A Dynamic Ontology Based Conversational Agent for Heterogenous Environment

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***Abstract*— By identifying concept associations during talks and drawing on prior knowledge, ontology-based chatbots preserve context. Even while these agents are able to adjust to their environment, in hostile circumstances they could still display abnormalities. These discrepancies could lead to poor action planning and ineffective adaptation. Therefore, we present a dynamic ontology-based conversational model that selects the best suited answer based on prior experience and knowledge base in order to better action planning and adaptation in hostile scenarios. Since emotions are important in human existence, our method shows the emotional state for different conversational agents instead of only emojis. For this reason, our research will illustrate a conversational bot that functions in a lifelike manner. We employ the ontology Rela-model for ontology, which consists of three parts (C, R,).**

***Keywords*— Ontology, Conversational Agent, Emotions, Ontology Rela Model, Previous Experience and Learning**

I. INTRODUCTION

THIS document is a template A software program with the capability to produce human conversation through text or voice communication is known as a conversational agent or chatbot (the name derives from the term chatterbot) [1]. They facilities artificial intelligence (AI) that can have a chat with a user in natural language done with internet, messaging services, mobile apps and telephone by conversational agent which is portion of software. To make our lives simpler though conversation agent by integrating artificial intelligence and they are suitably defined as intelligent agent. Frequently, they are employed in the area of psychology, business, education and health to give users and pupil's quick answers. Chatbots make use of human computational capacities where the knowledge of human-aided chatbots also existed in this context. Frequently, a in this perspective stated a chatbot is one of the most sophisticated and talented forms of machine-human interactions. Using a variation of assets and procedures, conversational agent may be established. There are enhanced suitable technologies of some precise conversational agents than others dependent on the software you desire to mark. May be the highest effective method to get the needed results is joining numerous AI methods, such as semantic understanding, natural language processing and machine learning [2].

The three kinds of Chatbot representations reachable are:

- Pattern-based (PB)
- Retrieval-based (RB)
- Generative-based (GB)

The three kinds of Chatbot representations reachable are generative models (GB), pattern-based (PB) and Retrieval-based (RB) [3]. The first kind is RB (rule-based chatbots), which are based on recognized patterns that reply to consumer input in reply to perspective. Retrieval-based chatbots are another name for it. They formed the reply to the input using human hand coding. It does not goods response on its own; instead, it relates the response to encoded patterns [4]. In conversational agent replies to conversations by resulting a collection of instructions is called pattern based. As a result, producing instructions that may cover all probable conditions need considerable quantity of period and Struggle if a Chatbot is destined to purpose more logically [5].

A chatbot produces replies using only a group of exercise queries and its response is called generative based (RB). Conversational agents are intelligent of this type, but it also creates it susceptible to errors if the training group is comprehensive sufficient to concealment the complete data field [6]. "Onto-logy" is used to refer to the study of what may exist, "metaphysics" is used to refer to the study of which of the many potential alternative ontologies is really accurate in describing reality in a more general sense (Ingarden 1964). Respectively, two philosophers created "ontology" or "onto logia" term independently, Jacob Lorhard (Lorhardus), Rudolf Göckel (Goclenius) in their works, Theatrum philosophicum and Lexicon philo- sophicum in 1613. Now we use ontology in computer science with different aspect ontology used in web semantic, conversational agents and also other field.

Ontology is the formal representation of concepts and relations. Now we focus on chatbots which think as human and chatbots react according to the environment. For this purpose, we used ontology. Many chatbots are created about ontology. for banking and finance, many chatbots make use of ontology-based conversation management systems, as well as ontology-based chatbots for e-commerce websites. Ontology is the learning of entities, contexts, classes and their interrelationships. The word ontology denotes the study of the association between things, items and the world. Instantiation, aggregation, inheritance and generalization are all fragments of the connection [7].

II. RELATED WORK

The entire document should be in Times A question answer (QA) pattern that services a order of conversations between users and the application to shorten user need and to authorization for extra accurate question-answering maintenances is called an interactive question-answering system (QA system). In a sensible way an interactive QA system works merged desires is directly preferred in the fields of requests connected to technical support and training. In this research methodology for producing and organizing chatbot-based interactive What- and How-QA systems based on a collective ontology-based knowledge base is offered. In this paper used three context, model domain and knowledge [8] .

