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ATHENA AN AVID TRAVELLER USING LSTM BASED RNN ARCHITECTURE

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Abstract

A chatbot is an interactive, user-friendly agent, which communicates with users when they type in requests. The bot responds appropriately to those requests using the database of queries it has. Athena is a travel chatbot (developed specifically for Indian tourism), is developed to aid users in planning a trip, book hotels, and so on. Various parameters act as a judging criterion for evaluating the performance of Athena. This is used by various travel organizations to determine how deep the chatbot places a mark in the organization's growth and developments. We present an insight into the basics of Athena and its implementation. Athena is distinct from other chatbots given the fact that it uses Interest Detection System (IDS) to provide recommendations to the customer based on the chat history of the customer with Athena. IDS use dialogue state tracking concept to demonstrate its resolve. This paper describes the concept of Chatbots in the field of travel and tourism. It is observed that Athena produces a performance accuracy of 98.67%.

Keywords: Chatbots; Dialogue state tracking; Interest detection system, LSTM, Personalization, RNN, Travel and tourism.

1. Introduction

A chatbot is a program which simulates conversations with a user either by using audio or by text. The chatbots portray how a human would behave during such conversations, thus passing the Turing test [1].

There are various reasons as to why chatbots are being developed and used. Most relate to productivity, motivation (pertaining to social factors) and the curiosity they provide. The studies conducted on above mentioned factors provide insights onto improving the human-computer experience in the near future [2].

A chatbot uses various techniques for learning such as syntactic, semantic and discourse NLP, deep learning, a mix of statistical and inductive knowledge. There are algorithms used to build such chatbots for any domain [3].

Chatbots are used for many applications such as healthcare, employee management, customer care service, and so on. In the field of healthcare, chatbots can diagnose diseases and provide recommendations. But the problem lies in building a trust between the user and the bot. Effective trust building increases the acceptance of chatbots, thereby utilizing the construction of a trust model [4].

The bots can also be deployed in human resource management. It involves studying how these social chatbots will affect managerial practices. They can be deployed in pre-onboarding modules, thus providing an opportunity to analyze the interaction between users and system in terms of organizational aspects [5].

During feedback collection, service providers need to measure the chatbot service encounter satisfaction. But these are limited to only posts surveys. Hence, sentiment analysis is used to determine the value of the metric by using sentiment scores as a proxy [6].

A major challenge college students face is the lack of counselling; this is due to low advisor-student ratio. To resolve the dilemma, chatbots are being deployed to provide counselling for students [7]. These have the capability to provide career advising at various levels, thus eliminating the need for a counsellor.

Chatbots can also be used for social appeal. They have the capability to appeal to the user's emotional connection, their requests; thus, satisfying their affections and social belonging [8]. Also, they have the ability to imitate the personality of various characters, thus creating an alter-ego of the characters [9]. This is achievable by training the bot on various characters and using a metric to evaluate them. Thus, a human can be fooled into thinking that the answer came from human.

It is also observed that users turn to social media due to lack of customer service. But most of these requests are not addressed at all. To overcome the crisis, chatbots can be deployed as a customer representative on social media, by generating responses for the users' request on social media. They are as good as human agents showing empathy to distressed users to cope with social situations [10].

Bots either can use complex systems, that rely on Natural language Processing systems to respond appropriately or use simple methods such as pattern matching algorithms- that extract text, match with the proper response and respond with the correct answer.

A travel chatbot is an interactable agent which aids a user in planning a trip to various locations and also provide relevant reviews. In contrast to a basic chatbot which requests and responds with relevant answers, a travel chatbot not only implements the basic functions, but also acts as a recommender system, helping the user to decide the mode of transport, selection of tourism packages and so on. Athena simulates the conversation with the user through a well-defined user interface. Athena is able to answer queries of the user relating to trains, flights and hotels respectively. As of now, there are no travel chatbots in place for the Indian Travel and Tourism Industry that simulate the functionalities of a travel chatbot. Athena is a prototype chatbot, which is currently in development. Consequently, it doesn't have access to much more complex functionalities.

Athena relies on the use of NLP systems to simulate a conversation between itself and the user. NLP or Natural Language Processing, is a field of computer science, which deals with the abilities of a computer program to understand the statements spoken by a user. NLP techniques include the disambiguation of the input sentence, or also called Natural language Understanding and the Natural Language Generation (involves searching through the database for an appropriate response, based on the semantics). Athena uses a tool called NLTK for demonstrating NLP [11].

