

E-Assistant: An Interactive Bot for Banking Sector using NLP Process

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Abstract - The aim of the project is to built a chatbot for the banking sectors. The main purpose of the application is to help the unaided customers and to reduce the disturbance of the workers. This project help the customers to fill the bank application forms such as account opening, loan claiming etc... The chatbot responds to the customer in textual, speech and visual form. This process is achieved by Natural Language Processing(NLP). NLP is the most commonly used method for developing Chabot applications, here we are implementing this method to build a user specific Chabot for customers in banking sectors. NLP detect the intent of the user entity with very high accuracy by processing the user input against three different engine. It is essential to understand the true voice of user and facilitate seamless interaction. This unibot provides personal assistance for the customer's need in the bank. Furthermore this research aims to accomplish high potential application specific knowledge system in the area of banking sector.

Key words: Natural Language Processing, Unibot, Artificial Intelligence, Knowledge base.

1. INTRODUCTION

NLP is an artificial intelligence method that is used for interacting with intelligence systems. In Artificial intelligence, a wide range of studies on chatbot using Natural Language Processing exist chatbot provide answers to any questions that the user posses irrespective of the domain they are operated in. Nowadays chatbots are used in various fields like university, Healthcare, entertainment etc.. Most popular example of chatbots are Siri, Cortana, Alexa etc... A lot of websites also uses chatbots to answer the user queries.

a) Chatbot using AI

A Chatbot is an artificial intelligence software that converse a human with real-time responses. These chatbots can respond through textual forms, voice or by visual representation. AI bots are designed in such a way that it can understand the human's requirements and respond accordingly, to do this a set of guidelines are applied to AI bots. Sometimes a set of questions that might be asked by the user are mapped with relevant answers. They are called limited chatbots. This is one way on how AI bots work. The other way is these chatbots provides real time responses to the user by analyzing what they are looking for. The responses will be based on the user's

preferences and behaviour. They are called Intelligent Chatbots.

b) Chatbots in banking sectors

The need for "Interactive banking sector" is due to the following reasons. [1]People with reading and writing disabilities may find it difficult to fill in the application, customers sometimes hesitate to approach the bank staffs for help.[2]The bank staffs are often reluctant to help the customers. The solution for all these problems leads us to the need for this application. The system summarizes the user queries and provides the output that user wants. Features of interactive bot are, Guides the clients in the process of cash deposit, account opening, loan process. Interactive bots are user friendly, low cost, easy to implement and provide low power operation. The bot analysis user queries and replies accordingly. Interactive bot uses AI and NLP algorithm.

The objective of this application is to implement user friendly bot to guide the customers in the bank. To save investing much on hiring different language resources. To provide an answer to user's queries effectively. To save the time of the client since he/she doesn't have to approach the bank staff.

2. PRELIMINARIES AND PREVIOUS WORK

2.1 Multiple Response

Matching an appropriate response with its multi-turn context is a crucial challenge in retrieval based chatbots. Current studies construct multiple representations of context and response to facilitate response selection, but they use these representations in isolation and ignore the relationships among representations. To address these problems, they proposes a hierarchical aggregation network of multi representation (HAMR) to leverage abundant representations sufficiently and enhance valuable information. First, they employed bidirectional recurrent neural networks (BiRNN) to extract syntactic and semantic representations of sentences and use a self-aggregation mechanism to combine these representations. Second, they designed a matching aggregation mechanism for fusing different matching information between each utterance in context and response, which is generated by an attention mechanism. By considering the candidate response as the real part of the context, they tried to integrate all of them in chronological order and then

accumulate the vectors to calculate the matching degree. An extensive empirical study on two multi-turn response selection data sets indicates that our proposed model achieves a new state-of-the-art result.