A like a house on fire stimulating task is maintaining the address formal in the conversational agent. An ontology-based dialogue manager is presented. OntoDM is a dialogue manager that uses domain ontologies to initiative the chat while maintaining the conversation's state and helping as a basis for anaphora resolution. The banking and financial area suggest significant chance for context explanation through a huge array of data, Proper verbs, things, name and nouns as well as their specificity. The conversation manager module and knowledge base module are slightly incorporated since we employed ontologies both as the foundation for the dialogue manager and as a knowledge base (KB). To have path of Objects of Interest, or ontology nodes (classes) that occur to denote services and goods, domain knowledge is utilized. In a sense, chat memory and inattention were also presented in this way. To create approaches of domain-driven conversation, we proficiently united, domain-driven keyword position, domain ontologies and semantic methods. Our core banking and finance chatbots in German device the suggested structure. Moreover, conversation system language models and vocabularies for the finance-banking production are offering, beside with common problems of German language processing. Since this work is presently under development, yet no achievement metrics have been applied [23].

[9] The proposed methodology used to construct an intelligent Chatbot for in view of programming information in a university library.to courses in object-oriented programming and programming. Offering the necessary expertise in both tactics used with pupils. It may work as a tutor. Proposed model in this study is called Integ-Rela model, which is used to incorporate various knowledge domains. An ontology Rela-model has relations every knowledge domain, which is knowledge model of structures.

[10] Proposed a chatty boundary performed as advise-giver in an information safety. This chatbot uses a knowledge base with Json file. This proposed Chatbot has many constructions which are based on various thoughts from information security ability, for many users on various on area of information security growing the awareness by given that accurate advice. Additionally, telegram stage is currently set out this Chatbot. This Chatbot is largely used on social network phase.

Google Assistant, Rose, Siri, Machine Comprehension Chatbot, Eliza, ALICE and Jabberwocky, they are comparison accurse between them, On the basis of answers provided by them to a set of default questions. In this paper we evaluated chatbots through the following constraints: 1. Evaluation of exceptional queries [EEQ), 2. Assessment of Conversational Attributes [ACA) and 3 Assessment of Factual Questions. MITSUKU is the 4th time winner, GOOGLE ASISTENT and SIRI got the second and third position and Alice, rose and jabberwocky 4^{th}, 5^{th}, 6^{th} rank respectively.

[11] Proposed work in the direction of executing a new communicating technological fashion for museum. The Semantic Web, Natural Language Processing/Generation and best progressive AI technologies of Machine Learning are the implements to participate with apps and human. The Mubot interface will build a Chatbot application for museum visitors, and the visitors will be capable of chatting with a ‘smart’ display. Mubot interface delivers the services of asking queries through text and voice and visitors also obtain the answer in the audio form or written form. The additional visitors ask, the more Mubot will acquire and collect new knowledge in its knowledge base through asking new queries which are not stored in the database. In this paper we present a model of Mubot interface255, experimenting with first prototype executions using the famous Dialog flow structure, as well as using a Knowledge Graph-based approach.

[12] For the comfort of anybody interacting with an emergency, the proposed approach is a mobile, ubiquitous healthcare service in the form of a connected smartphone application serving as a virtual assistant. The proposed chatbot provides online human-bot contact and provides multiple emergency case scenarios. Context component (CC), Information pre-processing component (IPPC), information post-processing component (IPoPC), alert message constructor component (AMCC), natural language processing component (NLPC) and response generator component (RGC)” are six independent components introduced by design of system.

A global pandemic of the coronavirus (nCOV-19) has emerged. To be able to the stream of the high number of circumstances has become a great challenge to healthcare system or hospitals. When the fast success of the epidemic has happened especially in remote areas it becomes extra tough to communicate with a doctor or a medical specialist. For avoiding this problem, [13] considered and deployed Chatbot which can provide service to patients living in remote areas by supporting decreasing psychological loss, precautionary actions and virus updates produced by anxiety and isolation. For the motive of diagnostic estimation and mentioning speedy methods when patients are unprotected to nCOV-19 we present a framework of a classy AI (artificial intelligence) Chatbot. Moreover, we can also degree 5 of the infection severity through virtual assistant. If signs become thoughtful, then links with registered doctors.

[2] Proposed methodology present “Happy Soul”, is a teen-age oriented intelligent conversational interface which performances as a virtual friend who can support to relief, inspire, recognize and offer the techniques to discharge out their bad and destructive feelings, thereby discharging the tension. For teenagers to interact with computer systems chatty interfaces or Chatbots offer a new way. This Chatbot will work in the same way that they would speak to a human through questioning answers with user. In this Chatbot we used the client server architecture with the help of Android

GUI and natural language processing ("NLP"), RNN as a technology.

