ChatBot for Distributed Departmental Stores

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***Abstract*—A ChatBot, is a conversational agent, that is a part of software that can converse with humans in natural language. Since its beginnings, the creation of a ChatBot has been the most challenging challenge in artificial intelligence. Although ChatBots may perform a broad variety of tasks, their primary responsibility is to interpret human speech and reply correctly. An intelligent ChatBot is a computer program that can converse with humans and respond to inquiries in a certain subject. ChatBot systems, which are often utilized in dialog systems for many practical purposes such as customer service or information collecting, are increasingly incorporating machine learning. Since the idea of machines being distributed came into fruition there is lots of research going on regarding the distributed systems and improving their performances further. In our paper we converged two ideas, the first one is building a general purpose ChatBot for supershops and the second one is making the ChatBot work for distributed systems which represent different branches of a supershop across the country. We used DNN models to train our ChatBot since end-to-end neural networks displaced these models due to increased learning capabilities and made our ChatBot work for different servers and locations in our work. Hence, this work combines ideas from both machine learning and distributed systems.**

***Index Terms*—ChatBot, DNN, distributed system, Machine learning**

I. Introduction

Chabots are artificial intelligence systems that mimic human speech. The development of a system to discover answers to issues is one of the most essential roles of Artificial Intelligence. ChatBots are the next phase in the growth of the internet. With the rise of globalization in the early twenty-first century, the internet has become the most convenient means to transmit information. It gives a platform for people to interact, provide comments, discuss ideas, and receive information. Furthermore, sensible resource management, appropriate messaging, and timely responses to inquiries on difficulties such as data structure questions and question-answering (QA) from the discussion are all critical. Building an intelligent Chabot with human-like skills such as remembering, accepting user choices, and responding appropriately might be critical for data structure issues. With the aid of linked neurons, the human brain retains information in various regions such as long-term memory and short-term memory in a decentralized fashion. This differs from a standard file system, which stores data in a centralized location. For complicated activities such as fixing data structure challenges, an intelligent assistant with brain-like qualities is capable of providing the best outcomes. Based on factors such as information recurrence, the seriousness of the scenario, or certain predetermined parameters, the assistant can recall significant information in long-term storage. Short-term storage can be used to store trivial information that will be erased in the future.

One of ChatBot's first and most important aims was to imitate an intelligent person and make it difficult for others to discover their true nature. ChatBot usage has exploded as additional ChatBots of varied architecture and capabilities have been developed [11].

The most difficult aspect of creating a ChatBot is figuring out how to respond to a message in an appropriate (human-like and natural) manner. Currently available approaches are either retrieval or generation based. The ability to effectively match input messages with appropriate responses is critical to response selection success. The matching scores can be utilized as features in a learning to rank architecture or used separately to rank response candidates.

Human language, in contrast to computer labor such as mathematical computations, which is direct and exact, is often ambiguous and hidden in semantics. As a result, getting computers to grasp language at a human level is tough. These apps have lately grown in popularity across a variety of mobile and web platforms. The most common sort of ChatBot, known as "virtual assistants," is used to meet the needs of consumers across a wide range of areas and industries.

Conversation between humans and computers is a difficult job in AI and NLP. Task-oriented dialog systems and non-task-oriented ChatBots are examples of existing discussion systems. The former attempts to assist individuals with specialized activities such as ordering and teaching, whereas the latter focuses on speaking like a person and engaging in social discussions about a variety of topics in open domains.

The idea of distributed systems is simple yet it is not. A distributed system is a collection of autonomous computing elements that appears to its users as a single coherent system [11]. This definition gives the idea behind a distributed system architecture but does not provide the necessity behind that. The growing need of moving to distributed systems for large or even relatively smaller organizations actually puts light on the fact that in the future this concept of machines not being in only one location and being distributed in multiple locations will only improve and there will not be any downgrade. All the services that tend to work fine on a single machine are required to work smoothly in a distributed system as well and there is research going on continuously regarding this fact. From the operating system [12] to all other necessary services were being made to work in a distributed system. Our work also discovers possibilities of contributing in the field of distributed systems.

The first goal of our work is to build a general purpose ChatBot which may not compete well with intelligence but provide clarity and proper customer satisfaction. Our second goal is to make the ChatBot distributed which actually combines two ideas in this paper.

II. Related Work

Shawar et al. [10] provided open-ended user testing, such as an Afrikaans ChatBot for Afrikaans-speaking academics and students in South Africa. This is assessed using "glass box" conversation efficiency measurements, as well as "black box" dialogue quality metrics and user input. The Qur'an and the FAQchat prototypes are two more examples provided in this study. In general, we believe that assessment should be tailored to the application and the needs of the users.

