Customer Support Bot

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***Abstract*—In recent times, chatbots have been implemented in all companies to keep customer content 24/7. Users are currently moving to social media and feel comfortable in requesting and receiving customer service and queries about any info. But it is very hard to respond with an answer to the query of the customers in time. Normally, it is seen that for a person to give a reply to a customer's query it takes thirty minutes to a day. And keep the customers waiting for a day with their query is never good for the business as it will be destructive to the relationship between the company and its customer. Instead of getting new customers, the companies will be starting to lose their members.**

***Index Terms*—Chatbot, customer service, deep learning, LSTM**

I. Introduction

Internet user rates are increasing annually by 1.9% worldwide. As a consequence, this is affecting immensely the way people make their purchases and approach customer service in the present time. And the biggest evidence is the advent of social media which has changed the ways user used to approach customer service or get any info about the product that they are interested in. And this massive change has only benefited the customers. From the perspective of the customers getting any products or any service via the internet is very synonymous with a wide range of products, less time spent, and efficiency which translates the convenience for people in their daily lives. Since users are moving towards social media there is a significant increase in user requests for a company's product or any service and it is becoming very challenging to process those requests and give a quick response.

To deal with such a problem, a lot of companies are forming a dedicated customer service team and their function is to give a quick response to the user's request. The team is based on the company's customer base and it is composed of dozen to a few hundred humans who are specifically trained to address users' issues and solve their issues. But still, this manual work is not that much of effective. Addressing people's issues manually is time-consuming and most often time it never reaches users' expectations. It is seen that a company's customer service team takes a minimum of thirty minutes to a day to give a response. There are two issues behind manually addressing users. One of them is staff gets repetitive queries about a similar thing and it is seen that the staff something do not reply to those queries. The other one is offering 24/7 service, which is quite difficult for companies, especially for non-global companies who do not even have the budget for such a team.

There were lots of chatbots created based on rule-based and template rules. There are different kinds of deep learning techniques that are being used in recent times in natural language generation. In our paper, we have created a new conversion system between the user and the chatbot. Deep Learning techniques such as LSTM (long short-term memory) and RNN (recurrent neural network) will be used to generate responses to customer requests.

This study will create a passage for companies to understand the insight of a chatbot in providing service to a customer and also providing information about their products. As a result, these kinds of tools will create loyalty between the company and its customer. Moreover, it will reduce the cost of having a customer service team and the problems related to its addressing customers manually as chatbots can address multiple customers at the same time. This research paper seeks to help and ensure companies the role and impact of chatbots by increasing their customer loyalty, resulting in higher profits, and the implementation of the chatbot.

II. Literature Review

Chatbots can be categorized based on several factors, such as the level of communication and how responses are generated. The first type of chatbot is based on the amount of data available to them, which can be classified into Open Domain and Closed Domain bots. Open-domain bots can address general topics and respond to them appropriately, while closed-domain bots focus on a specific subject matter and may not address other inquiries. The second type of chatbot is based on the level of personal interaction with the user and depends on the bot's task. They may make small talk or respond to the way the user's day is going, but their primary responsibility is to perform the task for which they were designed.

A. Sequence to Sequence

Seq2Seq AI Chatbot with an Attention Mechanism is another method used by various technological institutes/companies. This is mainly a combination of Retrieval-based and Generative models. The seq2Seq paradigm becomes one of the most used for machine translation and text summarization. It is formed of one encoder which is formed of RNN and a decoder which is also formed of RNN. The input which is the sequence (sentence) goes through the encoder and each time step involves the processing of one symbol (word). Its goal is to transform the sequence into a feature vector of fixed size that encodes just the significant part of the information in the sequence while discarding the extraneous information. Employ an attention mechanism such as long attention, which has been recommended in several articles. To increase chatbot performance, you may also experiment with other hyperparameters and assessment metrics.

B. Sentence Level Features

Sentence Level Features A sentence is represented as a weighted average of word embeddings, with their projection onto the first principal component removed from all sentences in the corpus. This feature's framework can be divided into two parts. The Offline one includes Knowledge Construction, Topic Classification Model, Emotion Classification Model. The Online one includes Knowledge-based Comfort, Emotion & Topic Comfort and lastly, Emotion-level Comfort.

