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A Review & Comparative Analysis on Various Chatbots Design

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Abstract– Human-Computer Expression is gaining momentum as a computer-interaction technique. In speech based search engines and assistants such as Siri, Google Chrome and Cortana, there has been a recent upsurge. Chatbots replace some of the tasks human workers have traditionally filled, such as remote customer service agents and educators. Effectiveness of chatbots continue to increase right from initial stage of rule-based chatbots. The purpose of this paper is to help researchers to find the research gap for future upgradation of chatbots. This paper presents a survey on the techniques used to design Chatbots and a comparison is made between different design techniques from nine carefully selected papers according to the main methods adopted.

Keywords- Chatbot, conversational agent, bibliometric analysis

I. INTRODUCTION

In introducing artificial intelligent systems, the evolution of information technology and communication has been dynamic. The systems approach human activities, such as support systems for decision-making, robotics, natural language processing, expert systems, etc. There are some hybrid techniques and adaptive techniques that make techniques more complex, even in the artificial intelligent fields. Many who could understand the natural language of humans could comprehend language and intelligent structures. These machines will learn themselves and refresh their skills by reading all the electronics articles that have been on the internet.

These systems are also referred to as answering-engines for the internet. Speech is one of the most efficient types of human communication; it is, therefore, the aim of researchers in the field of human computer interaction research to enhance human-computer speech interaction in order to model human-human speech interaction. In recent years, with contributions from Google, Android and IOS, voice communication with modern networked computing devices has gained growing attention. The primary form of interaction with a machine[1] starts to shape spoken dialogue systems as they are more natural than graphic-based interfaces. In the near future, speech contact would also play an important role in humanizing machines [2].

II. TAXONOMY OF CHATBOT

Two main innovations [3] can be attributed to the recent interest in chatbots. Firstly, over the past few years, messaging service growth has spread rapidly. It integrates functionality that would require a separate application or website, such as payments, ordering and booking. Users can perform task as buying products, book restaurants etc. and ask questions from their messaging apps instead of downloading a number of different applications. Examples of some of the most common apps include Facebook Messenger, WhatsApp, WeChat and Thread. Second. To get outcomes that transcend human efficiency, it can manage the enormous amount of data and process it. We split chatbot applications into four classes in this paper, such as goal-based, knowledge-based, service-based, and response-based, as shown in Fig.1.

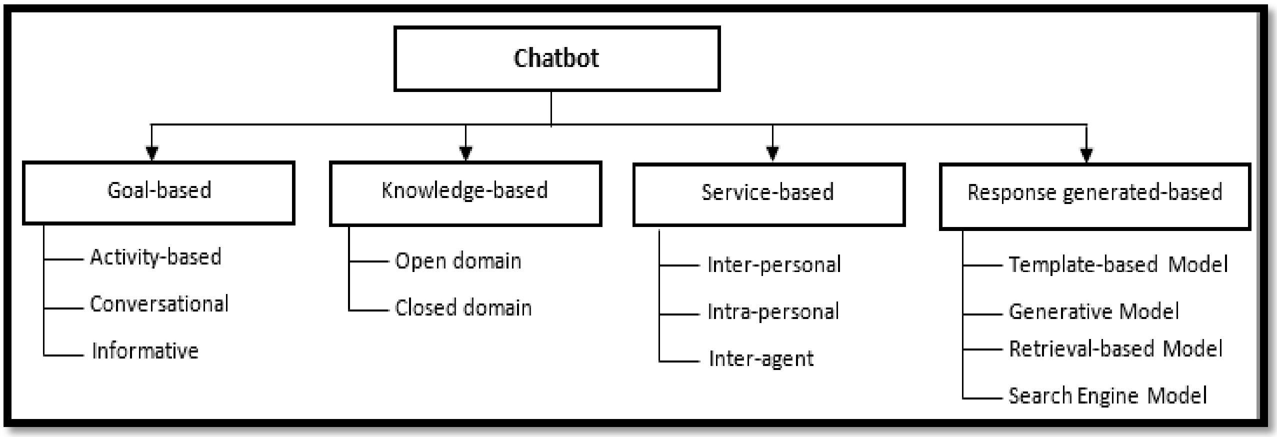

Fig 1: Taxonomy of Chatbot Application

i. Goal-based Chatbot

Based on the main objective to be accomplished, goal-driven chatbots are classified. To get details from the user to complete the task, they are designed to provide quick conversations for unique tasks and settings. For example, in order to help the client answer their questions or solve problems, a company deploys chatbot on its websites.

