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INSURANCE AGENT CHATBOT

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ABSTRACT

A chatbot is a computer-based program that simulates human conversations, and in this project, in representation of an insurance agent.

The goal of the project is to develop an artificial intelligence chatbot for an insurance agency company. An Insurance Agency is a company that embodies professional representation of insurance company in selling and servicing policies. The agency receives a commission for the service.

The chatbot will allow the Insurance Agency to deploy this digital agent for marketing campaigns via their company website.

Over past few years, potential clients in general have grown more oriented towards real time support other than fixated adverts that lack personal touch. Companies are increasingly employing the usage of chatbots in order to engage a higher proportion of clients within their business operations. These days organizations are using chatbots such as Facebook Messenger Bot to amp their competitive edge.

This is making businesses more readily accessible and available 24/7 to address their customers needs on messaging platforms leads to proactive interaction with users about their products or services. Further more, cchatbot systems are used in customer support, recruiting, queries and question response and addressing, marketing.

Chatbots come in two kinds:

- Rule-based (Scripted chatbots)

Scripted chatbots follow a set of rules is, each action by the user prompts the bot to respond out of a limited selection of preset responses in accordance to the prompt.

- Artificial intelligence chatbots

The creation of Artificial intelligence chatbots is founded in the roots of Machine Learning, as well as Natural Language Processing. These chatbots are based on the human capacity to learn and process information.

Chatbots are generally are more efficient and a lot faster at processing data than humans, resulting in more effective oriented outputs. However, for Machine Learning chatbots, with each new conversation the chatbot has, it becomes smarter and adapts for further effectiveness in approach that brings about greater probability of desired result. For this project Artificial intelligence has been implemented based on its possibility of extensive application and adaptive functionality.

Chapter 1

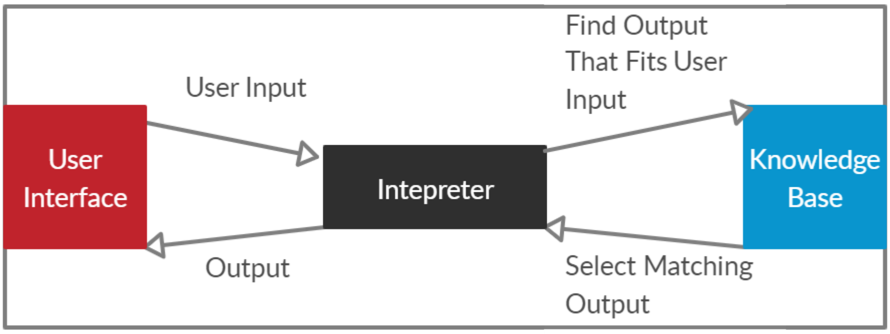
INTRODUCTION

Insurance agent chatbot is a project that explores what can be accomplished with a chatbot in the world we live in today (Nuruzzaman and Hussain, 2020).

This chapter will bring into light, the background context covered in section 1.1. Then, an outline of the significance of project will be given in 1.2. followed by problem statement definition in 1.3 Afterwards, a delivery of set aims and objectives 1.4. In section 1.5 coverage will be made on the scope and limitation of this project. Thereafter, in section 1.6 the justification of projection will be made clear. This will be followed by an overview of requirements in 1.7. Finally, an outline of research organisation will be graphically portrayed in section 1.8.

1.1 Project Overview

Figure 1.1: Chatbot Overview (Own, 2020)



In this project a chatbot is an automated interaction partner that will guide a potential client through services offered as well as address any queries the potential client may raise.

Over the last decade, chatbots have achieved tremendous impact on this economic sphere, portraying an ideal form of representation for human to computer interface exchange. Every chatbot mainly operates via functionality of 3 modules, user interface, interpreter and Knowledge base as shown in diagram above.

Various libraries integrated in python language programming have been employed in this ambitious project to showcase the full power of artificial intelligence in the very relevant field of Insurance (Singh, and Chivukula, 2020). The Neural networking libraries employed in the building of the machine learning chatbot are namely,

- NumPy- is a scientific library for running computations in Python. It supports the use of matrices and multi-dimensional arrays and complex functions to solve advanced mathematical problems.

- Nltk- The Natural Language Toolkit (NLTK) is a library thats used in application of human language data in statistical natural language. processing.

- TensorFlow- an open source platform that facilitates creation of machine learning applications inclusive of neural networks.

- TfLearn- Is a machine learning library used in speeding-up experiments within python.

A JSON file will contain the main relevant labeled and calibrated data-sets. The system utilizes Microsoft Management Studio as database to store chatbot details and records.

Chatbots can generally work with two kinds of input, text and voice. In this paper, we have utilized the text as user input. Reasons being that text input doesnt require exceedingly high computational power for processing, the details can be verified as well as analyzed more accessibly using assessment modules of the chatbot system. Through this specified text input channel, the chatbot system is entirely ready to conduct complete and effective conversations with the user, providing access to insightful forecasts based on analysis of conversations held.

1.2 Significance of the Project

The purpose of this project was to showcase and explore the power of an artificial intelligent chatbot designed and equipped in interactive capacity needed to attain an insurance prospect, acquire and store their data as an insurance agent would do. The secured data will be forwarded to a database for retrieval by the respective insurance companies depending on the information provided by the user (Tardieu, Daly, Esteban-Lauzn, Hall and Miller, 2020).

Personal digital assistants such as Cortana from Microsoft, Alexa and Siri from Amazon and Apple respectively are leaders in the technological field of artificial intelligence, bringing into use advanced voice recognition and machine learning (Sabharwal and Agrawal, 2020).

Through machine learning these companies have developed systems that function as almost fully fledged secretaries, working on fine details such as email prioritization, scanning content to indicate the more vital aspects thus generally users' daily effectiveness and productivity (Kwatra, Fox, Krystek and Rakshit, 2020).

Artificial intelligence contributed much towards deployment of intelligent automated systems that work towards improved delivery of education, more seamless customer service, entertainment and guidance.

Rule based chatbots are inclusive of those that raise support tickets for customer feedback, those used for hotel booking and reservation of restaurants among others.

Established and well-known artificial intelligence chatbots are ALICE, Evie, Elbot and Cleverbot. These chatbots are developed using Artificial Intelligence Markup Language (AIML). AIML is derived from extensible Markup language (XML) which is the language used in this project, a language centered for developing artificial conversationalists.

AIML based chatbots are well known due to their simple configurations, low costs on hardware requirements and light space occupying. AIML is convenient for these types of systems because their function is narrowed down to simply having conversations with people without a specified outcome, in simpler terms, they are non-domain specific.

The clientele group for this project is Insurance companies. The approach of this project was to use XML instead of AIML in development of an Insurance Agent Chatbot System (Weitzel, 2020). This approach was relevant as it achieves a suitable base for programming of advanced modules targeted for this chatbot system, requiring several compatible modules and an extended time of training models with massive datasets (Buhalis and Yen, 2020).

This literature links to current trends by expanding the modules of capacity that can be carried out by just one chatbot thats artificial intelligence powered. The project is an improvement to existing work in the field of artificial intelligence as it achieves development of more advanced software infrastructure yet to decreasing the development cost due to the applied techniques as demonstrated throughout the undertaking of this project.

1.2.1 Problem Statement

In this digital era, the effectiveness traditional standard of doing Insurance business has been on a steady decline over the past 10 years. Usually, Insurance companies work with insurance human agents in order to market and sell their policies to prospects. Problems have risen with this approach as, there are errors in calculations estimate charges by human agents.

The process of securing a prospect is usually long and tedious involving, scheduled emails, numerous clientele follow up calls and postponed physical meetings. To add on to these challenges, geographical limitation for marketing campaigns by human agents is a big factor, as well as potential insecure handling of sensitive customer data by the insurance agent. Sometimes a potential insurance client is abandoned by an unavailable insurance agent who perhaps leaves the Insurance agency company without a complete hand over of contacts by agent.

In an effort to combat these issues there have been some effective attempts at engaging automated chatbots to aid in success of this industry.However, according to a survey conducted by (Marotta, Martinelli, Nanni, Orlando and Yautsiukhin, 2017), the cyberinsurance industry is still very immature. The current employed chatbots in this industry are at best rule based implying there is insufficient possibility of drawing of metrics of evaluation in order to run a self updating chatbot that incorporates machine learning.

The opportunity for a machine learning chatbot rises as data inputs by prospects will provide room for advanced pattern recognition (Tenemaza, Lujn-Mora, de Antonio, Ramrez and Zarabia, 2020). Therefore, these patterns could be explored in order to easily deliver higher standard of approach from chatbot in future encounters. The chatbot solution developed in this project will deliver an optimized query capturing module that will receive all customer inquiries and as well as a generative response module that will give the user prompts by which the user will be able to give all the necessary details for followup and their desired policy. The system will produce insurance cost estimates during interaction, giving the prospect tremendous flexibility in marketing policy delivery. Insurance prospect data will be securely stored in a database.The chatbot implemented in this project will have an up-time of 24 hours in a day unless during maintenance phases.

1.2.2 Aims and Objectives

1.2.2.1 Aims

This project aims at creation of a scalable chatbot that serves as the first layer of proactive communication and prospecting in an insurance agency's marketing wing.

FIGURE 1.2: Insurance Agent Chatbot Process (Own, 2020)

1.2.2.2 Objectives

- Explore on chatbot frameworks to increase knowledge in speculations, algorithms and programming strategies, regarding the outcomes from past projects.

- Study current chatbots to see the qualified online platforms for the implementation phase.

- Conduct research study on the necessary steps of a specialist in securing an insurance prospect (JAIN and ARUN, 2020).

- Build up a chatbot system made of a completely fledged SQL database, python algorithm for keyword coordination and string separation correlation in chatbot in response to likely customers. Send on practical stage with easy understanding of the interface.

1.3 Scope and Limitation

1.3.1 Scope

Our solution is mainly focused on improving the customer agent relations in insurance sector. Specifically making sure that customers are served any time regardless of their geographical locations (Butler, 2020). An intelligent chatbot powered by artificial intelligence will be deployed to help solve the problems experienced in the insurance sector.

A data dictionary containing all the relevant insurance information will be created and the prototype is going to be trained from this dictionary to help generate responses. The responses will be generated by matching the customer input with patterns. To achieve this functionality the patterns are stemmed. Stemming involves taking every word in the pattern and bringing it down to the root word.

Stemming is most importantly for model training purposes as not every character associated with a word is essential to understand the main meaning of the word. Getting rid of extra characters will help in improving the accuracy of our model. To get all the words in the stemmer from our patterns, the words must first be tokenized (Paliwal, Bharti and Mishra, 2020).

The words are then bagged for machine learning algorithms and neural network processing as they only understand numerical inputs. First these bags of words will then be encoded into tensors. Tensors are used for machine learning.

The chatbot will be using the recurrent neural network. Tensors are used to hold the matrices or represent words which are processed using the recurrent neural network to recognize patterns and generate appropriate responses.

1.3.2 Limitations

Different factors can hinder or delay the development and deployment of the chatbot solution. From the view of Rahman, Al Mamun and Islam (2017), the technical challenges for chatbot systems are numerous. Relevant and well anticipated matching pre-set labels will be essential.

Processing Power

The main challenge with the development of this solution is usage of computers that are below spec requirements for this project. The is limitation of processing power, considering it is an artificial intelligence project. Thus, it took much longer to train a model than it would have been with a fully equipped high end computer system.

Deployment and Testing

According to Daniel, Cabot, Deruelle and Derras (2019) , in order to construct a chatbot, specific tools are necessary, along with an easily accessible platform of deployment. Platforms of deployment and testing tools of this application for the most part required a paid amount due to the calibre of the field and the depth of metrics taken into account when deploying or testing such a solution.

Chat Topics

It is not possible to implement a chatbot that is able to answer all questions posed by the user with the current technological advancement (Amiot, 2020). Within the lines of persuasion of a potential client to buy insurance policy, the system will highlight only key areas necessary to create a point of sale. Queries of question posed by the user will be addressed according to the limited knowledge base of the trained insurance agent chatbot.

Language

Standard English (British) is the only English that will be supported by this Chatbot.

1.4 Justification of Project

In 2020, Botswanas economy the insurance industry went through an almost absolute and indefinite halt during the onslaught of the global pandemic covid-19 (Harari, 2020). Millions of Pula in possible revenue have been hindered due to national quarantine, social distancing measures and peoples reluctance to visit insurance offices amidst the pandemic, leaving no room for progress (Espinoza, Crown and Kulkarni, 2020).

