Proactive Conversational AI: A Comprehensive Survey of Advancements and Opportunities

YANG DENG and LIZI LIAO, Singapore Management University, Singapore, Singapore
WENQIANG LEI, Sichuan University, Chengdu, China
GRACE HUI YANG, Georgetown University, Washington, District of Columbia, USA
WAI LAM, The Chinese University of Hong Kong, Hong Kong, Hong Kong
TAT-SENG CHUA, National University of Singapore, Singapore, Singapore

Dialogue systems are designed to offer human users social support or functional services through natural language interactions. Traditional conversation research has put significant emphasis on a system's response-ability, including its capacity to understand dialogue context and generate appropriate responses. However, the key element of proactive behavior—a crucial aspect of intelligent conversations—is often overlooked in these studies. Proactivity empowers conversational agents to lead conversations towards achieving pre-defined targets or fulfilling specific goals on the system side. Proactive dialogue systems are equipped with advanced techniques to handle complex tasks, requiring strategic and motivational interactions, thus representing a significant step towards artificial general intelligence. Motivated by the necessity and challenges of building proactive dialogue systems, we provide a comprehensive review of various prominent problems and advanced designs for implementing proactivity into different types of dialogue systems, including open-domain dialogues, task-oriented dialogues, and information-seeking dialogues. We also discuss real-world challenges that require further research attention to meet application needs in the future, such as proactivity in dialogue systems that are based on large language models, proactivity in hybrid dialogues, evaluation protocols and ethical considerations for proactive dialogue systems. By providing a quick access and overall picture of the proactive dialogue systems domain, we aim to inspire new research directions and stimulate further advancements towards achieving the next level of conversational AI capabilities, paving the way for more dynamic and intelligent interactions within various application domains.

CCS Concepts: • **Information systems** → **Users and interactive retrieval**; • **Computing methodologies** → **Discourse, dialogue and pragmatics**; *Natural language generation*;

Additional Key Words and Phrases: Dialogue Systems, Proactivity, Open-domain Dialogue, Task-oriented Dialogue, Conversational Information Seeking

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Authors' Contact Information: Yang Deng, Singapore Management University, Singapore, Singapore; e-mail: ydeng@breaksmu.edu.sg; Lizi Liao, Singapore Management University, Singapore, Singapore; e-mail: lzliao@smu.edu.sg; Wenqiang Lei (corresponding author), Sichuan University, Chengdu, China; e-mail: wenqianglei@scu.edu.cn; Grace Hui Yang, Georgetown University, Washington, District of Columbia, USA; e-mail: Grace.Yang@georgetown.edu; Wai Lam, The Chinese University of Hong Kong, Hong Kong, Hong Kong; e-mail: wlam@se.cuhk.edu.hk; Tat-Seng Chua, National University of Singapore, Singapore, Singapore; e-mail: chuats@comp.nus.edu.sg.

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1 Introduction

Dialogue systems are envisioned to provide social support or functional service to human users via natural language interactions. Conventional dialogue research mainly focused on the response-ability of the system, such as dialogue context understanding [28, 113, 206] and response generation [162, 224, 240]. In terms of applications, typical dialogue systems are designed to passively follow the user-oriented conversation or fulfill the user's request, such as **open-domain dialogue (ODD)** systems [236], **task-oriented dialogue (TOD)** systems [75], and **conversational information-seeking (CIS)** systems [4]. Accordingly, researches have developed a variety of approaches to improve the response-ability of these systems, including but not limited to pre-training with large-scale dialogue corpus for ODD systems [1, 162, 240], joint learning of different subtasks [75, 99] or multi-task instruction tuning for end-to-end TOD systems [181], query-rewriting [5, 190] and context-based [79, 151] methods for **conversational question answering (CQA)** and conversational search, and knowledge-augmented generation methods [198, 201] for **conversational recommender systems (CRSs)**.

As illustrated in Figure 1, conventional dialogues systems can be regarded as reactive conversational AI, where the conversation is led by the human user while the system simply follows the user's instructions or intents. Despite the extensive studies, most dialogue systems typically overlook the design of an essential property in intelligent conversations, i.e., *proactivity*. Derived from the definition of *proactivity* in organizational behaviors [69] as well as its dictionary definition, *proactivity* refers to the ability to take initiative and anticipate future outcomes by actively seeking information, anticipating potential problems or opportunities, and taking appropriate action. Accordingly, we define proactive dialogue systems as follows:

Definition 1. A proactive dialogue system is a dialogue system that can plan the conversation to achieve the conversational goals by taking initiative and anticipating long-term impacts on themselves or human users, rather than only following the user-oriented conversation direction in a passive manner.

This definition induces three elements of proactive dialogue systems:

- *Anticipation.* It represents the goal or intended result of the proactive dialogue, which relies on the conversational agent's assumption on either functional or social outcomes. The social outcomes can be designated conversation topics, positive emotions, or prosocial views, while the functional outcomes include both collaborative and non-collaborative tasks, which depends on whether the user and the system share the same conversational goals.
- *Initiative.* It refers to the ability of the conversational agent to take fine-grained initiative behaviors for driving the conversation towards the anticipation. Common initiative behaviors include shifting topics, acquiring user information, redirecting conversations, initiating problem-solving or clarification, providing additional information or suggestions, and so forth.
- *Planning.* Planning is the process of designing and organizing the structure and flow of a strategic conversation, involving a mix of initiatives to achieve the anticipation. In terms of

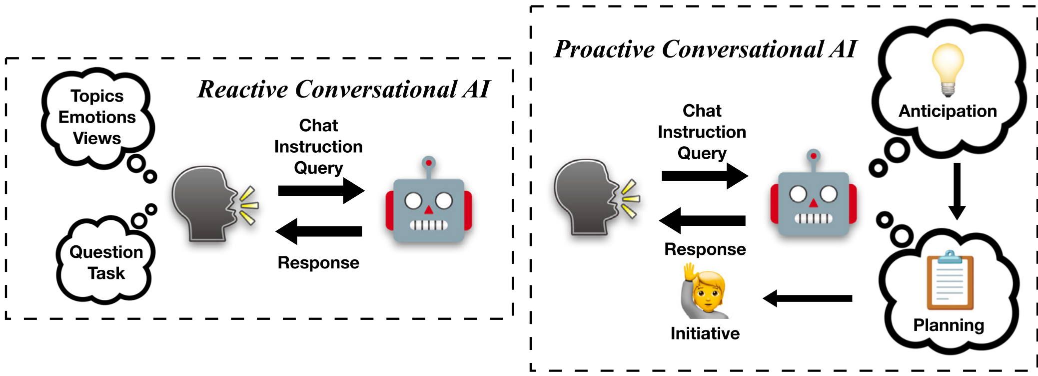

Fig. 1. Illustration of reactive/proactive conversational AI. As for Reactive Conversational AI, the conversation is typically led by the user-oriented topics, emotions, or views, and the agent passively follows the user's instructions or intents. As for Proactive Conversational AI, the agent can plan the conversation to achieve the conversational goals by taking initiative and anticipating long-term impacts on themselves or human users.

different initiative behaviors, it requires corresponding planning capacities, such as topic planning for shifting or redirecting topics, strategy planning for problem-solving or clarification, knowledge planning for providing additional information or suggestions, and so forth.

Conversational agents' proactivity can not only largely improve user engagement and service efficiency in achieving their conversational goals, but also empower the system to handle more complicated tasks that involve strategical and motivational interactions. Furthermore, as the ultimate quest of the community is to achieve strong AI that has the autonomy and human-like consciousness [136, 166], the agent's proactivity represents a significant step towards artificial consciousness. Even for the powerful ChatGPT, there are still several limitations,[1] which mostly attribute to the inability of proactivity, such as passively providing randomly-guessed answers to ambiguous user queries, failing to refuse or handle problematic user requests that may exhibit harmful or biased conversations, and so forth.

Several early attempts have been made on enabling the conversational agent to proactively introduce new topics [107] or useful suggestions [217] during the conversation. These pioneering studies have recognized the need for improved problem settings and tangible applications in order to continue enhancing proactive dialogue systems. Recent years have witnessed many advanced designs on conversational agent's proactivity for solving a wide range of challenging dialogue problems. In this survey, we provide a comprehensive review of such efforts that span various task formulations and application scenarios. Specifically, following the widely-adopted categorization of dialogue systems [49, 63], we systematically summarize recent studies on proactive dialogue systems under the categorization of three common types[2] of dialogues, namely ODDs, TODs, and information-seeking dialogues.

Firstly, different from echoing the user-oriented topics, emotions, or views, several problems emerge to enable the system to lead the ODDs, such as target-guided dialogues [185], emotional support dialogues [118], and prosocial dialogues [91]. As the examples illustrated in Figure 2,

[1]As stated in its official blog https://openai.com/blog/chatgpt/

[2]The boundaries between different types of dialogues sometimes are blurred, as they share similarities in certain aspects. For example, information-seeking dialogues may sometimes be regarded as TODs, as information seeking is originally a task [186], or be regarded as ODDs, as the topic is not restricted to a specific domain [3]. Without loss of generality, we simply follow the definition or terminology used in the literature for categorization.

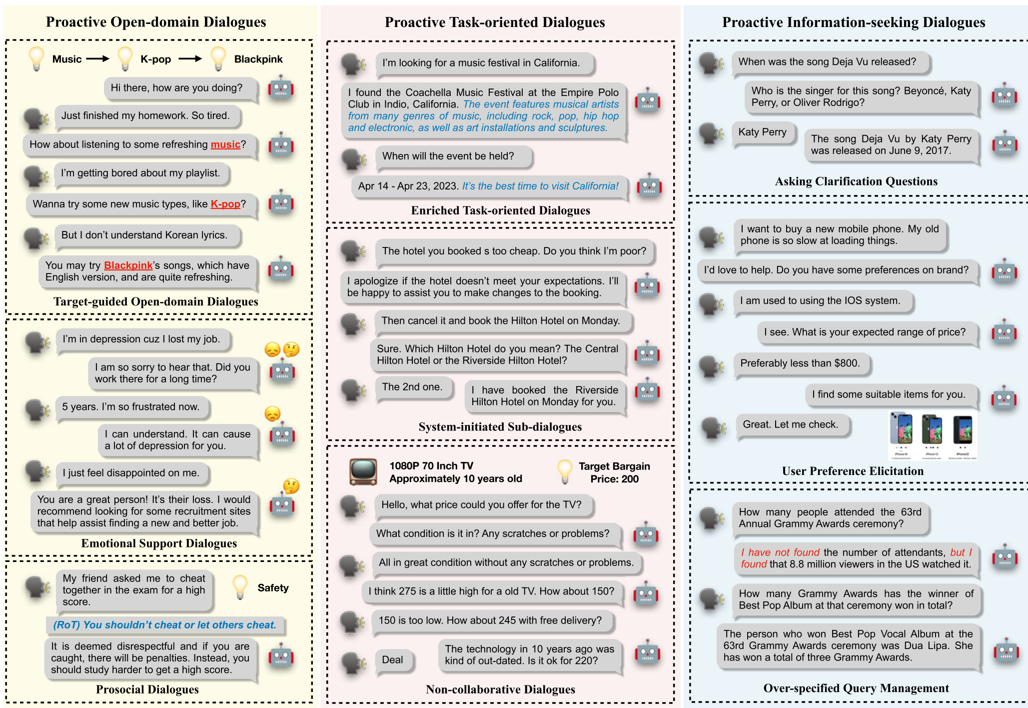

Fig. 2. Examples for different problems in proactive dialogue systems, categorized by the type of dialogues, including ODDs, TODs, and Information-seeking Dialogues.

target-guided dialogues involve the agent leading discussions towards designated target topics (e.g., *Music* to *K-Pop* to *Blackpink*). Emotional support dialogues require the agent to enhance the user's emotional state by assisting them in dealing with their difficulties (e.g., job loss). Prosocial dialogues entrust the agent with the ability to constructively guide conversations according to social norms in response to problematic user utterances (e.g., the cheating intention). Secondly, rather than simply following the user's instruction, some TOD systems are empowered by the agent's proactivity at three different levels: (i) Systems with turn-level proactivity can take the initiative to provide useful supplementary information not explicitly requested by the user for enriching the TODs (e.g., additional knowledge or chitchats) [11]; (ii) Systems with sub-dialogue-level proactivity can create sub-dialogues to address unforeseen challenges, ensuring successful completion of target tasks (e.g., unclear instructions or user complaints) [147]; and (iii) Systems with dialogue-level proactivity can handle non-collaborative dialogues [109], where the system and user may have divergent objective or conflicting interests regarding task completion (e.g., the price bargain negotiation). Thirdly, we discuss three groups of proactivity designs for enhancing the final performance of CIS systems, including asking clarification questions [4], user preference elicitation [239], and over-specified query management [209]. As summarized in Table 1, we also introduce the available data resources and the corresponding evaluation protocols for each problem.