Y. Wu et al. [9] by A topic-aware convolutional neural tensor network has been suggested (TACNTN). In TACNTN, message and response matching takes place not just between a message vector and a response vector produced by convolutional neural networks, but also between two topic vectors including additional topic information. The message and answer subject words are linearly combined in the two topic vectors. where the topic words are taken from a pre-trained LDA model and their weights are computed independently of the message vector and response vector. To produce a matching score, neural tensors are fed the message vector, the answer vector, and the two topic vectors. TACNTN outperforms state-of-the-art algorithms for message-response matching in an empirical investigation using a public data set and a human-annotated data set.

C. Tao et al. [8] suggested a multi-representation fusion network that can fuse representations into matching at any stage of the process: early, middle, or late. On two benchmark data sets, we empirically compare several representations and fusing methodologies. On both data sets, evaluation results show that late fusion is always better than early fusion, and that by fusing the representations towards the end, our model greatly outperforms previous techniques and reaches new state-of-the-art performance.

M. Adam et al. [7] In a randomized online experiment, researchers looked at how audible anthropomorphic design cues and the foot-in-the-door strategy affect user request compliance. Both anthropomorphism and the obligation to be consistent, according to our results, increase the likelihood that customers would assist with a ChatBot's request for service feedback. Furthermore, the data show that social presence mediates the effect of anthropomorphic design cues on user compliance.

This article [6] created a functional foundation for the ChatBot system and presents the RASA NLU concept, after which it combines RASA NLU and neural network (NN) methodologies and develops the system based on entity extraction after intent detection. Our designed system can achieve automatic learning and response of the gathered questions about finance using experimental comparison and validation. RASA NLU surpasses NN inaccuracy for a single trial, but NN has greater integrity to classify entities from segmented words, according to the system analysis of two approaches.

This article [5] examined a sample of developed museum ChatBots as well as systems for applying them. More crucially, the results of a systematic evaluation strategy for both ChatBots and platforms are presented in this research. In addition, the research introduces a revolutionary method for creating intelligent ChatBots for museums. This method focuses on multi-ChatBot conversational AI systems for museums that are graph-based, distributed, and collaborative. The study emphasizes the usage of knowledge graphs as a fundamental technique for possibly giving endless information to ChatBot users, answering the demand for rich machineunderstandable material that conversational AI requires. Furthermore, the suggested architecture is intended to provide a cost-effective deployment solution in which information may be disseminated (distributed knowledge graphs) and shared among several ChatBots that interact when necessary.

M. Nuruzzaman et al. [3] presented to solve these difficulties, we suggest a sequential matching network (SMN). SMN first compares a response to each utterance in the context on many levels of granularity, then uses convolution and pooling processes to extract crucial matching information from each pair as a vector. A recurrent neural network (RNN), which models interactions among utterances, then accumulates the vectors in chronological order. The RNN's hidden states are used to determine the final matching score. SMN outperforms state-of-the-art approaches for answer selection in multi-turn conversations, according to an empirical research based on two public data sets. This article gives an overview of current ChatBots and the approaches that have been used to create them. It compares and contrasts the existing ChatBots, as well as their strengths and weaknesses. We examined the features and technical characteristics of 11 of the most popular ChatBot application platforms. According to research, approximately 75% of consumers have had terrible customer service, and coming up with relevant, lengthy, and informative replies remains a difficult challenge. Previously, the development of ChatBots depended on handwritten rules and templates. These models were rapidly supplanted by end-to-end neural networks as deep learning became more popular. Deep Neural Networks, in particular, are a strong generative-based model for solving conversational answer generation difficulties. This article examined over 70 publications relevant to ChatBots published in the previous 5 years as part of an in-depth review of recent literature. This study compared chosen studies based on the approach used, based on a literature review. This research also discussed why existing ChatBot models do not consider context when generating replies, and how this impacts conversation quality.

S. Ayanouz et al. [2] conducted a thorough review of recent literature in this work. We looked at a lot of papers over the previous five years that were about ChatBots. Then we discussed many relevant efforts as well as the AI ideas required to create an intelligent conversational agent based on deep learning models. Finally, we provided a functional architecture for developing an intelligent ChatBot for health-care support.

This study et al. [1] has the ability to complete tough tasks. The neural network and machine learning algorithms utilized to resolve the data model problem can be extended to solve other problems like the Deep Coder problem, which generates code based on how the network is trained, finding the shortest path for graph traversal, and the Subway traversal problem, which finds the best possible path based on user preference.