[14] Proposed methodology, for designing a Chatbot platform to databases we planned a framework that presents an automatic technique. To the greatest of our knowledge, our approach is the first to utilize relational databases to bootstrap chat bots for response for natural language to structure query translation. From the databases, our structure is used to create usable initial conversational agent in a short time. We characterize numerous chatbots in various fields prove helpfulness in various fields Conversational agents have been employed in e-commerce contexts as well as in fields ranging from education to healthcare.

[15] Proposed methodology presents Hebron for the CUSM as a web based conversational agent. Admin Portal process and React.js and a MySQL (Structured Query Language) server were used as the database to organize the datasets and Python as the programming languages in this chat bot. for the Covenant University Community not difficult, comfortable and smart shopping available through CUSM (Covenant University Shopping Mall).

TABLE I
COMPARISON TABLE OF DIFFERENT CONVERSATIONAL AGENT

papers	Previous experience	ontology	environment
(9)	Not covered	Defined	Homogenous
(16)	Not covered	Defined	Homogenous
(8)	Not covered	Defined	Homogenous
(17)	Not covered	Defined	Homogenous
(13)	Not covered	Not defined	Homogenous
(18)	Not covered	Not defined	Homogenous
(19)	Not covered	Not defined	Homogenous
(20)	Not covered	Not defined	Homogenous
(21)	Not covered	Not defined	Homogenous
(10)	Not covered	Not defined	Homogenous

This comparison Table I shows that previously proposed conversational agent did not cover the different intents. These conversational agents have not ability to learn from previous experience. They have work within specific knowledge domain. Our proposed conversational agent has capability to learn from previous experience.

III. METHODOLOGY OF PROPOSED CONVERSATIONAL AGENT

Our conversational agent consists of different components. This is ontology based conversational agent. For ontology we use ontology Rela-model. Each affiliation must include, at the very least, the name of the company and the name of the country where the author is based (e.g., Causal Productions Pty Ltd, Australia).

A. Ontology Rela-Model

Ontology Rela model consist of three components$(C, R, Rule)$.

According to the ontology Rela-model where C is

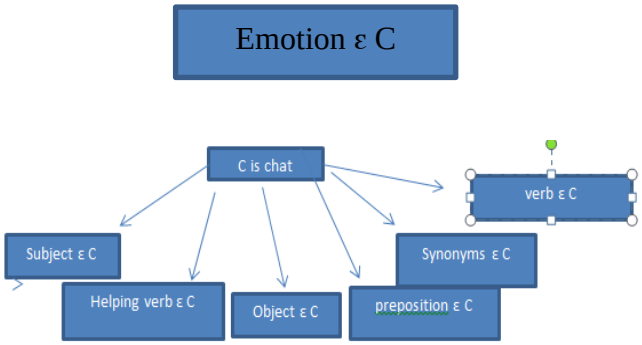

Fig. 1: Relations between concepts

R is relation in Ontology Rela-model. There are two types of relation between concepts.

R = $R_{hirerachy} \cup R_{related\ to}$

In our model we use $R_{related\_to}$, $R_{hirerachy}$ and related_to is set of related knowledge with main knowledge means each concept related to each other. For example:

$$c_s\ related_{to} c_{hl}$$
$$c_{hl}\ related_{to} c_0$$
$$c_{hl}\ related_{to} c_i$$
$$c_{hl}\ related_{to} c_e$$
$$(c_s\ , c_{hl}, c_0, c_i, c_s, c_e\ \in C)$$

$R_{hirerachy}$ is a set of relations as" is a" between concept and they are able to be considered as an inheritance relations.

$c_e\ is\ a\ c_w$: It means c_w inherited by c_e where $(c_w, c_e\ \in C)$

And the third module is Rule. In our model there are many inference rules created based on facts.