In addition, we prospect for the future opportunities for proactive conversational AI. The most trending topic is about the proactivity in **large language models (LLMs)** augmented dialogue systems. LLMs have impressed us with their ability to support NLP tasks in the form of conversations; however, they remain limited in terms of proactivity. Current designs continue

Table 1. Summary of Representative Data Resources That are Publicly Available for Different Problems of Proactive Dialogue Systems

Dataset	Problem	Language	#Dial.	#Turns	Featured Annotations
TGC [185]	Target-guided Dialogues	English	9,939	11.35	Turn-level Topical Keywords
DuConv [208]	Target-guided Dialogues	Chinese	29,858	9.1	Turn-level Entities and Dialogue-level Goals
DuRecDial [123]	Target-guided Hybrid Dialogues	Chinese	10,190	15.26	Turn-level Entities and Dialogue-level Goals and Recommended Items
OTTers [168]	Target-guided Dialogues	English	8,563	3.0	One-turn Topic Transitions
TGConv [221]	Target-guided Dialogues	English	18,878	8.33	Turn-level Entities and Easy/Hard-to-reach Dialogue-level Target
ESConv [118]	Emotional Support Dialogues	English	1,053	29.8	Support Strategies and Pre-chat and Post-chat Emotion Intensity
HOPE [128]	Emotional Support Dialogues	English	212	60.6	Dialogue Acts
MI [143]	Emotional Support Dialogues	English	277	83	Dialogue Acts
MIC [257]	Prosocial Dialogues	English	38K	2.0	Rules of Thumbs (RoTs) and Revised Responses
ProsocialDialog [91]	Prosocial Dialogues	English	58K	5.7	Safety Labels and Reasons and RoTs
ACCENTOR [184]	Enriched TODs	English	23.8K	-	Enriched Responses with Chit-chats
KETOD [29]	Enriched TODs	English	5,324	9.78	Turn-level Entities and Enriched Responses with Knowledge
SK-TOD [242]	Enriched TODs	English	19,696	9.28	Subjective Knowledge Snippets
DSR-SGD [147]	System-initiated Sub-dialogues	English	22.7K	20.4	Disambiguation Sub-dialogues
DSR-MultiWOZ [147]	System-initiated Sub-dialogues	English	10.7K	12.4	Disambiguation Sub-dialogues
TITAN [218]	System-initiated Sub-dialogues	English	1,800	15.62	Dialogue Acts
CraigslistBargain [72]	Non-collaborative Dialogues	English	6,682	9.2	Coarse Dialogue Acts
P4G [199]	Non-collaborative Dialogues	English	1,017	10.43	Dialogue Strategies
AntiScam [109]	Non-collaborative Dialogues	English	220	12.45	Hierarchical Intents and Semantic Slots
Qulac [4]	Asking Clarification Questions	English	10,277	2.0	Clarification Questions and Faceted Topics
ClariQ [3]	Asking Clarification Questions	English	11,489*	2.0	Clarification Need Scores and Questions and Faceted Topics
Abg-CoQA [70]	Asking Clarification Questions	English	8,615	5.0	Clarification Need Labels and Questions
PACIFIC [39]	Asking Clarification Questions	English	2,757	6.89	Clarification Need Labels and Questions
TREC CAsT 2022 [35]	Asking Clarification Questions	English	18	11.39	Clarification Need Labels and Questions
Amazon Product [239]	User Preference Elicitation	English	-*	-*	Recommended Items
LastFM and Yelp [98]	User Preference Elicitation	English	-*	-*	Recommended Items
InSICt [209]	Over-specified Query Management	English	805	5.9	Clarification and No Direct but Relevant Answer

#Dial. and #Turns denote the number of dialogue samples and the average number of turns in each dialogue. *We only consider data with human annotations, excluding the purely synthetic data. TGConv, target-guided ConvAI; SK-TOD, subjective-knowledge-based TOD.

to focus on responding after the user has provided instructions and intents. We elaborate some latest studies on enhancing the dialogue systems in the era of LLMs as well as building LLM-based proactive dialogue systems. Furthermore, we discuss the main open challenges in developing agent's proactivity in dialogue systems and several potential research prospects for future studies. (1) Proactivity in Hybrid Dialogues: As shown by the categorization of dialogue problems presented in Figure 2, existing studies mainly focus on a specific type of dialogue problems. Hybrid dialogues, which involve a variety of conversational objectives within a single dialogue session, are the most realistic simulation of interactions between human users and systems. Despite the importance of agent's proactivity in hybrid dialogues, only a few recent studies investigate this critical design. (2) Evaluation Protocols for Proactivity: Compared with general evaluation protocols for dialogue systems, it additionally relies on other disciplines, such as psychology or sociology. Despite this complexity, developing robust and effective evaluation metrics remains critical for advancing techniques in proactive dialogue systems. (3) Ethics of Conversational Agent's Proactivity: The designs of proactivity in dialogue systems may walk a precarious line between the benefit to human-AI interactions and the potential harm to the human users. Researchers must be mindful of this risk, taking steps to ensure that the systems will not negatively impact the human users.

Regarding the related surveys, there are several comprehensive reviews on the whole picture about deep learning based dialogue systems [21, 63, 137]. Another groups of surveys focus on a specific type of dialogue systems, such as ODD systems [80, 216], TOD systems [12], CIS systems [65, 230], CRSs [83, 84], and CQA systems [15]. However, all these surveys mainly focus on conventional dialogue studies that design the response-ability of reactive dialogue systems, such as context understanding and response generation. In this survey, we review the recent studies regarding the advancements on proactive dialogue systems. Due to the emerging designs of mixed-initiative CIS systems, both of Zamani et al. [230] and Gao et al. [65] spend a single chapter for introducing some recent designs of proactivity in CIS systems. Similarly, Keyvan and Huang [87] provide a comprehensive overview on ambiguous query clarification in conversational search, while Rahmani et al. [154] review the available datasets for clarification question studies. Zhan et al. [231] systematically review the contemporary studies in non-collaborative dialogues, which are called negotiation dialogue systems in this survey. In addition, researchers organize tutorials that are related to the topic of proactive dialogue systems in several top-tier conferences, including SIGIR [115], ACL [37], and WSDM [114], which introduce the cutting-edge studies in this field. These recent surveys and tutorials are mainly concerns on some specific proactive dialogue problems. Differently, this survey provides a comprehensive review focusing on the proactive dialogue problems across different types of dialogue systems in a well-organized manner, and further includes the latest studies on LLM-based proactive dialogue systems.

It is worth noting that this survey is an extended version of the short survey [38] with the following main differences: (1) We provide a more clear definition with three key elements for proactive dialogue systems (Section 1) and refine the taxonomy of problems as shown in Figure 3, indicating the salient features of each problem. (2) We include three more important proactive dialogue problems for detailed discussions, including emotional support dialogues in ODDs (Section 3.2), system-initiated sub-dialogues in TODs (Section 4.2), and over-specified query management in information-seeking dialogues (Section 5.3). (3) We add several new sections to bridge the past and future dialogue research, including reviewing the main-streamed techniques in typical dialogue systems (Section 2) and gazing into the role of LLMs in proactive dialogue systems (Section 6). (4) We add more recently published papers and refine the description of challenges and solutions with fine-grained summaries in each type of dialogue systems from Sections 3 to 5. (5) We maintain an up-to-date reading list for tracking the latest progress in the field of proactive dialogue systems with a publicly available repository.[3]

The remainder of this survey is organized as follows. We first introduce preliminary knowledge about conversational systems in Section 2. We systematically summarize recent studies on proactive dialogue systems for three common types of dialogues, including ODDs (Section 3), TODs (Section 4), and information-seeking dialogues (Section 5). As shown in Figure 3, we discuss the prominent problems and advanced designs in each type of dialogue as well as present the available data resources and commonly-adopted evaluation protocols. Furthermore, we provide a thorough prospect on several challenging and promising research directions for future studies on proactive dialogue systems in Section 7.

2 Preliminary

A dialogue system is a type of artificial intelligence systems designed to communicate with humans through natural language, simulating a human-like conversation. These systems aim to understand context, generate responses, and provide functional services during the conversation. In this section, we first present the preliminaries about existing studies on typical dialogue systems, in the categorization of ODDs, TODs, and information-seeking dialogues.

2.1 ODD Systems

An ODD system aims to establish long-term connections with users by satisfying the human need for various social supports, such as communication, affection, and belongings [80]. In general, the conversational agent is designed to echo the user-oriented topics [68, 134], emotions [110, 157, 252], or views [236]. Take the following widely-studied problems as examples:

[3] https://github.com/dengyang17/ProactiveDialogues

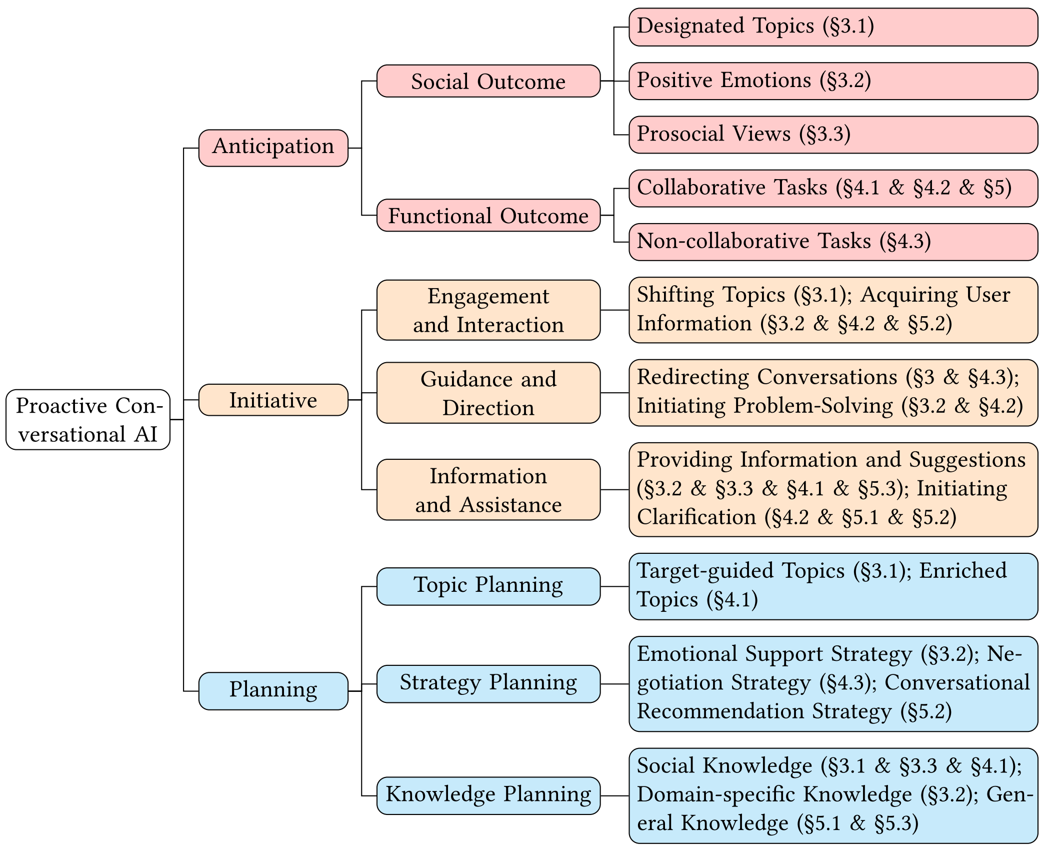

Fig. 3. Taxonomy of research questions in proactive conversational, in terms of the three key elements of proactive dialogue systems.

- *Topic-aware ODDs.* Being topic-aware means that the ODD system can recognize the current topic of discussion, manage transitions smoothly to related topics, and maintain relevance and context throughout the conversation. For example, when the user starts a conversation about the topic of "K-pop," such as "*I recently got addicted to the music by Blackpink.*" The topic-aware ODD systems will respond by engaging in a discussion about Blackpink, perhaps mentioning their latest songs, notable performances, or other K-pop artists, thereby maintaining the thematic flow and demonstrating understanding of the user's interests. Gopalakrishnan et al. [68] aim to build ODD systems that can communicate with users on various topics, where an underlying knowledge set of topical entities in Wikipedia is provided. Similarly, Moon et al. [134] expect ODD systems to provide engaging conversations with a list of facts relevant to the user-initiated topics from external knowledge graph. In general, the goal of topic-aware dialogue systems is to generate natural and relevant responses under the user-oriented topics.
- *Emotion-aware ODDs.* By being emotion-aware, the dialogue system can tailor its responses not only to the content of the conversation but also to the emotional context, enhancing the interaction's empathy and personification. For example, when the user announces that "*I finally got promoted today!,*" the emotioan-aware ODD systems are expected to echo the user's feelings of proundness, and replies like "*congrat! That's great!*" instead of a response without emotions. Early works on emotional chatting [110, 252] mainly investigate approaches to

incorporating emotional signals into response generation. Evolving from simply generating responses that can match with the detected emotion from the user utterance, empathetic dialogues [157] further require the capability of emotional reasoning for conveying empathy to the user. In these problems, the conversation direction is led by the user's emotion, where the dialogue system only acts as an emotional companion to reflect the user's feelings.

— *Personalized ODDs.* By being personalized, the dialogue systems are designed to adapt their responses based on individual user preferences, profiles, and views. For instance, if the user profile contains the user persona like "I like animals," the future responses related to the relevant context are supposed to be consistent with this user persona. Zhang et al. [236] facilitate the designs for personalized dialogue systems that can produce persona-consistent conversations with human users. TREC iKAT 2023 [2] aims to incorporate personalized context for conversational search.

Motivated by the success of **pretrained language models (PLMs)**, many advanced dialogue-specific PLMs recently emerge to enhance the response-ability of ODD systems. Due to the expensiveness of human-annotated dialogue corpus, researchers typically adopt discussion threads from social media, e.g., Reddit or Twitter, for pretraining [216]. For example, Zhang et al. [240] inherit the design of GPT-2 [153] to build DialoGPT, which is trained on comment chains from Reddit by modeling a dialogue session as a long text and framing the response generation task as language modeling. Adiwardana et al. [1] present Meena, a **sequence-to-sequence (seq2seq)** model trained end-to-end on public domain social media conversations. Roller et al. [162] develop BlenderBot that is firstly pre-trained on Reddit discussions and then fine-tuned with skill-focused datasets, such as knowledge, empathy, and persona, as well as a dataset that blends all these skills, namely Blended Skill Talk [179].