In a nutshell, Athena has two main components involved in its functioning. The first component is the Natural Language Understanding model and the second component is the Natural Language Generation model. The NLU model performs the intent classification and entity recognition tasks. The intent classification component (known as the Classifier), identifies the text input. An Intent is extracted from this input that provides detailed explanation for computer to understand. Entity Recognition is a process wherein an algorithm takes a string of text as input and identifies the relevant phrases that are mentioned in the input string. The model is developed and trained using data that contain certain conservations along with their respective entities and intents. The end user's input message can be understood by using patterns or machine learning classification algorithms. When the intent of the message is understood by the chatbot, it would generate an appropriate response. The unit also selects an appropriate response, which works best for the end user. The Natural Language Generation model is developed and trained using data, that specifies the response to be produced based on the intents and entities that have been previously classified and recognized.

The Rasa stack (the library which handles the NLU model) [12] has two main units: Rasa NLU and Rasa Core. The understanding section of the chatbot is taken care by the Rasa NLU. The main function of Rasa NLU is - to detect the intent in the input query and extract corresponding entities in the statement. The next component in Rasa stack pipeline is the Rasa Core. It accepts the organized input and decides an action the bot should do. It is also called as dialogue management model.

In machine Learning, RNN or Recurrent Neural network(s) is a class of Artificial Neural Network(s) wherein, the outputs from the stage (i-1) is fed as the inputs to the current stage (i). The distinguishing feature of an RNN is the hidden stage- which has the ability to remember a temporal sequence. The activations in this kind of network is assumed to be dependent of each other (it is done by the use of weights and biases). Hence all hidden layers have the same properties, thus converging them into a single layer.[13].

In deep learning, the Long short-term memory (LSTM) model is an RNN based architecture, that uses special units instead of standard units. LSTM was created so as to get rid of the vanishing gradient problem faced by RNN’s. The model contains feedback connections and processes a cascade of data points. A common LSTM unit includes three gates (input, forget and output) and a cell. The cell reminiscences values over random intermissions of time; and the gates are in charge of flow of information. LSTM networks are very appropriate to classify, process and make predictions on the basis of time series data; as there may be lags of unspecified period in a time series between important events. There are various LSTM architectures such as LSTM with forget gate, Peephole LSTM, Peephole convolutional LSTM, etc.

Athena also implements the concept of interest detection. It is able to identify the user without any explicit specification, and accordingly, recommend various hotels, flights and trains. It achieves this by utilising the previous conversations of the user with Athena (which is accomplished by the algorithm).

This article presents a research conducted on Athena- a travel chatbot, which aids the users in bookings and recommendations. The article presents a related work done on the chatbots, various architectures that are implemented, followed by the future enhancements that can be implemented.

2. Related Work

ELIZA is an early NLP system made in 1960's at the MIT AI Lab by Joseph Weizenbaum [1]. It exhibited how paltry the discussion was among man and machine, which was reproduced by utilizing a 'design coordinating' and substitution approach that gave clients a knowledge of deciphering with respect to the program; yet it had no role in the structure for contextualization. Protocols for communication were given by 'contents' composed initially in MAD-Slip, permitting Eliza to process client sources of info and utilize in verbalization following the principles and rules of the contents. The most well-known content ‘DOCTOR’ imitated a psychotherapist and connected tenets, edited in content, to react to directionless inquiries to client inputs. All things considered, ELIZA was one of the first chatbots, but at the same time was viewed as one of the principal programs, prepared to do go through the Turing test. Weizenbaum viewed the program as a strategy to demonstrate the trivial idea of pep-talk among man and machine, however was astonished by the quantity of people, who attributed human-like feelings to the program, including Weizenbaum's assistant. Numerous researchers trusted that the program won't almost decidedly command the lives of numerous individuals. ELIZA, was be that as it may, not ready to talk with genuine comprehension. Obviously, numerous early clients were persuaded of ELIZA's insight and comprehension, in spite of Weizenbaum's point of reference to the oddity.

ALICE (Artificial Linguistic Internet Computer Entity likewise alluded to as AliceBot [14], is an NLP chatbot-a program that utilizes its skills in a discussion with an individual by applying some Socratic examples of human’s info, and in its online structure, relies upon a concealed human judge. It was motivated by ELIZA. It is one of the industrious projects of its type and has won the Loebner Prize, granted to talkbots, thrice. However, the program is unfit to pass the Turing test as even the evaluator will frequently uncover its gimmal perspectives in short talks.

The Travel Booking Chatbot [15] is a system developed to aid users only to book a trip to specific destination within a given time period. The bot, depending upon the user input, hunts for flights, hotel accommodations and car rentals, then displays the options the user can select from. The goal of this porotype developed was to attain reliability, usability, in contrast to the traditional booking system. It also compares the systems based on speed, performance and the preferences of the user.

It is also to be noted that the intelligent travel chatbot [16] is similar to Athena in its functionalities, but varies on the implementation of the core concepts. The system relies on the use of Deep neural Network for gathering preferences and uses Restricted Boltzmann Machine (RBM) combined with Collaborative Filtering for recommendations, all done on Amazon Echo platform. The system aims to improve the human computer interaction in the travel and tourism domain.

