

# Development and Applications of Self-learning Smart Conversational Bots

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**Abstract:** *The original goal of the ai field was the construction of “thinking machines” – that is, computer systems with human-like general intelligence. Due to the difficulty of this task, for the last few decades most ai researchers have focused on what has been called “narrow ai” – the production of ai systems displaying intelligence regarding specific, highly constrained tasks.*

*In recent years, however, more and more researchers have recognized the necessity and feasibility of returning to the original goals of the field. Increasingly, there is a call for a transition back to confronting the more difficult issues of “human level intelligence” and more broadly artificial general intelligence (agi).*

*Artificial general intelligence (agi) is ai that can reason across a wide range of domains. It has long been considered the “grand dream” or “holy grail” of ai. It also poses major issues of ethics, risk, and policy due to its potential to transform society: if agi is built, it could either help solve the world’s problems or cause major catastrophe, possibly even human extinction.*

*The high potential stakes of agi raise questions of ethics, risk, and policy. Which agi, if any, should be built? What is the risk of catastrophe if an agi is built? What policy options are available to avoid agi catastrophe and, to the extent that it is desired, enable safe and beneficial agi? These are all questions under active investigation. However, the literature to date has tended to be theoretical and speculative, with little basis in the actual in agi. Given that agi may be first built many years from now, some speculation is inevitable. But agi r&d is happening right now. Information about the current r&d can guide current activities on ethics, risk, and policy, and it can provide some insight into what future r&d might look like. The purpose of this paper is to propose one of the means as to how we could achieve agi.*

**Keywords:** *Artificial general intelligence, intelligent chat bots, self-learning*

## I. INTRODUCTION

People have always projected human mental features and values onto non-human phenomena like animals, rivers, and planets, and more recently onto newer targets, including robots, and even disembodied intelligent software. Today, speculation about future artificial general intelligences, including those with superhuman intelligence, is also affected by the assumption that various human mental properties will necessarily be reflected in these non-human entities, wherein our case intelligent bots. Nonetheless, it is essential to understand the possibilities for these super intelligences on their own terms, rather than as reflections of the human model. Though their origins in a human environment may give them some human mental properties, we cannot assume that any given property will be present. Amidst the buzz of AI and chatbots, a lot of people are confused between the terms and they even tend to mix them up together. Chatbots and AI are closely related, but they are not the same thing and there are Difference between AI and chatbots! AI is the field of incorporating human intelligence into machines and thus majorly deals in Natural Language Processing (NLP) and Machine Learning. In NLP, AI deals with how the program understands and process the user’s input (audio or text). On the other hand, Machine Learning helps the code to evolve and learn from user’s interactions over the period. Now, talking about Chatbots which are intelligent non-fiction creatures designed for businesses to interact with their customers in a more personalized manner than ever. The difference between AI and chatbots is subtle yet extremely significant.

## II. INNOVATION OPPORTUNITIES

This section focuses on the application point of view using A.I. and Bots and how they could help in development of a AGI.

- 1) Quality Inspector – Machine vision (recognition)
- 2) Stock Broker (Stock market predictive bot)
- 3) Writer (Narrative)
- 4) Sales and Marketing (Digital Media)
- 5) Machine Operator (Instructs and performs tasks)
- 6) Chef (Teaches and guides and learns)

7) Personal Assistant (examples being Siri, Google now)

A. Translator

This characterizing has some merit, but glosses over the significant human expertise and ‘tweaking’ required to make these systems work. Moreover, if anything, these systems are even narrower than previous approaches: Their range of capabilities is almost entirely determined by their training data, while traditional approaches can in principle allow for real-time adaptive learning.

**III. PROPOSED METHODOLOGY**

First, we required a purpose that the bot would serve. Using the Google Maps API with the target to help users with their navigation requirements in real time over text conversation is among the purpose of the bot.

A Simple Bot was initially built using MySQL and Python to learn responses from previous sentences (conversational sentences) using a bag of words by mapping words. However, it did not give reasonable results. The limitations of Simple Bot are the motivation of diving into NLP and ML.