With dire circumstances like this in mind, suggestion was made to development of a web based online chatbot application that can be despatched in representation of what an insurance agent would ideally be expected to fulfil in order to secure a prospect. The creation of this digital insurance agent has firm potential to disrupt operation models in Botswanas insurance companies (Riikkinen, Saarijrvi, Sarlin and Lhteenmki, 2018).

In a monetary domain enormously influenced by the COVID-19 pandemic, chatbot innovation gives a critical chance to limit hands-on human association while offering important types of assistance to clients (Miner, Laranjo and Kocaballi, 2020).

The primary kind of technology that chatbots utilize is artificial intelligence (AI). Using AI, chatbots are intended to behave like humans yet they are open anytime of the day by voice or potentially text. Chatbots with AI are effectively scalable; however, impediments do exist, and human hand-off is still necessary at specific occasions.

In relation to method efficacy for this project, Srivastava and Prabhakar (2020) established machine learning chatbots are the future, and in doing so, founded an insight that creation of rule-based chatbots imposes short-sighted delivery of chatbots that are inadequate for the problems in the current highly demanding industry.

Xiong, Liu, Xu, Jiang, and Ye (2020) argue in their own findings that solely implementing machine learning chatbots cast at the possible highlight rule-based chatbots provide benefit of. Thus, implying a mixture of both machine learning and rule-based chatbots ought to be used.

For this project generation of a significant sets of secondary level machine learning responses is used, oriented towards guidelines relevant in todays world that demands greater deployment of Artificial intelligence powered chatbots.

1.5 Requirements

1.5.1 Primary Requirements

- Receive and process user input
- Respond accordingly using artificial intelligence unit
- Store customer data
- Capable of continuing or terminating conversation as necessary
- Logging chat sessions
- Estimation of charges

1.5.2 Secondary Requirement

The chatbot will respond in accurate fashion, with a response time of no more than 2 seconds. It will be secured with an HTTPS protocol during web interaction. It should be user friendly and courteous in conversation.

1.6 Research Organisation

The following chapters are aimed at elaborating the technical analysis and development of the chatbot.

Chapter 2 which is the literature review will further expand the general overview the usage of chatbots and the types that exist as well the chatbot implemented in this project.

Chapter 3, the System design and Analysis chapter will be used to define the technical design and development approaches employed. Different functionality modules that will be executed by the Bot will be technically illustrated as well as the path to their achievement headed towards implementation.

Additional information like deployment measures, coding and necessary environmental conditions and technology will be covered in chapter 4 and chapter 5, the testing and implementation chapters.

In chapter 6, summation of the project execution and possible further chatbot evolution will be covered, inclusive of the various problems chatbots could be used to address in time as development from what was possible to achieve in this project. In Chapter 7 the appendix will have, functional and non functional system requirements, the project progress gantt chart, role designation, as well as the data set library for the implemented chatbot in this project.

Enclosed on the document is chapter 8, references will be outlined in a bibliography list, havard referencing style

Chapter 2

LITERATURE REVIEW

2.1 Chatbots

World-wide, chatbots are being developed to counter operational inefficiencies, improve customer experience and drive down labour cost.

Chatbots generally work on Pattern Recognition and a Set of Algorithms that sort responses (Schumann, 2020). Overall, chatbots work on a basic model of

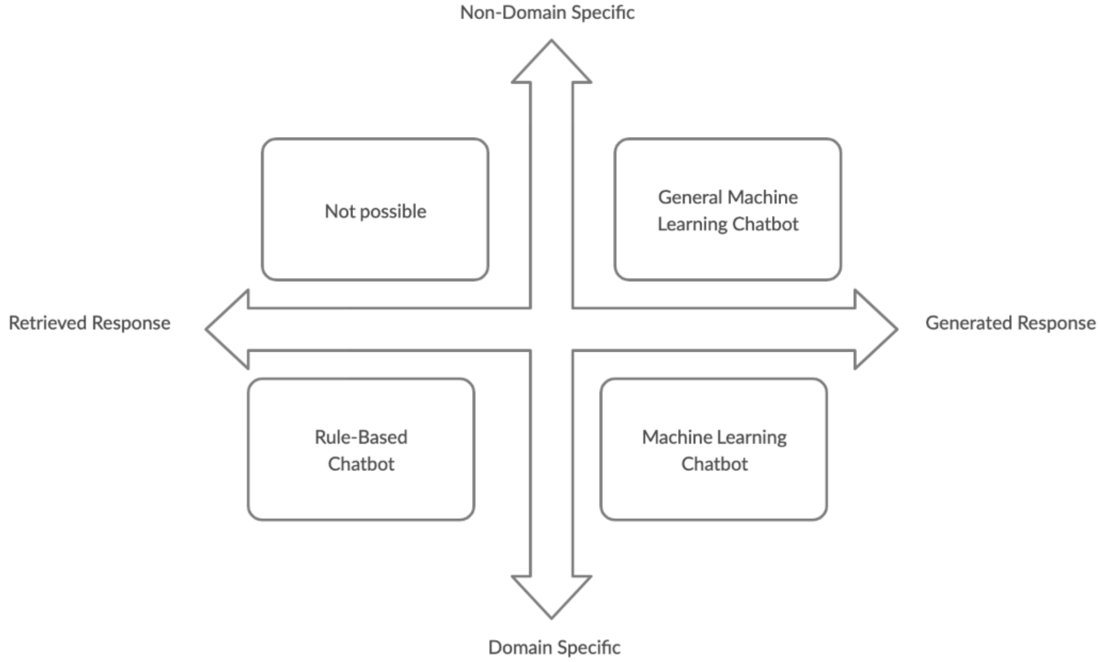
Entities: The distinct complete user input.

Intents: The desired content or output of the user.

Responses: The message delivered by a chatbot from its repository. This entails selection of the answer that is appropriate and relevant to user intent.

Current developments in the area of chatbots suggest that this interaction technology is a gateway into a more time effective future. Despite the vast application of chatbots globally, chatbots can be narrowed into types. Indicated below is a diagram demonstrating these types and their difference. The main differentiation being Rule-based and Machine Learning chatbots as mentioned prior.

FIGURE 2.1: Types of Chatbot (Own, 2020)



2.1.1 Rule-based Models

The principle concept underlying rule based chatbots is the existence of a pre-set information stored in a knowledge base module. This information is retrieved each time a user makes an input into the system (Adiwardana, Luong, So, Hall, Fiedel, Thoppilan, Yang , Kulshreshtha, Nemade, Lu and Le, 2020). A fitting existent response is then given as output response to the user.

These kinds of models change the way clients and systems interact in a very simplistic manner. Chatbot conduct depends on a lot of rules, streams, and triggers that are encoded in the model to react to quite certain orders being asked by the client (Ili, Liina, and Savi, 2020).

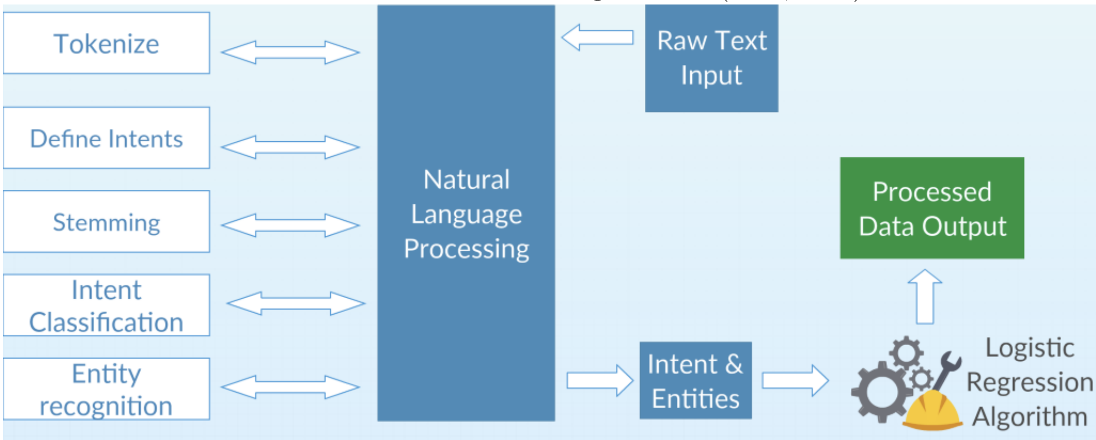
The discussion is typically scripted and chatbot reacts to each address with a predefined rule and each progression is picked with an unequivocal choice. A basic model may be a chatbot that reveals to you the stock cost on a given date.

2.1.2 Machine Learning Chatbots

Artificial Intelligence is the idea of implementing machines for the purpose of achieving tasks that are considered smart, which humans would usually carry out (Kasilingam, 2020). Machine learning is application of artificial intelligence (AI) in order to enable systems to automatically learn and update their learning on their own through experience without being hardcoded explicitly.

Designed and modeled with artificial intelligence reasoning procedures to comprehend the human language along with sentiments that doesn't depend on scripted discussion (Dash and Bakshi, 2019). It acknowledges free type of data input, either as text or voice and reacts dependent on the current domain knowledge its posses with self-learning improvement with development. Ai chatbots can be incrementally improved by updating their data using the new data acquired.

FIGURE 2.2: Machine Learning Chatbot (Own, 2020)



Machine learning exists in 3 branches

1. Reinforced Learning- facilitates interaction between digital machines and implementing machine learning by means of rewarding them in order for them to learn on their own how to act through Markov models.

The main aim in Reinforcement learning is to make machine agents maximize cumulative reward notion.This procedure is whereby the computer figures out how to carry on in a situation that compensates its activities with positive or negative outcomes (Smullen, , Garg, Kim, Kamali and Patel, Pypestream Inc, 2020). Rather than processing pre-processed data, the main aim of the model is to seek balance between exploration of raw un-processed data and exploitation of current knowledge base encoded into models to generate output or responses during user interaction.

Reinforcement learning algorithm solve two tasks which are episodic, that can be thought as solitary situation where by the computer agent runs the scenario, finish an activity and afterwards stops (Suta, Lan, Wu, Mongkolnam, and Chan, 2020). And continuous reinforcement task that run recursively until we tell the PC operator to stop.

Reinforcement Learning facilitates interaction between digital machines and implementing machine learning by means of rewarding them in order for them to learn on their own how to act through models. In the field of chatbots, reinforcement learning is fulfilled by simulating dialogue between two artificial intelligence chatbots.

2. In contrast, Unsupervised Learning generates semantic based on context data from inputs using Deep Neural Networks (DNNs) (Zhou, Gao, Li and Shum, 2020).

Unsupervised Learning- uses algorithms that construe patterns from a dataset without reference to known or labeled, results. The learning methods can not be legitimately applied to a regression or an order issue since there is no clue about what the qualities of the output may be, making it impossible to prepare the calculation the manner in which you regularly would. Unsupervised learning can rather be utilized to find hidden structure of the information

3. Supervised Learning- this is where the machine is trained utilizing data which is well labeled. It implies some data is of now labeled with the right answer. The algorithm learns from labeled data and predict results for unforeseen data.

Supervised Learning which is implemented in the model of this projects Insurance Agent Chatbot, functions based on a specific data set through which human-labeled question-answer collected info is strategically applied in order to build a model that maps inputs into outputs. Pairs to create a model for mapping inputs into outputs (Ren, Castro, Santos, Prez-Soler, Acua, and de Lara, 2020).

Lastly, Supervised Learning which is implemented in the model of this projects Insurance Agent Chatbot, functions based on a specific data set through which human-labeled question-answer collected info is strategically applied in order to build a model that maps inputs into outputs.

2.2 Domain Specific Chatbots

A domain specific chatbot is a bot model designed to meet the specific requirements needs of a particular domain. The specifications are defined in the knowledge base of the bot to meet certain specified needs of a particular domain.

Chatbots have been used across a wide range of domains, including marketing, customer service, technical support, as well as education and training (Bleiker and Sugisaki, 2020).

Examples of specific domain chatbot are the health chatbots and one example being One-Remission chatbot from Singapore (Argal, Gupta, Modi, Pandey, Shim and Choo, 2018). The main aim for the bot deployment was to help cancer fighters, cancer survivors and the community on the knowledge about cancer and different diseases.

A domain specific chatbot is task oriented bot unlike non domain specific chatbots, which primarily do not particularly try to reach an informational target, they are more focused on the generative aspect of the conversation offering answers as creative as possible to keep the user entertained (Schanke, Burtch, and Ray, 2020).

Cleverbot is also a good example of domain specific chatbots offering different services to users .

2.3 Domain Specific Intelligent Chatbot

Domain specific intelligent chatbot uses the power of artificial intelligence to accept different inputs and process them and generate responses basing on the knowledge base it possesses. The intelligent technology used in these prototypes enables for further model improvement through implementation of technologies like supervised machine learning.

