

Chat Bot X Stream

^[1]Dr. Muthusamy P, ^[2]Bala Sweatha S D, ^[3]Kavya T, ^[4]Indhujaa M

^[1]Head Of The Department, Department of Artificial Intelligence and Data Science, Muthayammal Engineering College, Rasipuram.
hod.cs@mec.edu.in

^[2] Student Department of Artificial Intelligence and Data Science, Muthayammal Engineering College, Rasipuram.
balasweathabtech2003@gmail.com

^[3] Student Department of Artificial Intelligence and Data Science, Muthayammal Engineering College, Rasipuram.
kavyathagavel0709@gmail.com

^[4] Student Department of Artificial Intelligence and Data Science, Muthayammal Engineering College, Rasipuram.
indhujavaruni@gmail.com

Abstract: utilizing contextual information to generate accurate and relevant responses, and implementing strategies to make conversations human-like. We propose a supervised learning approach for model development and make use of a dataset consisting of multi-turn conversations for model training. In particular, we first develop a module based on deep reinforcement learning to maximize the utilization of contextual information serving as insurance for accurate response generation.

Key Words: chatbot, reinforcement learning, sequence to sequence, generative adversarial nets.

I. INTRODUCTION

Chat bot research focuses on creating intelligent agents for human-machine interaction in a fashion similar to human-to-human communication. Chat bots have a variety of uses, including customer service, e-commerce, healthcare, finance, education, entertainment, HR, and emergency services. They can assist customers with inquiries and provide information and support in account management, scheduling, medical advice, and recruitment. As a result, the field of artificial intelligence and natural language processing is witnessing more research on building Chat bot applications. Recently, there have also been breakthroughs in the field, leading to practical applications such as Chat GPT.

It is clear that a chat bot can be considered to have human like quality if it can generate responses that are relevant, meaningful, and natural in conversations with humans. In an attempt to achieve that goal, we have recently developed a new model for conversational agents inspired by the Turing test and the idea of the adversarial learning method. Particularly, we designed a model based on deep neural networks that allow generating experimentally results in improvement of the model performance. However, the model cannot evaluate the effects of contextual information in an entire conversation, such as the relationship of contexts and their influence on future outcomes.

II. LITERATURE SURVEY

2.1 Contextual Chat Bot With Reinforcement Learning.

These models are trained to generate the following response based on a previous turn. As a result, these models often generate generic or uninteresting responses like “I don’t know” because there are many generic utterances in the training data. The decoder also fails to consider the full context of the conversation as it only generates responses based on the previous turn.

2.2 Human Like Chat Bot With Adversarial Learning.

Such models as ChatGPT and Bard rely on large language models to enhance their capabilities of natural language generation. In the proposed approach, instead of constructing a large language model to achieve highly natural and human-like language generation, we employ adversarial learning techniques to make the model capable of generating natural language. As is well known, the characteristic feature of the GAN model is its discriminator component, which is used to steer the generator’s output towards the desired direction.

III. EXISTING SYSTEM

Users interact with the chat bot through a web interface or a dedicated mobile application. A chat window where users can input messages and receive responses. The core logic of the chat bot resides in the chat bot engine.

The system identifies the user's intent to determine what action the chat bot needs to perform. The chat bot relies on a database to store and retrieve information. This can include FAQs, user preferences, and historical conversations. The chat bot is trained on a dataset that includes examples of user inputs and corresponding desired responses. The chat bot is trained on a dataset that includes examples of user inputs and corresponding desired responses.

IV. PROPOSED SYSTEM

As it allows consumers to put orders directly to the kitchen, this technology offers several benefits in terms of effective queue management by reducing waiting times. It also makes it easier to schedule orders ahead of time, which adds even more ease. By adding a card payment option, a lot less time is spent paying bills and making modifications at the payment counter. This approach guarantees user-friendliness in addition to time savings

4.1 Overview

The proposed app works in the following manner:

