EagleBot: A Chatbot to Help University Students with Their Questions and to Improve Their Class Quality

Abstract. In this paper, we propose a chatbot based unified system to tackle two major problems in the university domain. We present a system architecture for faster retrieval of answers to the questions asked by students' in university domain. Another contribution in this paper is the chatbot based automated real- and periodical-time course evaluation system for helping students' and teachers' by improving their course quality.

Keywords: QA in University Domain, Automated Course Evaluation, Chatbot in Education

1 Introduction

One of the big challenges at every university or college is how to answer vast amount of students' questions in a fast and efficient manner. Students usually check the university website, send emails, make phone calls or meet in person with the appropriate staff to get their information. Although these methods work, they are limited in certain ways: (a) since the number of university employees are restricted; (b) university staff are not available around the clock and more importantly (c) students mostly require to carry out extra work such as navigating the university website to extract the desired information from there. Another place where there is a scope of improvement in this university domain is the issue of course evaluation. Traditional way of taking feedback about a course at the end of the semester has the disadvantage of not benefitting the students who have already taken the course [1]. So, we propose a unified chatbot approach, called Eaglebot, to answer the variety of questions that students have asked on academic domain and for solving the traditional course evaluation approach. For the case study, we partially use the Georgia Southern University (GSU) portal.

Chatbots are increasingly gaining popularity in the university domain for different tasks. Jill Watson, the Georgia Tech teaching assistant chatbot [2], has demonstrated the strong possibility of chatbots in education domain. Jill Watson has shown the promise to be an alternative of teachers' in near future. In 2016, a Boston based EdTech startup named Admithub gained a huge success by launching a chatbot in Georgia State University for reducing Summer Melting [3-4] and helping high school students on their transition period to college [3-4].

Besides these two applications we have also seen chatbots deployed in university domain for answering question for a specific course by using previous years' chat discussion board as training data [5]. (1.) All these above mentioned chatbot systems work for a very specific domain and don't deal with the whole university domain. As of now, to the best of our knowledge, there is no such integrated system for answering all types of questions asked in the university domain. (2) All of these systems work from students' perspective (i.e. How to help students ' by providing required information) but none of them work from both students' and teachers' perspective. So, we aim to tackle this double-folded problem in our architecture.

2 Approach

Currently the EagleBot architecture consists of two major modules. 1.) The QA module, 2.) Course Evaluation Module. Below is a brief description of these two modules.

Question-Answer Module: Figure 1. shows the architecture of the QA module. User starts the conversation via a chatbot interface. We utilize Dialogflow's NLU engine to understand the user's query and identify the entities and intent of the question. We can recognize different variations of the same query using this NLU tool. Then, based on the analysis results, the Flask powered backend will try to select the answer of the question. For faster retrieval at the current state, we focus on three different routing for extracting the answers of the questions as follows:
Type 1- Question answering on Structured Data. This route gets the highest priority, so the system tries to find the answer from this module first. We pre-store all the frequently accessed tabular data and structured data in our data storage. So, once the server maps the user question into structured query, we search into our data storage to find the answer. If the answer is found, the server generates the answer from the returned data and reply back to the user. If the answer is not found in this module, the system search in the second module described below.
Type 2- Question answering from FAQ data. This route gets the 2nd highest priority during the retrieval time. Frequently asked questions (FAQs) are invaluable source of information for answering most common questions asked by the users. We collect all the possible FAQ web pages, extract the questions with their answers and then train a Recurrent Neural Network model on those questions and answers in order to be able to extract the answer of the exact question or a variation of it. But it comes out that simpler approaches like cosine similarity measures using TF-IDF and word2vec also perform reasonably well for this task [9]. We are also experimenting with LDA topic modeling for this task.
Type 3- Question answering from unstructured passage data. Questions not falling on the first two types come to this module. Many times answering questions needs analyzing unstructured text i.e. the answer is hidden inside a large span of text. Extracting answer in this of situation is the hardest among the three types we are describing here. Like many question answering systems [5,10], our architecture first tries to analyze the question, then select few candidate answer passages and finally from those candidate answer passages we extract the answer by using both supervised and unsupervised methods. We are using cosine similarity measures with Facebook Sentence Embedding (Infersent) and dependency parsing tree for unsupervised methods [11]. For supervised techniques, we are using logistic regression, random forest, XGboost methods.