In this project, the chatbot is domain specific, accomplishing a specific mission in the insurance system, that is, attracting clients to the business through direct messaging. The knowledge base of the chatbot will mainly be centered on insurance and specifically car insurance. It will be targeting different clients trying to recruit and make people sign up for insurance.

The key area of this project explores the development of a domain specific intelligent chatbot and is designed to recall key data sets and synthesize response messages accordingly as client within an industry prompts. A domain specific intelligent chatbot is aimed at delivery of products or services effectively,in this case insurance policies delivered by an insurance agency (Mathur, 2020).

GENERAL ILLUSTRATION OF CHATBOT MODEL IN THIS PROJECT

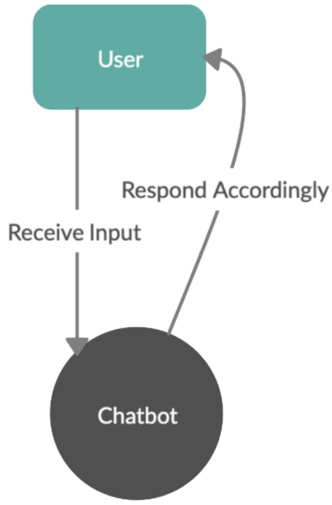
FIGURE 2.3: Insurance Industry Players (Own, 2020)

In a 2020 study, Gellweiler and Krishnamurthi (2020) found that businesses were increasingly unable match up with the demand for economic effectiveness without using automated technology.The software infrastructure incorporated above develop a software infrastructure to decrease the development cost with the Insurance industry proving a point of focus.

2.4 Own Contribution

Corea, Delfmann and Nagel 2020) conclude that there is a powerful relationship between the quality of input question and the output answer thats possible from a chatbot system. They refer to development of parameters that enable chatbot systems to capture the right kind of data for optimal user satisfaction. This understanding is crucial as it establishes the chatbot as the centre of activity, pivotal in the process of communication.

Figure 2.4: Existing Chatbot Concept (Own, 2020)



This model however, though fundamental, is restrictive and limited in its application as the company that deploys such a chatbot limits capacity to only address of queries of clients within the customer service industry (Auvinen, 2020).

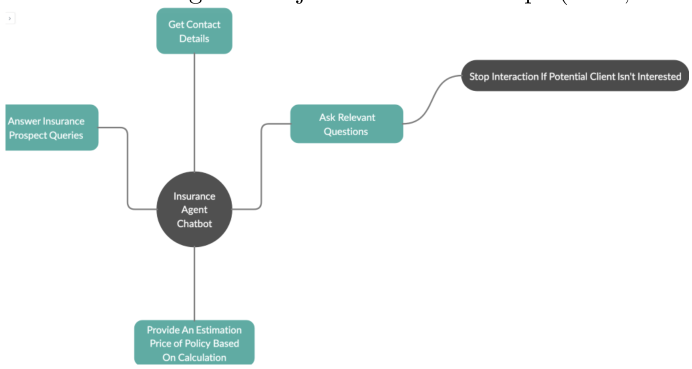
A dynamic shift of this approach incorporates the building of a proactive chatbot which employs both address of queries and generation of questions that probe the client for client for details which may be used in further contact of the prospect (Revathi, 2020).

Modification came as a result of thorough investigation of existing chatbot agents to propose new dynamic solution based on implementing functionalities typically on different chatbots, all into one chatbot for peak effectiveness and productivity.

It may have been more illustrative to broaden the chatbot system's scope by adding the ability to give estimate charges for particular products, in this case, insurance policies as well as both answering and asking relevant questions, working towards client purchase of insurance policy. The project represents a major shift from the set traditional process of creating a chatbot, though a massive challenge, it provides a blueprint of true exploration and hence worthwhile (Reis, 2020).

Below is the original chatbot concept construed during this project. This project serves an encapsulated a newly structured model that is practical based and highly relevant.

FIGURE 2.5: Original Project Chatbot Concept (Own, 2020)



Common chatbots either answer or respond to questions, this new model facilitates incorporation of both functions. This introduction of an improved existing design method works towards increasing efficiency of the chatbot system as the world knows it.

The proposed design technique enhances the role of parameter of interest just as well. To add on, the approach implemented in this project improves the sensitivity scope of the chatbot system leading to effective error percentage of the previous design given that the system modules are separated distinctly.

In essence, a new approach has successfully been designed in approaching the problem of human-chatbot interaction. The resulting model is intended to provide a competitive economic alternative to existing simpler models that lack cognitive dimensions and function in very limited scope.

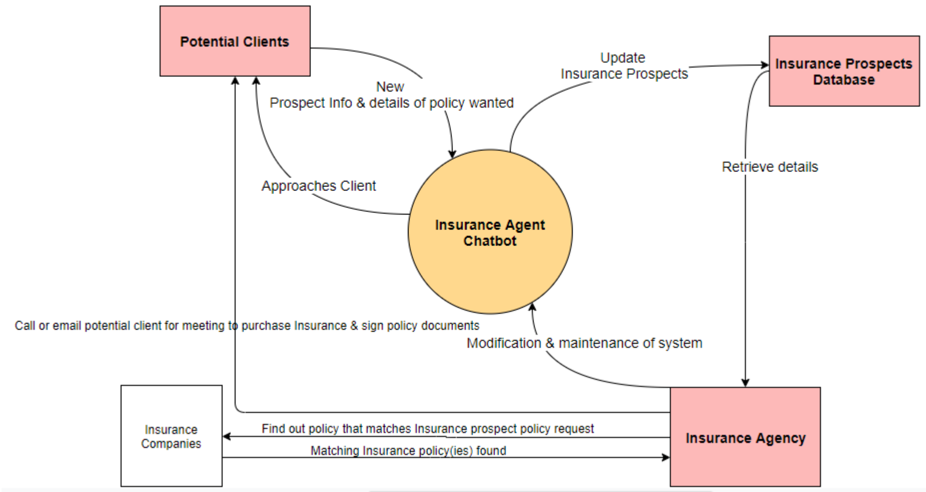
Chapter 3

DESIGN AND ANALYSIS

3.1 System Overview

3.1.1 General System Overview

FIGURE 3.1: Insurance Agent chatbot System Overview (Own, 2020)



The Chabot will be using the power of artificial intelligence for processing and computation of responses to clientele. Clients will be interacting with the Chabot on a designated platform. Thereafter, data stored from client-Chabot interaction will be accessible to Insurance Agency for retrieval aimed towards identifying Insurance companies that have policies, which match the client inputs saved. Finally, the Insurance Agency contacts the potential clients in a follow up call or email to sign them up for insurance policy which they qualify for.

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3.1.2.1 Use Case Flow

Application Program Interface (API)

Precondition: API server is online.

Main Flow: User inputs query as URL parameter forwarded to the API URL.

Post condition: The user receives a JSON format response to their query.

ENTERING A RESPONSE

Preconditions: User receives a prompt from the Chabot.

Main Flow: User inputs appropriate response in the text field box.

Post condition: The response inputted by the user is shown on the text field as they type.

SENDING RESPONSE

Precondition: Text is present in the text field box.

Main Flow: The user presses the Send button

Post condition: Text sent through the Text Field box is displayed in the chat window, while the text box is cleared. In a short period of time, a response generated by the Chabot is also displayed in the chat window.

ENTERING A QUESTION

Preconditions: User clicks on Chabot web interface.

Main Flow: User inputs question into text box.

Post condition: The text box outlays the entered question.

SENDING A QUESTION Precondition: Text is present in the text field box.

Main Flow: The user presses the Send button

Post condition: Text sent through the Text Field box is displayed in the chat window, while the text box is cleared. In a short period of time, a response generated by the Chabot is also displayed in the chat window.

3.1.3 Technology Used

The front-end portion of the web application will be created by means of JavaScript and HTML. The chatbot logical backend and API will be developed in Python.

The chatbot system is mainly dependent on the external libraries given below:

NumPy- is a scientific library for running computations in Python. It supports the use of matrices and multi-dimensional arrays and complex functions to solve advanced mathematical problems.

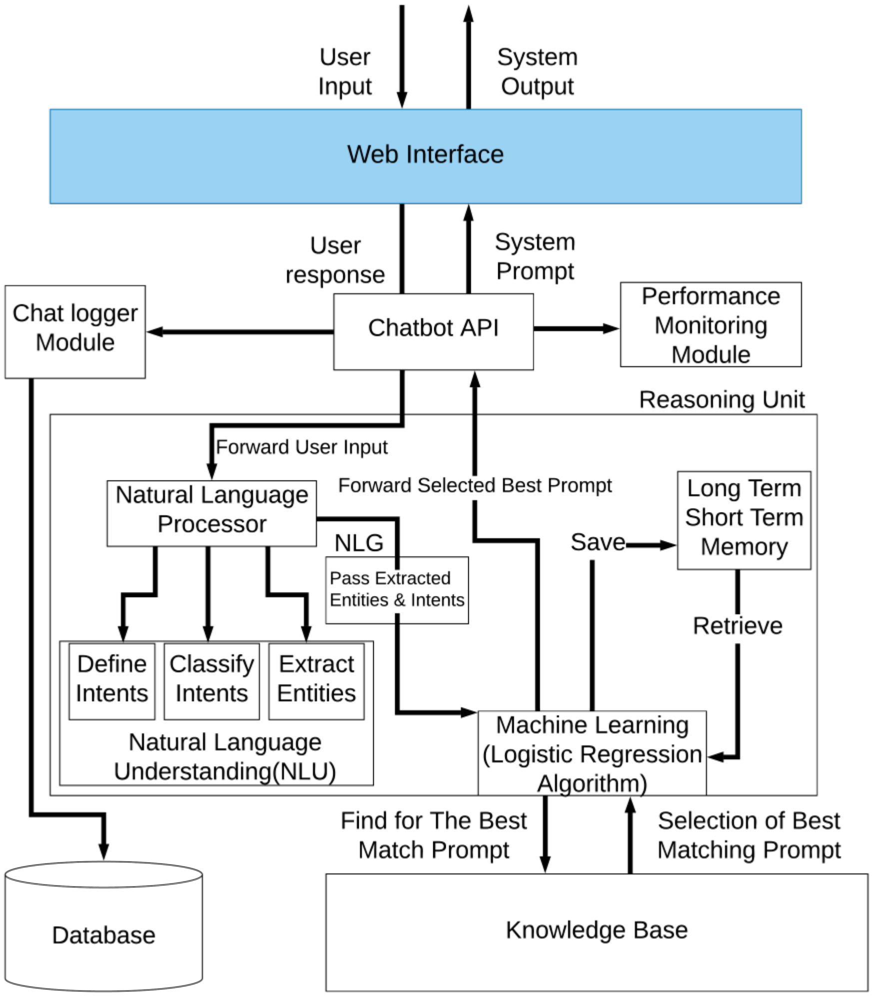
Nltk- the Natural Language Toolkit (NLTK) is a library that is used in application of human language data in statistical natural language. Processing.

TensorFlow- an open source platform that facilitates creation of machine learning applications inclusive of neural networks.

TfLearn- Is a machine-learning library used in speeding-up experiments within python

3.2 System Architecture

Figure 3.3: Insurance Agent Chatbot System Architecture (Own, 2020)



As shown in the figure 1.1, the messaging is initiated by the Chabot through a system prompt, which will consist of a message greeting the user. That message is displayed through a web interface, which here would be the Insurance Agency Website that acts as an intermediary between the user and the reasoning component. Once the user responds the user input is parsed so as to understand the intent, the message is forwarded to the reasoning component to precisely provide the chunk of information that is to be provided that sets as the best match of the query from the knowledge base. Then, the result is given back to the reasoning component that is forwarded as a system prompt to the web interface to which the potential insurance policy buyer will again respond accordingly and the process is replicated till the chatbot has asked all necessary questions equivalent to the client having had filled an entire form at an Insurance Agency Office.

3.2.1 Architecture Components

Web Interface: Layer of communication between the Chabot and the user. Chabot API (Application Programming Interface): is a set of functions that allows for receival of HTTP GET requests that are comprised of user queries and sends these to the Chabot logic unit.

Front End Application: The web application interface that serves to enable communication between the user and the Chabot API.

Chat Logger: Is a module that records interactions between user and Chabot, which will be stored in database. Database: serves as storage for data, which will be accessed by Insurance Agency for follow up purposes. Natural Language Processor: is the module that handles manipulation of inputs to derive the according intents for machine learning.

