Customer Service Bot For A Travel Agency Using Natural Language Processing

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

Traveling isn't new in the human race. Modern humans began migrating from Africa 70,000 to 50,000 years earlier. Again, modern tourism started in the 17th century in Western Europe and till today, humans didn't stop and continued traveling around the world in order to explore, discover the unseen, to experience incredible sites and tourist spots. As human civilization is getting digitized rapidly, technology has reached every corner of the world, including the whole travel procedure. In order to make the travel experience easier and more pleasant, we have come up with a customer service bot with the help of Natural Language Processing(NLP), which can be beneficial for both travel agencies and customers in terms of their communication procedures. We aim to decrease manual functions and make communication procedures more technology dependent, and increase the chatbot's ability to answer more questions that a customer would like to know before planning a tour. In a nutshell, our purpose is to make the traveling process easier, more comfortable, and handier by generating a digital program with the help of Natural Language Processing.

Keywords: Natural Language Processing, Customer Chatbot, Graphic Interface Unit, Preprocessing, Tokenization, Padding, Intent Recognition, Named Entity Recognition, Embadding Layer, Sequential Model, Softmax, Bidirectional LSTM, Unsloth LLM Model

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Nomenclature

The next list describes several symbols & abbreviation that will be later used within the body of the document

API Application Programming Interface

GIU Graphic Interface Unit

GPT Generative Pre-trained Transformer

LLM Large Language Model

$LSTM$ Long Short-term Memory

NER Named Entity Recognition

NLP Natural Language Processing

$NLTK$ Natural Language Toolkit

Chapter 1

Introduction

In the current digital era, customer service is a crucial part of every business, and this is also true for the travel industry. Organizations may automate customer service interactions and offer customized advice to clients whenever they need it as Chatbots and natural language processing (NLP) gain popularity. According to a Grand View Research report, the global chatbot market is projected to grow at a compound annual growth rate of 23.3 percent and reach $27,297.2 million by 2030 [36]. In this case, developing an NLP-based Chatbot for customer support could help travel agencies in Bangladesh and other nations respond to clients' inquiries in a timely and efficient manner. According to National Geographic's article "Restless Genes" by David Dobbs (2013), modern humans began migrating from Africa 70,000 to 50,000 years earlier [1]

Due to the growing demand for travel services, customer service has become an essential part of the travel industry. No matter what time of day it is, clients expect rapid and efficient responses to their questions. According to research by Zendesk, 67% of consumers choose self-service over interacting with a customer care agent, which is consistent with the rising trend of customers favoring self-service options [44]. By implementing a customer service chatbot leveraging NLP, travel agencies in Bangladesh and other nations may improve response times, alleviate the strain placed on customer care personnel, and ultimately raise customer satisfaction.

Additionally, it has been demonstrated that Chatbots may enable businesses to cut costs. According to a Juniper Research estimate, by 2022, Chatbots might save businesses up to $8 billion yearly [49]. Again, modern tourism started in the 17th century in Western Europe, and till today, humans haven't stopped and continued traveling around the world in order to explore, discover the unseen, to experience incredible sites and tourist spots[42]. By automating typical client requests, the Chatbot may relieve some of the load on customer service representatives so they may focus on more challenging issues. This may enable travel agencies in Bangladesh and other nations to reduce costs while maintaining high levels of customer service. There needs to be a thorough investigation of the efficiency and effects of creating an NLP-based customer support bot for a travel agency. Although NLP-based Chatbots have shown potential to improve consumer experiences across a range of industries, their unique uses and difficulties in the travel sector need further investigation. The research problem thus focuses on comprehending how NLP-powered

customer service bots might enhance support in travel agencies, meeting the special needs and complexity of the business. The main goal of this thesis is to use Natural Language Processing techniques to design and create a customer support bot for a travel agency. Modern NLP techniques will be used in the research to help the bot comprehend client questions, gather pertinent data, and provide accurate and prompt responses. By reaching this goal, the study aims to improve the travel industry's entire customer experience by streamlining communication channels and improving customer care skills.

In conclusion, developing a customer assistance chatbot for a travel agency is an effective way to improve customer care in Bangladesh and all around the world. Because of the rising demand for travel services, customer service has become more crucial, and chatbots offer a workable and economical solution. By automating frequent customer inquiries, travel companies can reduce the workload for customer service representatives, improve response times, and ultimately boost customer happiness.

1.1 Problem Statement

Traveling has always been an essential aspect of human activity. As world tourism is significantly evolving, the need for efficient customer travel service is increasing with it. With the digitalization of society, there is an indispensable need for travel agencies to enhance their interaction with customers, especially when it comes to accurate and timely responses. The utilization of Chatbots with the help of Natural Language Processing(NLP) has a remarkable potential for customer and travel agency interactions by automating the interactions between customers and travel agencies. However, operating such advancements in this industry is still unexplored. In this research, we studied how customer service Chatbots using NLP can elevate support within travel industries, keeping customers' different requirements and complications. We tried to build a travel Chatbot implementing different NLP methods and models that would be simple to work with and require less manpower to operate, which would be beneficial for both travel agencies and customers. As we know, time is money and humans are always on the run forward to their life goals, they always expect a responsible and proper service agent to help them on their way and that's why we also have kept in mind that our Chatbot can ensure better and more accurate responses and can save the time which would have been wasted if we were depended on manual services only. To put it briefly, this research paper aims to utilize advanced NLP techniques and models to develop a customer service Chatbot that will support customer interactions constructively and can respond with accurate and fast responses, thereby escalating the general customer experience in travel-related services.

1.2 Research Motivation

People travel to explore, to know the unknown, to get out of the box, and also to find better opportunities and other benefits. However, if the travel process is not practical and easy enough, it could hold people back from traveling freely. One of the articles on Forbes by Chaim Heber stated that long waits, visa processing, unapproachable customer service, complicated document requirements, ticket purchasing issues, etc. can even throw off regular travelers who have a long experience of traveling [37]. With the growing digitalization of society, people seek easier and effortless solutions to their problems, and this can be said for travel procedures too. Chatbots can be a significant solution to this problem as it will be able to guide people fast and effortlessly. If we see the UserLikes survey on the positive aspects people found using chatbots, we will see that 68% of people enjoy how fast and quickly they can receive answers to their queries [38].

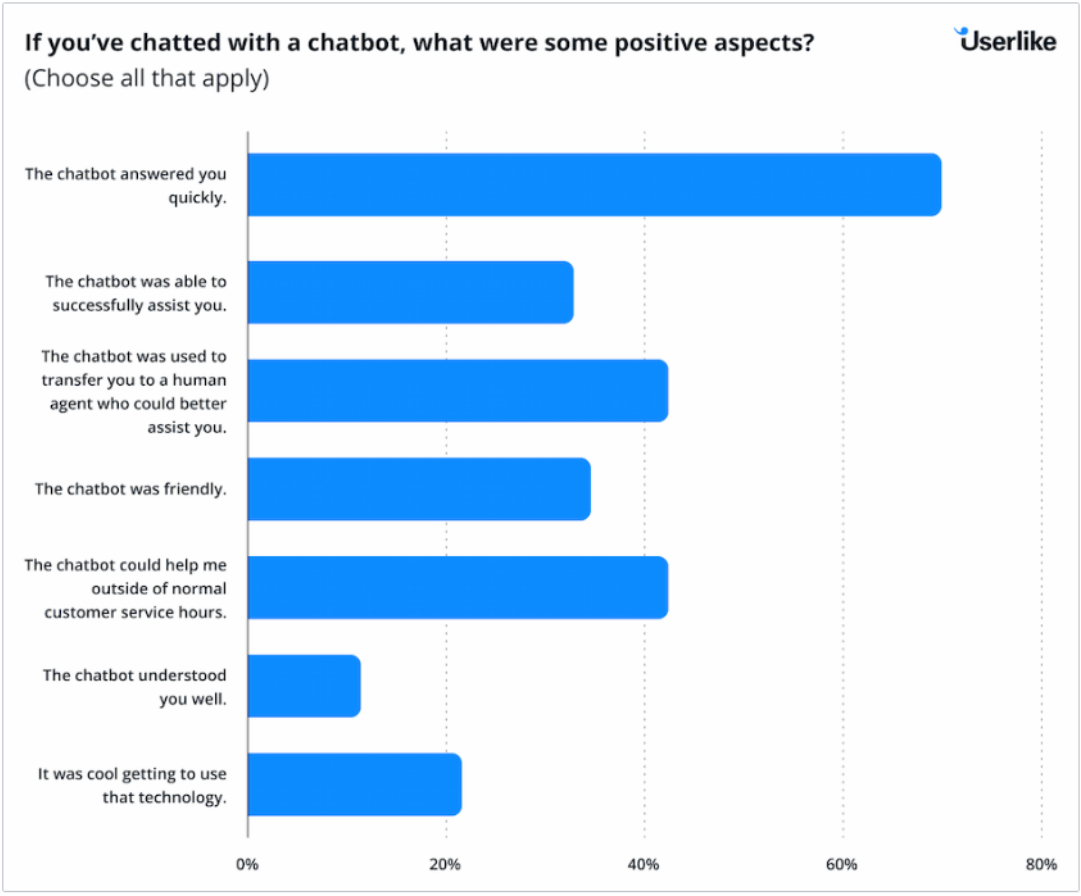

Figure 1.1: Userlike's survey on what positive aspects people found using chatbots. [31]

So, this can be said that as people want their traveling experience to be easier with proper and accurate guidance and especially the growing interest of people in Chatbot assistants worked as a motivation for our research paper.