There are some travel chatbots, that are actually deployed in the industry worldwide. Some include the Japan Trip navigator (JTN) [17], which offers a unique experience in planning a trip to Japan, along with various booking and sightseeing options; Mezi-the personal travel assistant [18], being developed by Pune twin brothers and sold to American Express. Mezi has more than 10 million users, and has learnt over 50 million words. The system was also grained on 10 million conversations. The intelligence of the system gets better as and when it acquires more users and learns more words.

The majority of queries that travel agencies or airline/hotel staff need to handle are routine queries and FAQ’s. Having human customer-care representatives repeatedly respond to such queries is highly inefficient. Particularly when a business has suitable alternatives available in the age of conversational AI. Chatbots can easily resolve these routine queries. This enables human employees to focus on resolving complex customer problems, and performing other managerial tasks, that actually require human intervention [19]. Being relieved of the mundane and repetitive task of responding to routine queries can prove to be a great motivating factor for employees. This further boosts their productivity and efficiency. Travel chatbots are on-call 24×7, 365 days a year, to resolve simple customer queries. This constant availability enhances the customer experience in any industry. But it is particularly useful in the travel industry, where customers need their problems to be resolved immediately, even as they travel across time-zones. Chatbots are not only available when required, but also bring an added level of personalization when it comes to helping customers [20-22].

NLP enables chatbots to be programmed to understand vague queries, such as “Resort” or “hill station retreats”. The bot can identify trigger words from the query and use them to carry out a customer’s search. This reinforces the idea of the chatbot as a ‘personal helper’. A helper who can be asked any question, who can be asked to service any request, and who can potentially give customers exactly what they want. The interactivity and feeling of flexibility that is offered to a customer is sure to boost engagement, especially when compared to the traditional option of making the customer fill a long static survey form with limited options [15, 22].

From a customer’s point-of-view, the ability to easily access their chat data on a conversational AI platform is yet another aspect that adds to the convenience of the medium. But from a business point-of-view, chatbots are a rich source of data on their consumers - offering insight into their purchase history, experience, positive and negative feedback, etc. [14] Travel industry players can then put this data to use in a number of ways. They can offer personalized recommendations based on inputs from a customer's interactions with their chatbot, as we've already discussed in the case of Foursquare's Marsbot [23]. They can tailor their marketing messages to individual users based on the insights gathered. AI-driven analytics can predict future customer behaviour and intent.

It is observed that systems depicted in references [15-18] are lot improved, much advanced and much more flexible, than Athena. The systems have capability to detect user preferences, provide directions to help the tourists and provide guest reviews. Athena, in general, provides information related to flights trains and hotels, but hasn't implemented the complex functionalities as of the systems which are superior to Athena.

3. Data and Methods

The file titled 'domain' consists of five components: intents, entities, actions, slots and the expected queries from the user [16] There are thirty-three intents, thirty entities, forty stories, forty slots and thirty queries on an average. It is to be noted that the above-mentioned components had a role in improving the accuracy of the bot, thus arriving at 98.67%. With each new session with the bot, the domain file was updated with the new session story, thus increasing the accuracy. Every new story had a key role in updating the chatbot's database when the bot was executed. Hence, during the procedure where sixty iterations were considered, the performance accuracy was 48%. At 100 iterations, the accuracy was 98.67%. Hence, this kind of accuracy metric was possible to be achieved since Athena is a prototype and doesn't have capabilities to perform complex transactions similar to a real world chatbot and the dataset provided is not large.

The bot accesses data required for responses by accessing API (Application Programming Interface, which allows an application to access functions to perform tasks by the use of a procedure call or use of a Uniform Resource Locator (URL), that accesses the online databases). These API's can access real-time data (such as PNR status, Hotel charges, Scheduled flights, etc.) by logging onto the developer sites. IRCTC (Indian Railways Catering and Tourism Corporation) API is used to access data related to train (class quotas, station codes, trains between stations, availability, etc.). Similarly, Goibibo API can access data related to hotels and flights. The file titled 'stories' consists of the various conversation archives that can be used to train dialogue management model (NLG) model. Consequently, the fifty stories archive, along with the above-mentioned components constituted the reason for a high accuracy.

In addition, a JSON file also exists, which consists of various statements, alongside intents and entities present in that corresponding responses, which at the end, train the NLU model.

