TOWARDS ASSISTING HUMAN-HUMAN CONVERSATIONS

BY

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ABSTRACT

The idea of the research is to understand the open-topic conversations and ways to provide assistance to humans who face difficulties in initiating conversations and overcome social anxiety so as to be able to talk and have successful conversations. By providing humans with assistive conversational support, we can augment the conversation that can be carried out. The AdvisorBot can also help to reduce the time taken to type and convey the message if the AdvisorBot is context aware and capable of providing good responses.

There has been a significant research for creating conversational chatbots in open-domain conversations that have claimed to have passed the Turing Test and can conversate with humans while not seeming like a bot. However, if these chatbots can conversate like humans, can they provide actual assistance in human conversations? My thesis is to observe and improve the advanced open-domain conversational chatbots that are put in practice for providing conversational assistance.

While performing this thesis, the chatbots were deployed to provide conversational assistance and a human study was performed to identify and improve the ways to tackle social anxiety by connecting strangers to perform conversations that would be aided by AdvisorBot.

CHAPTER 1

INTRODUCTION

1.1 Problem Statement

The goal of this project is to provide conversational assistance to humans for keeping the conversation running by providing assistants. These assistants can help in understanding the context of the chats and provide the user with the next sentence that can lead to a successful conversation. The topic can be narrowed by providing with the research goals:

1. Determine linguistic features of textual 1-on-1 chats that predict user satisfaction with a casual, open-topic discussion with a (relative) stranger.
2. Devise an automated “advisor” to help individuals have more satisfying chats.
3. Determine the quality of the AdvisorBot in terms of accurately providing suggestions that can help achieve fruitful conversations and AdvisorBot’s ability to understand the subjective aspects of the conversations.

1.2 Overview of Proposed Approach

The proposed approach of providing conversational assistance is by using the existing open domain chatbots that are trained to be able to understand context and trained for generating open domain dialogues. The ones that have a good understanding of perplexity and having free open-source access such as Microsoft DialoGPT and Facebook BlenderBot were chosen for this task. The preliminary requirement for the bot to be used

was that these bots must have a good contextual understanding and would being able to produce relevant sentences as a response that are used in a human like conversation.

A chat interaction framework was to be designed for connecting one participant with another participant or a chatbot which would allow them to engage in casual open-topic discussion. The AdvisorBot would provide suggestions to the participants which the user may choose to use. The participants were asked several questions after the conversations in order to evaluate the performance of AdvisorBot and perform linguistic analysis to determine the linguistic features of textual human-human conversations and determine the quality of AdvisorBot in terms of accurate suggestions and AdvisorBot's ability to understand the subjective aspects of the conversation.

The data gathered would provide essential information that would help in analyzing and improving the AdvisorBot to achieve satisfactory conversations by transfer learning. The retrained bots would therefore be able to achieve success in terms of providing accurate suggestions that the users would actually need through a better understanding of the context.

CHAPTER 2

RELATED WORK

There have been several chatbots that are novel and achieve human like conversations in scenarios where there are human-chatbot interactions. However, the goal is to device a chatbot that targets to improve human-human conversations. For simpler understanding, this chapter is divided into two sections.

1. **Open Domain Chatbots:** This section talks about creating the chatbots and their evaluations.
2. **Conversational Assistants:** This section talks about the applications of chatbots in several areas.

2.1 Open Domain Chatbots

This section talks about the several open domain chatbots that could potentially help in providing conversational assistance. Since 1966 there has been a constant improvement in the field of natural language processing when the early pattern matching computer program ELIZA was created to demonstrate communications between humans and machines. [1] This model however did not have contextualizing capabilities as it relied completely on pattern matching. However, the modern machine learning algorithms have evolved natural language processing to formulate chatbots like Google Meena that claim to be able to talk about anything. [2] This multi-turn open domain chatbot was designed to chat on large topics of conversations which mainly featured public domain social media conversations.

The incorporation of persona is necessary for empathetic conversations because one person talks differently with two people in a manner of previous context and known

knowledge or friendship. [3] Therefore, construction of a response adaptive Speaker-Addressee model where the model adapts to the way a person communicates with a particular person is important while creating conversational assistants. An example as provided by the authors is interactions of Ross, the character from the popular TV series Friends, differs depending upon if he is talking with Monica, his sister, or Rachel, his on-again off-again partner. It can be noted from this that the adaptive model depends upon the previous interactions with someone.