1.3 Research Objectives

The objectives of this research are:

1. Developing a customer service Chatbot with the help of advanced NLP techniques.
2. Developing necessary models from scratch like sequential models by implementing multiple layers.
3. Utilizing and learning about different models like BERTForToken classification, GPT Neo 125 M, and Unsloth LLM.
4. To develop a customer service Chatbot to enhance in general customer experience in travel-related services.

Chapter 2

Literature Review

The main purpose of this review is to revise the Background information on AI customer service Chatbots and travel agencies. The goal is to identify the key concepts, models, and techniques related to AI customer service Chatbots for travel agencies using natural language processing (NLP). The use of artificial intelligence (AI) and natural language processing (NLP) techniques for customer service in the travel industry has become increasingly popular in recent years. Chatbots, or conversational agents, have been developed to provide instant and personalized customer support, as well as to reduce costs and increase efficiency. In this literature review, we will explore the existing research on the use of AI customer service bots for a travel agency using NLP.

To achieve the goal of this paper intends to answer the following questions :

1. How an AI-based Chatbot will benefit a travel agency?
2. What are the limitations of existing Chatbots?
3. How can NLP improve the pre-existing chatbots?
4. What are the sections where the implementation of Chatbot is still unreached?
5. How to overcome the challenges in implementing AI travel service Chatbots?

Before looking into the benefits of an AI-based chatbot, it is worth mentioning that A research paper named "Natural Language Processing in Customer Service: A Systematic Review" (2022) shows that almost 75% of people experienced bad customer service in general [28]. In an article by Dilmegani (2023) 16% of travel agencies already use chatbots [38]. The article further shows that 87% of users would interact with a travel chatbot if it could save them time and money [34].

The benefits of AI chatbots are subtle and explicitly noticeable. Although there are still some rule-based chatbots. With a rule-based method, a chatbot can answer only a set of questions, which definitely limits the scope of a chatbot [22]. However, AI-based chatbots can be initially trained by a huge dataset and also can reply after training from the previous chat conversation. The usage of AI chatbots will increase customer satisfaction and loyalty. Because of their friendly behavior, chatbots ensure a better customer experience, which will eventually create better opportunities to generate business leads through chatbots. To validate this fact, the above-mentioned article shows that 84% of those who interacted with the bot shared their contact details and 40% of them had booking intent. In addition, the cost of rewarding

customer service will effectively decrease, and efficiency will be gained. Furthermore, the biggest benefit of replacing a human being with an AI chatbot will be 24/7 availability and providing instant support [24]. Because around 50% of customers expect firms to be open 24/7, real-time replies are a valuable perk [34]. Additionally, chatbots can simultaneously perform multiple personalized conversations [17]. With Chatbot, consistency of service quality can be ensured as there are no common employee-related risks such as strikes, discrimination, quitting the job with no notice, showing negative emotions, shirking from work, and getting ill [17][11]. Despite the incorporation of explicit or implicit ethics, no chatbot on the market has received complaints regarding its fairness or wrongdoing [24]. Furthermore, using AI allows chatbots to perform sophisticated and time-consuming analyses in a concise time. This helps the chatbot to quickly understand customers' requirements leading to better prediction and accurate replies thus improving the overall interaction [24]. Moreover, companies can achieve tangible financial benefits by using chatbots by saving employees' time from tedious and repetitive tasks [24].

While AI chatbots via NLP have become increasingly popular in the travel industry, there are still several limitations to their effectiveness in customer service. One major limitation is the lack of emotional intelligence and understanding of complex customer issues. Chatbots are programmed to respond to specific keywords and phrases and may not be able to understand the context or emotional tone of the customer's message [17]. Additionally, chatbots may not be able to handle complex or unique customer queries that require human empathy and creativity [17]. Another limitation is the risk of technical errors or glitches in chatbot performance, which can lead to customer frustration and dissatisfaction. It is also important to note that some customers may prefer speaking with a human agent and may perceive chatbots as impersonal or unreliable.

Besides, the implementation of AI is yet not fully utilized in destination recommendations and personalized travel planning. The capacity of chatbots to create customized travel experiences based on individual tastes and interests is currently limited, despite the fact that they can answer specific questions and offer generic information about places [17]. It is still difficult to create chatbots that can accurately evaluate user preferences, comprehend context, and produce individualized recommendations. To improve chatbot skills in this area, new NLP approaches including sentiment analysis and entity identification show potential.

Travel businesses must carefully take into account a number of things in order to overcome the implementation issues associated with AI customer support chatbots. First and foremost, there is a need for continual research and development to enhance chatbots' capacity for comprehending and producing natural language [34]. By utilizing cutting-edge NLP techniques, like deep learning and machine translation, chatbots may better understand and react to client inquiries in a natural and correct manner. In addition, managing privacy issues is essential to gaining user confidence. Protecting client information requires putting in place suitable security safeguards and having open data processing procedures [34]. Additionally, vast datasets and real-world discussions may be used to train chatbots to greatly improve their performance and increase their knowledge base [22]. The accuracy and relevance of chatbot replies may be increased by using machine learning algorithms and training data from previous customer encounters. To find and address any mistakes or weaknesses in chatbot performance, continuous monitoring, and feedback loops are crucial

[24]. The chatbot's replies may be improved by incorporating user input and sentiment analysis, which can also guarantee continuous improvement. Various chatbots have been created using NLP till now. Like the dialogue chatbot will answer questions related to programming and simulate dialogue and chit-chat on all non-programming-related questions, thus helping users find answers to programming questions present on the Stack Overflow website and also holding conversations with them [29]. Also, healthcare sectors have various NLP uses in chatbots [30].

Additionally, for a chatbot to be used successfully, human supervision and intervention must be incorporated [11]. While chatbots can answer various client questions, sometimes a human expert or assistance is necessary. When switching from a chatbot to a human agent, it should be done seamlessly to guarantee that clients get the support and help they require. The effectiveness and scalability of chatbots are combined with the knowledge and understanding of human agents in this hybrid approach, improving client interactions. A study shows that the use of chatbots in healthcare settings improves the overall experience for patients. Chatbots are conversational agents that interact with users using natural language, such as ELIZA, PARRY, and Erica. These systems have been developed to simulate various types of patients, such as psychotherapists, paranoid patients, and dental practitioners. [12]

The literature suggests that chatbots and NLP can significantly improve customer service in the travel industry. Chatbots can provide instant and personalized customer support, reduce costs, and increase revenue. However, successful chatbot adoption requires addressing challenges such as user trust, privacy concerns, technical limitations, and NLP performance.

An important fact to notice is that the power of NLP based chatbots still lagging behind in terms of interacting as a real human being in terms of convincing a customer to use a certain company service using business strategy and marketing knowledge. Chatbots should be designed with user experience and usability in mind and should be evaluated using appropriate metrics. The literature also highlights the importance of chatbot design in building trust with customers and ensuring customer acceptance. Our one of the main goals is to make a chatbot that will ace in this customer convincing system or open the gate for research in this sector. In the process, we first need to make a chatbot that is capable of basic human interaction. The chatbot will first perform the basic functions of NLP chatbots. To obtain words from a sentence we need stemming, tokenization, lemmatization, and segmentation. To perform these tasks, we will be using python libraries (PyTorch and NLTK).

The Python tensor library PyTorch is open-source and free, and it is frequently used to create different deep learning and neural network models. It has a variety of modules and APIs that are quite helpful for building these machine-learning models. In comparison to other libraries, it is also recommended for creating NLP models. As a fully open-source library, it is often updated and enhanced by the thousands of users who use it on a daily basis. It is the most widely used deep learning and tensor library for this reason, among others [40]

To perform a customized output that satisfies our goal which in this case is convincing the customer to take our service we need to train our model with personalized datasets. A dataset is a collection of relatively useful information which may or may not be in structured or provided in a tabular form. ML and deep learning models use these data

to perform the assignment task. The performed task or the output is directly related to the data we used to train the model. So in order to perform a biased output serving our interest, we need to train our model with personalized data.

