International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-8 Issue-12, October 2019

An Embodied Conversational Agent using Retrieval-Based Model and Deep Learning

Pui Huang Leong, Ong Sing Goh, Yogan Jaya Kumar

Abstract*: In accordance to the Fourth Industrial Revolution, the emergence of the digital transformation alongside with the collaboration between networked machines and human beings in decision-making has attracted much attention globally. The utilization of conversational agent to convey information on behalf of human have gained popularity and been used extensively. As a result, this research intends to examine and to innovate the current corporate website by providing the capabilities to deliver instantaneously replies and reliable information through the integration of a conversational agent via deep learning, comparable to communicating with the competent customer service consultant. This study is reliant on the Artificial Intelligence (AI) to offer natural language processing (NLP) by presenting retrieval-based model and Deep Learning to enable the conversation agent to make smarter and better decision in generating reliable and up-to-date responses. Furthermore, this research intends to automate the process of minimizing the need for human interference, specifically the botmaster to perform the knowledge maintenance manually.

Keywords: Conversational Agent, Retrieval-Based Models, Deep Learning, Artificial Intelligence, Predefined Questions Recommendation.

I. INTRODUCTION

In the present, end users are experiencing an information revolution whereby the attempt to retrieve relevant and appropriate information, resources and services quickly is now a challenge. In earlier times, offering a reliable contact information with an experienced customer service team to respond to the questions was suffice to please and fulfil the customers. Nevertheless, in the world nowadays, customers are expecting a speedy response or assistance whenever they posed a question or problem. The so-called fix-it-now attitude triggers frustration with info lines and talking to the customer service consultants who are either inexperienced, uninformed or detached from the customers' problems and needs. Due to customer requirements and in accordance with the Fourth Industrial Revolution, companies have made suitable plans and advances to become competitive[1].

Likewise, several enterprises have been seen to adopt the agent technology to boost productivity [2], [3], [4]. Furthermore, companies are starting to adopt conversational intelligence agent to innovate their existing corporate website by introducing a chat option as a means of instant communication with their clients. The chat option allows more freedom, allowing customers to start a conversation whenever and wherever with their questions, problems and issues whereby the services are obtainable every moment regardless of the time. A late reply, imprecise information, staff absenteeism, behavior or attitude of the staff in conveying information are the major issues faced by customers when seeking for information in every industry. In most of the cases, those who are approaching the customer service consultant are likely to have similar questions in which the consultant needs to repeat the series of same dialogues countless times in a day. The above-mentioned issues could be overcome by having the conversational agent to provide an automatic reply or response, comparable to chatting with the customer service consultant.

This research intends to innovate the information retrieval in the industries, by providing the capabilities to deliver instantaneously and reliable replies through the integration of a conversational agent to offer the service comparable to communicating with the competent customer service consultant. This study is reliant on the Artificial Intelligence (AI) to offer natural language processing (NLP) by presenting retrieval-based model and Deep Learning to make smarter decision making in generating reliable responses. Moreover, majority of the current approaches automate the knowledge base maintenance via supervised learning in which the botmaster has to regularly maintain and supply relevant information which are ineffective and tedious. This research is further improved by presenting the knowledge base builder to minimalize manual botmaster intervention. This research intends to automate the process of minimizing the need for human interference, specifically the botmaster to perform the knowledge maintenance manually. Via this enhancement, the botmaster or even the staff, is able to perform the knowledge base maintenance by updating the unanswered questions or adding the new FAQ without any programming Knowle dge. This is deemed vital as the botmaster might not always be available to perform the knowledge base maintenance manually.

Revised Manuscript Received on October 30, 2019.
***** Correspondence Author
Pui Huang Leong*, Faculty of Computing and Information Technology, Tunku Abdul Rahman University College (TAR UC), Johor, Malaysia. Email: leongph@tarc.edu.my
Ong Sing Goh, Centre for Advanced Computing Technology, Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM), Melaka, Malaysia. Email: goh@utem.edu.my
Yogan Jaya Kumar, Centre for Advanced Computing Technology, Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM), Melaka, Malaysia. Email: yogan@utem.edu.my

II. RELATED WORK

Conversational agents or commonly known as chatbots are getting much attention in many industries. For instance, the research conducted by [5] designed a healthcare system to provide assistance in the remote area to overcome the absenteeism of medical support, whereas [6] have advanced the medical industry by scheduling intelligent appointment. The author in [7] attempted to offer medical support via chatbot to predict the disease based on the symptoms given by the user besides providing the proper cure or treatment. The above-mentioned studies show that the chatbot is still lacking in intellectual properties upon a conversation. The application of chatbot has been seen promising and researchers have been advancing the chatbots over the years, such as incorporating the Natural Language Processing (NLP) and pattern matching [8]. On the other hand, [9] emphasized on creating an education chatbot for visually impaired users. This chatbot provides the capabilities to converse or interact with users via speech or voice recognition through the knowledge obtained from Wikipedia.

