

# Is Prompt All You Need? No. A Comprehensive and Broader View of Instruction Learning

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## Abstract

Task semantics can be expressed by a set of input-to-output examples or a piece of textual instruction. Conventional machine learning approaches for natural language processing (NLP) mainly rely on the availability of large-scale sets of task-specific examples. Two issues arise: first, collecting task-specific labeled examples does not apply to scenarios where tasks may be too complicated or costly to annotate, or the system is required to handle a new task immediately; second, this is not user-friendly since end-users are probably more willing to provide task description rather than a set of examples before using the system. Therefore, the community is paying increasing interest in a new supervision-seeking paradigm for NLP: **learning from task instructions**. Despite its impressive progress, there are some common issues that the community struggles with. This survey paper tries to summarize the current research on instruction learning, particularly, by answering the following questions: (i) **what is task instruction**, and what instruction types exist? (ii) **how to model instructions**? (iii) **what factors influence and explain** the instructions' performance? (iv) what challenges **remain in instruction learning**? To our knowledge, this is the first comprehensive survey about textual instructions.<sup>1</sup>

## 1 Introduction

One goal of AI is to build a system that can universally understand and solve new tasks. Labeled examples, as the mainstream task representation, are unlikely to be available in large numbers or even do not exist. Then, is there any other task representation that can contribute to task comprehen-

<sup>1</sup>We release the corresponding reading list of this survey to benefit the future research: <https://github.com/RenzeLou/awesome-instruction-learning>

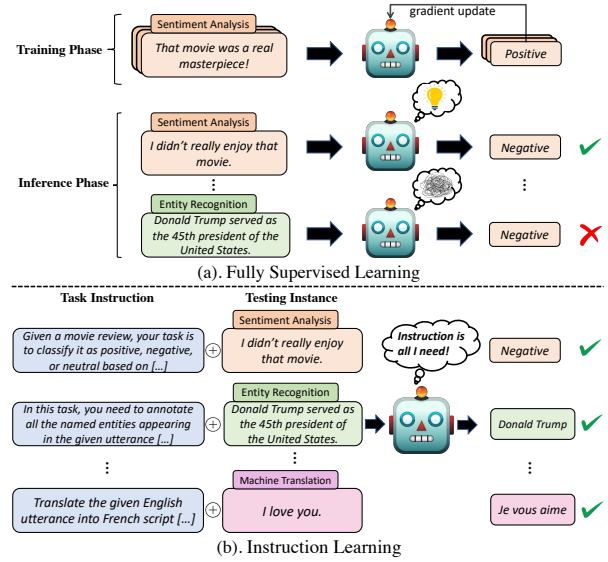


Figure 1: Two machine learning paradigms: (a) traditional fully supervised learning uses extensive labeled examples to represent the task semantics. It is expensive, and the resulting system hardly generalizes to new tasks; (b) instruction learning utilizes task instruction to guide the system quickly adapts to various new tasks.

sion? **Task instructions provide another dimension of supervision for expressing the task semantics.** Instructions often contain more abstract and comprehensive knowledge of the target task than individual labeled examples. As shown in Figure 1, with the availability of task instructions, systems can be quickly built to handle new tasks, especially when task-specific annotations are scarce. Instruction Learning is inspired by the typical human learning for new tasks, e.g., a little kid can well solve a new mathematical task by learning from its instruction and a few examples (Fennema et al., 1996; Carpenter et al., 1996). **This new learning paradigm has recently attracted the main attention of the machine learning and NLP communities** (Radford et al., 2019; Efrat and Levy, 2020; Brown et al., 2020, *inter alia*).

When talking about task instructions, most of us will first connect this concept with prompts—using

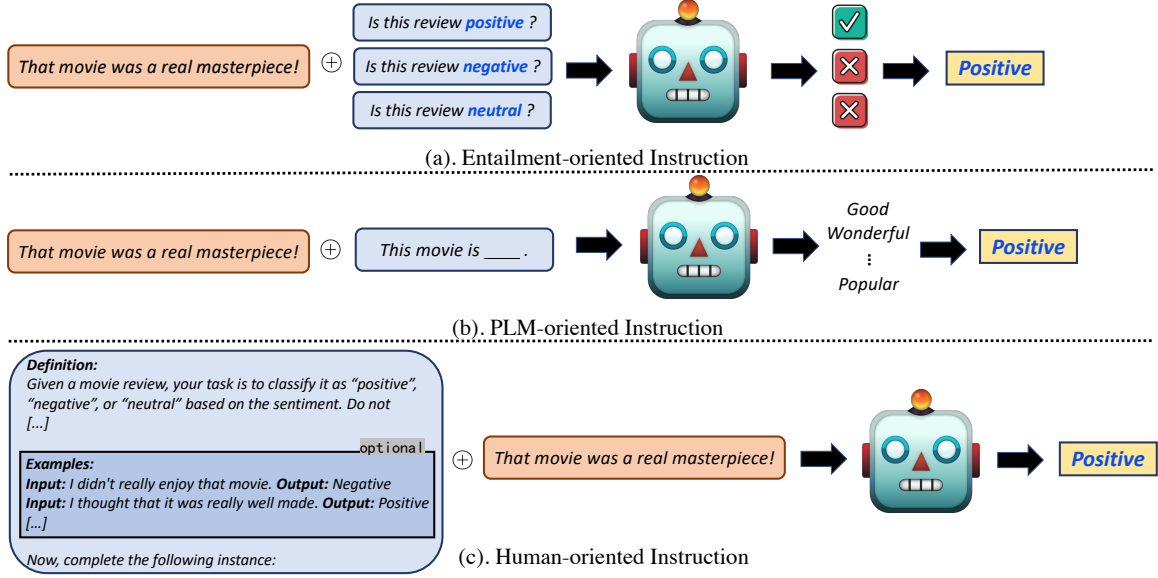


Figure 2: An illustration of three distinct categories of textual instructions. (a) **Entailment-oriented**: regarding the original input as a premise and converting each predefined label into a hypothesis (i.e., instruction). (b) **PLM-oriented**: using a template to construct the original task input into a cloze question. (c) **Human-oriented**: utilizing sufficient task information as instruction, such as definitions and optional few-shot demonstrations, etc.