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The neural network and machine learning algorithms used to solve the data structure problem can be extended to solve other problems like the Deep Coder [8] problem, which can write code based on how the network is trained, finding the shortest path for graph traversal, or the Subway traversal problem [8], which finds the best possible path based on user preference. [1]

III. Methodology

A. Data Preocessing)

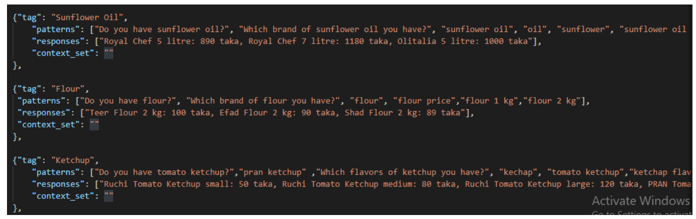

Fig. 1. Preview of the dataset.

We collected the data from the Supershop. The data was disorderly. We processed the data and converted it into a JSON format. So that it can be used to train the models. From figure: 1, we can see the preview of the dataset.

B. Stemming

After preprocessing we load the data. Then we perform stemming on each of the words. Stemming is the procedure of converting words to their base form. It is done by removing the affixes from the words. It is called stemming for the likeness of cutting down the branches from a tree to get the stems. We used Lancaster Stemming. In this stemming method, the Lancaster algorithm is used. We used it for its more aggressiveness than the other stemmer.

C. Training DNN Model

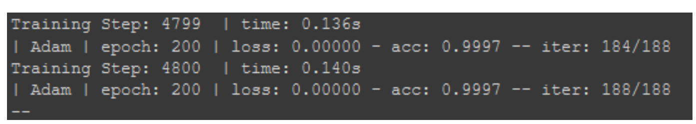

Fig. 2. DNN Model Matrix.

After the necessary preprocessing is done, we finally got the data eligible for training the Deep Neural Network (DNN) Model. We used tflearn to create the model and train the DNN. Firstly, we designed the input layer which contained neurons corresponding to the amount of classes in the training dataset. Then we used two hidden layers with each containing 8 neurons. And finally the final layer contained the same amount of neurons as the number of classes contained by the output class and we used the activation function softmax because it calculates the probability of each class for the input. Then we used regression in the model which helped us minimize the provided loss function loss. Then finally we used DNN on the model with batch size of 8 and epoch 200 to train it using the data we have. We were building a ChatBot to provide replies to the customers so it required nearly 100 percent accuracy to make the ChatBot work with proper customer satisfaction. But we also needed to keep in mind the effect of overfitting hence we set the parameters in that way. We trained different number models for each of the branches of the departmental store so that local people may get information about their nearest branch and other branches as well if they wish. Figure 2, shows the matrix.

D. Final Output

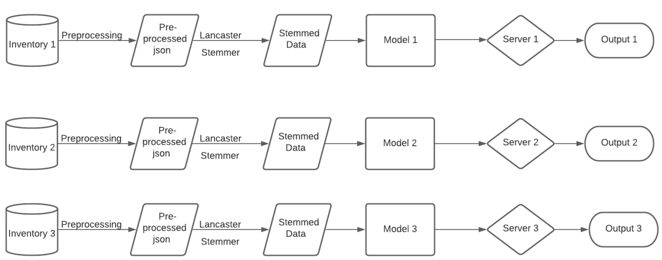

Fig. 3. Workflow Diagram

After successfully training the model we were finally able to use it as the middleware between the user and the departmental store. The user first needed to insert the server ID and from that we determined the location of the user and used the specific model which is trained using inventory information of that particular location's branch store. And that model took user's queries and matched them with the classes the model got and fetched replies when a match was found for the probability of 50% or more. Figure 3 shows the workflow of our proposed methodology.

IV. RESULT AND DISCUSSION

Server Id	**Query**	**Tag**	**Expected**	**Actual**
Server 1	Do you have sunflower oil?	Sunflower Oil	Royal Chef 5 litre: 890 taka, Royal Chef 7 litre: 1180 taka, Olitalia 5 litre: 1000 taka	Royal Chef 5 litre: 890 taka, Royal Chef 7 litre: 1180 taka, Olitalia 5 litre: 1000 taka
Server 1	salt 2 kg	Salt	Fresh salt 1 kg: 30 taka, ACI Salt 1 kg: 32 taka, Efad salt 1 kg: 28 taka, PRAN salt 1 kg: 34 taka	Fresh salt 1 kg: 30 taka, ACI Salt 1 kg: 32 taka, Efad salt 1 kg: 28 taka, PRAN salt 1 kg: 34 taka
Server 1	soap brand	Soap	Lux small rose: 30 taka, Lux large rose: 58 taka, Lux small lily: 28 taka, Lux large lily: 55 taka	Lux small rose: 30 taka, Lux large rose: 58 taka, Lux small lily: 28 taka, Lux large lily: 55 taka
Server 1	small horlicks	Horlicks	Not available	Not available
Server 1	fish name	Fish	Hilsha: 800/kg, Rui: 670/kg, Koral: 580/kg, Katla: 650/kg, Note: price are subjected to change each day	Hilsha: 800/kg, Rui: 670/kg, Koral: 580/kg, Katla: 650/kg, Note: price are subjected to change each day