2.2 Symbolic Processing

The authors proposed methods to learn symbolic processing with deep learning and to build question answering systems by means of learned models. Symbolic processing, performed by the Prolog processing systems which execute unification, resolution, and list operations, is learned by a combination of deep learning models, Neural Machine Translation (NMT) and Word2Vec training. The implementation of a Prolog-like processing system using deep learning is a new experiment that has not been conducted in the past. The results of their experiments revealed that the proposed methods are superior to the conventional methods because symbolic processing (1) has rich representations, (2) can interpret inputs even if they include unknown symbols, and (3) can be learned with a small amount of training data. In particular (2), handling of unknown data, which is a major task in artificial intelligence research, is solved using Word2Vec. Furthermore, question answering systems can be built from knowledge bases written in Prolog with learned symbolic processing, which, with conventional methods, is extremely difficult to accomplish. Their proposed systems can not only answer questions through powerful inferences by utilizing facts that harbor unknown data but also have the potential to build knowledge bases from a large amount of data, including unknown data, on the Web. The proposed systems are a completely new trial, there is no state-of-the-art methods in the sense of "newest". Therefore, to evaluate their efficiency, they are compared with the most traditional and robust system i.e., the Prolog system. This is new research that encompasses the subjects of conventional artificial intelligence and neural network, and their systems have higher potential to build applications such as FAQ chatbots, decision support systems and energy efficient estimation using a large amount of information on the Web. Mining hidden information through these applications will provide great value.

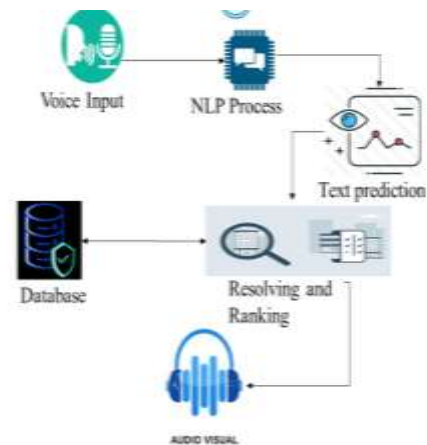
2.3 Audio Response

The response is retrieval-based. The reply is retrieved from the knowledge base. This is desired for easy information retrieval by the users. The output is given in the form of text as well as in audio format. It extends the chat by providing irrelevant content in the some cases.

3. PROPOSED SYSTEM

In this proposed system there are 5 modules, they are context recognition, Preprocessing, Intent classification, Entity extraction, context reset.

3.1. ARCHITECTURE



In first step the voice input is given to the UI. The UI passes the message to the Chatbot API. In API the audio format is converted into text format. This conversion is done using Google API. The audio is extracted and then the noise audio from the environment are eliminated and filters out the inappropriate and unwanted data. The voice is then broken down into individual sounds after every pause and punctuations (for example: commas, question marks, full stop) with the use of machine learning. Then the language of that sound is detected. Google API is capable of detecting 120 languages. Analyses and translates the sound to text.

In the second step, the input text from the Google API is given to the NLP engine for preprocessing. The input text is standardized as per the system requirement. In NLP process, consist of Intent recognition and entity extraction.

3.2. MODULE DESCRIPTION

3.2.1: Context Recognition

The user starts to speak just by clicking the microphone icon. The audio of the user's speech is broken down into individual sounds, each of which is analyzed to find out the probable word fit and translates the sound into text.

3.2.2: Preprocessing

In this section we extract the input text to normalize the input as per system's requirement when the system receives queries like loan, amount opening etc., the input text will be processed and keywords are extracted.

3.2.3: Intent Classification

The main aim of this module is to find the goal of what the user is looking for. It is to look for the intention of the user. Based on the keywords, the information is provided from the database. If a pattern is not recognized or not available, a random response is sent suggesting "Invalid input".

3.2.4: Entity Extraction

When a user wants some assistance for filling a particular details in a form, the response will be provided through this module. If the input matches a pattern in database, the appropriate, response will be sent to the user. If the database have no entry for that query then keyword are fetched from the input. The algorithm used for this purpose is NLP which finds the similarity between the input and the predefined set of questions pattern, whose answers is already available.

3.2.5: Context reset

If the user is satisfied with the response of the bot then user can exit the system. The input parameter will reset automatically.

4. CONCLUSION

A conversational banking strategy should include investing in the right human with skills in AI development and NLP experts, who can keep up the technological advancements and actively integrate them into existing tools. This interactive bot for bank aims to provide user friendly interface to solve queries relating to banks. In this, the architecture used integrates the language model algorithm to imitate the information online communication between user and computer using Natural Language. By using this chatbot it could be fast and efficient to search answers to the queries. The questions, answers and keywords are stored in the database.

5. Future enhancement

This chatbot can be implemented using other algorithms too. We can implement this in other domains like medical, forensics, sports, education, entertainment etc.. It will be beneficial to access information without much physical effort.

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