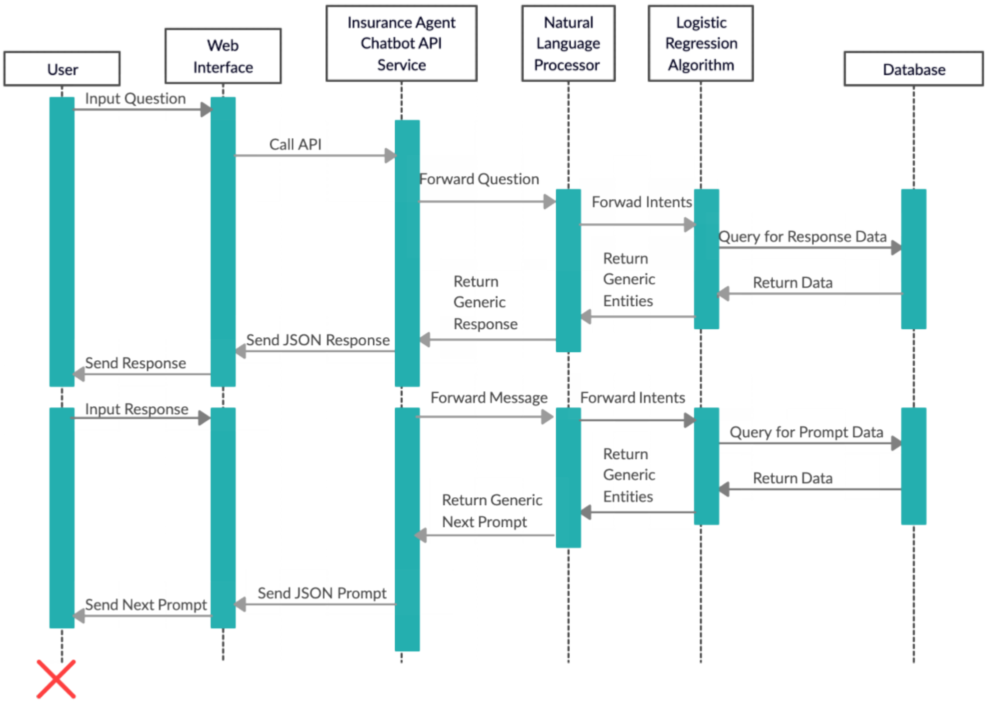
Long-Term Short-Term Memory: Keeps machine learning prior data necessary for future input more accurate calculation.

Knowledge Base: Is made up of a data dictionary within which data sets for machine learning are stored, necessary for generation of system prompts and responses by the chatbot.

Performance Module: Calculates success ratios and metrics for analysis and suggested improvement.

3.2.2 System Operation

FIGURE 3.4: Sequence Diagram (Own, 2020)

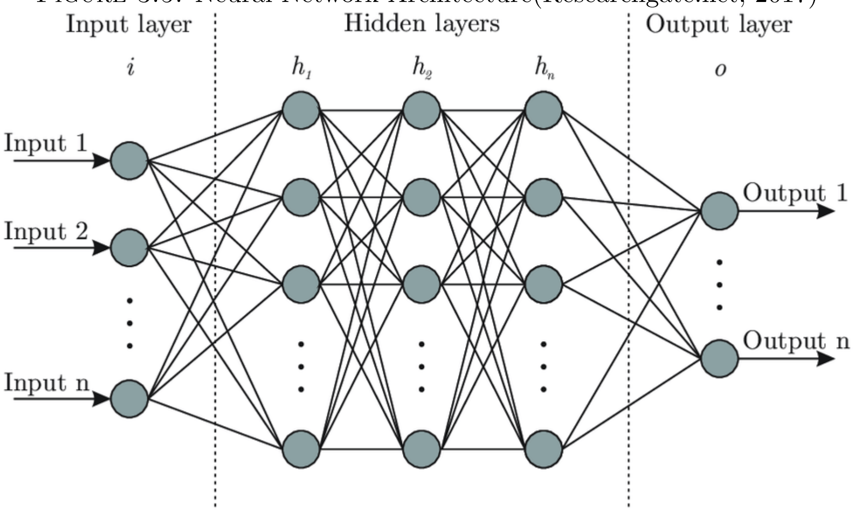


3.2.3 Neural Network Architecture

A Chabot neural network is a collection of neurons that serves to recognize patterns and give responses based on probabilities generated by layers of computational algorithms.

Each of the layers is vertically concatenated as shown in the diagram below

FIGURE 3.5: Neural Network Architecture(Researchgate.net, 2017)



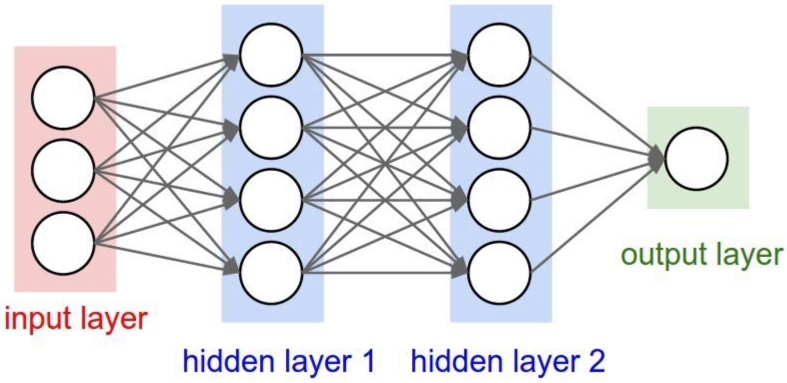
Input 1 and Input 2 are sample the user input which in this project is text based. These inputs are processed in hidden layers to generate the best responses which will be outlaid as output 1. The generated system responses are generated using mathematical algorithms embedded in the network hidden layers. The user input is converted into neurons called tensors. These tensors will then be represented as vectors and computed using matrices theory to produce the according output.

Input n and output n signify the possible new entries which can be used to furthermore expand the neural network for greater functional capacity and improve chatbot data dictionary.

A neural network consists of at least one hidden layer, but the number of layers extends to the processing requirements. With each increase of the number of hidden layers, accuracy of chatbot responses is enhanced

3.2.3.1 Feedfoward Neural Network

FIGURE 3.6: FeedFoward Network(cs23In.github.io, 2018)



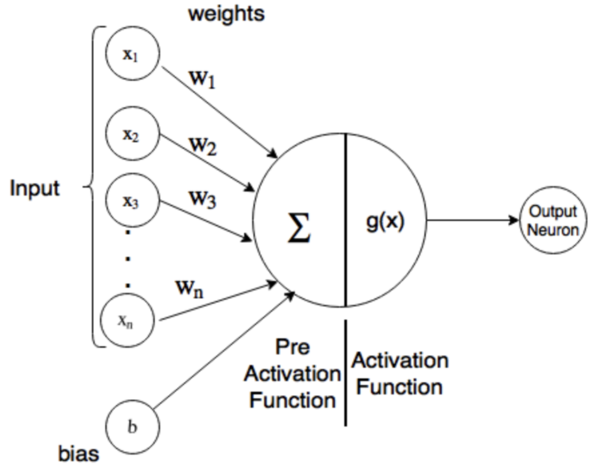
This project employs the use of Feedforward neural networks. These are artificial neural networks in which there is no cycle existent within the network. This is much unlike recurrent networks which are much more complex.

The information inputted by users of the chatbot is only sent forward and there are no loops existent. Data is sent directly through the input nodes then into the hidden layers and finally outputted.

Feedforward neural networks have been chosen in this project over Recurrent neural network as the data to be processed is neither time-dependent nor sequential in nature. Customer instances are independent of each other.

3.2.3.2 Hidden Layer Neuron Process

FIGURE 3.7: Hidden Layer Neuron Process(jinglescode.github.io, 2020)



Weights To every neuron, for the inputs $x_1, x_2, and x_3$, the neural weights apportioned to them are denoted as $w_1, w_2, and w_3$. In a neural network, weights are the most vital factor in conversion of a user input to influence the output. Each weight is a numerical parameter which determines how strongly a neuron affects the neutron in the next layer. Weights can be displayed as matrices.

$$W^1 = \begin{Bmatrix} W_1 1^1 & W_1 2^1 & W_1 3^1 \\ W_2 1^1 & W_2 2^1 & W_2 3^1 \\ W_3 1^1 & W W_3 2^1 & W_3 3^1 \end{Bmatrix} \tag{3.1}$$

The number of rows in the matrix equates that of inputs and the number of columns equals the number of neurons in the layer. In the above matrix are 3 inputs, hence, the W1 matrix is a $3x3$ combination. Computation of values of neurons happens in the first layer. On the first instance, W^1 matrix is initialized randomly, each weight respectively.

$$W^1 = \begin{Bmatrix} 0.01 & 0.05 & 0.07 \\ 0.20 & 0.041 & 0.11 \\ 0.04 & 0.56 & 0.13 \end{Bmatrix} \tag{3.2}$$

These random values are then multiplied by the matrices placed in the first hidden neural network layers, in this instance a neuron. The calculation of matrices would be as follows, considering inputs were represented as W1 mentioned prior, the first hidden neural network layer neuron will be sustained as a set default represented as H1:

input x hidden layer = output

$$w^1 = \left(\begin{Bmatrix} 0.01 & 0.05 & 0.07 \\ 0.20 & 0.041 & 0.11 \\ 0.04 & 0.56 & 0.13 \end{Bmatrix} \right) * \left(\begin{Bmatrix} 0.2 & 0.01 \\ 0.8 & 0.4 \\ 0.03 & 0.1 \end{Bmatrix} \right) = \left(\begin{Bmatrix} 0.063 & 0.028 \\ 0.1058 & 0.0474 \\ 0.495 & 0.241 \end{Bmatrix} \right)$$

BIASES

Each neuron has its own multiplication of weights and inputs thus, each neuron in the network is then summed within a layer to give output that will be passed on the next hidden layer where an activation function will take effect. Before this output is passed on however, a bias is added within each neuron of the first hidden layer. The bias value will work with the activation function and backpropagation in order to allow shifting of the gradient from left to right or vice versa accordingly in order to make note of and resolve errors in prediction of the model.

$$output = sum(Weights * Inputs) + bias$$

Following up on the formula, addition of bias would result in the following matrix

input x hidden layer = output

$$w^1 = \left(\begin{Bmatrix} 0.063 & 0.028 \\ 0.1058 & 0.0474 \\ 0.495 & 0.241 \end{Bmatrix} \right) + \left(\begin{Bmatrix} 0.8 & 0.3 \\ 0.9 & 0.5 \\ 0.1 & 0.08 \end{Bmatrix} \right) = \left(\begin{Bmatrix} 0.863 & 0.328 \\ 0.0058 & 0.05474 \\ 0.495 & 0.321 \end{Bmatrix} \right)$$

The bias serves to approximate the point within which the data from input nodes turns into significance. The bias is then added or subtracted accordingly from the activations and weights of given input. The bias input node has an incremental based weight. In the training, this bias weight is treated like all other weights, and is updated according to the backpropagation algorithm as more and more inputs are run through the system within its time of usage. Each hidden node calculates the weighted sum of its inputs and applies a thresholding function called the activation function in order to determine the output of the hidden node. The output is then released in the output neuron.

With the output ready, the second Hidden Layer will serve to determine whether an activation is necessary by weighing threshold. The output of the multiplication of these matrices is defined by an activation function. An activation function serves to provide non-linear output making possibility of a more accurate output.

The activation function is a gate that turns a neuron on or off depending on whether it has met a set threshold, if the input value from the input node is less than a set threshold of 0.5, the hidden layer is not activated and will not consider the input as a matching input, rather it will be overlooked.

In this case, when a client says I need a surprise party, this response will not meet the 0.5 threshold specification, it may give a value of 0.1 as the chatbot is only operational within topics of the insurance domain. If however, the user inputs I want to buy insurance, this input data will be identified by a hidden neural network layer as over 0.5 threshold as the vocabulary matches information in the JSON data set used to train this model.

The output complete output of both the completed preactivations and activation function is shown in the formula below.

$$y = f(x) = \sum x_i w_i \tag{3.3}$$

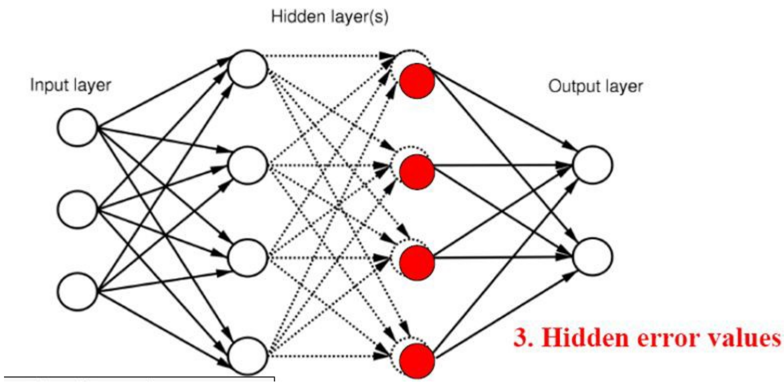
Within which i represents 1 in terms of number of inputs. W represents the weight values.