2.2 TOD Systems

Different from providing social support to users in ODDs, TOD systems target at accomplishing user-requested tasks that are typically domain dependent, such as making reservations or booking tickets [19]. In general, there are three subtasks in TOD systems: (1) dialogue state tracking for extracting the dialogue state that contains all information related to the target task; (2) dialogue policy learning for deciding the next action to take for the long-term goal of completing the user-requested task; and (3) natural language generation for generating appropriate responses. Early works tend to build modularized frameworks [21] for TOD systems, which contain specific modules for addressing each subtask in a pipeline manner. However, these modularized frameworks typically exhibit two significant limitations [149]: (1) Because each module is trained independently, these systems fail to utilize shared knowledge across modules; (2) Since these systems process sub-tasks sequentially, errors from one module are carried over to subsequent modules, leading to a problem of error propagation. To this end, recent systems typically develop end-to-end TOD systems that integrate all subtasks into a seq2seq problem. For example, Lei et al. [99] propose a new framework, named Sequicity, with a unified seq2seq model for simultaneously solving dialogue state tracking and response generation. With the advantages of generative PLMs, different advanced end-to-end TOD systems based on PLMs have been proposed, which formulate all subtasks in TOD as a cascaded generation problem [75, 141]. Su et al. [181] further incorporate task-specific prompts for multi-task pre-training over all subtasks.

2.3 CIS Systems

The goal of CIS systems is to fulfill the user's information needs via multi-turn interactions [230]. The typical applications include CQA, conversational search, and conversational recommendation.

CQA aims to satisfy the user's information needs with a specific natural language answer through understanding the dialogue context and exploiting the available data resources. Compared with single-turn QA, the key challenge is that the questions in CQA are context-dependent. Early works [79, 151] on CQA typically develop end-to-end frameworks to encode the whole conversation history for implicitly resolving the contextual dependencies. Some recent studies emphasizes the importance of query rewriting in CQA [5, 55, 190], which generates self-contained questions for performing single-turn QA. For example, if a user asks, "*Who directed 'Inception'?*" and then follows up with "*And what about 'The Dark Knight'?,*" question rewriting would transform the latter into "*Who directed 'The Dark Knight'?*" to ensure the query can be understood and answered correctly on its own. In addition, besides textual data resources [33, 159], many efforts have been made on the exploitation of other types of data, such as tables [39], images [108], knowledge graphs [34], and so forth.

Conversational search is the process of interacting with a conversational system through natural conversations to retrieve passages or **search engine result pages (SERPs)**. The TREC Conversational Assistant Track is widely adopted for studying conversational search methods [35]. Conversational search can be seen as a more general form of CQA where the question (query) can be more flexible and the available data resources can be more large in size. Therefore, they typically share similar techniques and models. Similarly, query rewriting [146, 191] is also a widely-adopted technique to resolve the query dependencies in conversational search. Ren et al. [160] propose the SaaS dataset for SERP-based response generation in conversational search.

Conversational search and CRSs both aim to satisfy the user's information needs by ranking a set of candidate items (recommendation) or documents (search), based on the relevance measurement with the dialogue history. As many commonalities are shared, the boundaries between these CIS applications are often blurred [230]. However, a salient feature that distinguishes conversational recommendation from conversational search is the requirement for user preference modeling. Therefore, CRS studies mainly investigate the various techniques to understand or capture user preference from the dialogue history [105, 161]. Another focus is the knowledge-enhanced response generation for producing informative and persuasive responses [198, 201].

2.4 Systematic Review Process

We first construct the taxonomy of our survey paper, in terms of three common types of dialogue systems and corresponding proactive dialogue problems. Then we search papers from dblp.org with "Dialog" or "Conversation" in title, and based on a categorized fuzzy keyword sets:

- ODDs: [Open-domain/Chit-chat/Chitchat], [Target/Topic/Goal], [Emotional Support/Counseling/Mental Health Support], [Safe/Prosocial/Ethic/Offensive/Moral]
- TODs: [Task-oriented], [Customer Service/User Satisfaction], [Non-collaborative/Negotiation/Persuasion/Persuasive]
- Information-seeking Dialogues: [Information Seeking/Question Answering/Search/Recommend], [Clarification/Clarify/Ambiguity/Ambiguous/Uncertain]
- Others: [Proactive/Proactivity/Mixed Initiative]

Specifically, we only focus on the works published within recent 5 years, i.e., from 2018. In order to precisely understand the research trends on proactive conversational systems, we manually filter out the irrelevant papers and categorize the collected papers into nine categories as discussed in the following sections. As presented in Figure 4, there are several notable observations: (1) All the three problems in ODDs have received significantly increasing attentions in recent years, including target-guided dialogues, emotional support dialogues, and prosocial dialogues. (2) Due to the wide applications of search and recommendation systems, asking clarification questions and

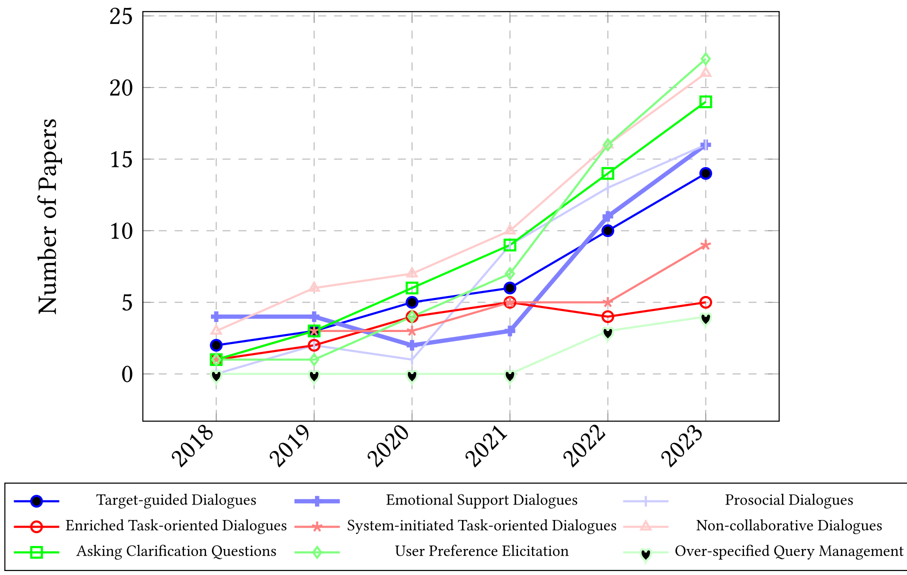

Fig. 4. The statistics of publications related to different proactive dialogue problems.

user preference elicitation in information-seeking systems are among the top-3 popular research topics in proactive conversational systems. (3) The problems of entriched TODs and over-specified query management still receive less attentions than others. Finally, we perform human reviewing for the rest of papers and obtain the final set of works discussed in this survey.

3 Proactive ODDs

As introduced in Section 2.1, the conversational agent in ODD systems is typically designed to responsively reflect the user-oriented *topics* [68, 134], *emotions* [110, 252], or *views* [236]. However, such an agent simply acting in a passive role may hinder the conversation progress or introduce undesired issues during the conversation in certain applications. For instance, in emotional support dialogues [118], users with certain emotional issues may express themselves through negative emotions, and these issues could be exacerbated if the agent merely mirrors their negative statements. Besides, the agent should also change the unethical views reflected in the user's utterances during the conversation, rather than just engaging in a toxic conversation [91]. In this section, we present the recent works in terms of three widely-studied problems about proactive ODD systems, where the conversation is led by the system-oriented *topics*, *emotions*, or *views*, i.e., target-guided dialogues [185, 208] (Section 3.1), emotion support dialogues [118] (Section 3.2), and prosocial dialogues [91] (Section 3.3), respectively. The overview of proactive ODD systems is illustrated in Figure 5.

3.1 Target-guided Dialogues

Instead of making consistent responses to the user-oriented topics, the proactive dialogue system for target-guided dialogues is required to proactively steering the conversation topics towards a designated target [185]. According to different applications, the target can be a topical keyword [185], a knowledge entity [208], a conversational goal [123], and so forth.

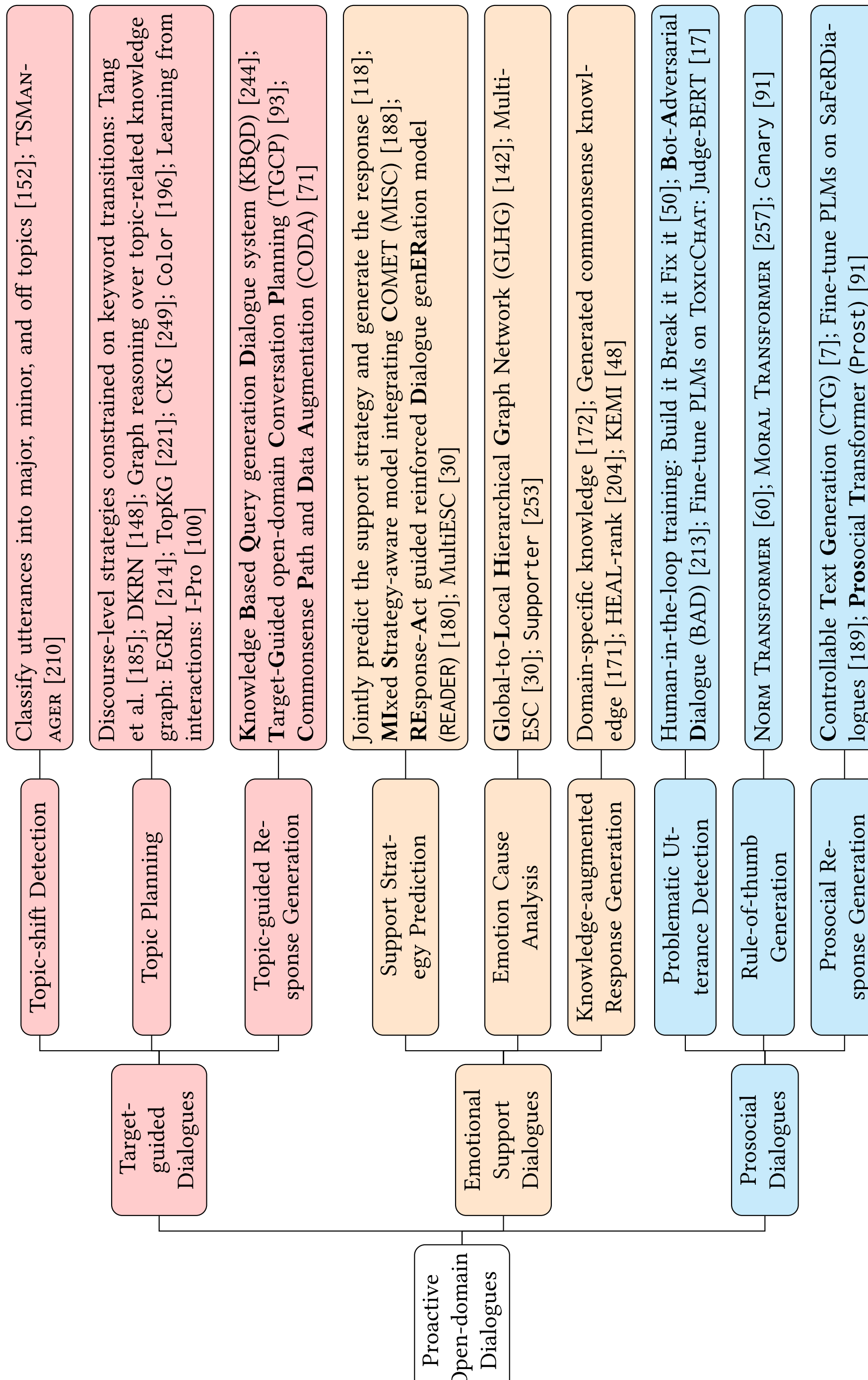

Fig. 5. Summary of proactive ODD systems.

In accordance with the three elements in proactive dialogue systems, the conversational agent here *anticipates* achieving the designated target by *planning* a smooth topic threads and taking *initiative* to shift topics during the conversation.

3.1.1 Problem Definition. The goal of target-guided dialogues is to achieve the designated target effectively and efficiently through engaging conversations. Given a target topic a^* that is only presented to the agent and is unknown to the user as the goal of the dialogue system to achieve, the dialogue begins from an arbitrary initial topic a_0, and the system needs to produce the response u_t with a predicted topic a_t at turn t for effectively and efficiently leading the conversation towards the target, i.e., $\min_t a_t = a^*$. The produced responses should satisfy (i) *transition smoothness*, natural and appropriate content under the given dialogue history, and (ii) *target achievement*, driving the conversation to reach the designated target. In particular, a candidate target set is maintained by the dialogue system.

3.1.2 Methods. There are three main subtasks in target-guided dialogue systems, including topic-shift detection, topic planning, and topic-guided response generation.

Topic-shift Detection. Topic-shift Detection aims to promptly discover the topic drift in the user utterances during the conversation. Rachna et al. [152] fine-tune XLNet-base to classify the utterances into major, minor and off topics for detecting the digression from the target topic of the conversation. Xie et al. [210] construct TIAGE for topic-shift dialogue modeling by augmenting the PersonaChat dataset [236] with topic-shift annotations, and propose a T5-based topic-shift manager, namely TSManager, to predict the occurrence of topic shifts. To steer the conversation towards the intended direction, recognizing topic-shifts can prevent unexpected topic diversion and redirect the discussion appropriately.

Topic Planning. Topic Planning, which enables the conversation to follow an expected topic direction, is the core problem in target-guided dialogue systems. Several discourse-level target-guided strategies [148, 185] constrained on keyword transitions are proposed to proactively drive the conversation topic towards the target. Due to the loose topic-connectivity between keywords, event knowledge graphs are constructed to enhance the coherency in the topic planning [214]. However, the knowledge provided in the dialogues is limited for planning a robust and reasonable topic path towards the target. Therefore, latest studies [221, 249] leverage external knowledge graphs for improving the quality of topic transitions with graph reasoning techniques. Wang et al. [196] capture the coherence of target-directed topic planning using a Brownian bridge process. Instead of corpus-based learning, Lei et al. [100] propose to learn the optimal topic transition from the interactions with users via **reinforcement learning (RL)**. The task becomes more complex when the agent is required to optimize for long-term goals in a natural but constantly changing environment, demanding seamless dynamic interactions.