a brief template to reformat new input into a language modeling problem so as to prime a PLM for a response (Liu et al., 2023). Despite prompts’ prevalence in text classification, machine translation, etc., **we claim that prompts are merely a special case of instructions.** This paper takes a comprehensive and broader view of instruction-driven NLP research. Particularly, we try to answer the following questions:

- What is task instruction, and what instruction types exist? (§ 3)
- Given a task instruction, how to encode it to help the target task? (§ 4)
- What factors (e.g., model size, task numbers) impact the instruction-driven systems’ performance, and how to design better instructions? (§ 5)
- What applications can instruction learning contribute? (§ 6)
- What challenges exist in instruction learning and what are future directions? (§ 7)

To our knowledge, this is the first paper that surveys textual instruction learning. In contrast to some existing surveys that focused on a specific in-context instruction, such as prompts (Liu et al., 2023), input-by-output demonstrations (Dong

et al., 2023), or reasoning (Huang and Chang, 2022; Qiao et al., 2022), we provide a broader perspective to connect distinct researches in this area in an organized way. **We hope this paper can present a better story of instruction learning and attract more peers to work on this challenging AI problem.**

## 2 Preliminary

For task instruction learning, we aim to drive the systems to reach the output given the input by following the instructions. Thus, a dataset consists of three items:

- **Input (X)**: the input of an instance; it can be a single piece of text (e.g., sentiment classification) or a group of text pieces (e.g., textual entailment, question answering, etc.).
- **Output (Y)**: the output of an instance; in classification problems, it can be one or multiple predefined labels; in text generation tasks, it can be any open-form text.
- **Template ( $\hat{T}$ )**: a textual template that tries to express the task meaning on its own or acts as a bridge between X and Y.<sup>2</sup>  $\hat{T}$  may not be an instruction yet.

In § 3, we will elaborate that a task instruction I is actually a combination of  $\hat{T}$  with X or Y, or the

<sup>2</sup>A plain template connecting X and Y, e.g., “The input is ... The output is ...”, no task-specific semantics.

task	TE premise (i.e., input text)	TE hypothesis (i.e., instructions Y)
Entity Typing	[Donald Trump] <sub>ent</sub> served as the 45th president of the United States from 2017 to 2021.	(✓) Donald Trump is a <b>politician</b> (✗) Donald Trump is a <b>journalist</b>
Entity Relation	[Donald Trump] <sub>ent1</sub> served as the 45th president of the [United States] <sub>ent2</sub> from 2017 to 2021.	(✓) Donald Trump is <b>citizen of</b> United States (✗) Donald Trump is <b>the CEO of</b> United States
Event Argument Extraction	In [1997] <sub>time</sub> , the [company] <sub>sub</sub> [hired] <sub>trigger</sub> [John D. Idol] <sub>obj</sub> to take over Bill Thang as the new chief executive.	(✓) <b>John D. Idol</b> was hired. (✓) <b>John D. Idol</b> was hired in 1997. (✗) <b>Bill Thang</b> was hired.
Event Relation	Salesforce and Slack Technologies have [entered] <sub>event1</sub> into a definitive agreement under which Salesforce will [acquire] <sub>event2</sub> Slack.	(✓) Salesforce acquires Slack <b>after</b> it enters into the agreement with Slack Tech. (✗) Salesforce acquires Slack <b>because</b> it enters into the agreement with Slack Tech.
Stance Detection	Last Tuesday, Bill said “animals are equal to human beings” in his speech.	(✓) Bill <b>supports</b> that animals should have lawful rights. (✗) Bill <b>opposes</b> that animals should have lawful rights.

Table 1: Entailment-oriented instructions construct hypotheses to explain the labels (in bold). “✓”: correct; “✗”: incorrect.

$\hat{T}$  on its own in some cases.

### 3 What is Task Instruction?

Various types of textual instructions have been used in previous zero- and few-shot NLP tasks, such as prompts (Hendrycks et al., 2021; Srivastava et al., 2022; Bach et al., 2022, *inter alia*), Amazon Mechanical Turk instructions (Mishra et al., 2022b; Wang et al., 2022c; Yin et al., 2022, *inter alia*), instructions augmented with demonstrations (Khashabi et al., 2020; Ye et al., 2021; Min et al., 2022b, *inter alia*), and Chain-of-Thought explanations (Wei et al., 2022b; Lampinen et al., 2022; Li et al., 2022c, *inter alia*), etc. Different instructions are initially designed for distinct objectives (e.g., Mturk instructions are originally created for human annotators to understand, and prompts are to steer PLMs). In this section, as illustrated in Figure 2, we first summarize these instructions into three categories that perform different combinations of  $\hat{T}$ , X, and Y (ENTAILMENT-ORIENTED, PLM-ORIENTED, and HUMAN-ORIENTED), then compare them and provide the formal definition of instructions.

#### 3.1 $I=\hat{T}+Y$ : Entailment-oriented Instruction

One conventional scheme to handle the classification tasks is to convert the target labels into indices and let models decide which indices the inputs belong to. This paradigm focuses on encoding the input semantics while losing the label semantics. To let systems recognize new labels without relying on massive labeled examples, Yin et al. (2019) proposed to build a hypothesis for each label—deriving the truth value of a label is then converted into determining the truth value of the hypothesis. As exemplified in Table 1, this approach builds instructions (I) combining a template ( $\hat{T}$ ) with a la-

bel Y to explain each target label (Y). Since this paradigm naturally satisfies the format of textual entailment (TE, where the task inputs and the instructions can be treated as premises and hypotheses, respectively), these kinds of instructions are termed “Entailment-oriented Instructions”.

The advantages of entailment-oriented instruction learning are four-fold: (i) it keeps the label semantics so that input encoding and output encoding both get equal attention in modeling the input-output relations; (ii) it results in a unified reasoning process—textual entailment—to handle various NLP problems; (iii) it creates the opportunity of making use of indirect supervision from existing TE datasets so that a pretrained TE model is expected to work on those target tasks without task-specific fine-tuning; (iv) it extends the original close-set labels classification problem into a recognition problem of open-domain open-form labels with few or even zero label-specific examples. Therefore, it has been widely used in a variety of few/zero-shot classification tasks, such as classifying topics (Yin et al., 2019), sentiments (Zhong et al., 2021), stances (Xu et al., 2022b), entity types (Li et al., 2022a), and entity relations (Murty et al., 2020; Xia et al., 2021; Sainz et al., 2021, 2022).