A classifier model is built to classify the sentences input by the user into 3 classes—chat, question and statement. The ‘chat’ class holds a set of random sentences, mostly salutations. The ‘question’ class consists of all queries that the user makes to the bot. Finally, the ‘statement’ class contains all statements which the user inputs to train the bot or otherwise. A Random Forest Classifier which gave a good prediction performance of about 80%.

Stanford Core NLP (A predefined library) assisted with the grammar parsing of the sentences to obtain and assign parts of speech tags to individual words of the sentence and extract the root word of the sentence. In the bot, the root word, subject and verb relation with different combinations to link a statement as the response to a question were used. The different combination allows the bot to respond to sentences which are paraphrases for each other without explicitly learning the response of each sentence.

The database maintains 4 tables which includes a chat table, a question table, a statement table and a directions table. The chat table stores all the inputs classified as chat, the question table stores all inputs classified as questions and the statement table stores all inputs classified as statements. The directions table maintains a record of all previous requests for directions between places to avoid repetitive requests to the GoogleMapsAPI.

The following diagram depicts this.

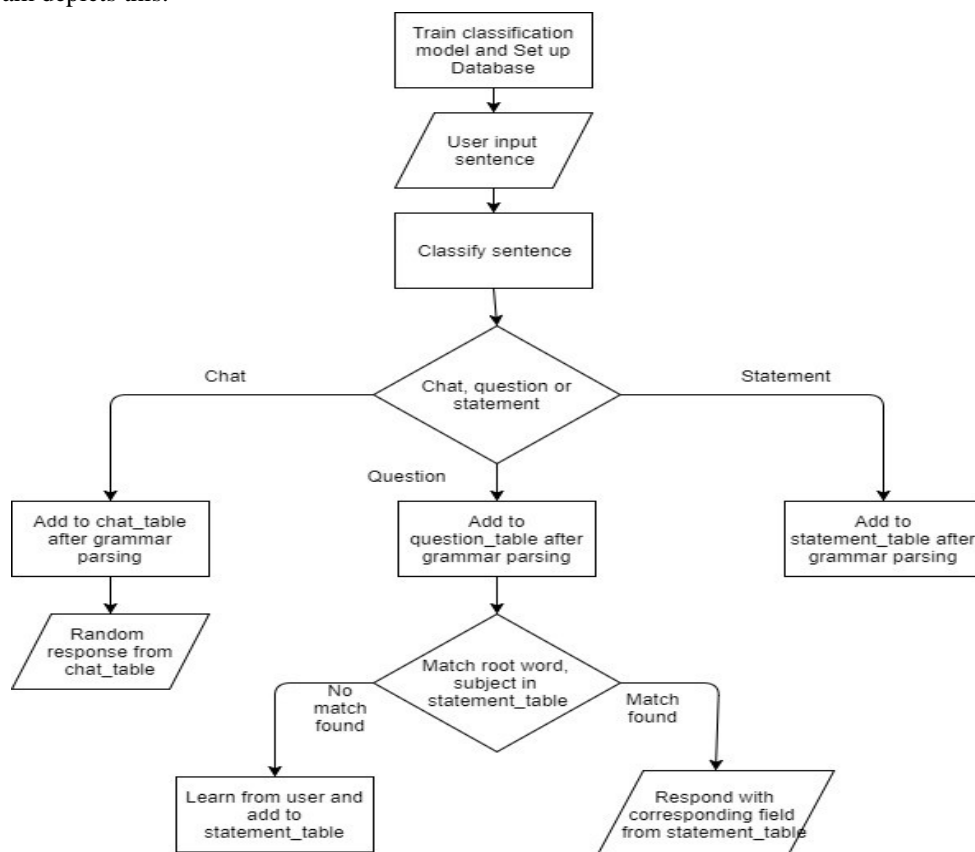


Figure 1 Architecture of Map-Bot

The response to the chat input by a user is a randomly selected entry from the chat table. In case the user input is a question, the bot parses the question to obtain the root word, the subject and the verb. It checks if the question is already in the question table indicating if it has been responded to in the past. If a matching entry is found, the corresponding entry from the statement table is picked as the response. If no entry is found the bot prompts the user to train it and records the response as the corresponding response to the question. In case of a statement input, the bot understands it as general information and adds to the statement table.