The effort to introduce a smart chatbot scheme with Collaborative Filtering in the travel domain via the Restricted Boltzmann Machine (RBM) to gather user preferences and provide recommendations can be seen in [10]. The work done by [11] can be seen to design a chatbot system to help in solving data structure problems. Apart from the researches above, [12] developed comprehensive review of implementing a chatbot by improving the search performance via natural language query. The research undertaken by [13] reveals the use of deep learning by linking different designs and metric choices to improve the efficiency of the image retrieval system. In addition to these, researchers [14] and [15] had applied deep learning for image retrieval. More applications of deep learning can be seen in the work by [16] which used deep learning for fast cover song retrieval and the work by [17] applied deep learning for multimedia retrieval. The research carried out by [18] as well as [19] applied the deep learning method, CNN to improve the performance of image retrieval. In addition, [20] integrated deep learning methods for reaction creation also known as response generation into a customer service chatbot. The research performed by [21] uses the model of neural networks for reading comprehension to forecast response depending on the text provided. It can be seen that deep learning is typically applied in the area of information retrieval and image retrieval. The above studies show that there is still a shortage of thought in applying deep learning to conversational agents. Hence, the idea of incorporating deep learning in the development of conversational agents has been deemed crucial and inspired this study.

III. SYSTEM ARCHITECTURE

This framework works similarly with the client-server computing. Initially, clients who poses questions in mind for the corporate are welcome browse through the corporate website. Tarie (The AI Revolutionization in Embodied Conversational Agent), a conversational agent is readily available in the corporate portal to act as customer service consultant in answering the queries. The chat interface in our research is innovated by presenting the capability to suggest the top twenty popular questions to users based on the popularity of the previous conversations. The queries will be subject to a sequence of identification to define whether the queries are posted in either speech or text-based type. The interpreter then performs corresponding patterns by relating to the records containing the chatbot's knowledge bases. These knowledge bases include the chatbot's associated data such as common knowledge and knowledge specific to the domain. This research is innovated by presenting the application of Retrieval-based model and Deep Learning. If the queries matched the keywords from any of the FAQs, predefined recommendations would be displayed on the chat interface based on the popularity on previous conversations. However, if the queries could not be found from either the common knowledge or corporate FAQs, the chatbot is capable to perform answer lookup from the corporate portal via a process called deep learning. The full conversation is registered for data analysis in the logged-file to enhance the chatbot's efficiency. The system architecture of this research is further explained in the following sub sections. The system architecture and entire flow of this research is portrayed as in Figure 1 and Figure 6.

A. Corporate Portal

Corporate Portal is a technological way of presenting information, services, products, details and information pertaining their corporates to the public through the form of webpage. It is intended to provide technical supports to users without having the users to visit the corporate personally. The corporate portal is revolutionized by integrating a chatbot to deliver consistent, enthusiastic and helpful assistance to locate the relevant information, similar to chatting with the customer service consultant. The conversational agent, named Tarie is installed into the corporate portal via a one-click plugin. Users may prompt their desirable questions either by typing in the text field provided or by using voice recognition. Upon receiving the input, the conversational agent will generate the appropriate responses accordingly.

i. Predefined Question Recommendations

In most of the cases, clients have questions pertaining to the corporate in mind. However, due to the reasons such as the language proficiency, culture, ethnic, they might not be able to put the words in the terms that is understandable by the chatbot. Similar to human conversation, one is only able to respond correctly if they are able to understand the question asked. Hence, if the chatbot is unable to understand the queries, the chatbot might interpret wrongly and the respond given might eventually be incorrect. To the worse extent, clients might not even know what questions to begin with. Hence the introduction of predefined question recommendation is able to solve the ambiguity of clients by suggesting what are popular questions posed by other clients previously. This research uses the similar concept as the Google's Suggest to speed up the search interaction, prevent ambiguity as well as to enhance the chatting experience. Initially, Tarie would predict what the client is searching via