#### 3.2 $I=\hat{T}+X$ : PLM-oriented Instruction (e.g., prompts)

The prompt is a representative of the PLM-oriented instructions, which is usually a brief utterance prepended with the task input (*prefix prompt*), or a cloze-question template (*cloze prompt*)<sup>3</sup>. It is basically designed for querying the intermedia responses (that can be further

<sup>3</sup>Please refer to Section 2.2.1 of Liu et al. (2023) for a detailed definition of prompt.

Task	Input X	Template $\hat{T}$ (cloze question)	Answer	Output Y
Sentiment Classification	I would like to buy it again.	[X] The product is __	Great Wonderful ...	Positive
Entity Tagging	[X1]: Donald Trump served as the 45th president of the United States from 2017 to 2021. [X2]: Donald Trump	[X1] [X2] is a __entity?	Politician President ...	People
Relation Tagging	[X1]: Donald Trump served as the 45th president of the United States from 2017 to 2021. [X2]: Donald Trump [X3]: United States	[X1] [X2] is the __of [X3]?	President Leader ...	The__president_of
Textual Entailment	[X1]: Donald Trump served as the 45th president of the United States from 2017 to 2021. [X2]: Donald Trump is a citizen of United States.	[X2]? __, because [X1]	Indeed Sure ...	Yes
Translation	Donald Trump served as the 45th president of the United States from 2017 to 2021.	Translate [X] to French: __	/	... été président des États-Unis ...

Table 2: PLM-oriented instruction utilizes a task-specific template to convert the origin input into a fill-in-blank question. In most classification tasks, the intermediate answer should be further mapped into the predefined label.

converted into the final answers) from the pre-trained LMs (PLM). Since the prompted input conforms to the pre-training objectives of PLM (e.g., the cloze-style input satisfies the masked language modeling objective (Kenton and Toutanova, 2019)), it help get rid of the reliance on the traditional supervised fine-tuning and greatly alleviates the cost of human annotations. Consequentially, prompt learning achieved impressive results on a multitude of previous few/zero-shot NLP tasks, e.g., question answering (Radford et al., 2019; Lin et al., 2021), machine translation (Li et al., 2022d), sentiment analysis (Wu and Shi, 2022), textual entailment (Schick and Schütze, 2021a,b), and named entity recognition (Cui et al., 2021; Wang et al., 2022a).

Despite the excellent performance of prompt techniques, there are still two obvious issues with PLM-oriented instructions in real-world applications: (i). **Not User-Friendly**. As the prompt is crafted for service PLM, it is encouraged to design prompts in a “model’s language” (e.g., model-preferred incoherent words or internal embedding). However, this PLM-oriented instruction is hard to understand and often violates human intuitions. (Gao et al., 2021; Li and Liang, 2021; Qin and Eisner, 2021; Khashabi et al., 2022). Meanwhile, the performance of prompts highly depends on the laborious prompt engineering (Bach et al., 2022), while most end-users are not PLM experts and usually lack sufficient knowledge to tune an effective prompt. (ii). **Applications Constraints**. The prompt is usually short and simplistic, whereas many tasks can not be effectively formulated with solely a brief prompt, making prompt hard to deal with the diverse formats of real-world NLP tasks (Chen et al., 2022).

### 3.3 $I = \hat{T} + \text{optional } \{X_i, Y_i\}_{i=1}^k$ : Human-oriented Instruction

Human-oriented instructions basically mean the instructions used for crowd-sourcing works on the human-annotation platforms (e.g., Amazon MTurk instructions). Different from the PLM-oriented instructions, human-oriented instructions are usually some human-readable, descriptive, and paragraph-style task-specific textual information, consisting of task title, category, definition, and things to avoid, etc. Therefore, **human-oriented instructions are more user-friendly and can be ideally applied to almost any complex NLP task**.

Accordingly, human-oriented instructions have attracted much more attention in recent years (Yin et al., 2022; Hu et al., 2022; Gupta et al., 2022; Longpre et al., 2023, *inter alia*). For example, Efrat and Levy (2020) tried to test whether GPT-2 (Radford et al., 2019) can follow the MTurk instructions to annotate some popular NLP datasets. Their results showed that HuggingFace’s off-the-shelf GPT-2 (Wolf et al., 2019) worked poorly on following these human-oriented instructions. While recent works found that multi-task instruction fine-tuned LMs could get more positive results. For instance, Mishra et al. (2022b) collected more than 60 NLP tasks with the corresponding MTurk instructions; Wang et al. (2022c) further extended this collection into a 1.6k cross-lingual tasks scale. They all concluded that, after the large-scale instruction fine-tuning, the text-to-text PLM, like BART (Lewis et al., 2020) and T5 (Raffel et al., 2020) can generalize to the challenging unseen tasks by benefiting from the MTurk instructions.



Task	Input X	Demonstrations $\{X_i, Y_i\}_{i=1}^k$	Template $\hat{T}$	Output Y
Named Entity Extraction	The last three days have been incredible. Eric Lauren sqiddly and diddly all happy.	[X1]: Let us wait for Tal August for a while. [Y1]: Tal August [X2]: I would like to make a face-to-face interaction with Sachin in August. [Y2]: Sachin ...	Definition: In this task, you will be given sentences ... to recognize the name of a person ... Examples: Input: [X1]; Output: [Y1] Input: [X2]; Output: [Y2] Now complete the following example: Input: [X]; Output: __	Eric Lauren
Summarization	A plane carrying U.S. Rep. Gabrielle Giffords departed Houston ...	[X1]: The goals just keep flowing for Lionel Messi ... [Y1]: Lionel Messi scores twice as Barcelona beat Mallorca ... [X2]: U.S. officials say they have specific reasons ... [Y2]: Chairman of the House Intelligence Committee complains about ... ...	Definition: In this task, you are given news articles, and you need to generate a highlight ... Examples: Input: [X1]; Output: [Y1] Input: [X2]; Output: [Y2] Now complete the following example: Input: [X]; Output: __	James McBride wins for The Good Lord Bird ...
Question Generation	Piedmont, or mountain, glaciers are found in many parts of the world ...	[X1]: There are a million times more viruses on the planet than stars in the universe ... [Y1]: How many segments of virus DNA does the human genome contain? [X2]: When mice are kept at high population densities ... [Y2]: When does the mice behavior change? ...	Definition: Given a paragraph, your job is to generate a question that can be answered from the passage ... Examples: Input: [X1]; Output: [Y1] Input: [X2]; Output: [Y2] Now complete the following example: Input: [X]; Output: __	What mountain ranges are present in South America?