A typical architecture adopted by real-world travel bot is depicted as follows [24]. Athena adopts this architecture (as shown in Fig. 1) for performing its task:

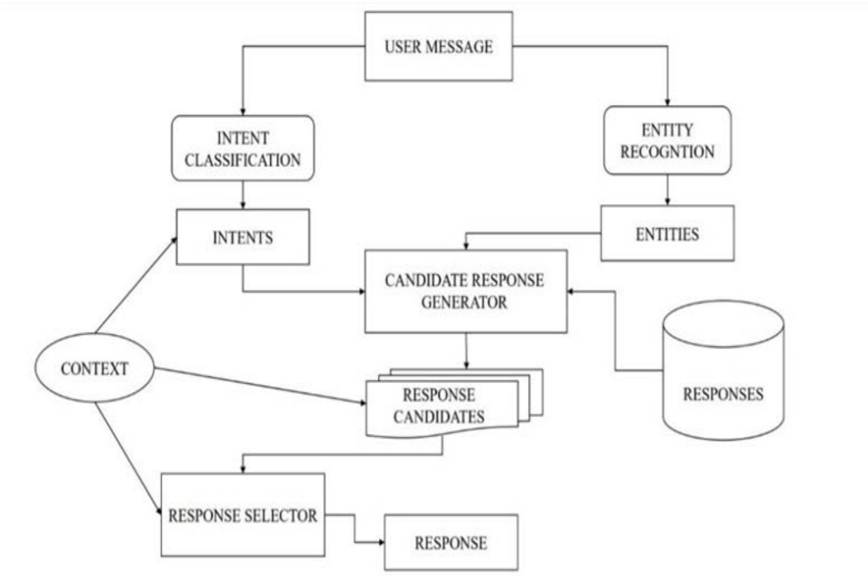

Fig. 1. System architecture of a travel chatbot.

Athena works as follows:

- The user provides an input in the form of a sentence. Athena must be able understand the human's intentions and extraction of relevant information from the intention, then take appropriate action.
- NLP plays an important role of extracting the intention of text and the corresponding relevant information. An intent is the user's intention. At the same time, NLP concurrently recognizes entities from the text. An entity modifies an intent and a name is given to it. Hence 'Intent' and 'Entities' are two separate data obtained in this phase and fed to the Candidate Response Generator.
- The candidate response generator is in-charge of performing domain-specific calculations which then processes the request of the user. It uses various algorithms, call some external APIs, or seek help from user with response generation.
- The response generator has to utilize the context of the conversation along with the intent and entities obtained in the previous step.
- The result is a list of response candidates which are then fed into the Response Selector.
- The Response Selector determines the best response from a list of candidates from choosing a best ranked candidate. The candidate is the response from Athena to the user's text.
- Hence, successful communication takes place between Users and Athena.

Thus, by adopting the typical architecture and making significant changes, an architecture for Athena is proposed which is depicted in Fig. 2.

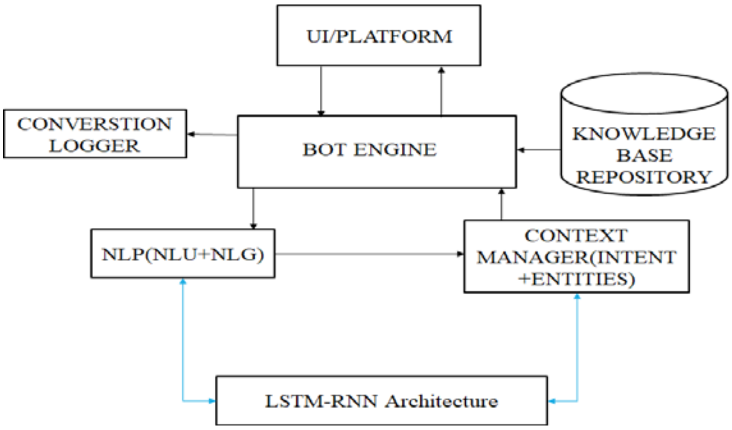

Fig. 2. A proposed system architecture.

The interest detection system recognises the user's preferences through his/her responses and recommends the various hotels, flights and trains. Athena records the user's interest and uses it in the future to not only recognise the user, but also to provide recommendations. The proposed algorithm for interest detection is as follows:

IDS algorithm (username, chat log of username):

```
begin
initiate algorithm when keyword 'name' or name of user is detected
activate sightseeing API
search for chatlog
if chatlog is present then
        access chatlog
else
        create new chatlog
        search for summary
 end if
 if summary is present then
        access summary
  else
         create new summary
  end if
 for every conversation
        scan for entire line
        move onto next statement
        extract sightseeing keywords
        update summary with keywords
        if keyword 'recommendation' or 'suggest' is found then
                scan summary
                access sightseeing database
                map keywords to top results in database
                print recommendations
        end if
   end for
 end
```

The flowchart for the pseudocode is shown in Fig. 3.