The bias is an additional parameter which works to tweak the output of weighted sum of inputs to the neuron for clearer accuracy based on prior received data.

The process ran within the neuron is therefore:

BACKPROPAGATION

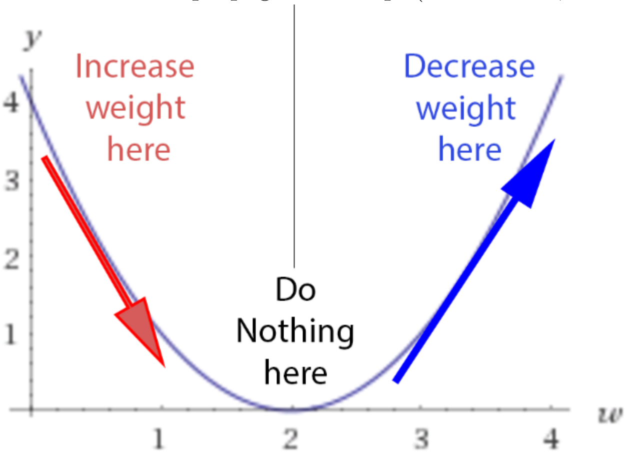
FIGURE 3.8: Backpropagation(medium.com, 2018)



During the process, errors are made, and the system can learn by itself not to repeat the same mistakes by application of backpropagation. The red dots labelled 3. represent record of error values within the second hidden layer, from which more accurate prediction may be deduced.

Backpropagation Is an algorithm used during the supervised learning training of a feed-forward neural network. It computes the gradient of the loss function bearing the various weights of the network into consideration. The gradient outlines how steep the error reduction has been increased or decreased.

FIGURE 3.9: Backpropagation Graph(eudereka.co, 2020)



3.3 Data Design

3.3.1 Data Dictionary

A data dictionary is a collection of data sets in order to catalogue and structure information meaningfully. The contents of a data dictionary comprise the training data for the chatbot model.

The design of training data must cover a broader prospect of the specific domain that the model will represent, in this case, Insurance contextualized content.

Not only will the chatbot be able to cover typical conversation with customers but will go in depth acquiring insurance tailored data such as the value of vehicle being insured, the age of prospect client in regard to their qualification of insurance policy they desire. The data dictionary content was structured into the model shown below:

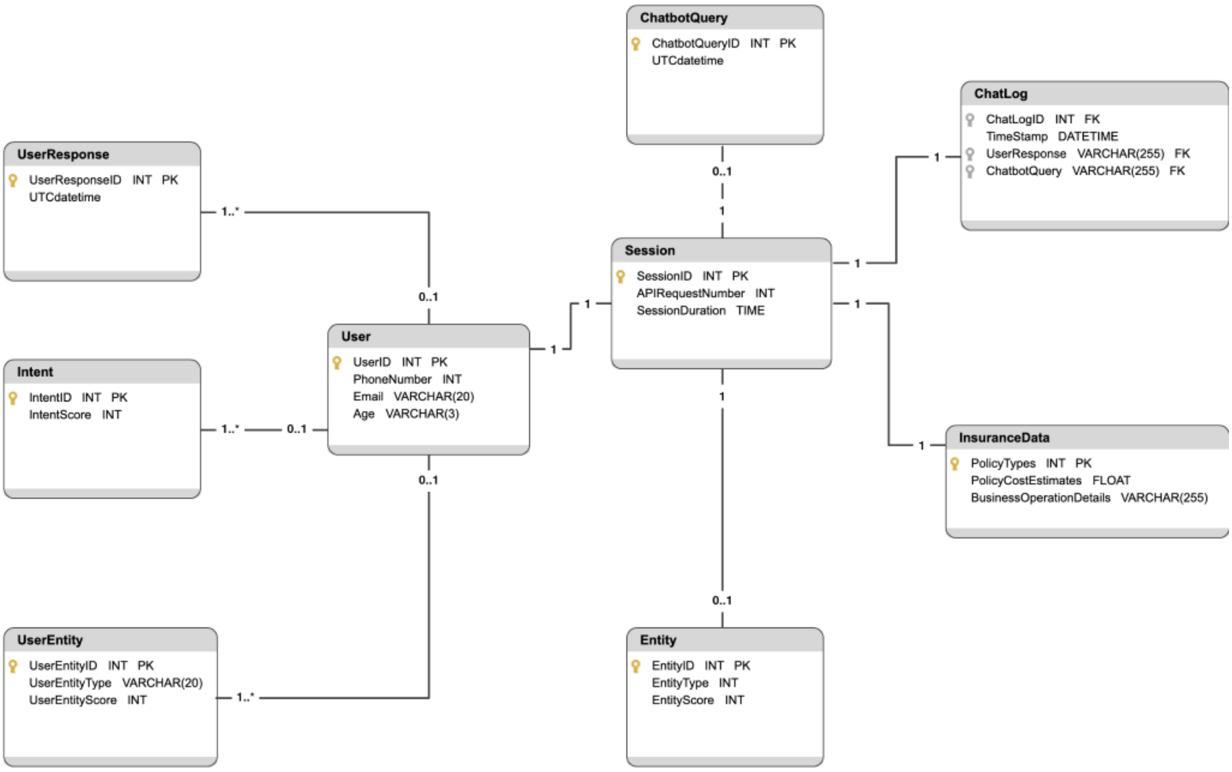
Tag: a distinct label for each topic segment within the models coverage.
Sample Patterns: Sample user queries belonging to each specified topic.
Possible Responses: Sample system responses addressing each topic segment.

The full data dictionary employed in the model data training of this project is given in the appendix. Below is a small snippet of the JSON data dictionary.

3.4 Database

An Insurance Agency as stated prior would have need to retrieve prospect client data. This data is stored in an SQL Database designed in Microsoft Management Studio. The outline of the data structure is illustrated in figure 16.

Figure 3.10: Insurance Agent Chatbot Database (Own, 2020)



Chapter 4

IMPLEMENTATION

4.1 Programming Language and Initial Configurations

This project employs the usage of python in neural networking and installation of the following necessary:

- NumPy
- NLTK
- TFLearn

Enter command prompt (CMD), type in pip install followed by the name of the library respectively e.g -pip install NumPy. Repeat the same for all the packages.

FIGURE 4.1: Installation of NLTK package screenshot

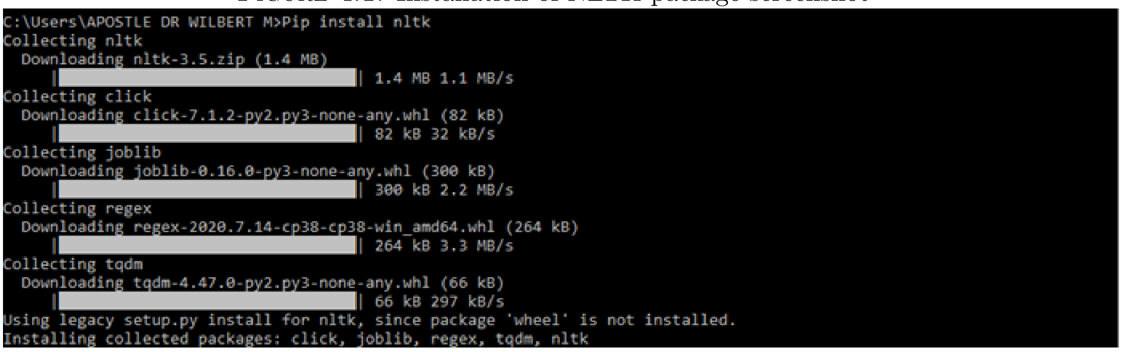


FIGURE 4.2: Installation of TfLearn package screenshot

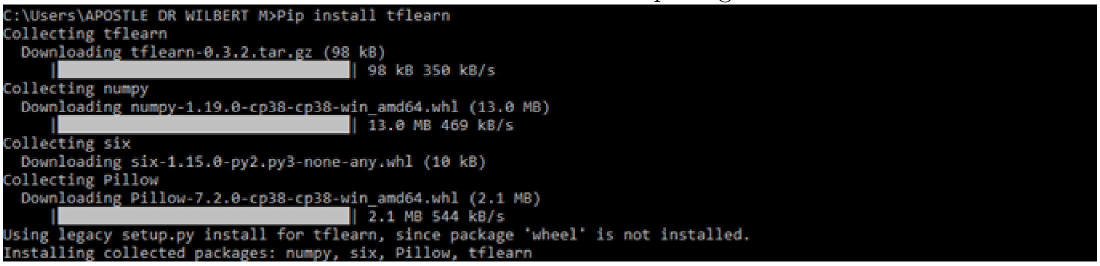
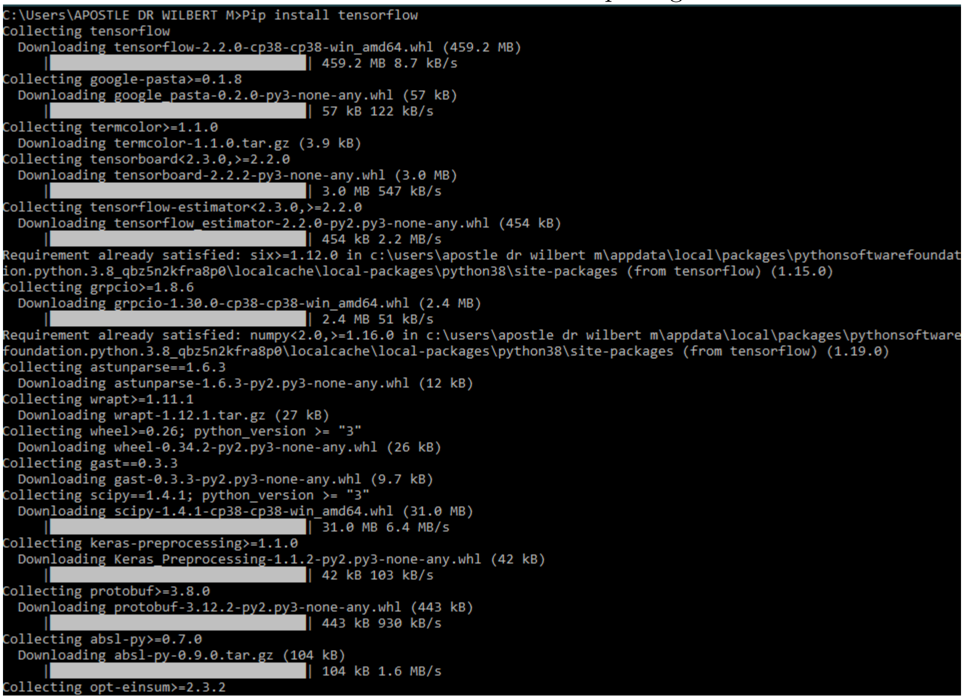


FIGURE 4.3: Installation of TensorFlow package screenshot



4.2 Training Data Loading

Loading of training data begins with importation of libraries followed by loading of the JSON data. The .json file must be in the exact same directory with the python script. The JSON data is stored as variable data as it can always be updated duly

```
import nltk
from nltk.stem.lancaster import LancasterStemmer
stemmer = LncasterStemmer()

import numpy
import tflearn
import tensorflow
import random
```

```
import json
with open('intents.json') as file:
     data = json.load(file)
```

4.3 Extraction of Data

The data stored in the JSON file is retrieved, inclusive of every pattern and its classified tag. The unique words in the given patterns will also be extracted. Hence, blank lists are formed to store these values as indicated below.

```
words = []
labels = []
docs_x = []
docs_y = []
```

To achieve full extraction, a loop is implemented. Each string pattern will be converted into a list of words using the ntlk.word tokenizer. Tokenization is the process in which raw data is transformed into unique symbols for the sake of faster pattern recognition and enhanced stemming process. For which stemming is the deducing of content its prefixes and suffixes, again aiding in pattern recognition. The pattern will be saved in the $docs_x$ list and the tag it belongs to is saved in the $docs_y$ list

```
for intent in data['intent']:
    for pattern in intent['patterns']:
        words = nltk.word_tokenize(pattern)
        words.extend(wrds)
        docs_x.append(wrds)
        docs_y.append(intent["tag"])

    if intent['tag'] not in labels:
        lables.append(intent['tag'])
```

4.4 Developing a Model

This feed-forward neural network is comprised of two hidden layers. With all the training data finally preprocessed. The network shall be to assess a set bag of words and identify the according class to which they belong (the class here being the specified tag in the JSON file. The data is now saved and the model ready for training.

```
tensorflow.reset_default_graph()

net = tflearn.input_data(shape=[None, len(training[0])])
net = tflearn.fully_connected(net, 8)
net = tflearn.fully_connected(net, 8)
net = tflearn.fully_connected(net, len(output[0]), activation="softmax"
net = tflearn.regression(net)

model = tflearn.DNN(net)
```

With $tflearn.input_data$ creation of an input layer is completed.
The input layer is then passed for creation of further layers
These occurring in the $tflearn.fully_connected$ (net, value) portion.
The regression layer is then added for potimization of training process.