Table 3: Examples coming from Wang et al. (2022c). The human-oriented instruction is similar to the PLM-oriented instruction, which also utilizes a template to convert origin input (in red) into a cloze question. However, the task template itself contains informative task semantics, i.e., the formal task definition. Meanwhile, few-shot alternative task demonstrations are also provided (in blue).

## 4 How to Model Instructions?

Instructions are versatile, but how does the model learn to correctly *understand* and *follow* instructions? This section summarizes several popular modeling strategies for instruction learning. Overall, we introduce three different modeling schemes: for the earlier rule-based machine learning systems, the (i) **Semantic Parser-based** strategy was the commonly chosen method for encoding instructions; as the neural networks and the pre-trained language models emerged, the data-driven-based method, namely (ii) **Fine Tuning-based** instruction learning became a highly favored paradigm; recently, (iii) **HyperNetwork-based** method also garnered greater interest.

### 4.1 Semantic Parser-based

At the early stage of machine learning, to help the systems understand natural language instructions, a great number of works employed semantic parsing to convert the instruction into the formal language (logical formula), which can be easier executed by the systems (e.g., “*You can move any top card to an empty free cell*”  $\rightarrow$  “*card(x)  $\wedge$  freecell(y)  $\wedge$  empty(y)*”) (Matuszek et al., 2012; Babeş-Vroman et al., 2012; Chen, 2012; Goldwasser and Roth, 2014, *inter alia*).

For example, Kuhlmann et al. (2004) first tried

to utilize natural language instructions to guide the systems to play soccer games, where they trained an individual semantic parser in advance, and then mapped the textual instructions into formal languages that can be used to influence the policy learned by the reinforcement learner. Since constructing a fully-supervised semantic parser requires laborious human annotations, the follow-up works also used indirect or weak supervision coming from the grounded environments (e.g., knowledge base) to train the semantic parser (Eisenstein et al., 2009; Chen and Mooney, 2008; Kim and Mooney, 2012; Artzi and Zettlemoyer, 2013; Krishnamurthy and Kollar, 2013). Besides using the converted formal languages to guide the systems to complete specific tasks, some works also utilized the logical formulae of the instructions to perform data and feature augmentations (Srivastava et al., 2017; Hancock et al., 2018; Wang et al., 2020; Ye et al., 2020). We will further introduce this sort of application in § 6.1.

### 4.2 Fine Tuning-based

As for the neural network-based systems, we can directly encode the natural language instructions into the model’s embedding without the help of an additional semantic parser. What’s more, benefiting from the rich prior knowledge, off-the-

	Entailment-oriented	PLM-oriented	human-oriented
indirect supervision	textual entailment	language modeling	other text-to-text tasks
instruction scope	instance-wise instruction	instance-wise instruction	task-wise instruction
update PLM?	yes	usually no	yes
need super large PLM?	no	yes	no
training tasks	textual entailment	no	many text-to-text tasks
end-user friendly?	no	no	yes
need additional label mapping?	yes	usually yes	no
has label information/output constraints?	yes	usually no	usually yes
can be without task input X?	no	no	yes

Table 4: Comparison of three types of instructions.

shelf PLMs could recover the task semantics conveyed in the instructions and perform zero-/few-shot learning (Radford et al., 2019; Brown et al., 2020). However, PLMs can not always successfully recognize and understand the instructions, especially for those complex human-oriented instructions (Weller et al., 2020). Therefore, more and more works try to fine-tune the models with instructions, i.e., instruction fine-tuning<sup>4</sup>.

Multi-task instruction fine-tuning is a representative strategy for the tuning-based method (Wei et al., 2022a; Sanh et al., 2022; Wang et al., 2022c). By converting the original task inputs into an instruction format (either prompted questions or prefix instructions), it fine-tunes the models on the massive multi-task datasets equipped with instructions. Besides multi-task learning, recent works also employed reinforcement learning to implement instruction fine-tuning (Ouyang et al., 2022). Although instruction fine-tuning still relies on the training (i.e., gradient backpropagation), different from traditional fine-tuning, the essence of instruction fine-tuning is training models to learn to follow instructions rather than completing specific tasks.

Existing works have demonstrated the effectiveness of instruction fine-tuning, where the fine-tuned models show better instruction-following ability than the off-the-shelf PLMs (Mishra et al., 2022b; Chung et al., 2022). We will further discuss the instruction fine-tuning in § 5.1.

### 4.3 HyperNetwork-based

There are two obvious problems in the instruction fine-tuning. First, it usually concatenates the task-level instruction with every instance-level input, the repeating procedure significantly slow-

ing down the processing/inference speed and the lengthy input also increasing the burden of computational cost (Liu et al., 2022). Second, it can potentially impact the optimization because the model can not explicitly distinguish the task input X from the prefix instructions I, thus the model can simply learn to complete the task and ignore the instructions (Webson and Pavlick, 2022; Deb et al., 2022).

To address the above issues, recent works began to employ the hypernetwork (Ha et al., 2016) to encode the task instructions (Jin et al., 2020; Deb et al., 2022; Ivison et al., 2022). The essences of using hypernetwork-based approach are (i). encoding the task instruction I and the task input X separately, and (ii). converting the instruction into task-specific model parameters. For example, Ye and Ren (2021) used the hypernetwork to convert the task instruction into several parameter-efficiency adaptors (Houlsby et al., 2019). Then they inserted these adaptors behind the multi-head attention layers of the underlying LMs to perform cross-task generalization.

## 5 Analyses

Instruction learning is proven to be effective in a lot of zero- and few-shot NLP tasks, but how to explain the impressive performance of instruction? And which aspects make a successful instruction learning procedure? To figure out the empirical rules in using instructions and better understand instruction learning, in this section, we summarize some insights from existing works for further research, i.e., some important factors that contribute to cross-task generalization.