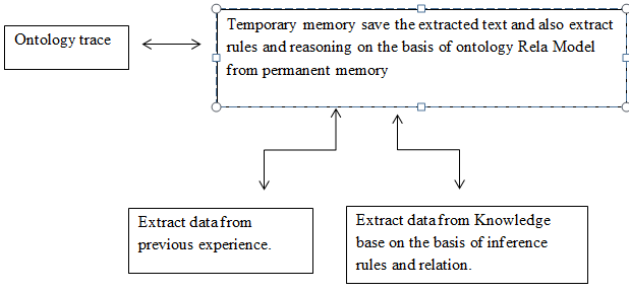

Fig. 1: Ontology trace

B. Working of proposed model

First, we get the input from environment send to knowledge base. After getting the response against input send to the analyser for extracting the features. For extract the features pre-processing the data of both input and output. For pre-processing first we tokenize the sentence into words. The function of Natural Processing language which is POS we use

the ontology Rela model and then get features. Features for input are:

- ***An emotion*** is a symbol that is used in computer mediated communications to how facial expression that indicate user emotional condition but, in our purpose, model generates the multiple emotions like sad angry happy worry surprising advising monitoring.
- ***Synonyms***
  In our proposed model we offer synonyms in Natural language processing. For this function we provide the more accuracy Natural language processing
- ***Tense identity***
  Tens identity means which tense is used in input and output. It gives the result on the usage of parts of speech basic functions in our proposed model. It provides 12 tenses which used in English grammar.
- ***Type***
  Several types of sentences are available. Our proposed model provides different types of sentences like simple, negative, interrogative, imperative, and exclamatory.
  Features of output are: we get the extra some feature from response sentence.
- ***Tens Response***
  When we give the input then output should be according to the input tense. For example, we give the input in present indefinite tense. Our conversational agent will give the answer in the present indefinite according to the situation.
- ***Intensity Response***
  Our conversational agent will give the intensity response according to the situation of given input. Our conversational agent will give intensity positive negative and neutral.
- ***Emotions Response***
  Meanwhile, there are no audio or visual signals to depend on then emotions can be challenging by using text to converse. Our conversational agent provides the emotions response according to the input request.

These features send to the evaluation. If previous response exist in the previous experience memory then get the response against the input both features are send to decision making. Decision making decides the final response on the weightage of the response emotions response intensity and response tense type. The final response shows to user and store into previous experience.

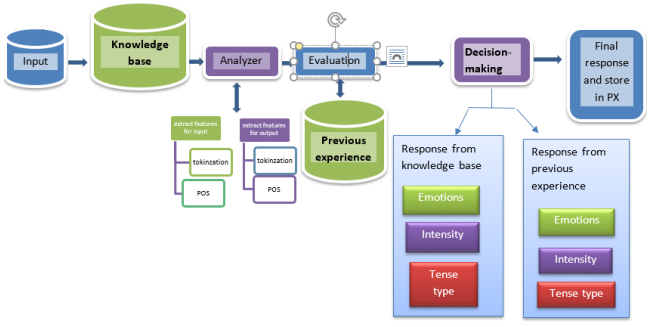

Fig. 3: Working of proposed conversational agent

Scripts + ontology Rela Model

We apply the ontology Rela Model for pre-processing. Through this model, we get the extracted features. And use the Dot Net language for retrieving the data and feature extraction. We store the data and concepts in Microsoft Access.

Fig. 4: Coding of intensity

In Fig. 4, we show that how to extract the intensity from word. Basically word extract from pre-processing. In this process reimplement the relation of related to which exist in ontology Rela model.

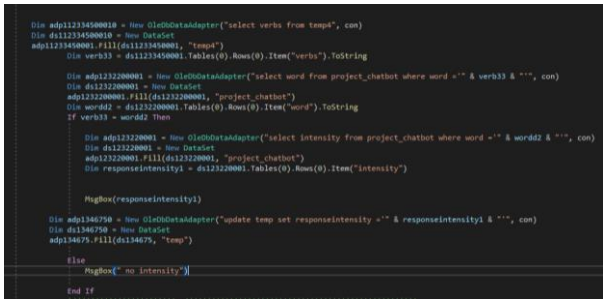

Fig. 5: Coding of intensity response

Fig. 5 shows that response intensity should be according to the input type of intensity, which is extracted from word or synonyms or verbs through given condition.

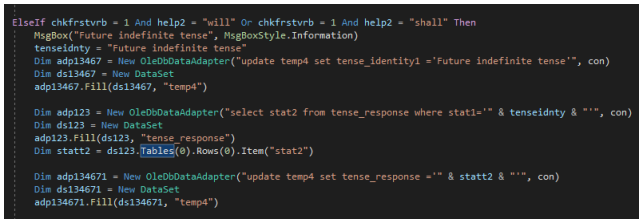

Fig. 6. Coding of tense identity

In Fig. 6, we extract text tense identity which can be any type of sentence like present indefinite, past, future etc. tense identity extracted through grammar rules which is based on facts.