The creation of chatbots has surged as a result of advancements in natural language processing (NLP) and machine learning. This research review examines the development of travel chatbots, with a specific focus on four natural language processing (NLP) subtasks: intent recognition, named entity recognition (NER), question answering (QA), and conversation production. Intent recognition is a crucial component for chatbots to comprehend the user's objective in dialogue systems. Keyword matching and rule-based approaches have been superseded by machine learning. Contemporary intent recognition models employ deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Bidirectional LSTM (BiLSTM) networks. Graves [6] discovered that BiLSTM networks are highly effective in handling sequential input and capturing dependencies in both past and future contexts for intent recognition. This is advantageous for intent identification, as context plays a significant role in understanding user queries. Xu and Sarikaya [2] discovered that BiLSTMs achieved superior performance compared to RNNs in the tasks of semantic slot filling and purpose determination. The dropout strategy, pioneered by Srivastava [4], mitigates overfitting in neural networks by periodically deactivating units during training. When thick layers are paired with this approach, it improves the model's ability to generalize and handle user inputs. Named Entity Recognition (NER) is the process of classifying textual entities, such as names, places, dates, and organizations, into predefined categories. Initially, rule-based systems and manually crafted features were employed in early techniques. However, more recent advancements have shifted towards utilizing deep learning models, particularly those based on Transformer architecture. Devlin [10] developed Bidirectional Encoder Representations from Transformers (BERT) for Named Entity Recognition (NER), establishing new benchmarks for a range of Natural Language Processing (NLP) applications. The bidirectional nature of BERT allows for accurate identification of entities by extracting contextual information from both directions in a text sequence. Liu [13] demonstrated that the model surpassed Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs) in Named Entity Recognition (NER) tasks. Transfer learning is essential for enhancing Named Entity Recognition (NER) systems, as highlighted by Ruder [14]. Enhancing the performance of pre-trained models such as BERT on specific Named Entity Recognition (NER) tasks can be achieved by fine-tuning them using a smaller number of annotated samples. Question-answering systems rely on pre-existing knowledge or contextual information to provide accurate responses to user queries. Conventional QA systems focus on information retrieval, whereas contemporary ones employ deep learning to comprehend and provide answers. Vaswani [8] proposed the Transformer model, which serves as the foundation for the majority of contemporary NLP models. The self-attention system effectively manages dependencies in the input text, irrespective of their spatial separation. Rajpurkar, Jia, and Liang [9] achieved high performance in extractive question-answering tasks by employing Transformer-based models on the SQuAD dataset. Brown [16] demonstrated that GPT-3, a type of large-scale language model, is capable of generating responses that are both coherent and contextually appropriate. EleutherAI's open-source GPT-Neo alternative has demonstrated exceptional performance in several question-answering applications with minimal fine-tuning. Dialogue generation aims to provide authentic and engaging conversations. The early models based on rules lacked flexibility. Deep learning is utilized in modern sequence-to-sequence (Seq2Seq) models and transformers. Sutskever [5] initially proposed Seq2Seq models for machine translation, which were subsequently used for dialogue generation. Bahdanau [1]

enhanced these models by incorporating attention mechanisms, which enabled the models to concentrate on pertinent regions of the input sequence while generating words. GPT-Neo, an advanced iteration of GPT-3, emulates human dialogues. Many conversational AI applications utilize the model's comprehensive training on diverse datasets to produce responses that are both contextually appropriate and engaging [26]. Incorporating these NLP subtasks into a chatbot system poses difficulties such as maintaining context, responding to ambiguous requests, and ensuring scalability. Henderson [18] investigated the frameworks of modularity and interoperability for combining NLP components. Chatbot systems employ modular components to do tasks such as intent recognition, named entity recognition (NER), question answering (QA), and discourse management. Li and colleagues [7] combine these features into hierarchical models to provide smooth data transmission and preservation of context. Overall, the progress in natural language processing (NLP), particularly in deep learning and transformer-based models, has significantly improved the capabilities of chatbots. Utilizing BiLSTM for intent recognition, BERT for Named Entity Recognition (NER), and GPT-Neo for Question Answering (QA) and dialogue creation establishes a robust framework for travel chatbots. The integration of various models results in a sophisticated system capable of comprehending user questions and delivering precise, contextually appropriate answers. Subsequent investigations have the potential to enhance the efficacy of the model, handle inputs in several languages, and enhance user satisfaction by means of interface design and user feedback.

Finally, we need a GIU or Graphic Interface Unit where the user will interact with the chatbot. The goal is to keep the GIU simple yet effective. The interface will consist of two components: the Chatbot and the Massage entry box. Chatlog will hold the chat history until the chat is ended and the message entry box will be used to ask queries with a send button. We can build the interface redirecting to a website. In addition, we can also use libraries like Tkinter. Simple GUI apps can be created using the Python package Tkinter. There are many features that simplify the process of designing and customizing a graphical user interface. It offers a wide range of widgets and capabilities, making it the best option for creating useful apps and demo interfaces [39]. With the help of this library, we can develop a graphical user interface for this project that allows users to communicate with the chatbot.

To conclude up, Natural language processing (NLP) advancements, particularly in the domains of deep learning and transformer-based models, have substantially broadened the functionalities of chatbots. A solid foundation for a travel chatbot can be established by employing models such as BiLSTM for intent recognition, BERT for NER, and GPT-Neo for quality assurance and dialogue generation. Through the integration of these models, a sophisticated system is formed capable of understanding user queries and delivering precise, contextually appropriate replies. Further inquiries may be directed towards enhancing the performance of the model, effectively handling multilingual inputs, and improving the user experience through the integration of user feedback and enhanced interface design.

Chapter 3

Data Analysis

3.1 Dataset Collection and Analysis

In our study, we've utilized the Schema-Guided Dialogue Dataset to make a chatbot. Rastogi et al. designed this dataset to serve as an effective environment for intent recognition, and text generation for large-scale virtual assistants [19] [20].

3.2 Dataset features

This dataset consists of over 22k multi-domains and task-oriented conversations between virtual assistants and human beings containing interactions with services and APIs ranging over 17 domains like calendar, travel, weather, etc. [20]. The dataset has over 30 unique intents that ensure enough data to build a smooth conversational virtual assistant or chatbot. Each intent was divided into multiple services that were labeled with a unique dialogue ID associated with turns, where we could find the related conversational data entries.

dialogue_id string · *lengths* 7 9	services sequence	turns sequence
1_00000	["Restaurants_1"]	{ "speaker": [0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1], "utterance": ["I am feeling hungry so I would like to…
1_00001	["Restaurants_1"]	{ "speaker": [0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1], "utterance": ["Hi i need a help, i am very…
1_00002	["Restaurants_1"]	{ "speaker": [0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1], "utterance": ["Help me find a good restaurant.", "In which city are you…
1_00003	["Restaurants_1"]	{ "speaker": [0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1], "utterance": ["I'm looking for a place to eat.", "Which city should I…
1_00004	["Restaurants_1"]	{ "speaker": [0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1], "utterance": ["I'd like to find a place to eat.", "Where should I…
1_00005	["Restaurants_1"]	{ "speaker": [0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1], "utterance": ["I'm looking for a Filipino place to eat.", "Which City…

‹ Previous 1 2 3 ... 162 Next ›

Figure 3.1: Sample entries of the dataset

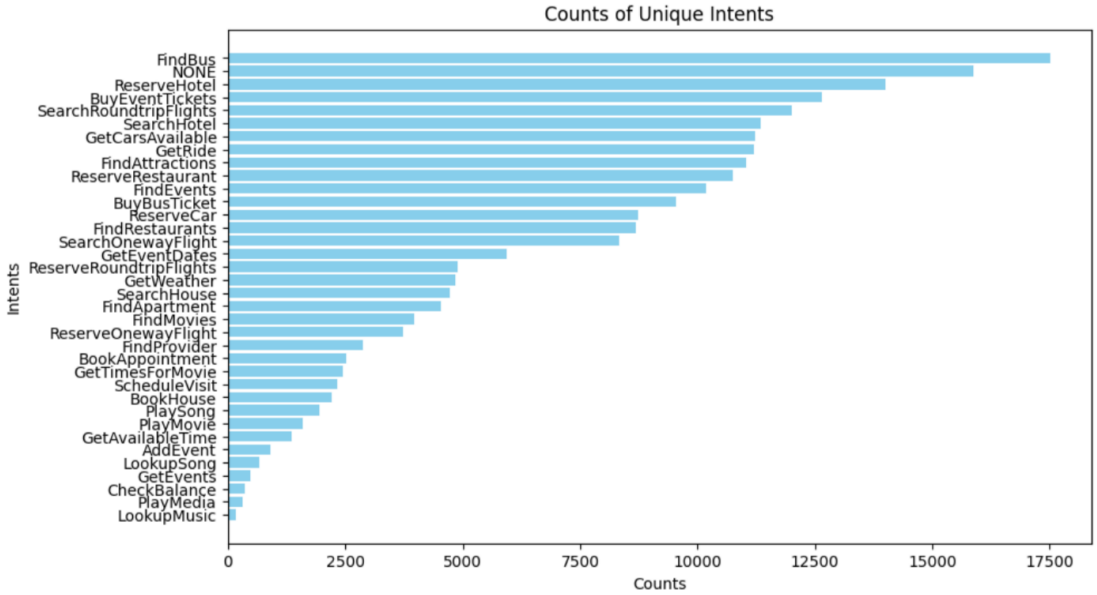

Figure 3.2: Unique Intent distribution graph

3.3 Data split

It is a pre-trained dataset where it was split into three splits: Test, Validation, and Train split. For dialogue entries, 16.1k rows were taken for train, 4.2k rows were for test, and 2.48k rows were taken for validation 48.4k turns were selected for train, 12.6k were chosen for test and 7.4k turns were selected for validation. There were some intents that were absent in the testing data whereas present in the training data to ensure the Chatbot was learning properly.

