Improving Task Generalization via Unified Schema Prompt

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Abstract

Task generalization has been a long-standing challenge in Natural Language Processing (NLP). Recent research attempts to improve the task generalization ability of pre-trained language models by mapping NLP tasks into human-readable prompted forms. However, these approaches require laborious and inflexible manual collection of prompts, and different prompts on the same downstream task may receive unstable performance. We propose Unified Schema Prompt, a flexible and extensible prompting method, which automatically customizes the learnable prompts for each task according to the task input schema. It models the shared knowledge between tasks, while keeping the characteristics of different task schema, and thus enhances task generalization ability. The schema prompt takes the explicit data structure of each task to formulate prompts so that little human effort is involved. To test the task generalization ability of schema prompt at scale, we conduct schema prompt-based multitask pre-training on a wide variety of general NLP tasks. The framework achieves strong zero-shot and few-shot generalization performance on 16 unseen downstream tasks from 8 task types (e.g., QA, NLI, etc). Furthermore, comprehensive analyses demonstrate the effectiveness of each component in the schema prompt, its flexibility in task compositionality, and its ability to improve performance under a full-data fine-tuning setting.

1 Introduction

Task generalization can be viewed as out-of-domain adaptation to unseen tasks with diverse task-specific knowledge. Pre-trained language models [Devlin et al., 2019] achieve state-of-the-art performance on a wide range of tasks without substantial task-specific architecture modifications, but they still require fine-tuning with one additional layer on task-specific datasets [Li et al., 2020; Gao et al., 2020; Sun et al., 2022]. Moreover, fine-tuned pre-trained model on a specific dataset cannot be generalized to other unseen tasks, especially when different tasks have diverse formats of inputs and outputs. This observation promotes recent works [Sanh et al., 2021; Raffel et al., 2020b; Xu et al., 2022] on using prompting methods to improve task generalization through explicit multi-task learning. Formulating the input of different tasks using human-written natural language (NL) prompts into a unified format, the prompting-based unified paradigm significantly improves zero-shot task generalization ability [Sanh et al., 2021].

Despite its great success, the paradigm of writing NL prompts involves huge human efforts. For example, T0 [Sanh et al., 2021] relies on a crowd-sourcing platform to collect 1939 human-written NL
Learnable Value Components with Task-attributed Prompt

Uniencoder-Decoder prompted Input Schema-based Output

With the aforementioned motivations, we propose a task schema-based prompting method, SchemaPro, which automatically composes learnable and shareable prompts for tasks according to their task schemas, and organizes the inputs of every NLP tasks into a unified format. Each colored box indicates a specific component type like "Question", and is represented with key prompts. The white box indicates special components (i.e., Format, Task, Output) representing tasks attributes. Importantly, the representations of every component types and task-attributed values residing in the special components are all learnable and storable. Each element in square brackets or colored boxes is a specific group of learnable soft prompts.

prompts from 36 contributors. These human-written prompts are tied with their tasks so that they are infeasible to be generalized to new tasks. Moreover, human-written prompts on the same task usually receive performance variance because they are not equivalently accurate in task description. Under the curiosity of exempting from manually writing prompts while keeping the generalization ability, we find the explicit data schema in the datasets of many NLP tasks can be used as-is for automatic prompting. For example, a QA task has the input schema “question: ...; answer: ...; passage: ...”. Instead of writing a prompt like “What is the best answer to the question ... given the passage ...?”, the compositional input components in the schema have already provided a super informative way for prompting: “question: xxx, passage: xxx, answer: ?”. In addition to alleviating the manual involvement for prompt writing, keeping the original data schema for prompting brings two benefits: (1) Treating task schema as keys in prompting can model different combinations of input components to discriminate different tasks. For example, natural language inference (NLI) task has input components “(premise, hypothesis)”, and question answering (QA) task has “(passage, question)”. (2) Different tasks may have shared input schema so that schema-specific knowledge could be shared across tasks. For example, schemas of QA tasks share common component like “question”, and the tasks of summarization and topic classification have common input “passage”.

With the aforementioned motivations, we propose a task schema-based prompting method, SchemaPro, to simultaneously model the shared knowledge and variances between wide variety of tasks, and to alleviate human efforts in prompt writing. As shown in Fig. 1 the schema prompt is composed of multiple components (represented as key-value pairs), whose composition is defined by the task input schema itself. The components have two types: (1) general components defined by task input schema (e.g., [passage] in Summarization task and [premise, hypothesis] in NLI), and (2) learnable task-specific attributes (i.e., [task: a specific dataset], [format: a general class of a NLP task, like NLI], [output: expected output type, like answer]).) In each component, the component type is a general key (e.g., passage, format, task), and the specific instance belonging to this type is taken as a value.

More specifically, SchemaPro has several important features. Firstly, each component key that helps the model in identifying the task schema in an explicit way, is represented by a group of learnable soft key prompts. Secondly, to automatically learn the description of tasks, the values that
belong to task-attributed components (i.e., task, format, output) are also learnable continuous soft prompts. This design provides a discriminating capability to different task schema, plug-in flexibility of task-attributed prompts, which leads to better generalization ability and minimal manual efforts for task description. Moreover, the framework is extensible and flexible when a new task schema is involved – SchemaPro only requires adding and learning a new component, or adding a new task-attributed value. The extensibility and flexibility bring faster model adaptation.