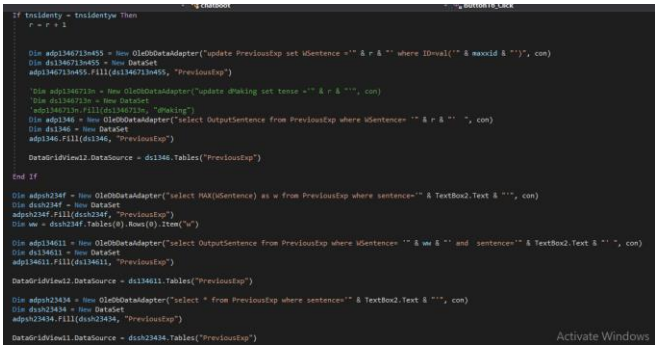

Fig. 7. Coding of previous experience

In Fig. 7 shows the weightage of response intensity and others features. Final response shows which is based on high weightage.

C. Result

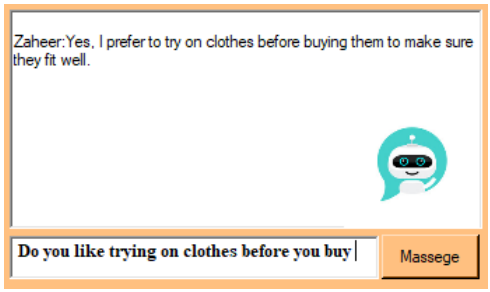

Fig. 8. response against input

Fig. 8 shows that conversational agent gets the input from environment and shows the response according to the input.

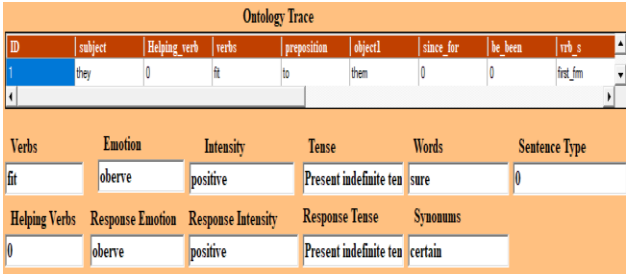

Fig. 9. Feature extract from output

Fig. 9 shows that pre-processing features and extracts intents which are intensity, intensity response, emotions and response emotions, tense type and tense identity. Response emotions and response intensity are verify that the emotions and intensity according to the input's emotions, intensity and tens types.

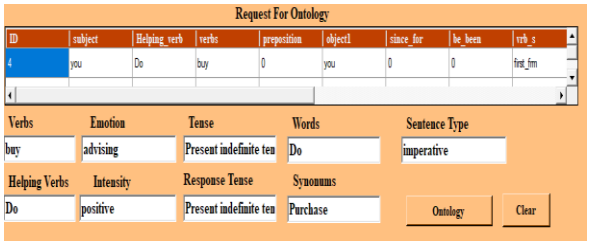

Fig. 10. Feature extract from input

Fig. 10. Shows that pre-processing features and also extracts intents which are intensity, emotions, synonyms, tense type and tense identity.

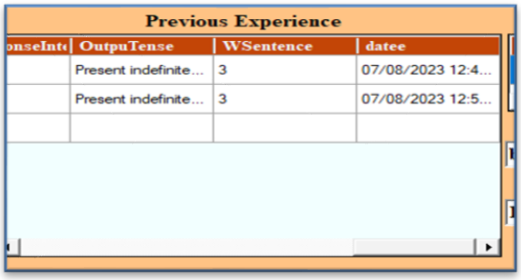

Fig. 11. Previous experience

In Fig. 11 shows the two responses with same weightage (W).

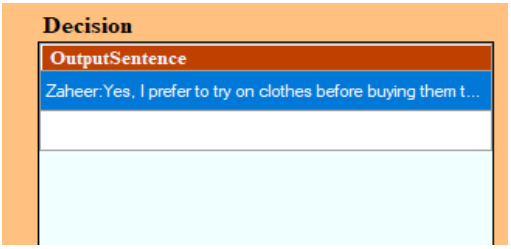

Fig. 12. Previous experience

Fig. 12 shows the final response and store to the previous experience with extracted emotions intensity and tense type intents.