TABLE I
SERVER 1

Server Id	Query	Tag	Expected	Actual
Server 2	How much does 2 litre sunflower oil cost?	Sunflower Oil	Not available	Not available
Server 2	Which brand of noodles you have?	Noodles	ACI: 20 taka, Kolson: 18 taka, Mr Noodles Cup: 30 taka, Maggi: 30 taka	ACI: 20 taka, Kolson: 18 taka, Mr Noodles Cup: 30 taka, Maggi: 30 taka
Server 2	Do you have wheat flour?	Flour	Teer Flour 2 kg: 105 taka, Efad Flour 2 kg: 90 taka, Shad Flour 2 kg: 89 taka	Teer Flour 2 kg: 105 taka, Efad Flour 2 kg: 90 taka, Shad Flour 2 kg: 89 taka
Server 2	Do you have salt?	Salt	Fresh salt 1 kg: 30 taka, ACI Salt 1 kg: 32 taka, ACI salt jar: 15 taka, PRAN salt 1 kg: 34 taka	Fresh salt 1 kg: 30 taka, ACI Salt 1 kg: 32 taka, ACI salt jar: 15 taka, PRAN salt 1 kg: 34 taka
Server 2	Anti hair fall shampoo	Shampoo	Sunsilk hair fall shampoo:330 taka, Clear large: 350 taka, Pantine small: 220 taka, Pantine large: 400 taka	Sunsilk hair fall shampoo:330 taka, Clear large: 350 taka, Pantine small: 220 taka, Pantine large: 400 taka

TABLE II
SERVER 2

We made a general-purpose ChatBot. As we can see from Table I, II, III the result tends to be 100% accurate. We've not focused on optimization, rather ensure accuracy for customer satisfaction. In the future, we'll try to improve this ChatBot with artificial intelligence and also will try to detect the location automatically using the location API. We'll also try to optimize the server by running one model instead of multiple. To ensure accuracy with the inventory changes, we reset the models and start again every 10 minutes.

V. CONCLUSION

According to the scientific community, ChatBots are highly user-friendly, and anybody who can type in their language on the desktop version and in the mobile application can utilize them pretty fast. Intelligent ChatBot systems rely heavily on natural language processing. However, the one we created focuses mostly on ensuring good client pleasure, thus we produced a common-reason ChatBot alternately a complicated one. To begin with, we collected data from inventory management and did significant preprocessing to prepare the data eligible for DNN models. Then we used the data to train different DNN models with each model containing 2 hidden layers with each containing 8 neurons. And we positioned the models to communicate with the users depending on the locations of super store branches, with the goal of making the ChatBot operate for dispersed systems. The models were able to predict customer queries satisfactorily which serves our purpose for this work. Our work is not free from room for improvements, in fact, there are plenty of them. In the future we will focus on keeping a balance between building a general-purpose ChatBot and an intelligent one and also we will try to come up with a more optimized architecture for the distributed systems to use our designed ChatBot.

Server Id	Query	Tag	Expected	Actual
Server 3	large complan	Complan	Complan small: 320 taka, Complan large: 580 taka	Complan small: 320 taka, Complan large: 580 taka
Server 3	chocolate brand	Chocolate	Not available	Not available
Server 3	Do you have wheat flour?	Flour	Teer Flour 2 kg: 105 taka, Efad Flour 2 kg: 90 taka, Shad Flour 2 kg: 89 taka	Teer Flour 2 kg: 105 taka, Efad Flour 2 kg: 90 taka, Shad Flour 2 kg: 89 taka
Server 3	corn flakes	Corn Flakes	Corn Flakes small: 480 taka, Corn Flakes large: 800 taka	Corn Flakes small: 480 taka, Corn Flakes large: 800 taka
Server 3	Anti hair fall shampoo	Shampoo	Sunsilk hair fall shampoo:330 taka, Clear large: 350 taka, Pantine small: 220 taka, Pantine large: 400 taka	Sunsilk hair fall shampoo:330 taka, Clear large: 350 taka, Pantine small: 220 taka, Pantine large: 400 taka

TABLE III
SERVER 3

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