# Design and Implementation of Conversational Agents for Harvesting Feedback in eLearning Systems

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**Abstract.** Traditionally conversational interfaces, such as chatbots, have been created in two distinct ways. Either by using natural language parsing methods or by creating conversational trees that utilise the natural Zipf curve distribution of conversations using a tool like AIML. This work describes a hybrid method where conversational trees are developed for specific types of conversations, and then through the use of a bespoke scripting language, called OwlLang, domain knowledge is extracted from semantic web ontologies. New knowledge obtained through the conversations can also be stored in the ontologies allowing an evolving knowledge base. The paper describes two case studies where this method has been used to evaluate TEL by surveying users, firstly about the experience of using a learning management system and secondly about students' experiences of an intelligent tutor system within the I-TUTOR project.

**Keywords:** Conversational Interface, Chatbot, Ontology, AIML.

## 1 Summary

The primary aim of the research behind this paper is to develop a method for implementing conversational agents, also known as chatbots, which can change domain knowledge easily and expand the base of knowledge through conversation for specific conversational situations. This technology could potentially be used in many situations, however this system has exclusively been used within learning situations. By using the developed ontological language (Owllang) together with a traditional chatbot development language a survey chatbot was developed.

This system works by using language prediction. Human is not random but follows a Zipf curve distribution of possible responses to preceding utterances [1]. For instance, if person A says 'Can I try?' to person B, it is very unlikely that person B will respond '2 plus 2 is 4'. The chatbot developer, therefore, can try to cover as many user responses to each chatbot output as possible, using a descriptive chatbot language such as the Artificial Intelligence Meta Language (AIML) [2] to build a map of possible responses to human interaction, in this paper termed conversational trees. One of the earliest examples of this approach is ELIZA which utilized the basic structure of Rogerian therapy sessions to emulate a psychiatrist [3]. This is a trial and error approach where the developer constantly monitors the chat logs to see if new chat

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patterns have been discovered that need to be added to the conversational trees. The problem with this approach is that it is laborious to change any knowledge within the conversational trees. The developed system aids that by allowing knowledge injection into the conversational trees from standard ontologies that can be used to describe world knowledge [4].

A surveying robot has been created that questions users about their opinions. It works in English, and can respond to 8 different types of responses from the users. The system has been tested to evaluate TEL. The first case study was a surveying students about their user experience of the University's Blackboard system. The second test case study has been as an integrated surveyor within an Intelligent Tutoring System through the i-tutor project. Creating these new surveyor chat systems using an ontological approach has proven to be very easy compared to the natural language approach.

It could be argued that the chatbot just works as an automated interviewer, and a human evaluator still has to read through all of the logs, however the chatbot automatically stores what it infers from the communication using the knowledge in the ontologies. These ontologies can be examined using semantic web tools and statistical tools. What the human evaluator needs to do is extract the gist of the value-added information from within the chat, as this is information which would be extremely difficult to automate. The users' responses has also been analysed and the system has proved to understand most users feedback with a 96.7% success rate. There are only minor issues with double negatives and one user clearly misunderstanding the chatbot's question.

## References

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