# Research Perspectives and Advancements in Open-Domain Chatbots

**Parinith R Iyer, Anala. M. R, Hemavathy R.**

*Abstract: The concept of open-domain chatbots has been one of the exciting problems in the field of research for a long time now. Open-domain chatbots are a class of chatbots that are expected to carry a conversation with a human on every possible topic in every context. This class of chatbots helps realize the goal of artificial general intelligence and is on the cutting edge of innovation and research unlike the various types of closed-domain chatbots. Success at building truly open-domain chatbots will also be coupled with man-made systems passing the Turing test and paving way for the next era of human-like systems. The objective of this paper is to highlight the key differences between the classes of chatbots and go on to showcase the advancements that have been made towards achieving this open-domain standard of conversation using reinforcement learning models. In doing this, various metrics are also explained and possible baselines that can be used as inspiration for future open-domain chatbots are presented.*

*Keywords : Open-domain, Chatbot, Artificial General Intelligence, Reinforcement-learning.*

## I. INTRODUCTION

Chatbots, sometimes referred to as conversational agents or dialog systems are a piece of interactive software that have back-and-forth with human beings and provide meaningful responses or perform relevant actions. The ideal for these chatbots is to behave in a very human-like manner. Many companies have led research and adoption while striving towards these ideals.

The number of chatbots being used by major organizations and industries has grown steadily in the recent past. These chatbots have been adopted in settings where a specific task needed to be accomplished and had well defined functions to perform. For increasing customer satisfaction and maximizing profits, major luxury brands have relied on chatbots before for customer e-service [1]. A comprehensive study was also made on the role of chatbots in the tourism industry [2] and the subsequent increase in user engagement. Apart from targeting a customer base for economic gain, there have been attempts at using chatbots to cater to people needing digital counseling for mental health reasons [3], and at supporting students' education by providing specific clarifications about academic topics [4]. These closed-domain chatbots have performed well and shown results as they are very focused for one task and one task only.

This paper studies and explores further into the categories and the respective capabilities of different kinds of chatbots. While the previously mentioned closed-domain chatbots have performed well for their use-cases, the strides in contemporary research tends to take place in the direction of open-domain chatbots which is expected to bring about the previously mentioned human-like aspect. The research towards on these fronts tend to revolve around the different model architectures used for the neural network that extract relevant information from a sentence and match it to a response to return back to the user. This paper aims to cover these techniques that have largely been responsible for and have enabled the recent and significant advancements taking place in the development of complete and partial systems that constitute an open-domain chatbot.

## II. LITERATURE REVIEW

The findings regarding the information obtained and presented in this paper come from various sources based on different topics. The cases of previous implementation of chatbot technologies in the closed-domain setting are drawn from the academic and industry-based publications. These include studies that highlighted the implementations of chatbots in commercial settings [1, 2] and in the public improvement domain [3, 4] of healthcare and education.

Establishing the fundamental differences and categorizing the various chatbots is a culmination of different sources of studies from industry leading writers [5, 12]. These sources also provide the base for understanding the numerous hurdles to building a chatbot in the first place, be it closed or open domain. Articles on open-domain chatbots [12] in specific go into detail by outlining the key challenges of context incorporation, coherent personality, model evaluation and intention and diversity in open-domain. These form the basis for understanding the problems associated with the many types of chatbots in the field in current times and lays emphasis on the need for extensive research in certain sub-categories.

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The leading first step towards the much discussed open-domain chatbots was seen with the shift in models used away from conventional deep learning architectures [13, 14, 15, 16] and introduction of the new sequence 2 sequence model in 2014 [17]. This architecture with the use of multiple LSTM networks [18, 20, 21], was able to obtain a very high BLEU [19] score for English to French translation. Since the introduction of the Seq2Seq network, most of the applications that deal with the natural language to natural language mapping for input and output use a variant of the same seq2seq network.

Studying the open-domain chatbots that have been researched and developed until now is based upon the work of leading researchers in the field who have contributed to new architectures. This paper explores chatbots like the Amazon Alexa prize winner MILABOT [22], the most popular online open-domain chatbot in china, Xiaoice [23], a superior language model from OpenAI, the GPT2 [27], and the conversational response model DialoGPT [29] that is based on GPT2. The article finally outlines the features and the stark differences from all these bots and the newly introduced Meena [31], the end-to-end neural conversation model from the Google Brain research team.

