# HOW MAY I HELP YOU?
# THE EVOLUTION OF CUSTOMER SERVICE CHATBOTS




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**CHATBOT: "HOW MAY I HEL PYOU?"**

**USER:"I'D LIKE TO REQUESTA WARRANTY SERVICE FOR M Y LAPTOP."**

Chatbots, a type of Artificial Intelligence system that enabled dialog with humans, are becoming increasingly popular as a solution to many problems in the service industries to help schedule meetings, online shopping, restaurant reservations, customer care and so on. In 2019, Facebook announced that there were 300,000 chatbots available on Facebook Messenger. The chatbots can not only offer 24/7 service and instant responses, but also reduce operational costs. It is predicted that around 80 percent of queries will be dealt with by chatbots within the next five years, resulting in cost savings of $0.70 per interaction [1]. By assisting users in solving problems that require multi-step solutions or by acting as an assistant and support in a specific task, chatbots are changing the patterns of interaction between humans and computers. Nevertheless, the extension of chatbots to more domains has led to more complex designs and architectures. And so, it has led to more industrial-level solutions.

## How Did I Help You: The Evolution of Chatbot Design

The Turing Test inspired humans to communicate with computers in human language. In 1966, Joseph Weizenbaum at MIT created the first chatbot, ELIZA[2], which could make multiple social interactions with humans by identifying keywords and generating responses according to a set of pre-programmed rules. Although ELIZA did not understand the meaning of the sentences –the semantics, nor the grammatical structure – the syntax, it gave the illusion of understanding both of them.

Since ELIZA, progress has been made in chatbot design. For example, the Artificial Linguistic Internet Computer Entity (A.L.I.C.E.), which was developed in 1995, utilized "category" as a unit of knowledge and generated corresponding responses [3]. In the late 1970s, LUNAR was able to answer queries about different attributes of the rocks taken from the Moon by the Apollo 11 mission[4]. This system was able to process both the syntax and the semantics of a user's query, to try to understand the information the user was requesting, and to look in its database for the correct answer.

The first task-oriented chatbot, named GUS, a contemporary of LUNAR, was released in 1977. GUS (Genial Understander System [5]) was a travel agent with which users could book air flights. GUS had a "reasoner" component that captures users' intentions. The "reasoner" component is an early prototype of the most popular rule-based method in constructing task- oriented chatbots in industrial scenarios. The rule-based chatbot design predefines the structure of a dialog state as a set of slots to be filled during a conversation andgenerates responses based on some hand- crafted rules. A dialogue manager records all the dialogue status and controls the dialogue process. For example, in a meeting booking chatbot, a slot can consistof the reserved date, number of participants, or the location of meeting room, while the rules can involve asking questions until all the slots are filled and generating responses based on the template. However, such kind of rule-based chatbots are limited to specific domains as manually constructing and updating rules for complex systems are usually laborious.

In the new century, intelligent assistants incorporated with smart devices – such as Apple's Siri (2011), Amazon's Alexa (2013), and Microsoft's Cortana (2014) – boost a new wave of research on applying chatbots in the customer service domain. The typical retrieval-based chatbots select responses that best match users' requests by searching pre-constructed conversational repositories. Specifically, a chatbot analyzes the user input word by word, then matches the most relevant


Figure 1. The key technical components of chatbot construction.

responses with the query or provides responses to the most similar query. The intelligent assistants provide advanced "information retrieval" processes, in which responses are generated based on information constructed from search engines.

Another chatbot design method adopted the generation-based approach, which can generate a new response word by word based on the input request [6]. New generation-based chatbots include MILABOT [7] and UniOntBot [8]. Although the generation-based chatbots can break through the limitations of corpus, the generated responses are likely to have grammar issues or contain limited useful information. Thus, generation-based chatbots are still in the laboratory demonstration phase.

In summary, chatbots have gone through rule-based design, retrieval-based design and is setting to embrace a new era of real human-computer conversations based on natural-language generation. New generation of customer service chatbots incommercial use - Microsoft XiaoIce (2017), Lenovo Moli (2017), etc., have shown mighty strength in offering companionship, providing technical support, answering repeated questions, andserving other customer service scenarios.

## How Can I Help You Better: Chatbot Optimization in Intelligence, Emotion, and Collaboration with Humans

As customer service chatbots is becoming more and more common in everyday life, users are expecting it to provide natural human-machine interaction. The responses generated by the chatbot are expected to be not only appropriate (e.g. the same topic; making sense), helpful (e.g., containing useful and concrete information), but even tone-aware (e.g. conveying feelings like empathy and passion) and good-mannered (e.g. conforming to social norms). However, according to many research studies, "expectations of the users were not met." Numerous studies have provided potentially useful solutions to meet users' expectations. Here, we will discuss three directions to optimize customer-service chatbot design: intelligence, emotion, andcollaboration with humans.

