation
(3) easy orchestration and remixing
(4) easy modelling of relationships between resources

3.2 Consumers

In the context of e-learning the consumer role is a learner. However, especially in the corporate context learning is often embedded (or integrated) into daily work. Thus, our didactic approach is largely based on the ideas of Mobile and Integrated Micro-Learning [1, 2]. Very few companies schedule dedicated (e-)learning times, as time invariance is typically an essential beneficiary effect of an e-learning systems in the corporate context. But also the learners benefit from the availability of learning resources. Especially certain forms of informal learning as described by [13] are supported: for *incidental learning* e-learning can provide just-in-time follow up activities, and for *self-directed learning* a pool of resources to chose from. To support long term memorization Micro-Learning systems often implemented spaced repetition strategies [1, 3], which appears also very suitable for Chatbots, as they can use messages to nudge learners to revisit certain learning resources.

Thus we define the following design objectives from the consumer perspective:

(1) ubiquitous availability
(2) short and relevant interaction sequences
(3) unobtrusive nudges for mandatory material

3.3 Legal Conditions

On the one hand, in corporate context we find regulations that hold companies responsible to instruct their employees on certain topics. Typical examples are safety, compliance, and hygiene. On the other hand, national and supra-national regulations (especially in Europe, c.f. GDPR[1]) require companies to only store and process data for legitimate purposes, and protect employees from surveillance-like activities of their employer. Depending on context and country, learning records might be touched by these regulations, and options to prevent data from being personally identifiable should be incorporated.

(1) verifiability of mandatory instruction
(2) anonymity of employer activity data

4 DESIGN AND IMPLEMENTATION

In the following subsections we will present our designed service architecture, data model and the user interface of our prototype implementation.

4.1 Architecture

The prototype is based on a microservice architecture consisting of multiple services which are communicating via different REST endpoints. Figure 1 shows a simplified, high-level diagram of the basic components, grouping multiple services.

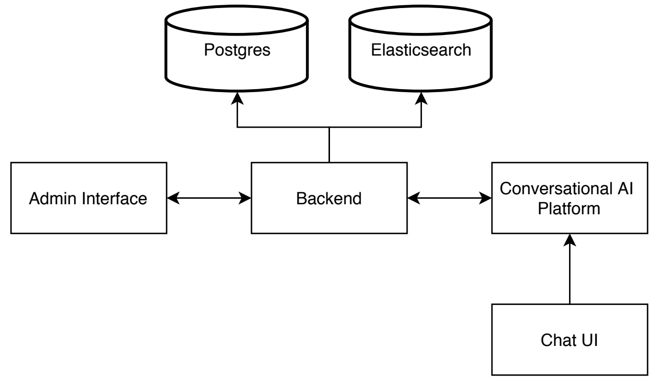

Figure 1: Simplified Architecture of our prototype including the admin area and the user chat client.

Admin Interface. This components allows administrators to manage the knowledge base by uploading documents to the system.

[1]General Data Protection Regulation (EU) 2016/679, http://data.europa.eu/eli/reg/2016/679/oj

These documents are analyzed and relevant information will be extracted for further use. The admin area contains an editor allowing the administrators to view and edit the extracted information. This data is later queried according to incoming user requests at the chat UI.

Backend. The backend is a set of services used for storing uploaded documents, and to read/write the extracted information from/to a relational database (Postgres) and a search engine (Elasticsearch). It is also contains services for providing customized responses for the Conversational AI Platform after a specific intent has matched (fulfilment).

Postgres. Stores all relevant data about uploaded documents like the headers and their content in a relational matter.

Elasticsearch. Indexes information about the uploaded documents which are relevant for queries.

Conversational AI Platform. For our prototype we currently use Google's Dialogflow[2] as Conversational AI platform. Dialogflow allows fast prototyping via a web UI (e.g.: intent modeling) and automatic model training. The integration of webhooks to our backend is also a very simple task. The component could be replaced by other conversational AI platforms such as RASA[3] or ONDEWO[4].

Chat UI. The chat UI is connected to the Conversational AI Platform (Dialogflow) and presents the user with a chat interface. Entered text is sent to the Conversational AI for further processing (intent matching, fulfilment).

4.2 Data Model

To structure learning resources for the learner, our data model uses `topics`. These `topics` can be defined by the provider. A topic contains an ordered set of learning resources, which could be documents, multimedia objects, or quiz questions. As stated in section 3 the transformation of existing digital artifacts into learning resources for the system is an important design objective. Documents are the most common form of preexisting input material - yet they are typically also too long to be consumed in an integrated manner. Thus our data model allows to divide documents into smaller units. We use a hierarchical tree structure of arbitrary depth to organized these document units. Additionally providers can associate learning resources with each document unit.