ii. Knowledge-based Chatbot

Based on the information they access from the underlying data sources or the amount of data they are educated on, knowledge-based chatbots are categorized. Open-domain and closed-domain are the two major sources of data. The answer from open-domain data sources relies on and correctly responds to general topics.

iii. Service-based Chatbot

Based on the facilities given to the client, service-based chatbots are categorized. It may be for commercial or personal reasons. For example, the logistics company can provide copies of dispatch documents via chatbot rather than phone calls, or a meal order can be made by MacDonald's client.

iv. Response Generated-based Chatbot

Answer Generated-based chatbots are categorized based on what step they take in the generation of responses. Input and output are taken by the answer models in the natural language text. It is the duty of the dialogue manager to combine response models together. The Dialog Manager takes three steps to produce an answer. First, to produce a collection of responses, it utilizes all response models. Second, a priority-based response returns. Third, if there is no priority response, a model selection policy selects the response. The focus of this study is on the chatbot that generates responses.

The four categories into which different response models are grouped are shown in Fig 2.

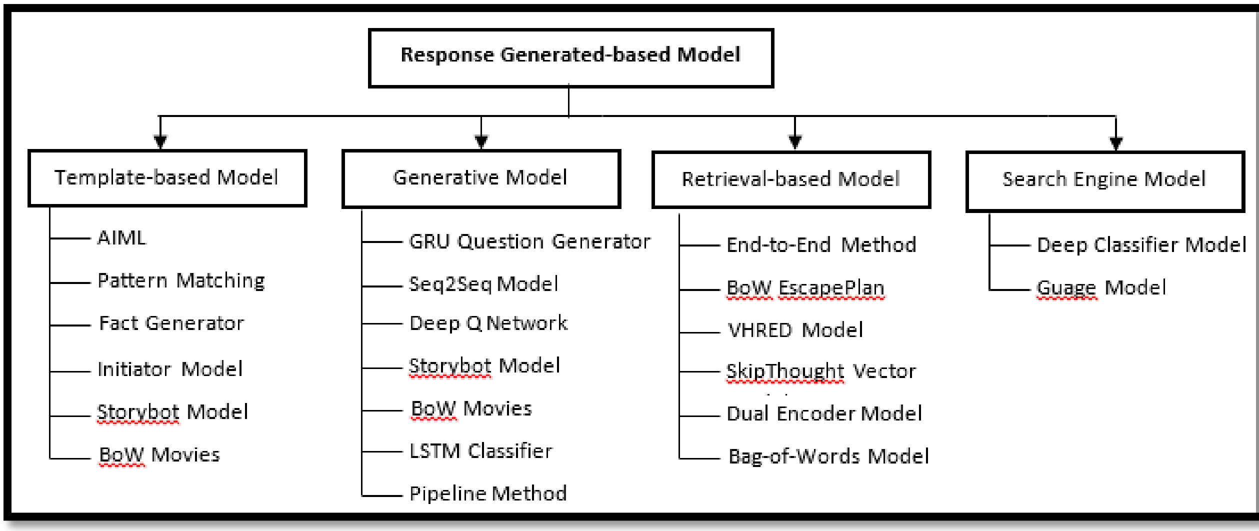

Fig 2: Taxonomy of Response Generated-based Model

III. EXISTING CHATBOTS

i. Elizabeth bot

It is an adaptation of the Eliza program developed by [4]. It has, however, been developed and generalized to enhance both flexibility and its possible adaptability in range, substitution, and phrase storage mechanisms. In order to generate a response, Elizabeth Bot uses four steps. First, in a text file, there is a command line script that starts each line with a script notation command, without a message with a keyword.