We explore the effectiveness of the schema prompt in the scenario of multi-task learning for general NLP tasks. We first formulate the inputs of each task with the schema prompt, where the key prompts and task-attributed values are learnable during training. Then, we train the mixture of NLP tasks under an encoder-decoder model using T5 \cite{Raffel2020ExploringTG}. Mixing a wide variety of NLP tasks helps the model in learning both the semantic meaning of the schema prompt and the common knowledge shared across tasks.

We evaluate the task generalization ability of schema prompt-enhanced model by zero-shot testing and few-shot adaptation on tasks that are unseen during training. From experiments on 16 unseen tasks belonging to 8 task types, we highlight the following findings: (1) SchemaPro outperforms NL prompt-based method under both zero-shot testing and few-shot learning settings, indicating that the schema prompt enhances the task generalization ability to unseen tasks; (2) The ability of identifying different schema can benefit model adaptation to new tasks, as our method improves few-shot performance when adapting to unseen tasks with compositional schemas of other learned tasks; (3) Eliminating task-attributed components residing in the schema prompt results in large performance drop, suggesting they model the task characteristics. (4) SchemaPro can also benefit model learning even when there is enough supervised data for downstream tasks.

2 Unified Schema Prompt for General NLP Tasks

2.1 Preliminaries: Unified Multi-task Learning Framework

We introduce some definitions in NLP task generalization. Throughout this paper, we denote “task” as “a dataset with specific data distribution or domain knowledge”, and “format” as a common task type, like QA or NLI. For example, “DREAM” \cite{Sun2019DREAMDA} is a task and its corresponding format is “Multiple Choice QA”. Although the definition of "task" is vague and has no a standard definition, there are still fundamental difference between different datasets with the same format that they emphasize different kinds of reasoning skills, domain knowledge, and data distribution. For example, commonsense QA emphasizes reasoning over commonsense knowledge while Hotpot QA emphasize multi-hop reasoning. Therefore, we largely follows popular works like GPT-3 \cite{Brown2020LanguageMA}, MAML \cite{Finn2017ModelAT} and Xu et al. (2022) and define “task” as “dataset with specific data distribution and domain knowledge”.

Since different NLP tasks have diverse formats of inputs and outputs, modeling several NLP tasks within a unified model requires different tasks sharing a unified form. Prompting is a feasible way to reformat different NLP tasks into the same input-output format, enabling the construction of a unified framework to solve various NLP tasks. For example, T0 \cite{Sanh2021PushingTD} uses natural language prompting to reformat the input of natural language inference task using the template “If {Premise} is true, is it also true that {Hypothesis}?” and formulate the output as an choice from options “{yes, maybe, no}”. With reformulated input-output pairs of NLP tasks via prompting, one can adopt encoder-decoder architecture with input fed to the encoder and target output produced by the decoder.

2.2 Formulation of Schema Prompts

We design a unified task schema-based prompting method, namely SchemaPro, to automatically customize the prompts for each task and reformat the task inputs, involving minimal human efforts. The design of SchemaPro consists of multiple components, where each component type (e.g., passage, task) is represented as a key, and its corresponding content is taken as a value. For each specific task, the compositions of components are defined by the task input schema itself, and task-attributed components required for task description. More specifically, there are two possible classes of components: (1) general components given in the task schema (e.g., passage, question, options), where the value is a text; (2) task-attributed components used for task description (i.e.,
We formalize the model input. Suppose we have task A with components within square brackets indicates that it is a specific group of learnable soft prompts. The component ("passage": a thoughtful, provocative, humanizing film, "options": Positive, Negative) for our experiment. As the task taxonomy shown in Fig. 3, we select several tasks (marked in blue) for multi-task prompted pre-training, and take the rest tasks (marked in yellow) that are unseen during pre-training for downstream evaluation. Essentially, the design of schema prompt has following specialties: (1) To learn and customize the functionality for each component, we represent each component type with a group of learnable soft key prompts; (2) To learn the soft task description, we also adopt learnable soft prompts as the values to represent the attributes of tasks. We define three kinds of task attributes, i.e., \( \text{Format}, \text{Task}, \text{and Output} \) where the value is a group of learnable soft continuous embeddings, which are flexible and pluggable, and are mainly adopted for parameter-efficient model adaption for pre-trained models.

We formalize the model input. Suppose we have task A with components \( C_A = \{c_1, c_2, \ldots, c_n\} \), each \( c_i \) represents the \( i^{th} \) component (key-value) pair. Then we represent the indicator of each key as \( k_i \), with a group of soft key prompts. We represent the value \( v_i \) as either (1) token embeddings for value in the form of the textual content (e.g., \( \text{passage: } \"a thoughtful film \ldots\" \)) or (2) a group of soft value prompts for learnable task attributes ("Format", "Task", "Output Type"). Afterwards, we represent each component \( c_i \) as \( c_i = [k_i; v_i] \), which is the concatenation of \( k_i \) and \( v_i \). Finally, we concatenate all the \( c_i \) as the reformatted model input \( X = [c_0; c_1; \ldots; c_n] \). Noting that both the key indicators and special task-attributed values are learnable, pluggable, and storable soft prompts.