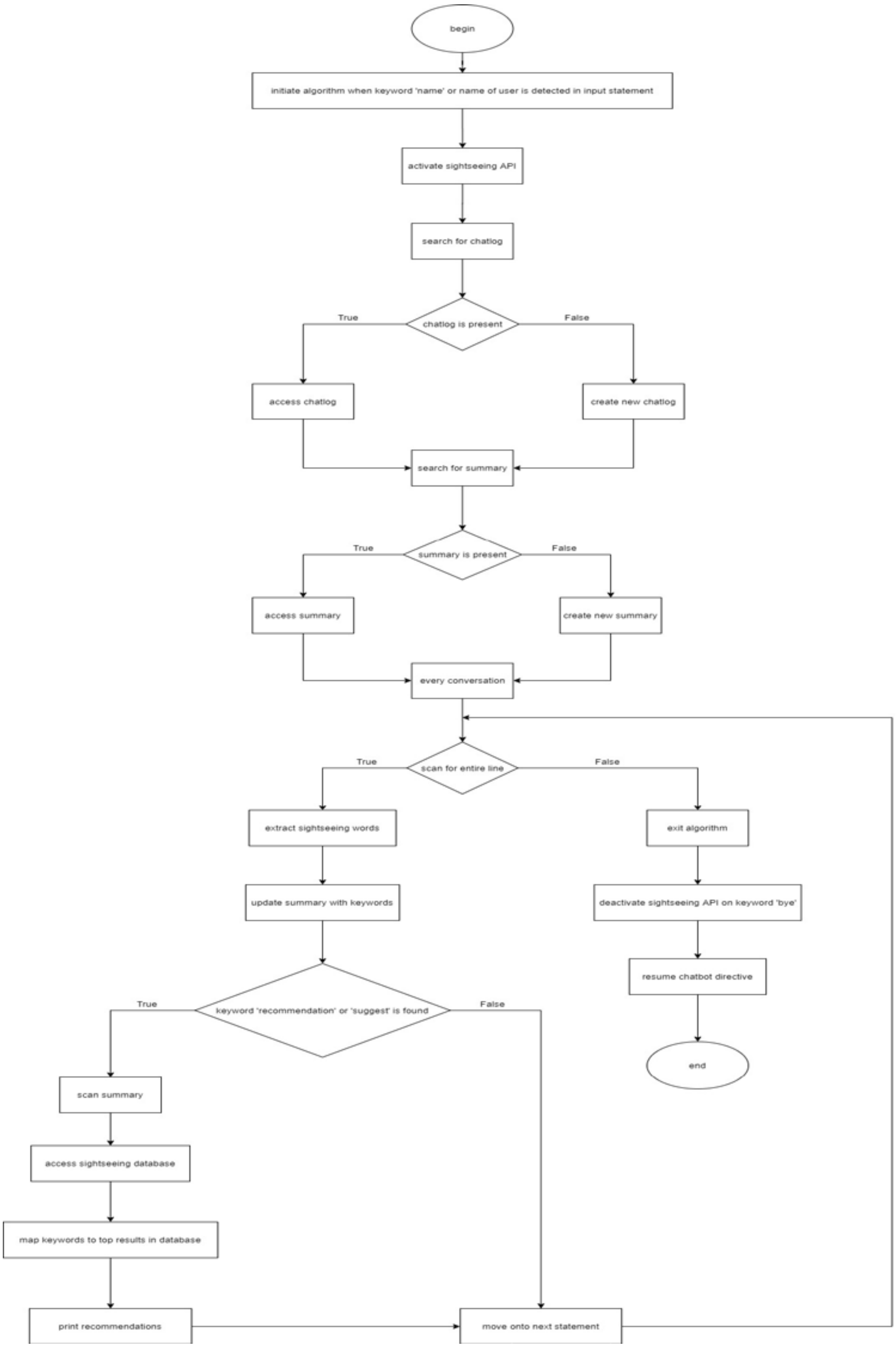

Fig. 3. Flowchart

4. Results

The bot (Athena) is implemented using the Long Short-Term Memory based RNN (Recurring Neural Network) type architecture. RNN is a varied type of neural networks where output data is fed to the node of the next stage as input data. The RNN model is trained in two phases. In the first phase, the model is trained to implement the NLU model. The data is provided to RNN, several epochs (A period/timeline that consists of iterations) were run and the results were noted. The data provided is in JSON format containing several texts, along with the intents and entities relating to that particular text. The epochs are run in multiples of 25 up to 100 epochs and the accuracy is noted for each. It is observed that the accuracy would increase with the increase in epochs. In order to standardize the procedure, a count of 100 epochs was considered. The accuracy here refers to how correctly the model is able to classify the intents and extract the entities. It observed that while training the model with 100 epochs, it is able to achieve the highest accuracy of 85.36%. Table 1 and Fig. 4 depict this stage.

Table 1. Tabulation of epochs and their corresponding accuracies-Stage 1.

