Research Article

Banking Chatbot (B-Bot

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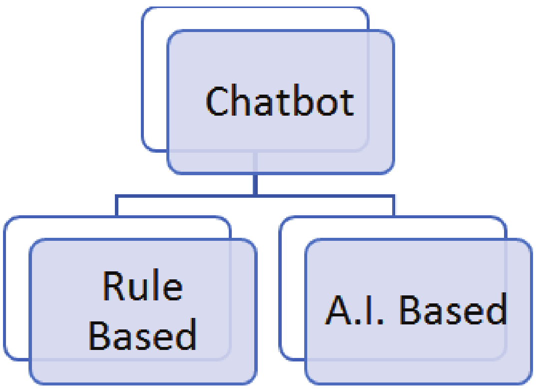
Abstract: Chatbots square measure intelligent systems that perceive a user's tongue queries and respond consequently during a conversation, that is the focus of this study. It's an additional sort of a virtual assistant, folks want they're talking with a real person. They speak a constant language we have a tendency to do, and will answer all queries. In banks, at customer care centers and enquiry desks, humans are lean and usually take very long time to method the only request which ends up in wastage of your time and additionally cut back quality of client service. In this paper we introduce a more efficient way to resolve customer queries. Today's customers have high expectations andthey want quick and accurate responses, completeand robust resolution, service that is available anywhere and anytime. All of these can be within well-designed chatbots. The entire experience is conversational. The aim is to implement a chatbot which may resolve client queries, search the knowledgebase for resolution and provide the solution. The chatbot can handle the queries ultimately reducing human effort.

Keywords: Natural Language Processing, Rasa framework, Rasa Natural Language Understanding (NLU), Rasa Core, Machine Learning.

1. INTRODUCTION

Technology has become a great impact on our day to day life and banking is not an exception. Since the advent of central banking systems, the banking sector has embraced technological advances in terms of internet banking, mobile banking, introduction of biometrics, big data analytics, artificial intelligence, Internet of Things (IoT). Banking organizations across the world are leaning towards technology to provide better experience to their customers. The rise of chatbots within the finance sector is that the latest turbulent force that has modified the approach customers move. within the industry, the introduction of computing has driven chatbots and altered the face of the interaction between banks and customers. A chatbot may be an informal agent that uses the tongue to speak with users. The chatbot has the power to retort immediately as they function around the clock agent that is available 24/7, 365 days. Chatbots reduce human error as well as personalize the client service. Chatbots are a major innovation within the field of AI. Chatbots are extremely responsive, interactive that resembles human conversations using AI tools and techniques and resolves client queries orwants anytime with the benefit of chat. A client will place aquestion or question and also the chatbot replies with the proper response. supported true, the chatbots will learn from the utterances within the spoken language and more personalize the responses and learn from the past connections. Chatbots have a ton of edges together with a 24/7 client service, timely responses and effective inquiry handling, reduced price of client service and best client satisfaction. They vanquish humans in terms of speed and accuracy. The chatbot has been used Over the past few years, however, the use of bots has attracted industries. Chatbots were first set up in the 1960s and have come a long way from their initial development. There are two different types of chatbots. The most common type of chatbot is based on rules,and the more advanced chatbot is powered by artificial intelligence.



Chatbots use natural language processing tools for artificial intelligence (AI). Computers are configured in this framework for reading, processing and analyzing large amounts of natural language information. Technologies for artificial intelligence also include deep learning and algorithms for machine learning. AI bots learn from people's conversations and interactions, expanding their database. On the other hand, rule-based bots consist of simple systems and thus have limited responses. The program scans and decides keywords and responds with the appropriate command type the user input. Unlike the AI-based chatbots, when they encounter unfamiliar commands and unrecognizedphrases, rule-based chatbots no longer respond.

2. RELATED WORK

Customer support and service is difficult to achieve. Customers buy products online, make payments, and have queries related to products as a result they want good customer service for solving their queries. Traditionally, people use telephones to contact the customer executive. This process is very time consuming as the customers need to wait on the line for a lot of time before their request is processed. The customers get frustrated when they ask the same question again and again, lodge complaints and they don't receive a response for days. Also, the cost of phone interaction between the customer as well as executive is also more. So, to solve this issue we introduce chatbots which is a computer program that we can talk to via text, chat or voice. Using Artificial Intelligence (AI) Powered chatbots, enterprises can be closer to achieving efficient and automated customer service which can lead to better engagement and understanding [1].