C. LSTM

The Long Short-Term Memory (LSTM) model network is renowned for its capacity to learn from sequential data. The final hidden statement of the LSTM, that is made up of gates and memory cells, provides the encoder implementation in this model.The gates control the flow of information and determine the preceding hidden state, while the memory cells store information from previous inputs. Standard recurrent neural networks fail to match the performance of the LSTM in a number of tasks, including language modeling.The study also suggests using parallel computing models for faster algorithm computation. The literature review of the LSTM model network has been extensively studied and widely used in various applications, such as speech recognition, language modeling, and natural language processing. The model's ability to handle long-term dependencies makes it an ideal choice for sequential data analysis. In a study by Prasnurzaki Anki1(2021), the authors proposed the LSTM model to overcome the vanishing gradient problem in recurrent neural networks (RNNs) and demonstrated the model's effectiveness in predicting sequential data. Further studies have been conducted to improve the LSTM model's performance, such as introducing variations of the model, including peephole connections and Gated Recurrent Units (GRUs). The LSTM model has also been applied in various fields, such as finance, healthcare, and natural language processing.In conclusion, the LSTM model network is a powerful tool for sequential data analysis and has been extensively studied and applied in various fields. The model's ability to handle long-term dependencies and its variations, such as GRUs, make it an ideal choice for many applications. Further studies can be conducted to improve the model's performance and explore its applications in new fields.

D. Bi-directional RNN

The development of chatbots involves the use of various machine learning techniques, and Bidirectional Recurrent Neural Networks (BRNN) is one of them. BRNN has shown promising results in improving the performance of chatbots. In this literature review, we will discuss the use of BRNN in chatbots. Bidirectional RNN is a one of the neural network that can be trained in both forward and backward directions. The forward pass of the network takes input from the past and predicts the future, while the backward pass takes input from the future and predicts the past. BiRNN is better than vanilla RNN as it processes longer dependencies and has been shown to perform well in natural language processing tasks. In recent years, BRNN has been extensively used in chatbot development. The study of Raji Sukumar (2021) describes the dataset source and format, workflow diagram, and data preprocessing steps for building a conversational chatbot. The dataset used for this project is saved with a name called JSON file, which includes tags, patterns, responses, and context to organize the information The workflow diagram outlines the steps taken by the chatbot from the time it receives a user's query until it responds with a response.The data preprocessing steps include tokenization, stemming, lemmatization, removal of stop words, spelling correction, normalization, the production of training data, and the removal of punctuation.The preprocessing steps are crucial to prepare the data for modeling and to ensure that the chatbot can understand the input.In conclusion, BRNN has shown promising results in improving the performance of chatbots. The ability of BRNN to capture the context of the conversation and handle long-term dependencies has made it a popular choice for chatbot development. The studies discussed in this literature review have shown that the BRNN-based models outperform traditional chatbot models in terms of accuracy and the naturalness of the conversation.

III. Methodology

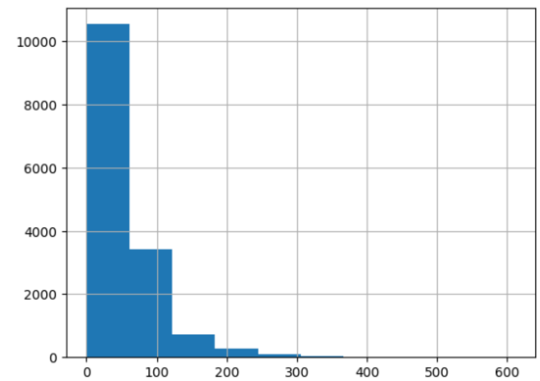
This section elaborates on the methodology proposed in this paper. The deep neural network models will be implemented after preprocessing the dataset and then we will be implementing different kinds of models like LSTM, BiLSTM and use evaluate metrics to check the accuracy of these models based on what the machine has understood.

A. Dataset

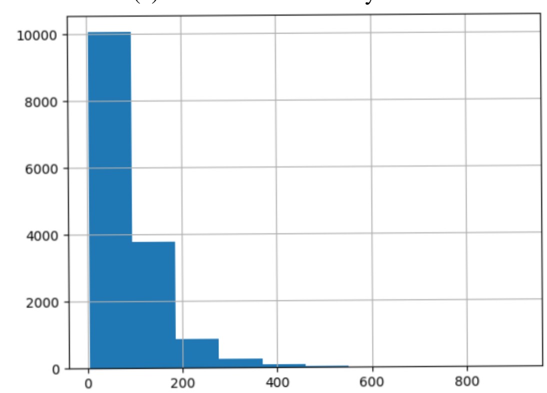
The dataset contains a dialogue between a driver and an assistant. And the dialog goes in multi turns and it is a task-orientated dialogue dataset. There are around twelve thousand conversations between the driver and the assistant.