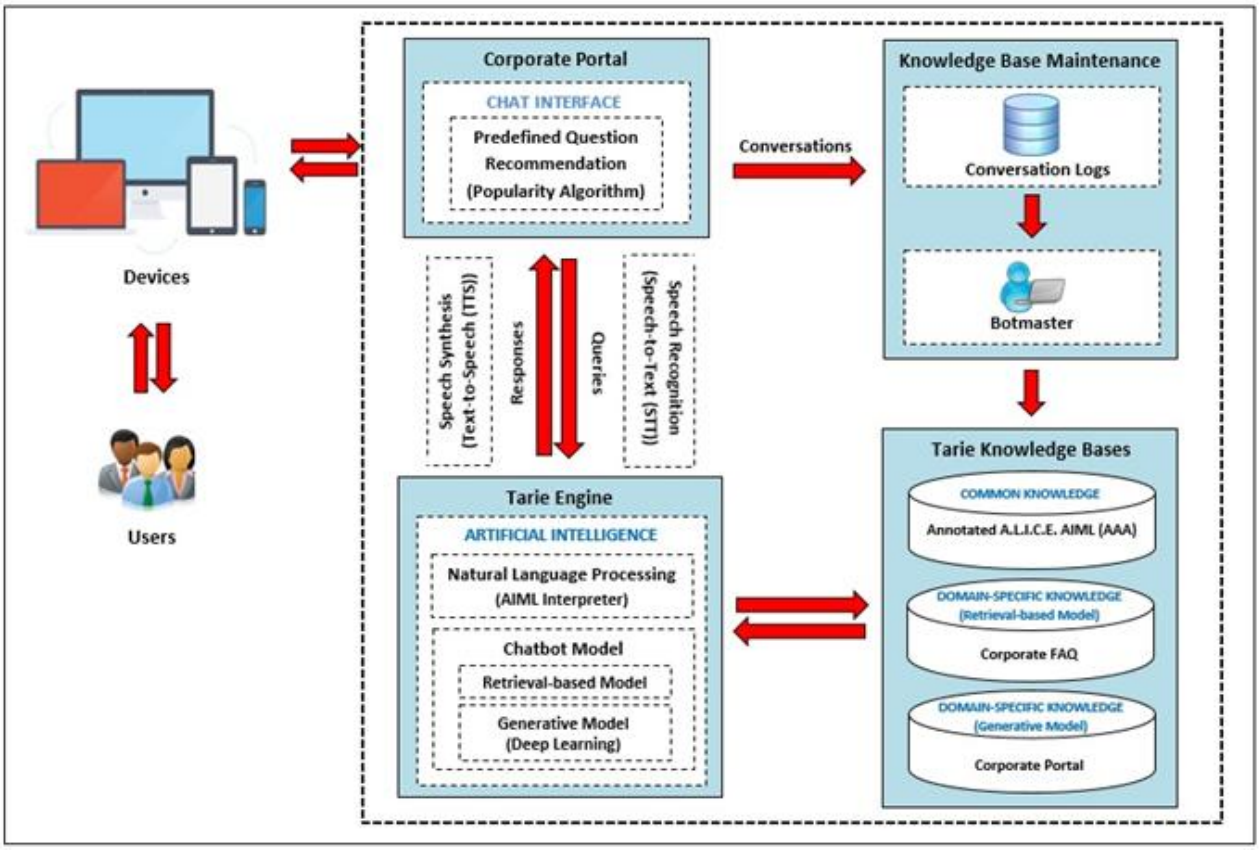

Fig. 1. System Architecture

the keywords typed. If the keywords matched the predefined set of questions based on the recent popularity; the popular questions would be displayed to the chat interface as to provide suggestions to the client as in (1) where I refers to predefine interface, n refers to numbers of questions, $1 \leq n \leq 20$, $Q_{P(1\ max)}$ refers to question with first popularity, $Q_{P(2\ max)}$ refers to question with second popularity and $Q_{P(n\ max)}$ refers to question with n popularity.

$$I_{[1 \rightarrow n]} = [Q_{P(1\ max)}, Q_{P(2\ max)}, \ldots Q_{P(n\ max)}] \quad (1)$$

For brevity, only top twenty popular questions would be displayed in the chat interface. Moreover, the keyword typed would be highlighted in red whereas the hover would be highlighted in grey to improve interactivity as portrayed in Figure 2. Then, client could generate the question simply by clicking the suggested predefined recommendations. The response for the predefined recommendation is illustrated as in Figure 3. The predefined recommendations use popularity algorithm to suggest the best matching search queries for the entered keyword in real time. It works on AJAX to lively update the popularity of the questions without reloading the page. The popularity algorithm is able to remember the conversations and to learn and grow over time. Unlike conventional keyword-based chatbots, the introduction of popularity algorithm enables the chatbot to be smart enough to self-improve based on what users are asking and to decide the information that is important to remember.