According to Dr. Wallace, perhaps, the biggest market of chat bot is Entertainment Markets, in which, we can imagine that chat bots can act as a talking book for childrenand provide foreign language instruction or can be a tutorin the Intelligent Tutoring system. One such study used an ALICE system to help Chinese university students practice their conversational English skills. The study was qualitative in nature and used pre-existing conversational English skills [2]

Eliza was the first famous chat bot, and ALICE was another milestone. The Loebner Prize and The Chatterbox Challenge are both annual competitions which have their roots in TIG. However, these are typically text only experiments, although some limited visual components are often added. This focus is on; however, whether with the text exchange alone, we can replicate human "behaviour" [3].

Conversional assistants are becoming an integral part of daily life. Rasa Core and Rasa Natural Language understanding (NLU) are easy to use tools for building conversational systems.[4]

Rasa is an essential set of tools for building more advanced and efficient AI assistants/chatbots. The benefit of rasa is the infrastructure and tools which provides the user with high performance, resilient and proprietary intelligent chatbots that work. Rasa helps all developers create better text and voice-based chatbots. Rasa's NLU helps the developers with the technology and the tools necessary for capturing and understanding user input, determining the intent and entities. Rasa supports multiple languages, single and multiple intent, and both pre-trained and custom entities.[5]

Rasa is an open source framework for building AI bots. Rasa open source framework consists of two components: -

Rasa NLU and Rasa core. Rasa recommends using bothRasa NLU and core, but they can be used independently of each other. Rasa core is the component which handles thedialogue engine for the framework and helps in creating more complex chatbots with customization. Rasa providesan opportunity for interactive learning. Chatbots can beenhanced because of the flexibility options provided by the Rasa framework. The chatbot can be easily deployed, integrated and connected to websites and applications. [5] Rasa being an open source framework it is very convenientand easy to customize. Most of the chatbot frameworksavailable are totally cloud based and provide software as a service. Business, enterprises and clients do not wish toshare their data on cloud or any third-party service. Rasafits the best when you don't want to send your data to an external device. We choose rasa as our framework because it is not cloud based and can be easily customized. Rasaallows the user to build, host and deploy Rasa internally inour server or environment. Deploying the Rasa on our ownserver can help to secure the data. Rasa provides better control and flexibility in deploying the chatbot. It is free and open source which makes a go to choice for building chatbots.[6]

2.1 CHATBOTS USING NLP VS RASA

neural networks, and algorithmic neural networks) ar commutation ancient handwoven models (e.g., SVM and supply regression) .

Collobert et al. argued that a straightforward deep learning framework performs higher in many IP tasks, particularly in named-entity recognition (NER). As RNNs have a lot of "memory" info than alternative previous procedure cells in the current process , it's associated more} standard to use an RNN language model for IP applications in recent years. Conditional Random Fields (CRFs), a sequence labelling, is additionally important in NER tasks. With these models, texts are trained to know the structure and which means.

Compared with laptop work like mathematical operations are straightforward, direct and correct, human languages are usually ambiguous and hidden in linguistics. so it is troublesome to urge computers nearer to a human-level understanding of language.

As a vital application of IP, chatbot builds its potential for computers to perceive the intent of natural language and make cheap responses. These applications have recently become standard on all completely different mobile and net platforms. Among many styles of chatbots, the most sort known as "virtual assistants" is served to support needs fromusers in wide varied domains and sectors.

2.1.1 NLP

Natural language processing (NLP) is one of

2.1.2 RASA

Rasa has two main modules:

theoretically advanced techniques for the automatic understanding of human beings and representation of their languages . It is one of the major areas of artificial intelligence, and IT is used in various situations like machine translation, text mining, speech recognition, and so on.

There are many phases in NLP, including phonetics, morphology, syntax, semantics, and pragmatics. To understand human language, the machine needs to divide the whole text into paragraphs, sentences, and words. Besides, it learns to differentiate relationships between different words , draw the exact meaning from the text, understand sentences in different situations, and consider the prior discourse context. In the early 21st century, a feed-forward neural network language model was proposed.

The use of word embedding with word2vec implementation created it economically to get a definite relation between words. A lot of recently, feed-forward neural networks have been replaced with repeated neural networks (RNNs) and long immediate memory networks (LSTMs) for language modelling . And current analysis in IP is shown that those with success applied deep learning ways (e.g.,convolutional neural networks (CNNs), repeated

1. Rasa NLU
2. Rasa Core

There square measure 3 main components in a very chatbot system: a tongue Understanding (NLU) half that gets the user's intents, a Dialog Management half that monitors the present system and oral communication state, and a tongue Generation half that responds to the user. NLU half plays a vital role within the whole system and there square measure many ways to realize the goal to know and respond. RNNs square measure is shown to be a good way to build a language model, which mayeven be used for tagging, sentence classification, generating text, and so on.