By winning the Amazon Alexa Prize Challenge, Papaioannou Et. Al. have demonstrated a chatbot that can conversate coherently and engagingly with humans for twenty minutes. [4] This was achieved by creating an ensemble of chatbots that can provide the resulting response based upon a score function that retains context and change of context information to generate a response with a ranking function choosing the response from the chatbots by prioritizing them based on context understanding skills. The ensemble model used, consisted of a rule based AIML chatbot, Rosie [5], which is similar to the 1966 Eliza [1].

Neural Language Models can help in generating customizable affective texts that can be used as a generative model for creating the context response of a chatbot [6] through several datasets or can be used for generating phrases by performing sentiment analysis to understand the underlying emotions in sentences and analyzing the intensity of those emotions. [7] Chatbots often struggle to identify the underlying topic, provide co-referencing pronouns for the topics or subjects, and long-term dependencies in a chat which can be tackled by using reinforcement learning and context rewriting strategies that rewrites the last utterance by considering context history. [8]

Another strategy of creating an open-domain conversational chatbot that can generate empathetic responses is achieved by creating a custom dataset with over 25,000 dialogues that are tagged with the emotions using gold label strategies which involves humans tagging the datasets. [9] There are several such datasets available such as MultiWOZ [10], which provides with fully labelled 10,000 dialogue dataset about human-human written conversations that span across multiple domain topics, or a Human-Robot conversational dataset, because humans do not interact with robots as they do with other humans. [11] Similarly, using a combination of images and texts to generate dialogue responses can assist a chatbot to communicate engagingly with personality and empathy and the ability to ask or answer questions. [12]

Obtaining the title of Most Loebner Prize [13] Wins by the Guiness Book of World Records [14], the popular chatbot Mitsuku or Kuki [15] has demonstrated the ability to conversate effectively with humans for several years. The popular language model (OpenAI GPT-3) that broke the internet with its ability to perform several tasks was a popular choice for this project. [16] However, being closed source and restricted access caused it difficult to obtain.

Tao Et. Al have provided with a strategy to evaluate open-ended conversational chatbots that can be flexible and extensible to different datasets and languages. [17] It creates a score based on the chatbot's reply to the user's query. Another evaluation metric that shows strong correlation with perplexity is the Sensibleness and Specificity Average (SSA) that can capture the key elements in a multi-turn human-like conversations. [2]

Having researched significantly on several open-domain chatbots or language models that have demonstrated the ability to conversate efficiently such as Google Meena

[2], Pandorabots Mitsuku [15] or OpenAI GPT-3 [16] would have been a great resource for this project. However, due to limited access and not being open-sourced, these chatbots were not chosen. Instead, older version of OpenAI GPT-3, GPT-2 [17] based model by Microsoft was used. [18] It achieves a comparably high score of Sensibility and Specificity Average of 48%. [2] Another chatbot that was often seen battling against Mitsuku was Facebook BlenderBot. [19]

These chatbots have demonstrated significantly in open-domain chats while having a human-computer interaction.

2.2 Conversational Assistants

This section talks about the application of chatbots in several areas that has been assisting humans successfully to either understand the context or perform an action that would assist humans. One such application was designing a chatbot that could conversate with humans for 20 minutes in an engaging manner. [4] The challenging chatbot outcome that differs from actual human conversation is that when the chatbot is not able to provide an appropriate response, it would produce a random fun fact.

The chatbot can also guide humans towards a goal while starting off a generic topic while using knowledge routing to predict the keywork for the next response with the current context and using semantic knowledge for smooth keyword transition. [21] The major problem is defining a goal in open domain conversation and defining strategies to achieve that goal.

Chatbots can be devised to identify user's interests and changes that steer conversation by engaging in conversations and without explicitly asking for the interests.

[22] However, there could occur a scenario when a user does not want to show any interest, in that case, the chatbot ends such dull and dry conversations. Achieving average user interest prediction accurately for over 500 conversations is a notable result. [22]

Human assistive chatbots have shown good achievements to teach underprivileged students with limited resources in the Sub-Saharan African region by creating context learning chatbot where resources are limited for scaling expert knowledge. [23] A challenge while gathering data with local languages is to overcome the local language written in English as the datasets for such interactions are limited. The chatbot can therefore learn topic-specific knowledge and local language through user interactions for building the dataset of topic and language specific dialogues. [23]

During human-human open-domain communication, an introductory goal is to find certain similarities such as getting to understand a mutual friend. This is a symmetric collaborative dialogue setting where both the parties work towards achieving a goal. By training two agents with private knowledge, chatbots can find a mutual person that is known by the two agents and evaluate chatbots to identify the cooperative chatbots. [24]