Table I: Result Of Testing For 03 Kinds of Intents

Intents	*Quantity*	*Correct*	*Accuracy*
Emotions	1685	1435	88.74%
Intensity	1685	1155	73.14%
Previous experience	1685	1389	81.47%
Total			81.03%

In order to determine the accuracy of conversational agent we conduct the usability testing for targeted parameters.

Chatbot Usability Questionnaire (CUQ)

The Systems Usability Scale (SUS), which is a widely used instrument for evaluating usability and has a benchmark score

of 68 out of a possible 100, is equivalent to the Chatbot Usability Questionnaire (CUQ), a usability questionnaire that is specialized to chatbots. The 16 CUQ elements are scored out of five, with a total of 160 points being tallied before being normalized to 100. A chatbot's personality, on boarding, user experience, and error management are all evaluated by the CUQ. Because they abuse other design principles, SUS is not advised for usability assessment of conversation-driven applications. Each participant's CUQ score, the mean CUQ score, and the median score may be easily calculated using a CUQ Calculation Tool, a Microsoft Excel spread sheet.

Graphs were made using Microsoft Excel to better analyse the CUQ results. The participants' judgments of the CUQ's positive and negative features were shown in bar charts, and their age groups and CUQ scores were shown in a scatter plot. An inductive thematic analysis of the participants' open-ended responses was done using a Google form. The comments from each participant were carefully reviewed and coded. Then, themes and/or subthemes were created using the generated codes.

Participant Characteristics

The 30 adult volunteers responded to the survey between July 17 and July 25, 2023. Nine of the 30 research participants were between the ages of 18 and 22 years, 18 were between the ages of 24 to 26 years and 49 years, and 3 were above the age of 27. Participant breakdown: 12 females and 17 males.

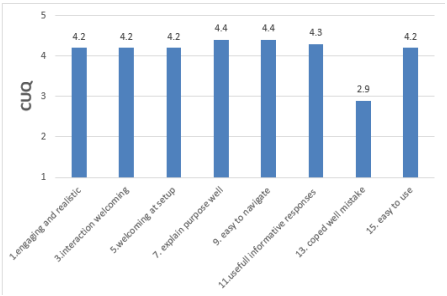

Fig. 13. Odd no questions

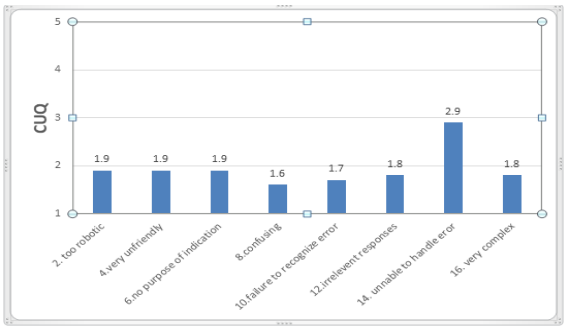

Fig. 14: Even no questions

IV. CONCLUSIONS AND FUTURE RECOMMENDATION

The version of this template is V2. The goal of this research is to develop an artificial intelligent conversational agent that interacts like a human in response to its environment. Through this model, logic will serve as the basis for our communication. Our proposed methodology proof that our model will performs in a heterogeneous environment. Our methodology based on ontology. Ontology means world and relation between things of world. It's all about classes and relation between classes. Retrieve the response on the basis of reasoning. Proposed model takes input from environment. Nlp basic functions like tokenization and parts of speech through ontology. We add some advance features in our model because our model claims that it interacts like human. These features are Tense response, emotions, intensity, synonyms and sentence type. Tense response give the tense type should be in the response. Emotion has vital role between human's conversations. Our knowledge base has the various types of emotions like happy fear sad worry friendly and many more. Result retrieves from knowledge base on the basis of words and synonyms to get more accurate result Intensity is the other more important thing in communication. Our ontological model present the three type of intensity negative, positive and neutral. Our proposed model gives the result on the basis of reasoning and logics. Sentence type has simple tense, imperative, exclamatory, interrogatives and negative.

We retrieve the response from knowledge base and same features add for output response.

In the last we have the two responses first response retrieve from knowledge base and second previous experience. Our decision making module decide the best fit response on the basis of emotions, intensity and tense response for getting the response according to the environment and more accurate result.

In future we will add strong and mature knowledge base in our model. Furthermore, we will add Meta cognation in our model to perform the actions in more intelligent way.

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