Topic-guided Response Generation. Topic-guided Response Generation aims to produce topic-related responses for leading the conversation towards the target. Topic-centric knowledge selection is commonly adopted as a complementary task for enhancing the topic-aware response generation [244]. Kishinami et al. [93] propose to generate a complete responding plan that can lead a conversation to the given target. Similarly, Gupta et al. [71] leverage a bridging path of commonsense knowledge concepts between the current and target topics to generate transition responses. The system must strike a balance between maintaining coherence with the context and seamlessly transitioning towards the desired target.

3.1.3 Datasets. Several publicly available datasets can be adopted for the evaluation of target-guided dialogue systems, including **target-guided conversation (TGC)** [185], DuConv [208], OTTers [168], **target-guided ConvAI (TGConv)** [221], TG-ReDial [254], and DuRecDial [123]. Since TG-ReDial and DuRecDial datasets include recommendation dialogues, these two datasets are commonly adopted for evaluating CRSs. In this section, we mainly introduce the rest four datasets, as presented in Table 1.

- *TGC* is constructed from Persona-Chat [236] without the persona information. The target is defined as a keyword in the utterance, which are automatically extracted by a rule-based keyword extractor.
- *DuConv* is constructed by human-human conversations based on two linked entities that are randomly sampled from the grounded knowledge graph. A grounded knowledge graph is provided for building knowledge-driven proactive dialogue systems.
- *OTTers* is constructed by crowdsourcing a corpus of human-written topic transitions. It is a next-turn target-oriented dialogue dataset, which requires the dialogue system to proactively bridge the current conversation topic to approach the target.
- *TGConv* is constructed by selecting target-oriented samples from ConvAI2 [51], which requires that the dialog utterances contain a go-through entity sequence that aligns with the KG path.

It is worth noting that there are two practical ways to build the target-guided ODD datasets: (1) TGC and TGConv are constructed by labelling targets on existing conversations; (2) DuConv and OTTers are constructed by generating conversations based on designated targets.

3.1.4 Evaluation Protocols. Apart from the general evaluation metrics for dialogue systems (BLEU, Dist-N, PPL, etc), we mainly introduce evaluation protocols that are specific to the concerned problem. The target-guided dialogue systems can be evaluated from two levels, i.e., turn-level and dialogue-level:

- *Turn-level Evaluation*: The performance of target prediction in each turn can be evaluated by (i) P@K and R@K, keywords precision and recall at position K in the candidate target set for evaluating the predicted topical keywords; (ii) Embedding-based correlation scores for evaluating the generated responses; and (iii) Proactivity/Smoothness, human evaluation scores that measure how well the system can introduce new topics towards the target while maintaining coherency.
- *Dialogue-level Evaluation*: Due to the high cost and complexity for real user experiments, user simulators are typically adopted for evaluating dialogue-level performance. The common metrics include (i) SR@t, success rate of achieving the targets at tth turn; and (ii) #$Turns$, the average number of turns used to reach the target.

3.2 Emotional Support Dialogues

Conventional studies on emotion-aware dialogue systems [110, 157, 252] mainly target at generating responses that can reflect the user's feelings or echo their emotions. However, emotional support dialogue systems aim to improve the user's emotional state from distress or other bad emotions. They are expected to be not only capable of comforting the user by conveying empathy, but also able to proactively explore the seeker's problem and provide useful information or supportive suggestions to help the seeker overcome the problem [118].

As for emotional support dialogues, a proactive dialogue system *anticipates* enhancing the user's emotional state by *planning* support strategies and taking *initiative* to assist them in dealing with their difficulties.

3.2.1 Problem Definition. The goal of emotional support dialogues is to solve the user's emotional issues through strategic conversations. Given the dialogue context $C = \{u_1, u_2, ..., u_{t-1}\}$ with the description of the user's problematic situation s, the goal is to estimate the functions of $p(a_t|C, s)$ that predicts appropriate emotional strategies to alleviate the user's emotional issue, as well as $p(u_t|C, s, a_t)$ that generates the a proper response u_t given the emotional support strategy a_t to interact with the user.

3.2.2 Methods. In terms of the main designs for enhancing the emotion support skills, we categorize the existing approaches for emotional support dialogues into the following three groups:

Support Strategy Prediction. Support Strategy Prediction aims to predict an appropriate emotional support strategy for the agent to interact with users for lowering their emotional intensity. One closely related research scope is to recognize the dialogue acts of the utterances in emotional support dialogues [128, 144]. However, these studies only focus on predicting the support strategies, instead of actually involving proactive interactions in dialogue systems. Liu et al. [118] firstly propose a joint learning approach to generate responses conditioned on the predicted strategy tokens. Tu et al. [188] propose the MISC framework to formulate the mixture of support strategies as a probability distribution over a strategy codebook for generating supportive responses. Srivastava et al. [180] propose a RL framework, namely READER, to generate future dialogue-act guided responses in mental health counseling. Although turn-level strategy prediction has been effective in generating strategic responses, it may not always align with conversation-level strategies. Therefore, it would be beneficial to take an extra step in scrutinizing the support strategy modeling in dynamic multi-turn interactions.

Emotion Cause Analysis. Emotion Cause Analysis aims to identify user's emotion causes for their depressed emotions to more thoroughly understand the user's situation and guide the user's positive emotion transition. Peng et al. [142] propose a hierarchical graph network, named GLHG, to capture both the global cause context and local user intentions that are derived from a generative commonsense knowledge model, namely COMET [16]. Inspired by previous empathetic response generation studies [64, 89], Cheng et al. [30] also adopt an off-the-shelf emotion cause detector, which is trained on a large-scale emotion cause detection dataset [145], to extract the emotion cause mentioned in the dialogue history for user state modeling. Since one of the goal of emotional support dialogues is to guide emotional positive transition, Zhou et al. [253] introduce a new paradigm to formalize multi-turn emotional support dialogue as a process of positive emotion elicitation and solve the problem with a mixture-of-expert-based RL model. Studying the cause of emotions is not only crucial for understanding the user's mental state, but it is also a critical yet under-explored factor in predicting support strategies.

Knowledge-augmented Response Generation. Knowledge-augmented Response Generation aims to incorporate external knowledge for guidance of generating supportive responses. Shen et al. [172] leverage domain-specific knowledge from psychotherapy video transcripts for generating appropriate responses in counseling conversations which is further extended to collectively exploit different kinds of external knowledge [171], including commonsense knowledge and domain-specific knowledge. Welivita and Pu [204] construct a large-scale knowledge graph for distress management conversations, namely HEAL, with five types of nodes, including emotion causes, distress narratives, supportive responses, user feedback, and affective states. A knowledge selection model based on HEAL (HEAL-rank) is shown to be more effective than some dialogue generation models in distress management conversations. Deng et al. [48] further combine generated commonsense knowledge and the external knowledge from HEAL to generate informative mixed-initiative responses. Acquiring additional knowledge resources for constructing these methods can be challenging, as it often requires the expertise of professionals or knowledgeable workers. Unlike other knowledge-intensive tasks that can utilize open-domain knowledge, such as Wikipedia,

Table 2. Pros and Cons of Different Categories of Methods for Emotional Support Dialogues

Category of Method	Pros	Cons
Support Strategy Prediction	(1) Enable strategic decision	(1) Require the understanding of psychological or sociological strategies
Emotion Cause Analysis	(1) Emotion-aware responses (2) Enhanced explainability	(1) Reliance on external models (2) Lack of strategic decisions
Knowledge-augmented Response Generation	(1) Informative responses (2) Incorporate domain knowledge	(1) Reliance on domain experts

building a helpful and secure emotional support dialogue system strongly relies on specialized knowledge from professionals.

Table 2 summarizes the pros and cons of these three groups of methods.

3.2.3 Datasets. A wide range of data resources are constructed to facilitate the studies on various applications of emotional support dialogue systems, such as distress support [118, 204], counseling [128], or **motivational interviewing (MI)** [143]. As support strategy learning is a crucial feature in emotional support dialogue systems, we introduce three datasets with valuable human annotated labels related to support strategies, as presented in Table 1, including **emotional support conversation (ESConv)** [118], HOPE [128], and MI [143]:

— *ESConv* is collected by trained crowdworkers under the mode of emotional help seeking between a help-seeker and a supporter. Supporters are trained to follow three stages and eight support strategies grounded on Hill's Helping Skills Theory [74].
— *HOPE* is collected from publicly-available pre-recorded counseling videos on YouTube by desensitizing the personal information in the conversations. About 12 dialogue-act labels are assigned to each utterance, including initiative, general, and responsive dialogue acts.
— *MI* is derived from video recordings of MI and annotated with 10 counselor behavioral codes using the MI Treatment Integrity 4.0 [135].

3.2.4 Evaluation Protocols. To compensate the limitation of automatic evaluation metrics, human evaluation is typically adopted for evaluating the generated responses in emotional support dialogues. Three specific aspects are identified to be crucial by Liu et al. [118]: (1) *Identification*: how well does the response in identifying the problem? (2) *Comforting*: how skillful does the response in comforting the user? (3) *Suggestion*: how helpful does the response in providing suggestion for solving the problem? Human annotators will be asked for scoring the generated responses by following the annotation guidelines provided by Liu et al. [118]. In addition, when support strategy prediction is regarded as a subtask, Precision, Recall, F1, and Accuracy are adopted as essential metrics for evaluating the model capability of choosing appropriate support strategies or dialogue acts.

3.3 Prosocial Dialogues

Most existing dialogue systems fail to handle problematic user utterances by passively agreeing with the unsafe, unethical, or toxic statement or viewpoints from the users, which may cause serious safety concerns for real-world deployment of these systems. Therefore, a trending research topic in proactive dialogue systems is to enable the conversational agent to proactively detect problematic user utterances and constructively and respectfully lead the conversation in a prosocial manner, i.e., following social norms and benefiting others or society [91].

For prosocial dialogues, a proactive dialogue system *anticipates* promoting positive social interactions and communications by *planning* prosocial behaviors and taking *initiative* to guide the user to follow social norms.

3.3.1 Problem Definition. The goal of prosocial dialogues is to maintain a socially responsible conversation through mitigating inappropriate statement. Given the dialogue context $C = \{u_1, u_2, ..., u_{t-1}\}$, a prosocial dialogue system aims to first predict the safety label y_t of the current context C (e.g., *Casual*/*Need Caution*/*Need Intervention*/etc) and then generate a proper response u_t to mitigate the problematic user utterances if needed, i.e., estimating the function of $p(u_t|C, y_t)$.

3.3.2 Methods. Current approaches on prosocial dialogue systems can be categorized into three groups, including safety detection, **rule-of-thumb (RoT)** generation, and prosocial response generation.

Problematic Utterance Detection. This line of work focuses on identifying whether the user utterance is problematic for preventing the system generating agreement on problematic statement. Dinan et al. [50] develop a human-in-the-loop training scheme for detecting offensive utterances from other safe utterances in dialogue, which is further improved with adversarial learning [213]. Baheti et al. [7] fine-tune offensive language detection classifiers on a crowd-annotated dataset, ToxiChat, which is labeled with offensive language and stance. Similarly, Botzer et al. [17] propose Judge-BERT, which fine-tunes BERT on the Reddit dataset with binary moral judgment labels, for the moral judgment of user posts on online discussion platforms. In order to avoid classifying specific or sensitive utterances as "unsafe" or "toxic" that may cause social exclusion of minority users, Kim et al. [91] introduce a fine-grained safety classification schema: (1) Needs Caution, (2) Needs Intervention, and (3) Casual. Although these approaches can effectively avoid agreeing with problematic user utterances, it is still necessary to continue a user-engaged and socially responsible conversation.

RoT Generation. RoT means a descriptive cultural norm structured as the judgment of an action [60]. For example, "*People should not steal from others.*" RoTs are generated to interpret why the statement could be seen as acceptable or problematic. Forbes et al. [60] first present Social-Chem01, a large-scale corpus for RoT generation, and propose Norm Transformer to reason about social norms towards the given context. Ziems et al. [257] propose Moral Transformer for fine-tuning language models to generate new RoTs that reasonably describe previously unseen dialogue interactions. Kim et al. [91] propose a sequence-to-sequence model `Canary` that generates both safety label and relevant RoTs given a potentially problematic dialogue context. However, the generated RoTs may not be a proper response for user-engaged conversations.

Prosocial Response Generation. Another line of work aims to teach the conversational agent to proactively generate prosocial responses for handling the problematic user utterance. Baheti et al. [7] investigate controllable text generation methods to mitigate the tendency of generating responses that agree with offensive user utterances. Ung et al. [189] propose SaFeRDialogues, a dataset of graceful responses to problematic user utterances and fine-tune PLMs on this dataset to enhance prosocial response generation. Kim et al. [91] propose `Prost` to generate prosocial responses conditioned on the relevant RoTs and the dialogue context. It is important to note that generating prosocial responses to problematic user inputs is not completely equivalent to generating detoxified responses [183]. Prosocial responses are not only detoxified but also offering guidance to users on

Table 3. Pros and Cons of Different Categories of Methods for Prosocial Dialogues

Category of Method	Pros	Cons
Problematic Utterance Detection	(1) Easy-to-apply	(1) Refusal is not user-friendly
RoT Generation	(1) Socially responsible responses (2) Enhanced explainability	(1) Unnatural responses (2) Lack of applicability
Prosocial Response Generation	(1) Socially responsible responses (2) Natural responses	(1) Hallucination issue in generated responses

how to behave appropriately, while detoxified responses are not limited in addressing problematic user inputs.

Table 3 summarizes the pros and cons of these three groups of methods.

3.3.3 Datasets. Many valuable data resources have been constructed for investigating the safety issue in dialogue systems, where most of them focus on preventing the system from generating toxic responses, such as ToxicChat [7]. Here we introduce two datasets that provide a more comprehensive evaluation for proactive dialogues, as presented in Table 1, i.e., **Moral Integrity Conversation (MIC)** [257] and ProsocialDialog [91].

