Exploring Format Consistency for Instruction Tuning

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Abstract

Instruction tuning has emerged as a promising approach to enhancing large language models in following human instructions. It is shown that increasing the diversity and number of instructions in the training data can consistently enhance generalization performance, which facilitates a recent endeavor to collect various instructions and integrate existing instruction tuning datasets into larger collections. However, different users have their unique ways of expressing instructions, and there often exist variations across different datasets in the instruction styles and formats, i.e., format inconsistency. In this work, we study how format inconsistency may impact the performance of instruction tuning. We propose a framework called "Unified Instruction Tuning" (UIT), which calls OpenAI APIs for automatic format transfer among different instruction tuning datasets. We show that UIT successfully improves the generalization performance on unseen instructions, which highlights the importance of format consistency for instruction tuning. To make the UIT framework more practical, we further propose a novel perplexity-based denoising method to reduce the noise of automatic format transfer. We also train a smaller offline model that achieves comparable format transfer capability to OpenAI APIs to reduce costs in practice. The codes and trained models will soon be available.

1 Introduction

Recently, instruction tuning has gained considerable attention as a potent strategy for enhancing large language models (LLMs) in following human instructions and generating appropriate responses. For instance, by reformulating various NLP tasks with an instruction template, models trained on the converted dataset exhibit powerful capabilities of zero-shot generalization on unseen tasks (Wei et al., 2021). Later studies have demonstrated that instruction tuning is critical to facilitating LLMs in grounding their inner knowledge to diverse real-world scenarios (Ouyang et al., 2022; Iyer et al., 2022; Chung et al., 2022; Ding et al., 2023). Up to now, considerable efforts have been dedicated to creating datasets for instruction tuning (Honovich et al., 2022a; Bach et al., 2022; Wei et al., 2021; Wang et al., 2022b;a; Aribandi et al., 2022) and researchers find that increasing the task diversity (i.e., the number of unique tasks) of the training data can consistently enhance generalization performance (Wang et al., 2022b; Iyer et al., 2022; Longpre et al., 2023). Therefore, the community has witnessed a growing endeavor to collect various instructions and integrate existing instruction tuning datasets into larger collections (Iyer et al., 2022; Longpre et al., 2023; Chung et al., 2022; Zhou et al., 2023).

While previous works strive to increase **task diversity** and merge existing instruction tuning datasets, they typically ignore the **format consistency** among these datasets. More specifically, different users have their unique ways of expressing instructions, even if these instructions correspond to the same intent. Hence, there often exist variations across different datasets in the instruction styles and formats, which is dubbed as the format inconsistency issue. Take the case of a summarization task, the instruction can be as detailed as "*In this task, you are given a conversation, and your task is to generate a summary... Input: ... Output: ...*" in Ni-v2 (Wang et al., 2022b) or simply composed of a few keywords, e.g., "*Summarize: ...*" in CrossFit (Ye et al., 2021b). Due to the format inconsistency issue, fine-tuned LLMs may have difficulty in handling unseen instructions in a different format at the test time, exhibiting poor out-of-distribution (OOD) generalization. Hence, before directly merging diverse datasets from various sources and performing multi-task training (i.e.,

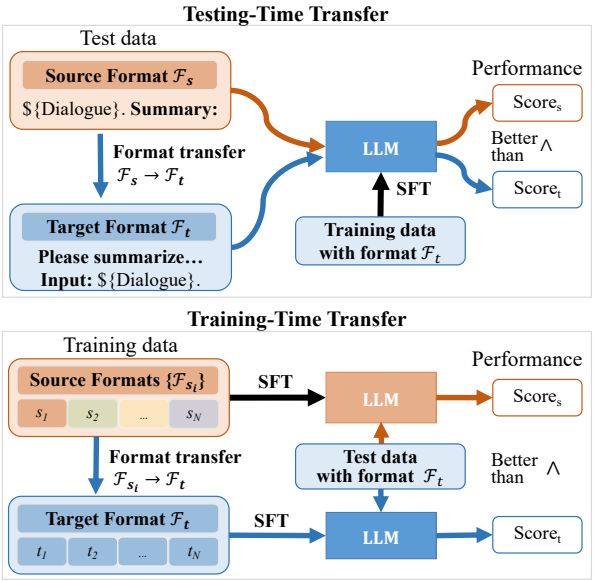

Figure 1: The proposed format transfer framework, which is applied to two settings: testing-time transfer and training-time transfer. $s_1, \cdots, s_N$ denote the training data in the original instruction format, $t_1, \cdots, t_N$ denote all the transferred training data in target format.

the common practice), it is essential to conduct a comprehensive study of how format inconsistency may impact the performance of instruction tuning and whether mitigating such inconsistency could enhance the generalization.