Number of EPOCHS	ACCURACY
25	41.28%
50	59.71%
75	72.98%
100	85.36%

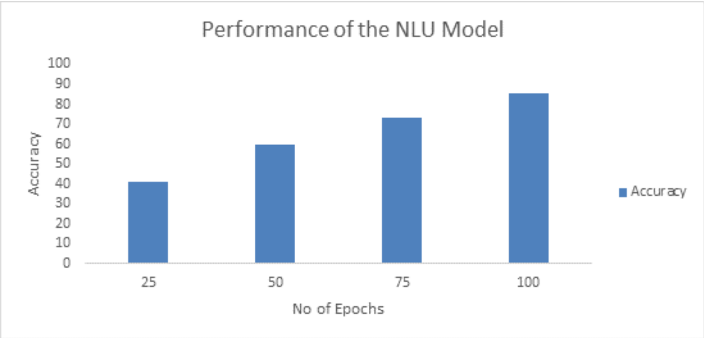

Fig. 4. Performance of the NLU Model.

In the second phase, the RNN model is trained to implement the NLG or the dialogue management model. The data is provided to RNN, several epochs are run and the results are noted. The data provided is in the form of stories, containing the various conservations between the user and Athena. Each story contains a flow of conversations on which the bot is trained. The epochs are run in multiples of 25 up to 100 epochs and the accuracy is noted for each. It is evident that the accuracy would increase with the increase in epochs. In order to standardize the procedure, a count of 100 epochs was considered. The accuracy here refers to how correctly the model is able to predict the response that must be provided by the bot. It observed that while executing the dialogue management model with 100 epochs, it is able to achieve the highest accuracy of 98.67%. Table 2 and Fig. 5 depict this phase.

Table 2. Tabulation of epochs and their corresponding accuracies-Stage 2.

Number of EPOCHS	ACCURACY
25	48.36%
50	65.45%
75	81.92%
100	98.67%

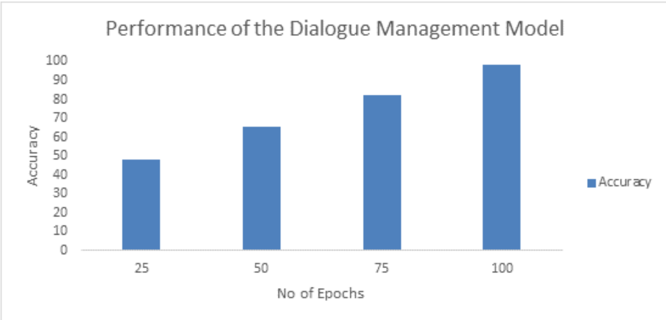

Fig. 5. Performance of the dialogue management model.

It is also observed that the time complexity of the algorithm is represented by Eq. (1)

$$T(n) = at\left(\frac{n}{b}\right) + O(n) \tag{1}$$

Also, the complexity is O(log *n*).

The screenshots (Figs. 6 and 7), that depicts one among those code snippets that are used for executing Athena is depicted below:

```
from rasa_nlu.training_data import load_data
from rasa_nlu import config
from rasa_nlu.model import Trainer
from rasa_nlu.model import Metadata, Interpreter

def train_nlu(data, configs, model_dir):
    training_data = load_data(data)
    trainer = Trainer(config.load(configs))
    trainer.train(training_data)
    model_directory = trainer.persist(model_dir, fixed_model_name = 'travelnlu')

def run_nlu():
    interpreter = Interpreter.load('./models/nlu/default/travelnlu')
    print(interpreter.parse(u"I need information on train route"))

if __name__ == '__main__':
    train_nlu('./data/data.json', 'config_spacy.md', './models/nlu')
    run_nlu()
```

Fig. 6. Main code of the bot, which executes the system.