B. Tarie Engine

This study is reliant on artificial intelligence (AI) for Natural Language Processing (NLP) by introducing Retrieval-based model and Deep Learning to enable the chatbot to make better choices when responding to queries.

i. Natural Language Processing (NLP)

NLP is an AI subset to help machines understand, interpret and manipulate human language, designed to close the gulf between human and machine communication. NLP could be driven from various disciplines, which includes the computational linguistics as well as computer science. NLP is needed in this research to assist the conversational agent to interpret and understand the meaning from human queries.

ii. Retrieval-based Model

Chatbot via retrieval-based model is trained via a repository of predefined responses in which the developer pre-determined the set of questions and the possible outcomes. The chatbot is capable to perform answer lookup for the most relevant answers based on the pre-determined questions and answers in the repository. As all the responses are pre-determined, the chatbot developed via this model is able to handle queries fairly good. For instance, the responses generated via this model are very unlikely to have issues such as grammatical, spelling or syntax errors. Despite of this, the drawback of this model is shown every time the queries are not to be found in the repository.

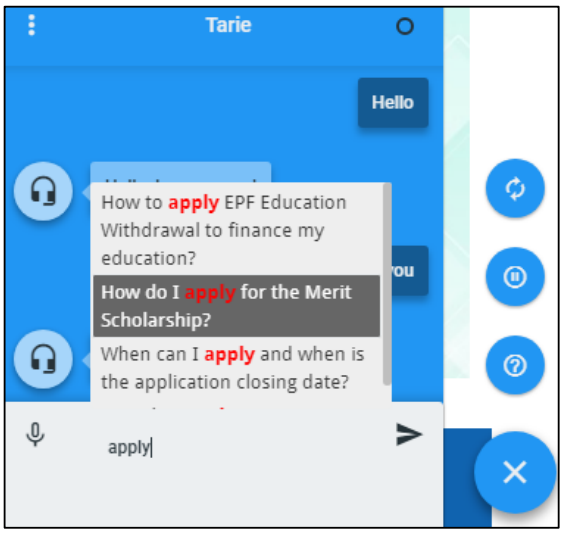

Fig. 2. Predefined Questions Recommendations

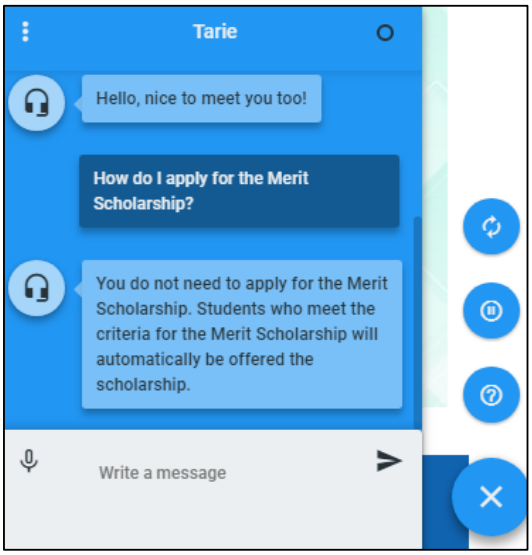

Fig. 3. Predefined Questions Selection

This drawback is then solved via Deep Learning in the next section. In this research, the conversation agent is first reliant on retrieval-based model to match the user queries to domain-specific (retrieval-based) repository to find the score as in (2) where S_Q refers to matching score of user queries to predefined question in repository, S_{preset} refers to preset score from each preset categories and $\sum[S_{preset}]$ refers to total score from all preset categories. This model then retrieve answer from domain-specific (retrieval-based) repository as in (3) where A_{RQ} refers to the answer from domain-specific (retrieval-based) repository, $S_{Q1}, S_{Q2}, S_{Q3,...} S_{Qn}$, refers to the matching score of user queries to predefined question in repository, $\max[S_{Q1}, S_{Q2}, S_{Q3,...} S_{Qn}]$ refers to the highest matching score whereas $A[\max[S_{Q1}, S_{Q2}, S_{Q3,...} S_{Qn}]]$ refers to the answer with the highest matching score. Figure 4 shows the example of the conversation via retrieval-based model.

$$S_Q = \sum[S_{preset}] \quad (2)$$

$$A_{RQ} = A[\max[S_{Q1}, S_{Q2}, S_{Q3,...} S_{Qn}]] \quad (3)$$

Both the question and answer are predefined in the repository and the chatbot will perform the answer lookup to locate most relevant answer. If the queries are not to be found in domain-specific (retrieval-based) repository, the conversational agent will then match the user queries to common knowledge repository to find the score as in (2) and (3). If no matching has been found, the conversation agent will then perform answer lookup via Deep learning which will be discussed in the following section.

iii. Deep Learning

Deep learning is a branch of research on machine learning to learn representations of data. The application of deep learning enables the conversational agent to acquire better representations for matching the intent and content which indirectly provide better decision making in providing smarter responses. The chatbot is much more advanced as it is capable to generate responses on its own, and not reliant on