*A. More About The Classifier*

The chatbot not only needs to deconstruct the sentence input by the user using NLP but also determine what kind of sentence it is for better accuracy. A supervised learning model with some pre-loaded data to extract features and build a Machine Learning model against the training set is used. Thus, started with a set of 100 diverse sentences and classified them with the labels ‘C’ for chat, ‘Q’ for question and ‘S’ for statement. The features are extracted from the data to build the required model by extracting the parts-of-speech tags (POS tags) in the form of triples which gives some clear patterns. With this approach we have generated some numeric data-features. With each sentence having a unique ID and classifier label (S/Q/C), the classification model can be built. This data is used to train a Random Forest model. It is split into test and training set with 75 sentences in the training set and 25 in the test set, the model is fit, and predictions are generated from the test data. Training of the model could be depicted as follows.

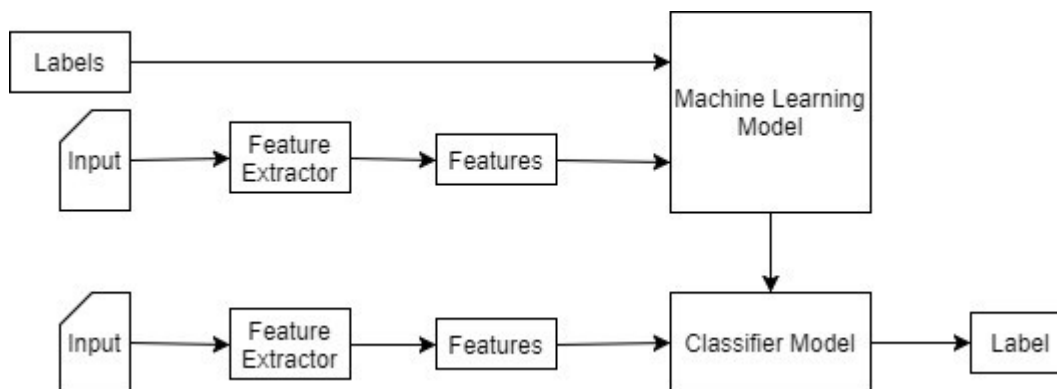


Figure 2 Training and prediction using Random-Forest

*B. Extensible Application Interfaces (APIs)*

The data flow may be easily integrated with the clients existing ERP / IT system or frontend through HTTP-Get/Post /APIs. Our A.I. would be hosted on the central node which would further expand to the individual nodes for better performance and to establish an intrinsic network, leading to a cloud-based Bot solution.

*C. Deep Neural Network*

Deep Learning has been very famous of late and a lot of research is going on over it. The reason to implement this is because of its capability for the neural network model to increase the performance and response time of the system. Selection of relevant parameters among the data is done to find the dependency among the variables. It can reduce the complexity of the problem to a large extent. Neural networks hence serve a huge purpose in machine learning. Deep learning methods are part of distributed representation learning algorithms that try to organize information from the data by discovering features that compose multilevel distributed representations. Deep neural networks are typically trained, by updating and adjusting neurons weights and biases, utilizing the supervised learning back propagation algorithm in conjunction with optimization technique such as stochastic gradient descent. Transfer learning is used in many areas of machine learning without retraining the whole system and DNNs are well suited for the transfer learning. In the methodology suggested above, it has been limited to a self-learning conversational Map based Bot but with the help of deep neural networks we are able to go beyond this utility. The bot learns about the user’s behaviour, state of mind and the actions thus becoming a somewhat replica of a user’s persona.

There are two major types of dialogue systems: goal-oriented (i.e. Siri, Alexa, Cortana, etc.) and general conversation (i.e. Microsoft Tay bot). The former help people to solve everyday problems using natural language, while the latter attempt to talk with people on a wide range of topics.

General conversation models can be simply divided into two major types: generative and selective (or ranking) models. Also, hybrid models are possible. But the common denominator is that such models take in several sentences of dialogue context and predict the answer for this context.