### 5.1 Instruction-based Fine-tuning

We first emphasize the importance of instruction fine-tuning. As we have introduced in § 4.2, instruction fine-tuning is one of the most popular

<sup>4</sup>We use the term “instruction fine-tuning” to distinguish it from “instruction tuning”, e.g., tuning soft prompts (Li and Liang, 2021; Tsimpoukelli et al., 2021; Han et al., 2021).

modeling strategies of instruction learning. It usually trains the LMs on various instruction datasets, where each task input is converted into an instruction style, to drive the models to learn to follow the instructions. A lot of works demonstrate that multi-task instruction-tuned LMs could better follow the instructions of the unseen tasks compared with no-tuned LMs (Wei et al., 2022a; Sanh et al., 2022; Yin et al., 2022; Chung et al., 2022; Prasad et al., 2022, *inter alia*).

However, since previous works demonstrated that a massive multi-task training procedure also benefits the downstream tasks learning of LMs (McCann et al., 2018; Aghajanyan et al., 2021; Aribandi et al., 2022), there is always a question that “*Whether instruction fine-tuning or multi-task learning plays a key role in cross-task generalization*”. To answer this question, we first introduce the work of Weller et al. (2020), who solely tuned LMs with a multi-task learning paradigm and discovered that the LMs could find it hard to follow the instructions of the unseen tasks. Wei et al. (2022a); Sanh et al. (2022) further conducted in-depth comparison between multi-task instruction fine-tuning and multi-task learning on cross-task generalization. They found that instruction fine-tuning is the key to cross-task generalization rather than multi-task learning itself.

Besides the performance gains on the unseen tasks, there are also many other benefits of instruction fine-tuning. For example, Wei et al. (2022a) showed that instruction fine-tuned LMs performed better on following the soft instructions. Meanwhile, Longpre et al. (2023) compared the convergences of Flan-T5 and T5 on single-task fine-tuning, and they found that instruction fine-tuned Flan-T5 learned faster than T5 on the downstream single-task fine-tuning. What’s more, some works also found that instruction fine-tuning makes LMs robust to some tiny perturbations in the instructions, such as the wordings (Sanh et al., 2022) and the paraphrasing (Gu et al., 2022). While off-the-shelf LMs are usually sensitive to the small instruction perturbations (Efrat and Levy, 2020; Weller et al., 2020), thus they require laborious prompt engineering (Bach et al., 2022). All in all, instruction fine-tuning tames the LMs to become much more user-friendly (Chung et al., 2022).

Despite these attractive attributes, instruction fine-tuning still relies heavily on massive task-specific training, which is costly and could be sub-

optimal for instruction learning. We will further discuss this point in § 7.3.

## 5.2 Instruction Paradigm

Keeping the instruction paradigm is also a crucial factor in instruction learning, which mainly means retaining the instruction conciseness of tuning and testing. Wei et al. (2022a) first investigated the performance impact of changing the instruction paradigm. And they found that, the performances of the LMs tuned with short task names dropped when evaluating with more extended sentence-style instructions (i.e., task names  $\rightarrow$  sentence-style instructions), compared with the results of keeping the instruction paradigm (i.e., task names  $\rightarrow$  task names, or sentence-style instructions  $\rightarrow$  sentence-style instructions). Meanwhile, Gu et al. (2022) also observed the performance dropping when changing paragraph-style instructions to sentence-style instructions in testing, further enhancing this conclusion.

Besides discrete instruction, the instruction paradigm is also critical in soft instruction learning. For example, Xu et al. (2022a) showed that the LMs fine-tuned with continuous instruction also require a same-size prefix embedding when testing on unseen tasks, even if this embedding is randomly initialized. Interestingly, similar results were also found in the few-shot demonstrations (i.e., in-context learning). For instance, Min et al. (2022c) concluded that breaking the demonstration paradigm (i.e., removing the  $y$ ) significantly harms the performance of MetaICL (Min et al., 2022b), which tuned with  $(x, y)$  pairs. Furthermore, Iyer et al. (2022) found that the number of demonstrations should also not be changed during evaluation (e.g., using 2 demonstrations in tuning and 3 in testing would result in lower performance, compared with using 2 demonstrations in testing).

## 5.3 Model and Task Scale

A series of recent works demonstrated that the scale also matters in instruction learning, including both model parameters and tuning tasks<sup>5</sup> (Wei et al., 2022a; Sanh et al., 2022; Mishra et al., 2022b; Wang et al., 2022c; Xu et al., 2022a; Deb et al., 2022; Prasad et al., 2022; Chung et al., 2022; Iyer et al., 2022; Longpre et al., 2023, *inter alia*). A representative work among them is Chung et al. (2022), who conducted extensive experi-

<sup>5</sup>Task scale includes numbers and categories of tasks.

ments with 1,836 tuning tasks and 540B models. The results illustrated that the cross-task performance takes advantage of both factors<sup>6</sup>, suggesting the research community continue scaling the instruction learning. However, the super large scale is usually unaffordable for most groups, and it also leads to huge carbon emissions (Strubell et al., 2019; Schick and Schütze, 2021c), making it unrealistic in real-world scenarios. Accordingly, recent works began to investigate a more efficient way to address the scale problem, such as the parameter-efficient fine-tuning (Schick and Schütze, 2021a; Liu et al., 2022). For example, Jang et al. (2023) employed the instruction-level experts (adaptors) to fine-tune LMs on a single task, which outperformed the multi-task fine-tuned LMs on the unseen tasks. It is also noteworthy that Longpre et al. (2023) adapted the idea of “noisy channel” (Min et al., 2022a) that extended the tuning task scale by simply inverting the input-output of instance and achieved a reasonable performance improvement.

#### 5.4 Instruction Diversity

Instruction diversity (e.g., various creativity) at fine-tuning phase also affects the cross-task performance and robustness of LMs (Chung et al., 2022; Longpre et al., 2023). Notably, Sanh et al. (2022) fine-tuned T5 (Raffel et al., 2020) model on the multi-task datasets, where each dataset is associated with various instructions collected from “Public Pool of Prompts” (P3) (Bach et al., 2022). These instructions are written in different ways and perspectives (but in similar conciseness)<sup>7</sup>. By varying the number of instructions per dataset used in fine-tuning, Sanh et al. (2022) found that the model fine-tuned with more diverse instructions achieved better and more robust performance on the unseen tasks. What’s more, Sanh et al. (2022) also found that the instruction diversity could compensate for the limited model scale, i.e., a relatively small LMs (T0-3B) could still benefit from multi-task fine-tuning due to the mixture of diverse instructions<sup>8</sup>.