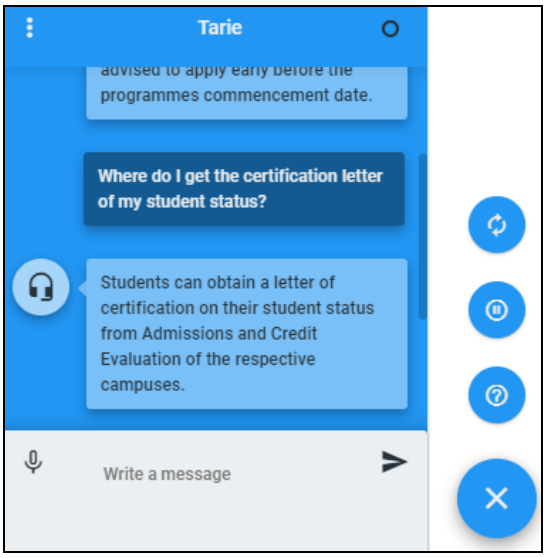

Fig. 4. Conversation via Retrieval-based Model

the predefined set of questions and answers. However, as this model is intelligent to make own decision and generate the answers based on its understanding from scratch, the possibilities of getting responses with spelling and grammatical errors need to be taken into account. This research is reliant on Deep Learning for answer lookup for any unanswered queries to make smarter decision. If the queries are not to be found under common knowledge or domain-specific (retrieval-based) knowledge bases, the chatbot is capable to perform answer lookup via Deep Learning to search for the possible answers via the corporate portal. This is vital as not all the relevant information is portrayed under the corporate FAQs; this approach could assist client to speed up the information retrieval by having answer lookup from the corporate portal.

Initially, the content from the website will be crawled via crawler to perform question and context encoder as in (4) and (5) in which r_t^Q refers to the new representation of all words in the questions, $BiRNN_Q$ refers to Bi-directional Recurrent Neural Network,

^{Q} refers to queries, w_t^Q refers to word-level embeddings, c_t^Q refers to character-level embeddings, t refers to node whereas