This final overview and study of Meena included in this paper goes on to present a new evaluation metric for evaluating the chatbots as well. By doing so, Meena is evaluated against other chatbots that are reviewed and is compared to a human as well. The corresponding BLEU scores are also compared and showcased. Currently this is the most advanced open-domain chatbot. The literature review points at further advancements in the future following the same trends and achieving even more human-like feel for the chatbots of the future.

### III. CLASSIFICATION OF CHATBOTS

Chatbots can be classified into different categories based on two broad criteria: the way the responses are gathered and the nature of the conversations. As shown in figure 1, there can be four broad categories arising from the two criteria just mentioned.
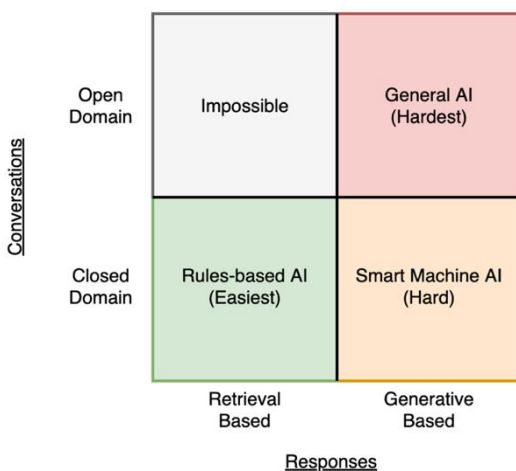


**Fig. 1. Illustrating the broad categories of chatbots**

Retrieval-based chatbots have a predefined set of responses ready to go when a user asks a question. They use direct matching of the user's phrase or employ heuristics [6] to match a question to select the appropriate response from the set. These chatbots do not generate any new text to answer questions. They do not make grammatical errors and have hardcoded responses for every query that they support. As a result, studies have found that this class of chatbots is highly desirable for use in production environments [7, 8] where it interacts with a company's customers. Lately, there have been certain multi-turn retrieval-based chatbots that are based upon recurrent neural networks as well [9, 10].

On the other hand, generative chatbots do not rely on pre-defined responses. These chatbots generate a new response for every user query from scratch. This generation of a response relies on the trained deep neural network that uses a large body of text conversations as the training data and knowledge base. The response is generated through machine translation techniques [11] that translates from an input to a response as in figure 2. For this reason, the grammar and the relevance to the context of the conversation is not guaranteed while interacting with generative bots as this is a very difficult task to achieve. This class of chatbots have not been adopted widely in the industry for the same reasons.
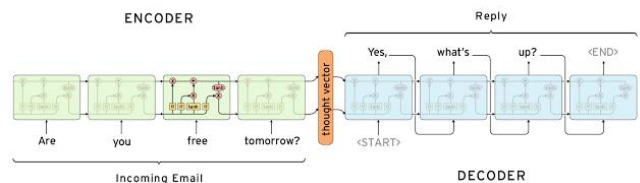


**Fig. 2. Illustrating machine translation for converting a query into a response [12]**

A closed-domain chatbot caters to queries that are limited to a very narrow domain and either has a default response to an out of domain query or rejects the query itself. An open-domain chatbot is one that accepts all types of queries from a user and effectively has a human-like conversation. Building an open-domain retrieval chatbot is impossible as one cannot write a template response for all the topics, so it has to be developed in a generative approach. To this end, research in open-domain generative chatbots have been increasing lately as more data is available from the internet.

### IV. HISTORY OF GENERATIVE CHATBOTS

Deep neural networks have always dominated as the standard solution for any complex problem posed in the artificial intelligence domain. They achieve very high accuracies in solving problems like speech recognition [13, 14], object detection [15, 16], etc. The key limitation of Deep neural networks is that they transform data into a vector of a fixed dimensionality. This limitation does not make deep neural networks a suitable fit to solve the problem of building a generative chatbot. The generative chatbots will be handling queries of arbitrary length and need to keep in mind the context of the conversation. After the study and introduction of the Sequence 2 Sequence model in 2014 [17],

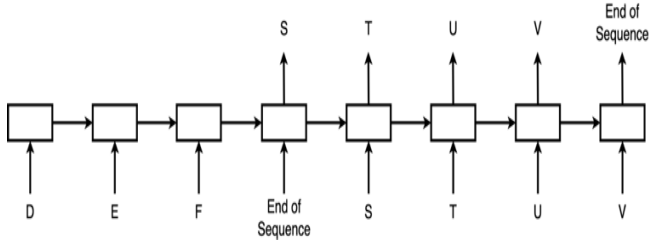the beginnings of text generation in chatbots were seen.