### 2.3 Task Generalization

In this part, we introduce the task taxonomy, and the underlying scenario for measuring the task generalization ability of the schema prompt. To test the task generalization ability on various NLP tasks at scale, we use 30 publicly available benchmark NLP tasks, belonging to 8 formats (e.g., QA, NLI, Summarization, etc.) for our experiment. As the task taxonomy shown in Fig. 3 we select several tasks (marked in blue) for multi-task prompted pre-training, and take the rest tasks (marked in yellow) that are unseen during pre-training for downstream evaluation.

**Rationale for Task Taxonomy.** The underlying reasons for using this taxonomy criterion are listed as follows. (1) In most real-world applications, model adaptation to an unseen task (with new data distribution or domain knowledge) is a much more frequent practice than adapting to a completely new format type (like QA or NLI). (2) Since Schema Prompt-based pre-training helps the model in learning prior knowledge about input components and task attributes, pre-training and evaluation on the similar format type is the best way to utilize the learned knowledge. It worth noting that we adopt this setup (generalization to unseen tasks with seen formats) for our main experiment (§ 3.2). We further conduct comprehensive experiments to explore the generalization ability of SchemaPro to unseen format (unseen tasks with unseen format), as detailed in § 3.4 and Appendix A.
The whole paradigm of adopting schema prompt for task generalization consists of following procedures. We first reformulate the inputs and outputs for each task using the unified schema prompt, and construct the mixed schema-based prompted pre-training corpus. After pre-training corpus construction, we pre-train a unified encoder-decoder model together with learnable parameters residing in the schema prompt. At this end, both the commonly shared knowledge across tasks and the semantic meaning of schema prompt are learned as a prior. For evaluating the task generalization ability, we measure the effectiveness of the schema prompt on tasks unseen during pre-training, under both the zero-shot testing and few-shot learning settings. The zero-shot testing setting evaluates the zero-shot generalization to unseen task while the few-shot learning setting aims to measure the effectiveness and performance of low-resource model adaptation to a newly involved task.

3 Experiments

3.1 Experimental Setup

Model Architecture  We set T5 (Raffel et al., 2020b) as the backbone of the encoder-decoder model. T5 is a strong Transformer-based language model that is pre-trained with C4. We adopt google/t5-v1_1-base from HuggingFace Transformers (Wolf et al., 2020) which is only pre-trained on C4 excluding any supervised data.

Training  Our model, namely SchemaPro, is trained with the training mixture as described in Section 2.3. To balance the number of instances in datasets, we set a constraint to each dataset in which the maximum number of training instances should be smaller than 700,000. It is worth noting that the learnable parameters in the schema prompt are learned together with the parameters of T5. The groups of soft key prompts are different and independent for different component types. Similarly, the format/task/output-specific values (also learnable soft prompts) are also independent for different format/task/output types. The detailed hyper-parameters and the dimension of the soft key prompts and special task-attributed value prompts are given in Appendix B.

Evaluation  We evaluate the task generalization ability on the unseen evaluation tasks (i.e., 16 yellow tasks in Fig. 3) under both zero-shot testing and few-shot learning settings. During few-shot learning, we adopt standard few-shot learning strategy that utilizes 32 randomly selected instances from each task for low-resource model adaptation. We evaluate the performance on the validation set of each task, or the test set if the validation set is not available. For the soft prompts corresponding to each common format/output type and soft key prompts that are seen during training, we directly initialize these learned prompts for evaluation. Since the task is unseen during training, the value (prompts) under the [Task] key will be randomly initialized.

Metrics  For the task belonging to “Extractive QA” that requires to extract an answer from the passage, we adopt commonly used exact match (EM) as the evaluation metric. For the tasks required to generate a free-formed description from the given context (e.g., “Summarization”), we adopt
Table 1: Main results on 16 evaluation tasks belonging to 8 formats, under both zero-shot testing and few-shot learning settings.

| Task          | Metric | Dataset            | Zero-shot | Few-shot | Zero-shot | Few-shot |
|---------------|--------|--------------------|-----------|----------|-----------|----------|
| MultiQA       | Acc.   | DREAM              | 47.16     | 43.14    | 58.24     | 54.75    |
|               |        | PIQA               | 49.62     | 49.62    | 58.32     | 54.95    |
|               |        | RACE               | 31.96     | 37.44    | 42.05     | 35.70    |
|               |        | WikiHop            | 14.37     | 19.92    | 16.37     | 17.17    |
| Extractive QA | EM     | ROESP              | 30.45     | 28.85    | 37.32     | 47.09    |
|               |        | Adversarial QA     | 20.40     | 18.80    | 24.59     | 22.70    |
| Sentiment     | Acc.   | IMDB               | 92.90     | 93.55    | 95.05     | 93.46    |
|               |        | Rotten Tomatoes    | 57.97     | 69.80    | 89.68     | 86.49    |
| Topic Class.  | Acc.   | TREC               | 27.60     | 18.93    | 24.60     | 72.00    |
| Paraphrase    | Acc.   | MRPC               | 31.62     | 37.42    | 72.30     | 68.63    |
| Summarization | RougeL | Multi News         | 6.42      | 5.88     | 6.16      | 6.62     |
|               |        | Samsam             | 10.70     | 10.15    | 20.32     | 30.39    |
|               |        | Xsum               | 11.81     | 10.41    | 12.86     | 15.28    |
| Sen. Comp.    | Acc.   | COPA               | 61.00     | 61.60    | 62.00     | 66.00    |
| NLI Acc.      | RTE    | RTE                | 75.81     | 72.68    | 80.87     | 76.80    |
|               | CB     | CB                 | 83.93     | 68.78    | 85.71     | 85.71    |
| Average       | -      | -                  | 40.86     | 40.12    | 49.15     | 52.11    |