4.3 Conversational Intent Model

The purpose of the chat interface is to deliver learning resources to learners. To do so, we developed a preliminary intent model that addresses certain situation where learners intend to learn. This preliminary intent model covers more active modes of learning, that are driven by a specific interest or question (see *Search*) as well as more more passive modes of consumption (i.e. the learner lets the bot decide what to learn). Consequently for our preliminary intent model, the following intents have been trained:

[2]https://dialogflow.com/
[3]https://rasa.com
[4]https://www.ondewo.com/

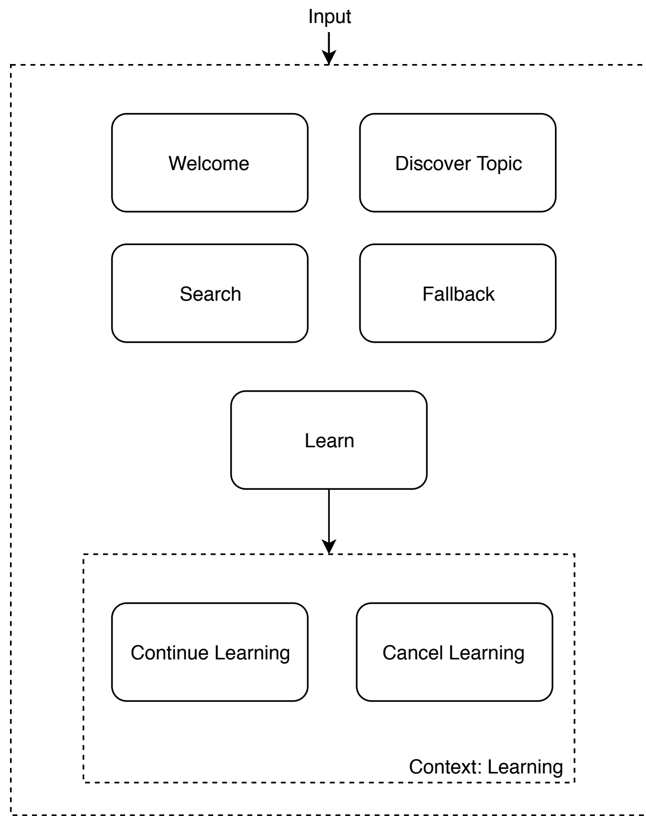

Figure 2: Preliminary intent model.

Welcome. This intent is derived whenever the user enters a greeting like "Hi" or "Hello".

Discover Topics. Responding with a custom message of all available topics in the database, this intent is triggered with phrases like "What information do you have?" or "What do you know?"

Search. "What do you know about conversational AI" could be a phrase triggering this intent. The search intent needs a search term as parameter ("conversational AI" in this case) for further processing. Our custom backend queries the search engine in order to determine the response. The backend can distinguish between a response about a whole topic or a specific chapter inside a topic.

Learn. The learn intent will start the learning process by entering phrases like "I want to learn something about conversational AI". This intent also needs a topic for search and will use slot filling if the parameter is not provided. As seen in Figure 2 the learn intent adds the learning context for further interactions.

Continue Learning. Can only be used when the context is about learning and is triggered when the user responds with words like "Continue" or "ok" and returns the next information about the current topic.

Cancel Learning. Can only be used when the context is about learning and is triggered when the user enters words like "Cancel" or "Stop" to remove the learning context from the current conversation.