**Fig. 3. Illustrating the 2 phase LSTM based seq2seq model**.

By using a 2-step approach as shown in figure 3, each relying on a different variation of a Long Short-Term Memory (LSTM) architecture [18], The seq2seq model was able to achieve a BLEU score [19] of 34.81 on the English to French translation, which exceeded the other solutions at the time. The first LSTM module is responsible for reading the input sequence, per timestamp and converting into a large vector of some given dimensionality. The second LSTM module is a recurrent neural network [20, 21] that extracts the output sequence but it is conditionally based on the extracted input sequence vector.

After achieving a high score on the English to French translation BLEU metric, the model also was able to obtain a score of 36.5 on a public set of texts and did not degrade in performance when given long sentences [17]. This architecture formed the foundation for further study on the text generation capabilities using neural networks. All significant advancements on open-domain generative chatbots have drawn architecture and technical inspiration from this original seq2seq model.

## V. OPEN-DOMAIN CHATBOTS

Open-domain chatbots are the systems that can converse with another human about any arbitrary topic. The conversation is free to be directed towards any domain and the chatbot is expected to give a coherent and logical answer and response to the human. This is the leading attempt at simulating human-ness and passing the Turing test, which tests if a bot can convince a human that the bot is human. This level of complex behavior is achieved through a variety of modification to the early seq2seq network [17]. Some have made so many advancements since that time that it seems far different from the seq2seq architecture. The architectures and approaches that have managed to make the most strides in this field are discussed in this section.

### A. MILABOT

Developed by a group of researchers from the Montreal Institute of Learning Algorithms (MILA) in Canada, MILABOT [22] was built for the Amazon Alexa prize competition in 2017. This system consists of multiple generative and retrieval-based components including template-based models, bag-of-words models, sequence to sequence neural network models and latent variable neural network models.

The main source of data and knowledge for training their bot was from crowd-sourcing it. By obtaining a huge repository of real-world text conversations from crowd-sourced data and applying reinforcement learning, the model was able to outperform the other submissions in the

competition. Through A/B testing which was also through crowdfunding, the bot fared starkly better than its competition and has shown that it might perform even better given more data.
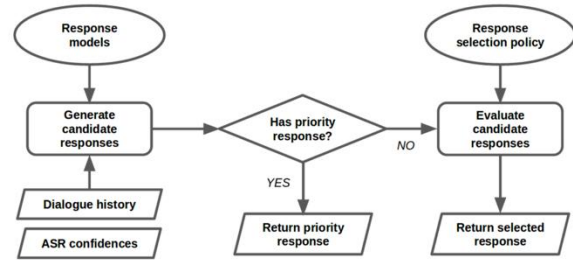


**Fig. 4. The dialog manager control flow for the MILABOT [22]**

As shown in figure 4, with all the different models at the MILABOT's disposal, the way it dealt with open-ended questions was to route every question with the relevant response selection model. Whenever a new user query was received, it was passed through a dialogue manager and it was decided which one of the available models (response selection policy) to use to respond to that specific user query. In this way, a very crude version of an open-domain chatbot came into being.

### B. Xiaoice

Developed in 2014, this is an AI system developed by Microsoft STCA [23]. This bot is the first truly inter-disciplinary chatbot that can answer questions on multiple domains. It does this by constantly taking in a huge corpus of data from the internet and evolving its own capabilities in stages. The most previous evolution took place on August 15th 2019 into its 7th generation. Apart from making small-talk and conversation, Xiaoice can perform creative tasks as well like composing songs, writing poems, create new images, imitate a journalist, etc. Leveraging these capabilities, it became the most popular social media bot on WeChat, a social media platform in China.