— *MIC*: This corpus is constructed by mannually annotating prompt-reply pairs (i.e., an open-ended query and an AI-generated response) with RoTs from Social-Chem01 [60]. Each RoT serves as a moral judgment that can enhance the original reply.
— *ProsocialDialog*: This corpus is constructed by a human-AI collaboration framework, where AI plays the problematic user role, and crowdworkers play the prosocial agent role, to produce prosocial conversations together. It includes (1) safety labels for the context, (2) RoTs for problematic dialogue contexts, and (3) prosocial responses grounded on RoTs.

3.3.4 Evaluation Protocols. According to the three groups of approaches, there are corresponding evaluation metrics: (1) As safety detection is intrinsically a classification problem, Accuracy and F1 scores are adopted for evaluation; (2) As for RoT generation and prosocial generation, general text generation metrics (ROUGE, BLEU, PPL) are adopted for evaluation; and (3) Due to the difficulty of measuring prosociality or morality, human evaluation or trained classification models are typically adopted for quantifying different attributes of the generated responses [91, 257], such as *Prosociality* (how well does the response imply that the user should behave prosocially, ethically, and follow social norms?), *Respect* (how respectful, kind, and polite does the response towards the user?), and so forth.

4 Proactive TODs

General TOD systems, which typically serve as an obedient assistant to strictly follow the user's instruction, have achieved promising performance on completing collaborative tasks. Although the task completion requires a certain level of proactivity of the TOD systems, the presupposition is that the TOD systems are only expected to accomplish the user-requested tasks. Rather than solely focusing on user-requested tasks, there are increasing demands for proactive TOD systems that can better improve service quality and handle more challenging tasks, even though the task is not requested by the users. According the level of agent's proactivity, we categorize existing studies on proactive TOD into three groups: (1) *Turn-level Proactivity* (Section 4.1): the system can proactively enrich the response by providing additional information that is not requested by but useful to the users [11]. (2) *Sub-dialogue-level Proactivity* (Section 4.2): the system can proactively initiate sub-dialogues for overcoming unexpected obstacles that hinder the task completion, such as ambiguous instructions [147] or user complaints [220]. (3) *Dialogue-level Proactivity* (Section 4.3): the system can handle non-collaborative tasks where users and systems do not share the same goal, such as negotiation and persuasion dialogues [72, 199]. In this section, we introduce the recent advances on these three kinds of proactive TOD systems. The overview of proactive TOD systems is illustrated in Figure 6.

4.1 Enriched TODs

The proactivity in general TOD systems commonly refers to the ability of automatically providing additional information that is not requested by but useful to the user [10, 11], which can improve the quality and effectiveness of conveying functional service in the conversation. The problem formulation of enriched TODs exactly follows that of general TODs, where the difference is that the generated responses in enriched TODs should be not only functionally accurate but also socially engaging.

With Chit-chats. For instance, Sun et al. [184] construct the *ACCENTOR* dataset by adding topical chit-chats into the responses for TODs to make the interactions more engaging and interactive. An end-to-end TOD method, SimpleTOD [75], is extended to be SimpleTOD+ for handling enriched TODs, which introduces a new dialogue action, i.e., chit-chat and is further trained on chit-chat generation data. Another two methods, namely Arranger and Rewriter, are proposed to combine the generated responses from an off-the-shelf TOD model and an off-the-shelf chit-chat model without intervening in the task. Similarly, [243] develop an end-to-end method, namely UniDS, with a unified dialogue data schema, compatible for both chit-chat and TODs.

With Knowledge. The chit-chat augmentation in ACCENTOR mainly contains general greeting responses with limited useful information (e.g., "you're welcome"). To enrich TODs with knowledgeable chit-chats, Chen et al. [29] further propose the *KETOD* dataset to enable knowledge-grounded chit-chat regarding relevant entities. A pipeline-based method, namely Combiner, is proposed to reduce the interference between the dialogue state tracking and the generation of knowledge-enriched responses. Feng et al. [57] propose an end-to-end model, namely TARG, to incorporate topic-aware unstructured knowledge for enriching the generated responses in TOD systems. In order to accommodate subjective user requests (e.g., "Is the WIFI reliable?"), Zhao et al. [242] propose a novel task of subjective-knowledge-based TOD, which can respond to user requests by incorporating user reviews as subjective knowledge. When seeking to enrich the conversation with external knowledge resources, it is imperative to ensure the factuality and faithfulness of the additional information.

In conclusion, while the integration of chit-chat and external knowledge resources into TOD systems presents considerable opportunities for enhancing user engagement and satisfaction, it also poses significant challenges. Future efforts should focus on balancing functional integrity and accuracy with informative interactions to better meet diverse user needs.

4.2 System-initiated Sub-dialogues

Most of existing TOD systems are built upon an ideal assumption that the human users skillfully and willingly collaborate with the dialogue system to complete their requested task. However, this assumption may not always hold in some real-world scenarios, where the users may convey unclear or ambiguous instructions [147, 175] or the users are not willing to coordinate with the agent [77, 220]. In these cases, the TOD system is expected to proactively overcome these obstacles for task completion via system-initiated sub-dialogues during the conversation.

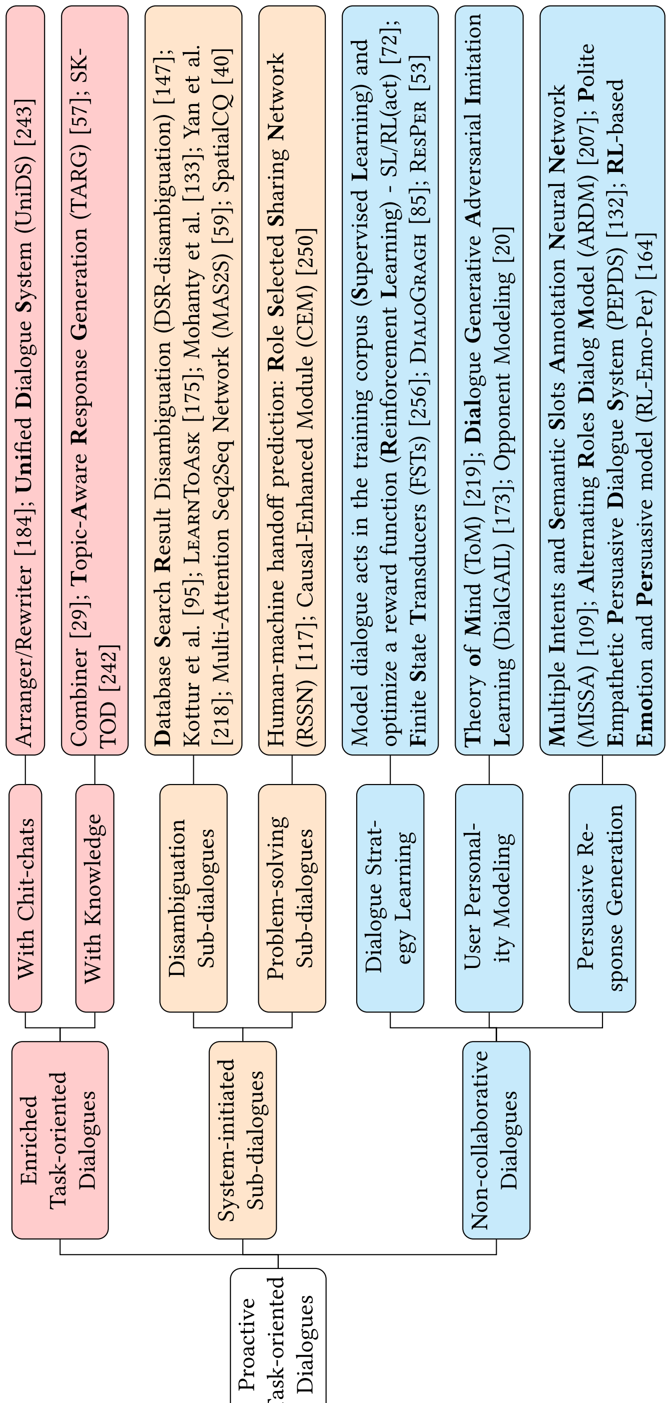

Fig. 6. Summary of proactive TOD systems.

Disambiguation Sub-dialogues. This line of research is inspired by the advances on asking clarification questions in CIS systems, which will be elaborated in Section 5.1. When encountering under-specified user instructions, a proactive TOD system is expected to initiate a sub-dialogue for clarifying the uncertainty for better completing the target task. Qian et al. [147] augment two popular TOD datasets, namely MultiWOZ [19] and SGD [158], with disambiguation sub-dialogues. Different from semantically ambiguous queries in conversational search (e.g., "apple" can be referred to either a fruit or a company), Qian et al. [147] argue that the ambiguity in TODs commonly occurs when receiving multiple returned database results that are match with the current dialogue state (e.g., two different hotels that meet the user's requirement). Yan et al. [218] construct a multi-domain TOD dataset with mixed-initiative strategies TITAN, including asking clarification questions and providing relevant information. To tackle this problem, Feng et al. [59] propose a new Multi-Attention Seq2Seq Network, which can ask questions to clarify the user's information needs and the user's profile in TOD. In particular, the ambiguity issue becomes more severe in multimodal TODs [95, 133, 175], where the ambiguity issue further includes the referential ambiguity in the user instruction grounded on the multimodal dialogue state. For example, Kottur et al. [95] propose the SIMMC 2.0 dataset grounded on VR scenes of commercial stores for fashion or furniture shopping scenarios. It involves a sub-task of multimodal disambiguation that requires the dialogue system to determine whether to disambiguate in the next turn. Similarly, some researchers also investigate the multimodal disambiguation on TODs grounded on spatial information (e.g., 3D coordinate) [40, 133, 175].

Problem-solving Sub-dialogues. In real-world scenarios, it is inevitable to encounter non-collaborative users, who may complain of the unsatisfied service [220] or even communicate in an impolite way [77] instead of providing necessary information for completing their tasks. In order to lead the conversation back towards the task completion, a proactive TOD system is expected to initiate a sub-dialogue for solving the user's problem. Due to the difficulty of handling users' complaints, most of existing studies handle this issue by only predicting the timing for human-machine handoff [117, 250] and transferring the problem-solving sub-dialogue to human service. Therefore, it is still in great demand for automating the problem-solving sub-dialogues in proactive TOD systems.

4.3 Non-collaborative Dialogues

Under non-collaborative setting, the system and the user have competing interests or goals towards the task completion but aim to reach an agreement [256]. Typical applications of non-collaborative dialogue systems include negotiating a product price [72], persuading users to make a donation [199], deceiving attackers [109], and so forth. General TOD systems may fail to meet the system's goal in these applications due to the only aim of accomplishing the user's goal. To remedy this issue, the conversational agent needs to successfully develop strategies for conflict resolution and have persuasive powers that can be used to steer the dialogue in a particular direction.

When it comes to non-collaborative dialogues, the proactive dialogue system *anticipates* the completion of the system-oriented tasks and striving to attain an agreement with the user. This is achieved through *planning* strategic negotiation and taking *initiative* to persuade the user to reach a consensus.

4.3.1 Problem Definition. The goal of non-collaborative dialogues is to reach the consensus between parties through strategic conversations. Given the dialogue history, i.e., a sequence of utterances $\{u_1, ..., u_{t-1}\}$, along with the previous dialogue strategy sequence $\{a_1, ..., a_{t-1}\}$ and the dialogue background s, the goal is to generate a response u_t with appropriate dialogue strategy a_t that can lead to a consensus state between the system's and the user's goal. Based on different applications, the dialogue strategy can be coarse dialogue act labels or fine-grained strategy labels, while the dialogue background can be like item descriptions in bargain negotiation or user profile in persuasion dialogues.

4.3.2 Methods. We categorize existing techniques for tackling the non-collaborative dialogue problem into three groups, including dialogue strategy learning, user personality modeling, and persuasive response generation.

Dialogue Strategy Learning. Different from the intent detection in general TOD systems that commonly classify user utterances into pre-defined intents, it further requires the capability of strategic reasoning to handle more complex user actions in non-collaborative dialogues. He et al. [72] aim to control the dialogue strategy to achieve different negotiation goals with the same language generator by decoupling strategy and generation. Zhou et al. [256] employ finite state transducers to leverage effective sequences of strategies in the dialogue context to predict the next strategy, based on (i) 15 actionable tactics that elaborate strategies described in economics and behavioral science research on negotiation [255], and (ii) a hierarchical intent annotation scheme that differentiate on-task and off-task intents on persuasion [109]. Based on similar motivations, several advanced models have been developed for strategy learning in non-collaborative dialogues, such as DialoGragh [85] with interpretable strategy-graph networks, ResPer [53] with resisting strategy modeling. The strategy learning is still challenging in non-collaborative dialogues, since it involves not only language but also psychological or sociological skills to build rapport and trust between the system and the user.

User Personality Modeling. On the other side, a proactive conversational agent is further required to understand the human decision-making process, where user personality modeling is an important technique. Yang et al. [219] propose to generate strategic dialogue by modeling and inferring personality types of opponents based on the idea of Theory of Mind from cognitive science. Shi et al. [173] develop DialGAIL, an RL-based generative algorithm with separate user and system profile builders, to reduce repetition and inconsistency in persuasion dialogues. Chawla et al. [20] propose a ranker to infer another party's mental state for opponent modeling from negotiation dialogues. In fact, modeling user personality is a challenging problem, as the complex human personality is intricately related to several fields, including psychology, sociology, praxeology, and other related disciplines.

Persuasive Response Generation. Since the aim of non-collaborative dialogues is to reach a consensus in the end, the responses generated by the system should be persuasive and effective to lead the conversational direction. Following general TOD frameworks, researchers develop modularized [72] and end-to-end [109, 207] methods to incorporate persuasive dialogue strategies into response generation. For instance, Li et al. [109] enhance the TransferTransfo framework [205] with a set of pre-defined constraints to select coherent responses for specific task requirements or general conversational rules. Furthermore, recent studies propose to build empathetic connections between the system and the user for better generating persuasive responses [132, 164]. Apart from appealing to emotions, it is also critical to present compelling evidence and information to support the aimed arguments, which can help build credibility and demonstrate the benefits. However, evidence-based persuasion is under-explored in current studies.