Rouge-L as the evaluation metric. For the rest tasks that involve choosing the best answer from several given candidate options (e.g., “Multiple Choice QA”, “Topic Classification”, etc.), we adopt accuracy as the metric. To calculate the scores of options for the classification tasks, we follow Sanh et al. (2021) and take the log-likelihood of each option as the score for options ranking, and select the option with the highest log-likelihood as the final answer.

Baselines In this work, we mainly target at comparing the task generalization ability between the NL prompt and schema prompt in the multi-task learning paradigm. Therefore, we adopt the reliable NL prompts source collected by T0 (Sanh et al., 2021), which introduces the most relevant and powerful NL prompted-based multi-task pre-training method. T0 adopts a crowd-sourcing platform to collect human-written NL prompts as templates to reformulate inputs and outputs of different tasks, and performs multi-task prompted pre-training. It collects a diverse set of NL prompts for each task, and the resulted collection is noted as Public Pool of Prompts (P3), which is mostly publicly available. Therefore, we pretrain two NL prompt-based baselines (NLPro-single and NLPro-multi) using P3 for us to directly compare the effectiveness between the NL prompt and the schema prompt in task generalization. Note that NLPro is different from T0 in the task taxonomy and model size. We use the same hyper-parameters and same supervisions as our method for fair comparison. (1) NLPro-single: In this variant, we adopt a single NL-prompt from P3 to reformulate each task completely. We randomly select the prompt from the collections for each task.

(2) NLPro-multi: To increase the diversity of NL prompts and improve the consistency with the original settings in T0, we also adopt multiple prompts (denoted as prompt_number) for each task in the pre-training mixture. During pre-training, we split each training dataset randomly into prompt_number parts, and formulate each part with the corresponding prompt. We set maximum prompt_number as 3 per task for training. During Evaluation, we report the averaged scores of all single tested prompts.

3.2 Main Results

Zero-shot testing and few-shot learning results on 16 unseen tasks from 8 formats are shown in Table 1. Our observations are listed as follows:

1. We don’t repeat the whole dataset for each prompt in training because we want to avoid the bias of data augmentation for fair comparison.
2. To further explore whether schema prompt is beneficial for unseen formats, we also experiment with task taxonomy that training and evaluation are separately conducted on different formats, and report results on Appendix B.

3. We don’t repeat the whole dataset for each prompt in training because we want to avoid the bias of data augmentation for fair comparison.

4. To further explore whether schema prompt is beneficial for unseen formats, we also experiment with task taxonomy that training and evaluation are separately conducted on different formats, and report results on Appendix B.
Our approach SchemaPro outperforms NL prompt-based methods on 15 out of 16 tasks. On average, SchemaPro significantly improves the zero-shot testing and few-shot learning performance by 8.29% and 4.85% respectively, demonstrating better task generalization capability than NL prompt.

- SchemaPro enables better modeling the transferable knowledge across different tasks because it helps the model to explicitly identify the components with learnable key indicators and thus can learn the general semantics of component types.
- The format/task-specific values customize the knowledge specialized for each format type and task, which is essential in helping the model to restore the knowledge required for each task, and better discriminating them.
- NLPro-single and NLPro-multi results exhibit large performance variance using different NL prompts in many tasks, which indicates that various NL prompts may lead to instability when adapting to unseen tasks [Sanh et al. (2021)].

3.3 Ablation Study

To evaluate the effectiveness of involving learnable key indicators and task-attribute specific components (i.e., Task, Format) as learnable key-value pairs into the schema prompt, we conduct three ablation experiments: (1) removing the format-specific key-value (SchemaPro w/o F); (2) removing the task-specific key-value (SchemaPro w/o T); (3) removing the learnable key indicator (SchemaPro w/o K). We report results on 8 unseen tasks under both zero-shot and few-shot settings in Table 2.

**Effect of Format-specific Prompt**  Removing format-specific prompt leads to significant performance drop, showing that format-specific prompt enables learning format-specific knowledge during multi-task pre-training and provides guidance to the downstream tasks.

