# Interactive Natural Language Processing

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# Abstract

Interactive Natural Language Processing (iNLP) has emerged as a novel paradigm within the field of NLP, aimed at addressing limitations in existing frameworks while aligning with the ultimate goals of artificial intelligence. This paradigm considers language models as agents capable of observing, acting, and receiving feedback iteratively from external entities.

Specifically, language models in this context can: (1) interact with humans for better understanding and addressing user needs, personalizing responses, aligning with human values, and improving the overall user experience; (2) interact with knowledge bases for enriching language representations with factual knowledge, enhancing the contextual relevance of responses, and dynamically leveraging external information to generate more accurate and informed responses; (3) interact with models and tools for effectively decomposing and addressing complex tasks, leveraging specialized expertise for specific subtasks, and fostering the simulation of social behaviors; and (4) interact with environments for learning grounded representations of language, and effectively tackling embodied tasks such as reasoning, planning, and decision-making in response to environmental observations.

This paper offers a comprehensive survey of iNLP, starting by proposing a unified definition and framework of the concept. We then provide a systematic classification of iNLP, dissecting its various components, including interactive objects, interaction interfaces, and interaction methods. We proceed to delve into the evaluation methodologies used in the field, explore its diverse applications, scrutinize its ethical and safety issues, and discuss prospective research directions. This survey serves as an entry point for researchers who are interested in this rapidly evolving area and offers a broad view of the current landscape and future trajectory of iNLP.

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# 1 Introduction

Natural Language Processing (NLP) has witnessed a remarkable revolution in recent years, thanks to the development of generative pre-trained language models (PLMs) such as BART (Lewis et al., 2019), T5 (Raffel et al., 2020), GPT-3 (Brown et al., 2020), PaLM (Chowdhery et al., 2022), to name a few. These models can generate coherent and semantically meaningful text, making them useful for various NLP tasks such as machine translation (Liu et al., 2020), summarization (Liu, 2019; Liu & Lapata, 2019), and question answering (Radford et al., 2019; Brown et al., 2020; Raffel et al., 2020). However, these models also have clear limitations such as misalignment with human needs (Wolf et al., 2023; Kenton et al., 2021), lack of interpretability (Wu et al., 2021; OpenAI, 2023), hallucinations (Welleck et al., 2019; Ji et al., 2022; OpenAI, 2023), imprecise mathematical operations (Schick et al., 2023; Mialon et al., 2023), inadequate experience grounding (Bisk et al., 2020), and limited ability for complex reasoning (Qiao et al., 2022; Huang & Chang, 2022), among others (Borji, 2023).

To address these limitations, a new paradigm of natural language processing has emerged: interactive natural language processing (iNLP) (Bisk et al., 2020; Bolotta & Dumas, 2022). There have been a variety of definitions for "interactive" in the NLP and Machine Learning literature, where the term typically refers to the involvement of humans in the process. For example, Wondimu et al. (2022) define Interactive Machine Learning (iML) as "an active machine learning technique in which models are designed and implemented with human-in-the-loop manner." Faltings et al. (2023) view Interactive Text Generation as "a task that allows training generation models interactively without the costs of involving real users, by using user simulators that provide edits that guide the model towards a given target text." Wang et al. (2021d) describe Human-in-the-loop (HITL) as "where model developers continuously integrate human feedback into different steps of the model deployment workflow." The popularity of  $ChatGPT^1$  also demonstrated the impressive capabilities of human-LM interaction via reinforcement learning from human feedback (RLHF). Although humans are the most common type of objects for interacting with language models, recent research has revealed other important object types for interaction, which include Knowledge Bases (KBs) (Li et al., 2022c; Hu et al., 2022b), Models/Tools (Qiao et al., 2022; Mialon et al., 2023; Dohan et al., 2022; Yao et al., 2022b; Shen et al., 2023; Qin et al., 2023), and Environments (Li et al., 2022e; Yang et al., 2023a; Ahn et al., 2022; Huang et al., 2022c; Vemprala et al., 2023; Bubeck et al., 2023). Therefore, in our survey, we first define interactive natural language processing which accounts for a broader scope of objects that can interact with language models:

# Interactive Natural Language Processing (iNLP) considers language models as agents capable of observing, acting, and receiving feedback in a loop with external objects such as humans, knowledge bases, tools, models, and environments<sup>2</sup>.

Specifically, through interaction, a language model (LM) can leverage external resources to improve its performance and address its limitations mentioned in the first paragraph. For example, interacting with humans aligns language models better with human needs and human values (e.g., helpfulness, harmlessness, honesty) (Ouyang et al., 2022; Bai et al., 2022a) and interacting with KBs can help language models alleviate hallucinations (Ji et al., 2022). Likewise, interacting with models or tools can improve the abilities of LMs such as reasoning, faithfulness, and exactitude of mathematical operations (Mialon et al., 2023; Schick et al., 2023). And finally, interacting with environments can enhance the grounded reasoning capability of LMs (Liu et al., 2022g) and promote the applications of LMs in embodied tasks (Zeng et al., 2022a; Yang et al., 2023a).

Furthermore, interaction may hold the potential to unlock future milestones in language processing, which can be considered the holy grail of artificial intelligence (Bisk et al., 2020). In 2020, Bisk et al. (2020) have examined the future direction of natural language processing and proposed five levels of world scope to audit progress in NLP: "(1) Corpus; (2) Internet; (3) Perception (multimodal NLP); (4) Embodiment; (5) Social." Notably, the recent release of GPT-4 (OpenAI, 2023) and PaLM-2 (Google, 2023), which are large

<sup>&</sup>lt;sup>1</sup>https://openai.com/blog/chatgpt

<sup>&</sup>lt;sup>2</sup>Observation involves all kinds of inputs to language models. Action involves all kinds of outputs of language models such as text generation (Ouyang et al., 2022), requesting for external objects (Yao et al., 2022); Schick et al., 2023), text editing (Faltings et al., 2023), etc. Feedback involves feedback messages passed from external objects to language models such as scoring from humans (Ouyang et al., 2022).

multimodal language models, has brought significant advancements to the third level "Perception". Embodied AI and Social Embodied AI fundamentally posit that a more comprehensive language representation can be learned through the establishment of an interactive loop involving language model agents, environments, and humans (Bisk et al., 2020; Bolotta & Dumas, 2022; Bandura; Tamari et al., 2020; Lake et al., 2016; Driess et al., 2023; Yuan & Zhu, 2023). This perspective highlights the need for the NLP community to shift its attention towards the fourth and fifth levels ("Embodiment" and "Social Interaction") to propel the field forward. In addition to models, humans, and environments, tools and knowledge bases that facilitate connections between language models and the external world also play a significant role in enabling (social) embodiment (Qin et al., 2023; Xie et al., 2022; Weser & Proffitt, 2019; Bisk et al., 2020). The future achievement of social embodiment of language models may lead to significant phenomena, including artificial self-awareness (Bubeck et al., 2023; Kosinski, 2023) and the emergence of a language model society (Park et al., 2023; Li et

Therefore, interactive NLP is beneficial for both NLP researchers and practitioners, since it has the potential to address limitations such as hallucination (Ji et al., 2022) and alignment (Wolf et al., 2023), while also aligning with the ultimate goals of AI (Bubeck et al., 2023; Bisk et al., 2020; Qin et al., 2023). Notably, with the recent release of ChatGPT and GPT-4 (OpenAI, 2023), which have overwhelmed the NLP community and are considered the spark of artificial general intelligence (AGI) by some researchers due to their remarkable universal capabilities (Bubeck et al., 2023), the NLP community is now experiencing a shift in focus towards posing new challenges in the field. This transition has prompted numerous surveys and position papers that aim to propose novel research directions, with many of them addressing the theme of interaction. For example, Mialon et al. (2023) survey the strategies that PLMs employ cascading mechanisms for reasoning (Dohan et al., 2022) and utilize tools for taking action. But (Mialon et al., 2023) lacks an in-depth discussion on interactivity, and focuses solely on tool use and reasoning, while overlooking other topics such as interaction with knowledge bases, and simulation of social behavior. Yang et al. (2023a) investigate the cross-disciplinary research field of foundation models and decision making, with a particular emphasis on exploring the interactions of language models with humans, tools, agents, and environments. But they primarily focus on decision-making settings and reinforcement learning formalisms, without providing a comprehensive discussion on interacting with knowledge bases or the interaction methodology from the perspective of NLP techniques, such as chain-of-thought prompting (Wei et al., 2022b). Bubeck et al. (2023) discuss the interactions of language models with the world based on tool-use and embodiment, as well as their interactions with humans based on Theory of Mind (ToM) and self-explanation. But they primarily focus on evaluating the abilities of large language models (LLMs) and lack a comprehensive discussion of the interaction methodology employed in the studies. Other surveys and works (Lee et al., 2022c; Qin et al., 2023; Vemprala et al., 2023; Yuan & Zhu, 2023) have also contributed valuable insights to the theme of interaction. However, they are also specific to certain aspects and do not offer a unified and systematic review that covers the entire spectrum of interactive NLP.

Clearly, the field of interactive NLP has undergone significant development in the past few years, with the emergence of new forms of interactive objects that go beyond the standard Human-in-the-loop approach. These new forms of objects encompass knowledge bases, models/tools, and environments. While the aforementioned works provide some coverage of interactions involving models/tools and environments, there is a notable absence of discussions regarding interactions with language models using knowledge bases (KB). Furthermore, there is a lack of a comprehensive review of methodologies in the context of interactive NLP. Hence, the main goals of our survey are:

- 1. **Unified Definition and Formulation**: to provide a unified definition and formulation of interactive NLP, establishing it as a new paradigm of NLP.
- 2. Comprehensive Classification: to provide a comprehensive breakdown of iNLP along dimensions such as interactive objects, interaction interfaces, and interaction methods, enabling a systematic understanding of its different aspects and components.
- 3. Further Discussion: to survey the evaluation methodologies used in iNLP, examine its diverse applications, and discuss the ethical and safety issues as well as the future directions in this field.

We believe that conducting such a survey is highly timely, and our paper aims to fill the gaps of aforementioned surveys by serving as an entry point for researchers who are interested in pursuing research in this important and fast-evolving area but may not yet be familiar with it. As illustrated in Figure 1, we will start with an in-depth discussion about interactive objects (§2), followed by an overview of interaction interfaces by which the language models communicate with the external objects (§3). We then organize a variety of interaction methods by which the language models fan in and out interaction messages (§4). This is followed by a discussion about evaluation in the context of iNLP (§5). Finally, we will examine the current applications of iNLP (§6), discuss ethical and safety issues (§7), and suggest future directions and challenges (§8). Taxonomy 2 gives a bird's-eye view of our survey.



<sup>a</sup>Self-interaction is also included.

(d) Interacting with Environments.

Figure 1: The paradigm of Interactive Natural Language Processing.



Figure 2: Taxonomy of interactive NLP.

# 2 Interactive Objects

In this section, we will discuss the objects that interact with language models as illustrated in Figure 1. When an entity is interacting with a language model, it is considered to be "in the loop", meaning that it is an active participant in the process of model training or model inference. As previously mentioned, the interactive objects include humans, knowledge bases, models/tools, and environments; each of which will be introduced in the following subsections.

# 2.1 Human-in-the-loop

Human-in-the-loop NLP represents a paradigm that emphasizes information exchange between humans and language models (Wang et al., 2021d). This approach seeks to more effectively address users' needs and uphold human values, a concept known as Human-LM Alignment (Bai et al., 2022a; Kenton et al., 2021; Ouyang et al., 2022; Leike et al., 2018). In contrast, earlier research on text generation primarily concentrated on the input and output of samples, overlooking aspects such as human preferences, experiences, personalization, diverse requirements, and the actual text generation process (Lee et al., 2022c). In recent years, as pretrained language models (PLMs) and large language models (LLMs) have matured, optimizing human-model interactions has emerged as a prevalent concern within the community. Incorporating human prompts, feedback, or configurations during the model training or inference stages, using either





real or simulated users, proves to be an effective strategy for enhancing the Human-LM alignment (Faltings et al., 2023; Ouyang et al., 2022; Wu et al., 2021).

Subsequently, we divide human-in-the-loop NLP into three types according to the schemes of user interaction, along with an additional section that delves into the simulation of human behaviors and preferences for these types, in order to enable scalable deployment of human-in-the-loop systems. These categories are:

- 1. Communicating with Human Prompts: users can interact with the model consecutively in a conversation.
- 2. Learning from Human Feedback: users can provide feedback to update the parameters of LMs.
- 3. Regulating via Human Configuration: users can configure the settings of LMs.
- 4. Learning from Human Simulation: simulations of users are employed for the three aforementioned types, ensuring practical implementation and scalability.

**Communicating with Human Prompts.** This is the most general form of Human-LM interaction, which allows a language model to interact with a human in a conversational manner. The main purpose of this interaction scheme is to maintain real-time and continuous interaction, so typical application scenarios include dialogue systems, real-time translation, and multiple rounds of question answering. This interactive process of alternating iterations allows the output of the model to realign gradually to meet user requirements.

Generally, this interaction scheme does not update the model's parameters during the interaction, instead requiring users to continuously input or update prompts to elicit more meaningful responses from the language model. As a result, conversation can be inflexible and labor-intensive due to the need for prompt engineering or dialogue engineering. To address these limitations, editing-based methods have been proposed by Malmi et al. (2022); Schick et al. (2022); Faltings et al. (2023); Shi et al. (2022a); Du et al. (2022a) to encourage the language model to modify existing output (c.f., §3.3). Additionally, context-based methods have been

developed that enhance model output by adding examples or instructions to the input context, such as few-shot prompting or in-context learning (Brown et al., 2020).

However, since these approaches do not involve adapting language models to accommodate human users, numerous trial edits or prompts may be required to achieve the desired outcome, resulting in lengthier dialogue rounds. As such, this interaction scheme can be inefficient and may lead to a suboptimal user experience.

**Learning from Human Feedback.** In contrast to "Communicating with Human Prompts", this interaction scheme provides feedback on the model's outputs, such as scoring, ranking, and offering suggestions, for model optimization. This feedback is therefore used to adjust the model's parameters, rather than simply acting as prompts for language models to respond. The primary objective of this interaction is to better adapt LMs for user needs and human values (Bai et al., 2022a).

For instance, Godbole et al. (2004) and Settles (2011) employ active learning to provide human feedback. By labeling a few examples based on model predictions, they update the model parameters to improve its understanding of human needs. More recently, Shuster et al. (2022) enhance a language model through continuous learning from user feedback and dialogue history. InstructGPT (Ouyang et al., 2022) initially trains GPT-3 using supervised instruction tuning and subsequently fine-tunes it via reinforcement learning from human feedback (RLHF), where the reward model is trained on annotated human preference data. This reward model, in turn, serves as a user simulator which can provide feedback for model's predictions. Ramamurthy et al. (2023) demonstrate that RLHF is more data- and parameter-efficient than supervised methods when a learned reward model provides signals for an RL method, not to mention that preference data is easier to collect than ground-truth data. Fernandes et al. (2023) and Wang et al. (2021d) provide a comprehensive survey on the topic of "learning from feedback". We refer the readers to these two surveys for more information.

**Regulating via Human Configuration.** The two interaction schemes previously discussed involve engagement with simulated or real humans through prompts or feedback. Regulation through human configuration, on the other hand, relies on users to customize and configure the language model system according to their needs. This customization can include adjustments to the system's structure, hyperparameters, decoding strategy, and more. Although it may not be the most flexible method, it is one of the simplest ways to facilitate interaction between the user and the system.

For example, Wu et al. (2021) predefine a set of LLM primitive operations, such as "ideation", "split points", "compose points", etc.; each operation being controlled by a specific prompt template. Users can customize the usage and chaining schemes of different operations to meet a set of given requirements. Similarly, PromptChainer (Wu et al., 2022a) is an interactive interface designed to facilitate data transformation between different steps of a chain. It also offers debugging capabilities at various levels of granularity, enabling users to create their own LM chains. Users can also configure some hyperparameters to control the performance of LLMs. This includes, but is not limited to, temperature (which controls the stochasticity of the output), the maximum number of tokens to generate, and "top-p" controlling diversity via nucleus sampling (Holtzman et al., 2019)<sup>3</sup>. Vemprala et al. (2023) have proposed the concept of "user-on-the-loop", implying that users can configure the LM-robot interaction with human instructions, ensuring that the process and results of the interaction are centered around the user's needs.

Learning from Human Simulation. In many cases, training or deploying language models with real users is impractical, prompting the development of various user simulators to emulate user behavior and preferences. For instance, Ouyang et al. (2022) initially rank generated responses with real annotators based on their preferences and then train a reward model—initialized from GPT-3 (Brown et al., 2020)—on this preference data to serve as a user preference simulator. Kim et al. (2023) propose a method to simulate human preference by utilizing a transformer model that captures important events and temporal dependencies within segments of human decision trajectories. Additionally, this approach relies on a weighted sum of non-Markovian rewards. Faltings et al. (2023) simulate user editing suggestions through BertScore-based (Zhang

<sup>&</sup>lt;sup>3</sup>https://platform.openai.com/playground

et al., 2020b) token-wise similarity scores and dynamic programming to compute an alignment between a draft and a target. Lynch et al. (2022) collect numerous language-annotated trajectories, with the policy trained using behavioral cloning on the dataset. These collected trajectories can also be viewed as a user simulator.

The design of a user simulator is critical for the successful training and evaluation of language models. For example, to accurately replicate the behavior and preferences of real users when developing a generic dialogue system, it is vital to collect a diverse and extensive range of user data for training the simulator. This allows it to encompass the full spectrum of user preferences and behaviors. Moreover, when developing language models for rapidly changing application scenarios, it is essential to continually update and refine the simulator to adapt to shifts in user demographics and their evolving preferences.

# 2.2 KB-in-the-loop

KB-in-the-loop NLP has two main approaches: one focuses on utilizing external knowledge sources to augment language models during inference time (Khandelwal et al., 2020; Guu et al., 2020; Lewis et al., 2020; Cheng et al., 2021; Izacard et al., 2022; Menick et al., 2022; Borgeaud et al., 2021; Nakano et al., 2021; Shuster et al., 2021; Wang et al., 2023a; Lewis et al., 2021; Chen et al., 2023b), while the other aims to employ external knowledge to enhance language model training, resulting in better language representations (Lu et al., 2021c; Liu et al., 2019a; Zhang et al., 2019; Sun et al., 2019; Févry et al., 2020; Sun et al., 2021b; Xiong et al., 2020; Liu et al., 2022e; Hu et al., 2022b). Interacting with KB during training can help improve the model's representation to incorporate more factual knowledge. In contrast, interacting with KB during inference can assist the language model in generating more accurate, contextually relevant, and informed responses by dynamically leveraging external knowledge sources based on the specific input or query at hand.

In this following sections, we will discuss knowledge sources and knowledge retrieval. As for knowledge integration, we refer the readers to §4.7 for more details.

**Knowledge Sources.** Knowledge sources are normally categorized into the following types:

(1) Corpus Knowledge: Typically, corpus knowledge is stored in an offline collection from a specific corpus, which the language model accesses to enhance its generation capabilities. Common examples of corpus knowledge include the Wikipedia Corpus (Foundation), WikiData Corpus (Vrandečić & Krötzsch, 2014), Freebase Corpus (Bollacker et al., 2008), PubMed Corpus<sup>4</sup>, and CommonCrawl Corpus<sup>5</sup>, among others. Most previous research has focused on corpus knowledge due to its controllability and efficiency. Retrieval-



Figure 4: KB-in-the-loop.

Augmented Language Models (Guu et al., 2020; Lewis et al., 2020; Borgeaud et al., 2021; Shuster et al., 2021; Izacard et al., 2022) have been proposed to develop language models capable of utilizing external knowledge bases for more grounded generation (Hu et al., 2022b; Li et al., 2022c). To further improve interpretability, subsequent studies (Lewis et al., 2021; Chen et al., 2023b; Wu et al., 2022f) have suggested using extracted Question-Answer pairs as the corpus for more fine-grained knowledge triple grounding. Recently, there has been growing interest in incorporating citations to enhance grounding in language models, as demonstrated by GopherCite (Menick et al., 2022). Another line of work, including KELM (Lu et al., 2021c), ERNIE (Sun et al., 2019; 2020b; 2021b), and others (Xiong et al., 2020; Févry et al., 2020), primarily employs recognized entities as the foundation for integrating knowledge graph information into neural representations.

(2) Internet Knowledge: One challenge associated with corpus knowledge is its limited coverage and the need for specialized retrieval training. A potential solution involves offloading the retrieval process to search engines and adapting them to find the desired content. The Internet-augmented language model (Lazaridou et al., 2022) was first introduced to answer open-domain questions by grounding responses in search results from the

<sup>&</sup>lt;sup>4</sup>https://pubmed.ncbi.nlm.nih.gov/

<sup>&</sup>lt;sup>5</sup>https://commoncrawl.org/

Internet. This approach has since been demonstrated to effectively answer time-sensitive questions (Kasai et al., 2022). The Internet has also been employed for post-hoc attribution (Gao et al., 2022a). WebGPT (Nakano et al., 2021) proposes powering language models with a web browser, which searches the web before generating knowledgeable or factual text. MineDojo (Fan et al., 2022) equips a video-language model with Internet-scale knowledge to tackle diverse tasks within a *Minecraft* environment. ToolFormer (Schick et al., 2023) similarly integrates a search engine into the tool-use adaptation of language models. ReAct (Yao et al., 2022b) suggests leveraging the Internet to augment reasoning capabilities in black-box large language models.

While corpus knowledge and internet knowledge are both valuable resources that language models can utilize to enhance their capabilities, they inherently differ in terms of controllability and coverage. Corpus knowledge is pre-collected and stored offline in a controlled setting, making it easy to access and integrate into a language model. However, it is limited by the information within the corpus and may not be up-to-date or comprehensive. In contrast, internet knowledge offers a vast and diverse pool of constantly updated information, providing more comprehensive coverage. However, controlling and curating internet knowledge is challenging, as the information obtained from the internet may be more noisy or even more misleading. Additionally, it is worth noting that there are other miscellaneous types of knowledge sources, such as visual knowledge (Wang et al., 2022d), rule-based knowledge (Saeed et al., 2021; Han et al., 2022b; Wang et al., 2021b; Liu et al., 2022g), implicit knowledge (Petroni et al., 2019), database knowledge (Li et al., 2023c), and documentation knowledge (Zhou et al., 2022c). These can be categorized into either corpus knowledge or internet knowledge, depending on their nature.

Knowledge Retrieval. Enhancing language models with knowledge requires careful consideration of knowledge quality. Knowledge quality is primarily affected by issues such as knowledge missing and knowledge noise (Ye et al., 2022). Knowledge missing can be mitigated by changing or extending the knowledge source to provide more comprehensive information. To tackle knowledge noise, an intuitive approach is to filter out the noisy information. Liu et al. (2019a) and Ye et al. (2022) propose addressing this issue by using a visibility matrix that functions on the attention scores between the knowledge and input. This helps in better integration of high-quality knowledge into the language model. Despite the success of these methods, improving knowledge retrieval remains the most critical aspect of addressing these challenges. This is because improving knowledge retrieval directly impacts the precision and recall of knowledge that is selected and integrated into the language model, leading to better overall performance. There are overall three methods for knowledge retrieval:

(1) **Sparse Retrieval**: In this approach, knowledge is retrieved based on lexical matches between words or phrases in the input text and a knowledge source or the similarity between sparse representations. For example, ToolFormer (Schick et al., 2023) employs BM25 (Robertson & Zaragoza, 2009) as a metric to retrieve knowledge from Wikipedia. DrQA (Chen et al., 2017) retrieves documents using TF-IDF vectors. RepoCoder (Zhang et al., 2023a) incorporates the Jaccard index (Jaccard, 1912) as one of its retrieval metrics. Moreover, researchers explore on utilizing the sparse representations from pre-trained language model compound with the lexical matching methods (Dai & Callan, 2020; Zhao et al., 2020a; Formal et al., 2021).

(2) **Dense Retrieval**: Dense retrieval approach retrieves knowledge based on the meaning of the input text rather than merely matching exact words or phrases. The meaning is typically encoded by a learned retriever. A dual encoder or cross encoder can be used as the retriever. For example, REALM (Guu et al., 2020) employs a latent knowledge retriever that is trained in an unsupervised manner to extract relevant information and context from a vast corpus during both the training and inference stages. Retro (Borgeaud et al., 2021) retrieves chunks from an external knowledge base using a dual encoder and integrates the retrieved chunks into language models through cross attention. Cai et al. (2021) jointly train a translation memory retriever and neural machine translation model. RepoCoder(Zhang et al., 2023a) also employs an embedding model to compute the cosine similarity between input and knowledge. Atlas (Izacard et al., 2022) retrieves knowledge with Contriever (Izacard et al., 2021), a dense dual encoder-based retriever trained via contrastive learning. Izacard & Grave (2021) and RePlug (Shi et al., 2023) propose distilling knowledge from a reader to a retriever model, which requires very few annotated training data.