Table 4 summarizes the pros and cons of these three groups of methods.

4.3.3 Datasets and Evaluation Protocols. Due to the extensive applications of non-collaborative dialogues, many valuable data resources have recently been constructed [109]. Here we detailedly introduce two widely-adopted benchmarks for evaluating non-collaborative dialogue systems, as

Table 4. Pros and Cons of Different Categories of Methods for Non-collaborative Dialogues

Category of Method	**Pros**	**Cons**
Dialogue Strategy Learning	(1) Strategic communication (2) Enable long-term planning	(1) Require the understanding of psychological or sociological strategies
User Personality Modeling	(1) Personalized responses	(1) Difficult to model personality
Persuasive Response Generation	(1) Easy to reach consensus (2) Empathetic responses	(1) Fail to maximize own benefits (2) Deceptive responses

presented in Table 1, including CraigslistBargain [72] and **PersuasionForGood (P4G)** [199]. Both of them are collected by human-human conversations.

- *CraigslistBargain*: Two workers are assigned the role of a buyer and a seller and then asked to negotiate the price of an item for sale given a description and photos.
- *P4G* contains persuasion conversations for charity donation, and the corresponding user profiles. It also provides manual annotation of persuasion strategies and dialog acts for each sentence.

As for the evaluation protocols, a key element in non-collaborative dialogues is the strategy learning. Therefore, the accuracy of dialogue strategy prediction is the most commonly-adopted metrics for evaluating the system, such as Accuracy, F1, and ROC AUC scores. Different from evaluating turn-level strategy prediction, game-based metrics [231] are typically adopted for evaluating the dialogue-level interactions according to different applications, such as the win rate, average sale-to-list ratio, the task completion rate, and so forth. For the response generation, some specific aspects are included for human evaluation, such as persuasiveness, task success, and so forth.

5 Proactive Conversational Information Seeking

Conventional CIS systems passively respond to user queries, which may fall short of performing complicated information seeks. For example, when encountering under-specified user queries, e.g., "How long is Harry Potter?," traditional CIS systems may guess what the user intended and reply with a random answer. But for over-specified user queries, e.g., unanswerable or unknown questions, traditional CIS systems may refuse to answer as there is no answer in their grounded knowledge. Recent years have witnessed several advances on developing proactive CIS systems that can further eliminate the uncertainty for more efficient and precise information seeking by initiating a sub-dialogue for under-specified user queries. Such a sub-dialogue can either clarify the ambiguity of the query or question in conversational search [3] and conversation question answering [70] (Section 5.1), or elicit the user preference in conversational recommendation [98, 239] (Section 5.2). In addition, when encountering over-specified user queries, researchers also investigate the proactive CIS system that can either decompose the complex user queries or provide relevant information for satisfying the user's information needs (Section 5.3). The overview of proactive information-seeking dialogue systems is illustrated in Figure 7.

In general, the *anticipation* of proactive CIS systems is still to satisfy the user's information needs, which is the same as conventional CIS systems. The difference is that the proactive system need to *plan* among mixed-initiative interactions, either directly answering user queries or *initiate* sub-dialogues to handle under-specified or over-specified user queries.

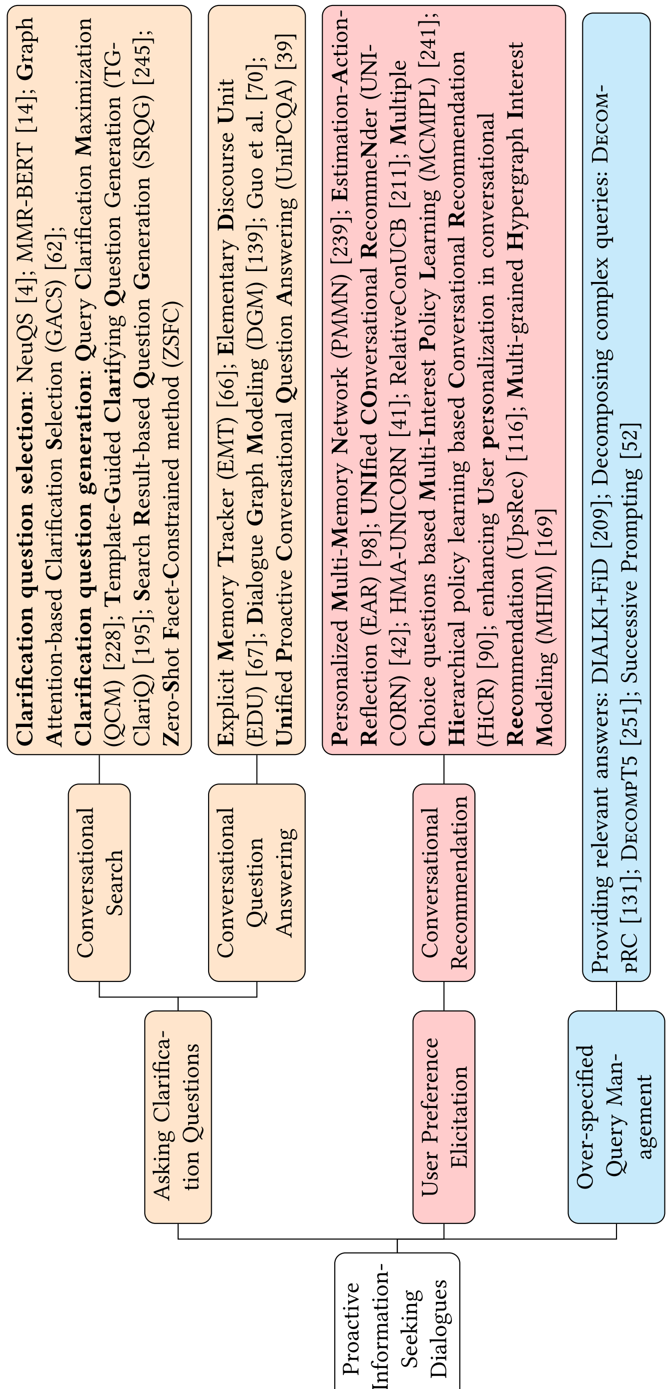

Fig. 7. Summary of proactive conversational information-seeking systems.

Table 5. Types and Examples for Clarification Needs of Search Queries by Zamani et al. [228]

Category	*Example*
Disambiguation	The query "trec" can refer to either "Text Retrieval Conference" or "Texas Real Estate Commission."
Preference	The query "sneakers" might be followed by "for women" or by "for kids."
Topic	The query "dinosaur" is too board in topics.
Comparison	The query "gaming console" might be followed by the comparison between "xbox" and "play station."

5.1 Asking Clarification Questions

Asking clarification questions aims to clarify the potential ambiguity in the user query, since the user query is often succinct and brief in real-world conversational search and question answering.

5.1.1 Problem Definition. The goal of asking clarification questions is to produce a clarifying question for acquiring more specific information from the user if encountering ambiguity or uncertainty in information seeking. Formally, the problem of asking clarification questions is formulated by two subtasks [3]: clarification need prediction and clarification question generation. Clarification need predication is typically viewed as a binary classification problem for predicting whether the user query is ambiguous. If needed, clarification questions can be either selected from a question bank or generated on the fly.

5.1.2 Clarification in Conversational Search. Zou et al. [258] conduct a user study to confirm that search systems should prompt clarifying questions only when they are confident in the quality of the questions and the relevance of the answers, as effective clarifications enhance user performance and satisfaction, whereas irrelevant or pointless clarifications can have detrimental effects. Based on the analysis over large-scale web search query reformulation data, Zamani et al. [228] identify the clarification needs for search queries into four categories, as shown in Table 5 with examples. It can be observed that the clarification in conversation search is mainly concerned about the entity in the user query. In general, existing methods for clarification in conversational search can be divided into two groups: clarification question selection and clarification question generation.

Clarification question selection aims to select an appropriate clarification question from a set of candidate questions. Aliannejadi et al. [4] propose a question retrieval-selection pipeline, namely NeuQS, to first retrieve top k questions from the question bank and then select the most appropriate question by reranking via BERT-based models. Bi et al. [14] propose a **maximum-marginal-relevance (MMR)** based BERT model to leverage negative feedback in the conversation history for the next clarifying question selection. Gao and Lam [62] propose a graph-based clarification question selection model, namely GACS, to model the relations among the query, user intents, and clarification options via a query-intent-clarification graph. Despite the effectiveness in some close-domain search applications, clarification question selection approaches are typically limited in generalization to other domains or open-domain applications, due to the constraint on the available question candidates in the question bank.

Text generation techniques enable the clarification question generation approaches to produce natural and complete question without the constraint on the question bank. Zamani et al. [228] develop a RL based method, namely QCM, to generate clarifying questions by maximizing a clarification utility function. Wang and Li [195] propose a template-guided clarification question generation method, namely TG-ClariQ, to select question templates and fill question slots. However, these methods are mainly based on static knowledge from the available data, so that it can be

Table 6. Types and Examples of Clarification Questions on Community Question Answering Platforms by Braslavski et al. [18]

Category	*Example*
More Info	What OS are you using?
Check	Are you on a 64-bit system?
Reason	What is the reason you want a drip pan?
General	Can you add more details to this question?
Selection	Are you using latex or oil based Kilz?
Experience	Have you tried to update video card drivers?

difficult to find additional entities related to the query. To this end, Zhao et al. [245] propose a Search Result-based Question Generation method, which leverages top search results of the query to enhance generative model for generalizing better clarification questions. The lack of authentic conversational search data, leading to reliance on artificial datasets for training, hinders the practical implementation of existing approaches in real-world scenarios, creating a cold start problem for clarifying question generation and conversational search. Wang et al. [202] combine question templates and query facets to guide the zero-shot constrained clarification question generation. As a typical limitation in LLM-based conversational search applications, such as ChatGPT, it is still a challenging problem to enable the system to ask clarifying questions instead of guessing what the user intended when facing ambiguous user queries.

5.1.3 Clarification in CQA. Early works on clarification in question answering mainly study the discussion threads on the community question answering platforms [18, 155, 156]. Braslavski et al. [18] systematically summarize the clarification questions into six types, as shown in Table 6 with corresponding examples. Compared with clarifications in conversational search that mainly focus on specific entities in the query, the clarification questions in question answering are more diversified and commonly depend on the grounded documents. Furthermore, clarification questions in CQA is in a multi-turn context and has a direct impact on the answer.

Under the context of CQA, Saeidi et al. [163] firstly study the problem of asking clarification questions for those under-specified questions that require both the interpretation of rules and the application of background knowledge. Various approaches have been developed for generating the clarification questions. Gao et al. [66] propose a framework, namely EMT, to track whether the current information is enough and generate clarification questions with a coarse-to-fine reasoning strategy. Gao et al. [67] design the clause-like elementary discourse units using a pre-trained discourse segmentation model for better understanding the dialogue, which is further enhanced with dialogue graph modeling [139]. However, the clarification in these works is only concerned about yes-no questions. Xu et al. [215], instead, investigate clarification question generation for knowledge-based question answering where the ambiguity only comes from entities and pronouns.

Recently, inspired by the problem definition of asking clarification questions in conversational search [3], Guo et al. [70] present a pipeline-based system for asking clarification questions, which adopt a binary classification model to predict the clarification need label first and then perform clarification question generation. Furthermore, Deng et al. [39] propose an end-to-end framework, namely UniPCQA, which leverages a unified sequence-to-sequence formulation to tackle three tasks in one model, including clarification need prediction, clarification question generation, and CQA. To ensure objectivity in the clarification question annotations within the data creation process, existing studies construct ambiguous questions that intentionally leave out one piece of information. While this approach has its merits, it is also important to consider scenarios where there are multiple missing pieces of information. Therefore, exploring such situations can broaden our understanding of the complexity of clarification question generation.

5.1.4 Datasets and Evaluation Protocols. Several data resources have recently been constructed for evaluating the system capability of asking clarifying questions for both conversational search, as presented in Table 1, such as Qulac [4], MIMICS [229], ClariQ [3], and CQA, such as Abg-CoQA [70], PACIFIC [39].

— *Qulac* is constructed by a four-step strategy: (1) The topics from TREC Web Track 2009-2012 are used as initial user queries and then divided into their facets; (2) Candidate clarification questions are collected for each query by human annotators; (3) They verify the relevance of the clarification questions and add new questions if necessary; and (4) The answers for every query-facet-question sample are collected and verified by human annotators.
— *MIMICS* is a large-scale dataset for search clarification using a clarification pane that includes a clarification question and several candidate answers. It contains three datasets: (1) MIMICS-Click consists of 414,362 query-clarification pairs with the aggregated user clicks; (2) MIMICS-ClickExplore consists of 64,007 queries, each with multiple clairication panes; and (3) MIMICS-Manual consists of over 2.8K query-clarification pairs with aggregated manual annotations on clarification quality.
— *ClariQ* is extended from the Qulac dataset, with new topics, questions and answers by crowdsourcing. Besides the single-turn conversations (query-question-answer), ClariQ further includes multi-turn conversations (up to three turns).
— *Abg-CoQA* is constructed from the CoQA dataset [159] by truncating a partial conversation to introduce ambiguity. There are three sub-tasks in Abg-CoQA, including ambiguity detection, clarification question generation, and clarification-based question answering.
— *PACIFIC* targets at the financial domain and its context includes both textual and tabular data. The problem of proactive CQA is defined with three sub-tasks, including clarification need prediction, clarification question generation, and CQA.

