Towards Conversation Chatbot for Educational Purpose

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***Abstract*—Chatbots are one of category of intelligent, conversation agents stimulated by natural language input and provide conversation output in response. This technology initiated in early 1960s, since then numerous amounts of methodology is used to develop a competent chatbot, which can interact with the user and mimic human conversation. Natural Languages Processing provide ample toolkits for understanding the contextual concept of text. In this study, utilizing the NLP toolkit we developed a rule based chatbot, which responses to user input, after identifying the dialogue act type and grasp the topic discussion of user input.**

I. Introduction

Chatbots or conversational assistants are software programs, which deliberately works on the principle of interpreting and responding to the conversation initiated by a user using some natural language processing-based technology.This includes personal assistant, informative bot and interactive game character, as an innovative concept that can serve plenty of purposes. Although there are intensive studies that undertake the development of the agents or assistant which can serve the purpose in accordance to user needs, only a limited prototypes have been successful [1]. This is mainly attributed to the complexity and variety of human language, combined with limited capabilities of existing natural language processing (NLP) techniques nowadays. Despite such inherent limitations, chatbots have seen rapid growth across various disciplines (e.g., insurance, travel, online stores), overtaking some of tradition jobs usually performed by the human workers. They are found to provide important cost and labor saving to the underlined companies. Distinguished examples of chatbots include Early chatbots: ELIZA, PARRY; Modern chatbots: A.L.I.C.E., Jabberwacky; Big companies products: Siri, Google Assistant.

They are developed to interact with the users to assist them in different fields such as health, banking, social media, maps etc. Chatbots have been identified as having significant promise and having different purposes with different conversation [2]. Along the wave of speech recognition and artificial intelligence, chatbots of various capabilities are emerging and being relied upon [3]. More complex bots are envisioned to engage in meaningful conversation with their users, relying on natural language processing and Artificial Intelligence (AI) to become more human-like and intelligent in their engagement [4]. One distinguishes two variants: rule-based and self-Learning. In the rule based approach, the bot responds based on some rules that it is trained on. The rules can be simple to complex. However, these bots are well suited to handle simple queries but mostly fail to handle complex ones. In self-learning approach, the bots often use machine learning like approaches. Self-learning approaches are further divided into two types: Retrieval based and Generative. In retrieval-based models, a chatbot utilizes some heuristic to choose a answer from a library of predefined responses. Whereas, in generative models the bots generally, generates the answers from a set of answers already known to it[5].

In this study, a rule-based chatbot approach is designed and implemented. The chatbot interaction is focused on the domain knowledge of course related materials and general life within university premises. The response decisions are made on the basis of outcomes obtained from the Dialogue act classifier and the utterances. We utilize the SentiStrength tool, which reports two sentiment strengths for positive and negative sentiments. Each sentiment is provided in the scale from -4 to +4. SentiStrength uses a dictionary of sentiment words with associated strength measures and exploits a range of recognised non-standard spellings and other common textual methods of expressing sentiment.

II. Background

A. Dialogue Act Identification

Dialogue types act are common in most of the conversation regardless of domain or medium. In linguistic and natural language understanding, dialogue is defined as an utterance in a conversational dialog. It includes question, statement, answers, request etc. There have been numerous amounts of studied conducted in tagging, identification and classifying the dialogue act in chat utterance[6].

B. Topic Modelling

Determining the dialogue act of the utterance is often not enough to trigger appropriate action by the intelligent assistant. A commonly employed additional parameter is the topic of the discussion that can be inferred automatically from the textual input. For this purpose, a standard Latent Dirichlet Allocation (LDA) [7]. The latter enables discovering latent semantic structure from text corpus without requiring any prior annotations or labeling of the original source document. In this context, each document (utterance) is viewed as a mixture of various topics where each topic is characterized by a distribution over all the words. Statistical techniques (e.g., Gibbs sampling) are then employed to infer the latent topic distribution of each document and the word distribution of each topic using higher-order word co-occurrence patterns. A rational when dealing with short text topic modelling as opposed to standard document is to restrict the number of topics to a minimum (one or two per LDA call). This approach has been widely employed in growing research of short text topic modelling (see, survey paper by Qiang [8])

C. Sentiment Analysis

Sentiment analysis concerns the determination of the polarity of the utterance, e.g., whether it has positive or negative or neutral polarity. For example, positive texts may include expressions of happiness, love, contentment and euphoria, while negative expressions include hate, negative emotions, among others.

III. METHODOLOGY AND USER INTERFACES

A. Dataset

We focused on th fifteen dialogue act model whose corpus is given by NPS Chat dataset put forward by Forsythand and Martell [2]. NPS Internet Chatroom Conversations dataset [2] was used in this study. It contains 10567 utterances (posts) from 15 online chatrooms. The corpus is focuses on the computer interceded communication instead of written conversation or traditional spoken. One of the reasons of employing this dataset, is the characteristic of annotating with a tag set consisting of 15 dialogue acts [9]. The dialogue-act tags are Accept, Bye, Clarify, Continuer, Emotion, Emphasis, Greet, No Answer, Other, Reject, Statement, System, Wh-Question, Yes Answer, Yes/No Question.