(3) Generative Retrieval : Instead of retrieving knowledge through matching, a generative retriever directly produces the document id or content as knowledge. As such, the generative retriever, typically in the form of a language model, can be considered a type of knowledge base, which is also known as implicit knowledge (Petroni et al., 2019; Jiang et al., 2020; Liu et al., 2022d). For example, DSI (Tay et al., 2022c) encodes numerous documents with their ids into the language model's parameters. During inference, the model generates the id of the most relevant document. Sun et al. (2022) propose augmenting language models with recitations, which are relevant knowledgeable content generated by language models. Yu et al. (2022b) prompt a large language model to generate diverse contextual documents based on a given question and then read the generated documents to produce a final answer, where the in-context demonstrations for the LLM prompting are sampled from a clustered document pool. It is worth noting that knowledge distillation may also fall within this category. For example, Ho et al. (2022) allow large language models large language models are generative retriever-like knowledge base for the smaller language models.

(4) **Reinforcement Learning**: Knowledge retrieval can also be formulated as a reinforcement learning problem. For example, WebGPT (Nakano et al., 2021) learns to retrieve and select documents via behavior cloning (BC) and reinforcement learning from human feedback (RLHF). Zhang et al. (2022g) formulate the example retrieval problem as a Markov Decision Process (MDP) and propose a reinforcement learning (RL) method to select examples.

#### 2.3 Model/Tool-in-the-loop

Addressing complex tasks often necessitates the implementation of strategic methodologies that can simplify the process. One such effective strategy is the explicit decomposition of the task into modularized subtasks and then solve these subtasks step by step (Wei et al., 2022b; Zhou et al., 2022a; Dohan et al., 2022; Qiao et al., 2022). Alternatively, another strategy involves the implicit decomposition of the task through the division of labor among multiple language model agents. This approach enables a natural and adaptive breakdown of the work, as each agent assumes a specific role in the larger task (Zeng et al., 2022a; Bara et al., 2021; Goyal et al., 2022). The procedure of task decomposition not only allows subtask modularization, but also enables subtask composition. Furthermore, by breaking the task into multiple steps, specific steps can be allocated to certain expert models or external tools, such as those specializing in arithmetic computation, web search, counting, and more (Schick et al., 2023; Yao et al., 2022b; Qin et al., 2023). Inspired by (Mialon et al., 2023; Yao et al., 2022b), there are primarily three fundamental operations involved in decomposing and solving these subtasks:



Figure 5: Model/Tool-in-the-loop.

- 1. Thinking: The model engages in self-interaction to reason and decompose complex problems into modularized subtasks (Yao et al., 2022b; Mialon et al., 2023; Bubeck et al., 2023; Dohan et al., 2022);
- 2. Acting: The model calls tools or models to solve these intermediate subtasks, which may result in effects on the external world (Yao et al., 2022b; Mialon et al., 2023; Qin et al., 2023);
- Collaborating: Multiple models with distinct roles or division of labor communicate and cooperate with each other to achieve a common goal or simulate human social behaviors (Clark, 1996; Premack & Woodruff, 1978; Bara et al., 2021; Kosinski, 2023; Park et al., 2023; Li et al., 2023b).

**Thinking.** For example, consider the question, "What is the biggest animal in Africa?", which can be decomposed into a chain of three subtasks: "What animals are in Africa?"  $\rightarrow$  "Which of these animals are

 $large?" \rightarrow "Which of these is the largest?"$  These three subtasks form a prompt chain (c.f., §4.2.3), allowing for the individual solving of each subtask by a single LM, multiple LMs, or even tools. That is, through the process of thinking, the overall task can be decomposed into multiple subtasks that can be efficiently tackled through interactions among language models or tools in a chained manner.

The preliminary instantiation of such a cognitive process is **Chain-of-Thought (CoT)** (Wei et al., 2022b), which seeks to elicit multi-hop complex reasoning capabilities from large language models using a cascading mechanism (Dohan et al., 2022). Instead of directly producing the answer, multiple thoughts (i.e., reasoning steps) are generated beforehand (Wei et al., 2022b; Wang et al., 2022f; Zhou et al., 2022a; Press et al., 2022). Thus, CoT decomposes the task into two sub-tasks: *thought generation*  $\rightarrow$  answer generation. However, typical CoT involves solving these subtasks in a single model run (Wei et al., 2022b) without an interaction mechanism.

Derivative works of CoT have shown an increasing tendency to utilize a self-interaction loop that involves iteratively calling the same language model to solve different subtasks (Zhou et al., 2022a; Wang et al., 2022a; Press et al., 2022; Yao et al., 2022b), also known as **multi-stage CoT** (Dong et al., 2023b; Qiao et al., 2022). Furthermore, some other derivative works share similar principles with CoT or multi-stage CoT but employ **different training strategies**, such as bootstrapping (Zelikman et al., 2022) (as discussed in §4.3.4). Some works go beyond the subtask of *thought generation* and **introduce new subtasks**, including *thought verification* (Weng et al., 2022), *fact selection and inference* (Creswell et al., 2022), and *self-refinement and self-feedback* (Madaan et al., 2023), among others. Indeed, all of these works can be seen as instantiations of the thinking cognitive process. They employ a self-interaction mechanism, wherein a single language model is utilized iteratively to decompose tasks into subtasks, and effectively solve these subtasks.

Acting. Different from the process of thinking, acting involves the interaction of the LM with external entities, such as other LMs and tools. Since different models or tools can possess specific expertise, the LM can invoke these external entities to perform specific subtasks when the task is decomposed into subtasks. For example, *thought verification* can be accomplished using a discriminative model (Chen et al., 2023d), and *fact selection* may utilize a retriever model (Guu et al., 2020). External tools such as calculators (Cobbe et al., 2021; Schick et al., 2023), simulators (Cranmer et al., 2020; Liu et al., 2022g), search engines (Yao et al., 2022b; Nakano et al., 2021), code interpreters and executors (Ni et al., 2023; Gao et al., 2022b; Chen et al., 2022c), and other APIs (Parisi et al., 2022; Yao et al., 2022b; Schick et al., 2023; Thoppilan et al., 2022; Shuster et al., 2022; Mialon et al., 2023; Liang et al., 2023b; Wu et al., 2023; Qin et al., 2023) can also be incorporated into the loop to tackle subtasks that language models typically encounter difficulties with. Generally, tasks emphasizing faithfulness and exactitude (e.g., real facts, complex mathematical operations) and tasks beyond the LM training corpus (e.g., up-to-date information, low-resource languages, awareness of time, image generation) are better solved using external tools than LMs (Welleck et al., 2019; Maynez et al., 2020; Patel et al., 2021a; Komeili et al., 2022; Lin et al., 2022b; Dhingra et al., 2022; Schick et al., 2023; Schick et al., 2022; Schick et al., 2022; Schick et al., 2022; Schick et al., 2023; Liang et al., 2022; Lin et al., 2022b; Dhingra et al., 2022; Schick et al., 2023; Mialon et al., 2023; Liang et al., 2023; Qin et al., 2023).

For example, ToolFormer (Schick et al., 2023) enhances language models with tool-use capabilities by retraining on a tool-use prompted corpus and involving tools such as calculators, calendars, search engines, question-answering systems, and translation systems. ART (Paranjape et al., 2023) begins by selecting demonstrations from a task library that involve multi-step reasoning and tool usage. These demonstrations serve as prompts for the frozen LLM to generate intermediate reasoning steps in the form of executable programs. ReAct (Yao et al., 2022b) combines both chain-of-thought reasoning and task-specific tool-use actions to improve the interactive decision-making capabilities of language models. TaskMatrix.AI (Liang et al., 2023b) presents a vision for a new AI ecosystem built on tool-use APIs, proposing an architecture composed of an API platform, API selector, multimodal conversational foundation model, API-based action executor, and integrating RLHF and feedback to API developers to optimize the system. This architecture benefits from its ability to perform digital and physical tasks, its API repository for diverse task experts, its lifelong learning ability, and improved interpretability. HuggingGPT (Shen et al., 2023) and OpenAGI Ge et al. (2023) use ChatGPT as a task controller, planning tasks into multiple subtasks that can be solved by models (tools) selected from the HuggingFace platform<sup>6</sup>.

<sup>&</sup>lt;sup>6</sup>https://huggingface.co/

Moreover, acting can have a tangible impact on the external world through tool-use (Mialon et al., 2023), also referred to as Tool-Oriented Learning (Qin et al., 2023). For instance, ChatGPT Plugins<sup>7</sup> empower LLMs to directly utilize tools for tasks such as travel bookings, grocery shopping, and restaurant reservations, among others. LM-Nav (Shah et al., 2022) leverages a visual navigation model (VNM) to execute the actions planned by the LLM, enabling real-world robotic navigation. In these cases, the overall task is still decomposed into subtasks, but some of which are connected with the external world. By employing specific models or tools to address these subtasks, tangible effects can be realized in the environment. Readers can refer to §2.4 for additional information related to the interaction between the language model and the environment.

**Collaborating.** Most of the aforementioned research relies on manual task decomposition. Although some existing works propose automatic task decomposition through distant supervision (Min et al., 2019; Talmor & Berant, 2018; Perez et al., 2020) or in-context learning (Zhou et al., 2022a; Press et al., 2022; Khot et al., 2022; Dua et al., 2022; Mialon et al., 2023), explicit task decomposition is not always straightforward. On the one hand, it requires human expertise or extensive manual effort. On the other hand, in certain cases, different language model agents may share a common goal that is difficult to explicitly decompose (Claus & Boutilier, 1998; Lazaridou et al., 2017; Li et al., 2023b; Bara et al., 2021). In such scenarios, task decomposition or division of labor may emerge implicitly as different agents with specialized skills assume different roles within the task and interact with one another (Clark, 1996; Premack & Woodruff, 1978; Goyal et al., 2022; Li & Zhou, 2020; Liu et al., 2022b; Bara et al., 2021; Kosinski, 2023; Li et al., 2023b). For example, in *MineCraft*, agents with distinct yet complementary recipe skills can communicate and collaborate to synthesize a material, where the specialized agents may automatically discover a potential division of labor (Bara et al., 2021). To the best of our knowledge, we can categorize collaboration-based approaches into three clusters:

(1) **Closed-Loop Interaction** refers to a collaborative process where multiple agents interact with each other in a feedback loop (Freedman et al., 2019; Ahn et al., 2022; Zeng et al., 2022a; Huang et al., 2022c; Dasgupta et al., 2023; Chen et al., 2023d). In the context of control theory, a closed-loop controller uses feedback to control states or outputs from a dynamical system<sup>8</sup>. Generally, closed-loop controllers are preferred over open-loop controllers as they offer greater adaptability and robustness in changing or uncertain environments. Likewise, closed-loop interaction between language model agents is more effective and robust compared to open-loop interaction (Huang et al., 2022b; Lynch et al., 2022), making it a primary paradigm for collaboration-based methods. For example, Socratic Models (Zeng et al., 2022a) and Inner Monologue (Huang et al., 2022c) enable language models to collaborate with vision-language models, audio-language models, or humans to conduct egocentric perception and robotic manipulation tasks, respectively. The language-based closed-loop feedback is incorporated into LLM planning, significantly improving instruction completion abilities (Huang et al., 2022c). Planner-Actor-Reporter (Dasgupta et al., 2023) uses an LLM (Planner) to generate instructions for a separate RL agent (Actor) to execute in an embodied environment. The state of the environment is reported back to the Planner (via the Reporter) to refine instructions and complete the feedback loop. Note that closed-loop interaction is highly applicable in Environment-in-the-loop scenarios, where closed-loop feedback from the environments can be transferred via a model connected to the environment (Huang et al., 2022c; Zeng et al., 2022a).

(2) Theory of Mind in language models has garnered growing attention in the research community (Premack & Woodruff, 1978; Rabinowitz et al., 2018; Zhu et al., 2021; Bara et al., 2021; Kosinski, 2023; Liu et al., 2023a). According to Kosinski (2023), "Theory of Mind (ToM), or the ability to attribute unobservable mental states to others, is central to human social interactions, communication, empathy, self-consciousness, and morality.". Kosinski (2023) demonstrates that large language models, like ChatGPT, can successfully tackle 93% of ToM tasks. This finding suggests that ToM-like capabilities may have naturally emerged in large language models. In line with this, MindCraft(Bara et al., 2021) assigns different material composition tables (sub-skills) to two dialogue agents, enabling them to cooperate and complete the material composition task through mutual communication. Zhu et al. (2021) provide a speaker and listener formulation of ToM, where the speaker should model the listener's beliefs (i.e., action possibilities over some instruction candidates). These ToM mechanisms are beneficial for collaborative tasks (Liu et al., 2023a).

<sup>&</sup>lt;sup>7</sup>https://openai.com/blog/chatgpt-plugins

<sup>&</sup>lt;sup>8</sup>https://en.wikipedia.org/wiki/Control\_theory

(3) Communicative Agent perceives language models as agents (Andreas, 2022) and delves into the study of multi-agent communication (Lazaridou et al., 2017). In addition to Theory of Mind, multiagent communication also investigates the scenarios of referential game (Lazaridou et al., 2017), language acquisition (Liu et al., 2023a), language emergence (Wang et al., 2022j), and role playing (Li et al., 2023b), implying an effort towards LLM society (Li et al., 2023b). For example, Wang et al. (2022j) enable two communicative agents, a speaker and a listener, to learn to play a Speak, Guess and Draw game and automatically derive an interaction interface between them, which is so-called machine language. Camel (Li et al., 2023b) proposes a role-playing framework that involves two cooperative agents, an AI user and an AI assistant. The two language models are prompted with a shared task specifier prompt and different role assignment prompts, which is referred to as *Inception Prompting*. With the condition of Inception Prompting, they communicate with each other without any additional human instruction to solve the specified task. Generative Agents (Park et al., 2023) introduces a novel architecture that extends a LLM to enable believable simulations of human behavior in an interactive sandbox environment, demonstrating the agents' ability to autonomously plan and exhibit individual and social behaviors. Yuan & Zhu (2023)'s formalism even views existing machine learning paradigms such as passive learning and active learning, as communicative learning, which is in line with ter Hoeve et al. (2021)'s interactive language modeling. In these paradigms, the language model agents are grouped into teachers and students, where the students learn from the teachers through interaction. They frame learning as a communicative and collaborative process.

#### 2.4 Environment-in-the-loop

A new trend within the NLP community is to harness the power of LMs to address embodied tasks such as robot manipulation, autonomous driving, and egocentric perception, among others (Ahn et al., 2022; Huang et al., 2022c; Liang et al., 2022b; Chen et al., 2022a; Shah et al., 2022; Zeng et al., 2022a; Dasgupta et al., 2023; Carta et al., 2023; Huang et al., 2023c). In these scenarios, the environment is integrated into an interactive loop with language models. The aim of environment-in-the-loop NLP is language grounding, which is to represent language with meaning reference to environments and experiences (Bisk et al., 2020). It has been argued that only if LMs are put into interaction with real-world or virtual environments can they learn a truly grounded representation of language (Bisk et al., 2020). During this interaction, the environment assumes the responsibility of furnishing the LM with low-level observations, rewards, and state transitions.



Figure 6: Environment-in-the-loop.

Simultaneously, the LM is tasked with generating solutions for environmental tasks, including reasoning, planning, and decision-making (Bisk et al., 2020; Li et al., 2022e; Yang et al., 2023a).

We define two dimensions for language grounding, as shown in Figure 7. The horizontal axis spans from the *concrete* end to the *abstract* end. The term *concrete* refers to models that capture high-dimensional data of the world, such as images, audio, and other similar sensory inputs. On the other hand, the term *abstract* pertains to models that capture low-dimensional data, such as language, code, or other symbolic representations. Compared to a more concrete representation, abstract or bottle-necked representation brings stronger generalization and reasoning ability (Kawaguchi et al., 2017; Trauble et al., 2023; Liu et al., 2021a).

The vertical axis ranges from the *low-level* end to the *high-level* end, where *low-level* means a more direct and embodied interaction with the environment, such as perception or manipulation, while *high-level* means a more indirect and conceptual interaction with the environment, such as reasoning, planning, and decision-making. This axis can reflect the degree of the model's contextual and situational understanding of the environment.

Generally, the environment can be the real world or virtual world simulated by programs such as Mu-JoCo (Todorov et al., 2012) and MineCraft<sup>9</sup>. Hence, the environment is in the bottom-left quadrant in Figure

<sup>&</sup>lt;sup>9</sup>https://www.minecraft.net



Figure 7: Two directions for language grounding. A third direction for language grounding may be social interaction (Bisk et al., 2020; Bolotta & Dumas, 2022; Lazaridou et al., 2017; Liu et al., 2023a) which is not illustrated in this figure but we have discussed it partly in §2.3.

7 with a concrete representation of data and low-level interaction processes. While the language model is in the top-right quadrant in Figure 7 with an abstract representation of data and high-level interaction processes. This discrepancy makes it necessary to ground language models for LM-env interaction. There are mainly two directions: modality grounding and affordance grounding.

(1) **Modality Grounding** (Beinborn et al., 2018) aims to move the language model from the abstract quadrant to the concrete quadrant. It is intuitive to incorporate information in image, audio or other modalities into it. In this way, language models can capture more complete observations from the environment.

(2) Affordance Grounding (Ahn et al., 2022) strives to transition language models from the high-level quadrant to the low-level quadrant. The goal is to align the outputs of language models with the contextual scene, ensuring that the generated text correspond to the surrounding environment rather than being detached from it.

It is worth noting that these two goals are not independent processes, and often form a synergy towards the environment. Moreover, other additional requirements such as preference and safety are also possible directions (Huang et al., 2023c), which may further involve human in the loop.

**Modality Grounding.** Modality-Grounded Language Model (MGLM) is designed to allow language models to process data of more modalities such as vision and audio. In the context of visual grounding (i.e., vision-language pre-trained model), for example, there are three ways: (1) Dual-Tower modeling which trains different encoders for different modalities (Tan & Bansal, 2019; Lu et al., 2019a; Radford et al., 2021; Xu et al., 2022c; Li et al., 2021b; Yu et al., 2022a; Zeng et al., 2022c); (2) Single-Tower modeling using the concatenation of multimodal data to train a single model (Su et al., 2019; Li et al., 2019; Chen et al., 2020d; Li et al., 2020b; Wang et al., 2022c; Reed et al., 2022; Brohan et al., 2022; Koh et al., 2023; Driess et al., 2023; Chen et al., 2022e; Wang et al., 2022e;b; Diao et al., 2023b; Huang et al., 2023c; Alayrac et al., 2022; Li et al., 2023d; Wu et al., 2023a; Zhu et al., 2023b; Chen et al., 2023d). These methods involve the utilization of visual information during both the training and inference stages of a language model. By incorporating visual signals, these approaches enable a visually grounded representation of language. This enhancement in

representation facilitates improved interaction efficiency between the language model and the environment, as it allows for increased information throughput.

For example, WebShop (Yao et al., 2022a) and Interactive Language (Lynch et al., 2022) use ResNet (He et al., 2015) and a Transformer model (Vaswani et al., 2017) to process visual and linguistic data respectively, and input the fused representations into another Transformer to generate action outputs; VIMA (Jiang et al., 2022b) and Gato (Reed et al., 2022) use one single model to simultaneously process the concatenated multimodal data and predict actions; Socratic Models (Zeng et al., 2022a), Inner Monologue (Huang et al., 2022c), and LM-Nav (Shah et al., 2022) use multimodal language models to convert visual inputs into language captions or phrases and use LLMs for planning, reasoning and question-answering in order to perform embodied tasks. ViperGPT (Suris et al., 2023) equips the LLM with an API for various perceptual and knowledge modules, along with a Python interpreter, enabling the LLM to generate executable code for visual reasoning tasks.

Another goal of Modality Grounding is to preserve as much high-level knowledge as possible in the language model to ensure that the model is still able to effectively perform tasks such as commonsense reasoning, planning, question answering, code generation, etc. These capabilities become more pronounced and complex as the size of the model increases, known as emergent abilities (Kaplan et al., 2020; Wei et al., 2022a). These capabilities serve as one of the primary purposes of leveraging language models for embodied tasks. An illustrative example of these capabilities is demonstrated in the context of completing long-horizon navigation tasks. In such tasks, the effective planning of instructions by the LLM is crucial (Shah et al., 2022).

Affordance Grounding. However, in general, in order to make MGLM knowledge-rich, the model needs to be pre-trained with a large amount of data from open domains, which may result in outputs that are too diverse and therefore do not match the conditions in the real environment (Ahn et al., 2022; Chen et al., 2022a; Huang et al., 2023c). Therefore, some low-level information from the environment is needed to be incorporated into language models, which is referred to as Affordance Grounding (Ahn et al., 2022).

According to Gibson (2014) and Khetarpal et al. (2020): "Affordances describe the fact that certain states enable an agent to do certain actions, in the context of embodied agents.". Likewise, according to Ahn et al. (2022): "The learned affordance functions (Can) provide a world-grounding to determine what is possible to execute upon the plan". However, Chen et al. (2022a) argues that Ahn et al. (2022)'s falls short in providing affordance grounding at the scene-scale, thus limiting the ability to reason about the potential actions a robot can perform within a given environment. Hence, following this thought, there are mainly two requirements for an affordance grounded lanugage model (AGLM): (1) scene-scale perception, and (2) possible action, conditioned on the language-based instructions. For example, when considering a smart home environment and asking the agent to "turn off the lights in the living room.", scene-scale perception aims to make the agent aware of all (or only) the existing and relevant objects, such as "bedlamps" and "droplights". Secondly, possible action tasks the agent to determine the executable actions on the objects that can complete the instructions, such as "press the switches."

For example, SayCan (Ahn et al., 2022) leverages large language models to generate a list of object-action proposals (i.e., task grounding) which are then scored by a value function connected to the environment (i.e., world-grounding). Similarly, Chen et al. (2022a) first construct a language queryable scene representation, NLMap, through pre-exploration of a robotic agent and then use the a LLM to generate a list of relevant objects to be filtered and located. The object presence and location are finally used for LLM planning. Abramson et al. (2022) train an agent via behavioral cloning on the interactions of paired human players. They then collect human feedback on the learned agent to train a reward model, which is finally used to post-train the agent. That is, they achieve affordance grounding via behavioral cloning and RLHF. Code as Policies (Liang et al., 2022b) enables a language model to generate executable code directly. The generated codes can be executed with a python interpreter for affordance verification (Ni et al., 2023). LM-Nav (Shah et al., 2022) converts the planning results of the language model to image form and then uses a Visual Navigation Model to convert them into executable instructions (i.e., action+distance). Grounded Decoding (Huang et al., 2023c) integrates the high-level semantic understanding of LLMs with the reality-based practicalities of grounded models, enabling the generation of action sequences that are both knowledge-informed and feasible

in embodied agent tasks like robotics. Wake et al. (2023) provide numerous examples of utilizing ChatGPT for generating executable action sequences to accomplish tasks assigned by users.

Note that KB-in-the-loop, Model/Tool-in-the-loop, or Human-in-the-loop approaches can also be employed for modality grounding or affordance grounding (Huang et al., 2022b; Yao et al., 2022b; Zeng et al., 2022a; Huang et al., 2022c; Lynch et al., 2022; Abramson et al., 2022). In these approaches, external objects or entities undertake these functions, such as utilizing humans to describe the visual scene for modality grounding (Huang et al., 2022c).

# 3 Interaction Interface

In this section, we discuss the interfaces through which language models communicate with interactive objects. The interfaces include three types of languages: natural language, formal language, and machine language, as well as two special interfaces: edits and shared memory.

#### 3.1 Natural Language

Natural Language is the most common interaction interface. Communicating via this interface requires that the interactive objects can effectively understand and produce natural language. This interface is therefore commonly used in Model-in-the-loop (Wu et al., 2021; Zeng et al., 2022a) and Human-in-the-loop (Ouyang et al., 2022; Lee et al., 2022c). Natural language interaction empowers users to express their needs with inherent expressiveness, enabling effective communication of their requirements without the need for specialized training. Additionally, this interaction interface facilitates a better understanding of the intermediate interaction process, leading to improved debuggability and interpretability of the interaction chain (Wu et al., 2021; Wei et al., 2022b; Lee et al., 2022c). Crucially, since LMs are primarily pre-trained on natural language, interacting with them through natural



Figure 8: Interacting via Natural Language.

language instead of other language is the most effective way to activate and utilize the knowledge encoded in the LMs. This alignment between the LM training data and the interaction interface allows for optimal utilization of the knowledge contained within the LMs.

However, interacting with a language model through natural language heavily relies on the organization and the utterance of the language, often necessitating intricate prompt engineering (Liu et al., 2022c; Gu et al., 2022; Zhao et al., 2021; Lu et al., 2022d; Dong et al., 2023b; Chen et al., 2022f). Organization of the language refers to the structure of a model's prompt, and can be categorized into **unstructural natural language** and **structural natural language**. Utterance, on the other hand, refers to the specific wording or language used to express a given prompt or query. Utterance is more flexible by nature and therefore difficult to determine an optimal one. Different utterances may produce different results as they differ from the activated pattern in the model parameters. Practically, suitable prompts can be discovered through manual or automatic search (Dong et al., 2023b; Liu et al., 2021b; Wallace et al., 2019a; Jiang et al., 2020; Li & Liang, 2021; Zhang et al., 2022g; Zhou et al., 2022f; Liu et al., 2022c). We refer the readers to §4.2 for more information.