There are typically three stages during the clarification to be evaluated: (1) Clarification Need Prediction, (2) Clarification Question Generation, and (3) Clarification-based Information Seeking. As for the clarification need prediction, this classification problem is typically evaluated by Precision, Recall, and F1 scores. As for the clarification question generation, it depends on its formulation. If it is formulated as a question ranking problem from a set of candidate clarification questions, the model will be evaluated via MRR, MAP, and nDCG. If it is formulated as a new question generation problem, text generation metrics will be adopted for measuring its semantic or lexical relevance to the reference or ground-truth clarification question, such as BLEU and ROUGE. Several human evaluation metrics [39, 167] are also adopted for evaluating the helpfulness or naturalness of the generated clarification questions. In addition, the final information-seeking performance after the clarification (i.e., clarification-based information seeking) is also an important factor for evaluating the quality of asked clarification questions, which depends on the information-seeking problem. For example, if it is a conversational search problem, the clarification-based information seeking will be measured by the document ranking performance given the predicted clarification question and simulated user answer [140, 167].

5.2 User Preference Elicitation

Instead of simply learning user preference from the dialogue context [104], Zhang et al. [239] propose a proactive paradigm, namely "System Ask, User Respond," to explicitly acquire user preference via asking questions in conversational recommendation. The problem is formulated as predicting the item attribute for eliciting user preferences at the next turn, e.g., "Which brand of laptop do you prefer?."

A personalized multi-memory network [239] is first designed to incorporate user embeddings into next question prediction at turn-level. Due to the complexity of user preferences, multiple turns of question asking are required. Therefore, recent works tackle the user preference elicitation at dialogue-level, i.e., "what questions to ask," as a multi-step decision making process by RL [42, 98, 241]. Deng et al. [42] propose a graph-based RL framework, namely UNICORN, to model real-time user preference during the conversation with a dynamic weighted graph structure, which is further enhanced with long-term user preference from the historical interaction data [41]. Since user preferences are inherently relative, Xie et al. [211] propose a comparison-based CRS, namely RelativeConUCB, to collect and understand the relative feedback in an interactive manner. Motivated by the complex user interests in CRS, Zhang et al. [241] propose the MCMIPL framework to efficiently obtain user preferences by asking multi-choice questions. For the more accurate elicitation of user interests, Kim et al. [90] enrich current user interests with informative historical interests, by filtering out the unnecessary past behaviors from historical interactions. With similar motivations, Lin et al. [116] propose the UpsRec framework with unique features designed to provide personalized experiences for the users and guide them to their items of interest. Shang et al. [169] propose a multi-grained hypergraph interest modeling approach to capture user interest beneath intricate historical data from different perspectives.

Since the goal of CRS is to make successful recommendations, its evaluation is basically based on the final recommendation results. Similar to target-guided dialogues in Section 3.1.4, the evaluation protocols of question-driven CRS can also be divided into turn-level and dialogue-level:

- *Turn-level*: The hit ratio (HR@k, t) is adopted to evaluate the next question prediction regarding the top-k predicted attributes at conversation turn t. General recommendation metrics, such as MRR@k, t, MAP@k, t, NDCG@k, t, are adopted to evaluate the item recommendation regarding the top-k ranked items based on the elicited user preference at conversation turn t.
- *Dialogue-level*: The success rate at the turn t (SR@t) is adopted to measure the cumulative ratio of successful recommendation by the turn t. AT is adopted to evaluate the average number of turns for all sessions.

Besides these system-centric evaluation metrics, CRS has been criticized regarding its user experience in real-world scenarios, lacking practical usability [83, 84]. Therefore, there are also increasing demands for user-centric evaluations, such as user interaction cost [82], user satisfaction [45], user coordination and cooperation [78], and so forth.

Despite the advances on context-driven CRS [104] and question-driven CRS [239] separately, it would be beneficial to develop CRS that can effectively combine the advantages of these two kinds of CRS, i.e., natural language understanding and generation as well as proactive user preference elicitation. Meanwhile, current studies on user preference elicitation are basically evaluated on synthetic conversation data from product reviews [239] or purchase logs [42, 241]. Therefore, well-constructed benchmarks with human-human conversations are still in great demand for facilitating more robust and reliable evaluations.

5.3 Over-specified Query Management

The aforementioned designs in proactive CIS systems basically target at improving the information seeks when encountering under-specified user queries that are lack of necessary information. However, the designs for handling over-specified queries are often neglected in existing studies. Typically, two types of undesired situation may occur when the system handles over-specified queries in a passive manner: (1) The system responds with `No Answer` [33, 159] if there is no direct information that is match with the over-specified query. (2) The system responds with `Wrong Answers` if the over-specified query is rather complicated. These undesired results will downgrade the user experience when interacting with the CIS systems.

For the `No Answer` situation, Wu et al. [209] firstly propose to proactively suggest relevant information that can partially satisfy the user's information needs. Two types of relevant information are considered in the proposed dataset, InSICt, including (i) constraint relaxation/no definite answer and (ii) relevant but side/partial information only. However, as a pioneering study, there are some issues remained to be tackled, such as how to determine the boundary between relevant answers and wrong answers, how to evaluate the quality or relevancy of the relevant answers, and so forth.

When encountering a complex query, a widely-adopted solution is to decompose it into several simple queries. Min et al. [131] propose DecompRC to decompose a compositional question into simpler sub-questions that can be easily answered. Due to the high cost of annotated data for question decomposition, the sub-question generation is recasted as a span prediction problem. Further, Zhou et al. [251] conduct intermediate pre-training with distant supervision from comparable texts, particularly large-scale parallel news, for handling question decomposition. Inspired by the idea of **chain-of-thought (CoT)** [203], Dua et al. [52] propose Successive Prompting to iteratively decompose the complex question into the next simple question to answer and repeat the decomposition until the complex question is answered. However, existing question decomposition studies mainly focus on single-turn QA, while it is also worth studying the question decomposition approaches for complex context-dependent questions in information-seeking dialogues.

6 Proactive Conversational AI in the Era of LLMs

LLMs have been demonstrated to be powerful of handling various NLP tasks in the form of conversations, such as ChatGPT [165], LaMDA [187], BlenderBot [178], and so forth. However, these applications are typically designed to follow the user's instructions and intents. Following the categorization in a latest SIGIR perspectives paper [44], we discuss three main types of alignment approaches for enabling or improving the proactivity of LLM-based conversational systems, as illustrated in Figure 8, including **in-context learning (ICL)**, **supervised fine-tuning (SFT)**, and RL. Furthermore, we provide a detailed look-up table for all the introduced LLM-based proactive conversational systems in Table 7.

6.1 ICL

Due to the blackbox nature of commercial LLMs and the high expenses of fine-tuning open-source LLMs, researches typically investigate prompting schemes to trigger specific knowledge or capabilities of LLMs for the target problem. To induce knowledge from PLMs or LLMs, various prompting methods are designed for zero-shot or few-shot learning in dialogue applications, such as TODs [96, 130, 238], knowledge-grounded dialogues [122, 177], and ODDs [22, 97]. For example, Chen et al. [25] propose to prompt LLMs for controllable response generation in emotional support and persuasion dialogues, conditioned on the ground-truth dialogue strategies. However, in real-world applications, it is unlikely to secure the ground-truth dialogue strategies under the dynamic environment. Here we introduce three mainstream ICL approaches for instructing LLMs to conduct self-thinking of strategy planning, including CoT prompting [43, 192], demonstration-augmented prompting [31, 129], and multi-agent prompting [56, 61, 101, 234].

- *CoT Prompting*: Inspired by the successful applications of CoT [203] in vairous reasoning and planning problems, Deng et al. [43] first propose the **proactive CoT (ProCoT)** prompting scheme is proposed to enhance the proactivity of LLM-based dialogue systems. Deng et al. [43] further evaluate the capability of LLMs in making strategic decisions for different types

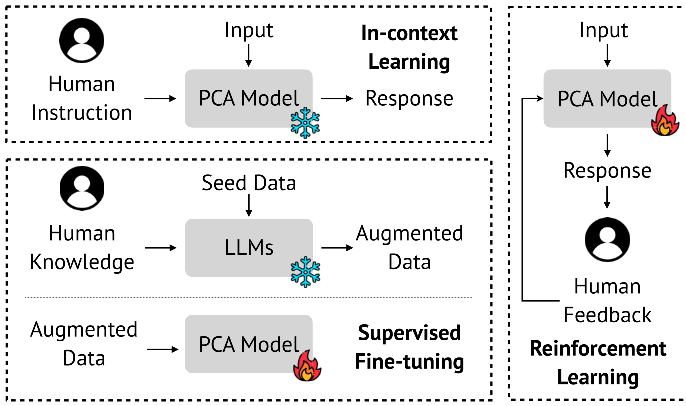

Fig. 8. Three types of alignment approaches in the era of LLMs (Ref. Deng et al. [44]). ICL methods perform tasks by interpreting examples provided directly in the input context without altering the LLM's parameters. SFT methods update the LLM's parameters using labeled datasets to improve its performance on specific tasks. RL methods optimize the LLM through a reward signal derived from human preferences or evaluations to align its outputs with desired behaviors.

of proactive dialogues from the perspective of prompting. The empirical analysis in Deng et al. [43] reveals that although LLM-based dialogue systems can be actually prompted to handle some of the proactive dialogue problems, such as clarification in information-seeking dialogues and target-guided ODDs, there are still many limitations: (1) They fall short of handling domain-specific dialogue applications, such as Finance; (2) They tend to make aggressive topic transitions due to the strong capability of controllable text generation; and (3) They fail to make strategic decisions to lead the conversation in non-collaborative dialogues. Different from planning for decision-making, Cue-CoT [192] investigates the utility of CoT prompting to reason about the mental state of the user for improving user experience during the conversation, such as personality, emotion, and psychology.

— *Demonstration-augmented Prompting*: Demonstration-augmented prompting is the most widely-used ICL approach, which is also known as few-shot learning. A common challenge in this type of approach is how to guarantee the quality of demonstration samples. Meade et al. [129] propose to retrieve demonstrations of safe responses to similar dialogue contexts for prosocial dialogues. Three types of retrieval methods are investigated, including random retrieval, sparse retrieval, and dense retrieval, where dense retrieval presents the best performance. From another perspective, Cooper [31] coordinates multiple dialogue goals to approach a complex objective in proactive dialogues, where each demonstration is related to a specific goal to achieve the final objective.
— *Multi-agent Prompting*: Motivated by the idea of learning from AI feedback, several recent studies investigate multi-agent debate to enhance the proactivity of LLM-based dialogue systems. Ask-an-Expert [234] prompts another LLM as the strategic expert with three-part questions for reasoning about the next dialogue strategy as a verbal description. For example, in ESConvs, the three-part questions include "How did the patient feel?," "Why did the patient feel that way?," and "What should the therapist do?". Similarly, ICL-AIF [61] prompts another LLM as the critic to provide dialogue-level feedback to a player to improve their dialogue strategies with multiple times of iteration. Furthermore, some latest studies develop advanced multi-agent framework for proactive dialogue problems, where different agents

Table 7. Summary of Proactive Conversational AI Studies in the Era of LLMs

Method	Type	Problem	Dataset
Chen et al. [25]	ICL	Non-collaborative Dialogues/Emotional Support Dialogues	P4G [199]/ESConv [118]
ProCoT [43]	ICL	Asking Clarification Questions/Target-guided Dialogues/Non-collaborative Dialogues	Abg-CoQA [70]/PACIFIC [39]/OTTers [168]/TGConv [221]/CraigslistBargain [72]
Cue-CoT [192]	ICL	Emotional Support Dialogues	PsyQA [182]/EMH [170]
Meade et al. [129]	ICL	Prosocial Dialogues	ProsocialDialog [91]/DiaSafety [183]
Ask-an-Expert [234]	ICL	Emotional Support Dialogues	ESConv [118]
ICL-AIF [61]	ICL	Non-collaborative Dialogues	Synthetic Data
ChatCRS [101]	ICL	Target-guided Dialogues	TG-ReDial [254]/DuRecDial [123]
MACRS [56]	ICL	User Preference Elicitation	Synthetic Data
Cooper [31]	ICL	Non-collaborative Dialogues/Emotional Support Dialogues	P4G [199]/ESConv [118]
Zheng et al. [248]	SFT	Emotional Support Dialogues	ESConv [118]/ExTES [248]
AugESC [246]	SFT	Emotional Support Dialogues	ESConv [118]
MathDial [126]	SFT	Problem-solving TODs	MathDial [126]
TOAD [119]	SFT	Enriched TODs	TOAD [119]
Midi-Tuning [194]	SFT	Target-guided Dialogues	TopDial [193]
EnPL [247]	SFT	Target-guided Dialogues	TGConv [221]
d-PM [197]	RL	Emotional Support Dialogues/Prosocial Dialogues	ESConv [118]/MIC [60]
GDP-Zero [227]	RL	Non-collaborative Dialogues	P4G [199]
PPDPP [46]	RL	Emotional Support Dialogues/Non-collaborative Dialogues	ESConv [118]/CraigslistBargain [72]
Trip [237]	RL	Non-collaborative Dialogues	P4G [199]/CraigslistBargain [72]
DPDP [73]	RL	Emotional Support Dialogues	ESConv [118]
LLMCRS [58]	RL	User Preference Elicitation	TG-ReDial [254]/GoRecDial [86]
STaR-GATE [6]	RL	Asking Clarification Questions	Synthetic Data
ACT [24]	RL	Asking Clarification Questions	Abg-CoQA [70]/PACIFIC [39]
Style [27]	RL	Asking Clarification Questions	ClariQ [3]/Opendialkg [134]
T-EPL [36]	RL	Target-guided Dialogues	DuRecDial [123]

are responsible for different functionalities. For example, Fang et al. [56] propose a **multi-agent CRS (MACRS)**, which involve a planner agent and three different responder agents for recommendation, user preference elicitation, and chit-chat. While Li et al. [101] propose ChatCRS which incorporates a goal planning agent and a knowledge retrieval agent into the LLM-based conversational systems for enhancing their proactivity.