Nevertheless, manually crafting instructions

with diversity is expensive and usually hard to achieve (Huynh et al., 2021; Parmar et al., 2022). Since large-scale PLMs, such as ChatGPT and GPT-4, exhibited excellence in automatic annotations with lower charges than human annotators (OpenAI, 2023; He et al., 2023; Pan et al., 2023), recent works began to employ models to compose innovative instructions (Zhang et al., 2020, 2021; Honovich et al., 2022a,b; Ye et al., 2022b; Taori et al., 2023; Peng et al., 2023). For instance, Wang et al. (2022b) tried to drive GPT-3 (Brown et al., 2020) to generate quantitative instructions from scratch iteratively. Although the self-generated instructions contain more noise, owing to the creative task types and diverse verb-noun structures (Kitaev and Klein, 2018), these instructions could still bring benefits to tuning the GPT-3 and show complementary effects with the human-written instructions. These results imply the profitability of instruction diversity, even at the expense of the correctness of instructions. We will further discuss it in § 7.2.

#### 5.5 Instruction Taxonomies and Situations

As we have introduced in § 3, there are several kinds of textual instructions. Although they were all widely adapted by the previous works, different taxonomies show various-degree effects. For example, existing works found that adding positive few-shot demonstrations in the textual instructions could lead to a significant performance improvement on the unseen tasks (Mishra et al., 2022b; Wang et al., 2022c; Yin et al., 2022; Deb et al., 2022; Gu et al., 2022), especially for the tasks occupying complex output space (Wei et al., 2022a). Surprisingly, Gu et al. (2022) further found that combining incorrect instructions with correct demonstrations could outperform using correct instruction without demonstrations, indicating the key role of demonstrations in instruction learning. This prominence is perhaps because the LMs prefer to exploit the more superficial aspects of the demonstrations rather than the other complex contents (cf. Min et al., 2022c).

In addition, the effectiveness of different instruction taxonomies also highly depends on the target evaluation tasks. For example, the concise cloze-style instructions are useful on tasks that can be naturally expressed as instructions (e.g., QA), while it seems to be redundant when facing language modeling tasks (cf. Wei et al., 2022a).

<sup>6</sup>Worth noting that the benefits of the model scale seem to outweigh the task scale. Please refer to the Fig. 4 of Chung et al. (2022) and the follow-up work of Longpre et al. (2023).

<sup>7</sup>See Appendix G of Sanh et al. (2022) for more details.

<sup>8</sup>While Wei et al. (2022a) only used a fixed number of instructions and found that instruction fine-tuning harmed the performance of smaller LMs (Flan-8B).



What’s more, CoT explanations seem to be necessary only for tasks that require multi-steps reasoning (cf. [Kojima et al., 2022](#)). To this end, a practical suggestion is to mix different instruction taxonomies when tuning the LMs, which has been proven to be efficient in tackling the various target evaluation tasks ([Chung et al., 2022](#); [Iyer et al., 2022](#); [Longpre et al., 2023](#)).

## 5.6 Model Preference

Another factor that can enhance the cross-task performance is making instructions conform to the *preference* of LMs, that is, converting the instructions into model-oriented styles.

Since the current instruction learning paradigm mainly employs the PLM as the backbone of the system, one of the potential explanations for why PLM-oriented instruction (i.e., prompt) can work is that prompt recalls the pre-training objective and activates the task-specific knowledge of the PLM. Some of the existing works demonstrated the importance of conforming to the pre-training objective of PLM when doing instruction fine-tuning ([Tay et al., 2022](#)). For example, [Schick and Schütze \(2021a,c\)](#) proposed the idea of *pattern exploit training* (PET), which used a prompt to convert the original task inputs into cloze-style questions and then fine-tuned the PLM on instruction datasets with the masked language modeling objective. They found that taking advantage of recalling the pre-training objective, relatively small LMs, such as ALBERT ([Lan et al., 2019](#)), can outperform GPT-3 on the SuperGLUE benchmark ([Wang et al., 2019](#)). Furthermore, [Iyer et al. \(2022\)](#) found that the PLM could perform better on the unseen tasks after mixing a small proportion of pretraining-style data in the instruction fine-tuning dataset. [Sanh et al. \(2022\)](#); [Wei et al. \(2022a\)](#) also found that the PLM was more likely to fail at the tasks whose objective differs from the language modeling but improved by adopting cloze-style instructions. All these results align with the empirical rules of prompt engineering ([Liu et al., 2023](#)), which highlights the importance of aligning the prompts with the PLM<sup>9</sup>.

Besides the objective of instruction fine-tuning, the way of designing instructions is also found critical. To better cater to the model’s preference,

recent works began employing continuous embedding (i.e., soft instructions) instead of human-understandable discrete instructions. ([Lester et al., 2021](#); [Liu et al., 2021](#); [Ye et al., 2022a, inter alia](#)). Similar conclusions are also found in the human-oriented instructions, where the PLM constantly fails at following the human-oriented instructions but gains significant improvements after reframing the instructions to cater to the model’s preference ([Mishra et al., 2022a](#); [Prasad et al., 2022](#); [Gonen et al., 2022](#); [Deng et al., 2022](#); [Wang et al., 2022b](#)). Despite the performance profits, it is still controversial whether it is worthwhile to convert the original human-oriented instructions into PLM-oriented style, because it impairs the interpretability of instructions and is highly contrary to human intuition ([Khashabi et al., 2022](#); [Webson and Pavlick, 2022](#); [Prasad et al., 2022](#)). We will further discuss it in § 7.2.

## 6 Applications

### 6.1 Human-Computer Interaction

Textual instructions can be naturally regarded as a human-computer interaction method. Numerous previous works employed natural language instructions to “guide” the computer to perform various real-world tasks.