	train	validation	test
Number of dialogues	16142	2482	4201
Number of turns	48426	7446	12603

Figure 3.3: Data Split

3.4 Data Filter

To generate the response, our Chatbot needs four types of information from the dataset which are, Intents, Entities, Utterances, and Responses. However, in the raw dataset, all of this information was disorganized and messy and it would be tough to work with this data. So, what we did was, we filtered the dataset, and organized it in such a way, that all the information is divided into some sets where each set contains one utterance and one Intent, Entity, and Response related to it.


```
[
  {
    "dialogue_id": "1_00000",
    "services": [
      "Restaurants_1"
    ],
    "turns": [
      {
        "frames": [
          {
            "actions": [
              {
                "act": "INFORM_INTENT",
                "canonical_values": [
                  "FindRestaurants"
                ],
                "slot": "intent",
                "values": [
                  "FindRestaurants"
                ]
              }
            ],
            "service": "Restaurants_1",
            "slots": [],
            "state": {
              "active_intent": "FindRestaurants",
              "requested_slots": [],
              "slot_values": {}
            }
          }
        ],
```


Figure 3.4: Raw Dataset


```
{
    "dialogue_id": "97_00003",
    "turns": [
        {
            "utterance": "Find me some interesting to do",
            "intent": "FindEvents",
            "entities": {},
            "response": "Any particular in mind, it could be music or sports"
        },
        {
            "utterance": "i do like concert events",
            "intent": "FindEvents",
            "entities": {
                "category": "Music"
            },
            "response": "any city prefrerred"
        },
        {
            "utterance": "Search for SFO",
            "intent": "FindEvents",
            "entities": {
                "city_of_event": "SFO"
            },
            "response": "I got 10 events. This evnt is Allan Rayman in August Hall on March 9th at 6 pm"
        },
```


Figure 3.5: Filtered Data

3.5 Balancing Intent Data

In the Intent Recognition Model, the Chatbot uses intent and Utterance data from the dataset and we proceed to pre-processing the data and then send them for training. However, after analyzing, we noticed that the intent data were highly imbalanced. From Figure 3.6, we can see that the "none" type data ranges over 12 thousand whereas most of the other intents ranged between 4 - 6 thousand. So, to balance the data we randomly deleted some excessive data after a certain range, in our case, the range we set is 5000.

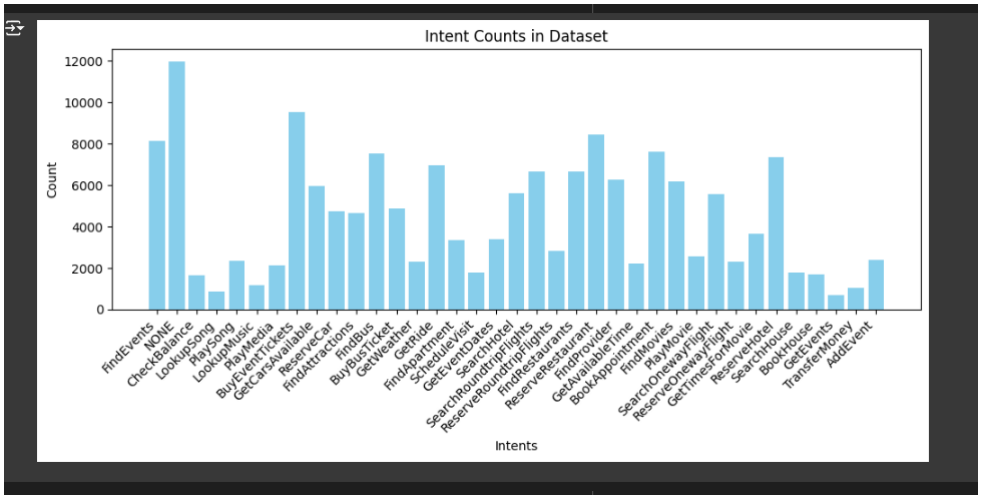

Figure 3.6: Data before balancing

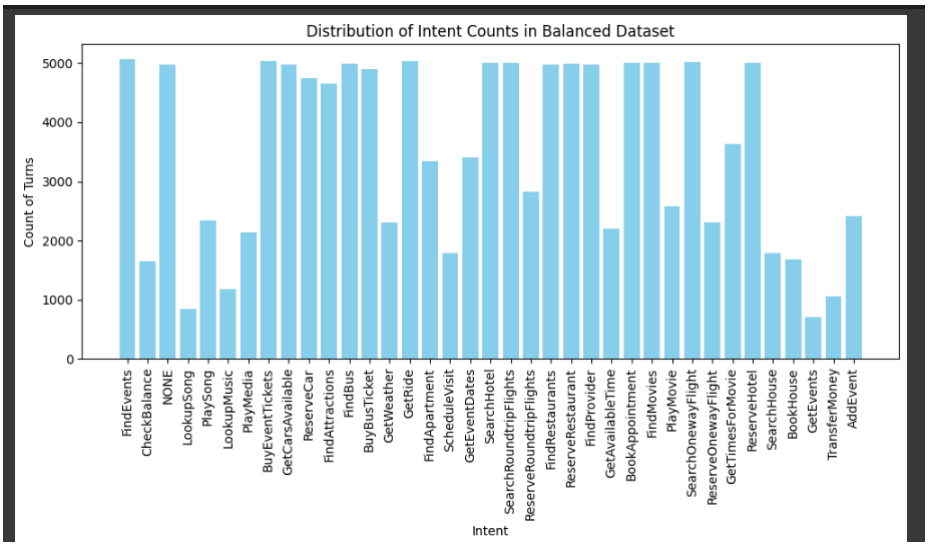

Figure 3.7: Data after balancing

3.6 Labeling Data for Named Entity Recognition

For the Named Entity Recognition (NER) model, we used the utterance and the entity from the filtered dataset. The entity in the dataset was given as {type : value}. We had to manually align the data with entities so that the model could easily recognize the entities. To achieve this, we first extracted all the possible entity types found in the entire dataset and assigned them a unique integer value, and labeled all the utterances with the allocation value like the following figure :

```
Sample 1
Input Text: Just one day on the 6th.
Entities: {'number_of_days': 'one', 'check_in_date': 'the 6th'}
Labels: [24, 50]
Encoded Input IDs: tensor([[  101,  2074,  2028,  2154,  2006,  1996,  5351,  1012, 30522,   102,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0,     0,     0,
             0,     0,     0,     0,     0,     0,     0,     0]])
Encoded Labels: tensor([ 0,  0, 24,  0,  0, 50, 50,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
         0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
         0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
         0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
         0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
```

Figure 3.8: Sample Data of NER model

3.7 Dialogue Dataset

In the dialogue dataset, we kept the user query, active intents, and Chatbot's response separate whereas in the conversation dataset as a single data sample and all the user utterances along with intent entities and the response for one full conversation are under the turn inside the dialogue with a unique dialogue ID. Figure 3.9 is one example of this :

```
[
    {
        "dialogue_id": "97_00000",
        "turns": [
            {
                "utterance": "I'm interested in
doing something fun. Is there any sort of
Concert going on sometime soon?",
                "intent": "FindEvents",
                "entities": {
                    "category": "Music"
                },
                "response": "What city are you
wanting to check out?"
            },
            {
                "utterance": "Let's see if
there's anything happening on the 14th in
Vancouver, BC. I would prefer a Blues concert.",
                "intent": "FindEvents",
                "entities": {
                    "city_of_event": "Vancouver,
BC",
                    "date": "the 14th",
                    "subcategory": "Blues"
                },
                "response": "Okay. I pulled up 1
event that matches your interests. Looks like
Smokey Robinson is performing at the PNE
Amphitheatre on March 14th. It's going on at 7
pm. How does that sound?"
            },
            {
                "utterance": "Where is that
venue located?",
                "intent": "FindEvents",
                "entities": {},
                "response": "It's over on 2901
East Hastings Street."
            },
            {
                "utterance": "Okay, that sound
perfect for me.",
                "intent": "FindEvents",
                "entities": {},
                "response": "Should I purchase
the tickets for you now?"
            },
            {
                "utterance": "That's okay for
now. I would like to check my bank account
balance though please.",
                "intent": "NONE",
                "entities": {},
                "response": "What account did
you want to check?"
            },
            {
                "utterance": "How about my
checking account first.",
                "intent": "CheckBalance",
                "entities": {
                    "account_type": "checking"
                },
                "response": "Okay. You currently
have $3,931.51 in your checking account."
            },
            {
                "utterance": "Alright. What is
the balance of my savings account?",
                "intent": "CheckBalance",
                "entities": {
                    "account_type": "savings"
                },
                "response": "You have $5,022.31
available in your savings account."
            },
            {
                "utterance": "Alright, thanks
for checking.",
                "intent": "CheckBalance",
                "entities": {},
                "response": "Did you need any
funds to be transferred?"
            },
            {
                "utterance": "That's alright.
I'm good on that for now. I'll catch you
later.",
                "intent": "NONE",
                "entities": {},
                "response": "Okay. Enjoy the
rest of your day!"
            }
        ]
    },
    {
        "dialogue_id": "97_00001",
        "turns": [
```