**Unstructural Natural Language.** Unstructural natural language is a free-form text. When it serves as an output from the language model, it does not have specific categorization, and the content can be free-form responses such as answers to questions and textual feedback. When it serves as an input to the language model, in addition to the main input content, such as interaction messages and queries, it primarily takes three forms of auxiliary context: (1) few-shot examples, (2) task description, and (3) role assignment (Mishra et al., 2022; Wang et al., 2022h; Li et al., 2023b). Thereof,

- Input format example of few-shot prompting: "[Example-1]; [Example-2]; [Example-3]; [input]" e.g. "sea otter → loutre de mer; plush girafe → girafe peluche; cheese →" for translation task.
- Input format example of task description: "[task description]: [input]" e.g. "translate English to French: cheese →".
- Input format example of role assignment: "[role assignment]. [input]" e.g. "Act as a python programmer: write codes to detect objects."<sup>10</sup>.

For example, some recent work, including Natural Instructions (Mishra et al., 2022) and Super Natural Instructions (Wang et al., 2022h), have built comprehensive collections of tasks and their corresponding instructions in natural language. Interactive Language (Lynch et al., 2022) enables humans to provide real-time instructions for the multimodal language model based on the current state of a given environment for robotic manipulation. Camel (Li et al., 2023b) defines an inception prompt that comprises a task specifier prompt and two role assignment prompts, namely the assistant system prompt and the user system prompt, which are utilized for role-playing tasks.

Structural Natural Language. Structural natural language usually imposes explicit constraints on the text in terms of content or formatting. Such constraints can be imposed on either the input (Zhong et al., 2022) or output (Ahn et al., 2022) of language models. For example, Drissi et al. (2018); Sun et al. (2020a); Yang et al. (2022b) define the overall structure of the generated article via an Outline or Plan (e.g., "(1) Introduction, (2) Related Work, (3) Method, (4) Experimental Results, ..." or a storyline). Ahn et al. (2022) and Chen et al. (2022a) unify the format of a generated text via a Template (e.g., "pick up [object]") to facilitate parsing of the action and the object to be acted upon. ProQA (Zhong et al., 2022) employs a prompt-based input schema that is designed in a structured manner, e.g., "[Format]: <Extractive QA>; [Task]: <SQuAD>; [Domain]: <Wikipedia>; [Question]: In what Country is Normandy located? [Passage]: ...". This schema allows for efficient modeling of knowledge generalization across all QA tasks, while also preserving task-specific knowledge tailored to each individual QA task. Note that although ProQA incorporates certain soft prompts in its input schema (c.f., §3.4), the main body of its instance still consists of natural language.

While unstructured natural language is a widely used interface for interaction due to its flexibility, simplicity, and readability, it suffers from certain drawbacks, including ambiguity, lack of coherence and parsability. Although these challenges can be partially addressed by employing structural natural language, all forms of natural language are inherently limited by its subjectivity and variability.

# 3.2 Formal Language

To further unlock the benefits of structural language, such as unambiguity, coherence, and parsability, and to mitigate the inherent limitations of natural language mentioned above, formal language emerges as another important interaction interface. According to Wikipedia<sup>11</sup>, "a formal language consists of words whose letters are taken from an alphabet and are well-formed according to a specific set of rules." Formal language is utilized in various domains such as mathematics, logic, linguistics, computer science, as well as other fields where precise and unambiguous communication is essential. Here are some examples of formal languages:

- 1. Programming Languages: examples include C, Java, Python, and many others. These programming languages are used to write scripts or commands that computers can execute (Cheng et al., 2022; Liang et al., 2022b; Chen et al., 2022d; Schick et al., 2023; Paranjape et al., 2023).
- 2. Query Languages: examples include SQL and XQuery, which are used to retrieve and manipulate data stored in databases (Cheng et al., 2022; Li et al., 2023c).
- 3. Mathematical Expressions: examples include boolean algebra, first-order logic, and equations. They are used to describe mathematical concepts and relationships (Wu et al., 2022e; Lu et al., 2021a; Han et al., 2022a).

 $<sup>^{10}\</sup>mathrm{Role}$  assignment can be considered a special type of task descriptions.

<sup>11</sup>https://en.wikipedia.org/wiki/Formal\_language

- 4. Formal Grammars: examples include context-free grammars, regular grammars, recursive grammars, etc<sup>12</sup>. They are used to describe the syntactic structure of natural language (Bai et al., 2021; Sachan et al., 2020; Wang et al., 2021b).
- 5. Others: for example, knowledge triples (Liu et al., 2022e; Sun et al., 2021b), and regular expressions (regex, Locascio et al.).

The interactive objects that use formal language as an interaction interface usually include knowledge bases (Liu et al., 2022e; Li et al., 2023c; Cheng et al., 2022), environments (Liang et al., 2022b), and models/tools (Liu et al., 2022g; Wu et al., 2022e; Lu et al., 2021a; Jiang et al., 2022a; Liang et al., 2023b). For example, Mind's-Eye (Liu et al., 2022g) uses a text-to-code language model to generate rendering codes for the physical simulation engine. Jiang et al. (2022a) involve a three-step approach to creating mathematical proofs. This approach includes formulating an initial informal proof, converting it into a formal sketch, and then employing a standard prover to prove the conjectures. This allows for the automated transformation of informal mathematical issues into fully formalized proofs using natural and mathematical languages. Binder (Cheng et al., 2022) first parses its input into programs (Python, SQL, etc.) given the



Figure 9: Interacting via Formal Language.

questions and knowledge bases, and then executes them to get the results. K-Adapter (Wang et al., 2021b) incorporates linguistic knowledge into PLMs through the use of adapters (Houlsby et al., 2019), exemplifying the application of formal grammars as an interaction interface. In some specific cases, other interactive objects may also use formal language. For example, human developers can interact with a code-based language model (Chen et al., 2021a) using formal language. Lahiri et al. (2022) create an interactive framework to refine user intents through test case generations and user feedback.

Compared to natural language, formal language offers distinctive advantages as an interaction interface, including: (1) It brings about precision and clarity, eradicating the ambiguity often associated with natural language. (2) Its structured syntax and rules make it directly parsable and easily interpretable by programs, enabling more efficient and accurate interaction with tools, for example. (3) It facilitates complex reasoning and logic-based operations more effectively, as codes or mathematical proofs are data formats that encompass a series of logical reasoning steps, which may provide opportunities to enhance models' reasoning abilities (Fu & Khot, 2022; Suris et al., 2023). However, the use of formal language may have certain limitations, including: (1) Limited accessibility: It often requires specialized knowledge or training for proper understanding and usage. And it relies on LMs specifically trained with formal language. (2) High sensitivity: E.g., even small errors in codes can render them non-executable. (3) Lack of expressiveness: It is unable to convey ideas in a nuanced and flexible manner.

#### 3.3 Edits

Text editing aims to reconstruct the textual source input to the target one by applying a set of edits, such as deletion, insertion, and substitution (Malmi et al., 2022). The motivation behind text editing is the recognition that source and target texts often share significant similarities in various monolingual tasks. Instead of reproducing the source words (Gu et al., 2016; See et al., 2017; Zhao et al., 2019; Panthaplackel et al., 2021), text editing models reduce such copying to predicting a single keep operation. Also, edits are often facilitated with rich metadata about language editing, including the inserted or deleted spans and the word order.

<sup>&</sup>lt;sup>12</sup>https://en.wikipedia.org/wiki/Formal\_grammar

Learning from the editing of textual data is gaining increasing attention, given its success in code pre-training (Zhang et al., 2022c), image editing (Ravi et al., 2023), drug design (Corso et al., 2022), and other areas. Previous cognitionrelated research has proven that mechanical editing operations require less cognitive effort compared to correcting transfer errors, which have no references to the source text version (Lacruz et al., 2014), and that iterative editing procedure plays an important role in improving students' writing abilities (Vardi, 2012; Gollins & Gentner, 2016). Moreover, these editing-related cognitive phenomena have shined upon various NLP topics. By addressing some limitations of the dominant sequence-to-sequence approaches (Sutskever et al., 2014), such as a relatively high computational requirement (Mallinson et al., 2020), text editing has found its wide



Figure 10: Interacting via Edits.

array of applications (Malmi et al., 2019; Mallinson et al., 2020; Stahlberg & Kumar, 2020) such as automatic post-editing (Bérard et al., 2017; Xu et al., 2022b), data-to-text generation (Kasner & Dušek, 2020), grammatical error correction (Awasthi et al., 2019; Zhou et al., 2020a; Hinson et al., 2020; Omelianchuk et al., 2020), punctuation restoration (Che et al., 2016; Kim, 2019; Alam et al., 2020; Shi et al., 2021), sentence simplification (Dong et al., 2019b; Agrawal et al., 2021), human value alignment (Liu et al., 2022f; Zhang et al., 2023b), style transfer (Reid & Zhong, 2021), and sequence-to-sequence pre-training (Zhou et al., 2021).

Similar to the pattern of repeated revisions made by humans to a manuscript until it is finalized, a complete process of text editing can be decomposed to multiple iterative rounds of editing, rather than one-pass edit (Ge et al., 2018; Gu et al., 2019; Stern et al., 2019; Kumar et al., 2020; Shi et al., 2020; 2022a; Faltings et al., 2023). On account of this, edits can be treated as one kind of interaction interface. Typically, text editing can be conducted through interaction between the editing model and itself, with the outputs of the previous iterations as the input of the current one until the text is fully edited to be returned (Schick et al., 2022; Kasner & Dušek, 2020; Kim et al., 2022; Madaan et al., 2023). Meanwhile, text editing can also be conducted through interaction among multiple different models or modules (Narayan & Gardent, 2014; Mallinson et al., 2022; 2020; Malmi et al., 2020). For example, an edit can be split into tasks, such as sequence tagging and masked language modeling, for models to cooperate. Specifically, a tagger first attaches an edit operation to each token. Afterwards, a masked language model fills in the placeholders for insertion and substitution operations to complete the edit (Mallinson et al., 2020; Malmi et al., 2020). Moreover, the participation of a code interpreter (Dong et al., 2019b; Shi et al., 2020), environment (Shi et al., 2022a), and user simulator (Faltings et al., 2023) can control the editing better and provide additional supervision signals.

Recent research proves that editing-based models can be expanded to various NLP downstream tasks by retrieving or generating prototypes, i.e., original text to be edited (Kazemnejad et al., 2020; Malmi et al., 2022). Additionally, text editing models have shown impressive performance in low-resource settings and can get rid of the typical autoregressive mechanism, thus improving inference speed (Mallinson et al., 2020; Awasthi et al., 2019). However, it is still under-explored how to automatically generate prototypes for general NLG tasks so as to expand the text editing paradigm to them (Guu et al., 2018), which hinders the broad use of edits as an interaction interface.

## 3.4 Machine Language

In some cases, the communication language between the language model and interactive objects is not humanreadable. This communication interface is referred to as Machine Language, as it can only be understood and processed by computers (e.g., models, tools). We can break down this type of interaction interface into two categories: **discrete machine language** and **continuous machine language**. **Discrete Machine Language.** It refers to an interaction interface that is not readable by humans and quantized. For example, OFA (Wang et al., 2022c) and BEiT-3 (Wang et al., 2022e) treat images as a form of "foreign language". That is, the sequence of image patches is obtained through image quantization and discretization techniques (van den Oord et al., 2017; Esser et al., 2020; Yu et al., 2021; Peng et al., 2022). This process allows the generation or understanding of an image token sequence that cannot be directly readable by humans but can be processed by models such as VQ-VAE (van den Oord et al., 2017) or VQGAN (Esser et al., 2020; Yu et al., 2020; Yu et al., 2020; Yu et al., 2021). Similarly, the hidden states inside the language model can also be discretized into discrete machine language in a similar manner. For example, Trauble et al. (2023); Liu et al. (2021a); Wang et al. (2022) have



Figure 11: Interacting via Machine Language.

demonstrated that discretized, human-unreadable hidden states can lead to better generalization and robustness.

**Continuous Machine Language.** It refers to an interaction interface through which the language models communicate with interactive objects using continuous scalars or vectors in a dense space. For example, Flamingo (Alayrac et al., 2022) encodes and re-samples images into dense and continuous vectors and then passes them to a language model via cross attention. BLIP-2 (Li et al., 2023d) encodes and maps images into numerous soft tokens <sup>13</sup> and passes them to a language model as prefixes of text inputs.

Note that metric signals, such as scalar rewards and ranking scores (Christiano et al., 2017; Ouyang et al., 2022; Ramamurthy et al., 2023), can also be regarded as a form of machine language employed by language models. In particular, if these signals belong to a discrete set of numbers (e.g.,  $\in \mathbb{Z}$ ), they can be classified as a form of discrete machine language. On the other hand, if they are represented as continuous values (e.g.,  $\in \mathbb{R}$ ), they can be classified as a form of continuous machine language.

#### 3.5 Shared Memory

The interaction interfaces discussed earlier focus on direct communication between language models and interactive objects. However, there is also a form of indirect communication facilitated through shared information units, commonly referred to as shared memory (Goyal et al., 2022; Zeng et al., 2022a; Madaan et al., 2022; Dalvi et al., 2022; Ryoo et al., 2022). That is, the message receiver does not directly receive the message from the sender, but instead retrieves it from a memory pool where the message has been pre-written by the sender. Depending on the form in which the message is stored and utilized, this type of interaction interface can be classified into two categories: hard memory and soft memory.



Figure 12: Interacting via Shared Memory.

**Hard Memory.** Hard memory often utilizes a human-readable history log to store shared information. For example, Socratic Models (Zeng et al., 2022a) employs a communication mechanism where Vision-Language Models (VLM), Audio-Language Models (ALM), and Language Models (LM) interact through a history log written in natural language. This log records the complete history of states perceived by each model (Zeng et al., 2022a). MemPrompt (Madaan et al., 2022) edits human prompts to GPT-3 with user feedback memory

 $<sup>^{13}</sup>$ Soft tokens, also known as soft prompts, refer to learnable parameters that are concatenated to the input prompt of a language model. Please refer to Liu et al. (2021b).

for better Human-LM interaction. Dalvi et al. (2022) augment a question-answering model with a dynamic memory of user feedback for continual learning.

**Soft Memory.** Soft memory typically employs queryable and human-unreadable memory slots to store shared information. These memory slots utilize a continuous machine language for efficient storage and retrieval of information. For example, Shared Global Workspace (Goyal et al., 2022) stores the information from multiple modules in a shared sequence of working memory slots to facilitate inter-module communication and coordination. Token Turing Machines (Ryoo et al., 2022) use an additional memory unit to store historical state information to aid long-horizon robotic manipulation.

Utilizing memory as an indirect interaction interface provides several advantages over direct communication. It allows interactive objects to retrieve messages from earlier moments, enabling them to access past information. Memory enables the storage of a large volume of information, facilitating high-throughput communication. However, memory can become noised or outdated, leading to potential confusion or errors. Retrieval from memory can be time-consuming, impacting the efficiency of the interaction. It can also introduce unpredictability and uncertainty into the interaction. Therefore, careful design is crucial to ensure the effective and efficient utilization of memory.

# 4 Interaction Methods

This section aims to explore the methodologies employed by language models for understanding and processing interaction messages. We begin with a quick tour through the pre-trained language models (§4.1). Next, we divide interaction methods into five categories: prompting without model training (§4.2), fine-tuning which involves updating models' parameters (§4.3), active learning (§4.4), reinforcement learning (§4.5) as well as imitation learning (§4.6). Finally, we propose to re-frame and formalize these methods in a unified manner, i.e., interaction message fusion (§4.7).

#### 4.1 Pre-trained Language Models

Model	Architecture	Strategy	#Parameters	Characteristics
BERT (Devlin et al., 2018)	Enc	MLM, SRC	Base110M/Large340M	MLM, NSP
RoBERTa (Liu et al., 2019b)	Enc	MLM	Base123M/Large354M	Dynamic Mask, No NSP
XLNet (Yang et al., 2019)	Enc/Dec	CausalLM	Base110M/Large340M	Permutation AR LM
SpanBERT (Joshi et al., 2020)	Enc	MLM	Base110M/Large340M	Span Mask
ERNIE (Sun et al., $2019$ )	Enc	MLM	Base110M	Entity Mask, Phrase Mask
ERNIE-2.0 (Sun et al., 2020b)	Enc	MLM, SRC	Base110M/Large340M	Learning lexical, syntactic, and semantic information across Multi-Tasks Learning
ALBERT (Lan et al., 2019)	Enc	MLM, SRC	Base12M/Large18M/ XL60M/XXL235M	Embedding Decomposeing, Parameters Share, SOP (sentence order prediction)
DistilBERT (Sanh et al., 2019)	Enc	MLM	66M	Teacher-Student, Dynamic Mask, No NSP Task
ELECTRA (Clark et al., 2020)	Enc	MLM	Small14M/Base110M/ Large335M	Token Generator, Discriminator to predict original or replaced
SqueezeBERT (Iandola et al., 2020)	Enc	MLM, SRC	62M	Replace FC layers with Convolutions
GPT (Radford et al., 2018)	Dec	CausalLM	117M	Decoder-based Model
GPT-2 (Radford et al., 2019)	Dec	CausalLM	1.5B	More parameters and data than GPT
BART (Lewis et al., 2019)	Enc-Dec	1 1	Base140M, Large406M	Arbitrary Noise
PEGASUS (Zhang et al., 2020a)	Enc-Dec	Seq2Seq	Base223M, Large568M	GSG (gap-sentences generation)
UniLM (Dong et al., 2019a)	Enc/Dec	PrefixLM	340M	Unified for Bidirectional, Unidirectional, and Seq2Seq LM

Table 1: Overview of PLMs.

Pre-trained language models (PLMs), especially large language models (LLMs), have demonstrated their tremendous potential to serve as the cornerstone of advancing language intelligence. Transformer (Vaswani et al., 2017), BERT (Devlin et al., 2018), GPT-3 (Brown et al., 2020) and ChatGPT are recognized as four major milestones of utilizing pre-trained language models for various NLP tasks, which also frame the roadmap of AI development. PLM is usually based on Transformer and can be categorized along two dimensions: (1) architectures, (2) pre-training strategies (Tay et al., 2022b).

Model	Architecture 1	Pre-training	#Parameters	Characteristics
T5 (Raffel et al., 2020)	Enc-Dec	Seq2Seq	Base220M/Small60M/ Large770M/3B/11B	Unified NLP tasks with the same input-output format
mT5 (Xue et al., 2020)	Enc-Dec	Seq2Seq	Base580M/Small300M/ Large1.2B/XL3.7B/ XL13B	Multilingual T5
ExT5 (Aribandi et al., 2021) FLAN-T5 (Chung et al., 2022)	Enc-Dec Enc-Dec	Seq2Seq Seq2Seq	$\frac{Base 220 M/Large 770 M}{8 B/62 B/540 B}$	T5 with Multi-Task Learning Scaling and Instruction Fine-tuning T5
ERNIE-3.0 (Sun et al., 2021b)	Enc-Dec	MLM, CausalLM, SRC	10B	Multi-Task Learning, External Knowledge Enhanced
ERNIE-3.0 Titan (Wang et al., 2021c)	Enc-Dec	MLM, CausalLM, SRC	260B	Large Scale of Ernie 3.0
GPT-3 (Brown et al., 2020)	Dec	CausalLM	175B	$100\mathrm{X}$ parameters compared with GPT-2
PANGU- $\alpha$ (Zeng et al., 2021)	Dec	CausalLM	2.6B/13B/200B	Query Layer to induce expected output
FLAN (Wei et al., 2021)	Dec	CausalLM	137B	Instruct Tuning
Gopher (Rae et al., 2021)	Dec	CausalLM	44M/117M/417M/ 1.4B/7.1B/280B	RMSNorm, RoPE
InstructGPT (Ouyang et al., 2022)	Dec	CausalLM	1.3B/6B/175B	Instruct, GPT, RLHF
PaLM (Chowdhery et al., 2022)	Dec	CausalLM	8B/62B/540B	SwiGLU, Parallel Layer, Multi-Query Attention, Shared Input-Output Embeddings, No Bias
UL2 (Tay et al., 2022b)	Dec, Enc-Dec	CausalLM, Seq2Seq	1B/20B	Unified Denoising Objectives for both Enc-Dec and Dec Architecture
PaLM-2 (Google, 2023)	Dec, Enc-Dec	CausalLM, Seq2Seq	1.04B/3.35B/10.7B	Multi-lingual and Multi-domain Training Data, More Efficient Model Architecture
OPT (Zhang et al., 2022e)	Dec	CausalLM	125M/350M/1.3B/2.7B/ 6.7B/13B/30B/ 66B/175B	Open Pre-trained Transformer
Galactica (Taylor et al., 2022)	Dec	CausalLM	125M/1.3B/6.7B/ 30B/120B	High-quaility Scientific Training Data, Prompt Pre-training
GLM-130B (Zeng et al., 2022b)	Enc-Dec	CausalLM, MLM	$\begin{array}{c} {\rm Base100M/Large340M} \\ {\rm 410M/515M} \end{array}$	2D Positional Encoding, Autoregressive Blank Infilling, Multi-Task Instruction Pre-Training
Bloom (Scao et al., 2022)	Dec	CausalLM	560M/1.1B/1.7B/ 3B/7.1B/176B	ALiBi Positional Embedding, Embedding LayerNorm
FLAN-PaLM (Chung et al., 2022)	Dec	CausalLM	Base250M/Small80M/ Large780M/XL3B/XXL11B	Scaling and Instruction Fine-tuning PaLM
LLaMA (Touvron et al., 2023)	Dec	CausalLM	6.7B/13B/33B/65B	Pre-normalization, SwiGLU, RoPE

Table 2: Overview of LLMs.

Architectures. There are overall three types of architectures: (1) encoder-only, where the model takes input tokens and produces a fixed-dimensional representation of the input text (Devlin et al., 2018; Liu et al., 2019b; Sun et al., 2019), (2) encoder-decoder, where the model first generates a fixed-dimensional representation of the input text with an encoder, and then autoregressively generates tokens based on this representation with a decoder (Lewis et al., 2019; Raffel et al., 2020), and (3) decoder-only, where the model directly generates tokens in an autoregressive manner based on the input text as context, utilizing only a decoder (Radford et al., 2018; 2019; Brown et al., 2020). The encoder-only architecture is especially well-suited for discriminative tasks, such as text classification (Adhikari et al., 2019). On the other hand, the encoder-decoder architecture is particularly suitable for sequence-to-sequence tasks, such as machine translation (Liu et al., 2020). Lastly, the decoder-only architecture is particularly well-suited for generative tasks, such as story generation (Guan et al., 2020).

**Pre-training Strategies.** LMs typically employ self-supervised training objectives for pre-training, including: (1) **CausalLM** (causal language modeling), where the model predicts the next token based on the preceding tokens from left to right (Radford et al., 2018; 2019; Brown et al., 2020). (2) **PrefixLM** (prefix language modeling), where the model predicts the next token using a bidirectionally encoded prefix as well as the previous tokens from left to right (Dong et al., 2019a). (3) **MLM** (masked language modeling), where the model predicts the input (Devlin et al., 2018). (4) **Seq2Seq** (sequence-to-sequence), where the model decodes the output from left to right based on the encoded input (Lewis et al., 2019; Raffel et al., 2020). (5) **SRC** (sentence relationship capturing), which includes tasks such as Next Sentence Prediction (Devlin et al., 2018) and Sentence Order Prediction (Lan et al., 2019), aimed at capturing relationships between sentences. Other pre-training objectives, such as Right-to-Left Language Modeling (Dong et al., 2019a) and Permutation Language Modeling (Yang et al., 2019), are less commonly used.

We briefly introduce the representative PLMs in Table 1, LLMs in Table 2, and Multimodal Foundation Models (MFMs) in Table 3. We refer the readers to Liu et al. (2021b), Zhou et al. (2023a), and Zhao et al. (2023a) for more information.

Model	Modality	#Parameters	Characteristics
RT-1 (Brohan et al., 2022)	Robotic	35M	End-to-End Robotic Transformer, mapping Text and Image to Action
VIMA (Jiang et al., 2022b)	Robotic	2M/4M/9M/20M/ 43M/92M/200M	leverage text-image prompt to produce motor actions auto-repressively
LAVA (Lynch et al., 2022)	Robotic	N/A	Real-time Speech and Natural Language Guidance to the Robots
PALM-E (Driess et al., 2023)	Robotic	562B	Embodied Multi-modal adds Robotic or Object states with Image and Text
Data2Vec (Baevski et al., 2022)	Text/Image/Audio	N/A	Unified framework predicts latent representations instead of modality-specific targets
CLIP (Radford et al., 2021)	Text/Image	428M	Jointly learn text and image representation interactively
VLMo (Bao et al., 2022)	Image/Multimodal	130M	Unified various modalities by MOME Transformer, trained jointly with ITC, ITM and MLM
Flamingo (Alayrac et al., 2022)	Image/Multimodal	3B/9B/80B	Few-shot in-context learning of visual and text multi-modal tasks
CoCa (Yu et al., 2022a)	Image/Multimodal	Base383M/Large787M/ 2.1B	Unified single-encoder, dual-encoder and encoder-decoder and trained with contrastive and captioning loss
PaLI (Chen et al., 2022e)	Image/Multimodal	3B/15B/17B	Joint training large scale of mixed mulit-modal and multilingual tasks
FLAVA (Singh et al., 2022a)	Text/Image/Multimodal	350M	Unimodal, Cross-Modal, and Multi-Modal Foundational Model trained with MMM, ITM, MIM and MLM
OFA (Wang et al., 2022c)	Text/Image/Multimodal	Tiny33M/Medium93M/ Base182M/Large472M/ Huge930M	Unified architectures, tasks, and modalities by instruction based pre-training and fine-tuning
BEiT-3 (Wang et al., 2022e)	Text/Image/Multimodal	1.9B	General multimodal foundation model on text, image and text-image pair with MDM (Masked Data Modeling)
BLIP (Li et al., 2022d)	Text/Image/Multimodal	446M	Use a synthetic caption producer and a noise caption filter boostrappingly train a unified multi-modal model with ITC, ITM and LM loss
BLIP-2 (Li et al., 2023d)	Text/Image/Multimodal	474M/1.2B	Bridge the gap between a frozen image encoder and a frozen LM in two stages by a Querving Transformer
KOSMOS-1 (Huang et al., 2023b) GPT-4 (OpenAI, 2023)	Text/Image/Multimodal Text/Image/Multimodal	1.6B N/A	Instruct and Multi-modal Transformer Multi-modal supported ChatGPT

#### Table 3: Overview of MFMs.

#### 4.2 Prompting

According to Khot et al. (2022), prompting refers to the interaction methods that focus on calling a model via prompts, without involving any parameter updating<sup>14</sup>. This line of research stems from in-context learning (Brown et al., 2020; Dong et al., 2023b), a significant capability of large language models. In-Context Learning (ICL) refers to the approach that allows large language models to learn from examples provided in context (Brown et al., 2020). Moreover, the task description can also be incorporated within the context, accompanied with few-shot examples (Sanh et al., 2021; Wei et al., 2021; Mishra et al., 2022; Wang et al., 2022h). Prompting is one of the simplest ways to incorporate interactive messages. However, making it effective can still be tricky, as we will discuss below.