For the non-NLP (multi-modal) tasks, most focused on environment-grounded language learning, i.e., driving the agent to associate natural language instructions with the environments and make corresponding reactions, such as selecting mentioned objects from an image/video ([Matuszek et al., 2012](#); [Krishnamurthy and Kollar, 2013](#); [Puig et al., 2018](#)), following navigational instructions to move the agent ([Tellex et al., 2011](#); [Kim and Mooney, 2012](#); [Chen, 2012](#); [Artzi and Zettlemoyer, 2013](#); [Bisk et al., 2016](#)), plotting corresponding traces on a map ([Vogel and Jurafsky, 2010](#); [Chen and Mooney, 2011](#)), playing soccer/card games based on given rules ([Kuhlmann et al., 2004](#); [Eisenstein et al., 2009](#); [Branavan et al., 2011](#); [Babeş-Vroman et al., 2012](#); [Goldwasser and Roth, 2014](#)), generating real-time sports broadcast ([Chen and Mooney, 2008](#); [Liang et al., 2009](#)), controlling software ([Branavan et al., 2010](#)), and querying external databases ([Clarke et al., 2010](#)), etc. Meanwhile, instructions are also widely adapted to help communicate with the system in solving NLP tasks, e.g., following instructions to manipulate strings ([Gaddy and Klein, 2019](#)),

<sup>9</sup>Using prefix prompts for the auto-regressive LMs, while using cloze prompts for the masked LMs. Please refer to [Liu et al. \(2023\)](#) for more details.

classifying emails based on the given explanations (Srivastava et al., 2017, 2018), and text-to-code generation (Acquaviva et al., 2021).

Recently, a growing body of research tended to design the human-computer communication procedure in an **iterative** and **modular** manner. For example, Li et al. (2020) built a system to help the users tackle daily missions (e.g., ordering coffee or requesting Uber). Benefiting from a user-friendly graphical interface, the system can iteratively ask questions about the tasks, and users can continually refine their instructions to avoid unclear descriptions or vague concepts. Similarly, Dwivedi-Yu et al. (2022) proposed a benchmark to iteratively instruct the PLM to improve the text, where each iteration only used a small piece of instruction with a precise purpose (e.g., “*Simplify the text*” or “*Make the text neutral*”). Besides, Chakrabarty et al. (2022) constructed a collaborative poem-writing system, where the user could initially provide an ambiguous instruction (e.g., “*Write a poem about cake*”) and then incrementally refine the instruction with more details (e.g., “*Contain the word – ‘chocolate’*”) by observing the model’s intermediate outputs. Meanwhile, Mishra and Nouri (2022) proposed a biography generation system<sup>10</sup> that progressively collected the necessary personal information from the users (by asking questions in a dialogue scene to guide the users) and generated a paragraph-style bio finally. As it is usually hard for non-expert users to write sufficient instructions in one shot, adapting an iterative and modular paradigm in designing instruction-based AI systems can help guide the users to enrich the task instruction step by step. Thus, this paradigm efficiently relieves the thinking demands of users and leads to a more user-oriented system. Due to its practical values, we emphasize the importance of this branch of work in this paper.

## 6.2 Data and Feature Augmentation

Task instructions are regarded as indirect supervision resources where sometimes superficial and assertive rules are embedded. These rules are also known as *labeling functions* that can be directly applied for annotations (e.g., the sentence “*a very fair price*” is sentiment positive because “*the word ‘price’ is directly preceded by ‘fair’*”). Therefore,

<sup>10</sup>Mishra and Nouri (2022) actually experimented with more than 60 text generation tasks.

some existing works also employed the instruction as a distant supervision to perform data or feature augmentation (Srivastava et al., 2018; Hancock et al., 2018; Ye et al., 2020). For instance, Srivastava et al. (2017) used a semantic parser to convert natural language explanations into logical forms, and applied them on all instances in the dataset to generate additional binary features. While Wang et al. (2020) utilized the label explanations to annotate the raw corpus automatically and trained the classifier on the resulting noisy data.

Besides the straightforward augmentation, Su et al. (2022) further used the task instruction to enrich the model representation and achieved strong cross-task generalization. Specifically, they trained an embedding model (a single encoder) on the diverse instruction datasets with contrastive learning, and then used this model to produce task-specific representations based on the instruction for the downstream unseen tasks.

## 6.3 Generalist Language Models

According to the definition of Artificial General Intelligence (AGI), the “generalist model” is usually a system that can be competent for different tasks and scalable in changeable contexts, which shall go far beyond the initial anticipations of its creators (Wang and Goertzel, 2007; Goertzel, 2014). While specific to the NLP domain, a generalist language model is supposed to be an excellent multi-task assistant, that is skilled in handling a variety of real-world NLP tasks and different languages, in a completely zero/few-shot manner (Arivazhagan et al., 2019; Pratap et al., 2020; Wei et al., 2022a). As numerous existing works demonstrated the incredible power of using instructions in cross-task generalization (Wei et al., 2022a; Sanh et al., 2022; Mishra et al., 2022b; Wang et al., 2022c; Chung et al., 2022, *inter alia*), the instruction is likely to become a breakthrough in achieving this ultimate goal.

Notably, the recent two remarkable applications of instructions, namely InstructGPT (Ouyang et al., 2022) and ChatGPT<sup>11</sup>, also indicated a big step towards building generalist language models. However, unlike the other works that mainly employ instruction learning, ChatGPT also adopts some other components, e.g., reinforcement learning with human feedback (RLHF)<sup>12</sup>. Although

<sup>11</sup><https://chat.openai.com/>

<sup>12</sup>At the time of writing, there is no published paper about

the answer to “which component contributes more to the dramatic results of ChatGPT” remains ambiguous and needs further investigation, we introduce some recent works highlighting the critical role of instruction learning. For example, [Chung et al. \(2022\)](#) conducted extensive experiments to evaluate the human-preference alignments of PaLM ([Chowdhery et al., 2022](#)). They found that, even without any human feedback, the instruction fine-tuning significantly reduced the toxicity in the open-ended generations of PaLM, such as gender and occupation bias. In addition, some other works also solely employed creative instructions instead of human feedback and achieved notable cross-task results ([Bai et al., 2022](#); [Honovich et al., 2022a](#); [Wang et al., 2022b](#)).

Although ChatGPT still suffers from many unsatisfactory aspects and is far from the generalist language model ([Qin et al., 2023](#); [Guo et al., 2023](#); [Koco’u et al., 2023](#); [Wang et al., 2023](#)), we hope the goal of AGI can continue to be promoted by adopting and evolving more powerful techniques, including instruction learning.