This bot takes into consideration both the emotional and intelligence quotient of a human being and tries to mimic it. The decision process for choosing an appropriate response is performed by a Markov-Decision process while constantly keeping track of the conversation-turns per session.
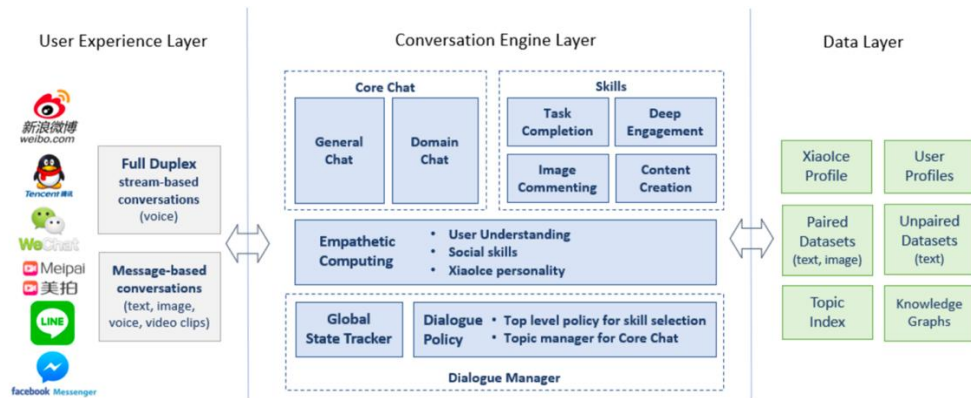
**Fig 5. Xiaoice system architecture [23]**

The incoming queries from the chat platforms are processed by a hierarchical decision making process and using the required modules of computation as presented in figure 5, the queries are either answered using normal conversation continuing phrases according to the bot's profile and the user's profiles or they are made to query the knowledge-base of the bot and give factual information to the user. This architecture has enabled Xiaoice to beat other social chatbots and widely become adopted in all chat platforms.

**C. DialoGPT**

DialoGPT is a model used for large scale response generation to any user query. This implementation uses a specialized hugging face transformer written in PyTorch and attains great performance in single-turn and multi-turn conversations. The system is dependent on another state-of-the-art language model called the OpenAI-GPT2 for making sure the grammatical errors are minimized in the responses that are generated. This language model and the Conversation response generation together make up the open-domain chatbot which is identified as the DialoGPT.

**1) OpenAI-GPT2 – Language model**

Drawing upon their previous work on GPT [24] which was a combination of attention-based transformers [25] and semi-supervised sequence learning [26], the OpenAI-GPT2 [27] is a language model that is trained to predict the next word in a given complete sequence of words using 40 gigabytes scraped from the internet as its knowledge base.

The dataset is obtained from scraping close to 80 million web pages and the diversity that comes from this wide source of data ensures that the language model generates the very natural next word and leads to very human-like sentences with correct grammar most of the time. This results in the model being able to generate long texts and paragraphs and write stories based on a small starter prompt. An example of this is shown in figure 6. This capability is highly desirable for any open-domain generative chatbot as following the grammar rules is an extremely difficult problem for these bots.
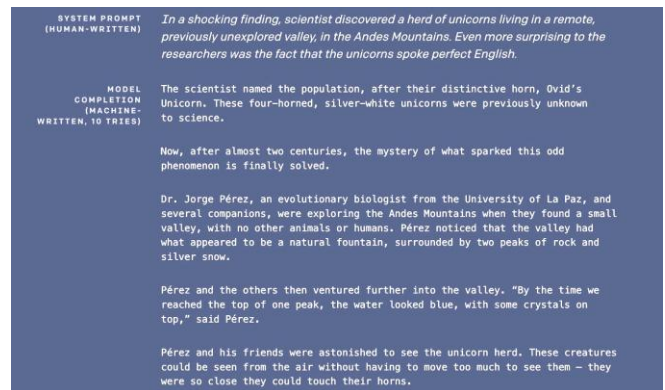


**Fig. 6. Highlighting the OpenAI-GPT2's capability to adhere to proper grammar. [28]**

**2) DialoGPT – Conversational response generation model**

Using the exceptional language model developed by OpenAI's team [27], the DialoGPT [29] is a response generation model that ties the other end of generative chatbots to support dynamic user questions and answer them in an accurate way. It is trained on 147 million conversation-like exchanges from the popular internet site Reddit's comment chains. Adding to this, it is a multi-turn conversational agent that takes into account the way the conversation flows and diverges with a human and generates an appropriate response from the context saved.

As is common with all these open-domain chatbots, crowd-sourcing was used to evaluate the chatbot and score based on pre-defined metrics like relevance, informativeness and human-likeness. Following this evaluation, the DialoGPT mode managed to convince humans that it generates more human like results than some of the human written responses for a subset of tests that were carried out. Overall, DialoGPT is hailed as the most human-like chatbot with respect to the grammar and sentence formation and relevance to the original user queries.