Note that in this subsection, the discussion focuses on large-scale generative language models, as prompting is challenging to implement with small language models, which may necessitate fine-tuning with prompts (Wang et al., 2022a).

In the following subsections, prompting methods are classified into three categories according to their characteristics and objectives: (1) Standard Prompting with straightforward task descriptions and demonstrations (i.e., examples) as context for instruction-following; (2) Elicitive Prompting with the context which can stimulate the language model to generate intermediate steps for reasoning; and (3) Prompt Chaining, which cascades multiple language model runs for complex reasoning and pipelined tasks.

## 4.2.1 Standard Prompting

<sup>&</sup>lt;sup>14</sup>This definition is a bit different from that of Liu et al. (2021b). We align this definition as "Tuning-free Prompting" in Liu et al. (2021b)'s categorization. Additionally, we put "Promptless Fine-tuning", "Fixed-prompt LM Tuning", "Prompt+LM Tuning" in §4.3 and "Fixed-LM Prompt Tuning" in §4.3.3.

Standard prompting represents the most elementary form of In-Context Learning. The prompting context primarily comprises a concise, answer-focused task description, along with few-shot examples, as elucidated in Section §3.1. In Natural Instructions (Mishra et al., 2022) and Super-Natural Instructions (Wang et al., 2022h), the fundamental structure of a context, or instruction, is composed of: task definition, several positive examples accompanied by explanations (demonstrations), and numerous negative examples with clarifications. Despite its simplicity, various approaches to standard prompting continue to be proposed, as large language models tend to be context-sensitive, often resulting in a lack of robustness (Liu et al., 2022c; Gu et al., 2022; Zhao et al., 2021; Lu et al., 2022d; Dong et al., 2023b; Chen et al., 2022f).



Figure 13: Standard Prompting.

This line of research endeavors to enhance the organization of instructions to improve the performance of ICL (Dong et al., 2023b), which enables a language model to better understand and respond to the interaction messages. In accordance with Dong et al. (2023b), this primarily entails optimizing the subsequent factors: (1) instance selection; (2) instance processing; and (3) instance combination.

**Instance Selection.** In order to find useful examples, various unsupervised prompt retrieval methods can be utilized, including distance metrics (Liu et al., 2022c), mutual information (Sorensen et al., 2022), and n-gram overlap (Agrawal et al., 2022), which have been discussed in Dong et al. (2023b). Additionally, Rubin et al. (2022) and Cheng et al. (2023a) utilize learned retrievers to identify the most relevant demonstrations to the input. Zhang et al. (2022g) select demonstrations using reinforcement learning. Li & Qiu (2023) propose *InfoScore*, a metric designed to evaluate the informativeness of examples, which facilitates example selection using feedback from language models. It employs an iterative diversity-guided search algorithm to improve and assess the examples. Most studies along this line build upon the premise that an increased relevance of demonstrations directly correlates with enhanced ICL performance (Liu et al., 2022c). However, Si et al. (2022) find that using randomly sampled demonstrations leads to similar results with GPT-3 (Brown et al., 2020) compared to in-distribution demonstrations. Li et al. (2022a) reveal that controllability and robustness in LLMs can be improved by incorporating counterfactual and irrelevant contexts during fine-tuning.

**Instance Processing.** The processing of context involves four main types: expansion, filtering, edit and formatting. For example, SuperICL (Xu et al., 2023b) expands in-context examples by incorporating labels, predicted by a small plug-in model, and their associated confidence scores to augment the context for large language models. Zhou et al. (2022f) employ LLMs for instruction generation, example generation, and filtering through a scoring model. Honovich et al. (2022b) generate task descriptions based on examples. GrIPS (Prasad et al., 2023) employs a gradient-free, edit-based approach to conduct instruction search (processing). In particular, it follows an iterative process of modifying the base instruction at the phrase-level and subsequently evaluating the candidate instructions to identify the optimal one. ProQA (Zhong et al., 2022) uses a structured schema to format the context.

**Instance Combination.** The order and structure of demonstrations in a given context also play a crucial role (Liu et al., 2022c; Lu et al., 2022d; Ye et al., 2023; Dong et al., 2023b). For example, Liu et al. (2022c) and Lu et al. (2022d) sort examples in the context according to their distance and entropy metrics with the input, respectively, as mentioned in Dong et al. (2023b). Batch prompting (Cheng et al., 2023b) enables LLMs to perform inference on multiple samples in a batch, thus reducing token and time costs while maintaining the overall performance. Structured prompting (Hao et al., 2022a) involves encoding multiple groups of examples into multiple LM replica, which are then merged using rescaled attention. This process allows LMs to incorporate and contextualize 1000+ examples. ICIL (Ye et al., 2023) puts multiple task instructions composed of task definitions and groups of examples together in the context to improve LLMs' zero-shot task generalization performance.

Note that although the diverse approaches mentioned in this part are mainly designed for general-purpose in-context learning, they can be used as methods for interaction message communication. During the interaction with language models, determining the most appropriate way to organize context for interaction messages via elaborate prompt engineering is crucial for performance gain. For example, in the scope of KB-in-the-loop, Lazaridou et al. (2022), Izacard et al. (2022), and Ram et al. (2023) work on how to feed the retrieved knowledge into language models via ICL; in the scope of env-in-the-loop, Weir et al. (2022) demonstrate how to generate task instructions and enable cross-environment transfer to help agents generalize their execution.

# 4.2.2 Elicitive Prompting

Extending standard prompting, elicitive prompting improves the abilities of LLMs, such as reasoning and planning, by providing them with extra step-by-step guidance in context.

**Few-Shot Demonstrations.** Typical chain-of-thought (Wei et al., 2022b) uses few-shot examples with reasoning steps to elicit reasoning as shown below:

**Question**: If a rectangle has a width of 5 units and a length of 8 units, what is its perimeter? **Answer**: The perimeter of a rectangle is the sum of the lengths of all its sides. In this case, the rectangle has two sides with a length of 5 units and two sides with a length of 8 units. Therefore, its perimeter is  $2 \ge 26$  units.

**Question**: If I need to be at work by 9:00 am, and it takes me 20 minutes to drive there, what time should I leave my house?

**Answer**: [to be generated]

For example, Scratchpads (Nye et al., 2021) and CoT (Wei et al., 2022b) are two representative techniques for elicitive prompting. They explicitly describe the reasoning steps in the few-shot examples, significantly improving math reasoning abilities compared with standard prompting. Leastto-most prompting (Zhou et al., 2022a) aims to tackle complex tasks that CoT struggles with. It achieves this by decomposing a complex problem into smaller and more manageable ones with few-shot demonstrations. Other follow-up works focus on how to improve the robustness of CoT, such as majority voting on results (Wang et al., 2022f), perplexity check (Fu et al., 2022), or retrieving CoTs from pre-defined clusters (Zhang et al., 2022i).



Figure 14: Elicitive Prompting.

**Other Forms of Instructions.** According to recent studies, it may not be necessary to rely solely on human-written, step-by-step rationales for eliciting prompts, as other forms of instructions may be useful. For example, zero-shot CoT (Kojima et al., 2022) uses a simple phrase "Let's think step by step." to induce the CoT-style reasoning in zero-shot settings:

**Question**: If I need to be at work by 9:00 am, and it takes me 20 minutes to drive there, what time should I leave my house?

Answer: Let's think step by step: [to be generated]

The format of answers (Marasović et al., 2021) and task descriptions (Mishra et al., 2022) have also been explored to serve as elicitive prompts. In addition to text-form CoT, Program-of-Thought (PoT) (Chen et al., 2022d), Program-aided Language Model (PAL) (Gao et al., 2022b), and ViperGPT (Suris et al., 2023) leverage program-form CoTs to obtain reliable reasoning performance in many tasks that programs can solve. PoT, PAL, and ViperGPT offer advantages over text-based CoT since they deliver verified, stepwise

results by executing the programs. Vanilla CoT, on the other hand, cannot verify results. Furthermore, through specially-designed prompts (e.g., "Search[query]", " $\langle API \rangle$  Calculator(735 / 499)  $\rightarrow$  1.47  $\langle API \rangle$ "), humans can unlock tool-using abilities of language models, such as web-searching (Schick et al., 2023; Yao et al., 2022b), calculators (Schick et al., 2023), physical simulation (Liu et al., 2022g), etc (c.f., §2.3).

Note that in the scope of interactive natural language processing, elicitive prompting can be used to enhance reasoning and planning capabilities of language models during interactions with other objects (Yao et al., 2022b; Wu et al., 2021; 2022a; Yang et al., 2023b; Zhang et al., 2022i; Qiao et al., 2022). Furthermore, the idea of elicitive prompting is usually instantiated within the scope of model/tool-in-the-loop (§2.3), which will be discussed in detail in the next part (§4.2.3).

#### 4.2.3 Prompt Chaining

An increasing number of studies are using multi-stage chainof-thought to improve multi-hop reasoning capabilities. In this approach, LMs are cascaded and can be prompted via different contexts, allowing for more complex reasoning. This is in contrast to typical elicitive prompting, which generally only performs one stage of chain-of-thought via In-Context Learning for reasoning. This approach is intuitive as it can aid in generating precise reasoning steps by conducting multiple model runs with different yet interdependent prompts (Qiao et al., 2022). In contrast, elicitive prompt relies on a single model run with only one context (Qiao et al., 2022).



Figure 15: Prompt Chaining.

By decomposing the task and cascading language models for different reasoning steps or sub-tasks, prompt chaining can

not only perform multi-hop reasoning (Dohan et al., 2022; Qiao et al., 2022), but also work well in pipelined tasks such as peer review writing (Wu et al., 2021) and advertisement generation (Wu et al., 2022a). Prompt chaining is one of the fundamental methods for model/tool-in-the-loop natural language processing (c.f.,  $\S2.3$ ).

LM Cascades (Dohan et al., 2022) has presented some works in this line, including sequential reasoning mechanisms (Nye et al., 2021; Wei et al., 2022b; Creswell et al., 2022), reasoning procedures with verifiers or tools (Cobbe et al., 2021; Nakano et al., 2021; Liu et al., 2022g), and multi-agent interacting question-answering (Srivastava et al., 2022)<sup>15</sup>. Qiao et al. (2022) investigated the enhancement of reasoning through language model prompting, focusing on strategy enhancement and knowledge enhancement. The study explored various aspects, such as prompt engineering, process optimization, external engines, and both implicit and explicit knowledge. However, to the best of our knowledge, no survey has systematically examined the structure of prompt chaining. Hence, in this part, we divide the prompt chaining schemes into four categories according to their topology, as shown in Figure 16. Furthermore, instead of fixed prompt chaining schemes, users can customize them (§4.2.3 Customization). And they can also be constructed automatically (§4.2.3 Automatization).

Sequential. The nodes are arranged in a straight line, where each node takes as input the specific outputs of the previous nodes, including the initial input query. For example, Self-Ask (Press et al., 2022) and Successive Prompting (Dua et al., 2022) construct the reasoning chain via sequential question generation (QG) and question answering (QA) nodes. Wang et al. (2022a) further enable smaller language models to construct the similar QG-QA chain via a learned context-aware prompter. Selection-Inference (Creswell et al., 2022) begins by utilizing the selection module to choose a group of relevant facts based on the given question. Subsequently, the inference module generates new facts by utilizing this subset of facts. Multimodal-CoT (Zhang et al., 2023d) addresses the visual reasoning problem through a two-step processing consisting of rationale generation and answer inference conditioned on the image, question, and the generated rationale. Mind's-Eye (Liu et al., 2022g) first generates the rendering codes for an intermediate environment simulator to get grounded

 $<sup>^{15} {\</sup>tt https://github.com/google/BIG-bench/tree/main/bigbench/benchmark_tasks/twenty_questions}$ 



Figure 16: Examples of prompt chaining schemes. Gray, yellow, and green circles refer to input queries, intermediate reasoning steps, and final responses, respectively. Solid and dashed arrows represent indispensable and optional (i.e., none, single, or multiple) conditional probabilities (P(Y|X)), respectively. The rounded rectangle refers to a looping block.

rationales, and then generates the final answer based on the simulation results. Note that when the number of looping blocks becomes zero, it is reduced to standard prompting (§4.2.1). When the intermediate reasoning steps and the final answer are simultaneously prompted in a single model run, it is reduced to single-stage CoT (§4.2.2).

**Branched.** The nodes are arranged in a tree-like structure, where a node's output may serve as input to multiple other nodes, and a node's input may come from multiple other nodes' outputs. For example, Perez et al. (2020) decompose one multi-hop question into many single-hop sub-questions and then aggregates their answers to get the final answer. Wang et al. (2022f) first generate a range of reasoning paths through sampling from the language model's decoder and then aggregates the most consistent answer in the final answer set by computing the likelihood of the reasoning paths. Ask Me Anything (Arora et al., 2022b) first reformats the question into diverse possible ones with different in-context demonstrations, which are then answered respectively. Finally, the answers are aggregated into the final answer via a learned probabilistic graphical model. Tree of Thoughts (Yao et al., 2023) constructs the language model's reasoning chain in a tree form, enabling evaluation of states via heuristic approaches, and exploration of potential solutions via Breadth-first search (BFS) or Depth-first search (DFS), significantly improving the model's problem-solving capabilities. Liu et al. (2021b) have investigated multi-prompt learning, including prompt ensembling, prompt composition, and prompt decomposition, which can all be viewed as in this line.

**Decomposed.** The overall process is linear, but some nodes can be broken down further into nested or hierarchical chains recursively that follow any of the four schemes described. For example, Zhou et al. (2022a) first call an LM to reduce the problem into multiple sub-problems and then iteratively call the language model to solve these sub-problems step-by-step (i.e., the first node serves for problem reduction while the second node is another sequential chain). Decomposed Prompting (Khot et al., 2022) decomposes the question into a sequence of sub-questions, each being answered immediately after generation by utilizing another prompt chaining block or just standard prompting. This approach facilitates the hierarchical and recursive decomposition of tasks.

**Interactive.** The nodes are split into multiple groups, each with their own functions. These groups communicate with each other in an alternating fashion to construct a chain of interactions. For example, Socratic Models (Zeng et al., 2022a) and Inner Monologue (Huang et al., 2022c) partition the groups of nodes according to the modality. They utilize LLMs for planning and reasoning while making use of VLM for observation. *ChatGPT Asks, BLIP-2 Answers* (Zhu et al., 2023b) use ChatGPT to ask questions about an image, while BLIP-2 (Li et al., 2023d) is used to answer these questions. This communication through question-answering is performed interactively to generate the image captions. The visual reasoning path in (Chen et al., 2023d) can be divided into two groups, one for answer and explanation generation, and another for explanation verification via a multimodal classifier. The frameworks of Cobbe et al. (2021); Weng et al. (2022) can be viewed as interaction between the thought generation group and the thought verification group.

MindCraft (Bara et al., 2021) first assigns two agents with different skills (i.e., recipe knowledge) and then lets them interact through question-answering to accomplish the task in the *MineCraft* environment.

Customization. The prompt chaining scheme depends on several factors related to the nature of the problem, such as its complexity, structure, and the availability of relevant data. Hence, due to their diversity and variability, a fixed prompt chaining scheme may not satisfy the users' needs. An intuitive solution is to enable users to create or modify the prompt chaining scheme on their own accord, which can further enhance the debuggability and configurability of the system (Wu et al., 2021; 2022a). Generally, this feature is more important for pipelined tasks such as peer review writing, brainstorming, personalized flashcard creation, writing assistant, etc (Wu et al., 2021; 2022a). For example, AI Chains (Wu et al., 2021) defines a set of primitive operations such as classification, factual query, information extraction, split points, compose points, etc. These primitive operations are implemented with different instructions fed into the language model. An interactive interface then shows the prompt chaining schemes, which users can customize to construct a pipeline. PromptChainer (Wu et al., 2022a) also introduces an interactive interface that facilitates the visual programming of chains. It divides the nodes into three types: LLM nodes, such as generic LLM and LLM classifier; Helper nodes, such as model output evaluation, data processing, and generic JavaScript; and Communication nodes, such as data inputs, user actions, and API calls. The workflow defined by the graph of nodes is also transparent and configurable. It has been shown that this approach can assist users in building a satisfactory pipeline for applications such as music chatbots, advertisement generators, image query generators, and writing assistants (Wu et al., 2022a).

Automatization. The prompt chaining schemes can also be constructed automatically. For example, ReAct (Yao et al., 2022b) and MM-ReAct (Yang et al., 2023b) determine whether a thought should be generated or a tool should be called automatically based on the context. ToolFormer (Schick et al., 2023) can determine which tools to utilize or whether to use tools based on the context, as it is trained on tool-use prompted data.

# 4.3 Fine-Tuning

Fine-tuning refers to the process of updating the parameters of a model. The ongoing interaction provides an increasing amount of interaction messages that can be used to update the models' parameters, resulting in better language model adaptation to interactions like instruction following (Wei et al., 2021; Sanh et al., 2021; Aribandi et al., 2021; Xu et al., 2022a; Ouyang et al., 2022; Fu & Khot, 2022) and grounding (Xie et al., 2022; Sharma et al., 2021; Suglia et al., 2021; Pashevich et al., 2021). This line of research also explores how to make effective use of this new data without catastrophic forgetting (Gururangan et al., 2020; He et al., 2021; Dhingra et al., 2022; Jang et al., 2021; Jin et al., 2021; Qin et al., 2022b), how to ensure generalization to new tasks (Wei et al., 2021; Sanh et al., 2021; Aribandi et al., 2021; Xu et al., 2022a; Ouyang et al., 2022; Fu & Khot, 2022), and how to adapt the language model more efficiently (Liu et al., 2021b; Ding et al., 2022; Li & Liang, 2021; Lester et al., 2021; Houlsby et al., 2019; Hu et al., 2022a).

In this subsection, we discuss four commonly employed fine-tuning-based methods: (1) Supervised Instruction Tuning, which aims to adapt language models for instruction following and to enhance their task generalization abilities (§4.3.1); (2) Continual Learning, which aims to infuse new data into language models without catastrophic forgetting (§4.3.2); (3) Parameter-Efficient Fine-Tuning, which focuses on the efficient adaptation of language models (§4.3.3); and (4) Semi-Supervised Fine-Tuning, which further tackles the problem of unlabeled data, as in some cases, the interaction message may not provide adequate supervision to train the model (Li et al., 2023d; Taori et al., 2023; Zelikman et al., 2022; Ho et al., 2022; Huang et al., 2022a) (§4.3.4).

#### 4.3.1 Supervised Instruction Tuning

Supervised instruction tuning involves fine-tuning a pre-trained language model using data that provides task instruction supervision. Various studies (Raffel et al., 2020; Aribandi et al., 2021; Xu et al., 2022a; Sanh et al., 2021; Xie et al., 2022; Li et al., 2022k; Weller et al., 2022; Ouyang et al., 2022; Wei et al., 2021; Chung et al., 2022; Longpre et al., 2023; Iyer et al., 2022; Glaese et al., 2022; Zhang et al., 2023c) have been

conducted in this area. These methods fine-tune a pre-trained model by using supervised instructions on a multitask mixture, covering various tasks and inducing zero-shot generalization capabilities.

The first line of work, investigated by researchers such as Raffel et al. (2020); Aribandi et al. (2021); Xu et al. (2022a); Sanh et al. (2021); Wang et al. (2022i); Xie et al. (2022); Muennighoff et al. (2022); Li et al. (2022k); Weller et al. (2022); Wei et al. (2021), focuses on providing instructions to language models as part of the input. Typically, these instructions are prepended to the input and contain specific details about the task the model is expected to perform. These models explore different aspects, such as training and evaluation data, model architectures (decoder-only v.s. encoder-decoder), instruction formatting, task mixtures, and other related factors. The discussed studies offer conclusive evidence that fine-tuning language models on multiple NLP tasks and incorporating instructions allow these models to generalize to unseen tasks and better understand and respond to user queries (Fu &



Figure 17: Supervised Instruction Tuning.

Khot, 2022). As demonstrated in Kaplan et al. (2020) and Wei et al. (2022a), scaling up language models leads to improvements in performance. The researchers also study the impact of different scales of instruction data, aiming to better understand the influence of the amount and diversity of this kind of training data (Zhang et al., 2023c).

Subsequently, OpenAI releases the InstructGPT (Ouyang et al., 2022) and develops a series of GPT-3.5 variants, all of which are built upon the foundation of GPT-3 (Brown et al., 2020). These variants include *code-davinci-002* and *text-davinci-002*, which only involve supervised instruction tuning, as well as *text-davinci-003* and *gpt-3.5-turbo*, which are refined through both supervised fine-tuning and reinforcement learning from human feedback (RLHF). These modifications enhance the models' alignment with human intent, resulting in more truthful and less toxic responses from the language models. Along with this line, DeepMind's Sparrow (Glaese et al., 2022) and Anthropic's Claude<sup>16</sup> also use instruction tuning and RLHF to teach models to produce answers that align with human values (Liu, 2023). Furthermore, apart from scaling up the instructional fine-tuning process by increasing the number of tasks and the model size, Chung et al. (2022); Longpre et al. (2023) improve the process by jointly integrating chain-of-thought data during instruction tuning. They fine-tune the T5 (Raffel et al., 2020) and PaLM (Chowdhery et al., 2022) into FLAN-T5 and FLAN-PaLM models (Longpre et al., 2023), resulting in robust performance across a diverse range of natural language processing tasks, including translation, reasoning, and question answering.

Apart from supervised instruction fine-tuning using existing instruction datasets or human-annotated instruction datasets, recent studies have also highlighted semi-supervised approaches for creating instruction-following data generated by LLMs (Wang et al., 2022g; Taori et al., 2023; Xu et al., 2023a; Peng et al., 2023; Zhou et al., 2023b; Honovich et al., 2022a). This synthetic data can be utilized for fine-tuning PLMs (Taori et al., 2023; Xu et al., 2023a). We refer the readers to §4.3.4 for more information.

Supervised instruction tuning can be regarded as one of the crucial steps in interactive natural language processing. By fine-tuning language models with supervised instructions, their ability to comprehend and respond to a diverse range of queries can be enhanced, enabling them to perform tasks such as question-answering and task completion with greater precision and efficiency.

## 4.3.2 Continual Learning

LMs that have been pre-trained on static data may become outdated and no longer aligned with new domains or tasks (Schick et al., 2023; Qin et al., 2022b). Therefore, it is beneficial to utilize interaction messages accumulated over time to fine-tune LMs. This guarantees that the LMs are up-to-date with the newest information and perform optimally in novel scenarios (Dalvi et al., 2022). Although typical fine-tuning is an effective approach to updating an LM, it can suffer from catastrophic forgetting (Robins, 1995). As

<sup>&</sup>lt;sup>16</sup>https://www.anthropic.com/index/introducing-claude

data size increases, attempting to incorporate new knowledge into a fixed-sized LM may result in losing previous knowledge. Continual Learning (CL) is a promising solution to this problem. It seeks to continuously integrate knowledge from novel sources without expunging prior learning (Wu et al., 2022b).

First of all, we present a mathematical formalization of continual learning. Consider a language model that is presented with a sequence of n tasks  $(T_1, ..., T_n)$ . For each task  $T_k$ , the model is provided with a set of N i.i.d. training examples  $(x_i, y_i)_{i=1}^N$ . Assuming that the language model is parameterized by  $\theta$  and is aware of the task identity during both training and inference, the overall learning objective across all tasks is:

$$\max_{\theta} \sum_{k=1}^{n} \sum_{(x,y)\in T_k} \log p(y \mid x; \theta)$$
(1)

In the continual learning setting, it involves sequentially optimizing the loss for each task  $T_k$  via fine-tuning:

$$\max_{\theta} \sum_{x,y \in T_k} \log p(y \mid x; \theta) \text{ for } k \text{ in } \{1, \dots, n\}$$
(2)



Figure 18: Continual Learning.