Each script command has an index code that's automatically created. It can be indexed using a special user code, too. Second, to be consistent with the specified keywords, input transformation rules and map input to another type are used. Third, the rules of production transformation and adjustments to fit personal pronouns as an answer. Fourth is the first pattern of keywords to fit. By using different selection responses for the same question[5], it attempts to give a different answer. The design of some rules can trigger iteration in the Elizabeth bot, which is solved by applying the rule only once.

The downside of the Elizabeth bot is that it does not have a way for the user input sentence to be partitioned or separated and then combined with its output. It will be difficult to do the separating, according to the structure of Elizabeth Bot.

The use of grammatical analysis, extraction of keywords and pattern matching.

ii. Microsoft LUIS

Language Understanding Information Service (LUIS) is a Microsoft [6]-developed domain-specific AI engine. It allows natural language and processing of knowledge using the model of intents and prebuilt domain entities. To find intentions from a sentence, LUIS performs NLP against Big Data. In conversations, it is intended to define useful knowledge, interpret user objectives (intents) and extract data (entities). In order to constantly increase the consistency of natural language models, active learning is often used. A model begins with a list of general user intentions such as "Book Flight" or "Contact Help Desk." User distribution example phrases called utterances for th utterances once the intentions are identified.

Then mark the utterances with such basic data that LUIS wants the user to take out of the utterance. Upon formation, training and writing of the prototype, utterance is ready to be received and processed.

iii. Alicebot

The Entity for Artificial Linguistic Internet Computers is also known as ALICE. It was driven by[7] and generated by[8]. Alicebot is based on the pattern or architecture of the Eliza version that has been updated. Nevertheless, Alicebot continues to be focused solely on pattern matching and the search technique for depth-first user data. It is a type of XML dialect that encodes laws with questions and responses. A collection of Artificial Intelligence Markup Language (AIML) models are used for generating dialog history and user utterance responses[9]. The user phrase is initially received by AIML as an input and placed in a category. Each category consists of a response template and a set of conditions, known as context, that give meaning to the template. Therefore, string-based rules are necessary to determine if the answer produces a correct or substantive response. The drawback of Alicebot is personality modeling to explain the actions of the chatbot, such as attributes, attitudes, mood, emotions and physical states[10]. Personality elements inside the AIML must be integrated by the botmaster. This is not a simple mission, however. Alicebot is also unable to produce adequate responses, little potential for reasoning and unable to generate human-like responses (Turing test). To build a stable bot, it needs a large number of categories which can lead to unworkable, hard to manage or time-consuming applications. To structure a sentence, Alicebot does not have intelligence features like NLU, sentiment analysis and grammatical analysis. Furthermore, if the same feedback is repeated throughout the discussion, much of the time, Alicebot gives the same answers.

iv. Mitsuku

A standalone human-like chatbot developed by[11] using AIML is the most commonly used Mitsuku. It was intended to serve as a personality layer for general typed communication based on rules written in AIML[12] and to integrate into a bot network such as twitter, telegram, firebase, twilio. Using heuristic patterns and hosted at Pandorabot, Mitsuku Bot uses NLP. A lot of the work that goes into developing a stable chatbot framework is abstracted by Bot modules. With a view to incorporating its Some AIML categories need to be included in the module to route inputs from users. Whenever the bot fails to find a better fit for the data, the default category will be redirected automatically.

The ability to reason with concrete objects requires its features. If somebody asks, for example, "Can you eat a house?" The data is sent to the human manager for verification when it discovers something new. The app can only further integrate and use checked data. However, without a large amount of training data, Mitsuku is not successful, failing to provide components of dialogue management.

v. IBM Watson

Watson is an AI chatbot based on rules that was developed by the DeepQA project of IBM[13]. It is intended for data retrieval and question-answering systems that combine natural language processing and the machine-learning hierarchical method. Watson uses a broad variety of mechanisms, such as names, dates, geographical locations or other entities, to identify and assign feature values to generated responses. The machine learning system then learns how to combine the values of these traits into a final score for each response. Based on that ranking, it ranks all possible responses and selects one as its top answer.