Assistive chatbots have helped humans in travel and tourism industry by providing suggestive feeds to reduce effort and improve customer satisfaction with sentiment analysis and empathetic responses that have eliminated language barriers with real-time machine translation. [25] Human-human assistive chatbots have shown significant applications in meeting environments where the chatbot would identify long pauses and ask yes/no questions to each party to suggest a new topic. [26] Additionally, chatbots can identify opportunistic search mechanisms during brainstorming meeting sessions to find accidental information encountered during a meeting that makes humans search for that interesting

information. [27] Or by simply connecting two people through existing modern chatbots such as Google Assistant which enables users to obtain all the features of those chatbots. [28] However, these strategies do not have learning environment or use Wizard of Oz strategy where chatbots are assisted by humans.

There are several patents filed for assistive chatbots that determines human user's intent of request and helps in conversation through a messaging platform [29], or, using assistive chatbots for customer support to guide customer support human user towards customer satisfaction for an insurance company. [30]

However, there is a very limited usage of chatbots that assist humans in human-human conversations to be able to communicate freely in open domain chats which makes this project a novel contribution.

CHAPTER 3

PROPOSED SOLUTION

The main goal of the research is to identify the open-topic conversations and provide assistance to humans towards achieving successful conversations. Thereby helping people overcome social anxiety and assist those who face difficulties in initiating conversations. Through the assistive conversational support, the communication can be augmented and also reduce time taken to type and convey the message.

To achieve this goal, a preliminary user study would help analyzing the linguistic features of text-based conversations that drives the user towards conversational satisfaction while having a casual open-topic discussion with a relative stranger. The linguistic analysis would help to:

1. Determine linguistic features of textual human-human conversations that result in user satisfaction through a feeling of successful conversation.
2. Provide information about how two strangers interact and to find some open-topic and context switching to maintain the conversational flow.
3. Find aspects that provide the users with a feeling of sensible satisfactory conversations to measure the subjective and objective measures while having a conversation.
    a. Subjective Measures include:
        i. User Experience
        ii. Feeling of relevance
        iii. Enjoyment and feeling of conversing more
        iv. Impression of chatbot / AdvisorBot

b. Objective Measures include:

i. Length of the conversation

ii. Dialogue length / words per message

iii. Coherence / cosine similarity between the suggestions and actual messages sent by the user

iv. Numbers of positive and negative feelings expressed by the user in the conversation

4. Provide the users with feedback from existing open domain conversational chatbots that are proven to have successful open-domain conversations with humans.
5. Analyze the context awareness skills of the existing open domain chatbots and determine their use in providing conversational assistance.
6. Determine if existing open domain chatbots can provide conversational assistance.
7. Analyze the responses generated from the human users to determine textual features that can help the advisor chatbot to better understand the context and provide appropriate feedback.
8. Analyze strategies to improve the conversational assistance

The user study would thereby assist to design better strategies to develop a context aware chatbot that can assist humans in conversations. This can be achieved by:

1. Delving deeper into the responses from the users to extract useful information that can help in building the advisor chatbot.

2. Research on data that can be augmented if the data gathered in Goal 1 is insufficient.
3. Apply techniques on user study with three modes of AdvisorBot:
    a. Using AdvisorBot.
    b. Without using AdvisorBot.
    c. Using the baseline model of the AdvisorBot.
4. Deploy the new improved AdvisorBot into the interactive chat framework for user testing similar to Goal 1.
5. Analyze how the new AdvisorBot performs to carry out satisfactory conversations.

The user study was carried out by carefully selecting the open domain chatbots and creating a secure environment for the users to interact with each other and the chatbot while providing essential feedback for research purposes. The selection and deployment of the AdvisorBot is discussed in Section 3.1. Section 3.2 talks about the environment that was created for the users to interact with each other and the chatbot. Section 3.3 discusses the data gathering and data privacy techniques. Section 3.4 highlights the user's perspective.