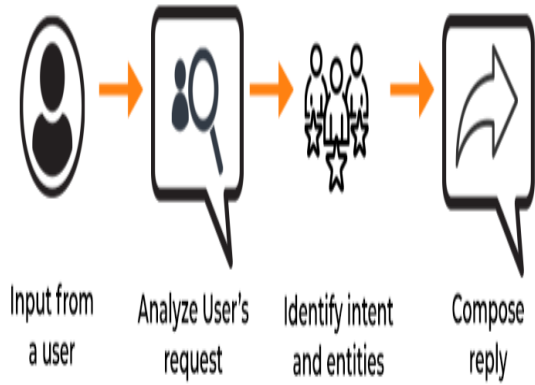
- In this study, we address the problem in a multi-turn scenario using a dataset of conversations.
- In recent years, RL has gained significant attention in chat bot development. This technique plays an important role in the success of Chat GPT.
- In a multi-turn scenario, we frame response generation as a source-to-target problem, treating conversation history as the source and the next response as the target.
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- By considering a sequence of responses, our model can capture the flow and coherence of the conversation more effectively.
- In low-resource scenarios, there remains a demand for solutions to effectively develop models capable of operating with limited data and computing resources.

4.2 Functionalities

- The chat bot should be able to understand and respond to basic questions and inquiries from users. This can include providing information about products, services, or company details.
- Implement natural language processing (NLP) to enable the chat bot to understand and interpret user inputs, allowing for more conversational interactions.
- The chat bot can use information about the user, such as their history with the company or their preferences, to provide personalized recommendations or assistance.
- The chat bot should be able to help users troubleshoot issues, provide support, and escalate to a human agent if necessary.
- Chat bots often need to integrate with existing systems, such as customer relationship management (CRM) platforms, inventory management systems, or support ticketing systems.
- The chat bot can be used to collect feedback from users, conduct surveys, or gather data for market research.
- Chat bots can be designed to continuously learn from interactions and improve their responses over time using machine learning techniques.

V. FLOW CHART

5.1 Mechanism of the Chat Bot



5.2 User Flow Chart

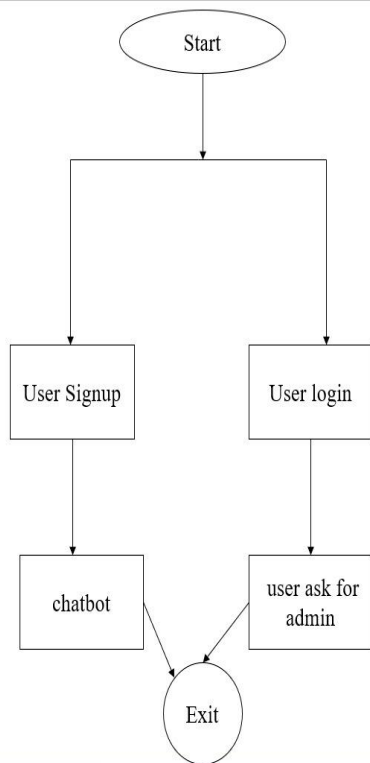


Fig 2: User Flow Chart

5.3 Admin Flow Chart

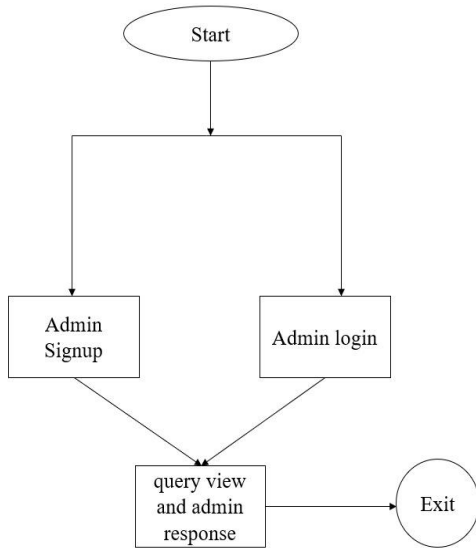


Fig 3 : Admin Flow Chart

VI. CONCLUSION

We performed a comprehensive set of experiments to assess the proposed model’s performance compared to the baselines. These experiments’ results showed our approach’s effectiveness, as evidenced by significant improvements in the quality of generated responses. It is experimentally shown that our developed architectures yielded significantly better results in comparison to recently related studies in the literature. We believe that the proposed model can be incorporated into chat bot systems to improve their quality in practice. Building on the improved results of this study, our future work will involve the design of additional rewards that align with human decision-making characteristics. By incorporating these rewards into the chat bot’s training process, we aim to guide its behavior better to match human expectations, leading to higher-quality interactions and more natural conversations.

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