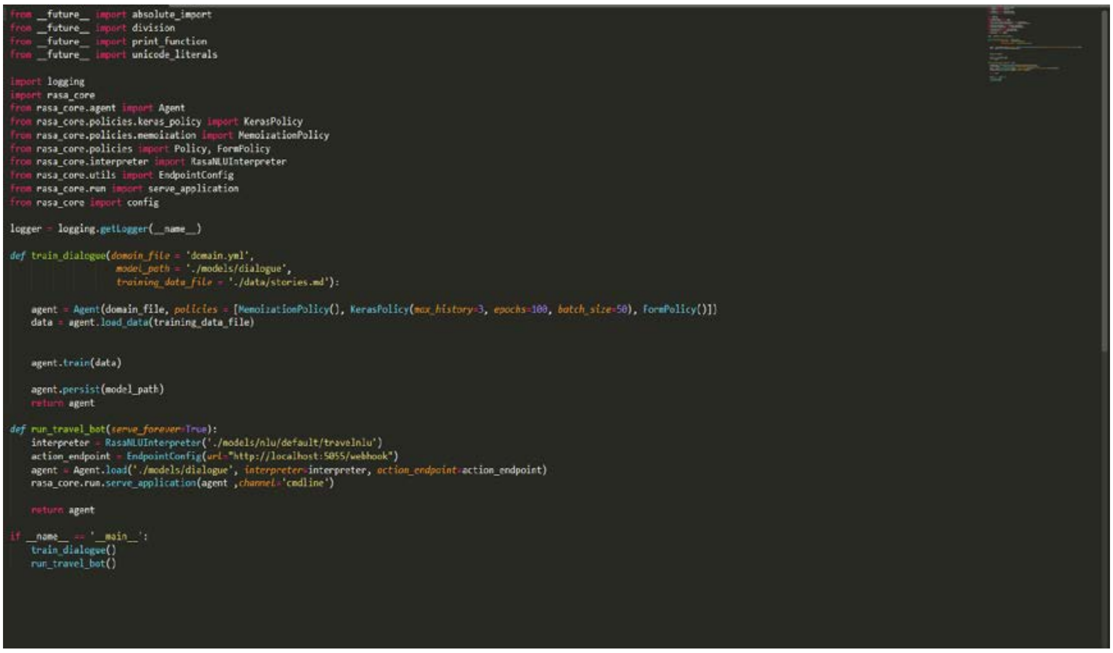

Fig. 7. Screenshot of dialogue management model.

The following screenshots, Figs. 8 to 10 show the implementation of Athena. These figures depict the various conversations between the user and Athena. The bot is able to answer the user's queries accurately, relating to flights, trains and hotels [25]. The user interface is integrated with bot through the Slack API [26]. Slack provides a way to make communication secure, but although there are some security loopholes that are yet to be resolved.

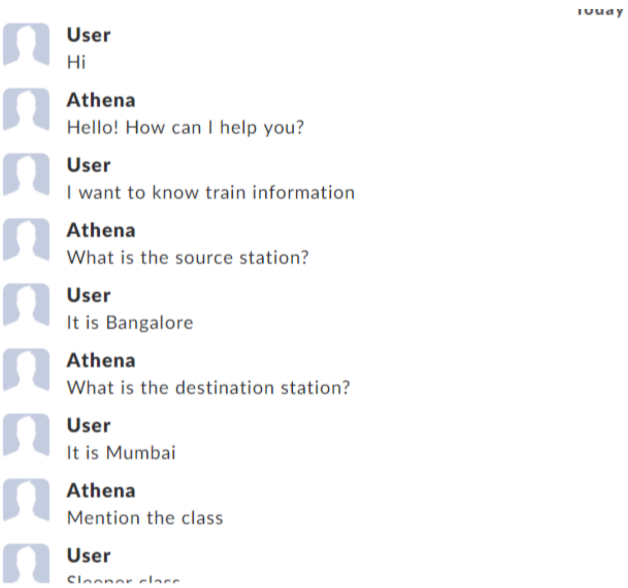

Fig. 8. Screenshot to depict basic conversation.

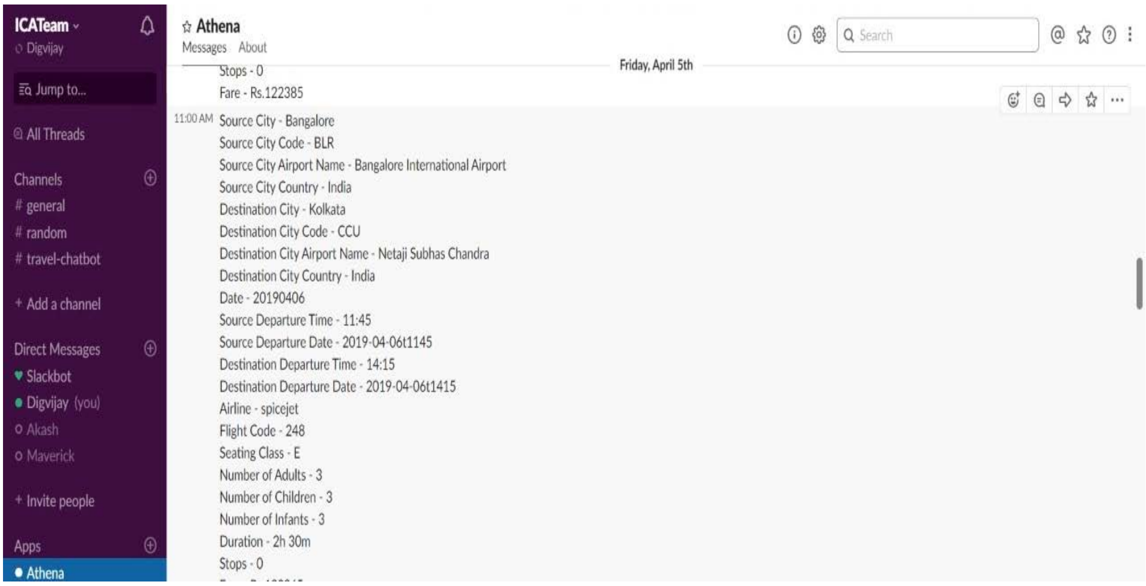

Fig. 9. Screenshot of Train details enquiry.