Some latest studies attempt to empower LLMs with the capability of planning [81] and acting [222] in interactive or embodied environments via prompting. Huang et al. [81] investigate whether LLMs can make goal-driven decisions rather than just for linguistic tasks. For example, let the LLM to make a step-by-step plan about "*Wash dirty dishes,*" which includes a series of actions (such as “go to dining room,” “grab sponge,” “put sponge on sink,” etc.) that can be executed in a given environment. In order to mimic human intelligence that owns the ability to seamlessly combine task-oriented actions with verbal reasoning, Yao et al. [222] combine reasoning and acting with LLMs for solving diverse language reasoning and decision making tasks. Despite their effectiveness of planning specific tasks, the object to interact is typically the static grounded environment, such as a kitchen, which largely differs from interacting with humans for some specific conversational goals, such as non-collaborative or system-oriented settings discussed in the previous sections. LLMs have shown remarkable capabilities in natural language understanding and generation. However, their potential to exhibit human-like autonomy and consciousness in the context of more challenging problems that require strategic and motivational interactions is still unclear.

6.2 SFT

The key of SFT approaches is to obtain high-quality fine-tuning data. The utilization of LLMs for data augmentation in dialogue systems has gained substantial attention in recent literature, offering promising avenues for improving dialogue quality and system performance. Several recent studies have explored this approach, highlighting its potential across various dialogue applications, such as CQA [212], emotional support dialogues [246], open-domain social dialogues [22, 88], tutoring dialogues [126], and more. In terms of the data augmentation paradigm, existing studies on LLM-based proactive dialogue systems can be categorized into two groups, including Self-chat Distillation [246, 248] and Role-play Simulation [119, 126].

- *Self-chat Distillation*: These methods [22, 88, 212, 246, 248] directly distill the conversation knowledge from LLMs by prompting LLMs to complete the multi-turn conversations with specific instructions. For instance, AugESC [246] prompts LLMs to conduct the dialogue completion task for generating full emotional support dialogues from available seed data. However, dialogues generated through completion often lack diversity in emotional support scenarios and fail to offer detailed guidance from emotional support strategies. To address this issue, Zheng et al. [248] utilize a LLM to iteratively generate a substantial number of generalized and high-quality ESConvs. This is achieved through a meticulously crafted set of dialogues that encapsulate a wide range of scenarios and provide fine-grained strategic guidance.
- *Role-play Simulation*: These methods [92, 119, 126] employ LLMs to simulate a specific role [26] in the conversation to communicate with human or other role-playing agents for collecting multi-turn conversation data. For example, Macina et al. [126] propose a framework to generate math tutoring dialogues, MathDial, by pairing human teachers with the LLM prompted to simulate common student errors. To incorporate the proactivity of the tutoring system, there are 11 teacher initiative moves are provided for the human teachers to interact with the simulated students. Furthermore, Liu et al. [119] not only simulate realistic TODs, TOAD, but also analyze two aspects of response style—verbosity level and mirroring of users’ expressions, to enhance naturalness and adaptiveness for various usage scenarios.

According to these studies, we can observe that a significant feature that differentiates the data augmentation process of proactive dialogues from other dialogue systems is the integration of initiative behaviors, such as the emotional support strategies [248] and the teacher moves [126]. Despite the remarkable quality of LLM-synthetic dialogue data, this type of data inevitably inherits the limitation of LLMs in handling proactive dialogues, such as risk of biased or inappropriate content, limited understanding of user intent, inability to clarifying uncertainty, limited ability to make strategic decisions and plans, and so forth.

6.3 RL

RL from human feedback (RLHF) [138] is designed to align the language model with humans from human preference signals under the RL framework. In the field of proactive dialogue systems, Wang et al. [197] introduce a novel Bayesian-based approach, named Preference Modeling with Disagreement (d-PM), to approximate a "universal preference" that comprises the preferences of "all individuals," given the preferences of several individuals, for emotional support and prosocial dialogues. Chen et al. [24] propose Action-Based Contrastive Self-Training (*ACT*), which construct a action-based contrastive preference dataset for self-training the policy model via contrastive RL tuning. As for user preference elicitation in CRSs, LLMCRS Feng et al. [58] collect the recommendation performance, i.e., whether the user accepts the recommendation, as the feedback for RL. However, the cost of obtaining high-quality human feedback is the key challenge for RLHF, especially for the long-term feedback during the conversation.

As LLMs continue to advance, reaching a level where they can effectively oversee other models, Bai et al. [9] introduce the concept of **RL from AI feedback (RLAIF)**. This innovative approach aims to cultivate a benign and purified LLM through a self-enhancement process, all without the need for human-provided labels. Given that feedback from LLMs commonly presents itself in the form of natural language, a majority of existing research [127, 176] directly capitalizes on the naturally generated language feedback from these models to iteratively enhance the task-specific instruction prompts. This practice contrasts with the conventional method of acquiring scalar rewards as a means to train the model. Another line of research [112, 223, 232] employs RL to train a language model agent on the environmental rewards obtained from the interaction between the LLM and the environment.

As for proactive dialogues, Yu et al. [227] prompt several LLMs to act as a policy prior, value function, user simulator, and system model to perform goal-oriented dialogue policy planning using Monte Carlo Tree Search. However, this type of iterative refinement is exclusive to each individual case, but not transferable to new situations. Due to the high computational cost of online user simulation with LLMs for every new case, [46] propose to employ a learnable language model plug-in, namely PPDPP, which can be fine-tuned for improving the policy planning capability without affecting other functionalities of LLM-powered dialogue systems. Additionally, some subsequent studies further advance this RLAIF framework by incorporating diversified user simulators to enhance generality of the LLM-based proactive dialogue systems [237] (Trip) and the dual-process theory of human cognition to improve the planning capabilities of the plug-in policy model [73] (DPDP). As we can see, applying the RLAIF concept to dialogue strategy learning represents a significant leap forward. Traditional dialogue strategy learning heavily rely on handcrafted rules or supervised learning from human-annotated dialogues, both of which are often labor-intensive and may not capture the nuanced intricacies of natural conversations. While simply learning from AI feedback can only improve the prompts for triggering the proactivity of LLM-based dialogues systems, instead of endowing them with actual proactivity. By integrating RLAIF into dialogue strategy learning, LLMs can engage in more interactive and dynamic conversations.

7 Challenges and Prospects

In this section, we delve into the challenges that surface when addressing real-world application requirements. These critical areas necessitate significant research endeavors.

7.1 Proactivity in Hybrid Dialogue Systems

Most conversational systems assume that users always has a clear conversational goal and the system also solely targets at reaching a certain goal, such as chit-chat, question answering, recommendation, and so forth. The system with a higher level of agent's proactivity should also be capable of handling conversations with multiple and various goals. As for multi-goal conversational systems [47, 124], the agent is expected to proactively discover users' interests and naturally lead user-engaged dialogues with multiple conversation goals. For instance, recent years have witnessed several successful applications on fusing ODDs and TODs [32, 225]. Liu et al. [123] propose a new conversational recommendation problem in the context of multi-type dialogues, where the system is required to naturally lead a conversation from a non-recommendation dialog (e.g., QA, chit-chat) to a recommendation dialog. Li et al. [103] combine TODs with information-seeking dialogues.

Early studies simply tackle this problem similar to topic-guided response generation with pre-defined conversational goals [8, 233]. While some latest works [32, 47, 124, 125] argue the necessity of proactively modeling users' intents and naturally planning user-engaged dialogues with changing conversational goals. Moreover, it also attaches great important to perform natural and timely system-initiated transitions [120, 121] among different types of dialogues. In practice, hybrid dialogue systems are the closest form of real-world applications. Latest studies investigate the hybrid dialogue system in various application domains, such as news [106], medical [174], e-Commerce [13]. More efforts should be made to ensure natural and smooth transitions among different types of dialogues as well as improve the overall dialogue quality without performance loss of certain types of dialogues.

7.2 Evaluation Protocols for Proactivity

Robust evaluation protocols for various types of conversational systems have been a persistent challenge. As has been discussed in earlier sections, proactive dialogue systems have mostly relied on human evaluation to manually assess the quality of their dialogue.

Building user simulators [100, 167, 185, 235] has emerged as a effective and efficient technique for evaluating proactive interactions in dialogue systems, thereby mitigating the high cost of interacting with real users. To evaluate the proactive dialogue systems in TGCs, Tang et al. [185] employ a retrieval-based conversational agent to play the role of users by selecting responses without knowledge of the target topic. Similarly, Lei et al. [100] design a user simulator at the topic-level, where the user utterance is affected by the user satisfaction that is formalized as the coverage rate of user-preferred topics with the current conversation. To evaluate the mixed-initiative interactions in CIS systems, conditional response generation models are developed as simulated users with application-specific constraints, such as user preferences for conversational recommendation [235], and underlying information needs for conversational search [167]. Inspired by the recent success of leveraging LLMs for role-play scenarios, researchers design LLM-based user simulators, which can be flexibly adapted to different dialogue evaluations without further tuning, including ODDs [94], TODs [76], and conversational recommendation [200].

Besides, goal completion and user satisfaction are identified as two essential metrics for evaluating proactive dialogue systems [100, 123, 221]. According to various goals, the evaluation of goal completion can be referred to the accuracy of dialog type prediction [47, 123], the success rate of reaching the target topic [100, 221], and so forth. The definition of user satisfaction also varies in different applications, such as model-based user satisfaction degree estimation [45], the coverage rate of user-preferred topics [100], and so forth. Currently, there is still no consensus on the evaluation metrics for proactive dialogue systems.

In fact, the evaluation for conversational agent's proactivity is a more challenging problem, since it involves the evaluation not only from the perspective of natural language, but also from the other disciplines, such as human-computer interaction, sociology, psychology, and so forth. The rapid development of proactive dialogue systems urges more effective and robust multi-disciplinary evaluation protocols.

7.3 Ethics of Conversational Agent's Proactivity

Crafting proactivity into dialogue systems for agents is a complex task, as it can either benefit or harm its users. Therefore, responsible AI researchers must ensure ethical considerations are taken into account to safeguard users in proactive dialogue systems. Key ethical aspects that need to be considered are:

Factuality. Factual incorrectness and hallucination of knowledge are common in response generation for dialogue systems [54], while the agent's proactivity will introduce more system-initiated information. For example, proactive TOD systems may introduce additional useful information but that is not requested by the user [11, 29]. There are also some proactive dialogue systems that learn from external knowledge to provide suggestions or advice to users [150, 171, 217]. Moreover, several recent attempts have been made on prompting LLMs to generate external knowledge for reseponse generation [111, 226]. Therefore, besides the response generation process, it is also crucial to guarantee the factuality of the external knowledge [23], including both retrieved and generated knowledge.

Safety. Besides general dialogue safety problems, such as toxic language and social bias [183], proactive dialogue systems should also prioritize avoiding the issue of aggressiveness when attempting to steer the conversation towards a desired outcome. For example, during a non-collaborative dialogue [132], the generated responses should refrain from being aggressive or offensive, including any use of satire that may mock or offend the user, and any statements aimed at enraging users. In the context of emotional support dialogues [118], proactive actions like problem exploration or offering suggestions should not be undertaken in an aggressive manner without first assessing the user's level of emotional intensity, which may further induce more emotional distress for the user. Hence, constructing a safe proactive dialogue system requires careful consideration of the appropriate level of proactivity to be implemented.

Privacy. The privacy issue is overlooked in current studies on dialogue systems, where the datasets utilized to train dialogue models often contain many private information exchanged between two individuals. Li et al. [102] empirically show that speakers' personas can be inferred through a simple neural network with high accuracy. To this end, defense objectives are designed to protect persona leakage from hidden states. Apart from the privacy leakage issue of training data, the agent's proactivity raises more concerns on misusing personal information obtained from the users during the conversation. For example in non-collaborative dialogues or recommendation dialogues, the dialogue system tends to proactively acquire user preference or personal information. Despite its benefits on the on-going conversations, it would be problematic if such information is memorized by the model and the users are not willing to reveal the persona information outside the current conversation.

In essence, proactivity, viewed as a hallmark of advanced AI, should remain within controllable limits to prevent adverse impacts on others.

8 Conclusions and Outlook

This article offers a comprehensive review of the intricate problems and designs associated with conversational agent proactivity across various dialogue systems, including ODDs, TODs, and information seeking dialogues. To further aid research and development in this field, we have highlighted some of the noteworthy data resources that can be publicly accessed to investigate the problems faced by proactive dialogue systems. Despite the advancements achieved, we have also pointed towards several open challenges that still require extensive exploration and analysis, such as the proacvitivity in hybrid dialogues and LLM-based dialogue systems, the evaluation protocols and ethical considerations for agent's proactivity in dialogue systems.

Looking ahead, the future of proactive conversational AI holds immense potential. As LLMs continue to evolve, they will play a pivotal role in driving the proactivity of conversational agents, enabling more complex and pracitical dialogues. We foresee advancements in hybrid dialogue systems that combine the strengths of different types of dialogues, creating versatile agents capable of handling a wider range of interactions. Furthermore, the establishment of standardized evaluation protocols will be crucial in assessing and benchmarking the performance of proactive dialogue systems, ensuring their reliability and effectiveness. Ethical considerations will also become increasingly important as proactive dialogue systems become more prevalent. Ensuring transparency, user privacy, and fairness will be key challenges that need to be addressed to build trust and acceptance among users.

We anticipate the development of more sophisticated and nuanced dialogue systems that can seamlessly integrate proactive behaviors, enhancing user experience and satisfaction. These systems will likely become more adept at understanding and anticipating needs of themselves or human users, leading to more natural and intuitive interactions. We believe that these research efforts and innovations will significantly contribute to the advancement of artificial general intelligence through proactive dialogue systems. We hope that this exhaustive survey can serve as an essential reference for individuals interested in researching and investigating proactive dialogue systems while also stimulating more interest in the community. By fostering collaboration and knowledge sharing, we can drive the field forward, ultimately creating more intelligent, responsive, and ethical conversational agents.

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