RASA NLU is typically used as a tool to build informal systems, that is associate open supply tongue understanding modules. It includes loosely coupled modules combining a variety of tongue process and machine learning libraries in a very consistent API . Rasa predicts a set of slot-labels and slot-values related to totally different segments of the input instead of a sequence of slots for every input word .

3. PROPOSED METHODOLOGY

In this paper we present a chatbot which is a banking Chatbot called B-BOT which resolves all the bank related queries. The chatbot's model can be divided into three sections – Backend, ML model and Frontend. The main functionality of the chatbot is carried out by Rasa Framework.

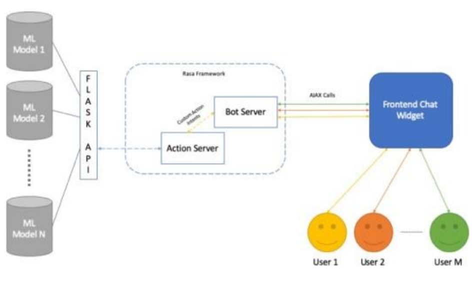


Figure 1: Frontend usingML

The B-Bot is made on Rasa Framework. Rasa framework relies on Python. Rasa is to blame for handling the user input, characteristic of the intents and entities and making the responses. We've used each Rasa NLU and Rasa core. Rasa NLU provides the aptitude for classification of intent and extraction of entities from the user input and helps in understanding what the user is saying.

3.1 RASA NLU

Rasa NLU handles all information science stuff. Rasa NLU deals with teaching a chatbot on the way to perceive user inputs. The idea of intents is employed by Rasa to explain how user messages ought to be classified. Rasa NLU classifies the user inputs into one or multiple intents. As soon as the user enters the question or question, Rasa receives the message from the top user, it extracts the “intent” and “entities” gift within the message. Intent is what the user aims to mention or what the user desires.

3.2 RASA NLU TRAINING DATA

The goal of NLU (Natural Language Understanding) is to extract structured data from user messages. This typically includes the user's intent and any entities their message contains. you'll add additional data like regular expressions and search tables to your coaching information to assist the model to establish intents and entities properly.

3.3 THE NLU PIPELINE

The NLU pipeline definesthat convertunstructured user messages into intents and entities.

The NLU pipeline is outlined within the `config.yml` in Rasa. This file describes all the steps within the pipeline which is used by Rasa to find intents and entities. It starts with text as input and it keeps parsing till it's entities and intents.

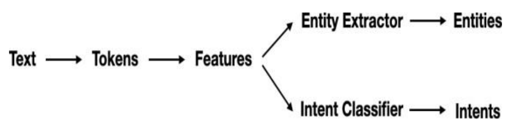


Figure 2: NLU pipeline

There are different types of components that you canexpect to find in a pipeline. The main ones are:

1.Tokenizers 2.Featurizers 3.Intent Classifiers4.Entity Extractors

4. COMPONENTS

4.1 TOKENIZERS

The first step is to separate AN auditory communication into smaller chunks of text, referred to as tokens. This happen before the text is featurized for machine learning, that is why you’ll typically have a tokenizer listed 1st at the beginning of a pipeline.

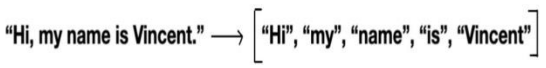


figure4: Tokenizers

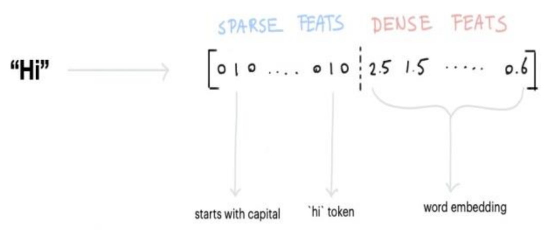
The tokenizer splits every individual word within the vocalization into a separate token, and ordinarily the output of the tokenizer could be a listof words. we get additionally separate tokens for punctuation reckoning on the tokenizer and also the settings that we have a tendency to undergo.

For English, we have a tendency to sometimes use the WhiteSpaceTokenizer except for non-English it may be common to choose different ones. spacey could be a good selection for non-English European languages however Rasaadditionally supports Jieba for Chinese.

Note that tokenizers don't amendment the underlying text, they separate text into tokens.

4.2 FEATURIZERS

Featurizers generate numeric features for machine learning models. The diagram below showshow the word "Hi" might be encoded.



fig(5)Featurizers

There are 2 sorts of features:

Sparse Features: typically generated by a CountVectorizer. Note that these counts could represent subwords also. we have a tendency to even have a Lexical Syntactic Feature that generates window-based options helpful for entity recognition. once combined with unconventional, the Lexical Syntactic Featurizer is designed to additionally embrace a part of speech options.