Such a naïve continual fine-tuning may cause catastrophic forgetting, ultimately leading to a decline in overall performance on earlier tasks after the learning of new tasks (McCloskey & Cohen, 1989).

In this part, we briefly introduce recent CL methods that aim to alleviate the forgetting phenomenon, which can be categorized into three groups: (1) Regularization, (2) Rehearsal, and (3) Modularization, following Delange et al. (2021); Biesialska et al. (2020).

**Regularization.** Regularization has been widely adopted to inhibit catastrophic forgetting by penalizing the model when it deviates significantly from its previous state. This is typically accomplished by determining the essential parameters for the prior task and domain data, and subsequently integrating a regularization term into the loss function, which encourages the model to preserve this knowledge while learning new tasks (Delange et al., 2021). For example, Kirkpatrick et al. (2017) propose Elastic Weight Consolidation (EWC), which involves measuring important parameters using a Fisher information matrix, derived from the magnitude of the gradient update step corresponding to each parameter. Following this work, Chen et al. (2020b) introduce a pre-training simulation mechanism that enables the memorization of knowledge for pre-training tasks, eliminating the requirement for pre-training data access. Li et al. (2022h) introduce a novel approach for continual learning in pre-trained models, which calibrates both the parameters and logits. This approach helps in retaining the acquired knowledge while also facilitating the learning of new concepts. As a concurrent work, Li et al. (2022b) propose to selectively memorize important parameters from previous tasks through a recall optimization mechanism facilitated by regularization, which is evaluated on interactive dialogue generation datasets.

**Rehearsal.** A rehearsal-based approach to continual learning involves replaying previous task data or synthetic previous task data while learning new tasks. For example, He et al. (2021b) conduct preliminary experiments on interactive dialog models, assuming access to the pre-training corpus during fine-tuning. Throughout the training process, they mix random subsets of the pre-training corpus based on a mix-ratio that anneals towards the target task. ELLE (Qin et al., 2022b) employs a memory replay mechanism, where several data from previous tasks is mixed with current task data for tuning. Moreover, the synthetic previous task data generated by the old model can be utilized to train the new model as memory replay (Cappellazzo et al., 2022).

**Modularization.** Modularization refers to separating model parameters into distinct modules or subnetworks, where each module is responsible for performing a specific task or set of tasks (Delange et al., 2021; Biesialska et al., 2020; Pfeiffer et al., 2023). The modularization can be achieved by adapter-based methods, which introduce new parameters corresponding to new tasks; Alternatively, it can be based on partial tuning, which freezes or prunes previous task parameters as discussed in Pfeiffer et al. (2023); Biesialska et al. (2020) and §4.3.3. For example, Lee et al. (2022a) propose a plug-and-play approach for incorporating the target knowledge into new parameters by applying multiple large-scale updates on plug-in modules, thereby avoiding the risk of forgetting the previously acquired source knowledge in old parameters. In SupSup (Wortsman et al., 2020), a network is first initialized as a base network, and task-specific sub-networks are separately learned for different tasks and acquired with a network-level mask. During testing, the task identity can be provided or inferred using gradient-based optimization, allowing the appropriate sub-network to be retrieved.

Continual learning is crucial for interactive NLP, enabling the model to adapt to the dynamic and diverse nature of user inputs, tasks, and environments. Despite considerable efforts to address the issue of catastrophic forgetting, the problem persists, especially in large language models, as they impose substantial computational requirements. Additionally, various other questions, such as evaluation for CL and sample efficiency, remain unanswered. Researchers persistently strive to improve the efficiency and effectiveness of continual learning for NLP, and advancements in this field will significantly impact the future of interactive NLP systems.

#### 4.3.3 Parameter-Efficient Fine-Tuning

When the size of a pre-trained language model grows larger and larger, it becomes more and more difficult to fine-tune the model, especially when the size of interaction message data is limited. This is because very large models often require impractical amount of GPU memory to fine-tune, and over-fitting easily happens when the training data is limited. Thus, to avoid these issues, various parameterefficient tuning methods are proposed. Parameter-efficient fine-tuning, as its name suggests, only updates a small number of parameters compared to the number of parameters of the full model. By reducing the number of trainable parameters during fine-tuning, parameter-efficient fine-tuning methods consume much less GPU memory and substantially diminish



Figure 19: Parameter-Efficient Fine-Tuning.

the risk of overfitting. Therefore, parameter-efficient fine-tuning methods have become the de facto practice for fine-tuning LLMs.

Parameter-efficient fine-tuning can be formalized as:

$$\mathcal{L}_{\theta_0 \subset h(\theta)}(LM(x;h(\theta))) \tag{3}$$

where  $\theta_0$  is the set of tunable parameters,  $h(\theta)$  is the change of model parameters by introducing additional modules, pruning, and reparameterization (Ding et al., 2022).

Following Delta-Tuning (Ding et al., 2022), parameter-efficient fine-tuning methods for iNLP can be divided into two main categories based on whether they introduce additional modules or parameters. The first category includes **partial fine-tuning** techniques, which select a small number of parameters of the pre-trained model during fine-tuning. In contrast, the second category of parameter-efficient fine-tuning methods keeps the model frozen and adds extra parameters that are updated during fine-tuning. These newly added and tuned modules are called adapters, belonging to **adapter-based methods**.

**Partial Fine-tuning.** This fine-tuning method, also known as "specification-based tuning", updates only a strict subset of the model parameters while keeping the remaining parameters unchanged during finetuning (Ding et al., 2022). This approach does not add any new parameters to the model, meaning that the number of parameters remains the same (i.e.,  $|h(\theta)| = |\theta|$ ). Instead, the method specifies explicitly or implicitly which parts of the model's parameters should be optimized by indicating  $\theta_0$  and  $|\theta_0| << |\theta|$  (Ding et al., 2022). For example, we can choose a few layers to freeze and only update the remaining layers. Howard & Ruder (2018) initially freeze all layers except for the last layer, which contains less general knowledge, and then gradually unfreeze the remaining layers during the fine-tuning process. Moreover, BitFit (Zaken et al., 2022) optimizes only the bias terms of a pre-trained model, specifically the "query" and "middle-of-MLP" bias terms, resulting in a significant reduction in the number of tunable parameters while still maintaining high performance on several benchmarks. Diff pruning (Guo et al., 2021) involves learning a delta vector to be applied to the initial pre-trained model parameters. It uses a differentiable approximation of the L0-norm penalty which facilitates the delta vector becoming more sparse, thereby resulting in a more parameter-efficient approach to fine-tuning. Similarly, Voita et al. (2019) encourage the model to prune less important attention heads through regularization, effectively reducing the number of attention heads that need to be fine-tuned. SupSup (Wortsman et al., 2020) selectively updates the critical weights of a PLM for specific tasks by learning a sub-network called supermask. It learns a superposition of supermasks with gradient-based optimization for an unseen task during inference.

Adapter-based Methods. Adapter tuning (Rebuffi et al., 2017) inserts small modules called *adapters* to a model:  $\theta \subseteq h(\theta)$  and  $|h(\theta)| - |\theta| << |\theta|$  (Ding et al., 2022). With adapters, we can completely freeze the model and only optimize the newly introduced adapters, i.e.,  $\theta_0 = h(\theta) - \theta$ . Conventional adapters follow Houlsby et al. (2019)'s practice of placing a two-layer feed-forward neural network with a bottleneck after each sub-layer within a Transformer layer, including both the multi-head attention sub-layer and the feed-forward network sub-layer. In addition, recent works have introduced many other parameterizations of adapters. The most representative ones include Prefix Tuning (Li & Liang, 2021), Prompt Tuning (Lester et al., 2021), LoRA (Hu et al., 2022a), and Compacter (Karimi Mahabadi et al., 2021). As pointed out by He et al. (2022), these approaches can be unified into a single framework, wherein a module is added as a residual to specific components of the original computational graph in the Transformer architecture. As a result, they can all essentially be considered as different variants of adapters. For example, Prefix Tuning (Li & Liang, 2021) introduces learnable tokens to the input, which are prepended to the keys and values of self-attention, with the model weights being frozen. LoRA (Hu et al., 2022a) introduces a module of low-rank trainable parameters, while the pre-trained model's weights keep frozen. In addition to low-rank approximation, Compacter (Karimi Mahabadi et al., 2021) also utilizes parameterized hypercomplex multiplications layers (Zhang et al., 2021). Compared to partial fine-tuning, adapter-based methods incorporate task-specific additional modules, offering increased flexibility, modularity, compositionality, and shareability (Pfeiffer et al., 2020; 2023). These features also allow adapters to function as a form of task representation. For example, recent works (Zhou et al., 2022e; Vu et al., 2022) show that the additional parameters introduced in adapter-based approaches reveal inter-task similarities and transferability between tasks. Specifically, Zhou et al. (2022e) show that intermediate task transferability can be effectively predicted by calculating the cosine similarity between adapter parameters for two tasks under the same backbone model.

**Applications in iNLP.** Parameter-efficient fine-tuning has been successfully applied in interactive NLP scenarios since it substantially reduces the parameters required for training and storage. For example, in the model-in-the-loop setting, BLIP-2 (Li et al., 2023d) uses prompt tuning-like method to implement vision model-language model interaction, where the interaction interface is learnable soft tokens which is mapped from the output of a vision model. In the KB-in-the-loop setting, K-Adapter (Wang et al., 2021b) uses trainable adapters to infuse knowledge retrieved from knowledge bases into pre-trained language models while keeping the model parameter frozen. ROME (Meng et al., 2022a) and MEMIT (Meng et al., 2022b) first locate the factual knowledge on some critical MLP layers of the language model via causal tracing. And then modify their weights to write memories into the model. Liang et al. (2022a) also investigate adapter tuning techniques to train a Transformer-based policy model through imitation learning for robotic manipulation (environment-in-the-loop). Additionally, parameter-efficient fine-tuning can be applied to improve the modularity of models, leading to better out-of-distribution generalization, knowledge composition, prevention of catastrophic interference, and continual learning (Pfeiffer et al., 2020; Qin et al., 2022b; Pfeiffer et al., 2023), which are beneficial for iNLP.

#### 4.3.4 Semi-Supervised Fine-Tuning

According to Liang (2005); Chapelle et al. (2006); Zhou (2017), semi-supervised learning aims to use both labeled data and unlabeled data to train a model. Semi-supervised learning can be used for interactive

natural language processing in that interaction messages are without sufficient supervision in some cases such as lack of instructions (Wang et al., 2022g; Taori et al., 2023), misaligned image-text signals (Li et al., 2022d), etc. We can formulate semi-supervised fine-tuning as follows:

Let  $D_l$  be the set of labeled data points,  $D_u$  be the set of unlabeled data points, and  $D = D_l \cup D_u$  be the full dataset. Denote  $P(y \mid x; \theta)$  as the language model with initial parameters  $\theta_0$ . The initial training of the model on the labeled data can be formalized as:

$$\theta_1 = \operatorname{argmax}_{\theta} \frac{1}{|D_l|} \sum_{(x,y) \in D_l} \log P(y \mid x; \theta) \qquad (4)$$

The model is then used to make predictions on the unlabeled data:

$$y_u = \operatorname{argmax}_y P\left(y \mid x_u; \theta_1\right) \tag{5}$$



Figure 20: Semi-Supervised Fine-Tuning.

where  $y_u$  can refer to both generated labels (for sample matching) or output distribution (for distribution matching) (Fu et al., 2023). The top s fraction of the most confident predictions (with high probability) is added to the labeled data set:

$$D'_{l} = \{(x_{u}, y_{u}) \mid P(y_{u} \mid x_{u}; \theta_{1}) > \text{ threshold } \}$$

$$(6)$$

which is finally used to train the model  $P(y \mid x)$  in turn (self-training) or another model  $P'(y \mid x)$  (semi-supervised knowledge distillation).

Self-Training. Self-Training uses the model-generated data to train the model itself, which is also known as bootstrapping. For example, BLIP (Li et al., 2022d) employs a captioner to generate novel captions derived from the given image, and utilizes a filter to eliminate noisy generations. Subsequently, the models are fine-tuned using the refined data obtained after filtering. Huang et al. (2022a) generate multiple reasoning paths with the help of a language model, and then majority voting (Wang et al., 2022f) is used to predict the most reliable answer. The reasoning paths with this answer are then used as synthetic training data for language model self-training. Zelikman et al. (2022) aim to train the language model to perform CoT reasoning in a semi-supervised setting, where the rationales are not always available. They first generate an intermediate rationale, and if it induces an incorrect answer, the model attempts to produce an inversely rationalized explanation. Subsequently, the model is fine-tuned using the question, the newly generated rationale, and the answer. Alpaca (Taori et al., 2023) uses a set of 175 seed tasks, each comprising a single instruction and a single example, to enable the large language model to generate additional instructions and examples through In-Context Learning for self-training. This technique is known as Self-Instruct (Wang et al., 2022g). TALM (Parisi et al., 2022) uses a self-play way to improve performance. It generates a tool input based on the task input, and then incorporates the output of the tool and the tool input to produce the final task output. These synthetic data generated through self-play are employed to iteratively fine-tune the language model.

Semi-Supervised Knowledge Distillation. Similar to self-training, semi-supervised knowledge distillation also leverages a model to annotate unlabeled data for model tuning. However, instead of generating the synthetic data with the trainable model itself, semi-supervised knowledge distillation uses another teacher model for data generation, and the student model is trained with this new data. For example, Ho et al. (2022) use large language models to generate chain-of-thought data, which is then used to fine-tune a smaller language model. Fu et al. (2023) first use a LLM to generate responses for unlabeled questions and then use its output distribution to train the smaller student language model for specialization. Shridhar et al. (2022) propose a method to disassemble a LLM into two smaller models, namely a problem decomposer and a problem solver, using a distillation approach.

#### 4.4 Active Learning

Active learning (AL) is a machine learning approach where an algorithm selects a subset of unlabeled data points iteratively to be manually labeled by a human annotator or automatically labeled by an automated labeling system. The goal of this approach is twofold: (1) to obtain a larger and more desirable set of labeled data points that can be used to further train the model, and (2) to maximize the model's performance gain with minimal data expansion, thereby improving sample efficiency. The human annotator or automated labeling system is commonly referred to as the Oracle  $(O(\cdot))$ , which is an (interactive) object or a function that can label the data points (Ren et al., 2021). While traditional AL research has primarily focused on finding an optimal query strategy  $(Q(\cdot))$  with humans as the oracle (Ren et al., 2021;



Figure 21: Active Learning.

Wang et al., 2021d), recent work has shown that other interactive objects such as LMs can also serve as oracles (Dossou et al., 2022). Furthermore, AL involves selecting data points from an unlabeled data pool, which can include sources such as the internet (Li et al., 2023a) and knowledge graph (Seo et al., 2021). The presence of interactive objects in the loop highlights the strong relationship between active learning and iNLP.

Formally, let  $D_u$  be the unlabeled dataset. We aim to find the optimal subset  $Q(D_u) \subseteq D_u$  of samples to be labeled. Subsequently, when we construct a newly labeled set  $D_l = O(Q(D_u))$  or then add them to the existing labeled dataset, we aim to minimize the loss of the model  $P(y|x;\theta)$  on the labeled dataset. This process is repeated iteratively. Thus, given an unlabeled data pool such as corpus, internet (Li et al., 2023a), and knowledge graph (Seo et al., 2021), the main effort on active learning is twofold: (1) find the optimal **query strategy**  $Q(\cdot)$ , and (2) choose a suitable **oracle**  $O(\cdot)$ .

Query Strategy. Zhang et al. (2022h) summarize two major concerns of AL query strategy design: informativeness and representativeness. Informativeness-based query strategies aim to identify unlabeled data points that can provide the maximum amount of additional information when being labeled, with the objective of maximizing the information gained at each iteration. Common informativeness-based query strategies include uncertainty sampling-based strategies (Schröder et al., 2022), disagreement basedstrategies (Shelmanov et al., 2021), and performance based-strategies (Zhang & Plank, 2021; Shen et al., 2021). Representativeness-based query strategies aim to account for correlations among samples to avoid sampling bias and excessive weighting of outliers. Common representativeness-based query strategies include density based-strategies (Zhao et al., 2020b) and batch diversity based-strategies (Yu et al., 2022d). We refer the readers to Zhang et al. (2022h) for more details. Traditional AL query strategies rely on statistical metrics (Tong, 2000; Settles & Craven, 2008) that may lack representation richness compared to neural representations, particularly those based on PLMs. As such, there is a growing interest in exploring how to effectively leverage PLMs and LLMs in the design of AL query strategies. For example, several useful empirical conclusions on the combination of BERT (Devlin et al., 2018) and traditional AL query strategies are illustrated in Ein-Dor et al. (2020). See et al. (2022) propose a query strategy that is based on a task-independent triplet loss, which leverages task-related features provided by task classifiers and PLMbased knowledge features to enhance batch sample diversity. ALLSH (Zhang et al., 2022d) designs a query strategy that is guided by local sensitivity and hardness utilizing a PLM-based representation, in order to improve the performance of prompt-based few-shot fine-tuning on various NLP tasks. However, adapting PLM-based representations to AL query strategies poses several delicate challenges. For example, Schröder et al. (2022) point out that adapting state-of-the-art LLMs for query strategies can lead to prohibitive costs, even outweighing expected savings. They also conduct preliminary experiments that explore the combination of transformer-based models with several traditional uncertainty-based AL strategies. Margatina et al. (2022) suggest that a PLM-based representation that is fine-tuned using poor training strategies can be detrimental to AL performance. They highlight the significance of effectively adapting PLMs to the specific downstream tasks during the AL process. These challenges suggest that there is a vast research space for the NLP community to explore more efficient and effective AL query strategies. This effort may be in line with the roadmap of retriever methods (c.f.,  $\S$ 2.2), incorporating metrics that are specific to active learning. For example, Zhang et al. (2022g) situate the RL-based retrieval method mentioned in  $\S$ 2.2 within the context of active learning (AL), with the "additional gain" upon acquiring a label for an example being the AL-specific metric.

**Oracle.** The oracle applied for labeling are usually humans in most previous NLP AL research (Zhang et al., 2022h; Wang et al., 2021d), including annotation of coreference resolution (Li et al., 2020a), word sense disambiguation (Zhu & Hovy, 2007), non-literal language identification (Birke & Sarkar, 2007), and especially small corpora construction with intensive professional knowledge or cost (Peshterliev et al., 2018; Quteineh et al., 2020; Grießhaber et al., 2020; Maekawa et al., 2022). PLM, as an alternative, has shown considerable potential in playing a role as an oracle for AL. For example, Yu et al. (2022e) propose to actively annotate highly uncertain samples with pseudo-labels generated by PLMs and use low uncertainty data points for self-training. Dossou et al. (2022) adopt PLM to generate new sentences to enrich the corpora of low-resourced African languages for pre-training a multilingual model. Wang et al. (2022g) formulate the data augmentation problem as a relabeling mechanism. They iteratively collect a batch of data points with removed instruction or input-output example for relabeling, and then leverage PLM and ICL to generate new instruction labels or input-output labels to train the model. Furthermore, to the best of our knowledge, despite the scarcity of related work, other interactive objects such as knowledge bases, tools, and environments may have the potential to serve as oracles for active learning. For example, as a special type of knowledge base, ontology may contain structured information that can facilitate labeling (Ye et al., 2022), making it a potential candidate to serve as an oracle. ReAct (Yao et al., 2022b) and PoT (Chen et al., 2022d) integrate web searching and code execution, respectively, into the answer generation process. During the AL process, we can intuitively leverage these tools to label data points. MineDojo (Fan et al., 2022) finds action guidance from an internet-scale knowledge base when faced with a difficult open-ended task (i.e., task without guidance label) in the *MineCraft* environment. NLMap-SayCan (Chen et al., 2022a) equips the LLM with an open-vocabulary and queryable scene representation which can actively propose involved objects and their locations in the environment to label incomplete and non-reifiable planning of the LLM. These work highlight the potential for using knowledge bases, tools, and environments for labeling.

# 4.5 Reinforcement Learning

With the advent of reinforcement learning from environment feedback (RLEF) (Ahn et al., 2022; Chen et al., 2022a), human feedback (RLHF) (Christiano et al., 2017; Ouyang et al., 2022), and artificial intelligence feedback (RLAIF) (Bai et al., 2022b; Liu et al., 2022h), there has been a surge in reinforcement learning for natural language processing. In the context of Reinforcement Learning (RL), generated text or tool-use can be treated as an "action", while both surrounding text and non-text inputs can be viewed as "observations". The "reward" for the language model mainly includes human preference feedback (Christiano et al., 2017; Ouyang et al., 2022) and affordance grounding feedback (Ahn et al., 2022; Chen et al., 2022a). Therefore, our survey focuses on examining the interaction of language models with environments and



Figure 22: Reinforcement Learning.

humans. We also refer the readers to Yang et al. (2023a) for more information. In the following part, we will provide a brief introduction to RL for iNLP, focusing on two aspects: (1) feedback loop, and (2) reward modeling.
### 4.5.1 Feedback Loop

There are two main approaches to build RL frameworks with language models: online reinforcement learning and offline reinforcement learning. In these approaches, language models serve as RL agents or policies. As shown in Figure 23, online reinforcement learning involves updating models with real-time synchronous rewards during training (Carta et al., 2023; Yu et al., 2022c), whereas offline reinforcement learning leverages rewards derived from a static data source (Li et al., 2022e). The choice between online RL and offline RL depends primarily on practical scenarios. Generally, online RL is more suitable for LM-environment interaction as obtaining feedback from environments is a more automated process (Yang et al., 2023a). On the other hand, offline RL is more practical for LM-human interaction since human feedback may not always be readily available (Fernandes et al., 2023). Consequently, while there are studies on online RL for LM-human interaction (Wang et al., 2021d) and offline RL for LM-environment interaction (Yang et al., 2023a), our survey mainly focuses on online RL for LM-environment interaction and offline RL for LM-human interaction<sup>17</sup>.



Figure 23: Online RL uses the actions of the training agent to generate feedback in real-time, or synchronously (Prudencio et al., 2023). This means that the agent interacts with the environment, takes actions, and immediately learns from the consequences of those actions. On the other hand, Offline RL, also known as batch RL, uses feedback from actions that were generated by other entities, not the training agent itself (Levine et al., 2020). This feedback is calculated and stored in a buffer, allowing the training agent to learn from it asynchronously.

**Online RL.** Online RL empowers language models to tackle specific tasks by learning from real-time feedback provided by external entities such as the environment or more intricate reward models (Carta et al., 2023; Fan et al., 2022; Huang et al., 2022c). This feedback, similar to other RL models, is typically used as rewards for the online RL models. Standard online RL allows language models to learn from immediate rewards after each step. These dense rewards are often scalar values (Carta et al., 2023) or boolean values (Huang et al., 2022c) derived from the agent's state, observation, and outputs. For example, in tasks that necessitate continuous movement and multiple actions, RL agents can learn from real-time feedback during the process. Abramson et al. (2022) sample multiple discrete time points during the agent's continuous movement and provides real-time binary feedback (positive or negative) based on the relative progress of the task. Moreover, in tasks with a long horizon, where each task involves multiple actions, sparse rewards can be employed to avoid the inefficiency of dense rewards. These rewards are given once per episode instead of after each step, as seen in studies like Ahn et al. (2022); Yao et al. (2022a); Yuan et al. (2023a). For large-scale, production-ready online services, language models can be trained with buffered feedback and re-deployed periodically to minimize learning costs (Bai et al., 2022a).

<sup>&</sup>lt;sup>17</sup>For the counterpart, we refer readers to Wang et al. (2021d) and Yang et al. (2023a).

Offline RL. According to recent research (Ouyang et al., 2022; Li et al., 2022e), offline reinforcement learning agents can utilize PLMs as the policy and share the same reward mechanism as online reinforcement agents while using different learning procedures. Specifically, they asynchronously apply feedback by finetuning the PLM rather than updating it in real time. During such a procedure, offline reinforcement learning with language models can utilize several algorithms <sup>18</sup> to align language models with human preference. These algorithms include Proximal Policy Optimization (PPO) (Schulman et al., 2017; Ouyang et al., 2022), Advantage Actor-Critic (A2C) (Mnih et al., 2016; Glaese et al., 2022), Implicit Language Q-Learning (ILQL) (Snell et al., 2022), Trust Region Policy Optimization (TRPO) (Schulman et al., 2015), Natural Language Policy Optimization (NLPO) (Ramamurthy et al., 2023), among others. These RL methods usually introduce alignment costs, resulting in performance degradation for other tasks, known as alignment tax (Askell et al., 2021; Ouyang et al., 2022). To address this issue, Korbak et al. (2023) employ offline reinforcement learning during model pre-training, leading to better alignment while preserving superior performance. RAFT Dong et al. (2023a) demonstrates that employing early stopping can find a more favorable balance between text quality and preference reward. Another line of works focus on improving the optimization algorithms such as computational efficiency (Dong et al., 2023a), robustness (Yuan et al., 2023b), and training stability (Ramamurthy et al., 2023).

#### 4.5.2 Reward Modeling

Reinforcement learning agents are trained using rewards that are computed based on feedback from external entities, which primarily include interactive environments, and humans. Various feedback sources and mechanism contribute to the development of distinct reward models.