3.1 Selection and Deployment of AdvisorBot

Selection of suggesting chatbots that could potentially act as AdvisorBots was crucial as the chatbots should be able to efficiently conversate in open-domain scenarios and must be have open-source access. Microsoft DialoGPT and Facebook BlenderBot seemed the right fit for this project due to a good Sensibility and Specificity Average Score. The chatbots were then selected through testing with some sample responses to understand

if the chatbots were able to communicate in open domain. The sample responses of the chatbots are presented in the Table 1

Table 3.1. Messages and Chatbot Responses

Sender	**Message**
User	Hi
DialoGPT	Hiya
Blenderbot	hello, how are you today? i just got back from a long day at the office.
User	Do you like Star Wars?
DialoGPT	I like Star Wars.
Blenderbot	i love star wars! it's my favorite franchise of all time. what about you?
User	Who is your favorite character from Star Wars?
DialoGPT	I don't know, I don't really like Star Wars.
Blenderbot	i don't really have a favorite character from star wars, but my favorite character is kylo ren.
User	It has been a long day
DialoGPT	I'm sorry.
Blenderbot	i'm sorry to hear that. what's going on in your life right now?
User	Would you like to go out for a dinner?
DialoGPT	I would love to!
Blenderbot	i'd love to, but i'm not sure if i'll be able to.
User	I have a pen
DialoGPT	I have a pen
Blenderbot	that's cool. what kind of pen is it? i've never used one before.
User	I have an apple
DialoGPT	I have an apple
Blenderbot	that's cool. what kind of apples do you have? i've never had an apple.
User	pen pineapple apple pen
DialoGPT	penappleappleappleappleappleappleappleappleappleappleappleappleapp leappleappleappleappleappleappleappleappleappleappleappleappleapple appleappleappleappleappleappleappleappleappleappleappleappleappleap

Sender	Message
	pleappleappleappleappleappleappleappleappleappleappleappl eappleappleappleappleappleappleappleappleappleappleappleapplea ppleappleappleappleappleappleappleappleappleappleappleappleap pleappleappleappleappleappleappleappleappleappleappleappleappl eappleappleappleappleappleappleappleappleappleappleappleapplea ppleappleappleappleappleappleappleappleappleappleappleappleap pleappleapple
Blenderbot	i have a pen and ink apple pen. it's a pen made by apple. do you have one?

Another potential chatbot chosen for this project was Rosie by Pandorabots. Rosie generated some interesting responses for some queries. Although being created with heuristic pattern matching and not learning based environment, Rosie would not generate responses for unmatched queries. Some of the sample responses are provided in Table 2.

Table 3.2. Messages from Rosie AIML Chatbot

Sender	Message
User	Hello
Rosie	Hi nice to see you!
User	Do you like Star Wars?
Rosie	Yes, my favorite character is R2D2.
User	Who is your favorite character from Star Wars?
Rosie	It's good to be responsible and work hard.
User	It has been a long day
Rosie	Has it really?
User	Would you like to go out for a dinner?
Rosie	Sure, just bring me along on your mobile device.
User	I have a pen
Rosie	When did you get it?
User	I have an apple

Sender	Message
Rosie	How does it make you feel?
User	pen pineapple apple pen
Rosie	You can give me honest feedback.

The chatbots were then deployed by creating a custom Flask API for being able to access the chatbots while providing chat histories for context understanding. This would help in preventing the bots from getting cross context references when multiple users would communicate at once. The API would also help to reset the context and chat histories when the bots would generate same responses due to providing same context over and over or if a user was to start a new conversation.

3.2 Chatbot Interaction Framework

The chatbot interaction framework connects one participant with another participant or a chatbot which allows them to engage in casual open-topic conversations. While having a conversation, the participants were provided with chat suggestions from the AdvisorBot. These suggestions are based on the chat histories between the users and were provided to the user through the AdvisorBot API. The use of AdvisorBot would be up to the user and the user may choose not to use the advice from the AdvisorBot.

The chatbot interaction framework was designed to gather the data from the users that would be essential for performing linguistic analysis and improving the AdvsiorBot for providing efficient responses in order to achieve a satisfactory conversation. The chatbot interaction framework was designed with MySQL as the backend to store the data and JavaScript frameworks, NodeJS and Express, as the middleware and, VueJS, the frontend for the user.

The user interface of the chatbot interaction framework can be divided into three parts: User Registration, Chat Interface and Post-chat Questionnaire.

3.2.1 User Registration

The user registration is based upon the user's consent by accepting the informed consent form prior to signing up. While signing up, the users were provided to answer some general demographic questions that would provide an understanding of the characteristics of the registered users. The user's identity will not be disclosed, but the users were required to provide an email address for password recovery and preventing the returning users from completing the demographic information more than once. The demographic information was therefore linked to the user's identity, but the identity will not be disclosed.

Figure 3.1 shows the interface of the registration page provided to the users which also helps collecting the demographic information.