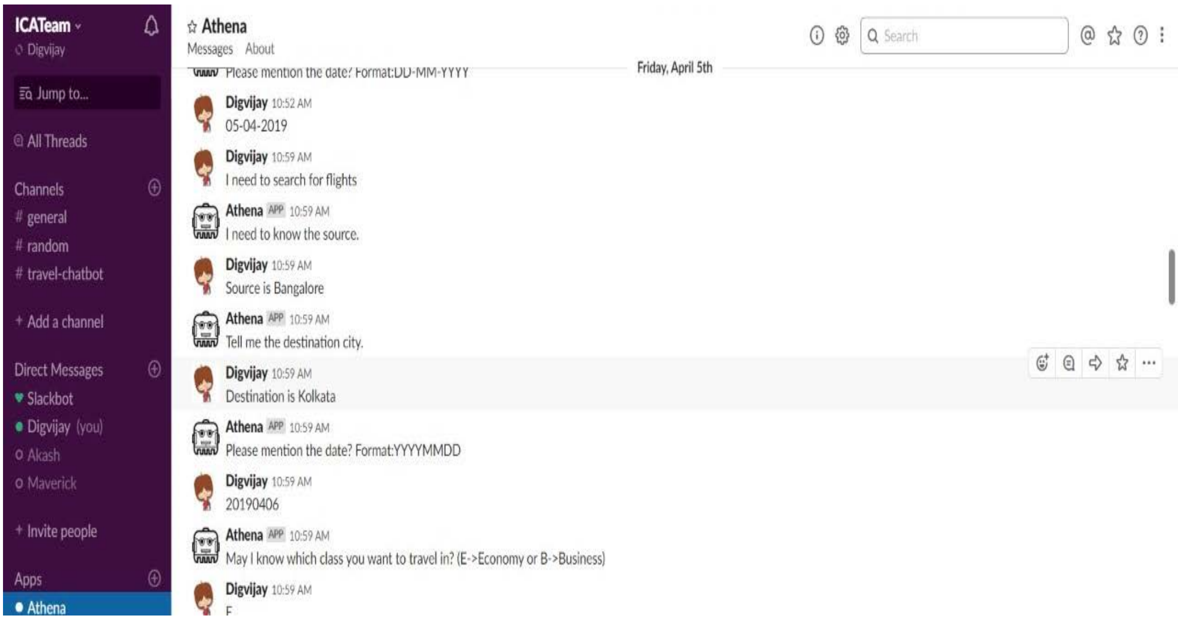

Fig. 10. Screenshot to depict conversation.

5. Conclusion and future work

We have created a travel-query chatbot that uses the concept of machine learning alongside neural networks to simulate an agent-user conversation to provide travel options to the user based on his preferences. It uses a variety of API's to communicate and thereby avoids the install and use of a dedicated application eliminating the disadvantages of doing so.

Chatbots with Artificial Intelligence technologies are dramatically changing our society. The aim of chatbot developers should be to design functional tools that can help society, facilitate work at ease and pace and allow more interaction with computers through natural language. With a vast scope in Chatbot applications it is observed that chatbot is capable of ensuring that tasks are easily handled. At the same time, Chatbots are being improved every day and each day, and are becoming more connected to human beings than ever before. Hence, Chatbots have earned their alias as "The Artificial Human".

Athena can further be trained with different varieties of data. It could also be extended to answer queries relating to sightseeing and holiday package suggestion. The interest detection algorithm that is proposed, could be further extended to the sightseeing domain. The queries can be provided through voice commands by the user, rather than providing textual commands. Personalization system of the bot can be upgraded to a level that matches the personalization of modern chatbots.

It is also expected that, in the future, the bot is able to take over the entire travel industry. Athena can also be secured by providing a way of conversing with the potential users by means of secured protocols such as SSH.

Abbreviations

API	Application Programming Interface
IDS	Interest detection System
IRCTC	Indian Railway Catering and Tourism Corporation
JSON	JavaScript Object Notation
LSTM	Long short-term memory
NLG	Natural Language generation
NLP	Natural Language Processing
NLTK	Natural Language Tool Kit
NLU	Natural Language Understanding
RBM	Restricted Boltzmann Machine
RNN	Recurrent neural network
SSH	Secure Shell
URL	Uniform Resource locator

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