**Effect of Task-specific Prompt**  Removing task-specific performance prompt largely harms the performance on all tasks under all settings, especially in the few-shot learning settings. This observation verifies that it is important to record the specialized knowledge for each task, as different tasks require different kinds of knowledge (e.g., "commonsense reasoning") or have different data distribution. Noting that the effect of format prompt is more significant than task prompt in the zero-shot setting, because the format-specific knowledge is already learned during pre-training and task knowledge is unknown for the unseen task without few-shot training. However, the task prompt is helpful in discriminating different tasks (even a new task), which is beneficial for zero-shot task generalization.

**Effect of Learnable Key Prompts**  Removing the special key prompts from the schema prompt harms the model in terms of identifying the different input components of each task. Therefore, it performs worse because it is harder to model the common knowledge of tasks and discriminate different components.

Table 2: Ablation study under zero-shot testing and few-shot learning settings on 8 datasets. “w/o F/T” indicates eliminating the format/task components from the schema prompt. “w/o K” indicates eliminating learnable key prompts.

| Setting  | Model   | MultiChoiceQA | Extractive QA | Sentiment | Par. | Summary | NLI | Avg. |
|----------|---------|---------------|---------------|-----------|------|---------|-----|------|
|          |         | DREAM WikiHop | ROPEs Adv. QA | IMDB      | MRPC | Samsam  | RTE |      |
| Zero-shot| SchemaPro | 58.2          | 37.3          | 95.1      | 72.3 | 20.3    | 80.9| 50.6 |
|          | - w/o F  | 55.3          | 31.4          | 92.8      | 68.9 | 16.0    | 75.5| 47.1 |
|          | - w/o T  | 56.6          | 32.9          | 93.8      | 70.8 | 17.7    | 76.5| 48.3 |
|          | - w/o K  | 56.8          | 30.2          | 93.7      | 70.6 | 19.0    | 75.3| 47.6 |
| Few-shot | SchemaPro | 59.7          | 50.6          | 95.9      | 75.5 | 32.9    | 83.0| 56.9 |
|          | - w/o F  | 58.4          | 49.2          | 94.9      | 71.6 | 32.0    | 78.3| 54.9 |
|          | - w/o T  | 57.2          | 44.8          | 94.9      | 72.8 | 32.1    | 79.6| 54.3 |
|          | - w/o K  | 57.4          | 43.5          | 94.8      | 71.5 | 32.1    | 79.0| 53.8 |
Table 3: Task compositionality experiment. The model is trained on the combination of 3 datasets (QuoRef, DuoRC, ROPES) from extractive QA task with components “{passage, question}”, and 3 classification datasets (AgNews, DBPedia, IMDB) with components “{passage, options}”. The model is evaluated on 6 multiple choice QA datasets with compositional components “[passage, question, options]” from the learned tasks, to explore the compositionality of tasks.

| Setting   | Prompt Type     | Dataset          |
|-----------|-----------------|------------------|
|           |                 | DREAM  | PIQA   | RACE   | WikiHop | Cosmos QA | Social IQA |
| Zero-shot | NL Prompt       | 34.2   | 51.9   | 22.1   | 12.9    | 25.1      | 33.9       |
|           | SchemaPro       | 35.1   | 49.5   | 27.1   | 11.8    | 28.0      | 34.6       |
| Few-shot  | NL Prompt       | 35.8   | 50.3   | 26.6   | 13.2    | 30.8      | 37.6       |
|           | SchemaPro       | 39.3   | 51.4   | 30.9   | 25.0    | 38.4      | 41.0       |

3.4 Task Compositionality with Key Prompts

In this part, we target on exploring whether identifying the semantic meaning of different components (keys) can actually benefit task generalization. We design a scenario to investigate the effect of key prompts: "Once SchemaPro learns two formats A and B with components types $K_A$ and $K_B$, can it generalize the learned semantic meaning of components $K_A$ and $K_B$ to an unseen format $C$ with compositional components $K_C = K_A \cup K_B$, with only a few examples?"

To answer this question, we set a specific scenario of task compositionality: we utilize tasks belonging to two formats A and B for model training, and evaluate on an unseen format with compositional components from these two formats. Specifically, we train our model with the combinations of 3 tasks (i.e., QuoRef, DuoRC and ROPES) belonging to format $A = \text{Extractive QA}$ with components $K_A = \{\text{passage, question}\}$, and 3 tasks (i.e., AgNews, DBPedia and IMDB) belonging to format $B = \text{Text Classification}$ with components $K_B = \{\text{passage, options}\}$. During evaluation, we adopt 6 tasks (i.e., DREAM, PIQA, RACE, WikiHop, Cosmos QA and Social IQA) belonging to new format $C = \text{Multiple Choice QA}$, with compositional components $K_C = K_A \cup K_B = \{\text{passage, question, options}\}$.

We compare SchemaPro with NL prompt on the compositional scenario. As the results shown in Table 3, schema prompt achieves better performance than NL prompt in 4 of 6 held-out compositional tasks under the zero-shot testing setting, and significantly outperforms NL prompt in all tasks under few-shot learning setting. This supports our hypothesis that learning semantics of components in an explicit way can benefit task generalization, even for an unseen format type. Since our method has already explicitly learned the semantics of components $K_A$ and $K_B$, we can teach the model about their compositional semantics with only a few examples, to make faster and better generalization. Noting that the relatively weak zero-shot performance is reasonable, because NL prompt can provide additional human-written instruction to tell the model how to solve a task belonging to a completely unseen format type with unknown reasoning skills.