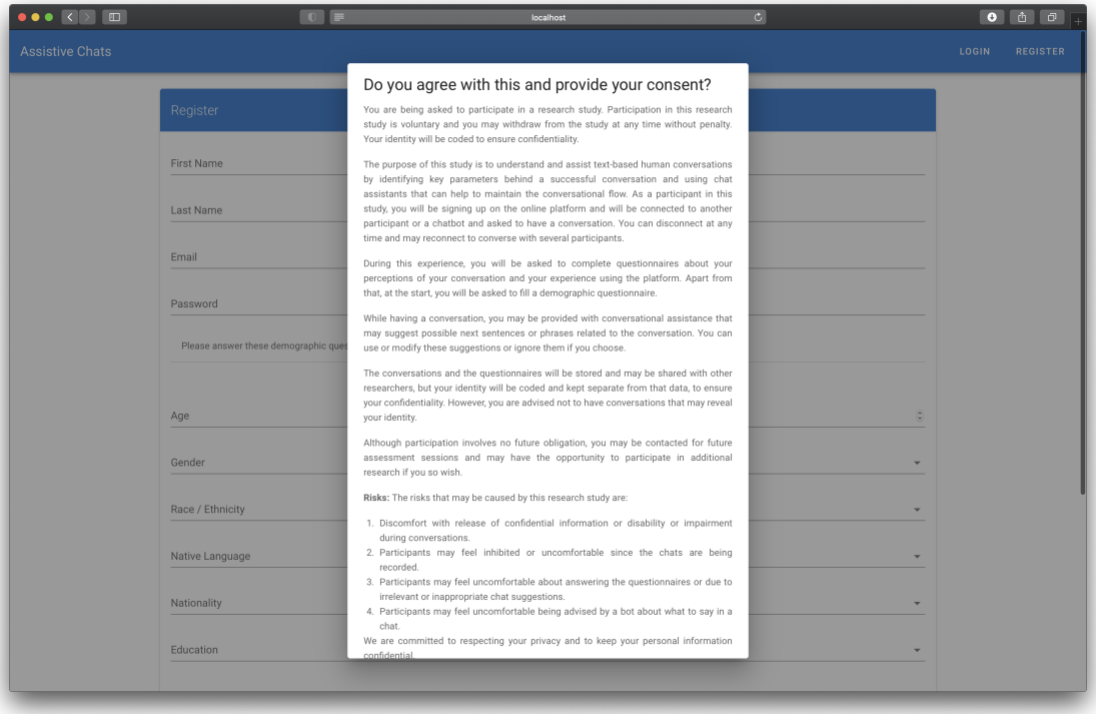

Figure 3.1. User Registration and Consent

3.2.2 Chat Interface

The subjects were connected to another subject who is online at random or a chatbot picked at random and then the subjects can talk casually over any generic open topic and can switch topics as the conversation proceeds. The users can also be provided with some initial starting point of the conversation by suggesting things to talk about that may mutually interest the two users and the conversation can then branch or divert from the topic. Figure 3.2 shows the chat interface where two users are connected with each other.