Figure 3.9: Sample Data of Conversational Dataset

Chapter 4

Methodology

Customer service Chatbots for travel agencies address numerous objects such as travel-related booking, queries, flight duration, payment, etc., and people recently trusted more to use chatbots. The main goal of this research is to identify people's travel-related queries and respond to those queries. In this research, we covered the maximum level of travel-related questions that our chatbot can answer. Also, to make questions more convenient, we observed many areas, like a form survey where people filled out their opinions to make the chatbot more useful in travel agencies. Again, we went to one of the travel agencies and observed how their agency works and the questions that were asked of them. This study focuses on fine-tuning a model that operates a domain-specific dialogue as a chatbot. To fulfill those things and additional things, we need to, first, pre-process our collected dataset and then need to use various NLP subdivisions to build a Chatbot that can efficiently communicate with the user. These subdivisions are intent recognition or classification, named entity recognition, question answering, and dialogue generation. For each section, some models will be used to develop an advanced system for predicting word sequence, translation, and message application.

4.1 Pre-processing the Data

Data pre-processing is a major step before analyzing any data and it is required to prepare the data so that we can effortlessly work with it. In our study, we performed tokenization, and padding to process our dataset.

Tokenization means to convert a text into a sequence of tokens or words. It is required for the Chatbot to be able to understand the user's query by traversing the tokens. Again, to be able to train and test data simultaneously, the length of data in the dataset needs to be of the same length, otherwise, it'd be hard to work with different data sizes. So, to shape the data, we need padding. Padding finds the data with maximum length and converts all other data into the same length.

```
Padded Training Sequences:
 [[ 26  27 118 ...   0   0   0]
 [ 16  32  62 ...   0   0   0]
 [ 40   7   5 ...   0   0   0]
 ...
 [ 76  34 789 ...   0   0   0]
 [  1  31 716 ...   0   0   0]
 [ 16   6   8 ...   0   0   0]]
Padded Validation Sequences:
 [[  1  21   3 ...   0   0   0]
 [ 57  55  98 ...   0   0   0]
 [ 55 439   8 ...   0   0   0]
 ...
 [  6  28  30 ...   0   0   0]
 [ 16   6   8 ...   0   0   0]
 [ 40   7   6 ...   0   0   0]]
Padded Test Sequences:
 [[315  80   7 ...   0   0   0]
 [ 80   7  53 ...   0   0   0]
 [150   6   8 ...   0   0   0]
 ...
 [ 16   6   8 ...   0   0   0]
 [ 22   5   2 ...   0   0   0]
 [ 26  40   7 ...   0   0   0]]
```

Figure 4.1: Padding Sequence

4.2 Model Implementation

4.2.1 Intent Recognition

Intent recognition is a classification where bots are being trained to categorize customers' messages, find out the intents behind their messages, and reply to those more accurately. Chatbots must understand or interpret a user's message and intention efficiently, which makes the Chatbot more like a human type of response [3]. For example, if a user inputs a query like 'price of the flight from Dhaka to Cox's Bazar', then the Chatbot figures out the intent. Here is the "price of the flight" and the Chatbot will respond by checking out the price.

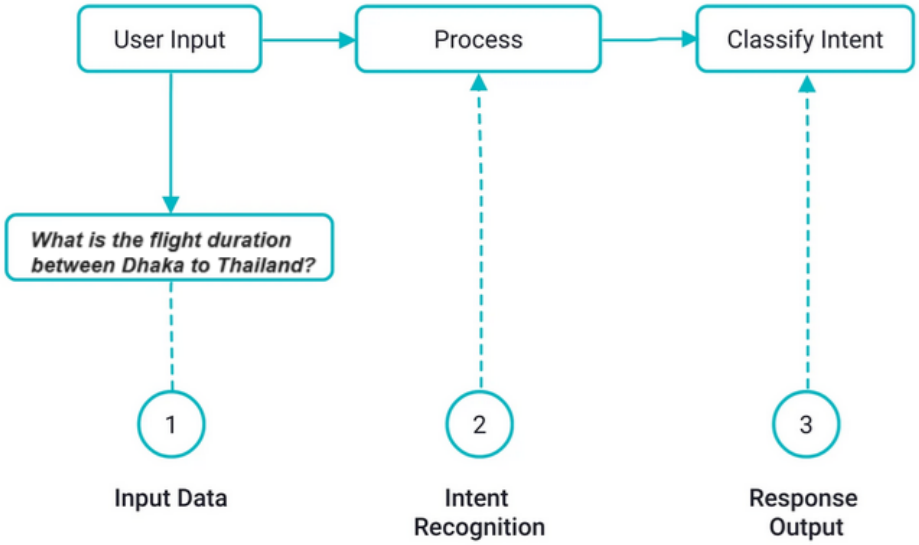

Figure 4.2: Intent recognition process
[23]

In the above figure, if a user inputs a query, then the query goes through the process and recognizes the intent. After classifying the intent, the chatbot responds to it through output. It also helps to understand user preferences, which helps customers have a personalized experience.

4.2.2 Named Entity Recognition (NER)

Named entity recognition or entity extraction defines the classification and identification of name entities in user input or text. NER extracts information from unorganized text and puts that information into different categories such as name, date, organization, places, and much more [30]. It is used in our research as it also increases the accuracy of tasks and finds relationships in entities. For instance, if a user inputs text like "ticket price from Thailand to India at 2 pm" then NER categorizes Thailand [location], India [location], and 2 pm [time] and this becomes the named entity.

In the figure below, first raw text is segmented into small strings, then it goes to the tokenization part. Here, the text is split into tokens, like phrases, or words. The tokenized words go through the part of speech that makes the list of strings. Then entity identification is required where many potential named, or statistical methods are identified. After identification, entities become classified into predefined categories such as places, names, organizations, and monetary values. Then, the context is properly analyzed because NER is mainly used for better context, and after doing and detecting all the entities post-processing is required to refine the text and results.

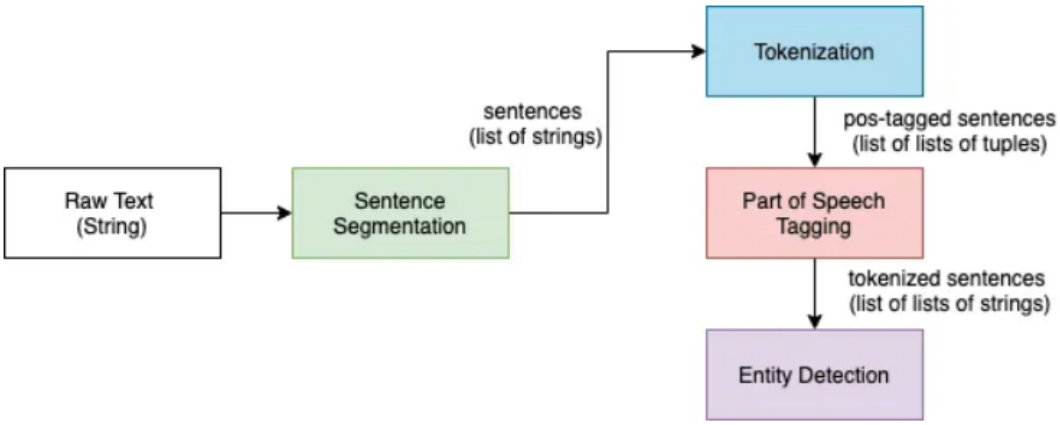

Figure 4.3: Named Entity Recognition
[25]

4.2.3 Question Answering & Dialogue Generation

Question answering task is the most crucial part where giving the right answers to the user input is a must. There are different types of conversion and one of them is closed Q&A. Our chatbot is a closed Q&A chatbot where travel-related questions can be asked and the chatbot will answer accurately. Dialogue generation makes a chatbot more reliable if responses are appropriate. Dialogues that come from the dialogue history usually generate the responses well [27]. It acts like conversing with humans by delivering many types of communication and maintaining this communication productively.