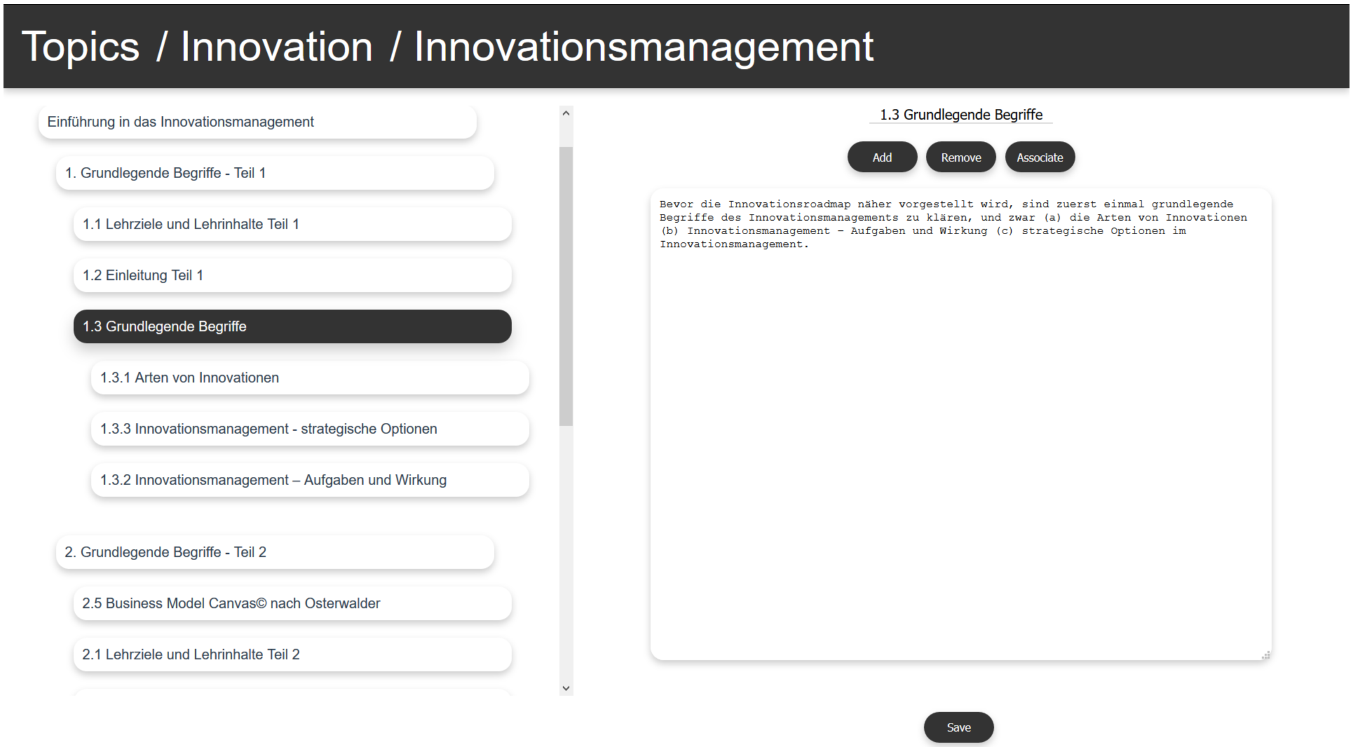

Figure 3: The Document Editor in the Admin Interface allows hierarchical structuring (tree structure on the left) and arbitrary associations between document units and learning resources.

Fallback. When none of the above intents matches a random fallback message is presented to the user like "I didn't get that. Can you say it again?".

4.4 User Interface

The user interface for the provider was designed to streamline the process of uploading and structuring existing artifacts. On the top level it lists the available topics. The detail view of a topic lists the uploaded resources. For documents, another detail view allows to modify the structure, content and associations (i.e. links to other resources) of the document units as shown in Figure 3.

The user interface for the consumer is a chat interface. For our prototype we used existing chat clients supported by dialogflow. Figure 4 illustrates an example dialog from the learners perspective. In the example the learner starts with a welcome intent, followed by a discover topic intent. Subsequently the learner initiates a learning step through a message understood as a learning intent and continues learning with a message classified as a continue learning intent.

5 CONCLUSION AND FUTURE WORK

So far we focused on experimenting with our prototype to optimize the translation of large documents into a fine grained corpus of learning resources. We believe this to be the key process to put conversational AI into the practice of corporate e-learning. For our experiments we used arbitrary documents either from our own

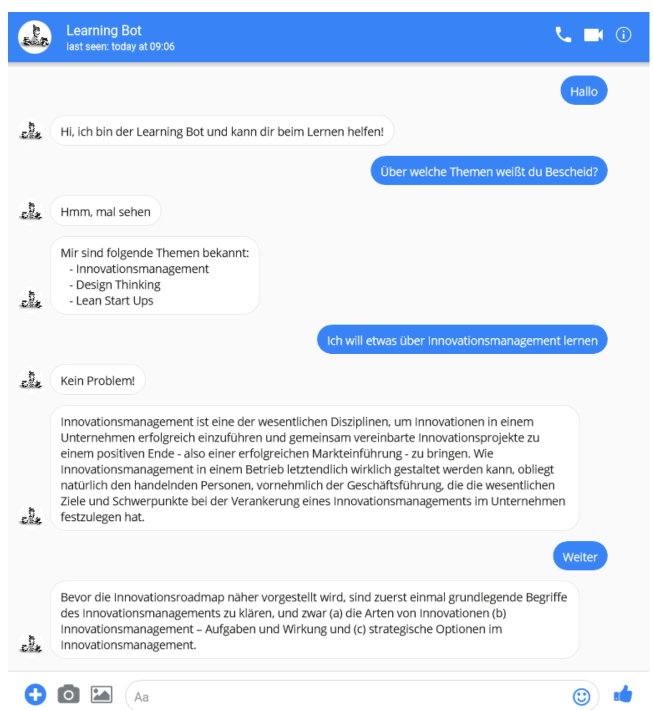

Figure 4: Example Dialog

company or provided by our customer. The prototype was able to extract the structural information of most documents, tremendously reducing the amount of manual structuring and orchestration work.