## Enhancing The Intelligence Of Chatbot By Knowledge Graph

Chatbots are expected to have higher search efficiency and to provide personalized services. In natural language

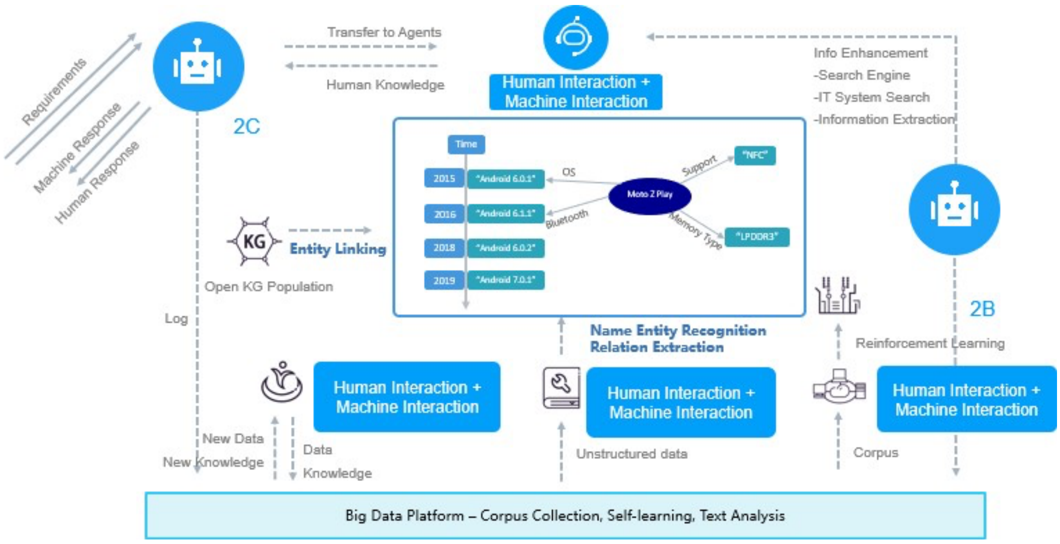


Figure 2. An industrial use case of knowledge graph construction.

processing, it is complicated but important to help computers learn how to understand a person's common sense and generate results accordingly. Knowledge graph, depicting both nature and human society, can help a chatbot to memorize, associate and make inferences. The mission of a knowledge graph embedded in a chatbot is to provide the customers with a personalized knowledge service and a precise answer, as well as to help the chatbot solve a sophisticated inference problem.

However, existing knowledge graphs only focus on specific domains, failing to answer questions that are out of range. A practical dialogue system requires a large-scale and complete knowledge graph; its construction, however, faces various challenges such as cost and efficiency. The construction of knowledge graphs adopts several strategies. For example, we can pre-set entities and their relations, and transfer the task to humans when encountering a failure. Meanwhile, we can apply the reinforcement learning method, where human agents label the dialogue based on real data and gradually construct the knowledge graph. Yoo and Jeong proposed a BERT-based for relation extraction method to auto-generate growing graph [9]. Figure 2 shows an industrial use case of knowledge graph construction on the customer service chatbot, Moli, which adopts a knowledge graph construction method that combines both pre-set entities and learning from real cases.

## Enriching Social Skills by Emotional Design

Similar to human-human communication, emotional elements -- such as tone and expression -- will affect user experience during interaction. Therefore, chatbots should be enriched with social characteristics that are coherent with users' expectations. Research has shown that customers' emotions have significant influence on their satisfaction with a service chatbot[10]. Unlike customer services delivered by human agents where positive emotions dominate, typical emotions expressed in the context of a service chatbot include anger and frustration, along with gratitude and cheerfulness[11].

In terms of emotional strategies in human-machine interaction, considerable amount of work has explored chatbots using empathy, politeness, apology, humor, etc., to build up the relationship with customers. For example, Hu et al. [12] trained a tone-aware chatbot based on customer care conversation from Twitter and found that empathetic tone significantly reduces users' frustration and sadness. Some other studies such as Ashktorab et al., [13] have demonstrated that emotional strategies without considering the conversation context have limited effects, especially when the customer's problem remained unsolved.

Appropriateness within the context should be one of the major criteria for an effective emotional strategy. The emotional strategies should consider the contextual features (e.g., when to express emotions and to whom) to provide problem solutions as well as emotional support. Lenovo Research designed fine-grained emotional strategies, i.e., responses to customer emotions based on major contextual features, derived from real human-machine conversations[14]. In the study, they extracted three contextual features from a conversation flow: 'when' (e.g., at the beginning of the conversation) does a customer express 'what' kind of emotion (e.g., anger) to 'whom' (e.g., product)? For example, if a customer complains about his new smartphone at the beginning, an appropriate strategy could be comforting the customer and guiding him to state his problem in detail. In addition, they proposed that 'where' (e.g., through webpage or social media) the customer expresses his emotion could be another contextual feature affecting the responses to emotional strategies. Empirical studies demonstrated fine-grained emotional strategies could enhance overall customer satisfaction.