$$Z_t^{cx} = \text{BiRNN}\,(Z^{cx}_{t-1}, [qar_t^{cx}, c_t]) \quad (7)$$

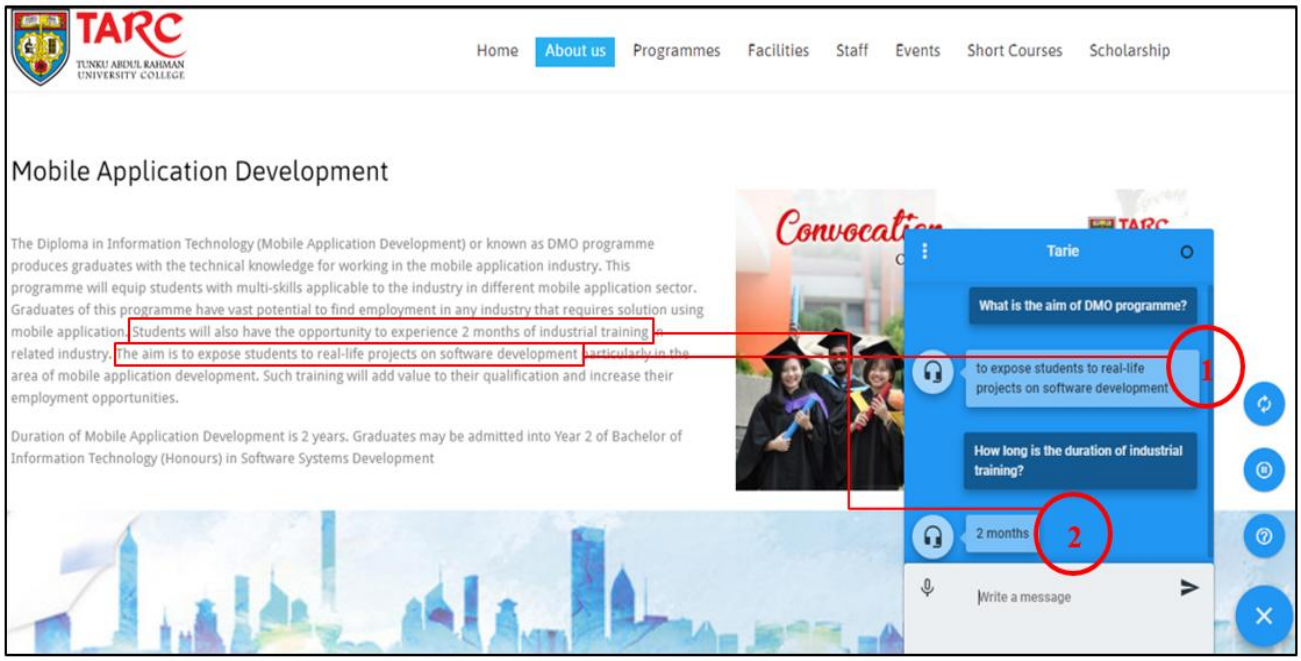

Fig. 5. Conversation via Deep Learning

t – 1 refers to the previous node. On the other hand, r_t^{cx} refers to the new representation of all words in the context, BiRNN_{cx} refers to Bi-directional Recurrent Neural Network, $_{cx}$ refers to context, w_t^{cx} refers to word-level embeddings, c_t^{cx} refers to character-level embeddings.

$$r_t^Q = \text{BiRNN}_Q(r^Q_{t-1}, [w_t^Q, c_t^Q]) \quad (4)$$

$$r_t^{cx} = \text{BiRNN}_{cx}(r^{cx}_{t-1}, [w_t^{cx}, c_t^{cx}]) \quad (5)$$

After performing question and context encoder, it will then undergo gated attention-based recurrent network to generate sentence-pair representation and to determine the importance of passage parts to queries as in (6) where qar_t^{cx} refers to question-aware context representation, RNN refers to Recurrent Neural Network, c_t refers to attention-pooling vector of the whole question, qar^{cx}_{t-1} refers to question-aware context representation from previous node, r_t^{cx} refers to new representation of all words in the context, $[r_t^{cx}, c_t]$ refers to input of Recurrent Neural Network, g_t refers to another gate with the function, $\text{sigmoid}(w_g[r_t^{cx}, c_t])$, w_g refers to the weight of the gate and $[r_t^{cx}, c_t]$*refers to $g_t \odot [r_t^{cx}, c_t]$.

$$qar_t^{cx} = \text{RNN}(qar^{cx}_{t-1}, [r_t^{cx}, c_t]^*) \quad (6)$$

Next, self-matching attention is performed to match the question-aware context representation from whole context as in (7) where Z_t^{cx} refers to context representation which include relevant context + matching question information, BiRNN refers to Bi-directional Recurrent Neural Network, c_t refers to attention-pooling vector of the whole passage (r^{cx}), qar_t^{cx} refers to question-aware context representation whereas Z^{cx}_{t-1} refers to context representation of previous node.

Then, pointer network will be used to predict the position of the answer as in (8) where p^t refers to the position of the answer, a_n^t refers to the current predicted probability, argmax refers to the value of *a* which will give maximum *p*.

$$p^t = \text{argmax}\,(a_1^t, \ldots a_n^t) \quad (8)$$

More comprehensive reading regarding machine reading comprehension for the Deep Learning part could be retrieved in [21]. Figure 5 shows the example of the conversation via Deep Learning approach in which the question posed by the user is not found in the domain-specific (retrieval-based) or common knowledge knowledge bases. These circumstances trigger Deep Learning to perform representations to match the intent and content from the corporate portal via Deep Learning to enables the chatbot to make its own decision based on the generalization from the context and generate a response to the user. The highlighted parts indicate that the chatbot is capable to understand the context and produce the responses accordingly.

C. Tarie Knowledge Bases

Knowledge base is regarded as the brain of the conversational agent. Tarie's knowledge base in this study consists of two parts which are common knowledge and domain-specific knowledge. The knowledge for common knowledge is equipped with the knowledge from the award winning chatbot whereas the knowledge for domain-specific knowledge is derived from the contents of the respective corporate portal, particularly the FAQs. The knowledge is then improved through the knowledge base maintenance.

i. Common Knowledge

Common knowledge is regarded as the knowledge of various subjects including the people, places, common knowledge, political as well as factual information. The general knowledge of Tarie is obtained from the AAA (Annotated A.L.I.C.E. AIML) from the brain of ALICE, the award-winning virtual chatbots.

ii. Domain Specific Knowledge (Retrieval-based Model)

The domain-specific knowledge for retrieval-based model derives solely from the corporate FAQs. An FAQ denotes the series of frequently asked questions alongside with the potential answers on a particular matter, subject, issue or topic. Very often, FAQs are written in the corporate portal to provide information on the concern or frequent questions inquire by the other clients. Moreover, FAQs act as a platform in alleviating the burden of the customer service consultant by publicly answering common questions. In this research, the FAQs from the respective corporate would be saved into the retrieval-based model repository as predefined questions and answers. If the queries probe by client matches the keywords of the predefined set of questions, the questions would be displayed to the chat interface based on the recent popularity as to provide recommendations to the client and the potential response would be generated accordingly.