RL from Environment Feedback. As discussed in §2.4, reinforcement learning from environment feedback (RLEF) facilitates affordance grounding of language models (Ahn et al., 2022). For tasks with clear and easy-to-compare evaluation metrics, such as shopping and object arrangement tasks (Yao et al., 2022a; Fan et al., 2022; Yu et al., 2022c), reinforcement learning agents can be optimized using absolute reward evaluated by corresponding environments and other evaluation models. Typically, reinforcement learning agents can be trained with binary reward functions, receiving positive reward if they conducted correct actions, and negative reward otherwise (Huang et al., 2023c; 2022c). Further, Goyal et al. (2021) involve evaluators that map visual environment and natural language descriptions to scale reward. Additionally, reinforcement learning agents can also receive rewards that are more complex and specifically handcrafted. For example, Yao et al. (2022a) involve a carefully-designed reward function that considers various attributes of the chosen product and text-based instruction-product similarity, thereby reducing the need for human-in-the-loop evaluation. For tasks where it's hard to build such efficient and sensitive evaluation metrics that maps agents' states and actions to absolute scores and establish totally-ordered relations among all actions, such as text generation tasks, reinforcement learning agents can be optimized using comparative reward, such as the relative relationship between generated actions, where the policy is rewarded whether the generated action is better than the previous one (Zhou et al., 2020b). In addition to considering the relative relationship between actions within the same state and input, reinforcement learning agents in long-horizon tasks can also be rewarded based on the relative progress made in reducing the distance between the current state and the target state (Yuan et al., 2023a).

**RL from Human Feedback.** Reinforcement Learning from Human Feedback (RLHF) is receiving increasing attention as a crucial post-training procedure for LLMs (Ouyang et al., 2022; Glaese et al., 2022; Fu & Khot, 2022; Fernandes et al., 2023). For general-purpose text generation tasks, which is an open-ended task without deterministic answers, reward models are often preferred than handcrafted reward functions due to their higher sensitivity and better performance (Fan et al., 2022; Li et al., 2022e; Mialon et al., 2023). Specifically, the reward models for offline RL are trained with a small set of human feedback that is cost-effective to gather, and subsequently are used to reward reinforcement learning agents (Bai et al., 2022b; Kiseleva et al., 2022). Similar to environment feedback, the reward mechanism of human feedback also varies among tasks. In embodied tasks, the reward model can observe the agent's history and provide

 $<sup>^{18}</sup>$  Please note that these algorithms are not specific to offline RL but are frequently utilized in offline RL settings within the context of iNLP.

binary feedback (Abramson et al., 2022). In natural language generation tasks, reward models simulate human annotators to label outputs and provide numeric scores (Ouyang et al., 2022; Stiennon et al., 2020; Bai et al., 2022a). In more complicated tasks like reasoning tasks, reward models learn to follow specific rules and provide more complex and structural feedback (Glaese et al., 2022). Note that feedback isn't limited to simple binary or numeric forms. It can also be generated in natural languages. Language models can process this type of feedback, make adjustments, and ultimately produce corrected outputs (Chen et al., 2023a; Scheurer et al., 2023). Further, the use of a reward model trained on human preference data can also be considered as "RL from Model Feedback". For example, Bai et al. (2022b) propose "RL from AI Feedback" (RLAIF), where agents can self-adjust their outputs by providing self-feedback and self-prompts, resulting in higher-quality outputs. These AI feedback mechanisms essentially provide indirect human feedback as they are trained on data annotated by humans.

#### 4.6 Imitation Learning

Imitation learning enables an agent to learn a policy (Pomerleau, 1988; 1991; Ross et al., 2011) or a reward function (Ng et al., 2000) by mimicking an expert behavior represented by given demonstrations. In contrast to reinforcement learning, a primary advantage of imitation learning is that it does not depend on a manually designed reward function or a learned reward model, but solely relies on behavior demonstrations. Such an advantage becomes especially prominent when accessing an expert at a low cost is possible, leading to a scalable generalization to various fields such as autonomous driving (Bansal et al., 2018), computer control (Humphreys et al., 2022), game playing (Pomerleau, 1991; Silver et al., 2016; Baker et al., 2022), human-agent interaction (Team et al., 2021), robotic learning (Jang et al., 2022; Lynch et al., 2022; Karamcheti et al., 2023), skill acquisition (Zhang et al., 2018; Peng et al., 2020), and even surgery (Tanwani et al., 2020). It has also been applied widely to tasks in NLP, including paraphrase generation (Du & Ji, 2019), textual adversarial attack (Chen et al., 2021b), text editing (Agrawal & Carpuat, 2022; Shi et al., 2022a), and text generation (Hao et al., 2022b).



Figure 24: Imitation Learning.

In imitation learning, the goal is to learn a policy  $\pi_{\theta}$  parameterized by  $\theta$  that mimics the behavior of an expert policy  $\pi_E$  in a given task. The behavior of the expert policy is represented by a set of demonstrations  $D = \{(s_1, a_1), (s_2, a_2), ..., (s_T, a_T)\}$ , where  $s_t$  is the state at time step t and  $a_t$  is the action taken by the expert policy  $\pi_E$  in that state. The objective of imitation learning is typically formulated as:

$$\max_{\theta} \sum_{i=1}^{T} \log \pi_{\theta} \left( a_i \mid s_i \right) \tag{7}$$

Imitation learning for interactive natural language processing can be divided into offline and online imitation learning.

Offline Imitation Learning. Demonstrations can be collected and stored offline as pairs of state observations and corresponding expert actions. Directly training models on such datasets in a supervised learning manner frames the basic type of imitation learning, namely behavior cloning (Pomerleau, 1988). Numerous supervised text generation approaches can be classified into this group by reformatting the autoregressive decoding into a Markov decision process at either token (Gu et al., 2019; Agrawal & Carpuat, 2022) or sequence (Shi et al., 2022a; Faltings et al., 2023) level. The learning process from the local expert's demonstrations can be considered an offline interaction. The expert policy is encoded in the data as an offline source to acquire the correct action given the current state. The model learns through offline interaction with the expert, and can later perform the task or behavior independently.

**Online Imitation Learning.** For some cases where the model can consult an expert, imitation learning can be conducted through an online interaction for additional supervision and evaluation. When incorporating online interaction or online imitation learning (Ross et al., 2011), the trained model can be updated on-the-fly using feedback from the expert, thus improving its performance over time. In particular, the expert response can be simulated by a separate system that knows the goal state, which proves beneficial in scenarios where accessing a human expert is infeasible or impractical (Faltings et al., 2023). This approach also provides the advantage of reinforcing or discouraging specific behaviors to aligning models with human expectations by adjusting the expert simulator.

Imitation learning often suffers from exposure bias, leading to distribution shifts and error accumulation in sequential decision-making tasks (Ross et al., 2011), such as robotic control or text generation (Williams & Zipser, 1989). When the model is only exposed to the prior trajectories generated by the expert policy, it rarely experiences the state updated by the action of its own policy. This mismatch can lead to a distribution shift where the model may encounter states it has not seen during training, thus exacerbating error accumulation. To address exposure bias in imitation learning, researchers have proposed methods that alternate between the policy of the expert and that of the model being trained. Upon the model predicts actions, the expert provides feedback or corrections, allowing for fine-tuning (Ross et al., 2011). These approaches share the same principle with interactive natural language processing which involves both offline and online interaction. How to eliminate exposure bias in language generation (Arora et al., 2022a). Furthermore, imitation learning has other limitations, including its reliance on the quality of expert demonstrations and the need for a large amount of demonstration data, impeding its broader application in interactive natural language processing.

### 4.7 Interaction Message Fusion

In this subsection, we strive to provide a comprehensive and unified framing of the interaction message fusion methods, including all the methods presented in this section. Note that this framing also systematically categorizes the knowledge integration methods as mentioned in §2.2.

As illustrated in Figure 25, the interaction message fusion methods can be divided into three dimensions, each having three categories. Thus, we have a total of 3 \* 3 \* 3 = 27 clusters of ways to incorporate interaction messages into language models. The following will present the basic definition and examples for each dimension.

Along the data dimension. (1) "Metrics" refers to simple signals such as scalar rewards or ranking scores. (2) "Constraint" means that the interaction message is in form of keywords, templates, skeletons, constrained vocabularies and the like for message formatting, conditioning, refinement as well as data augmentation, etc. (3) "Freeform" involves providing an unconstrained and unstructured text as an interaction message. For example,

- 1. Metrics: Most reinforcement learning methods are related to this (§4.5) as they rely on reward signals. For instance, RLHF (Christiano et al., 2017; Ouyang et al., 2022) utilizes a feedback mechanism wherein the language model outputs are scored to indicate their quality and safety. Several methods employ heuristics to filter interaction messages (Li et al., 2022; Hu et al., 2021), which can also be considered related, since the boolean signals are leveraged.
- 2. Constraint: The constraint on the input end involves some conditional signals such as skeletons (Wu et al., 2018; Cai et al., 2019), and outlines (Yang et al., 2022b). For instance, Re3 (Yang et al., 2022b) generates an outline to condition long-text story generation. The constraint on the output end involves constrained decoding (Shin et al., 2021; Hokamp & Liu, 2017), output refinement via a verbalizer which transforms the output (Hu et al., 2021), etc.



Figure 25: The three dimensions of interaction message fusion methods.

3. Freeform: Most of the methods deal with freeform data, as defined by its unstructured nature.

Along the model dimension. (1) "Model-Invariant" approach does not modify any part of the model architecture. (2) "Model-Adjusted" approach makes changes to the existing modules of the model architecture. (3) "Model-Expanded" approach involves adding new modules to the model architecture. For example,

- 1. Model-Invariant: Prompting methods ( §4.2) belong to this line. Most of the tuning methods are also in this line of research. In most cases, the interaction message is concatenated or inserted to the input along sequence length dimension so that it is unnecessary to change the model architecture (Guu et al., 2020; Izacard et al., 2022; Paranjape et al., 2023; Xie et al., 2022). We can also only modify some critical mediating modules of the language model to incorporate knowledge (Meng et al., 2022a;b) with the model architecture unchanged.
- 2. Model-Adjusted: VaLM (Wang et al., 2022d) replaces one layer of self-attention block with crossattention block to fuse retrieved visual knowledge. K-BERT (Liu et al., 2019a) uses a superposition of text embedding and knowledge embedding (i.e., token embedding+soft-position embedding+segment embedding) and an attention mask matrix to fan in the knowledge.
- 3. Model-Expanded: K-Adapter (Wang et al., 2021b) adds additional adapters to the model for knowledge enhancement as mentioned in §4.3.3. Retro (Borgeaud et al., 2021) adds cross-attention modules to the model for retrieval augmentation. RelationLM (Liu et al., 2022e) uses an additional GRU function to fuse knowledge into the language model. KELM (Lu et al., 2021c) uses additional hierarchical knowledge enhancement module to incorporate heterogeneous information from knowledge graphs and text into PLMs. This module employs a relational Graph Neural Network (GNN) to dynamically representing inputted knowledge, an attention mechanism to resolve knowledge ambiguity, and a self-attention mechanism for further interactions between knowledge-enriched tokens.

Along the training dimension. (1) "Frozen" means that all the model parameters are fixed and cannot be tuned. (2) "Partial Tuning" means that only a part of the model parameters are tuned. (3) "Full Tuning" refers to updating all model parameters. For example,

- 1. Frozen: This category mainly involves prompting methods (§4.2). Besides, some constrained decoding-based methods (Shin et al., 2021; Hokamp & Liu, 2017) also do not update model parameters. Another example is KPT (Hu et al., 2021), which refines the output verbalizer using metrics that consider the frequency and relevance of knowledgeable words.
- 2. Partial Tuning: For those which introduce additional modules or leverage a strict subset of model parameters to fan in external information (Meng et al., 2022b;a; Wang et al., 2021b), partial tuning is a trivial way as mentioned in §4.3.3. For instance, K-Adapter (Wang et al., 2021b) only tunes the adapter modules with the main body of the language model frozen. SpoT's generic variant (Vu et al., 2022) learns a source prompt on some source tasks with the language model frozen and then uses it to initialize another learnable soft prompt of the target task for knowledge transfer.
- 3. Full Tuning: Most methods require full tuning of the model parameters to integrate external information into the language model. For instance, ToolFormer (Schick et al., 2023) trains all the language model parameters on API call inserted corpus to enable the language model to use tools. Kepler (Wang et al., 2019) tunes all the model parameters with both knowledge embedding loss and masked language modeling loss. KnowBERT (Peters et al., 2019) embeds structured knowledge from multiple knowledge bases into PLMs. It uses a combined entity linker to obtain relevant entity embeddings and further enhances contextual word representations through word-to-entity attention, where the model parameters are also fully trained.

In summary, integrating external information into language models has emerged as a rapidly evolving research area in recent years, with numerous strategies available for its implementation. By breaking down the interaction message fusion methods into three dimensions along the data, model, and training dimensions, we provide a systematic categorization of the existing methods, which can help researchers and practitioners better understand and design new approaches. It is worth noting that these dimensions are not mutually exclusive, and different methods can combine different categories from each dimension. The selection of an appropriate category relies on the specific task, data, and resources, as well as the trade-off between performance and computational efficiency.

## 5 Evaluation

Evaluation is undoubtedly important in tracking the NLP progress (Sai et al., 2023), and even helps to outline future directions of NLP, e.g., Turing test (Elkins & Chun, 2020; Srivastava et al., 2022). Existing surveys have comparatively elaborated on both automatic evaluation and human evaluation methods from general (Sai et al., 2023) to task-specific metrics, e.g., evaluating controllable text generation (Zhang et al., 2022a). However, interactive NLP is slightly different from the general NLP tasks, as it devotes greater attention to the quality and effectiveness of model interactions with humans, environments, etc. In the interest of brevity and simplicity, this section will shed light on the relationship between iNLP and evaluation, yet does not retrace nor depict the historical evolution of general NLP evaluation. For further information, please refer to related NLP evaluation surveys (Khapra & Sai, 2021; Sai et al., 2023). Please note that our survey primarily focuses on generative natural language processing, i.e., natural language generation (NLG).

Interactive scenarios occur naturally in various general natural language generation (NLG) tasks, such as dialogue (Chen, 2022; Stoyanchev et al., 2022; Chen et al., 2020a) and question answering (Gordon et al., 2018; Yuan et al., 2019). However, a large number of existing NLG metrics mainly evaluate the non-interactive performance of an NLG model (Lee et al., 2022c), which ignores evaluating the interactive quality and effectiveness happening in the model inference stage. Specifically, these metrics focus on comparing the difference between the model completion with the pre-specified human reference to determine whether the performance is beyond previous models, such as Meteor (Banerjee & Lavie, 2005), Rouge (Lin, 2004), and CIDEr (Vedantam et al., 2015). While they are convenient and time-saving, the interaction quality may not be improved if the model only resorts to feedback from such evaluation metrics, resulting in it being hardly fit for usage in the real world. For example, BLEU (Papineni et al., 2002) is one of the most commonly used metrics for NLG systems. Instead of directly telling the generation quality of the system, it focuses on comparing the differences between the model output and reference by n-gram matching. In this case, a higher

lexical similarity leads to a higher score. Thus, a sentence whose expression is not similar to the reference will get a low score, even if it meets the user's given preferences (Sellam et al., 2020). Although interaction evaluation is still in its fledgling stage, researchers are aware of such insufficiency in current NLG evaluation and are diverting their attention to the interaction performance of a NLG model.

In this section, we make the attempt to summarize recent progress of interaction evaluation. We split interaction evaluation into four types according to the interactive objects.

#### 5.1 Evaluating Human-in-the-loop Interaction

Evaluating human-in-the-loop aims to evaluate the performance of human-system interaction, which can be divided into two technical routes: general and task-specific metrics.

General Metrics. These metrics are agnostic to specific tasks and primarily aim to evaluate the general performance of PLMs. The key challenge is to evaluate the alignment between the language model and humans, that is, whether the NLG model satisfies certain human preferences. To solve this problem, Ouyang et al. (2022) give a specific interpretation of this nebulous concept-a model is aligned if it is helpful (i.e., helps to solve the task), honest (i.e., ensures the authenticity of information), and harmless (i.e., conforms to ethics). In detail, they evaluate the helpfulness property by preference rating from human labelers, while the honesty property is automatically evaluated by a hallucination dataset and the TruthfulQA dataset (Lin et al., 2021). As for the harmlessness property, they use both Real Toxicity Prompts (Gehman et al., 2020) and CrowS-Pairs datasets (Nangia et al., 2020) to evaluate the bias and toxicity of the NLG model. To further expand the dimensions of interaction evaluation, HALIE (Lee et al., 2022c) proposes a human-language model interaction evaluation framework, which includes a user interface to facilitate the interaction between humans and language models. Based on this system, HALIE introduces metrics that expand the non-interaction evaluation in three dimensions: (1) **Targets**, evaluating extra interactive processes except model completions, such as user edits; (2) **Perspectives**, adding human evaluation involving users who come into direct interaction with PLMs; (3) Criteria, highlighting human preference when evaluating the model completions, e.g., enjoyment. and helpfulness. Comprehensive experiments in HALIE demonstrate a significant disparity between human evaluations conducted by third-party annotators and those provided by interactive system users. This disparity underscores the crucial need to investigate interaction-based evaluation methodologies.

**Task-specific Metrics.** Task-specific metrics are concerned with designing a customized interaction evaluation method for generation tasks, including task-specific feature measurement when evaluating humanmodel interaction. Such task-specific metrics are most commonly found in dialogue system (Liu et al., 2018), question answering (Wallace et al., 2019b), creative writing (Lee et al., 2022b), etc. For example, dialogue system is interested in assessing the quality of human-model interaction in specific conversation scenarios (Liu et al., 2018; Lu et al., 2019b) and evaluating the performance gain of adding human feedback in the model inference stage (Li et al., 2017). In particular, the metrics of task-oriented dialogue interaction evaluation largely consist of three items: (1) the success rate of tasks Testoni & Bernardi (2021), such as successfully booking flights or movies; (2) dialogue turn size (Lu et al., 2020), fewer numbers indicate that the dialogue agent is better at completing a task with less time cost; (3) the accuracy in the dialog state track (DST) (Henderson et al., 2014), i.e., determining if the key information is accurate throughout the conversation. Additionally, human experience and knowledge have also been employed in the evaluation of question-answering systems. For instance, Wallace et al. (2019b) involve human authors in the process to enhance the generator's ability to create a diverse set of adversarial questions. This approach enables a more comprehensive evaluation of the robustness of question-answering systems. As for creative writing, CoAuthor (Lee et al., 2022b) introduces a dataset capturing interactions between writers and LLM, and demonstrates its usefulness in exploring LLM's language, ideation, and collaboration capabilities for creative and argumentative writing.

Despite the advancements made in Human-LM interaction evaluation metrics, the development of a comprehensive general benchmark remains largely unexplored (Wang et al., 2021d; Wu et al., 2022c). A unified benchmark and metric play a crucial role in evaluating models from an interactive perspective; however, designing and collecting such a benchmark pose significant challenges. One of the primary difficulties stems from the specificity of interaction evaluation, which necessitates detailed tracking and recording of the interactive process rather than merely collecting model completions. In addition, the interactive nature of human-in-the-loop evaluation can lead to data inconsistencies due to inherent individual diversity. This further complicates the task of constructing a general benchmark. Building such a benchmark necessitates careful consideration in terms of the user interface, means, and interaction process.

### 5.2 Evaluating KB-in-the-loop Interaction

Evaluation of KB-in-the-loop interaction naturally arises in knowledge-augmented NLG models as a means of assessing their ability to acquire knowledge for enhanced generation.

Knowledge Acquisition. As discussed in §2.2, knowledge acquisition can be achieved through retrieving from external knowledge sources (e.g., knowledge graph, database, and even web browsing). Therefore, these KB-in-the-loop methods based on knowledge retrieval are interested in evaluating the effectiveness and efficiency of the knowledge retrieval process. For example, REALM (Guu et al., 2020) conducts ablation experiments comparing different retrievers used for knowledge acquisition, using "top-5 recall" metrics. Atlas (Izacard et al., 2022) analyzes how the frequency of the text in the correct answer option appearing in retrieved passages is influenced by the number of retrieved passages. Such an evaluation is useful for analyzing and improving the intermediate component of KB-in-the-loop NLG systems.

Knowledge-Enhanced Generation. Another line of research focuses on evaluating the models' capabilities for knowledge-enhanced generation. The most common and important way lies in hallucination detection, which utilizes extra knowledge graphs or databases to detect factual errors (Ji et al., 2022). For example, Knowledge F1 (Shuster et al., 2021) measures the word overlap between the model's completion and the fact knowledge used to ground the dialogue. Several fact-checking benchmarks have been presented in recent years to facilitate this area. For example, BEGIN (Dziri et al., 2022) introduces three types of knowledge-grounded dialogue responses based on the evidence from Wikipedia. In this case, factual knowledge is in the form of paragraph-level text. In contrast, DialFact (Gupta et al., 2022) utilizes manually annotated instance-level knowledge snippets as evidence. The Attributable to Identified Sources (AIS) framework (Rashkin et al., 2021) assesses whether the statements produced by an NLG system can be attributed to a specific underlying source. Another type of evaluation method focuses on the comparison of the differences between humans and models when choosing to add additional knowledge. For example, WebGPT (Nakano et al., 2021) evaluates model completions by comparing them with human-written answers based on the same web-browsing environment to determine whether the model's retained knowledge is different from that of users. GopherCite (Menick et al., 2022) computes the ratio at which the model produces plausible and supported claims (i.e., evidence) in human evaluation.

### 5.3 Evaluating Model/Tool-in-the-loop Interaction

As discussed in §2.3, model/tool-in-the-loop encompasses three types of operations: (1) thinking, (2) acting, and (3) collaborating. Thus, evaluating model/tool-in-the-loop interaction involves assessing the following aspects: (1) (multi-stage) chain-of-thought capability, (2) tool-use ability, and (3) collaborative behavior analysis.

Chain-of-Thought Capability. Chain-of-Thought (CoT) (Wei et al., 2022b) is regarded as one of the most crucial emergent abilities, which tends to become more pronounced as model size scales up (Kaplan et al., 2020; Wei et al., 2022a). It is frequently triggered by elicitive prompts (§4.2.2) and can be instantiated through prompt chaining (§4.2.3). Typically, CoT aims at improving models' multi-step reasoning abilities (Wei et al., 2022b; Qiao et al., 2022). Thus, some reasoning-intensive benchmarks such as GSM8K (Cobbe et al., 2021), DROP (Dua et al., 2019), and ScienceQA (Lu et al., 2022a), can be used to evaluate CoT capability. We refer the readers to Qiao et al. (2022) for a more comprehensive survey on the reasoning tasks. In our survey, we introduce additional perspectives focused on intermediate steps or reasoning trajectories for evaluating the CoT abilities. For example, we can assess the error propagation between reasoning steps. Dua et al. (2022)'s successive prompting technique encounters three primary error sources: incorrect answer predictions,

incorrect question decomposition, and out-of-scope reasoning types. By understanding and addressing these errors happened in the intermediate reasoning steps, we can develop more robust models that mitigate the impact of errors throughout the multi-step reasoning process. Another approach is to analyze the effects of varying the number of reasoning steps or the number of reasoning branches. For example, Zhou et al. (2022a) conduct experiments to investigate the influences of different numbers of reasoning steps. Wang et al. (2022f) compare the influence of different numbers of sampled reasoning paths on performance.

**Tool-Use Ability.** Following Yang et al. (2023a) and Li et al. (2023e), evaluating the tool-use ability of language models involves examining: (1) **tool-use triggering**: whether the LM can determine when to use tools, (2) **tool-use accuracy**: whether the LM selects the correct tools to perform a specific task, (3) **tool-use proficiency**: whether the LM can effectively and efficiently use the tools for reasoning and decision making (Yao et al., 2022b). For example, Toolformer (Schick et al., 2023) evaluates tool-use triggering by calculating the API invoking rate, that is, how often the model requires the corresponding API to help with some text generation tasks such as machine translation, question answering, and mathematical calculation. ART (Paranjape et al., 2023) compares various strategies employed by language models to select prompts from a task library for correct tool-use prompting, which can also be viewed as a measurement of tool-use accuracy. WebShop (Yao et al., 2022a) examines the success rate of language agents in utilizing web tools for shopping tasks, which serves as an indicator of the tool-use proficiency of language models. Since tool-use ability has been shown to be capable of enhancing the reasoning capability of language models in Tool-Augmented Learning settings (Qin et al., 2023), certain metrics used to evaluate CoT ability (§5.3) can also be employed to assess tool-use proficiency (Chen et al., 2022d; Cobbe et al., 2021; Yao et al., 2022b).

**Collaborative Behavior Analysis.** The analysis of collaborative behaviors of language model agents can be divided into **result-oriented analysis** and **process-oriented analysis**. Result-oriented analysis mainly focuses on the output or the final result of the collaboration. For example, MindCraft (Bara et al., 2021) measures whether a task can be solved through collaboration between two language model agents. Socratic Models (Zeng et al., 2022a) evaluates the success rate of tasks that are solved through closed-loop interaction involving a large language model, a vision-language model, and an audio-language model. BIG-bench (Srivastava et al., 2022) has incorporated several tasks for evaluating Theory of Mind (ToM) abilities. Furthermore, Kosinski (2023) demonstrates that ChatGPT has achieved a performance level comparable to that of nine-year-old children on certain ToM tasks. Process-oriented analysis is more concerned with the dynamics of the collaboration itself. For example, MindCraft (Bara et al., 2021) also assesses the communication efficiency by measuring the number of dialogue exchanges required to accomplish a task.