## 7 Challenges and Future Directions

### 7.1 Negated Instruction Learning

Negation is a common linguistic property and has been found to be crucial for various NLP tasks, e.g., textual entailment ([Naik et al., 2018](#); [Kassner and Schütze, 2020](#)). Specific to instruction learning, negation denotes any *things-to-avoid* information of in-context instructions, such as negated task descriptions and negative demonstrations. Although humans can learn a lot from the negation ([Dudschig and Kaup, 2018](#)), existing works found LMs often fail to follow the negated instructions ([Mishra et al., 2022b](#); [Li et al., 2022b](#); [Jang et al., 2022](#)). For example, [Mishra et al. \(2022a\)](#) conducted error analyses on GPT-3 and found GPT-3 constantly unable to understand the negated task constraints in the MTurk instructions. [Wang et al. \(2022c\)](#) further found that adding negative demonstrations and explanations to the instructions could even harm the cross-task generalization performance of PLM.

Since negation has increasingly become a challenge in instruction learning, we provide several

hints to inspire future work. One potential solution to handle the negated instruction is unlikelihood training ([Hosseini et al., 2021](#); [Ye et al., 2022b](#)), which trains the LMs to minimize the ground truth probability when negated instructions are conditioned. In contrast, [Yin et al. \(2022\)](#) proposed to pre-train the LMs on the negative demonstrations with maximizing likelihood objective to exploit the useful information in the negation. Some other methods, such as contrast-consistent projection ([Burns et al., 2022](#)) and n-gram representations ([Sun and Lu, 2022](#)), also provided insights into tackling this problem.

### 7.2 Explainable Instruction Learning

As we have mentioned in § 5, in order to achieve a promising cross-task performance, one of the critical factors is to convert the human-oriented instructions into a much more PLM-oriented format, i.e., making the instructions conform to the model’s preference. Numerous previous works have verified the effectiveness of catering to the model’s preference in designing instructions, such as using the model’s perplexity in choosing appropriate instructions ([Gonen et al., 2022](#)). Despite the performance gains of the PLM-oriented instruction selection, the resulting instructions consistently violate human intuitions, questioning the reliability of PLM-oriented instruction ([Webson and Pavlick, 2022](#)). For example, [Prasad et al. \(2022\)](#) tried to rephrase the human-oriented instructions by using performance rewards as the criterion. Surprisingly, the resulting instructions that yield better performance are constantly semantically incoherent, task-irrelevant, or even misleading instructions. Similar results are also found in [Khashabi et al. \(2022\)](#), which mapped the continuous instructions back into the discrete space and found those effective instructions are usually associated with semantic-irrelevant utterances. These results prove the conflict between performance profits and the human interpretability of instructions, which is tricky to trade-off.

Although [Mishra et al. \(2022a\)](#) demonstrated that it is possible to maintain both the faithfulness and effectiveness of instructions, manual rewriting requires laborious human efforts. Therefore, one of the future trends is to investigate how to automatically rephrase the instructions, in a way that matches both human and model preferences, such as setting an additional criterion during the

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ChatGPT. Thus, our discussion is mainly based on the underlying techniques of InstructGPT because they share similar philosophies. See OpenAI’s blog for more details: <https://openai.com/blog/chatgpt>

instruction optimization.

### 7.3 Explicit Instruction Learning

As we have discussed in § 5.1, multi-task instruction fine-tuning is becoming a fundamental factor in the current instruction learning paradigm. Obviously, there are two issues in such a learning paradigm: (i) it relies on training on the massive labeled examples to learn the instructions, which is still expensive and unrealistic for using large-scale LMs; (ii) although the ultimate goal of instruction-based fine-tuning is learning to follow instructions by observing various training tasks, the current training objective is still the maximum likelihood of traditional generation tasks. This implicit instruction learning objective can lead to sub-optimal optimization (i.e., LMs can easily learn to complete specific training tasks).

To this end, one desired future direction is to evolve a new learning objective to help LMs explicitly learn to follow instructions, which might alleviate the reliance on large-scale tuning instances. Moreover, a more ambitious and challenging idea is to drive the system to follow instructions without additional tuning on the labeled examples of any specific tasks, which is somehow similar to the conventional semantic parser-based paradigm (§ 4). Recent work on in-context instruction learning can be considered an initial step toward this goal (Ye et al., 2023)<sup>13</sup>.

### 7.4 Scalable Oversight: A New Evaluation Paradigm for Generalist AI Systems

The evaluation procedure of the current research paradigm basically follows two steps: First, driving the systems to complete specific tasks; Second, using some automatic metrics to evaluate the systems. While in the context of evaluating advanced instruction learning systems (i.e., generalist language models), this traditional paradigm suffers from two issues: (i). Limited by the automatic metrics, we will find it hard to measure the progress of the system if the system has already been more capable than non-expert humans on these tasks; (ii). We could have no idea whether the system is a qualified generalist “assistant” for non-expert humans.

<sup>13</sup>In-context instruction learning provides PLMs with fixed instruction-learning demonstrations. Although it doesn’t require training, the lengthy and complex input makes the inference more costly and requires large-scale models.

Accordingly, recent works proposed the idea of *scalable oversight* (Cotra, 2021; Bowman et al., 2022), which denoted a new research paradigm for appraising the generalist language models, including the following steps: (i). **Task Choices**. Choosing the tasks where the LMs can outperform the non-experts but underperform the experts; (ii). **Non-experts Annotation**. Instead of driving the model to complete the tasks, ask the non-experts to annotate the challenging tasks by acquiring useful information from the untrustworthy LMs, i.e., the LMs need to follow some general instructions (w/o any domain-specific prompts) of non-experts to provide assistance; (iii). **Experts Evaluation**. At the end of the experiments, ask the experts to evaluate the annotation correctness of non-experts. In doing so, we can continue to promote the progress of generalist LMs by aligning the highly capable LMs with domain experts. Meanwhile, we simulate a real-world application scenery for most non-expert users, where the generalist LMs play the role of an assistant w/o any domain-specific knowledge aided. By adopting this paradigm, Bowman et al. (2022) found that the non-experts can outperform both LMs-alone or human-alone results by benefiting from the assistance of LMs.

Overall, the scalable oversight paradigm can help future research to test whether current LMs (e.g., ChatGPT) can effectively assist non-expert users in solving challenging tasks.

## 8 Conclusion

In this survey, we comprehensively summarize numerous existing pieces of literature about instruction learning and provide a systematic overview of this field, including different instruction taxonomies, modeling strategies, some critical aspects of using instructions in engineering, and several popular applications. We also emphasize some distinct challenges and the corresponding hints for future research. To our knowledge, this is the first extensive survey about instruction learning. In summary, we hope this survey can offer insights and inspiration for further in-depth research on instruction learning.

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