Now, intent recognition, named entity recognition, question answering, and dialogue generation need models to be implemented properly in chatbots. We have applied models and trained them which are best for our dataset to implement it accurately as well as improve accuracy gradually.

4.3 Model Training

4.3.1 Intent Recognition Model

Many layers have been trained here to build the model and use it in intent recognition. The model we used for intent recognition is from scratch the layers that we have included are:

Embedding Layer: The embedding layer defines the discrete or categorical data to represent this data into a continuous vector. The vector that has been translated finds out the relationships between various classes. When the model needs to be trained, there should be a necessity for tokens to be present as a continuous value, and this is why an embedding layer is needed. The vector comes from the continuous iterative training process to improve the prediction accuracy [51]. During the training process, fine-tunes have been made in embeddings to adjust the particular domain. In our research, word2vec is being used as prior or initializations. It makes it easier to handle large amounts of data and use it through vectorization.

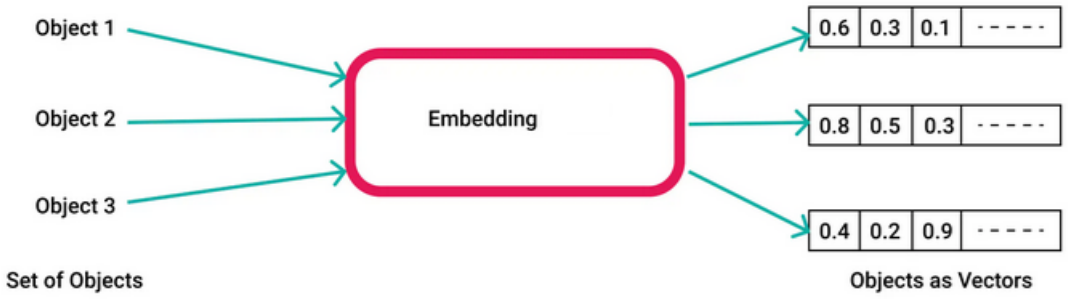

Figure 4.4: Embedding
[41]

In Figure 4.4, we can see an object whether it is text or sentence taken as input and translated into vectors like numerical values to understand it easily.

The embedding layer can handle data very well by transferring text into a format that is accessible to chatbots. Also, pre-trained embeddings such as word2vec improve the efficiency of a model. It also can figure out the relationship between vectors, which enhances model performance and understanding of data.

Bidirectional LSTM Layer: In this study, we use deep bidirectional LSTM, meaning 3 BiLSTM layers. Each layer has two LSTM layers-one is for the input processing in the forward side and another one is for the processing input in the backward direction. As the processing input happens on both forward and backward sequences, the model is trained sequentially and understands better sequences. We used 3 layers, expecting that typically using deep layers helps the model understand deeper context. For example, the 1st layer extracts word or token level context, the next layer does the same for sentence level and the 3rd layer might bring out the context of the entire paragraph sequence.

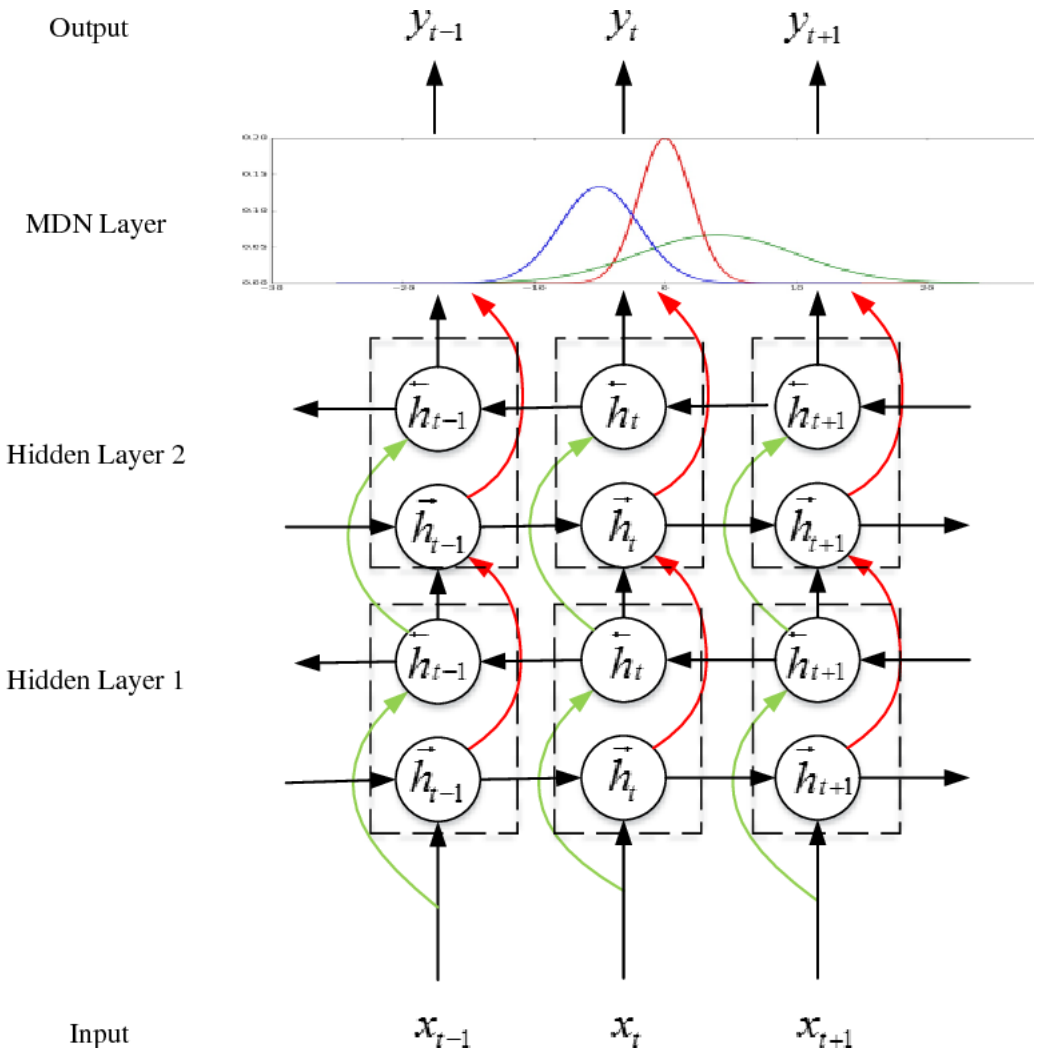

Figure 4.5: Bidirectional LSTM layer
[32]

This is important for our research as a bidirectional LSTM layer has two sides, it can easily catch the information and hold the consistency of information well. Again, there will be no loss in context as both sides keep the information effectively.

In Figure 4.5, the first input goes through the input sequence. Now, input is like words in a character, and each character or word is presented as a vector in the input sequence [32]. Then, the input vector is converted into a dense vector representation. This helps to give data in a compact representation.

Dropout Layer: The dropout layer is the layer where random layer outputs are being dropped or left out throughout training. In our chatbot, we used two dropout layers in intent recognition. During model training, the dropout layer randomly deactivated one of the layers and did not activate again [43]. Then, this deactivated layer drops out, which improves data representation. Also, it requires removing the overfitting problem, which ensures the effectiveness of the model.

Dense Layer: Dense layer is the layer where each node is connected to the previous node.

As they are connected with the previous layer, the extraction from the complex data is much more simple. It optimizes the flow of the gradient in the training model. We use dense layers in our research as they can work with much more complex datasets and as our dataset is huge, model training will be more difficult if dense layers are not used.

Softmax: Softmax is one kind of function that transforms vectors into a probability distribution. It is the final activation function to transform into probability, which makes it easier to interpret.

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \quad for\ i = 1, 2, \ldots, K \qquad [50]$$

In this equation, the vector z contains the raw output. e^{zi} represents the exponential function of the input vector, and e^{zj} represents the exponential function of the output vector. Now, this softmax range is limited between 0 and 1. Through this, the logistic function is converted to multiple dimensions to use in our model.

4.4 BertForToken Classification

Bert for token classification is a pre-trained model that has been used in NER. Above all the models that have been used in our research, the Bertfortoken Classification works best more than any other model. It is a model where it pads the input on the right with position embedding. It encodes the data for particular token representation at higher levels [21]. This data belongs to the meaningful knowledge that is avoided in other classifications.