TABLE I. 15-DIALOGUE ACT AND THEIR OCCURRENCES IN NPS CORPUS

Dialogue Act	% in NPS Chat Corpus
Statement	42.5%
Accept	10.0%
System	9.8%
Yes-No-Question	8.0%
Other	6.7%
Wh-Question	5.6%
Greet	5.1%
Bye	3.6%
Emotion	3.3%
Yes-Answer	1.7%
Emphasis	1.5%
No-Answer	0.9%
Reject	0.6%
Continuer	0.4%
Clarify	0.3%

B. Methods and Approach

Initially, the utterance text messages undergo a preprocessing task. The latter includes identification of various textual chunks, tokenization, part of speech tagging, and uncommon characters. For each utterance, the system outputs i) the corresponding dialogue act using SVM based approach trained on NPS dataset; ii) topic keyword (s) using a reshaped LDA based approach tuned to output only one single topic; iii) sentiment score using SentiStrength tool. The three outputs of the three submodules (dialogue act, topic, sentiment) are then combined through a set of heuristics in order to yield appropriate response of intelligent assistant (chatbot). The detail of this heuristic is not detailed in full but follows commonsense reasoning of discussions occurring among students with respect to course related topic materials. For this purpose, the skeleton of approach is summarized below:

1) A simple dictionary of main keywords that are relevant to such discussion is elaborated. This includes for instance, Teacher, Class, Modules, Exam, Laboratory, Mark, among others.
2) An initial set of dictionary terms is obtained by gathering two distinct dataset: a dump version of University of Oulu website (English version) and student guide for University of Oulu Master students, which contains both technical details about the various courses, including course syllabus, and general life in university of Campus. The key advantage of such dictionary is to limit the growing challenges of chatbot when the discussion is unbounded.
3) The keywords *S* appearing in the title of section and/or subsections of either university website damp data or student guide document are treated with cautious. Therefore, these keywords are expanding using a list of semantically equivalent words. For this purpose, the PYThesaurus API was employed. Besides, in order to avoid possible miss-constructions and misconceptions, the outcomes of the API for each individual words is also manually checked by two experts.
4) A set of rules involving keyword (s) in S is elaborated. In each rule, say, R_j the consequent part is constituted by a set of statements Y_i (i=1 to mj). For example if the utterance contains statement “I failed Information Theory course”, the consequent part contains statements like “no worry, you still have chance”, “there is always another chance I guess”, “maybe you can compensate by another course”. Another example relate when the user’s utterance fits with “Accept” dialogue act class, for instance “OK”, “YES”. In that case, the prototype answers should accommodate the sentiment of the previous user’s utterance. If the latter is positive sentiment, then a set of prototype answers include Good, nice to hear, very good, great. If the user’s utterance does include any element of S, and not of obvious dialogue act classes (agreement, accept), the prototype answers are such that to terminate the discussion with the user, e.g., thank you for your chat, need to leave now, wish all the best, have nice rest of the day.
5) The system chooses a response at random among the statements in the consequent part of the rule Y_i. This expects to avoid boredom type of situations, which can cause the user to leave the chatbot.
6) The process of mapping involves matching the utterance topic with statement involving keywords *S*. This would discard situations in which the discussion is not related to any university like topic.

Therefore, the dictionary enables us to design specific prototypes of answers when dealing with specific utterance message. An example of such construction is provided in Fig. 3

C. Interfaces

The conversional assistant “Chatbot” is built as a web user interface (UI). Django web framework is used for the UI

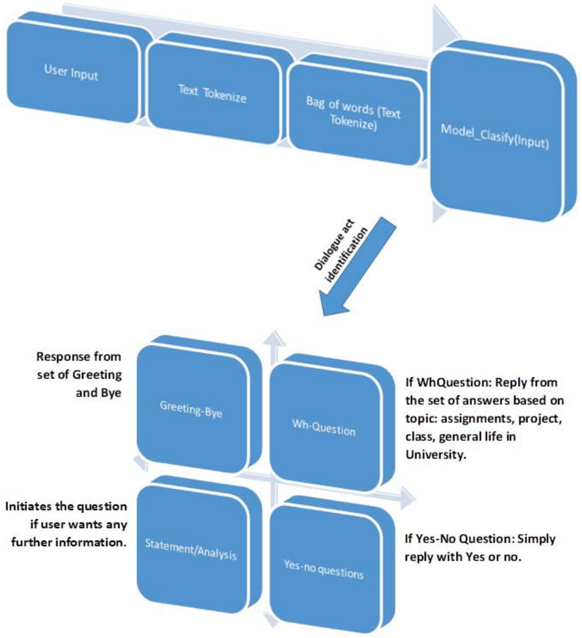

Fig. 1. Example of Chatbot response

implementation due to its fast response in connecting backend and frontend. The user interface is simple as shown in Fig.4. Besides, a mobile interface is also constructed as shown in Fig 5. The application has main welcome screen. The welcome screen has a 'Ask Bot' button when the user clicks the ask bot button it open a new screen where the ROBO welcome the user with 'hi, May I help you?'. The user user can put a query and send it the backend server where SVM if applied and display a response from chatbot.