Recently, BiDAF (Bi-directional Attention Flow) [12] and DMN (Dynamic Memory Networks) [13] have shown great promise in the field of NLP particularly in question answering, text comprehension and understanding. Thus, we are experimenting with these methods too. If the answer is not found in this module, the system takes the human assistance finally.

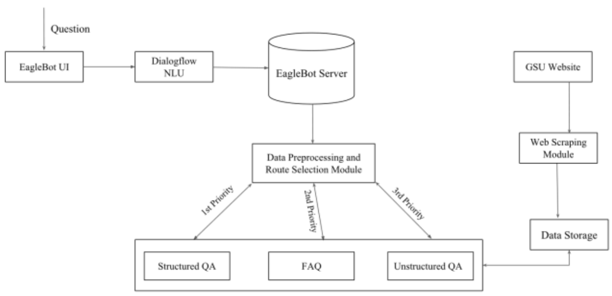

Fig. 1. The Question-Answer Module Architecture of EagleBot

Course Evaluation Module. To get benefit from course evaluation, feedbacks should be taken during the semester [1]. A lot of researches have already been done for analyzing real time sentiment analysis using students' feedback. For gathering the feedback data methods like clickers, SMS, Mobiles Phones [14-15] and even Twitter data was used [16]. Some of the above mentioned methods (Clicker, SMS, Mobile Phones) affect students' attention during the class-time and again some of the methods (i.e. Twitter) don't assure bold and honest participation of students as they can reveal students' identity. So, we propose an anonymous method based on chatbot for solving both above issues (As shown in figure 2.). Student can put their opinion anytime through EagleBot in an anonymous way (shown in figure 3.b) as we hash their identity to assure the privacy. After receiving the students opinion EagleBot cleans and preprocess the data and pass it to the evaluation module which calculates the sentiment of each courses (gives teacher the idea of students' sentiment in a specific course), the bot then extracts the most talked topics using LDA (gives teacher the idea of which topics need the attention) and summarize the texts using Attention mechanism (saves teachers' time as the teachers don't need to read all the comments). Teachers can get the report in two ways. Either they can request to the bot for the report or they can have the report in a periodical fashion on their emails.

Prediction accuracy of a Machine Learning model depends on the quality of the data fed into the model. The model will perform poorly if the quality of the training data is not good. Interactive Machine Learning approach solves this issue by including human involvement in the training process [16]. For EagleBot we use Interactive ML system where users' can provide their valuable feedback data to the system for better learning. The bot is using these feedbacks to improve its learning every day and alleviate the necessity of a dedicated human assistant for this task.

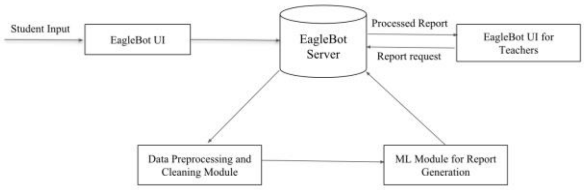

Fig. 2. Course evaluation module architecture

Data Collection and Evaluation

Collecting data is one of the main challenges in this project, as there is no existing dataset of QA in University domain. With the help of GSU Administration and using Google Analytics we extracted the most frequent topics. In our architecture we give higher priority to these topics when we search for the answers for any asked question. Currently, we are collecting the dataset using several different techniques. We are collecting and extracting data from all the relevant websites in GSU.

We have done qualitative assessment to check the performance of the system. We chose eight volunteer testers to check the effectiveness of the system. According to the reviewers' opinion, performance of the system is decent and satisfactory. On the next phase of the project, we plan on making it available for the students of the GSU. Therefore it will allow us to comprehensively test the framework qualitatively and quantitatively, as well as helping us to enrich our dataset.

Fig. 3. 1.) Left image presents a basic EagleBot UI, 2.) Bot is taking feedback about Dr. "X" from a student, 3.) The bot is answering to a student's question about RAC/Gymnasium timing.

Conclusion

Although the project needs more time to become mature and fully developed, it is already showing great promise in this field. The proposed chatbot approach is a general framework that can be utilized in other institutions and universities. Additionally, this project can be easily adopted for use in other domains.

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