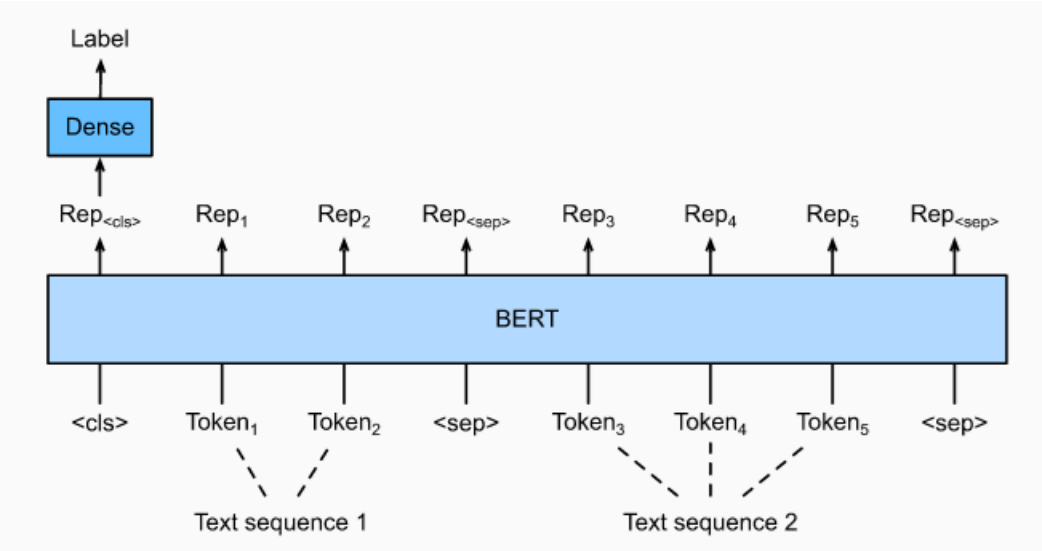

Figure 4.6: BertForToken Classification
[35]

In the above figure, the sequence is divided into 1 to N for multiclass classification. Trivial changes are applicable in semantic textual similarity. The first and second token are mixed and make the text sequence and after that other tokens will behave in the same pattern to make sequences. [CLS] basically represents the start of the input text and [SEP] represents the separation of the input text. At the end, softmax has remained in the last transformer layer, where the highest entity is the output of the entity word.

4.5 GPT Neo 125 M

GPT Neo 125 M is a pre-trained model that is used in question answering and dialogue generation for smooth communication. It falls into the transformer category and is used for text classification. It has a low memory. As it is a pre-trained model, it has already included many packages and layers prior. After tokenization, padding happens and the input is truncated. Mainly, it uses self-attention techniques to acquire contextual representations in tokenizing words.

4.6 Unsloth LLM Model

The unsloth model defines the fine-tuning process of language models, where model performance improvement occurs. During fine-tuning, this model works effectively with the least memory usage [48]. This model has been used to generate dialogue efficiently without any repetitive way. The model ensures the generation of relevant responses to a specific input text through fine-tuning.

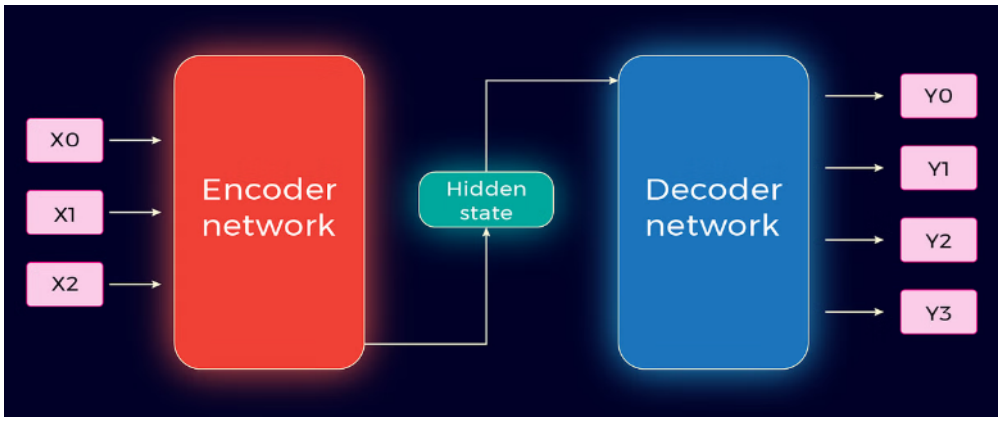

Figure 4.7: Unsloth LLM Model
[47]

In the figure, the encoder part determines the context relation which goes through the hidden part and the output response comes out in a decoder network. By fine-tuning the models or pre-training on domain data, it is not impossible to analyze the LLM on domain data [45]. Unsloth operates in the Hugging Face Transformers library, which is efficient in LLM workflows.

Chapter 5

Result Analysis

After training our dataset with several models, we come to the next and final step which is evaluating our models and analyzing the outcome from our Chatbot.

5.1 Model Evaluation and Result

1. Intent Recognition Model: We have trained our dataset with the Intent Recognition model and the final Validation Accuracy is 60% and Train Accuracy is 63%. So, we can observe that there's no major over-fitting.

Validation Loss	Validation Accuracy	Train Loss	Train Accuracy
1.28	0.6015	1.1073	0.6386

Table 5.1.1: Result for not using Attention Layer

In a nutshell, we can say that even though the Accuracy is not that high, we observe that the model can predict right intention almost all the time.

2. Name Entity Recognition(NER): This was a pre-trained model and this type of model generally can be evaluated using different evaluation models like the entity-level model, standard classification matrix, confusion matrix, classification report, etc. We have used two evaluation models, which are the classification report and the confusion matrix, to evaluate the model.

A) Training Result : The training gives us a bird's eye view of how the model has trained. At the initial stage, immediately after training, we can predict if a model is good or bad by looking at the training loss and validation loss.

Epoch	Training Loss	Validation Loss

[2490/2490 1:07:05, Epoch 10/10]

Epoch	Training Loss	Validation Loss	Precision	Recall	F1
1	No log	0.200790	0.860379	0.877021	0.868620
2	No log	0.095265	0.948725	0.956120	0.952408
3	0.435100	0.069912	0.966072	0.969977	0.968021
4	0.435100	0.062143	0.975202	0.976328	0.975765
5	0.066500	0.054888	0.977253	0.979792	0.978521
6	0.066500	0.053592	0.977861	0.981813	0.979833
7	0.034000	0.052418	0.979574	0.982968	0.981268
8	0.034000	0.053355	0.979850	0.982679	0.981263
9	0.022900	0.052534	0.980150	0.983545	0.981844
10	0.022900	0.052547	0.980991	0.983256	0.982122

Figure 5.1: Training Result

Training Loss: Here, it refers to the loss rate on the training dataset. We can see the Training loss value is decreasing significantly in our model, which means, the model is fitting in the training data well. It also indicates that our model can learn quickly from the dataset. We can see that after the 10th epoch the training loss is around 2% which means the model is significantly performing well in the training dataset.

Validation Loss: Refers to the loss rate on the validation dataset. Here, we can see that the values start with low values but fluctuate in some places, indicating that our model is learning but also fluctuates in some cases. From Figure 5.1, we can see that the validation loss after the 10th epoch is 5% meaning the model is not suffering from over-fitting issues.

B) Classification Report: A classification report is used when we analyze any prediction model to see how the model is performing typically on a test dataset [46] The evaluation happens based on some subordinate terms like Accuracy, Recall, Precision, and F1 score.

	precision	recall	f1-score	support
0	0.00	0.00	0.00	0
departure_date	0.79	0.72	0.76	2001
event_date	0.69	0.80	0.74	546
category	0.76	0.76	0.76	217
return_date	0.97	0.83	0.90	928
number_stops	0.93	1.00	0.97	14
title	0.88	0.70	0.78	662
location	0.86	0.73	0.79	882
travelers	0.35	0.78	0.48	76
party_size	0.96	0.82	0.88	98
destination	0.81	0.68	0.74	947
group_size	0.61	0.20	0.30	97
time	0.80	0.90	0.85	2062
account_type	0.98	0.99	0.99	185
number_of_riders	0.88	0.59	0.71	71
area	0.77	0.84	0.81	266
leaving_date	0.49	0.65	0.56	602
recipient_account_type	1.00	0.79	0.88	19
cuisine	0.99	0.98	0.98	617
number_of_adults	0.91	0.69	0.78	58
accuracy			0.82	35078
macro avg	0.82	0.80	0.80	35078
weighted avg	0.84	0.82	0.83	35078

Figure 5.2: Classification Report

i) Precision: It indicates if our model's predicted entity is actually what it was supposed to predict. This means the percentage of actual correct predicted positive results of all predictions the model predicted as correct. Formula:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

From Fig 5.2, we can see that we get almost 82% precision on average which means 82% of all the correct predictions from the validation dataset by the Chatbot are actually correct.

ii) Recall: It means how many correct entities the model could predict compared to how many entities there were. Formula:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

For our model, the recall result is almost the same as the precision which is 80% almost near the state of the art.

iii) F1 Score: It refers to how our model balances between the recall and precision value. The higher the F1 score, the better the model is. Formula:

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

In our model, we can see the F1 score initially starts low but increases significantly to 82% which shows our recall and precision value was well balanced.

C) Confusion Matrix: Confusion Matrix gives us an overall view of the performance of our model across different classes and also highlights the strong performance through a graph.