Generative models	Selective models
<ul style="list-style-type: none"> <li>+ Can possibly generate arbitrary answer (more similar to general AI)</li> <li>+ Can generate answer in correct grammar form (e.g. with correct speaker gender)</li> <li>- Can generate answer with incorrect grammar/syntax</li> <li>- Prone to "general answer" problem</li> <li>- Difficult to impose properties on model replies (e.g. no obscene words, speak like some specific person), but possible!</li> </ul>	<ul style="list-style-type: none"> <li>- Restricted pool of answers which can not cover all dialogue topics</li> <li>- For context "What is your name, girl?" can select "My name is Stephen." (inconsistency)</li> <li>+ Predefined answers have good grammar/syntax</li> <li>+ Less prone to "general answer" problems</li> <li>+ You can customize answers for your own needs (without obscenities, kind answers)</li> </ul>

Figure 3 Difference in the conversational models

#### D. Regression Analytics

It is a predictive modelling technique which investigates the relationship between a dependent (target) and independent variable (s) (predictor). This technique is used for forecasting, time series modelling and finding the causal effect relationship between the variables. Which in our case are the actions performed by the user using the bot or by the bot for the user for an activity. Various types of regression are linear, polynomial, stepwise, logistic regression etc. Thus, embedded methods within our model consist of two types of regression techniques LASSO (L1) and RIDGE (L2) regression where L1 and L2 are regularisation levels. Recursive Feature Elimination (RFE) is also used along with L1 regression but in terms of Area under Curve (AUC) parameter L1 is more stable and accurate.

### IV. CONCLUSION

Now as we know in NLP, AI deals with how the program understands and processes the user's input while Machine Learning helps the code to evolve and learn from user's interactions over the period. So now as to how many types of Chatbots we have, as per convention here is a brief description.

#### A. Rule-based chatbots

These types of chatbots are one-dimensional and are intended to perform only the core function of the business. In technical terms, the code is rather simple as they are developed to perform based on defined parameters. The main motive of simple rule-based chatbots is to understand the requirements of the customers in a better way. However, they do lack the ability to learn and scale over the period.

#### B. Ai-Based Chatbots

AI chatbots are heavy programmed bots which use the concepts of Natural Language Processing (NLP) and Machine Learning (ML) to handle business tasks efficiently. Unlike rule-based chatbots, they learn and scale from their past experiences and give almost a human touch to the customers. These chatbots are usually backed complex and state of the art designed machine learning and NLP algorithms. Best of all, they can take real-time decisions based on the past data and understand customer's context to an extent while interacting.

AI is basically a program which is very good at solving problems on its own as compared to chatbots. Intelligently written code doesn't count into AI unless the developer is using heavy machine learning algorithms. So, AI is a process of enhancing a program to take real-time decisions more efficiently, accurately, and with a minimal requirement of human touch.

The AI engine learns over time, and we also keep on updating the code side to make them more efficient. There are projects where AI is empowering whole business and not only consumer, like on one hand it is selling stuff to the consumer, and on another hand

handling the ordering system, managing inventory, and then out of the money earned running campaigns. Despite Difference between AI and chatbots, both mostly go hand in hand and we should efficiently utilize power of both to achieve right results.

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#### REFERENCES

- [1] Ameixa, D., Coheur, L., Fialho, P., and Quaresma, P. (2014). Luke, i am your father: dealing with out-of domain requests by using movies subtitles. In Intelligent Virtual Agents, pages 13–21. Springer.
- [2] Banchs, R. E. and Kim, S. (2014). An empirical evaluation of an ir-based strategy for chat-oriented dialogue systems. In Asia-Pacific Signal and Information Processing Association, 2014 Annual Summit and Conference (APSIPA), pages 1–4. IEEE.
- [3] Banchs, R. E. and Li, H. (2012). Iris: a chat-oriented dialogue system based on the vector space model. In Proceedings of the ACL 2012 System Demonstrations, pages 37–42. Association for Computational Linguistics.
- [4] Bessho, F., Harada, T., and Kuniyoshi, Y. (2012). Dialog system using real-time crowdsourcing and twitter largescale corpus. In Proceedings of the 13th Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 227–231. Association for Computational Linguistics.
- [5] Martin, J. R. (2002). Meaning beyond the clause: area: self-perspectives. Annual Review of Applied Linguistics 22.
- [6] Ritter, A., Cherry, C., and Dolan, W. B. (2011). Data driven response generation in social media. In Proceedings of the conference on empirical methods in natural language processing, pages 583–593. Association for Computational Linguistics.

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