There are nearly infinite uses for Watson's underlying cognitive computing technology. Since text mining and complex analytics can be processed on large volumes of unstructured data and enormous amounts of data can be managed. As the application gathers more input knowledge, it can find enough patterns to make specific predictions.

vi. Cleverbot

Cleverbot is one of the most popular entertainment chatbots that implements AI methods based on human interaction rules[14]. It is generated by[15] to collect a vast amount of data based on conversational interactions with individuals online via crowd sourcing. The answers given by Cleverbot, unlike other chatterbots, are not preprogrammed. Instead, it simulates natural conversation by learning from user input and relying on feedback to connect. When the user enters a sentence, all keywords or phrases matching the input are identified by Cleverbot. It responds to the input after browsing through its saved conversations, by seeing how a user responded to that input when it was asked.Cleverbot is one of the most common chatbots for entertainment that implements AI techniques based on rules to interact with humans[14]. It is created by[15] to gather a large amount of information through crowdsourcing based on online conversational exchanges with individuals. The answers given by Cleverbot, unlike other chatterbots, are not preprogrammed. Instead, it simulates natural communication by learning from user input and relying on feedback to communicate. When the user enters a sentence, all keywords or phrases matching the input are identified by Cleverbot. It responds to the input after browsing through its saved conversations, by seeing how a user responded to that input when it was asked.

vii. Chatfuel

For building a rule-based chatbot, Chatfuel provides a drag and drop user-friendly gui. It was produced by [17]. The bot is equipped to map input phrases to output through an artificial intelligence module. This makes it possible to react and incorporate prompts with tools such as social media, third parties, CRM. With analytics features, users can quickly and securely collect and view valuable information on chatbot results and subscriptions. The most appealing service point is simply to build a rule-based bot that is suitable for small enterprises. The drawback of Chatfuel is that, in terms of conversation flows, it is rather inflexible and does not accept multi-language and knowledge-based flows. Moreover, NLP is limited, configuration is funky and documentation is bad. However, it is capable of comprehending the user's purpose.

viii. Amazon Lex

For developing conversational interfaces using voice and text we use Amazon Lex which is an AWS service. It has been constructed by Amazon[18]. To construct highly immersive user interface deep learning functionality and the flexibility of natural language understanding (NLU) is provided. Amazon Lex combines with AWS Lambda, allowing users to enable the features of back-end business logic execution for data retrieval and updates quickly.

Chatbot	Technical Specification		Limitation
	Input/Output	Technique Involved	
Elizabeth [4-5]	Command line script as I/P rules and O/P transformation rules for generating responses.	Iterative	Doesn't split I/P & combine the result
LUIS [6]	Identify valuable info from user conversation	NLU with prebuilt domain active learning	Required azure subscription
Alice[7-10]	Pattern matching to represent I/P & O/P	Recursive techniques	Grammatical analysis to structure sentences
Mitsuku [11-12]	AIML category to route I/P from user	NLP with heuristic pattern, supervised ML	Failed to provide dialogue components
Watson [13]	Identify feature values to generate response based on score	Rule based NLP, UIMA	Does not process structure data, No relational databases
Cleverbot [14-16]	Matches keyword for I/P and response	Rule based	Unpredictable responses without context
Chatfuel [17]	Maps I/P sentence to O/P	Rule based	Inflexible conversational flows
Amazon Lex [18]	Matches keywords for I/P & response	NLU, AWS Lambda	Not multilingual, mapping utterances & entities are difficult

Fig 3: Comparison Between Different Chatbots

IV. RELATED WORKS

The purpose of this study is to review the literature of business domain conversational agents with a focus on machine learning. In this regard, several surveys have been performed from a professional perspective to study conversational agents. The research proposed by Hussain et al.[19] focuses on the classification of chatbot and chatbot design approaches, where the authors discussed task-oriented and non-task-oriented chatbot categories. These categories have been taken into account in a debate about how the conversational meaning is treated by chatbots. Several machine learning techniques, such as Recurrent Neural Network, Sequence to Sequence neural models and Long Short-Term Memory Networks, were examined by the authors for this reason. Lokman and Ameedeen[20] presented a scientific analysis of five recent literature chat-bot systems. Features such as the information domain, response generation, text processing and machine learning models were considered by the authors. In addition, to evaluate the performance of the chatbot, they checked the implementation and the assessment approach. A research on task-oriented and non-task-oriented models was performed by Chen et al.[21], identifying deep learning techniques and algorithms.