### 5.4 Evaluating Environment-in-the-loop Interaction

Since the objective of environment-in-the-loop NLP primarily focuses on utilizing language model agents for embodied tasks, which significantly differ from typical text generation tasks, the evaluation of LM-Env interaction may require a distinct paradigm. Generally, the research in this field primarily focuses on two main aspects: (1) constructing embodied task platforms, and (2) determining the appropriate evaluation metrics. We also refer the readers to §6.3 and §6.4 for more information.

**Embodied Task Platforms.** To name a few, EvalAI (Yadav et al., 2019) provides an open-source platform for evaluating models and agents, which involves tasks of visual question answering, visual dialog, and embodied question answering (Das et al., 2018). SAPIEN (Xiang et al., 2020) introduces a simulated household environment specifically designed to simulate daily objects and their interactions within a household setting. Similarly, Alexa Arena (Gao et al., 2023b) introduces a user-centric simulation platform for Embodied AI models and presents an instruction-following benchmark based on human-agent dialogue. Shridhar et al. (2020) build a benchmark, ALFRED, to evaluate the ability of agents to transform visual observations and textual instructions into action sequences for everyday tasks. Building upon this setup, Akula et al. (2022) introduce a new test set called ALFRED-L. This test set is created by modifying instructions from examples in the ALFRED validation splits. The modifications involve eliminating the need for actions manipulating objects and incorporating directives to approach more objects. Furthermore, Shridhar et al. (2021) extend both *TextWorld* (Côté et al., 2019) and ALFRED platforms to create ALFWorld. This novel platform establishes a

connection between textual descriptions and commands, and the physical simulation of embodied robots, offering an enhanced alignment between them. Lastly, Bara et al. (2021) explore collaborative situations where agents are placed in interactive scenarios. They aim to model the mental states of participants in these collaborative interactions. To facilitate this research, they introduce MindCraft, a fine-grained dataset that includes the beliefs of partners when collaborating on tasks within the virtual world of Minecraft, a 3D environment consisting of blocks. We refer the readers to Yang et al. (2023a) for more examples.

**Evaluation Metrics.** To name a few, the mission success rate and the average number of robot actions are both metrics that can be utilized to assess the model's capabilities in terms of interacting with the environment (Gao et al., 2023b). The mission success rate measures the model's effectiveness by computing the average proportion of missions in which all the goal conditions are met, indicating successful completion of the mission. While the average action number examines the model's efficiency by recording the average number of actions performed by the robot for each task. Ahn et al. (2022) employ the plan success rate and the execution success rate to evaluate the performance and effectiveness of the system. The plan success rate assesses the system's ability to successfully execute those plans and accomplish the specified tasks. Huang et al. (2023c) report the text instruction generation speed in the inference stage (referred to as "token count" in the paper) to evaluate the efficiency of the involved large language model.

# 6 Application

### 6.1 Controllable Text Generation

The Controllable Text Generation (CTG) technique is an NLP approach that empowers language models to generate text that is not only coherent and meaningful but also allows users to control particular aspects of the output. The need for CTG arises from the desire to customize generated text according to user-defined constraints, such as length constraint (Li et al., 2022g; Zhou et al., 2023b), inclusion of particular keywords (Hokamp & Liu, 2017; Carlsson et al., 2022), and adherence to a specific sentiment or style (Dathathri et al., 2019; Qian et al., 2022). Conventional CTG methods typically involve training models with explicit objectives that optimize for the control attributes (Hu et al., 2017; Li et al., 2022g; Keskar et al., 2019; Lu et al., 2022b; Clive et al., 2021; Zhou et al., 2023b), constrained decoding (Hokamp & Liu, 2017; Anderson et al., 2017; Post & Vilar, 2018; Lu et al., 2021b; 2022c; Qin et al., 2022a; Kumar et al., 2022), and prompting (Zou et al., 2021). We refer the readers to Zhang et al. (2022b) and Weng (2021) for more information. In this section, we briefly discuss the potential applications of iNLP in CTG.

Interacting with humans can enhance controllability in CTG by enabling users to directly provide their preferences and constraints during the generation or training process. AI Chains (Wu et al., 2021), for example, allows users to chain together LLM steps and modify them in a modular way, improving transparency, controllability, and collaboration. Lee et al. (2022c) suggest the importance of controlling the intermediate generation process rather than just the final output, and highlight the need to consider more control attributes related to first-person subjective experience and user preferences. Christiano et al. (2017); Lu et al. (2022b); Ouyang et al. (2022); Fu & Khot (2022) imply the use of RL or RLHF for controlled text generation, which enables not only control over helpfulness, harmlessness, and honesty, but also allows potential optimization to meet length constraints and other criteria.

**Interacting with knowledge bases** can potentially enhance the robustness and factuality of CTG, as suggested by Li et al. (2022a), who propose Knowledge-Aware Fine-Tuning (KAFT) to improve the controllability of language models while maintaining their robustness. KAFT fine-tunes LMs using a combination of the vanilla supervised dataset and augmented data, which includes instances with counterfactual contexts (i.e., contexts that contradict the model's memorized knowledge) and irrelevant contexts (i.e., contexts that are unrelated to the task).

Interacting with models and tools may have the potential for more complex and fine-grained control over text generation. For example, classifier-guided CTG approaches put a classifier in the loop to provide control signals or feedback (Dathathri et al., 2019; Li et al., 2022g). Similar to Diffusion-LM (Li et al., 2022g) which

iteratively denoises the text with the control feedback from a classifier at each iteration, Self-Refine (Madaan et al., 2023) lets a LLM generate an output and then provide multi-aspect feedback on it. This feedback is used to iteratively refine the output until it reaches a satisfactory quality or a specific criteria. Notably, typical classifier-guided CTG relies on external classifiers, while Self-Refine employs the LLM itself as a classifier through self-interaction.

**Interacting with environments** inherently requires great controllability due to the essential need for affordance grounding, as discussed in §2.4. SayCan (Ahn et al., 2022), as a representative example, leverages a scoring mechanism over action candidates to achieve such controllability.

Overall, various interactive objects may offer different avenues for optimizing CTG systems. By harnessing the power of interaction, we can achieve more user-oriented, robust, fine-grained, complex, and even realityoriented control over text generation.

### 6.2 Writing Assistant

Intelligent and interactive writing assistants constitute a rapidly growing area of research that explores the potential of AI-powered tools to modify, enrich, and even co-create content with humans. These assistants can be broadly categorized into four types based on their level of involvement in the content generation process: (1) Content Supporting, (2) Content Checking and Polishing, (3) Content Enrichment, and (4) Content Co-creation.

**Content Support.** Content supporting writing assistants do not generate content for use, but just provide functional assistance for writers such as on-the-fly summarization (Dang et al., 2022) and real-time visualization (Singh et al., 2022b). For example, Arnold et al. (2021) propose an interaction scheme where human writers are provided with questions for inspiration instead of content snippets for use. Dang et al. (2022) propose a writing assistant that continuously updates summaries, keywords, and central sentences of existing content for user reference, rather than generating content directly. Singh et al. (2022b) design a writing assistant offering visual and aural suggestions as writing supports. Although content supporting writing assistants provide minimal aids for human writers, they benefit from avoiding the dominance over the writing process in some cases, which is one of the main challenges of PLM-based writing assistants (Arnold et al., 2021; Jakesch et al., 2023). Moreover, writing support may reduce the manual effort to trigger or manipulate the writing assistant such as heavy prompt engineering (Dang et al., 2023). Specifically, Dang et al. (2023) indicate that manual effort is required for non-diegetic prompting, and thereby humans tend to prefer selecting suggestions from writing assistants over controlling automatic content generation through non-digetic prompts. Jakesch et al. (2023) point out that human writers' content creation can even be affected by opinionated PLM-powered writing assistants. These challenges can be mitigated by reducing the level of involvement of writing assistants to content supporting.

**Content Checking and Polishing.** The processing procedure for content checking and polishing typically involves taking manually written sentences as input and producing output that has been grammar-checked and rephrased, allowing users to interactively and iteratively improve their writing. Famous real-world products include QuillBot<sup>19</sup>, Effidit (Shi et al., 2022b)<sup>20</sup>, Pitaya<sup>21</sup>, Grammarly<sup>22</sup>, and Xiezuocat<sup>23</sup>. There is also growing interest in incorporating iterative editing operations into writing assistants (Kim et al., 2022; Du et al., 2022a;b), which can be considered an application of editing-based iNLP (§3.3). For example, Kim et al. (2022) suggest incorporating transfer learning from other text editing tasks to improve the quality of iterative text revision by linking editing actions to content quality. Du et al. (2022a) raise a novel human-in-the-loop iterative text revision system that combines model-generated revisions with human judgments and specifically fine-tuning a PEGASUS model (Zhang et al., 2020a) as a revision generation model with which a revised sentence is generated based on a given sentence and an edit intention.

<sup>&</sup>lt;sup>19</sup>https://quillbot.com/

<sup>&</sup>lt;sup>20</sup>https://effidit.qq.com/en

<sup>&</sup>lt;sup>21</sup>https://www.facebook.com/Mypitaya/

<sup>&</sup>lt;sup>22</sup>https://www.grammarly.com/

<sup>&</sup>lt;sup>23</sup>https://xiezuocat.com/

**Content Enrichment.** Content enrichment, unlike content checking and polishing, involves more creative content generation but still relies on manually provided context or configuration. Classic content enrichment features include text completion (AutoCompletion) (Van et al., 2020; Sun et al., 2021a; Li et al., 2021a; Casacuberta et al., 2022), and keywords-to-sentence (K2S) (Miao et al., 2019; Sha, 2020; Nie et al., 2022; Zheng et al., 2022). Note that both AutoCompletion and K2S simply supplement manual input, rather than co-creating new content from scratch through manual collaboration or guidance. AutoCompletion is an interactive writing assistant feature that involves humans in the content generation process by providing suggestions to complete their prompts, thereby enhancing their overall writing experience. For example, Sun et al. (2021a) propose an Intent-Guided Authoring (IGA) Assistant, which follows fine-grained author specifications to process the input text for AutoCompletion. The scheme proposed in IGA is similar to the recent trend of instruction tuning ( $\S4.3.1$ ), which suggests that more complex and controllable user preferences in writing assistants can be formatted as instructions to further activate instruction-tuned LLMs. AutoCompletion can also be adapted to various NLP downstream tasks, including medical text simplification (Van et al., 2020), human-computer collaborative translation (Li et al., 2021a), and interactive word completion of morphologically complex low-resource language (Lane & Bird, 2020). Moreover, K2S is highly in line with controllable text generation (c.f.  $\S6.1$ ), but places a greater emphasis on controllable interactivity. Practical K2S applications typically allow users to customize the fine-grained control attributes according to their specific needs and preferences in an interactive manner. For example, CueBot (H. Kumar et al., 2022) proposes a conversational assistant capable of generating responses that can be controlled by users using cues/keywords. It suggests responses for users to choose from and incorporates a keyword loss during training to generate lexically constrained outputs.

**Content Co-creation.** Content co-creation refers to the collaborative process between humans and AI systems to generate new content from scratch, rather than simply improving existing content. Content co-creation is widely explored in interactive fiction writing (Manjavacas et al., 2017; Tapscott et al., 2018), screenplays and theatre scripts writing (Mirowski et al., 2022), academic writing (Fok & Weld), and poem writing (Astigarraga et al., 2017; Oliveira et al., 2017; Hämäläinen, 2018). For example, Tapscott et al. (2018) models story generation as simulating role-play games and tracing player interaction sequences. Yang et al. (2022a) develop DOC, which includes a detailed outline generator and a detailed controller, significantly improves the coherence of long story generation. Chakrabarty et al. (2022) proposes CoPoet, an interactive poem writing assistant powered by instruction prompts and LLM, and verify that co-created poems are usually preferred compared to those written without *CoPoet* involved. Dramatron (Mirowski et al., 2022) adapts hierarchically controlled PLMs to allow expert writers to control style tags, logic lines, character descriptions, and environment descriptions. This enables writers to easily generate the necessary material for various use cases. However, while practical writing assistants for content checking, polishing, and enriching have become increasingly mature, content co-creation writing assistants still face various challenges that need to be addressed. For example, Ippolito et al. (2022) point out that current NLG techniques for story generation often exhibit poor performance in maintaining the author's voice and the coherence of the storyline. Wu et al. (2021); Yuan et al. (2022); Chen et al. (2022b) demonstrate that there is often a trade-off between controllability and creativity in the generated content. Moreover, the evaluation of content co-creation-based writing assistants can also be particularly challenging due to the subjective nature of creative writing. Despite various efforts to construct reliable benchmarks for evaluation (Lee et al., 2022b; Zhou et al., 2022b; Shen & Wu, 2023), Mirowski et al. (2022); Ippolito et al. (2022) suggest that professional writers have become increasingly important for evaluation compared to crowd-sourcing annotators due to the ever-improved quality of artificial intelligence generated content (AIGC).

### 6.3 Embodied AI

Embodied AI enables language models to impact the real-world and virtual environments through which agents observe and update states of themselves and their surroundings. One method for bridging language models with the physical world is interaction with grounded language as mentioned in §2.4, which allows language models to see, listen, and control external objects.

**Observation and Manipulation** are fundamental to many embodied tasks, where agents acquire external states and perform actions to update those states. Thanks to text descriptions and textual controlling

interfaces, language models usually observe their surrounding environment through input text and operate on objects by sending textual commands. For instance, a visual perception mapper converts visual input to text in natural language (Zhao et al., 2023b). Additionally, human intervention can be part of agent observation, so that agents can be guided by real-time human feedback (Lynch et al., 2022). Typical observation and operation tasks include object rearrangements (Huang et al., 2022c), tool usage (Paranjape et al., 2023), item creation and modification (Jiang et al., 2021; Elgohary et al., 2021), and other robotic controlling tasks.

Navigation and Exploration enable agents to move around and study their surrounding environment by using dynamic observation and manipulation. That is, unlike observation and manipulation tasks, navigation and exploration tasks allow agents to move within the environment to adjust their observation and manipulation. These agents not only plan routes and actions, but also combine observations collected from different locations to make decisions, answer questions and reason, allowing them to accomplish complicated tasks that require multi-location multi-object observation and long-horizon manipulation. Text commands in both natural languages and programming languages (Huang et al., 2023a) bridge the gap between language model agents and available actions and tools. During such process, these agents also combine different data sources, including cameras, microphones, other sensors (Gan et al., 2020), and textual commands from human controllers (Sharma et al., 2022; Gao et al., 2022c). Moreover, agents can also work as assistants to guide human operations. For instance, an interactive driving assistant can continuously observe the driving environment and guide human drivers to handle various situations (Ma et al., 2022).

Multi-Role Tasks require agents to cooperate and compete with humans and other agents to reach specific goals. Unlike agents with multiple skills, agents with social capabilities usually observe others' behaviors and communicate through textual messages, including messages in natural languages and data in more structured styles. Typical social tasks include multi-player gaming (Suh et al., 2021; Lai et al., 2022), human-AI collaboration (Krishnaswamy & Alalyani, 2021; Puig et al., 2020), multi-agent collaboration (Patel et al., 2021b), and other communication tasks, such as interview (Xiao et al., 2020), negotiation (Verma et al., 2022), recruitment (Nawaz & Gomes, 2019), and opinion gathering (Bittner et al., 2019). In text-based gaming tasks, agents learn from human behaviors and play as human players (Xu et al., 2022d). In multi-agent environments, agents coordinate with each other to accomplish complex tasks that cannot be accomplished by any single agent (Bara et al., 2021). Agents also act as human delegates and communicate with others to complete day-to-day tasks, such as restaurant reservations and appointment scheduling (O'Leary, 2019). MetaAI's Cicero (, FAIR) enables language model agents to play in an online Diplomacy league.

### 6.4 Text Game

Text games, also referred to as interactive fiction games (Osborne et al., 2022), are capable of understanding player commands, simulating player states, and updating the current status of game environments (Osborne et al., 2022). Language models have shown great potential in these game-playing scenarios (Meta et al., 2022; Kramár et al., 2022; Fan et al., 2022; Yuan et al., 2023a), which are a specific type of Embodied AI (c.f., §6.3). Specifically, language models can be used to play or power text games through text-based interfaces, such as state descriptions (Sironi & Winands, 2021), commands (Tennenholtz & Mannor, 2019; Ammanabrolu & Hausknecht, 2020; Zhang et al., 2022f), situated dialogue (Bara et al., 2021), and multi-party dialogue (Park et al., 2023). Thus, text games are intrinsic applications of iNLP, in which the environment or other agents are involved in the game-playing loop. We can divide text games into two distinct categories: (1) text-only games which rely solely on text, and (2) text-aided games which use text as a supplement to other forms of media, such as graphics or audio. In this subsection, we will begin by discussing interactive text game platforms. We will then provide a brief overview of how language models are utilized to play text-only games and to power text-aided games.

**Interactive Text Game Platforms.** Interactive Text Game Platforms provide a framework and engine for building and running text-based games, often including features such as game state tracking, parser-based natural language understanding, and scripted events. Some examples of such platforms are:

(1) **Text Adventure Games** are games that allow players to interact with adventurous worlds solely through textual descriptions and actions (Ammanabrolu et al., 2019). Osborne et al. (2022) summarize two major text adventure game platforms: *TextWorld* (Côté et al., 2019) and *Jericho* (Hausknecht et al., 2020). Additionally,

they define seven major challenges that need to be addressed in developing solutions for Text Adventure Games, including partial observability, large state space, and long-term credit assignment, among others.

(2) Social Deduction Games are games where players attempt to discover each other's hidden role or team allegiance through strategic conversations, logical deduction, and deceitful actions<sup>24</sup>. For example, classic examples of social deduction games include  $Werewolf^{25}$ ,  $Mush^{26}$ ,  $SS13^{27}$ , and  $Among Us^{28}$ . Specifically, Lai et al. (2022) propose a multimodal dataset containing text and visual signals to model persuasion behaviors in *Werewolf*. Lin et al. (2020) is another *Werewolf*-based corpus with self-revealing and role-estimation behavior annotation. Tuin & Rooijackers (2021) construct a corpus aimed at player role detection, based on the game Among Us, and verify that it is a challenging yet learnable task.

(3) **Strategic Games** are games that heavily rely on player decision-making skills and situational awareness to determine the outcome<sup>29</sup>. For example,  $Diplomacy^{30}$  is a strategic board game that involves multiple players who each assume control of the armed forces of a European power. The objective of the game is to move one's units skillfully and defeat those of opponents in order to gain possession of a majority of strategically important cities and provinces referred to as "supply centers." The contested nature of this gameplay often requires players to engage in extensive and complex interactions and diplomacy with each other in order to achieve their goals. *Diplomacy* is gaining increasing attention and is widely regarded as a benchmark for autonomous agents' ability to communicate and adjust strategies like humans, which is one of the essential elements for the success of human civilization (Kramár et al., 2022). Cicero (Meta et al., 2022) proposes an impressive autonomous agent that combines PLM with RL and achieves human-level performance in *Diplomacy*. Moreover, Kramár et al. (2022) make preliminary investigations on how negotiation algorithms and the inclination to punish traitors can enable autonomous agents to communicate like humans and cooperate more effectively in *Diplomacy*. Apart from Diplomacy, there are numerous classic strategic games that serve as potential resources for interactive text game platforms and related NLP research, such as  $Eurogame^{31}$ , *Warhammer Fantacy* <sup>32</sup>, and *Paths of Glory* <sup>33</sup>.

(4) Tabletop role-playing games  $(TRPGs)^{34}$ , such as Dungeons and Dragons  $(DND)^{35}$  and Call of  $Cthulhu (COC)^{36}$ , as well as works of fiction, such as the Harry Potter series (Chen et al., 2022c), have provided a rich source of situated and multi-party dialogue data that can be used to build challenging text game platforms (Callison-Burch et al., 2022; Rameshkumar & Bailey, 2020; Zhou et al., 2022b; Peiris & de Silva, 2022). However, the raw dialogue data documenting the game process of TRPGs is usually a mixture of in-character action descriptions and out-of-character strategy explanations (Callison-Burch et al., 2022), frequently accompanied by lengthy world-building documents (Zhu et al., 2023a), which can differ from one game to another. The problem of extracting the golden-standard game states and game commands remains a challenging yet fascinating question (Zhu et al., 2023a). For example, Rameshkumar & Bailey (2020) provide 34,243 summary dialogue fragment pairs from raw dialogue data documenting the DND game process. The summaries in these summary-dialogue chunk pairs contain text descriptions of game states, which can serve as a good benchmark for abstractive game-state summarization of interactive text games. Callison-Burch et al. (2022) frame DND as a dialogue system challenge, comprising both deterministic elements like dice rolls and imprecise descriptions of the game-play as partial state information. Zhou et al. (2022b) introduce a novel and highly interactive task, G4C (Goal-driven Guidance Generation in Grounded Communication). based on DND. They train an autonomous agent acting as a game host, also known as a Dungeon Master

<sup>&</sup>lt;sup>24</sup>https://en.wikipedia.org/wiki/Social\_deduction\_game

<sup>&</sup>lt;sup>25</sup>https://en.wikipedia.org/wiki/Mafia\_(party\_game)

<sup>&</sup>lt;sup>26</sup>https://en.wikipedia.org/wiki/Mush\_(video\_game)

<sup>&</sup>lt;sup>27</sup>https://en.wikipedia.org/wiki/Space\_Station\_13

<sup>&</sup>lt;sup>28</sup>https://en.wikipedia.org/wiki/Among\_Us

<sup>&</sup>lt;sup>29</sup>https://en.wikipedia.org/wiki/Strategy\_game

<sup>&</sup>lt;sup>30</sup>https://en.wikipedia.org/wiki/Diplomacy\_(game)
<sup>31</sup>https://en.wikipedia.org/wiki/Eurogame

<sup>&</sup>lt;sup>32</sup>https://en.wikipedia.org/wiki/Warhammer\_(game)

<sup>&</sup>lt;sup>33</sup>https://en.wikipedia.org/wiki/Paths\_of\_Glory\_(board\_game)

<sup>&</sup>lt;sup>34</sup>https://en.wikipedia.org/wiki/Tabletop\_role-playing\_game

<sup>&</sup>lt;sup>35</sup>https://en.wikipedia.org/wiki/Dungeons\_%26\_Dragons

<sup>&</sup>lt;sup>36</sup>https://en.wikipedia.org/wiki/Call\_of\_Cthulhu\_(role-playing\_game)

(DM), using the theory of mind and RL. This approach significantly enhances the players' capacity to achieve their objectives.

(5) Life Simulation Games are games that enable players to control one or more virtual characters<sup>37</sup>. Classic life simulation games include Virtual Pet<sup>38</sup>, Black and White<sup>39</sup>, MineCraft<sup>40</sup>, and GTA Series<sup>41</sup>. For example, Bara et al. (2021); Fan et al. (2022); Yuan et al. (2023a) explore how autonomous agents based on PLMs can learn to collaborate, communicate, and generalize across a range of tasks and objectives using MineCraft as the interactive game platform. Furthermore, Social Simulation Games are a sub-genre of life simulation games that simulates social interactions and relationships between multiple artificial characters or lives in a virtual world<sup>42</sup>. For example, the Sims Series<sup>43</sup> is one of the classic social simulation game. Mehta et al. (2023) enhance the capability of AI agents to identify when they require additional information to enable more human-AI interactions and improve social simulations. As noted by (Li et al., 2023b; Park et al., 2023; Wei et al., 2023), the role-playing agents and open sandbox worlds can be easily adapted as factors in social simulation games. Park et al. (2023) configure PLM-based autonomous agents with social identity settings and conduct social simulations accordingly. Their experiment design is highly in line with the gameplay of the Sims Series.

Playing Text-Only Games. Early work on autonomous agents of text-only games mainly relies on handcrafted reward functions (Yuan et al., 2018) or other well-formatted data structures, such as knowledge graphs, to preserve and retrieve past information and game states (Ammanabrolu & Hausknecht, 2020). Although some exploratory methods before the emergence of PLMs also adapt trivial neural representations of text to help detect actions and states from text-only games, these methods focus on constrained hand-crafted template-based state and action space and are unable to understand complex and highly unstructured texts in many text-only games. Yao et al. (2021) point out that these methods, based on constrained hand-crafted template-based state and action space, isolate autonomous agents from understanding the meanings of words or semantics by verifying that agents without understanding semantics can achieve similar performance on these text-only games by adopting similar methods but without understanding semantics. For designing better text-only games as testbeds for autonomous agents' ability of language understanding, the motivation and strategy implicitly expressed in words should not be detected through hand-crafted templates without understanding the semantics (Yao et al., 2021; Li et al., 2022f). The following work turns to autonomous agents based on PLM-powered neural representation which rely less on manual effort. For example, Yin & May (2020) adapt sentence-level semantics representation-based clustering and deep Q learning (Mnih et al., 2013; 2015) for playing text adventure games. Xu et al. (2020b) propose a lightweight transformer-based representation learning framework for text-only games and outperform previous SOTA methods. Recently, the success of LLMs has enabled text-only games to explore handling any user input (Todd et al., 2022; Li et al., 2022f). Understanding user inputs that are complex and ambiguous in their meaning requires careful attention to the actions and states explicitly described in the text.