3.5 Full-data Fine-tuning

The aforementioned experiments demonstrate better task generalization ability of schema prompt in the low resource settings. We are still curious about whether the schema prompt is beneficial when there is enough supervised training data for downstream tasks? To answer this question, we also conduct experiments under the full-data fine-tuning setting on 7 downstream tasks that are unseen during multi-task pre-training, and report results in Table 4. As shown in the table, schema prompt demonstrates better performance than NL prompt (NLPro-single) on these 7 downstream evaluation tasks. This observation shows that the shared knowledge and the discriminating ability of different components and task attributes modeled by the schema prompt are still essential for model learning, even there is enough supervised data. This finding also indicates broadening potential applications of the schema prompt as a unified input schema.
Table 4: Results on 7 downstream tasks under the full-data fine-tuning setting.

| Setting       | Prompt Type  | Task                  | DREAM | RACE | ROPES | Adversarial QA | Rotten Tomatoes | Samsun | COPA |
|---------------|--------------|-----------------------|-------|------|-------|----------------|-----------------|--------|------|
| Full-Data NL Prompt | 69.4 | 61.2 | 53.8 | 33.7 | 88.5 | 40.2 | 71.0 |
| Full-Data SchemaPro | 72.4 | 70.1 | 54.8 | 35.4 | 90.7 | 41.0 | 73.0 |

4 Related Work

Prompt-learning (Liu et al., 2021a) on pre-trained language models (Devlin et al., 2019; Raffel et al., 2020a; Brown et al., 2020; Han et al., 2021) has demonstrated effectiveness on a wide range of NLP tasks under the few-shot and zero-shot settings. The primal prompting adapted by GPT-3 (Brown et al., 2020) does not involve parameter updates, but simply introduces additional contexts to perform “in-context learning” to obtain promising results in low data scenarios. Then a subsequent series of methods show that projecting downstream tasks to pre-training tasks via manually written or automatically generated prompts is effective on pre-trained language models across different sizes and structures (Shin et al., 2020; Schick & Schütze, 2021a,b; Gao et al., 2021; Le Scao & Rush, 2021; Ding et al., 2021), especially when labeled data is insufficient. Prompts are not necessarily textual, some works develop prompts in continuous space (Li & Liang, 2021; Zhong et al., 2021; Lester et al., 2021; Liu et al., 2021c; Qin et al., 2021; Liu et al., 2021b) and it is found that such soft prompts could not only represent vague semantics, but also serve as a parameter-efficient method (He et al., 2021; Ding et al., 2022) to fine-tune pre-trained language models. In addition to evaluation on separate NLP tasks, prompting is also explored in multi-task scenarios (Sanh et al., 2021; Xu et al., 2022). ProQA (Zhong et al., 2022) adopts structurally-designed prompt to unify QA tasks. However, it targets at using minimal supervision to build a general QA model and only focuses on QA tasks, while our work focuses on improving task generalization ability for general NLP tasks at scale and involves more complicated task schemas. T0 (Sanh et al., 2021) trains a sequence-to-sequence model with a number of human-written prompts guided by professional crowd-source instructions and shows that such a model could show remarkable capability of zero-shot generalization on held-out NLP tasks. Our work also explores low-resource prompt-based task generalization, but based on an automatically constructing strategy according to the data schemas. In terms of the constructing process, our approach relies only on some explicit information of datasets, thus eliminating a large amount of overhead in writing diverse prompts. It is also worth noting that although the cost of writing a prompt is greatly reduced, our schema differs from T0’s due to the fact that this automatically constructed schema prompt requires knowledge transferring across tasks under a broad category.

5 Discussion

We target on discussing the limitations of our approach, and exploring the potential future direction of SchemaPro to shed a light on future directions.

As we mentioned before, SchemaPro is capable of modeling common knowledge shared across tasks by learning explicit prior knowledge about shared schema and task attributes (i.e., format and output), and enhancing task generalization ability. Intuitively, our model will be weakened in task generalization to a completely new format type with no ever presented component types. In this case, natural language prompts can provide some human-written guidance to hint the model in problem solving.

Furthermore, we point out some interesting future directions for extending SchemaPro. Firstly, SchemaPro can be adopted to more modalities. Multi-modal tasks can involve complex input schema with components from different modalities, e.g., video, language, image, audio, etc. SchemaPro can be utilized to flexibly compose inputs from different modalities and discriminate their variances. Secondly, SchemaPro can be extended to store supported knowledge as a new component. Solving many realistic problems requires to retrieve and use knowledge from different domains (Zhong et al., 2019; Hu et al., 2021) (e.g., tables, passages, knowledge graphs). Knowledge type and retrieved knowledge can also be extended as learnable components, to share knowledge across domains and also discriminate them. Moreover, SchemaPro can have hierarchical structure. That means, the
value in it can have nested components to store fine-grained information. For example, we can parse POS tags or Entity type for a textual value, and take them as nested components under this value, to give fine-grained clues to the model.