**3) Meena – An end-to-end neural conversational model**

The most recent addition to the open-domain chatbots is the Meena chatbot [30] developed by google and published to the public in February 2020. Meena is a 2.6 billion parameter end-to-end neural conversational model [31],

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which means that it includes all the functions of dialog management, language and grammar modelling, relevant data and fact fetching and the response generation in one single package. This offering is really a considerable technological leap in the domain considering the structure and architecture of the other bots before Meena. Researched and developed by the Google Brain Research Team, the Meena whitepaper [30] highlights how it can conduct and carry out conversations that are more specific and sensible than other open-domain chatbots. To justify this claim, the paper also proposes a new evaluation metric for open-domain chatbots called the Sensibleness and Specificity Average (SSA) which captures key characteristics that define a human conversation. This metric is also a crowd-funded process that judges the bot on sensibleness and specificity to the asked question.

The core of the Meena model is based upon the Google Brain research team's previous contribution to the domain, the Evolved Transformer (ET) seq2seq architecture [32]. As seen in figure 7, this was found by conducting an evolution-based neural architecture search on the original transformer architecture [25] that was already a proven well-performing model on various language tasks.
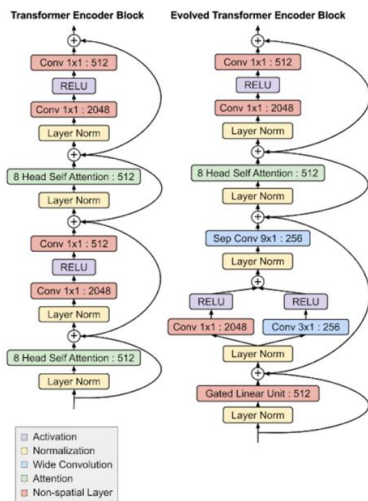


**Fig. 7. Compares the Evolved Transformer and the original Transformer architecture.**

To truly understand the prowess of the ET architecture, the graph in figure 8 shows that the increase in BLEU score [19] is significant for all number of model parameters.
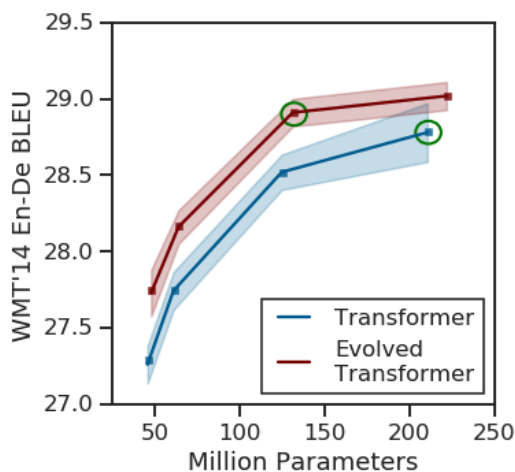


**Fig. 8. Comparing BLEU scores of ET and the original transformer architectures. [33]**

With this new and powerful ET module, the Google team found through analysis that using multiple of these transformers stacked together in the decoding phase of a response is key to generating a more human like conversation. This led to architecture of the Meena model which has a single ET module for the encoding phase and 13 stacked ET modules acting as decoders as shown in figure 9.
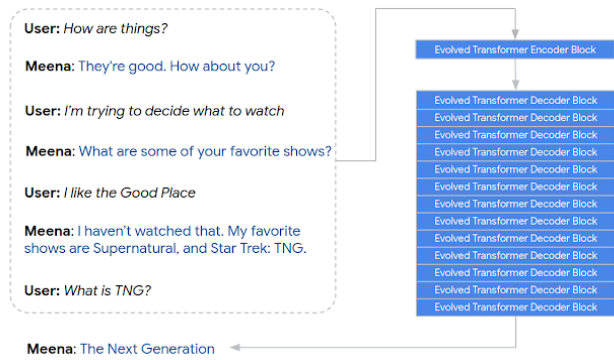