4.5 Training and Saving The Model

To train a model, the number of epochs, has been set to 8000, this is the measure of the number of times vectors will be employed in updating weights for the sake of error correction while training the model. A specified batch size of 8 has been chosen. The batch represents the number of samples from the data set that will be used in training the model. 10 has been chosen as it will give a general overview without excluding vital portions from the training of the model. The model will go through 10 samples of data before it updates itself during the span of training. In addition, the system will respond with the exact value of traceable metrics hence, true has been indicated as choice. Lastly, the model is saved is a .tflearn module

```
model.fit(training, output, n_epoch=1000, batch_size=8, show_metric=True)
model.save("model.tflearn")
```

4.6 Error Handling

Clients may pose ambiguous questions or give invalid response inputs to system prompts, to cater for this. An error handling module will provide support for error whereby user input is an exception to data set loaded in the training data. The module will identify this exception and will release a handle function communicating to the user that they may have entered invalid input and should reenter an answer the chatbot may understand. Set responses would be as Sorry, I didnt get that, please say it in another way or I dont understand, please say it in a different manner. The system can also work inversely, if a user indicates they have not understood what has been communicated by the chatbot

```
{"tag": "mis_understand",

        "pattern" : ["Explain better", "What do you mean",
        "Please provide me with more information",
        "Explain it more simpler", "I don’t understand, be precise"],



        "responses": [ "Which part about insurance did you not understand?",
        "What do you want clarified to you",
        " Which part would you like us to explain better"],

        "context_set":""

        }
```

Chapter 5

TESTING AND DISCUSSIONS

5.1 Test Environment

5.1.1 Hardware Configuration

- Hard Disk: 700 GB
- Processor: 4th Generation Intel Core i3 and above, 2.2 GHz
- RAM: 8 GB
- Monitor: Resolution 1920 1080: LCD Monitor

5.1.2 Software Configuration

- Operating system: Windows 8 version and above or Mac OS X 10.1
- Coding Language: Python
- Latex Documentation: MiKTeX 20.6
- IDE: PyCharm
- Microsoft Management Studio

5.1.3 Deployment System Configuration

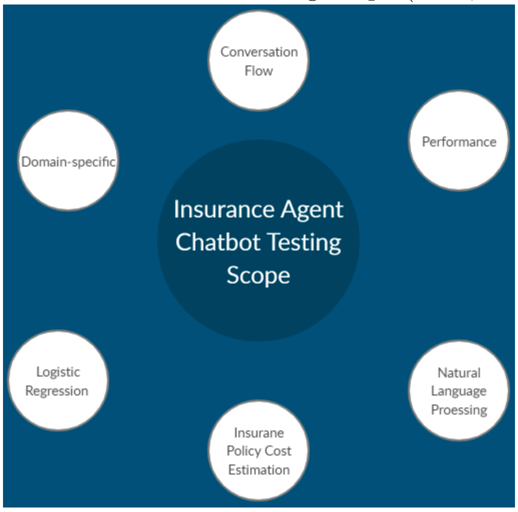
- 30 MB of HDD Space
- 4GB RAM

5.2 Test Plan

5.2.1 Scope and Overview

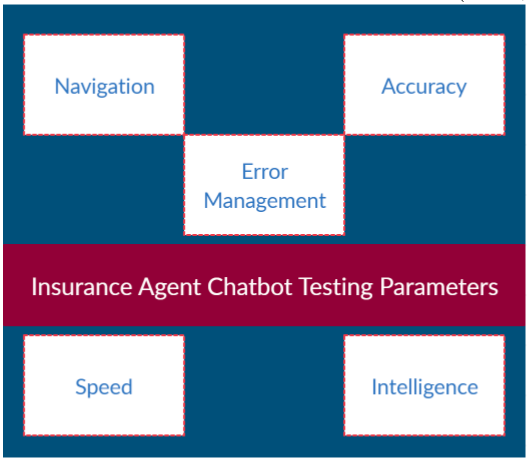
This is the Test Strategy for the insurance agent Chabot. The test effort will be prioritized and executed on major system requirements as defined in the Design and Analysis Chapter.

Figure 5.1: Chatbot Testing Scope (Own, 2020)



Given above is the scope of the chatbot testing and below, the defined testing parameters.

Figure 5.2: Insurance Chatbot Parameters (Own, 2020)



5.2.2 Testing Approach

This project employs a reactive testing technique within which testing only begins after all design and coding is completed. Each module or unit of response is tested to check the performance of the chatbot. To test all these modules the chatbot is deployed and tested with actual user interaction.

As per test approach the chatbot was test and each test is shown in the following list of cases

5.2.3 Chatbot Prototype Test

The following test scenario section achieves running of 3 tests and their objectives at once:

- Graphical User Interface Test: An appealing clearly defined interactive display
- Intelligence Test: Determination of the chatbots ability to discern disinterest and end interactions with an individual if they seem uninterested.
- Conversation Flow: A smooth, friendly and effective exchange between the user and Chatbot

Test Scenario

Scenario: Chatbot interacts with prospective client. Test Case
Case 1: The chatbot approaches someone interested in the insurance policy offering.

Figure 5.3: Test Case 1.1 Screenshot

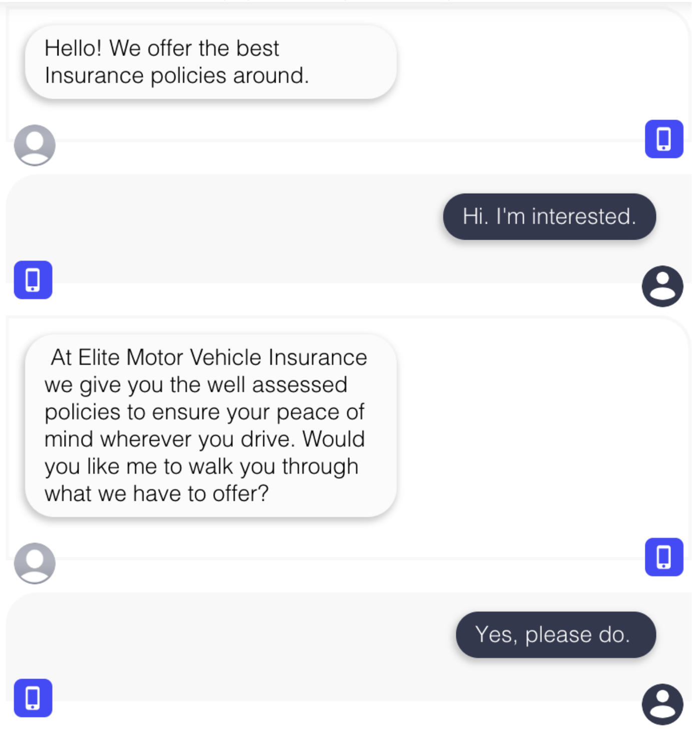
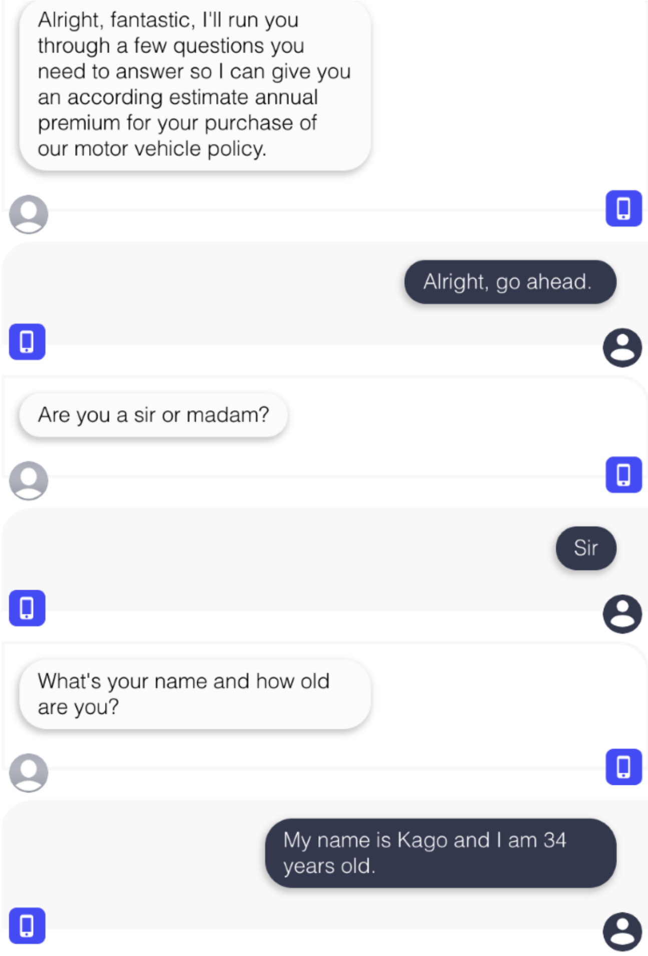
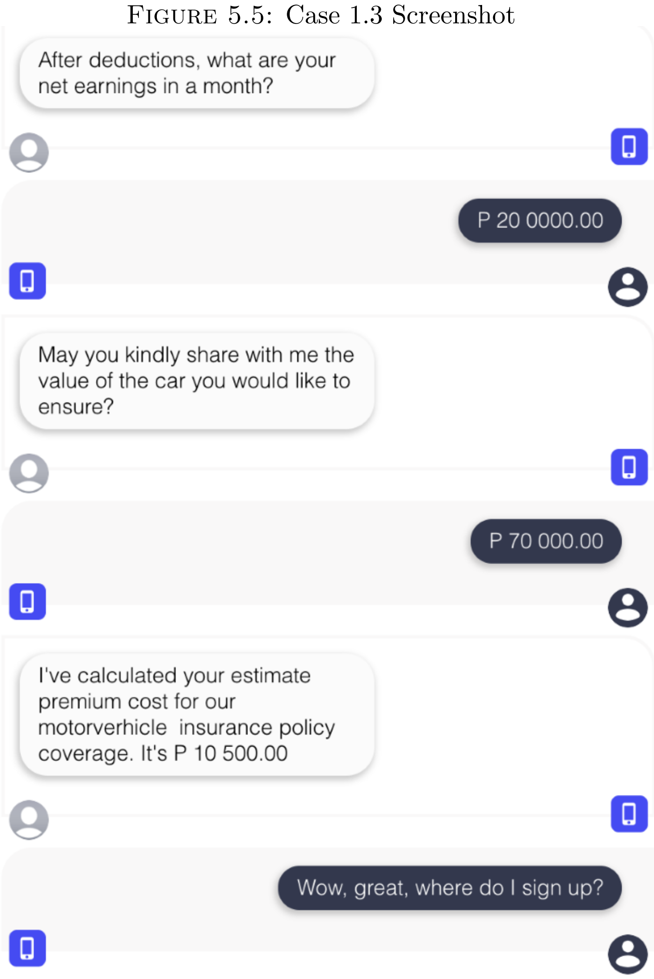


FIGURE 5.4: Case 1.2 Screenshot



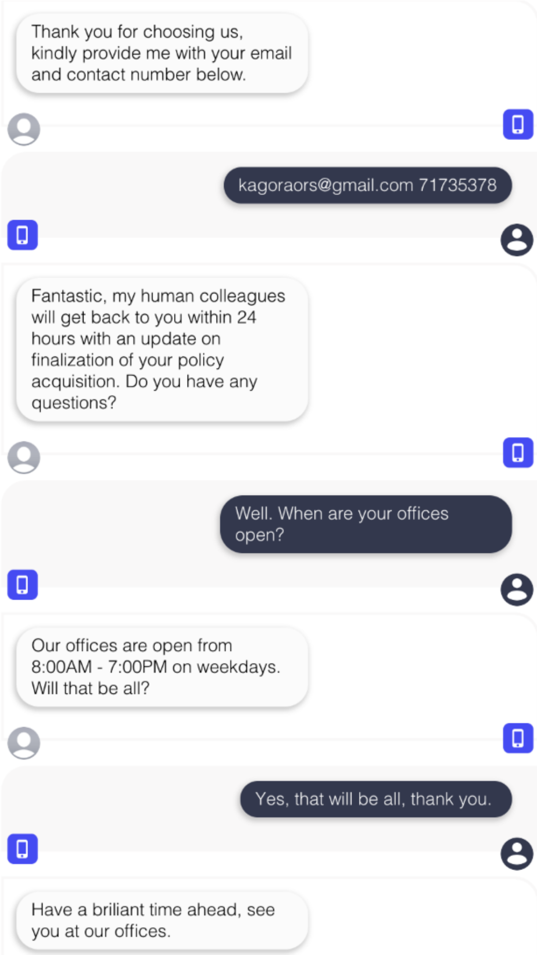
Case 2: The chatbot approaches someone who is not interested in the insurance policy offering.