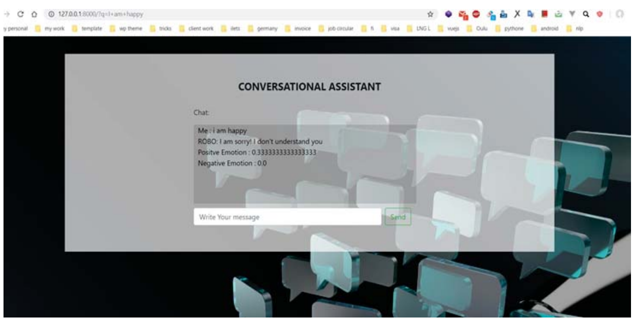

Fig. 2. Example of Chatbot response

IV. Conclusion

The emerging trend in AI and ML, creating an opportunity for conversation assistant or Chatbot to be the assistant for human in near future. In this paper, the main motive is to investigate the design and implementation of a chatbot restricted to educational purpose. The design includes the development of ontology related to the student life and course content of University of Oulu master degree program. The chatbot

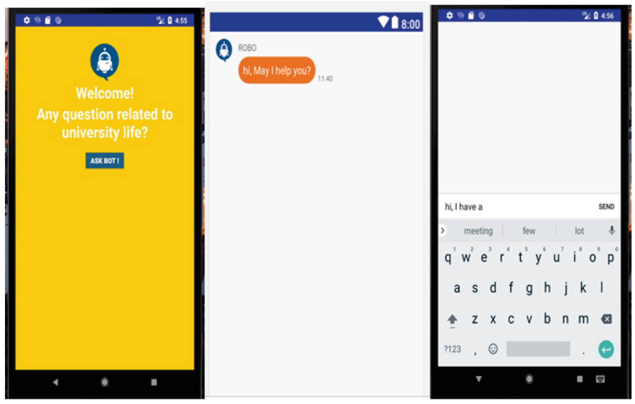

Fig. 3. Example of Chatbot response

utilizes outcomes from three key processing units:dialogue act classification, topics analysis and sentiment scores. A set of hot-hoc prototype answers are therefore elaborated based on the outcomes of the three units and intersection with ontology previously elaborated. A simple test case examples are highlighted in the paper. Further development will concern the process of automating the elaboration of ad-hoc prototypes answers. There is also a room for further enhancement of the process by incorporating selflearning models that learn from previous discussion and utilize some metadata and benchmark data available elsewhere. We believe such development will be very relevant in student exhibition activities as well as recruitment process.

References

[1] B. A. Shawar and E. Atwell, "Chatbots: are they really useful?," in *Ldv forum*, vol. 22, pp. 29–49, 2007.

[2] E. N. Forsythand and C. H. Martell, "Lexical and discourse analysis of online chat dialog," in *International Conference on Semantic Computing (ICSC 2007)*, pp. 19–26, IEEE, 2007.

[3] L. Bradeško and D. Mladenić, "A survey of chatbot systems through a loebner prize competition," in *Proceedings of Slovenian Language Technologies Society Eighth Conference of Language Technologies*, pp. 34–37, 2012.

[4] H. Lynn, "Dialogue Act Recognition for Conversational Agents," Master's thesis, Utrecht university, 2017.

[5] K. Shridhar, *Rule based bots vs AI bots*, 2017 (accessed February 13, 2019).

[6] A. Stolcke, K. Ries, N. Coccaro, E. Shriberg, R. Bates, D. Jurafsky, P. Taylor, R. Martin, C. V. Ess-Dykema, and M. Meteer, "Dialogue act modeling for automatic tagging and recognition of conversational speech," *Computational linguistics*, vol. 26, no. 3, pp. 339–373, 2000.

[7] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *Journal of machine Learning research*, vol. 3, no. Jan, pp. 993–1022, 2003.

[8] Q. Jipeng, Q. Zhenyu, L. Yun, Y. Yunhao, and W. Xindong, "Short text topic modeling techniques, applications, and performance: A survey," *arXiv preprint arXiv:1904.07695*, 2019.

[9] T. Wu, F. M. Khan, T. A. Fisher, L. A. Shuler, and W. M. Pottenger, "Posting act tagging using transformation-based learning," in *Foundations of data mining and knowledge discovery*, pp. 319–331, Springer, 2005.