To conclude, although there once existed debate about whether emotional design is needed since solving problems is the priority of customer-service chatbots, researchers have demonstrated that emotional strategies could smooth the task-oriented process and ease the barriers of human-machine communications.

## Enabling Complicated Problem Solving by Involving Human in the Loop

Due to the complexity of human-machine conversations, chatbots based on manual corpus can solve limited requests, and machine-generated responses may contain useless solutions. Therefore, it is necessary to involve human agents in real-world chatbots. Researches demonstrated that simply knowing there are human agents in the loop will enhance customer satisfaction towards the AI-generated results [15].

Next, we discuss how human agents and chatbots can cooperate to deal with user requests. A conventional practice is to let chatbots play the role as a junior worker, and if the interaction fails, the conversation will be escalated to higher-level human agents [16]. Reinforcement learning methods are also applied to construct chatbots, where human feedback would be used to update and optimize the chatbot-generated-suggestions [17]. Along with the development of crowdsourcing, new human-bot task allocation methods emerge, in which the whole conversation is decomposed into conversation turns, with the hard ones allocated to and answered by human workers [18].

There are many ways to deal with the relationship between human workers and chatbots. Figure 3 illustrates three examples of human-chatbot collaboration. When it comes to dealing with complex real-world conversations, chatbots still have a long way to learn from human experts.

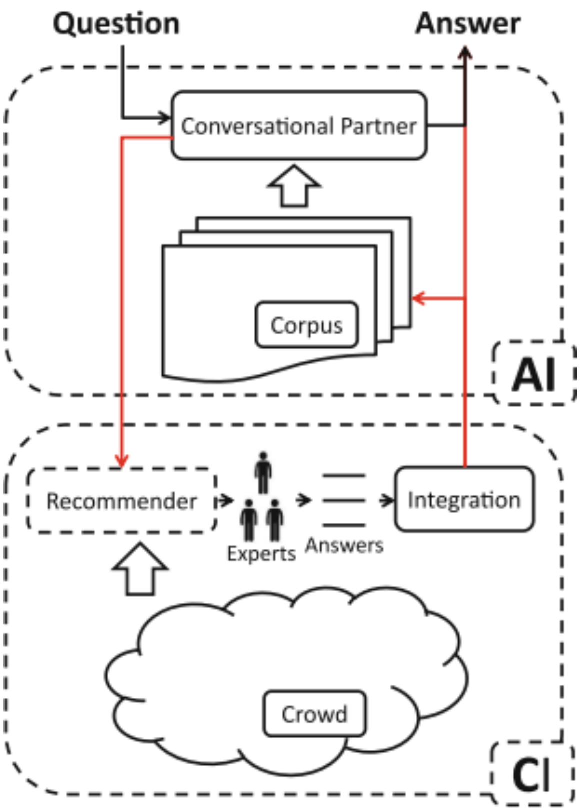


Figure 3. The crowd-sourcing framework of CI-Bot [18].

## How Will I Help You: Future Directions in Customer-Service Chatbot Design

With the rapid development of science and technology, we believe service chatbots would evolve to accustom to humans' diverse needs. There are three directions in which service chatbots would likely develop.

*1) Multi-platform application for multi-scenarios*

With the popularity of social media marketing, more and more brands are choosing to deploy chatbots on multiple platforms. For example, the same backend service may connect to different clients, such as product official website, WeChat, WhatsApp, and Messenger. New challenges have appeared, e.g. maintaining design consistency with respect to customer behavior.

*2) Multi-modal integration for vivid expression*

The development of artificial intelligence and human-computer interaction provides users with multi-modal elements to interact with chatbots, such as text, voice, picture, and video. Current human-computer interactions are limited to passive reactions to user requests. For example, when a user cannot elaborate on his problem, he or she can choose to use relevant pictures instead. With the development in conversation concurrent quantity, it might be the turn of the chatbot to decide when and how to provide customer service.

*3) Multi-chatbot combination for effective interaction*

Most customer service chatbots are experts that are good at solving specific tasks (e.g. booking flights or providing technical suggestions on PC repair), but they are hardly "know-it-alls". A single chatbot hardly satisfies users' multi-domain needs. Therefore, there is an emerging demand for integrating multiple chatbot agents to meet users' diverse requests. Research questions, including how the multi-chatbot efficiently leverages the domain knowledge of each chatbot, and how users perceive them as one, might be crucial for providing automated customer services.

There are many other examples of research in the optimization of human-machine communication. Thanks to cost reduction and increase in concurrent quantity, chatbots are being widely used in solving simple questions. However, there is still a conflict between chatbot utilization and user satisfaction. We look forward to seeing future customer service chatbots meeting customer requirements and bringing users a better service experience.

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