The authors addressed research directions that can exploit research into the dialog method, such as the warm-up stage in domain-specific chatbots, a deep understanding of language and the real world, and sensitive information-related privacy issues. Nuruzzaman and Hussain[22] suggested a survey to compare eleven applications with features and technical requirements for the implementation of chatbots. In order to provide productive and efficient chatbot communications, the authors outlined current limitations. Latest studies, on the other hand, have reviewed literature based on the business application of conversational agents. The authors explain the reasons for the increase in the utility of chatbots and their future in the scope of business in the study presented by Kaghyan et al.[23]. In addition, by contrasting capacities, strengths, and weaknesses, they suggested a discussion about building platforms. The analysis that most approximates this work was done by Meyer von Wolff et al.[24].

V. LIMITATIONS OF CHATBOTS

There are many studies that aim to establish a chatbot's ideal application, which can have a normal conversation and cannot be differentiated from humans. But it's far from attainable. The following drawbacks occur from the summary of the literature to provide successful and productive chatbot conversations.

i. Fixed rule-based: On previous chatbots, a fixed set of rules, template-based matching and a very simple machine learning method have been created.
ii. Grammatical Errors: Grammatical errors are not remembered.
iii. Predefined or closed-domain: Most of them can only answer closed-domain or predefined database queries.
iv. Ambiguity: The purpose and meaning of the sentences with the word is ambiguous or not sufficient.
v. Structure of the Language: Each language has a different structure of sentence making. The arrangement of documents, punctuation and the use of spaces, for instance, vary between languages. It cannot be distinguished from current chatbots.
vi. Semantics: The meaning of phrases or terms in the context of a natural human language is semantics. Previous chatbots, whether for the production of an answer or the review of questions, do not cope with natural language processing.
vii. Sentiment Analysis: The new chatbots are unable to sense the human subject's feelings they're talking about. The chatbot should be able to tell whether the person is upset, sad or happy from the way that the text or speech pattern is delivered.
viii. Recommend System: Current chatbots do not ask questions about the user subject, do not clarify or advise. They just gather information from the knowledge base and provide answers. Based on previous responses, the chatbot should be capable of writing questions.
ix. Accuracy: Chatbots are designed to have a human-like conversation to perform a mission. Current chatbots, however, have a weak propensity to change the subject unexpectedly and produce unexpected responses. It reacts without meaning often. Accuracy is therefore not achieved at a sufficient stage.

With deep learning capabilities, a newer chatbot is needed to resolve the limitations described above. Not only will it evaluate human feedback, but appropriate responses will also be produced. If chatbots are well educated, they can understand the natural languages of humans and can respond to any situation accordingly. The major drawback, however, is that to be able to learn the vast amount of potential inputs, these natural responses require a significant amount of learning time and data. The training would demonstrate whether the AI chatbot is able to deal with the more complex problems that are typically barriers to simpler chatbots.

VI. CONCLUSION

In this article, a number of selected articles have been covered in the literature review, concentrating primarily on Chatbot design techniques in the last decade. A survey of selected studies that affect Chatbot design has been presented, and the contribution of each study has been identified. In addition, in the chosen studies, a distinction was made with Chatbot design techniques and then with the Chatbot techniques that won the Loebner Award. From the above study, due to the range of methods and approaches used to build a Chatbot, it can be said that the growth and advancement of Chatbot design is not increasing at a predictable pace. In addition, in the selected studies, chatbots designed for dialogue systems are, in general, limited to unique applications. By developing more robust knowledge bases, general-purpose chatbots need improvements.

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