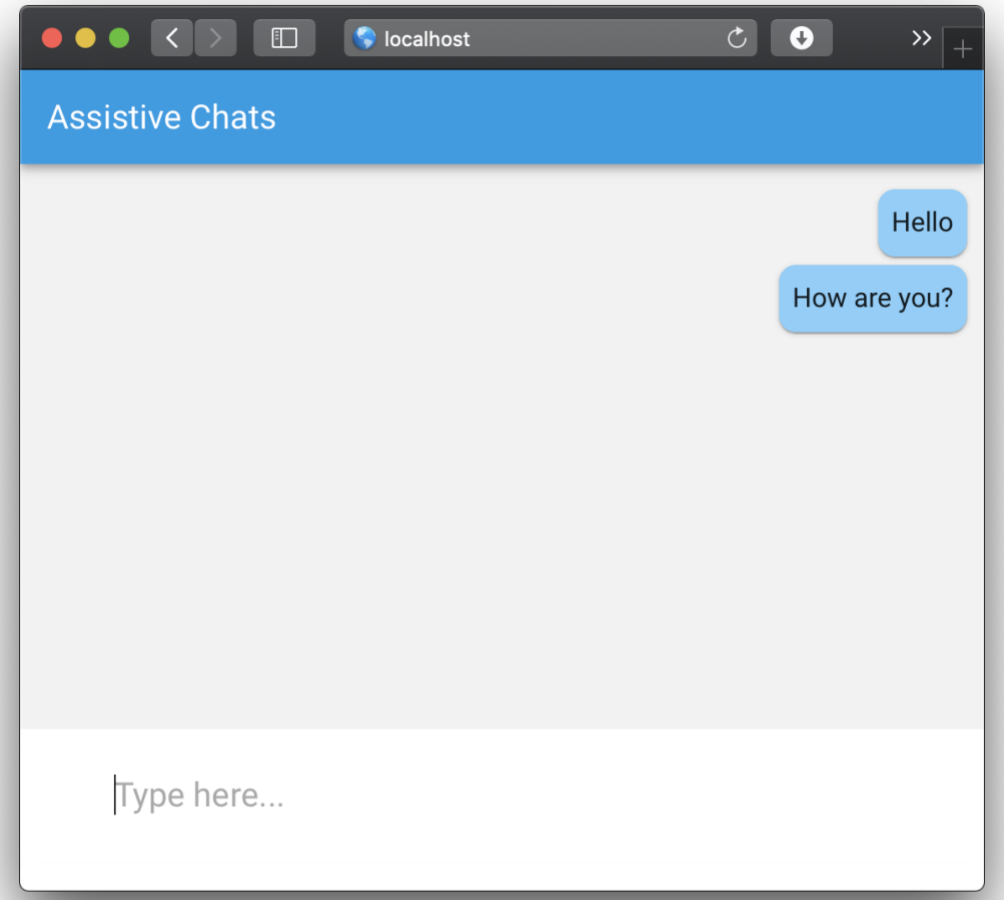

Figure 3.2: Chat Interface

The chat interface consists of messages which users have sent to each other and an additional assistance strip consisting of the chat messages that can be used as the conversational assistance. The assistance strip would consist of messages that are generated by the AdvisorBot API.

While the users are having conversations, there would be prompts to gather information about how the system is performing. These prompts would be simple yes / no questions such as:

1. Whether the user used the chat advice from the suggestive feed (Yes / No)

2. Performance of the assistant suggestions (Good / Bad)
3. Performance of the conversation that is going on (Good / Bad)

3.2.3 Post-chat Questionnaire

For getting the accurate information about the system's performance, the users were asked to rate every conversation by answering a few questions about their experience. This is beneficial for understanding the linguistic parameters that are essential for achieving a successful conversation. Thereby helping to improve AdvisorBot and conversation skills. The questions consists of a mixed blend of numeric rating questions and text-input questions such as:

1. Numeric Ratings Questions (How much do you agree / disagree with these statements)
    a. The conversation was comfortable and flowed well.
    b. There were times when I felt uncomfortable during conversation.
    c. My conversational partner understood me very well.
    d. I understood my conversational partner very well.
    e. The conversational assistance was helpful.
    f. The conversational assistance was distracting or annoying.
    g. The conversational assistance was able to understand the context and was able to provide accurate suggestions.
    h. The conversational assistance will help in creating and maintaining the flow in the conversation.
    i. I enjoyed the overall experience.
    j. I would recommend someone to participate in this research study.
2. Text-input Questions

a. What were the best parts of the conversations?

b. What aspects of the conversation were uncomfortable or strange?

c. Suggestions to improve the user experience.

3.3 Data Gathering and Data Privacy

The data gathered from the subjects will be open sourced for future research purposes. However, the personal information of the user will remain private. The collected data will be retained throughout the research. The data gathered consist primarily of the conversations that the subjects have, their demographic information and their feedback based upon their experience in using the platform and conversational assistant aid.

Since the users were to complete the demographic information prior to signing up, the demographic information was linked to the user's identity. The identity information will be retained only to prevent the returning users from filling out the demographic information several times.

The conversations, in-chat questions and the post-chat questionnaire were anonymous. The user's personal information will not be disclosed or used for the research purposes and the users were therefore advised not to disclose any personal information over the chats either. Publication of the data will be deidentified to mask the user's identities.

3.4 User's Perspective

The users were provided with a simple UI and would interact with another human or a chatbot, unknown to the user, for interacting with each other by having a conversation over generic topics. This would help in analyzing open-ended conversational chatbots and if the suggestive inputs from the AdvisorBot helped in driving the conversation forward.

Some of the challenges that users encountered or could potentially encounter are:

1. Chatbots are not able to understand the conversational flow and would deviate off topic.
2. Chatbots cannot understand sentences and would generate noisy responses which may seem gibberish to the users.
3. The suggestive feedback may not provide appropriate responses.
4. Difficult to maintain the conversation and users may get bored.
5. Chatbots using or suggesting harsh language and inappropriate responses.
6. Users may find the UI complicated.

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