iii. Domain Specific Knowledge (Deep Learning)

The domain-specific knowledge for Deep Learning derives from the contents of the respective corporate portal. As not all the information is portrayed under the FAQs sections, the conversational agent is smart enough to seek for the related information via the corporate portal for undefined queries. Undefined queries indicate that any queries probe by client are not to be found under the knowledge bases of common knowledge and retrieval-based knowledge. This is reliant on the Deep Learning technology for answer lookup by offering the capabilities to make smarter decision to deliver the best possible response. As the responses are generated by scratch through Deep Learning, the responses would be saved in the Deep Learning knowledge repository, intended for the botmaster to perform supervise learning for any answers enhancement.

D. Knowledge Base Maintenance

In order to provide clients with precise and up-to-date information, the data on each commercial website must be retained continuously. Majority of current approaches automate knowledge base maintenance through a supervised method whereby the botmaster has to provide the relevant information on a regular basis and provide training to the conversational agent which is ineffective and tedious. In order to minimalize manual botmaster intervention, the knowledge base maintenance in this research is further improve by introducing a feature which reliant on the Crawler technology. The feature enables the new knowledge, particularly the corporate FAQ to be added into the knowledge base by one-click button. The feature works with crawler technology whereby the botmaster simply have to enter the URL of the corporate website with FAQ and the FAQ would automatically be added to the knowledge base under domain-specific knowledge.

This is deemed vital as the botmaster might not always be available to perform the knowledge base maintenance manually. The conventional approach is tedious and time consuming as the botmaster would have to logged on to the knowledge base maintenance file to view all the unanswered questions and update accordingly one after another via coded texts. Imagine if the logged file contains one thousand unanswered questions daily, the botmaster would have to maintain the knowledge base manually in a timely manner. Hence, to overcome this issue, any available staff without any prior knowledge in programming is able to perform the knowledge base maintenance.

i. Conversation Logs

Conversation logs or commonly known as chat history refer to the archive of saved conversations between the clients and the conversational agent. The conversation between the clients and Tarie are recorded into the conversation logs for the botmaster to perform monitoring purpose as a way to improve the chatbot performance.

ii. Botmaster

As the conversational agent is smart enough to perform answer lookup via the corporate portal for undefined queries, botmaster might need to perform supervise learning to indicate the reliability and accuracy of the responses generated by the Deep Learning. If the responses generated are not precise, botmaster would need to perform knowledge enhancement. Furthermore, botmaster is able to monitor the chatting interaction between the clients and conversational agent to perform the necessary knowledge maintenance via the chat history in conversation logs.