6 Conclusion

This paper improves task generalization ability of NLP tasks, with a unified schema-based prompting method - SchemaPro, which is capable of automatically constructing the prompt according to the task schema, modeling the shared knowledge across tasks, and simultaneously capturing their specialties. Our approach SchemaPro conducts schema prompt-based multitask pre-training and achieves strong zero-shot and few-shot performance on 16 unseen downstream tasks. Further analyses demonstrate the effectiveness of each component residing in the schema prompt, shows that it is more flexible in model adaptation to compositional tasks, and has better performance in the full-data setting.

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A Out-of-Format Analysis

In this part, we target to investigate the effectiveness of the schema prompt during zero-shot testing on a completely unseen format type. The task taxonomy of the out-of-format analysis is shown in Fig. 4. We select tasks belongs to “Sentence Completion” and “Natural Language Inference” for evaluation, and the rest tasks are used for multi-task pre-training. We compare with NLPro-multi, and report the averaged performance (NLPro-multi (AVG)), and the standard deviation of all the results (NLPro-multi (STD)) of all the tested NL prompts. The results are reported in Table 5. Noting that to better enhance prior knowledge learned from SchemaPro, we use component types \{sentence1, sentence2\} to represent the task schema of Sentence Completion, NLI and Paraphrase. It can be observed that SchemaPro still outperforms NLPro-multi in most of the tasks, excluding RTE, showing that SchemaPro is still more effective in modeling the common knowledge shared across
formats. Moreover, it can be also observed that the standard deviation of results on the all tested NL prompts in NLPro-multi is high for many tasks (e.g., 13.47% for CB task, and 8.99% for COPA task). This finding also shows that different NL prompts may lead to larger performance variance on downstream tasks.

| Method         | Hellaswag | RTE | CB  | COPA | ANLI |
|----------------|-----------|-----|-----|------|------|
| SchemaPro      | 31.14     | 58.6| 62.5| 63   | 33.6 |
| NLPro-multi (AVG) | 27.28     | 62.5| 30.95| 61.6 | 31.71|
| NLPro-multi (STD) | 0.99      | 6.69| 13.47| 8.99 | 1.2  |

Table 5: The results of zero-shot testing on tasks belongs to unseen formats. NLPro-multi (AVG) is the averaged performance, and NLPro-multi (STD) is the standard deviation of all the tested NL prompts.

B Implementation Details

B.1 Multi-task Pre-training

During multi-task pre-training, we formulate each task with the schema prompt, and construct the multi-task pre-training corpus. We map each type of key indicator or each format/task/output-specific value into a specific group of learnable soft prompts, and randomly initialize their representations. The parameters of all the groups of key/value prompts are learned together with the model parameters of T5. We train the model with 10 epochs, and evaluate with the last checkpoint, to be more consistent with the setting in real zero-shot testing scenario. We use T5-v1_1-base as the model backbone, and set learning rate as 1e-4, batch size as 4 per gpu, gradient accumulation steps as 10, respectively. We adopt 8 V100 GPUs for pre-training.

B.2 Zero-shot Testing

During zero-shot testing, the key problem is how to initialize the corresponding key-value prompts for an unseen task. After being pre-trained by the mixture of the pre-training tasks, the semantic representations of every key indicators and every format/output-specific values are leaned beforehand. Therefore, we reload the corresponding soft prompts for these elements. For the soft prompts correspond to the task-specific values, we randomly initialize a group of new task-specific prompts, to inform the model that it is a newly involved task.
B.3 Few-shot Learning

During few-shot learning, we begin by initializing the schema prompt for each task following the same way as in the zero-shot setting. Then, we adopt a standard few-shot learning strategy that randomly selects 32 examples on the downstream task for few-shot learning. In the few-shot learning procedure, the soft prompts of the task-specific value are learned for each downstream task. We set learning rate as 1e-5, batch size as 1 per GPU, gradient accumulation steps as 1, and training steps as 800.

C Data Statistic

The data statistic of all the tasks is shown in Table 6.