From the whole dataset, the number of words said by the driver is from one word (for example "Thanks") to five hundred words, generally, the word range stays mostly from one word to hundred words. The visualization of this is in figure1a On the other side, the assistant has used one word to four hundred words, generally around two hundred words. The visualization of this is in figure1b

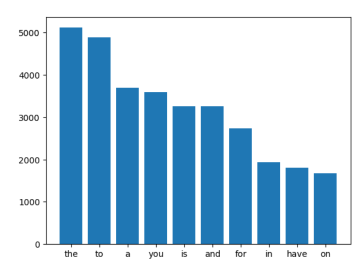
Moreover, figure 2a and figure 2b shows the top ten most used stopwords by the driver and assistant in their dialogs. If we look in both of the graphs it is visible that the ten most used stopwords are the same but the frequency of the words is very different. And in the preprocessing part, we will remove them for the improvement of the models that will be implemented later.



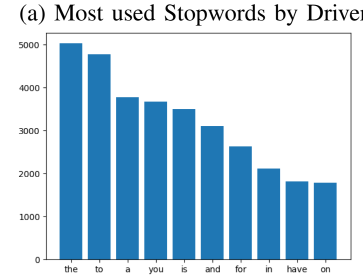
(a) Number of Words by Driver



(b) Number of Words by Assistant



(a) Most used Stopwords by Driver



(b) Most used Stopwords by Assistant

B. PreProcessing

Firstly , there would be preprocessing required in the dataset to clear the noise present in the dataset. For preprocessing the raw data's id , multi-turn conversations were converted to two different lists. The reason between converting is to assimilate with the format of Sequnce to Sequence(Seq2Seq) model's input format. And the first column is question's asked by the driver and the second column is the answers replied by the assistant. After the separation of these two columns from the raw data, the preprocessing was done simultaneously. Firstly, different kinds of digits attached with words or without words are preprocessed. Secondly, all the text was converted to lowercase. Thirdly, all the stopwords that do not have any meaning have been removed from the text and space instead of that for increasing the accuracy of the models. Fourthly, different punctuations that are present in the text are removed to reduce the noise from the text. In the present time, there are lots of contractions that are used in the text but the machine does not understand these contractions. For that, a huge amount of contractions and their normal form are added manually.

IV. Result

Seq model	LSTM	BiLSTM
0.92	0.96	0.97

Different kinds of models have been implemented and there is a positive accuracy among all of the models. In the sequential model we have used word embedding of our own. Then we add global average pooling1d and then two layers of dense with activation function of relu and finally an output layer. And running the training set on the model for 500 epochs the accuracy was 0.92. Then , double layered LSTM was implemented. Here also we have used our own word embedding and then added two layers of CuDNNLSTM of 126 nodes instead of basic LSTM. The reason behind this is that CuDNNLSTM works faster than than LSTM so it would reduce lot of time. After that we have used two layers of dense of of 16 nodes with activiation of relu on an epoch of 500. And from this double layered LSTM , the accuracy was 0.96. Finally , BiLSTM was implemented where word embedding layers was added then two BiLSTM were added and after that one dense layers of 150 nodes were added. And form this model the accuracy was 0.97. The reason behind BiLSTM having advantage over other models is that it encodes the value viewing the past and future words. And it makes more sense this model will have higher accuracy than others.

V. Future Work

In this work, different kinds of models were taken into consideration but there are also works that can be done. A Bigger dataset can be taken into consideration and then this model's accuracy will be different. Moreover, implementing different other natural language techniques can be implemented and the result can be very different.

VI. Conclusion

The aim of this research was to investigate the effectiveness of chatbots in customer service and their relevance in improving customer service quality. Through an extensive review of the literature, the study identified five key functions of chatbots that are related to customer service. These functions were divided into two categories: "improvement of service performance" and "fulfillment of customer's expectations." The first category includes functions such as interaction, entertainment, and problem-solving, all of which aim to enhance the quality of service performance. The study found that a chatbot's personality, interaction style, and empathetic approach positively affect customer satisfaction and service performance. Furthermore, providing an entertaining experience can also have a positive impact on customers' attitudes toward chatbots. The second category, ”fulfillment of customer’s expectations,” includes functions such as customization and trendiness, which aim to meet the evolving expectations of customers. Providing personalized and unique experiences through chatbots can enhance customer satisfaction and loyalty. Furthermore, trendiness has become an important factor in meeting the expectations of customers who value a fancy lifestyle. The study suggests that this categorization of chatbot functions can help software engineers identify key features necessary for improving service performance and meeting customer expectations. This could lead to better service quality in industries that rely heavily on customer service, especially in the B2C sector. The study concludes by suggesting further research on chatbot applications in e-commerce and identifying opportunities for improving their effectiveness in specific sectors. Empirical studies could help evaluate chatbot performance in terms of service quality and identify factors that have the most significant impact on customer satisfaction.

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