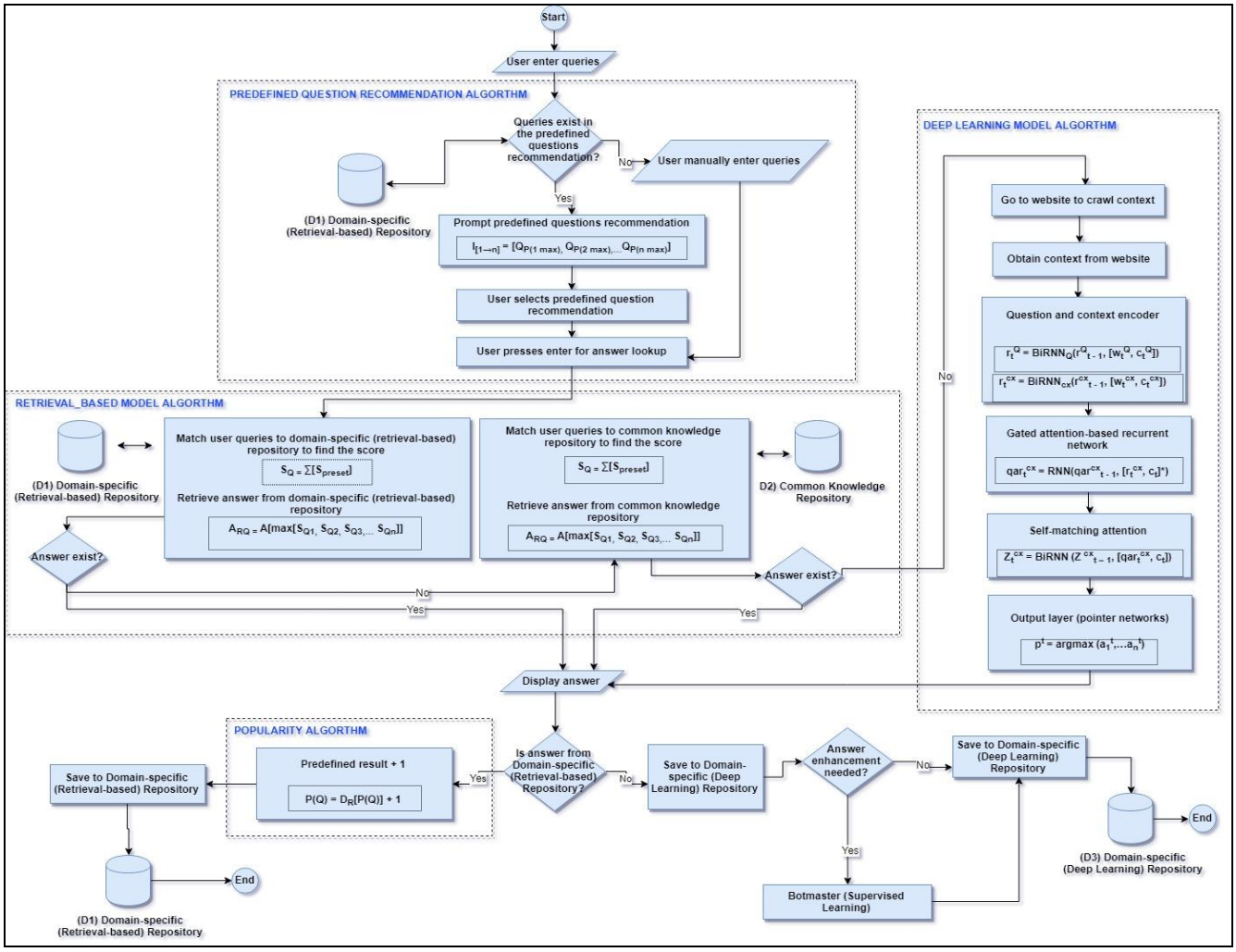

Fig. 6. Flow Chart of The Entire Model

IV. CONCLUSION

Research on the use of Deep Learning for intelligent conversational agents is still limited. Realizing the gap, it is undeniable to mention that the field of artificial conversational framework requires more studies. This study is reliant on the Artificial Intelligence (AI) to offer natural language processing (NLP) by presenting retrieval-based model and Deep Learning to enable the conversation agent to make smarter and better decision making in generating reliable and up-to-date responses, comparable to communicating with an accomplished client support advisor. Moreover, this research intends to minimalize manual botmaster intervention in knowledge base maintenance. It is hoped that this research will be able to achieve a breakthrough in the field of artificial conversational agent by offering a chatbot which is able to provide reliable and accurate information. This is an ongoing research in which the data and analysis will be discussed further in the next paper.

ACKNOWLEDGMENT

Special thanks to the Natural Language Computing Group, Microsoft Research Asia for the machine reading comprehension research, the grant from UTeM (GLuar/BIGTECH/2017/FTMK-CACT/A00009) and the scholarship from MyBrain15 awarded by the Ministry of Higher Education, Malaysia.

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AUTHORS PROFILE

Leong Pui Huang is a Programme Leader in the Department of Computing and Information Technology at Tunku Abdul Rahman University College (TAR UC). She earned both her bachelor degree and master from Universiti Teknikal Malaysia Melaka (UTeM), in the field of Computer Science in year 2013 and 2015. She is currently pursuing her PhD and her research involves intelligent agent and AI applications.

Prof. Ts. Dr. Goh Ong Sing started his career as an academician since 1990 at Universiti Sains Malaysia (USM). In August 2002, he joined Universiti Teknikal Malaysia Melaka (UTeM) and in 2015 he was appointed as a Director of Industry Liaison Centre and Lead Samsung IoT Academy. Now he is working as Assistant Vice Chancellor at Office of Industry and Community Network. His main research interest is in the development of intelligent agent, natural language processing and speech technology to facilitate graceful human-computer interactions, conversational robot and mobile services. He is the author of more than 100 peer-reviewed scientific journal, books, conference papers, and book chapters. He has led and worked on research grants funded by Malaysian Government's Intensified Research, Malaysia Technology Development Corporation, Big Data Technology Pty Ltd, Murdoch University, and Australian Research Centre for Medical Engineering at University of Western Australia.

Dr. Yogan Jaya Kumar is a Senior Lecturer at the Department of Intelligent Computing and Analytic in the Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM). He earned both his bachelor degree and master degree from Universiti Sains Malaysia (USM), in the field of Mathematical Science in year 2003 and 2005. He completed his PhD studies at Universiti Teknologi Malaysia, in 2014 in the field of Computer Science. Currently, his research involves in the field of Text Mining,Information Extraction and AI applications.