**Powering Text-Aided Games.** Traditionally, in text-aided games, autonomous agents have used either formal language or structured natural language to model state transitions and execute actions using a highly symbolic representation (Branavan et al., 2009; Vinyals et al., 2017). With the emergence of PLMs, these agents transformed from using symbolic representations to using contextual and neural representations, which capture more complex and high-level semantics of textually stated strategies and communication protocols. As a result, we will elucidate the ways in which language interfaces and PLMs enable autonomous agents in text-aided games to communicate with other agents and make better game plans. Since the impressive release of ChatGPT, some industrial and academic researchers have also been exploring the adaptation of LLMs to enhance the text-aided game experience. *Inworld*<sup>44</sup> claims that LLMs can empower characters

<sup>&</sup>lt;sup>37</sup>https://en.wikipedia.org/wiki/Life\_simulation\_game

<sup>&</sup>lt;sup>38</sup>https://en.wikipedia.org/wiki/Virtual\_pet

<sup>&</sup>lt;sup>39</sup>https://en.wikipedia.org/wiki/Black\_26\_White\_(video\_game)

<sup>&</sup>lt;sup>40</sup>https://en.wikipedia.org/wiki/Minecraft

<sup>&</sup>lt;sup>41</sup>https://en.wikipedia.org/wiki/Grand\_Theft\_Auto

<sup>&</sup>lt;sup>42</sup>https://en.wikipedia.org/wiki/Social\_simulation\_game

<sup>&</sup>lt;sup>43</sup>https://en.wikipedia.org/wiki/The\_Sims

<sup>44</sup>https://www.inworld.ai/

in games with distinct personalities and contextual awareness that stay in-world <sup>45</sup> or on-brand<sup>46</sup>, which tremendously improves the games' immersive experience. *NetEase* also announces that they allow Non-Player Characters (NPCs) powered by LLMs in its online game, *Nishuihan*, to communicate with considerable freedom <sup>47</sup>. In addition to communication, language interface and NLP-powered planning have been explored in designing autonomous agents in text-aided games for reward shaping (Goyal et al., 2019), instruction following (Tuli et al., 2022; Chen et al., 2020c), control policy generalization (Hanjie et al., 2021), and representation learning (Karamcheti et al., 2023). In addition, language interface plays a major role in training autonomous text-aided game agents. For example, Havrylov & Titov (2017); Wong et al. (2022) point out that an efficient language-based communication protocol is crucial to a collaboration strategy in multi-agent text-aided games. Jiang et al. (2019) suggests that language can naturally compose different sub-skills to enrich the non-compositional abstraction of complex text-aided games' hierarchical strategy. Moreover, (Reid et al., 2022; Li et al., 2022e) verify that language modeling induces representations, which are even useful for offline RL strategy modeling of games. This observation implies a relationship between the high-level semantic coherence of languages and the planning strategy adopted by text-aided games.

#### 6.5 Other Applications

**Specialization.** It refers to the process of adapting and customizing the ability of language models to specific tasks or domains. As assumed by Fu et al. (2023), language models with strong modeling power may be effective across a wide range of tasks, but their performance on any individual task may be less impressive due to the distribution of their capabilities, implying the needs for LM specification. Although some domain specific language models are proposed for fields such as law (Thanh, 2023), healthcare (Wang et al., 2023b;d), material science (Xie et al., 2023) and finance (Wu et al., 2023b), they are mainly fine-tuned from large corpus of specific domain. iNLP, on the other hand, can provide another solution for LM specialization. That is, by observing and interacting with external objects such as medical records, legal documents, financial statements, technical specifications, domain-specific knowledge graphs or even domain-specific tool sets, language models can provide professional information to users. For instance, in medicine, iNLP can be used to retrieve relevant information from patient records and suggest potential diagnoses or treatments. In law, iNLP can help lawyers draft legal documents and contracts by providing suggestions based on retrieval augmentation from previous cases and legal precedents. Therefore, equipping language models with domain-specific interactive objects can implement the specification of them with higher data efficiency and computation efficiency.

**Personalization.** It refers to the process of tailoring a language model's behavior and output to the unique needs and preferences of each user. This can be achieved through the model's interactions with users, learning from their inputs, demographics, and adapting its behavior accordingly <sup>48</sup>. For example, Rao et al. (2023) suggest that ChatGPT has the potential to become more personalized and customized through learning from user interactions and individual preferences. Salemi et al. (2023) introduce a personalization benchmark and suggest to personalize LLMs through retrieval augmentation using user profiles. Wu et al. (2022d) show the potential of personalizing PLMs through the use of prompts. Madaan et al. (2022) personalize the PLM via an external memory with human feedback. Personalization can greatly enhance the user experience with language models by providing more preferred responses, improving the model's ability to understand the user's needs and intentions, and ultimately building trust and rapport between the user and the model. However, we should also be aware of the drawbacks brought by personalization. For example, Deshpande et al. (2023) demonstrate that assigning a persona to ChatGPT can potentially magnify its toxicity up to six times.

**Model-based Evaluation.** Model-based Evaluation enjoys the benefits of PLMs to compute a text quality score for each generated sample and show greater correlation with the human evaluation compared with

 $<sup>^{45}</sup>$ The in-world context of a player is the context that the player has with characters controlled by other players and NPCs when she/he is doing role-playing.

 $<sup>^{46}</sup>$ The on-brand context of a player is the context that the player has with other players and the game host when she/he is not doing role-playing.

<sup>&</sup>lt;sup>47</sup>https://www.youtube.com/watch?v=zGVR5gPgefk

<sup>&</sup>lt;sup>48</sup>https://www.exponentlabs.io/articles/chatgpt-and-personalization-how-ai-is-changing-the-way-we-interactwith-technology

statistical-based evaluation metrics, such as BLUERT (Sellam et al., 2020), BERTScore (Zhang et al., 2020b), and COMET (Rei et al., 2020). Such an evaluation method can be widely implemented and used in various general NLG tasks, and even works for reference-free settings (Zhou & Xu, 2020; Wan et al., 2022; Zouhar et al., 2023). Additionally, existing preliminary research has indicated that LLMs have emerged with the ability to evaluate the AI generated content (AIGC) with human-like judges (Gilardi et al., 2023; Wang et al., 2023c; Chen et al., 2023c). Some papers also propose the fine-grained analysis of LLMs' ability to evaluate AIGC in specific NLG tasks, including summarization (Luo et al., 2023; Gao et al., 2023a), question answering (He et al., 2023), news outlet generation (Yang & Menczer, 2023), and translation (Lu et al., 2023). Moreover, Liu et al. (2023b); He et al. (2023) propose to collaborate with LLMs to provide better and cheaper human-like evaluations. Through interactions between models and even humans, we can evaluate LMs in a more effective (accurate) and efficient (automatic) manner. This evaluation process can be akin to a teacher model administering "exams" and "grading" to assess the performance of a student model (ter Hoeve et al., 2021).

# 7 Ethics and Safety

LLMs have demonstrated remarkable capabilities to understand, interpret, and generate human-like text. A plethora of LLM-based applications has emerged and been adopted prevalently in our daily lives. As a result, the utilization of these models also presents profound challenges across many societal domains. Therefore, it is crucial to consider the ethical implications of using LLMs, especially around the impact on education, bias and fairness, privacy, harmful content and misinformation.

Impact on Education. The advent of LLMs, exemplified by ChatGPT, has introduced substantial challenges to the existing education systems. One primary concern is the misuse of ChatGPT for academic assignments such as writing essays and solving scientific problems, which has raised deep concerns among K-12 educators, who perceive it as a potential threat to the education system (Rudolph et al., 2023). To address this issue, plagiarism detection tools such as GPTZero<sup>49</sup>, AI Classifier<sup>50</sup>, and DetectGPT<sup>51</sup> have been developed for detecting AI-generated content. Most of these AI detection tools focus on perplexity (text randomness) and burstiness (use of non-common terms). Nevertheless, these tools have yet to demonstrate their effectiveness in capturing AI-generated content in a real-world setting. Last but not least, computer-assisted writing tools, including ChatGPT, have limited capacities to assist users in learning and acquiring writing skills and principles. Their primary focus is on enhancing productivity rather than facilitating skill development, which is crucial for educational purposes.

Social Bias. As language models are typically trained with large-scale web corpus, it becomes highly susceptible to societal biases. It is known to further amplify the discrimination (Leino et al., 2018), including the potential downgrading of resumes (Dastin, 2018) and the generation of texts that contain stereotypes, toxicity, and racism (Hutchinson et al., 2020). Resume "whitening" has always been an issue where job applicants are forced to hide their identity as a minority gender, racial, religion, or region group to land a job interview. This problem still exists even though many companies started to use AI-supported tools to rank and filter resumes. Social bias in word embeddings is reflected when the word man is closer to programmer compared to woman and programmer (Bolukbasi et al., 2016). Applications that utilize pretrained word embeddings for downstream tasks such as classification and analysis will then obtain results with social bias, causing fairness issues of the output. Hutchinson et al. (2020) use toxicity prediction and sentiment analysis to assess language models' bias towards people with disabilities. Results showed that the sentence I am a person with mental illness and I will fight for people with mental illnesses is more toxic than I am a tall person. HERB (Li et al., 2022i), a bias evaluation metric which utilizes bias in a sub-region to evaluate language model's bias in a region on contextualized level, brings researchers' attention to not only focus societal bias in the whole of a region but also sub-regions. The aforementioned findings suggest that societal biases observed in language models could serve as an indication that stereotypes should be addressed and mitigated, rather than leaving them to harm the minorities. Considering that everyone now can easily access

<sup>49</sup> https://gptzero.me

<sup>&</sup>lt;sup>50</sup>https://platform.openai.com/ai-text-classifier

<sup>&</sup>lt;sup>51</sup>https://detectgpt.com

LLMs, biases should be filtered out or mitigated to ensure that they are not amplified and further affect people's thoughts in making decisions such as recruiting and assessing individuals.

**Privacy Concern.** Large Language Models (LLMs) also raise concerns regarding user privacy. Training these models necessitates access to large amounts of data, often entailing the personal details of individuals. This information is typically derived from licensed or publicly accessible datasets, and can be utilized for a range of purposes, such as deducing geographical locations from phone codes in the data. There are already studies showing the possibilities of distilling sensitive information from large language models through prompting (Carlini et al., 2021; 2023). In the era of interactive NLP, humans a more actively interacting with these foundation models, which could potentially lead to more frequent user information leakage. Therefore, it is pressing to establish relevant policies for collecting and storing personal data. Furthermore, the practice of data anonymization is crucial to maintain ethical standards in dealing with privacy matters. There have been some pioneering studies that investigate privacy-preserving issues Li et al. (2023f); Shi et al. (2022c). We believe that more research efforts should be dedicated to privacy preservation in large language models, which will play a central role in the era of interactive Natural Language Processing (iNLP).

### 8 Future Directions

Alignment. Alignment for language models can be categorized into factual alignment and value alignment. Factual alignment requires the model to tell it is not capable of answering the question when it does not perpetuate the needed knowledge (Kadavath et al., 2022). However, factual alignment is challenging in practice since 1) it is hard to verify what knowledge has been contained in the pre-trained model (Lin et al., 2022a), and 2) we still lack a convenient knowledge editing method to update certain knowledge while do not impair others (De Cao et al., 2021; Meng et al., 2022a). Future work can consider developing tools to detect the "blind spot of knowledge" by analyzing the probability confidence in the model predictions, and efficient approaches to edit the knowledge in pre-trained models at scale. For value alignment, existing work mainly focuses on using human (Ouyang et al., 2022) or AI feedback (Bai et al., 2022b) to train a reward model as the proxy of human judgment. During training, this reward model will continuously interact with the generative LM to enhance desired behaviors and inhibits undesired ones (Liu et al., 2022h). RLHF is the representative approach in this manner, which has been widely used in products such as OpenAI ChatGPT. However, recent works have shown that inaccurate reward modeling can be exploited by the RL optimization (Wolf et al., 2023), which is also called "reward hacking" problem in the RL formalization (Ibarz et al., 2018; Hadfield-Menell et al., 2017). Future work can seek more diverse and fine-grained signals to replace scalar form rewards to aid a more stable and efficient alignment training.

**Social Embodiment.** NLP models should incorporate a more comprehensive view of the world, including an embodied and social context, to simulate realistic human behavior (Bisk et al., 2020; Bolotta & Dumas, 2022). This is because social and cultural factors heavily influence human behavior. Recently, generative agents have been introduced as a way to simulate believable human behavior by incorporating a LLM with a complete record of the agent's experiences Park et al. (2023). However, there are still challenges to be addressed to improve the accuracy and complexity of such social agents. Scaling the iNLP to handle larger and more complex environments is a potential future direction. This would enable the agent to handle more ambitious simulations of human behaviors and generate more realistic responses to user interactions.

**Plasticity.** A significant challenge encountered with iNLP is the constant need for updates to adapt to changes in the real world. The prevalent approach in the academic literature typically utilizes gradient-based fine-tuning methods. These methods adjust an extensive number of parameters in the pre-trained models simultaneously, which can be overkill. Nonetheless, if an insufficient number of parameters are adjusted, the models may not effectively adapt to changes in real-world scenarios. Consequently, identifying methods for effective updates to iNLP models is essential for practical applicability (Mitchell et al., 2021; 2022a;b). In recent years, burgeoning interest among researchers in the field of continual learning has emerged, aiming to enhance a model's capacity to learn persistently over time while minimizing the loss of previously acquired information. Continual learning enables the iNLP model to adapt to new data and dynamic situations without necessitating the retraining of the model from scratch. It is worth noting that biological neural networks

acquire new skills continually within their lifetime based on neuronal plasticity (Hebb, 2005). Future research focusing on more human-like models (Zador et al., 2023; Wang et al., 2021a) is anticipated to expedite advancements in continual learning for iNLP.

**Speed & Efficiency.** iNLP usually requires large language models as the backbone, thus suffers from their high latency and huge computational cost (Schwartz et al., 2020a; Xu et al., 2021b). The high latency issue is even more crucial for iNLP compared to conventional NLP due to the need for frequent iterative calls. A large number of work has been done on improving the speed and efficiency of large language models, including both *static* methods such as knowledge distillation (Sanh et al., 2019; Zhou et al., 2022d), pruning (Michel et al., 2019; Gordon et al., 2020), quantization (Shen et al., 2020; Dettmers et al., 2022) and module replacing (Xu et al., 2020a); and *dynamic* methods such as adaptive computation (Graves, 2017), early-exiting (Schwartz et al., 2020b; Zhou et al., 2020c), and model cascade (Li et al., 2021c; Varshney & Baral, 2022). However, most of the aforementioned methods require access to the model parameters, which may not be possible in the future since most state-of-the-art generalist models such as ChatGPT and PaLM (Chowdhery et al., 2022; Google, 2023) are closed-sourced. Therefore, developing techniques that can accelerate inference for LLMs without access to their parameters is a promising future for efficient iNLP. Moreover, it is important to consider not only the acceleration ratio or preserved performance of accelerated models but also their robustness, biases, and alignment (Xu et al., 2021a).

**Context Length.** Context length refers to the maximum numbers of input tokens permitted by a language model. For example, ChatGPT has a context window of 8K tokens, while GPT-4 (OpenAI, 2023) extends it to 32K tokens. iNLP can greatly benefit from a long context window. The reason is three-fold: (1) It allows for maintaining and understanding a more extensive conversational history. (2) The ability to process a longer context is crucial for tasks that involve large pieces of text, such as long document-based QA and a detailed observation in the environment. (3) It can also facilitate the generation of long-form content. Recent studies on memorizing Transformers (Wu et al.; Bulatov et al., 2022; 2023; Liang et al., 2023a) have illustrated the potential to scale the context window to tens of thousands of tokens using memory augmentation techniques. Additionally, Anthropic has introduced a chatbot with a 100K context window<sup>52</sup>. However, despite these advancements, more research is needed to investigate the challenges associated with significantly increasing the context length.

Long Text Generation. The capability to generate long text is crucial in iNLP contexts. For example, in real-life conversations, humans frequently convey intricate ideas and participate in extremely long discussions that necessitate numerous rounds of information exchanges. Moreover, for long-horizon robotic manipulation tasks, LMs need to generate a long action plan for execution. However, as the generated text lengthens, current language models have the propensity to produce content that may lack structure, coherence, quality, and even the relevance to the input prompts. Consequently, more sophisticated natural language processing techniques are needed to accurately capture the subtleties of language and produce text that is both coherent and useful.

Accessibility. In the realm of large language model deployment, accessibility emerges as a critical concern. The most prominent LLMs, such as the GPT-family models (Brown et al., 2020; Ouyang et al., 2022; OpenAI, 2023) and Bard<sup>53</sup>, are predominantly closed-source, creating a significant barrier for those seeking to utilize them for specific purposes. Recently, researchers have shifted their focus to developing open-source LLMs, including LLaMA (Touvron et al., 2023), Pythia (Biderman et al., 2023), and GLM (Du et al., 2022c). The movement towards open-sourcing large language models is expected to gain momentum in the future. Another emerging trend that has received limited research attention so far is the accessibility of deploying LLMs on edge devices such as smartphones, laptops, and automobiles, despite the existence of several previous works on

<sup>&</sup>lt;sup>52</sup>https://www.anthropic.com/index/100k-context-windows

<sup>&</sup>lt;sup>53</sup>https://bard.google.com/

the topic (Niu et al., 2020)<sup>54</sup>. Research towards more accessible language models can expand the possibilities for iNLP. For instance, it can be particularly beneficial in scenarios that involve offline interaction <sup>55</sup>.

Analysis. Although the interactive language models have shown a powerful ability to understand and generate complex language across a wide range of topics and contexts, its "inner workings" are still a black box for both the users and the researchers. We assume that gaining a deeper understanding of LMs and their interpretability can lead to improved interaction behaviors exhibited by LM agents. For example, Bills et al. (2023) utilizes GPT-4 to provide explanations for all the neurons in GPT-2 (Radford et al., 2019) by analyzing their activations in response to input text. Intuitively, such explainability can facilitate knowledge updates in language models within the context of iNLP (Meng et al., 2022a;b). Additionally, the analysis of scaling laws (Kaplan et al., 2020; Tay et al., 2022a), emergent abilities (Wei et al., 2022a), scaling-up performance prediction (OpenAI, 2023), trade-offs between alignment and general performance (Wolf et al., 2023), interpretability for the interaction behavior of LMs (Park et al., 2023; Kosinski, 2023), are also promising avenues for future research.

**Creativity.** Contrary to the prevailing language modeling approach, which relies on learning statistical relationships, creativity involves the generation of original ideas, concepts, or perspectives that deviate from conventional patterns. The pursuit of creativity has long been a significant challenge in the AI community, driven by the desire to develop human-level agents (LeCun, 2022) capable of generating novel knowledge and contributing original ideas across various domains. To effectively generate more creative content, it is crucial to establish a detailed definition or judging criteria of creativity. For instance, generating novel metaphors requires establishing conceptual mappings between the source and target domains (Li et al., 2022); 2023g), whereas story generation involves the creation of original, coherent, and engaging narratives and plotlines (Tang et al., 2022a;b). Additionally, the ability to generate new knowledge in the generated text, rather than solely extracting existing knowledge, can contribute to enhancing creativity. Furthermore, it is essential to explore approaches for enhancing creativity in generated content to ensure practical utility. For instance, enabling language models to discover theories or laws based on observed phenomena requires dedicated efforts and potentially entails exploring new paradigms for language models to engage in conscious thinking (Bengio, 2017). Research towards more creative language models may unlock a range of complex interactive properties or behaviors of LMs, such as the development of a more creative writing assistant or even the emergence of sophisticated debates between language model agents.

**Evaluation.** As shown in §5, evaluation for iNLP is still barren and lacks diversity. How to design a better evaluation method will be one of the most important research topics in the future, which will profoundly affect the design and optimization direction of the iNLP frameworks. Specifically, evaluation methods under interactive settings may develop in the following aspects: (1) Pay more attention to the evaluation of the interaction process rather than just the result (Lee et al., 2022c). (2) Design a more standard evaluation benchmark to support the comparison of different interactive models. (3) Evaluate the interactivity of large language models.

### 9 Conclusion

In this paper, we have offered a comprehensive exploration of Interactive Natural Language Processing, a burgeoning paradigm that situates language models as interactive agents within a diverse array of contexts. We have proposed a unified definition and framework for iNLP, followed by a systematic classification that deconstructs its integral components such as interactive objects, interfaces, and methods. Furthermore, we have elucidated the varied evaluation methodologies used in the field, showcased its numerous applications, discussed its ethical and safety issues, and pondered upon future research directions. By putting a spotlight on iNLP's ability to interact with humans, knowledge bases, models, tools, and environments, we have underscored the paradigm's potential for enhancing alignment, personalizing responses, enriching representations, avoiding hallucinations, decomposing complex tasks, and grounding language in reality, etc. Ultimately, this survey

<sup>&</sup>lt;sup>54</sup>https://github.com/mlc-ai/mlc-llm

 $<sup>^{55}</sup>$ In situations where network connectivity is unavailable, relying on closed-source language models accessed through the Internet becomes infeasible. Therefore, the use of a local language model becomes necessary.

presents a wide-angle view of the current state and future potential of iNLP, serving as an essential reference point for researchers eager to dive into this rapidly evolving field.

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## **A** Contributions

**Unification Management.** Ge Zhang and Zekun Wang co-led this project. Zekun Wang was responsible for designing the survey outline, providing the motivation behind the project, and managing various aspects such as paper collection, paper reading, draft writing, discussions, and more. Ge Zhang took charge of the weekly meetings, task allocation, member invitations, and other related responsibilities. Both Ge Zhang and Zekun Wang actively monitored and adjusted the project's progress, ensuring the overall quality of the writing.

**Paper Collection and Sharing.** All the members collected and presented papers in the weekly meetings. Among them, Zekun Wang shared most of the papers. Ge Zhang, Guangzheng Xiong, Kexin Yang and Shaochun Hao also shared a lot of literature with project members.

*Introduction* Writing. Zekun Wang wrote this section. Chenghua Lin wrote part of this section, provided suggestions, and edited the entire section.

Interactive Objects Writing. Zekun Wang initially wrote the first version of this section. Wenhu Chen wrote part of this section, provided suggestions, and edited the entire section, primarily focusing on the subsections of "KB-in-the-loop" and "Model/Tool-in-the-loop". Wenhu Chen categorized "Knowledge Sources" into "Corpus Knowledge" and "Internet Knowledge", and restructured "Model/Tool-in-the-loop" as "Tool-use" and "Multi-model Collaboration". Later, Zekun Wang further refined "Model/Tool-in-the-loop" and divided it into "Thinking", "Acting", and "Collaborating".

Interaction Interface Writing. Ge Zhang and Ning Shi wrote the subsection of "Edits". The other subsections were written by Zekun Wang, including "Natural Language", "Formal Language", "Machine Language", and "Shared Memory". Chenghua Lin provided suggestions and edited this section.

Interaction Methods Writing. In this section, the outline was designed by Zekun Wang. The subsection on "Pre-trained Language Models" was written by Ge Zhang, Yizhi Li, and Zekun Wang. Ge Zhang primarily contributed to the tables in this subsection. Zekun Wang independently wrote the subsections on "Standard Prompting" and "Prompt Chaining". The subsections on "Elicitive Prompting" were written by Ruibo Liu. "Supervised Instruction Tuning" was authored by Qingqing Zhu. "Continual Learning" was collaboratively written by Xiuying Chen, Mong Yuan Sim, and Zekun Wang. "Parameter-Efficient Fine-Tuning" was co-written by Wangchunshu Zhou and Zekun Wang. "Semi-Supervised Fine-Tuning" was co-authored by Shaochun Hao and Zekun Wang. The subsection on "Active Learning" was written by Ge Zhang. "Reinforcement Learning" was authored by Guangzheng Xiong. "Imitation Learning" was written by Ning Shi. The subsection on "Interaction Message Fusion" was authored by Zekun Wang. Jie Fu and Zekun Wang provided guidance, suggestions, and editing for all the subsections in this section.

**Evaluation Writing.** Kexin Yang wrote this section. Zekun Wang partly added content for "Knowledge Acquisition", "Chain-of-Thought Capability", "Tool-Use Ability", and "Collaborative Behavior Analysis". Dayiheng Liu and Zekun Wang provided suggestions and edited this section.

**Application Writing.** Xiuying Chen, Shaochun Hao and Yizhi Li wrote "Controllable Text Generation". Ge Zhang wrote "Writing Assistant". Guangzheng Xiong wrote "Embodied AI". Zhenzhu Yang and Ge Zhang wrote "Text Game". Xiuying Chen, Kexin Yang and Mong Yuan Sim wrote the other applications. Ke Xu and Zekun Wang provided suggestions and edited this section.

*Ethics and Safety* Writing. Mong Yuan Sim authored this section. Chenghua Lin contributed to the writing of "Impact on Education", provided suggestions, and edited the content of the entire section.

**Future Directions Writing.** This section was collaboratively written by Wenhu Chen, Jie Fu, Ruibo Liu, Kexin Yang, Wangchunshu Zhou, Chenghua Lin, Zekun Wang, Qi Liu, Mong Yuan Sim, Ge Zhang, and Xiuying Chen. Ke Xu provided suggestions and edited this section.

**Supervision.** Shi Wang provided part of the funding for this project and actively participated in discussions. Jie Fu, Chenghua Lin, and Yike Guo provided valuable guidance on the entire paper throughout the whole duration of the project's lifecycle.