Dense Features: these encompass several pre-trained embeddings. ordinarily from SpaCy Featurizers or from huggingface via LanguageModelFeaturizers. If you wish to figure, you must additionally embrace the Associate in Nursing applicable tokenizer in your pipeline. additional details are within the documentation. Besides features for tokens, we also generate featuresfor the entire sentence. This is sometimes also referred to as the CLS token.

Note that you're utterly unable to add your own parts with custom featurization tools. As an Associate in Nursing example, there's a community-maintained project referred to as rasa-nlu-examples that has several experimental featurizers for non-English languages. it is not formally supported by Rasa, however will be of facilitation to several users as there are over 275 languages depicted.

4.3 INTENT CLASSIFIERS

Once we've generated options for all of the tokens and for the complete sentence, we are able to pass it to AN intent classification model. we tend to suggest exploitation of Rasa's DIET model which may handle each intent classification additionally as entity extraction. it's conjointly able to learn from each the token- additionally as sentence options.

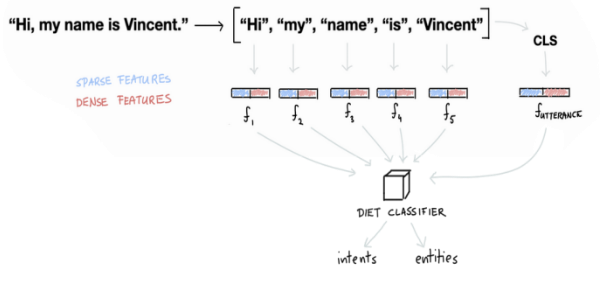


Figure 6 : Intent classifiers

4.4 ENTITY EXTRACTION

Even though DIET is capable of learning a way to observe entities, we tend to don't essentially advocate victimization for each variety of entity out there. For instance, entities that follow a structured pattern, like phone numbers, don't really want Associate in Nursing algorithmic rules to observe them. you'll be able to simply handle it with a RegexEntityExtractor instead.
This is why it's common to have more than one type of entity extractor in the pipeline

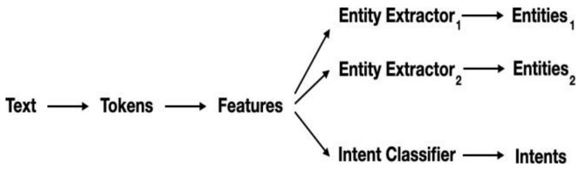


Figure 7: Entity Extraction

4.5 INTERACTION: MESSAGE PASSING

As you'll imagine, the parts during a Rasa pipeline rely on one another. therefore you may be inquisitive however they act. to know however this works, it helps to pore on Associate in Nursing example `config.yml` file.

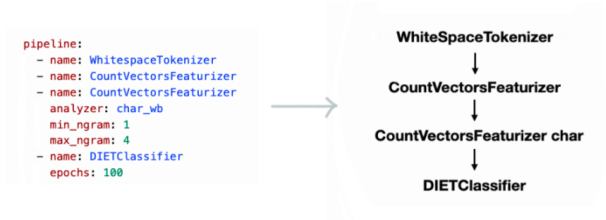


Figure 8: Message passing

The NLU pipeline could be a sequence of elements. These elements square measure trained and processed within the order they're listed within the pipeline. This implies that a pipeline configuration is thought of as a linear sequence of steps that the info has to go through.

Whenever a user talks to the assistant, Rasa internally keeps track of the state of associate degree vocalization via a `Message` object. This object is processed by every step within the pipeline.

Figure 9: message passing pipeline

The message initially starts out as an instrumentation withsimply the plain user vocalization.

After the message passes through the tokenizer it's split into tokens. Note that were representing the tokens as strings within the diagram whereas internally they portrayed by a token object.

when the message passes through a count Vectors Featurizer you'll notice that thin options areaunit value - added. There's a distinction between options for the sequence and also the entire sentence. also, note that when passing through the second featurizer the scale of the thin options will increase.

The DIETclassifier can explore for 'sparse_features' and 'dense_features' within the message so as to form a prediction. when its done process it'll attach the intent predictions to the message object.

Every time a message passes through a pipeline step the message object can gain new info. That additionally means you'll keep adding steps to the pipeline if you would like to feature info to the message. That's additionally why you'll attach additional entity extraction models.