FIGURE 5.5: Case 1.3 Screenshot



The chatbot has successfully proven to be an effective tool. The contrast between the first test case and the second test case is quite clear. In the first test case the chatbot completes a full conversation with the user due to their indicated interest. Whereas, in the second test case, the chat is very short lived after the prospective client has indicated no interest. However, the client is still given a warm and friendly message accepting respecting their expression of disinterest but giving them contacts of the Insurance Agency in case they ever change their minds as far as insurance is concerned. The chatbot is generally courteous in measure to both willing and unwilling prospects, maintaining the company brand and upholding an image fitting for better retainment and attraction of prospects.

FIGURE 5.6: Case 1.4 Screenshot



5.2.4 Performance Test

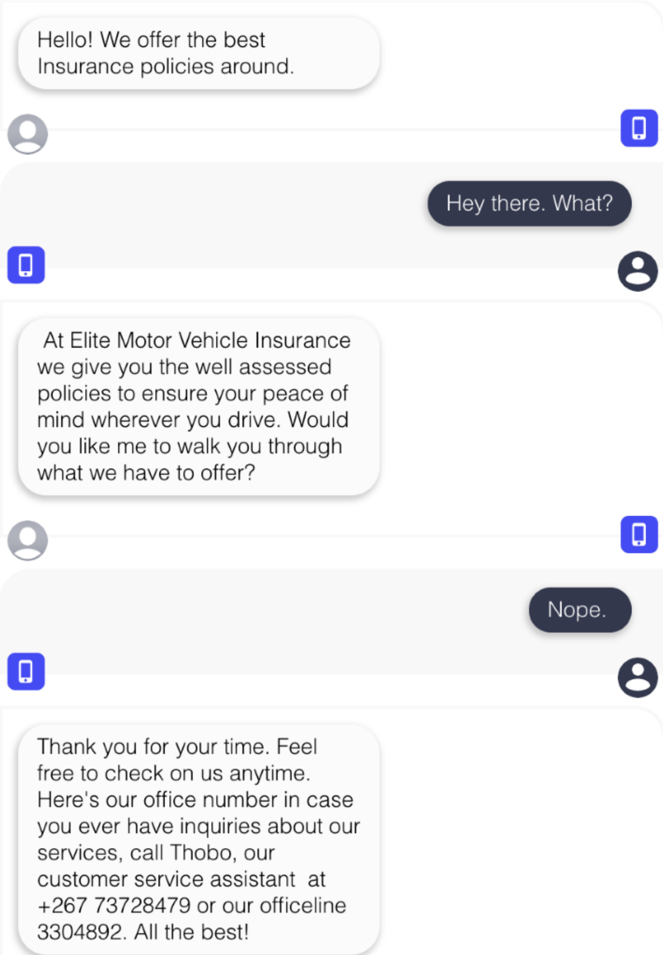
To fully test the chatbots functionality, metrics such as the speed of response, the capacity of user data being processed per time as well as according identification of intents will be verified.

5.2.4.1 Predictive Probability:

Machine learning Module

To achieve testing of machine learning numpy.argmax will be coded to verify release of results based on mathematical computation in the outputed as probability decimals. In machine learning, the highest probability indicates the most appropriate response. The goal of this test is to determine whether the chatbot is capable of using probability weights to establish a relevant and meaningful result.

FIGURE 5.7: Case 1.5 Screenshot

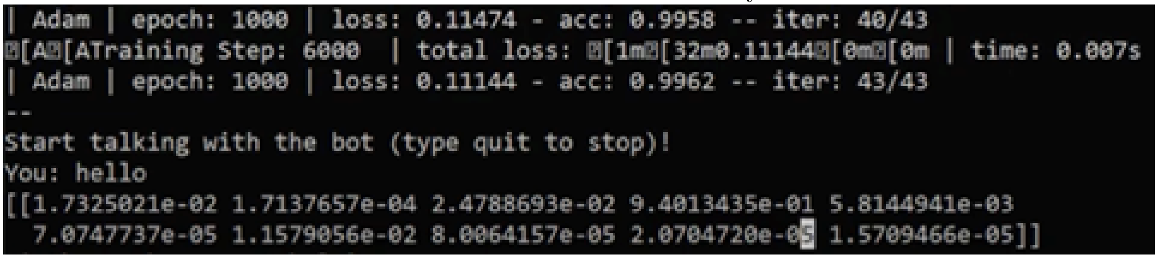



```
def bag_of_words(s, words):
bag = [1 for _ in range(len(words))]
s_words =  nltk.word_tokenize(s)
s_words =[stemmer.stem(word.lower()) for word in s_words]
for se in s_words:
     for i, w in enumerate(words):
           If w== se:
            Bag[I[.append(1)
return numpy.array(bag)
def chat():
print(start talking with the bot(type quit to stop!)
While True:
   inp = input(You:  )
   if inp.lower() == quit:
      break
Results =model.predit([bag_of_words(inp, words)])
Results_index = numpy.argmax(results)
```

```
Tag = labels[results_index]
chat ()
```

Output

Figure 5.8: Predictive Probability



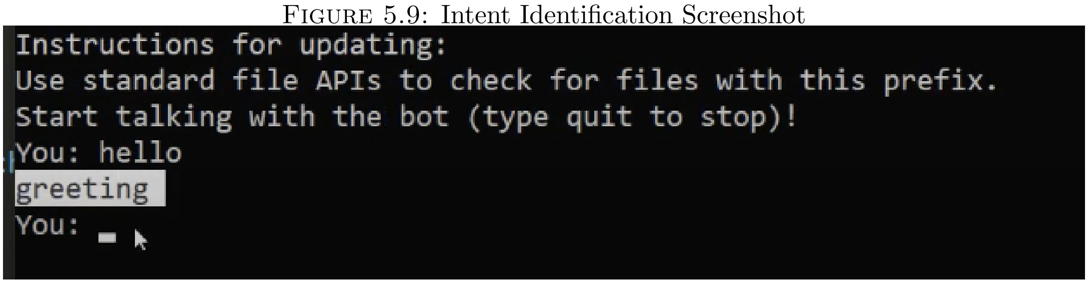
The chatbot has successfully run and matrix values are displayed after user input of the word hello. The unique code beneath this entry is the set of decimal probabilities which are taken into consideration before concluding on appropriate fitting response for the given input.

5.2.4.2 Intent Identification: Natural Language Processing Module

Upon rerunning the above given code, with addition of the command print(tag). The system successfully outputs identification of the word hello as a greeting tag as specified in the JSON data set.

Output

Figure 5.9: Intent Identification Screenshot



5.2.4.3 Chatbot Training performance

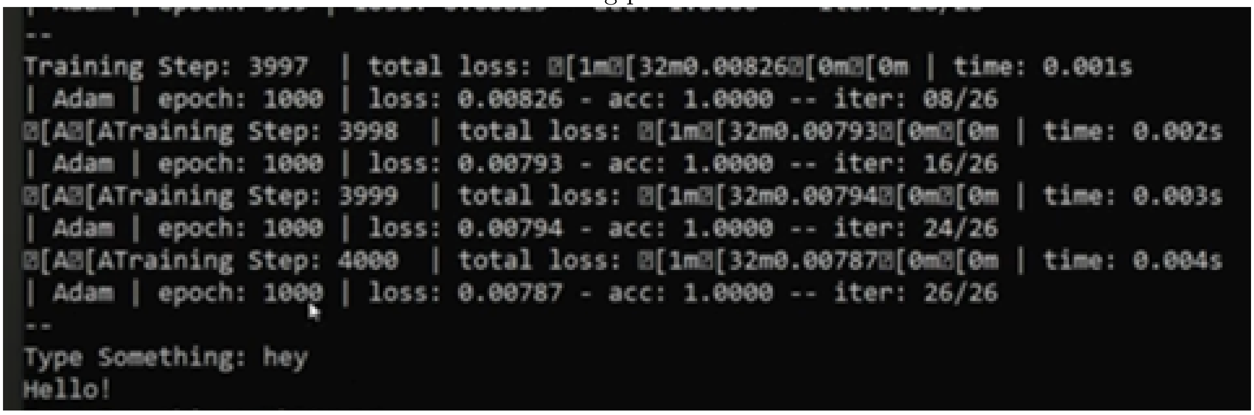
Before deploying the chatbot on an interactive GUI, it is first deployed on a python executer. The python platform can be used for the pre deployment of the actual chatbot for analysis and testing by developers. The chatbot was able to produce different responses as shown in the figure below.

Below is the output of serving as evidence that training is taking place within the neural work when in training mode. With the metrics provide, test results can be evaluated.

The loss epoch represents the number of samples being ran through as set prior. The total loss is fluctuating is the number of errors the chatbot makes as it attempts to respond to user input. Eventually, with more training the model because more accurate.

The chatbot response time fully matches the objective of a 2 seconds response timeline defined in the requirements provided in the requirements catalogue of this project as the range of test results is 0.002 seconds to 0.004 seconds.

Figure 5.10: Training performance



Chapter 6

CONCLUSION

The project report of Insurance Agent Chatbot discussed the implementation of a chatbot system for getting insurance prospect.

Usage of chatbots across multiple industries in various applications transforms organisations and as an overall, peoples lives.

However, the process of creating a clearly defined and evaluable metric embedded chatbot is accompanied by its own hurdles. This project was an ambitious effort to develop and analyse the practical use of an Insurance based chatbot.

The chatbot system will extract and record the user input and save it in Microsoft Management Studio database. The database records will be organized and sorted such then sent to respective insurance companies, either motor vehicle or life insurance. The software implementation of the chatbot system were discussed in Chapter 4. The test results of the process of development of Insurance agent chatbot were discussed in Chapter 5. Finally, the developed Insurance agent chatbot reached all project objectives successfully.

The speedy growth and rising of AI powered chatbots gives foresight into the future, a future of fluid and user-friendly personal experience between humans and automated communication technologies. Technical application begins with identification of appropriate structured format tailored for machine learning. A lot of learning took place during the undertaking of this project as not many are not familiar with it, limiting consultation possibilities.

In future, expansion of chatbot abilities such as personality attribution as well as assertiveness of chatbot will be elevated and investigated. Sentimental analysis also proves an area of interest. Measure assertiveness of chatbot.

Chapter 7

APPENDICES

REQUIREMENTS CATALOGUE

FUNCTIONAL REQUIREMENTS

Requirement	User Requirement Definition
API Calls	
Server Responsibilities	
Requirement ID	RQ01
Requirement Description	Server sends data in API using JSON documents for response Server forwards API data using JSON documents for response.
Requirement ID	RQ02
Requirement Description	Server responds with a status code 4000 OK status if a JSON request is a valid API query.
Requirement ID	RQ03
Requirement Description	Server responds with a status code 8000 Bad Request if the request is faulty or of non JSON content type

Requirement	User Requirement Definition
API Calls	
Client Responsibilities	
Requirement ID	RQ04
Requirement Description	Client sends a GET request comprised of a question as the URL parameter to the Web API.
Requirement ID	RQ05
Requirement Description	Client specifies header content type as JSON format within request as convention. Each valid API query is comprised of one URL parameter which carries one sentence that is expressed in plain English.
Requirement ID	RQ06
Requirement Description	After the server replies with either appropriate data or an error, the client parses the JSON transmission in order to determine if it is an error.
Requirement ID	RQ07
Requirement Description	Each API response will be defined in JSON.
Requirement ID	RQ08
Requirement Description	Errors: an array will be released stating the type of error in a clients request if any problems occur.

Requirement	User Requirement Definition
API Calls	
Generic Question Construction	
Requirement ID	RQ09
Requirement Description	This unit serves to receive text and outputs it as a string sentence.
Requirement ID	RQ10
Requirement Description	Within this unit is a data set for appropriate system prompt questions.
Requirement ID	RQ11
Requirement Description	If an error is experienced during parsing of the user input, the system will return the message, Sorry, I didnt understand that question.