| Format | Task            | # Train  | # Evaluation | # Test  |
|--------|-----------------|----------|--------------|---------|
|        | Multiple Choice QA |          |              |         |
|        | DREAM           | 6,116    | 2,040        | 2,041   |
|        | Social IQA      | 33,410   | 1,954        |         |
|        | Cosmos QA       | 25,262   | 2,985        | 6,963   |
|        | PIQA            | 16,113   | 1,838        | 3,084   |
|        | RACE            | 62,445   | 3,451        | 3,498   |
|        | Wiki Hop        | 43,738   | 5,129        |         |
|        |                 |          |              |         |
|        | Extractive QA   |          |              |         |
|        | Quoref          | 19,399   | 2,418        |         |
|        | DuoRC (ParaphraseRC) |       | 69,524    | 15,591  | 15,857 |
|        | DuoRC (SelfRC)  | 60,721   | 12,961      | 12,559  |
|        | Ropes           | 10,924   | 1,688       |         |
|        | Adversarial QA  | 10,000   | 1,000       |         |
|        |                 |          |              |         |
|        | Sentiment Analysis |      |              |         |
|        | Amazon          | 3,600,000| 40,000       |         |
|        | IMDB            | 25,000   | 25,000       |         |
|        | Yelp            | 650,000  | 50,000       |         |
|        | Rotten Tomatoes | 8,530    | 1,066       | 1,066   |
|        |                 |          |              |         |
|        | Topic Classification |     |              |         |
|        | DBpedia         | 560,000  | 70,000       |         |
|        | AG News         | 120,000  | 7,600        |         |
|        | TREC            | 5,452    | 500          |         |
|        |                 |          |              |         |
|        | Summarization   |          |              |         |
|        | CNN Daily Mail  | 287,113  | 13,368       | 11,490  |
|        | Gigaword        | 3,803,957| 189,651      | 1,951   |
|        | Multi News      | 44,972   | 5,622        | 5,622   |
|        | Samsun          | 14,732   | 818          | 819     |
|        | Xsum            | 204,045  | 11,332      | 11,334  |
|        |                 |          |              |         |
|        | Paraphrase Identification | |         |         |
|        | MRPC            | 3,668    | 408          | 1,725   |
|        | QQP             | 363,846  | 40,430      | 390,965 |
|        | PAWS            | 21,829   | 3,539       | 3,536   |
|        |                 |          |              |         |
|        | Sentence Completion |      |              |         |
|        | COPA            | 400      | 100         | 500     |
|        | HellaSwag       | 39,905   | 10,042      | 10,003  |
|        |                 |          |              |         |
|        | Natural Language Inference |   |              |         |
|        | ANLI (R1)       | 16,946   | 1,000       | 1,000   |
|        | ANLI (R2)       | 45,460   | 1,000       | 1,000   |
|        | ANLI (R3)       | 100,459  | 1,200       | 1,200   |
|        | RTE             | 2,490    | 277         | 3,000   |
|        | CB              | 250      | 56          | 250     |

D Schema Prompt Formulated Examples

In this part, we show the thorough schema promoted examples for all the task types in Fig. 5.
| Format                   | NLI                                      | Sentiment Analysis                                      | Summarization                                      |
|--------------------------|------------------------------------------|----------------------------------------------------------|-----------------------------------------------------|
| **Task Input Schema**    | (“premise”: Dana Reeve…,                | (“passage”: a thoughtful,                              | (“passage”: The full cost of damage in Newton      |
|                          | “hypothesis”: Christopher had an        | provocative, humanizing film,                            | Stewart…)                                           |
|                          | accident, “options”: Contra., Entail;)   | “options”: Positive,                                    |                                                     |
| **Schema Prompted Input**| [Format] [NLI] [Task] [RTE]              | [Task] [IMDB]                                            |                                                     |
|                          | [Premise] Dana Reeve …                   | [Passage] a thoughtful …                                 |                                                     |
|                          | [Hypothesis] Christopher …               | [Options] Positive,                                      |                                                     |
|                          | [Options] Contradiction, Entailment      | [Output] [Sentiment]                                     |                                                     |
|                          | [Output] [Class]                         |                                                          |                                                     |
| **Format**               | Multi-choice QA                          | Extractive QA                                            | Topic Classification                                |
| **Task Input Schema**    | (“passage”: The rain continued…,        | (“passage”: …Immediately behind the basilica is the Grotto, | (“passage”: The Google auction begins on Friday An auction of shares in Google…) |
|                          | “question”: What did Nancy…? ,          | “question”: What is the Grotto at Notre Dame?)           |                                                     |
|                          | “options”: Opt1, Opt2, Opt3, Opt4}       |                                                          |                                                     |
| **Schema Prompted Input**| [Format] [MultiQA] [Task] [RACE]         | [Task] [SQuAD]                                           |                                                     |
|                          | [Passages] The rain continued…          | [Passage] Immediately behind the basilica is the Grotto, |                                                     |
|                          | [Question] What did Nancy…?             | “question”: What is the Grotto at Notre Dame?)           |                                                     |
|                          | [Options] Opt1, Opt2, Opt3, Opt4}        | [Output] [Answer]                                        |                                                     |
|                          | [Output] [Class]                         |                                                          |                                                     |
| **Format**               | Sentence Completion                      | Paraphrase                                               |                                                     |
| **Task Input Schema**    | (“Passage”: The man writes over the     | (“text1”: They had published an advertisement on the Internet, |                                                     |
|                          | snow covering the window …              | “text2”: The ship’s owners had published an advertisement.) |                                                     |
|                          | “Endings”: end1, end2, end3, end4}      |                                                          |                                                     |
| **Schema Prompted Input**| [Format] [Sentence Completion]           | [Task] [MRPC]                                            |                                                     |
|                          | [Task] [HellaSwag]                       | [Text] They had published …                              |                                                     |
|                          | [Passage] The man writes over …         | [Text2] The ship’s owners …                              |                                                     |
|                          | [Options] end1, end2, end3, end4}       | [Options] Equal, Not_Equal                                |                                                     |
|                          | [Output] [Class]                         |                                                          |                                                     |

Figure 5: Examples for schema prompted inputs of all task types.