Concerning the actual learning conversation, we will need to further refine our intent model. For future work, we will conduct a wizard-of-oz study to better understand how learners interact with the conversational AI to inform our model. Subsequently, we plan to thoroughly evaluate the attractiveness and effectiveness of our system for learners. Therefore, we will conduct several case studies on different subjects to demonstrate the domain independent operational capability of our approach. If successful, our approach could decrease implementation and modeling costs of conversational AI systems for corporate e-learning.

REFERENCES

[1] Peter A Bruck, Luvai Motiwalla, and Florian Foerster. 2012. Mobile learning with micro-content: a framework and evaluation. *Bled eConference, 25th Bled eConference eDependability: Reliable and Trustworthy eStructures, eProcesses, eOperations and eServices for the Future* (2012), 17–20.

[2] Gerhard Gassler, Theo Hug, and Christian Glahn. 2004. Integrated Micro Learning–An outline of the basic method and first results. *Interactive Computer Aided Learning* 4 (2004).

[3] Christian Glahn. 2012. Supporting Learner Mobility in SCORM-Compliant Learning Environments with ISN Mobler Cards. *Connections: The Quarterly Journal* 12, 1 (2012).

[4] Alan R. Hevner, Salvatore T. March, Jinsoo Park, and Sudha Ram. 2004. Design science in information systems research. *MIS quarterly* 28, 1 (2004), 75–105.

[5] Alice Kerly, Phil Hall, and Susan Bull. 2007. Bringing chatbots into education: Towards natural language negotiation of open learner models. *Knowledge-Based Systems* 20, 2 (2007), 177–185. https://doi.org/10.1016/j.knosys.2006.11.014

[6] Esther Levin, Roberto Pieraccini, and Wieland Eckert. 1997. Learning dialogue strategies within the markov decision process framework. In *1997 IEEE Workshop on Automatic Speech Recognition and Understanding Proceedings*. IEEE, 72–79.

[7] Esther Levin, Roberto Pieraccini, and Wieland Eckert. 2000. A stochastic model of human-machine interaction for learning dialog strategies. *IEEE Transactions on speech and audio processing* 8, 1 (2000), 11–23.

[8] Benjamin D Nye, Arthur C Graesser, and Xiangen Hu. 2014. AutoTutor and family: A review of 17 years of natural language tutoring. *International Journal of Artificial Intelligence in Education* 24, 4 (2014), 427–469.

[9] Ken Peffers, Tuure Tuunanen, Marcus A. Rothenberger, and Samir Chatterjee. 2007. A design science research methodology for information systems research. *Journal of Management Information Systems (JMIS)* 24, 3 (2007), 45–78. https://doi.org/10.2753/MIS0742-1222240302

[10] Joseph Psotka, Leonard Daniel Massey, and Sharon A Mutter. 1988. *Intelligent tutoring systems: Lessons learned.* Psychology Press.

[11] Jost Schatzmann, Karl Weilhammer, Matt Stuttle, and Steve Young. 2006. A survey of statistical user simulation techniques for reinforcement-learning of dialogue management strategies. *The knowledge engineering review* 21, 2 (2006), 97–126.

[12] Astrid Schmulian and Stephen A. Coetzee. 2019. The development of Messenger bots for teaching and learning and accounting students' experience of the use thereof. *British Journal of Educational Technology* 50, 5 (2019), 2751–2777. https://doi.org/10.1111/bjet.12723

[13] D Schugurensky. 2000. The forms of informal learning: Towards a concceptualization of the field. *WALL Working Paper* (2000).

[14] Satinder P Singh, Michael J Kearns, Diane J Litman, and Marilyn A Walker. 2000. Reinforcement learning for spoken dialogue systems. In *Advances in Neural Information Processing Systems*. 956–962.

[15] Marilyn A Walker. 2000. An application of reinforcement learning to dialogue strategy selection in a spoken dialogue system for email. *Journal of Artificial Intelligence Research* 12 (2000), 387–416.

[16] Steve Young, Milica Gašić, Simon Keizer, François Mairesse, Jost Schatzmann, Blaise Thomson, and Kai Yu. 2010. The hidden information state model: A practical framework for POMDP-based spoken dialogue management. *Computer Speech & Language* 24, 2 (2010), 150–174.

[17] Steve Young, Milica Gašić, Blaise Thomson, and Jason D Williams. 2013. Pomdp-based statistical spoken dialog systems: A review. *Proc. IEEE* 101, 5 (2013), 1160–1179.