**Fig 9. Example of encoding and decoding a 7-turn conversation. [34]**

Using this newly found architecture and the more advanced evaluation metric for deciding the human-likeness of an open-domain chatbot using the SSA, Meena was put to test against other popular open-domain chatbots that are mentioned previously in this survey. Each bot was put through around 100 conversations each involving 1600 to 2400 turns. Judging each bot on sensibleness and specificity and then averaging the two gives the final SSA score. After this experiment, as shown in figure 10, it was found that Meena achieves marked improvements from the other bots and is closer to the goal of being a human like bot that research has been ever before.
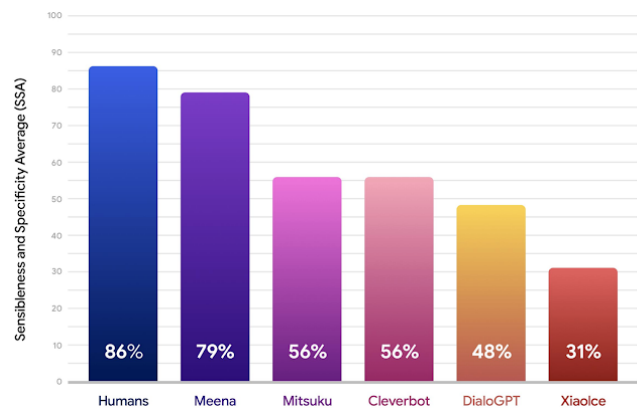


**Fig. 10. Meena SSA score compared to other bots and humans. [34]**

This recent advancement in the field has led to much inspiration for various teams across the world to draw from these finding and work towards an even better open-domain chatbot to reach human level conversation. Meena's prowess in the domain is definitely a good indicator of the direction and the pace of the research and this trend will only grow in future research undertakings.

## VI. RESULTS AND DISCUSSION

Through the survey conducted on various approaches to the problem of building generative open-domain chatbots, the results have been very promising considering the steady advancement in the field. This section discusses how the results of each contribution added upon the previous one and contributed to becoming a standard for the next one.

The initial breakthroughs came from the usage of Long Short-Term Memory (LSTM) architecture [18] for the Seq2seq model [17] which achieved a BLEU score [19] of 34.81 on English to French translation without failing on long sentences. Presenting itself as a mix of generative and retrieval based models, the MILABOT [22] used the seq2seq architecture with some standard retrieval based dialogue managers. The crowdsourced training for this bot made huge strides compared to other competing bots during the time and won this bot the Amazon Alexa Prize competition.

With an evolutionary model, changing its architecture and abilities over years, the 7th generation of the Xiaoice in 2019 bot attempts to mimic the emotional and the intelligence aspect of human. Although being a partially retrieval based bot, along with logical separation of speech and text processing and reply generation, it became the most popular and widely adopted social media chatbot. The Markov-Decision model based bot is the standard for social media chatbots to this day.

Extending the idea of the separation of concerns between language model to structure grammar of the replies and the generation of the content itself, the DialoGPT [29] became the most advanced generative chatbot by using the OpenAI-GPT2 [27] as the grammar safe language model. After training on a sea of reddit comments, the crowdsourced evaluation based on testing relevance, informativeness and human-likeness put DialoGPT at the top of all other chatbots in terms of human-ness. It is still the only system with near flawless grammar adherence.

Diverging from all these precedents of separating concerns among different aspects of a chatbot, the Meena chatbot [30] from Google uses a self-contained end-to-end neural conversation model [31]. This coupled with the usage of a stack of heavily modified evolved transformer (ET) seq2seq [32] modules pushed the performance of this bot by a large margin. The model based on a stack of decoders has proposed a new crowdsourcing-based evaluation metric called the Sensibleness and Specificity Average (SSA), on which it outperforms every other bot discussed in the paper by a huge margin obtaining a 79% score, almost reaching human level score at 86%. This result is very promising for future improvements for any bot in the field.

## VII. CONCLUSION

The field of open-domain chatbots has a research history dating back to early 21st century and has advanced a lot through the two decades. The initial piecewise components based models achieved the first breakthroughs in providing information to the humans on all topics and were the standard for a long time. Being a mix of retrieval and generative based bots didn't allow for more expansion of a chatbot's capabilities so a completely generative based approach was desired.

With the research on language models like the OpenAI GPT and the OpenAI GPT2, complete open-domain chatbots such as the DialoGPT came into light and became the benchmark for human-like speech for a long time. The very recent addition of the Meena bot to this family of open-domain chatbots presents a huge increase in technical prowess and the factor of human-likeness which is a very positive thing for this research field in specific. Further advancements will certainly draw inspirations from the architecture design and the component usage of the bots mentioned in this survey and achieve a score of evaluation even closer to the human level.

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