4.6 Demo

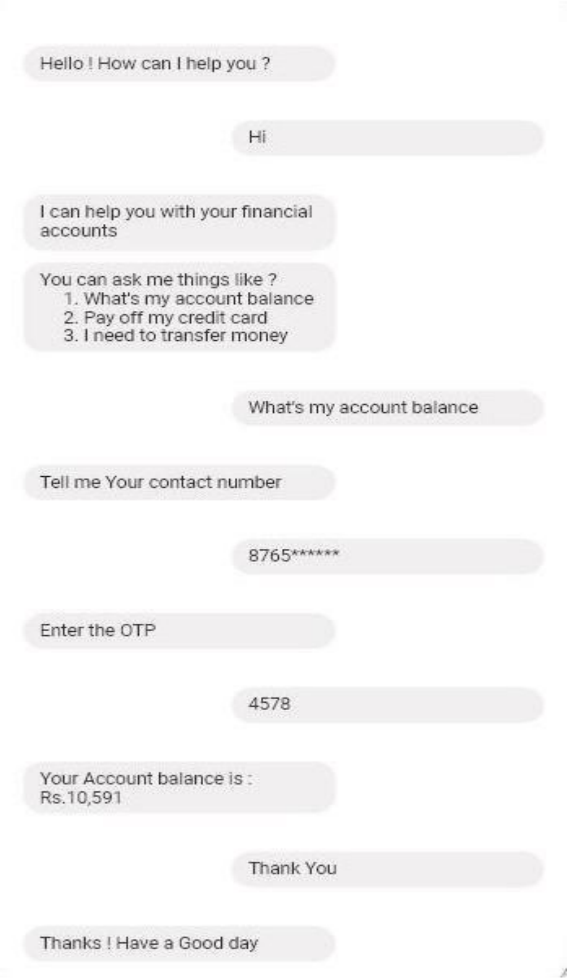


Figure 10: Demo of chatbot in English

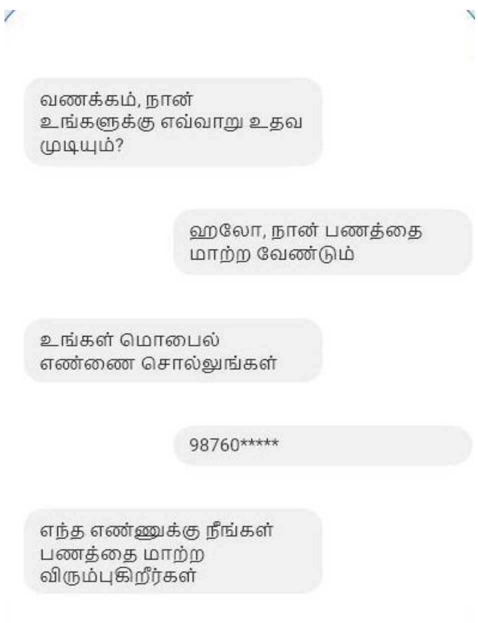


Figure 11: Demo of chatbot in tamil

5. RESULTS AND ANALYSIS

The proposed model is scalable and secure. Since the chatbot can be deployed on internal servers, it eliminates the scare of data loss or interception of data. Rasa makes use of natural language processing libraries like spaCy. These libraries can detect and process spelling errors, abbreviations, etc. This makes the chatbot tolerant to users' mistakes and handles common language conventions seamlessly. The ML models are deployed such that they are accessible via a Flask API. Multiple models can be integrated to the chatbot. Each model can be defined as a separate intent(s) in the chatbots domain. These models will be accessed through custom actions defined in the chatbots domain.

COMPARISON

OTHER SYSTEM	B-BOT
The questions set will have a definite standard by the chatbot development team.	There are no specific standards for this .
The accents and usage of language by the clients would be with limited specifications.	There are no language limitations, the AI mechanisms that power your chatbot work well with almost every language.
Cannot answer multiple questions at the same time.	Could answer multiple queries at the same time.
It is not used by all the users though it is not user friendly.	It is user-friendly.

6. CONCLUSION AND FUTURE WORKS

Chatbots are becoming an integral part of the digital world. It is necessary that the customer needs are addressed as well as customers are satisfied through the business. Customer expectations are growing with increasing technological development. Customer satisfaction is very important to businesses and enterprises because if the customers are not satisfied with the service customers never return.

Natural language processing is a vital component of intelligent Chatbot systems. In this paper, a function framework is designed and the principle of RASA NLU is introduced for the Chatbot system.The designed system integrates RASA NLU and neural network (NN) methods and implements the system based on entity extraction after intent recognition. This paper has compared our methods in recognition accuracy and integrities of entity or sentence, and has also validated the developed system in realistic situations. Rather than contacting a person,this bot helps in making appointments ensuring security.

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