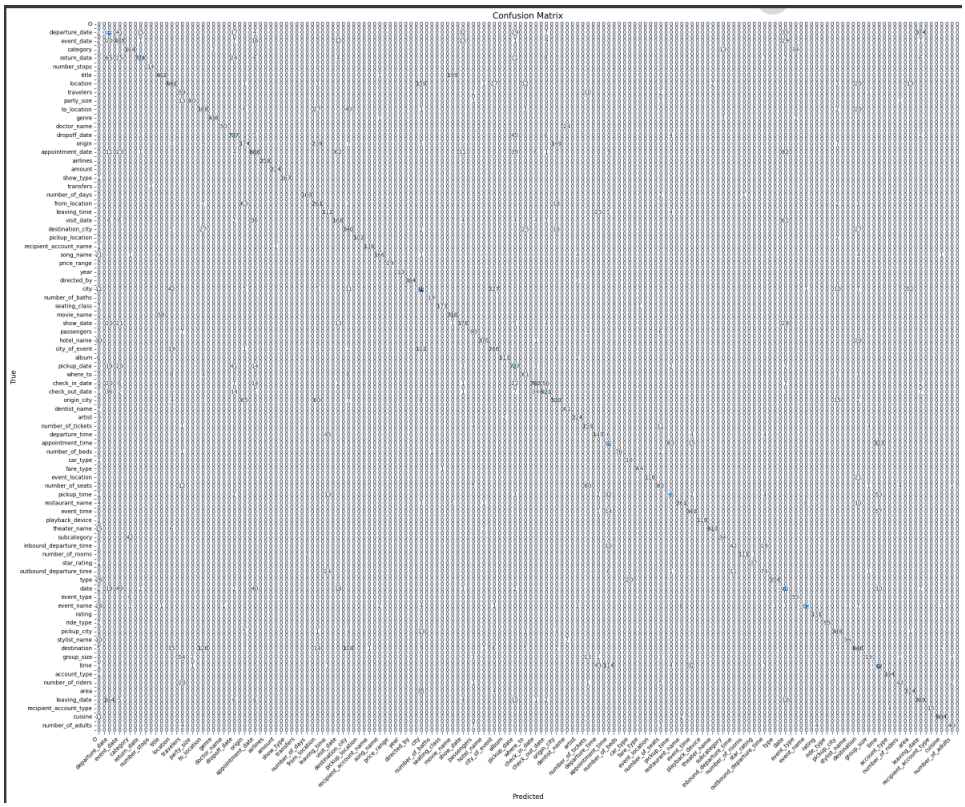

Figure 5.3: Confusion Matrix for NER Model

In Fig 5.3, the Y-axis represents real labels and the X-axis is the predicted labels. In a confusion matrix, if there is non-zero value, ideally the number of data entries under a certain label or class, where the X and Y axis label value is the same, then we can say the model performance is good and in our case, we can also see from the figure that we get 0s in most of the find other that the field where label value for X and Y axis is same, but we can also notice that there's some fluctuation in the value which means our model performance is good in most of the cases.

3) Dialogue Generation: For dialogue generation, we used the Unsloth Model, which is a pre-trained model, and trained them in an input-output pair. Fig 5.4 shows the conversation between the Chatbot and the user where the Chatbot is correctly responding to the user giving different destination suggestions.

```
Intent: FindRestaurants, Entities: NONE,  Can you help me find a place to eat?
<|im_start|>assistant
What city are you looking for?
<|im_start|>user
Intent: SearchHotel, Entities: NONE, i like deserts
<|im_start|>assistant
Intent: SearchHotel, Entities: NONE,  What city are you looking for?
<|im_start|>user
Intent: SearchHotel, Entities: NONE, i want dubai
<|im_start|>assistant
Intent: SearchHotel, Entities: NONE,  I found 1 hotel for you.  It is called JW Marriott Marquis Hotel Dubai.  It is a 5 star hotel.
<|im_start|>user
Intent: ReserveCar, Entities: NONE, ok book it
<|im_start|>assistant
Intent: ReserveCar, Entities: NONE,  What date do you want to pick up the car?  What time do you want to pick up the car?  What time do
```

Figure 5.4: Conversation between chatbot and user with unsloth model

Chapter 6

Future Plan

Although the actual process of our project can be a bit complex, the algorithm or the work plan is very straightforward. It is necessary to keep in mind that we need to have access to almost every piece of data related to traveling, for instance, people would want to know about transportation and stay expenses, where to stay, food availability which suits their cultural taste and affordability, the average daily necessity cost, which places one must visit if they visit a specific country or city, Hotel information, etc. Therefore, our chatbot must be able to provide all of this data and information according to the customers' wishes.

Although our current model can successfully give almost all travel-related information, as the Chatbot is trained with a specific dataset, if any of the information in the real world, for example, a specific flight's time, a hotel's price, etc. is changed, it might not be able to respond with new information if we don't update our dataset. Therefore, we are looking forward to developing our current Chatbot in such a way that the dataset is linked with real-time information from various resources. To make it happen we can do a few things, we can use an API interface to collect data from websites or use a database server. API or Application Programming Interface helps the chatbot connect with the website's data server and fetch all the necessary data by creating an interface between the chatbot and the website. A recent renowned API system is Dialog Flow which is a natural language understanding platform by Google that allows us to create a conversational system, like chatbots [15]. Also, this kind of API matches the inputs with its intent fixed by the developers to find suitable information that the user is asking for [33]. Dialogflow reads questions and texts from the users by analyzing the keywords that will be set by the developers and can answer by fetching required information from the data server [33]. It would also help us to reach our next future goal which is to make the Chatbot capable of generating audio response because Dialogflow can not only work for texts but also for audio inputs [33]. Thus, an API can be a good choice for a chatbot, as it can play a significant role in keeping the data up to date with real-time data from the website itself. However, this process can be a bit complex as not every website permits to connect an external system with its data server. Figure 6.1 shows a basic demonstration of how an API interface works to fetch data from a website or its data server.

Another goal that we plan to reach is to upgrade the Chatbot so that it can support multiple languages in order to reach a wider range of people. It would make it easier for people to understand and interact with the Chatbot easily. We intend to enhance the functionality of the Chatbot with greater efficacy to utilize it in a broader or industrial platform. By utilizing and training with more models, we can enhance the chatbot's response accuracy more efficiently. As global tourism is becoming popular and increasingly digitized,

Chatbots hold a significant potential to expand the travel industry and attract travelers. Therefore, our approach for the future is to enhance our customer service Chatbot more effectively, with the aim of having a significant impact on the travel industry.

Chapter 7

Conclusion

7.1 Limitations

There are some limitations in our study, for example, the Chatbot can only be operated in the English language. It doesn't support any other languages. Again, the chatbot keeps repeating its response after a few moments. Lastly, another limitation of this study is that the dataset contains dialogues between humans and virtual assistants rather than two human beings. So, The response of the Chatbot can be straightforward and emotionless, which might not have happened if we had worked with a dataset with humans and real conversations.

7.2 Conclusion

Traveling has always been a part of human civilization. As we are heading towards a modern, digital world, customer service chatbots for travel agencies can be a way to take the whole traveling experience one step further toward modernization. We all can relate to the fact that most of us lose half of our excitement and intensity for visiting a country or a city just by thinking of going through all those long procedures of arranging the tour. Sometimes it is really hard and time-consuming to find every detail of transportation to a country, information about visas, and other important documents that are needed, and process those documents. Also, getting information about the average expenses of those destinations, and proper and safe stay places by going and meeting the travel agency in person takes a lot of time. As the world economy is constantly going up and down, the average expenses and tourism facilities also change from time to time, and it can take time to stay updated with the upgraded economics and expenses of a country manually. So, it can be problematic when someone wants to know the travel information of a country from the agencies in person. However, as we know the information in the data server continuously updates and keeps the latest news, it is quite sufficient and a better option to use technology to collect the latest information directly from the server rather than wasting time on going to the agency and asking all the questions in person. This chatbot will help travelers to find necessary information about their destination, and travel expenses easily and in a short amount of time. Furthermore, many people, especially students who are thinking of traveling to a distant location from their home for the first time, might find themselves lost in this long process of organizing the tour. Therefore, the travel Chatbot

will also be a blessing to those new travelers. To add more, this BOT system can also affect a country's tourism field by increasing visitors as the pre-travel process will be much easier than before. As we aim to head towards a world where people can get their work done easily and in the minimum amount of time possible, we cannot let such an important part of human society as "traveling" stay in the dark. As the world is modernizing, people have become busier and the value of their time has become higher. Creating a chatbot that can give guidance to travelers with more information in the shortest amount of time will help both the customers and a country's tourism and economics. In a nutshell, this research aims to develop such a chatbot for a traveling agency that can not only provide necessary information to the customers but also is easier to use and takes less amount of time possible, can be beneficial not only for the travelers and agents but also for a country's tourism and economic development.

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