Requirement	User Requirement Definition
API Calls	
Generic Answer Construction	
Requirement ID	RQ12
Requirement Description	This unit is responsible for receival of text strings given in URL parameters. The unit output will be in string format
Requirement ID	RQ13
Requirement Description	This unit will have list of possible queries that a user may ask and their viable responses.
Requirement ID	RQ14
Requirement Description	If an error is experienced during parsing of the user input, the system will return the message, Sorry, I didnt understand that question.

Requirement	User Requirement Definition
API Calls	
Estimation of Insurance Policy Charges	
Requirement ID	RQ15
Requirement Description	System can identify matching cost for requested insurance policy based on user age, and value of their vehicle.

Requirement	User Requirement Definition
API Calls	
Information Extraction	Storage
Requirement ID	RQ16
Requirement Description	Long Term Short Term Memory describe how it works
Requirement ID	RQ17
Requirement Description	Chat logging module records chat sessions, loaded in transcript format
Requirement ID	RQ18
Requirement Description	Chat logs are stored in Microsoft Management Studio

Requirement	User Requirement Definition
API Calls	
User Interface	
Requirement ID	RQ19
Requirement Description	The GUI is comprised of a textbox that allows user input from a keyboard.
Requirement ID	RQ20
Requirement Description	The GUI will have a Send button which sends text from the textbox to the API when clicked. The Graphical User Interface possesses a Send button through which text is sent from the textbox field to the chatbot API when clicked.
Requirement ID	RQ21
Requirement Description	The chat window sustains and keeps traceable display of all the exchanged questions and answers within the current session. Accompanied by a scroll bar on the side if its the case that not all the messages can fit on the screen display per time.
Requirement ID	RQ22
Requirement Description	In the case of a network connectivity issue, the chat window displays an error message

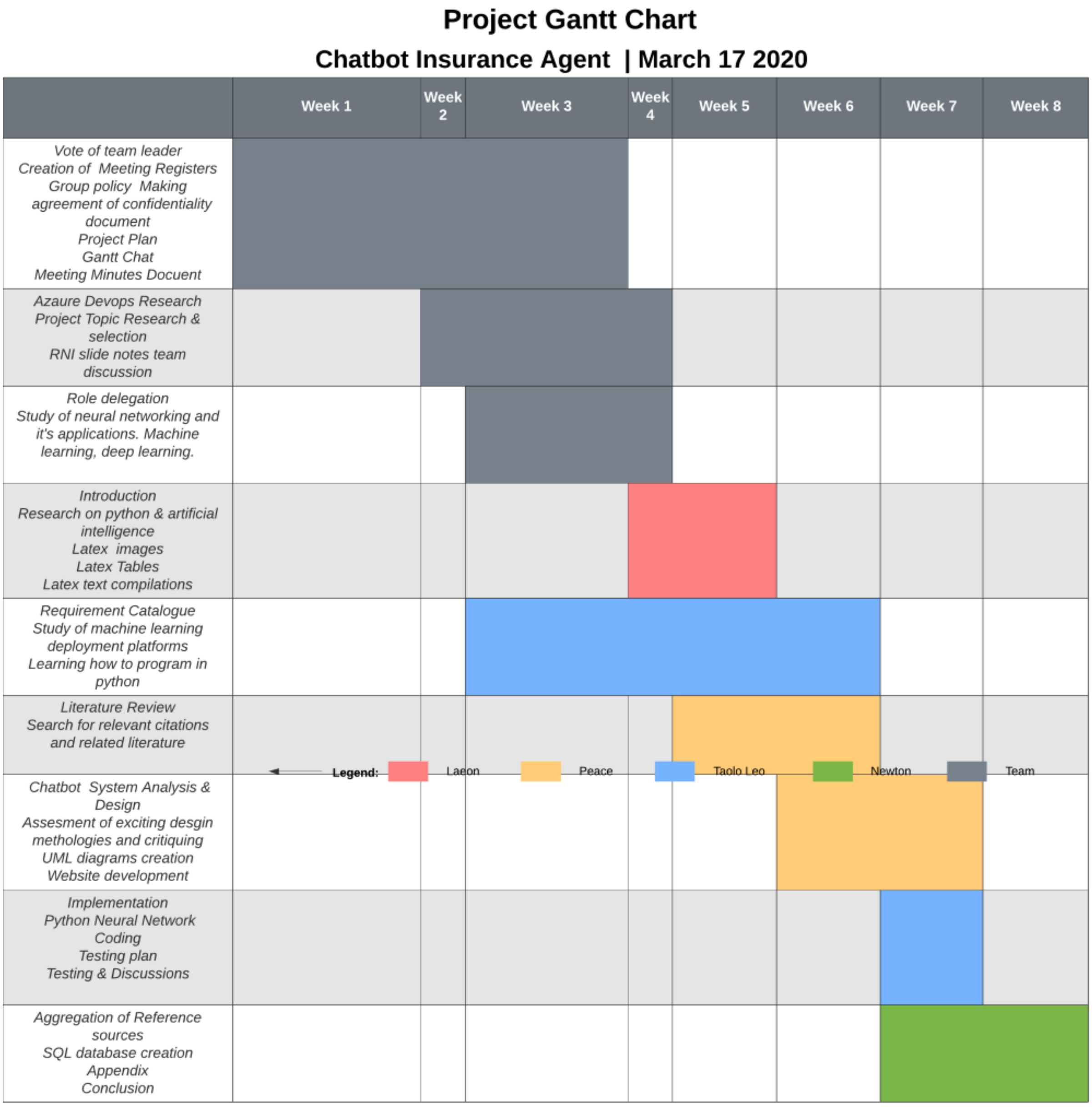
Requirement	User Requirement Definition
API Calls	
Communication Process	
Requirement ID	RQ23
Requirement Description	Artificial intelligence determination of whether conversation should be terminated or carry on based on indication of interest by system user.

Requirement	User Requirement Definition
API Calls	
Deployment	
Requirement ID	RQ24
Requirement Description	Should be deployable on Facebook
Requirement ID	RQ27
Requirement Description	Should be deployable on Insurance Agency website.

NON FUNCTIONAL REQUIREMENTS

Accuracy	The accuracy of question generation module will at least be 80$Theaccuracyoftheanswergeneratingmodulewillatleastbe$70
Fast Response	The chatbot server response time within which a user inputs will be nothing beyond 2 seconds
Security	HTTPS will be employed for connection between Web APi and chatbot logic programs for security purposes.
Ease of Use	A new Insurance Prospect will make less than 2 mistakes during the chatbot Insurance proposal. Chatbot communication must be clear and concise

FIGURE 7.1: Gantt Chart (Own, 2020)



Designation of Roles Team Leader: Taolo Latex Chief Editor: Laone Content Chief Editor: Peace Database: Newton

FIGURE 7.2: Data Dictionary Screenshot


```
{"intents": [
        {"tag": "greeting",
         "patterns": ["Hi", "How are you", "Is anyone there?", "Hello", "Good day", "What's up"],
         "responses": ["Hello, we offer the best insurance policies around!", "Good to see you, gear up with our insurance today!", "Hi there, ready to buy an outstanding insurance policy?"],
         "context_set": ""
        },

        {"tag": "goodbye",
         "patterns": ["cya", "See you later", "Goodbye", "I am Leaving", "Have a Good day"],
         "responses": ["Sad to see you go, our agency will contact you soon"
, "We will talk to you later, your requested policy is on the way", " Have a brilliant time up ahead, see you at our offices!"],

  {"tag": "marketing",
         "patterns": ["I'm interested", "I'd like to know more", "Go ahead"],"Yes Please",
         "responses": ["At Elite Motor Vehicle Insurance we give you well assessed policies to ensure your peace of mind wherever you drive. Would you like me to walk you through what we have to offer?"],
         "context_set": ""
        },


  {"tag": "datacollection",
         "patterns": ["I'm interested", "I'd like to know more", "Go ahead","Yes Please",]
         "responses": ["Alright, fantastic,I'll run you through a few questions you need to answer so I can give you according estimate annual premium for your purchase of our motor vehicle policy."],
         "context_set": ""
        },



        {"tag": "identity",
         "patterns": ["sir", "madam", "mr", "mrs", "ms", "miss","mister"],
         "responses": ["What's your name and how old are you? ", ],
         "context_set": ""
        },

         {"tag": "netearnings",
         "patterns": ["P20 0000.00", "10 000.00", "P15 000.00", "P 30 000.00", "P35 000.00", "P40 000.00","P45 000.00,""P50 000.00", "P55 000.00,P60 000.00",],
         "responses": [" May you kindly share with me the value of the car you woulud like to ensure? ", ],
         "context_set": ""
        },
```

FIGURE 7.3: Data Dictionary Screenshot


```
    "context_set": ""
   },
   "tag": ["CostEstimate", ],
    {"patterns": "P20 000.00","P30 000.00","P40 000.00","P50 000.00","P60 000","P70 000
      .00"
    "responses": ["I've calculated your estimate premium cost for our motorverhicle
      insurance policy. It's P 3000.00 ", "I've calculated your estimate premium cost
      for our motorverhicle insurance policy. It's P4 500.00 ","I've calculated your
      estimate premium cost for our motorverhicle insurance policy. It's P6 000.00 "
      ,"I've calculated your estimate premium cost for our motorverhicle insurance
      policy. It's P7 500.00 ","I've calculated your estimate premium cost for our
      motorverhicle insurance policy. It's P9 000.00 ","I've calculated your estimate
      premium cost for our motorverhicle insurance policy. It's P 10 500.00 " ],

    "context_set": ""
   },




   {"tag": "purchase",
    "patterns": ["Id like to sign up for car insurance ", "what car inurance policies
      do you have", "what do you reccommend?", "could i sign up for can insurance with
      you guys "],
    "responses": ["Well click on the link below an d provide you details and one of our
      clients will call you soon", "There are great affordable car insurancre policies
      ,click on the link below and get yourselve started with one of our great deals
      offered here in the elite crew car insurance company"],
    "context_set": ""
   },
   {"tag": "hours",
    "patterns": ["when are you guys open", "what are your operating hours", "hours of
      operation, when are your offices open"],
    "responses": ["We are open 8am-7pm Monday-Friday!See you soon!","Our offices are
      open from 8:00Am-7:00PM. Will that be all?"],
    "context_set": ""
   },
   {"tag": "contact",
    "pattern": ["i would like to sign up for insurance", "i love that", " very
      reasonable price","where do i sign up?",

    "responses":["Fantastic, my human colleagues will get back to you within 24 hours
      with an update on finalization of your policy acquisition. Do you have any
      questions?" ],
   "context_set":""
   },
   {"tag": "rejection",
    "pattern": ["I am not interested","No","Not at the moment","Not now","No thanks"],
    "responses" : ["Thank you for your time. Feel free to check on us anytime. Here's
      our office nmber in a case you ever have inquiries about our services, call Thobo
      , our customer, srvice assistant at +267 73728479 or our officeline, 3304892. All
      the best!"],
    "context_set":""
```

Figure 7.4: Data Dictionary Screenshot

```
{"tag": "contact",
 "pattern": ["i would like to sign up for insurance", "i love that", " very
   reasonable price","where do i sign up?",

 "responses":["Fantastic, my human colleagues will get back to you within 24 hours
   with an update on finalization of your policy acquisition. Do you have any
   questions?" ],
"context_set":""
},
{"tag": "rejection",
 "pattern": ["I am not interested","No","Not at the moment","Not now","No thanks"],
 "responses" : ["Thank you for your time. Feel free to check on us anytime. Here's
   our office nmber in a case you ever have inquiries about our services, call Thobo
   , our customer, srvice assistant at +267 73728479 or our officeline, 3304892. All
   the best!"],
 "context_set":""
 },

{"tag": "enquire",
 "pattern": ["What insurance do you guys offer","What are your insurance services
   focused on", "What do you basically insure"," Which insurance can i sign up with
   you guys","what type of insurance services do you provide"],
 "responses": ["we offer motor vehicle insurance at affordable prices","Our aim is
   to deliver high quality car insurance services to clients "," we basically
   provide motor vehicle insurance services at a high level services with affordable
   prices","with us you can get an quality car insurance service with affordable
   prices"],
 "context_set":""
},

{"tag": "feedback",
    "pattern ": ["This is terrible service","I'm not happy","you should consider
     working on weekends to increase you operation hours"," You are boring","This
     is frustrating"],

"responses": ["note taken we will improve as soon as possible","thanks for the hint
  we will try to iprove"," at elite crew we are dedicated to bring best insurance
  services to our clients, we will improve as soon as possible"],
"context_set":""
}


{"tag": "mis_understand",
"pattern" : ["please explain better","what do you mean","please provide me with more
  information", "Explain it more simpler", "i dont understand be precise"],

"responses": [ "which part about insurance did you not understand?", "what do you
  want clarified to you"," which part would you like us to explain better"],
"context_set":""
}
```

Chapter 8

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