However, unifying the format across different datasets is not easy. First, instructions are inherently diverse and nuanced, and the vast range of possible expressions makes it challenging to devise a fixed rule for format transfer. Second, standardizing formats can sometimes inadvertently change the meaning of the original instructions. This is particularly problematic for complex tasks where the instruction's wording and style are crucial to correctly guiding the model behavior. In this paper, we introduce a format transfer framework, **Unified Instruction Tuning (UIT)** (Figure 1) to explore the effects of format consistency. Specifically, we use OpenAI GPT3.5[1] for automatic instruction format transfer. Leveraging its powerful in-context learning capabilities, GPT3.5 can successfully transfer the instruction from a source format to a target format based on only a few handcrafted examples. Then we analyze how format inconsistency could affect generalization under two settings: (1) testing-time setting, which simulates the format inconsistency between the training data and the testing data, and (2) training-time setting, which simulates the format inconsistency among different sources of instructions in the training data. We perform analysis across five benchmarks and show that our method successfully mitigates the format inconsistency issue and improves the generalization performance on unseen instructions in both settings.

Despite its simplicity and performance, the above framework encounters two practical challenges. To begin with, the converted instructions are not perfect as human-written ones and sometimes involve noises. For instance, an auto-converted instruction may express a slightly different meaning than the original one. To address this issue, we propose a novel perplexity-based denoising strategy which samples multiple possible conversions of a source instruction and then filters those low-quality ones based on perplexity. Experimental results reveal that this strategy effectively reduces the noises of format transfer and improves robustness and performance. Second, converting large-scale instructions via OpenAI API can result in substantial costs for API calls, which is infeasible in practice. To this end, we propose to learn an offline model for format transfer by distilling from GPT3.5. We demonstrate that with a few examples generated by GPT3.5, a much smaller model can be trained to achieve almost equivalent performance in format transfer, which saves the costs for API calls in practice.

[1] `https://platform.openai.com/docs/models/gpt-3-5`

In general, our findings sheds light on an essential but previously overlooked aspect, i.e., format consistency, for instruction tuning. We envision our research could inspire more efforts in advancing the instruction tuning methodologies for LLMs.

Table 1: A comparison of representative instruction tuning datasets of different instruction formats. "Num.", "Cate.", "Exp.", "Inst.", "Unnat-Inst", refer to Number, Category, Example, Instruction, and unnatural-instructions respectively.

Resource	Task Num.	Cate. Num.	Total Exp.	Inst. format
Ni-v2 (Wang et al., 2022b)	1616	76	5M	task-level
Flan 2021 (Wei et al., 2021)	62	12	4.4M	instance-level
CrossFit (Ye et al., 2021a)	159	13	7.1M	keywords-level
P3 (Bach et al., 2022)	62	13	12M	instance-level
Unnat-Inst (Honovich et al., 2022a)	117	–	64k	task-level
OPT-IML (Iyer et al., 2022)	1545	93	17.9M	mixed
Flan 2022 (Longpre et al., 2023)	1836	162	15M	mixed

2 Related Work

Instruction Tuning Instruction tuning regulates LLMs to accurately comprehend and interpret natural language instructions. Prior works in this field focus on reformulating NLP tasks using the templates of instructions. Wei et al. (2021) pioneered to show that fine-tuning LLMs on large collections of tasks formatted in instructions enables the model to generalize to unseen tasks in a zero-shot manner. Since then, there is a surge of interest in manually constructing high-quality instruction datasets by first reformulating the formats of existing NLP datasets and then merging them (Mishra et al., 2022; Bach et al., 2022; Ye et al., 2021b; Ouyang et al., 2022). Another line of study (Longpre et al., 2023; Iyer et al., 2022) demonstrates that scaling the number of training tasks and task diversity can further enhance the model's generalization performance. However, all these works directly mix all the existing instruction datasets while ignoring the potential issue of format inconsistency. Instead of investigating the number and diversity of training instructions, we instead explore an under-explored facet, i.e., the instruction format of instruction tuning, and investigate its impact on generalization.

Data Augmentation Besides manually curating instruction tuning datasets, Honovich et al. (2022a) show that fine-tuning LLMs with machine-generated instruction tuning data achieves excellent performance compared with human-written data, indicating that data augmentation is an effective method to enhance the data quantity and task diversity, which overcomes the time-consuming issues of human annotation. Recently, Taori et al. (2023); Peng et al. (2023); Ding et al. (2023) adopt machine-annotation method (Wang et al., 2022a) to generate real-world human instructions (rather than instructions that describe NLP tasks) and model responses based on powerful LLMs such as ChatGPT. Similarly, in this paper, we also leverage LLMs for automatic format transfer and data augmentation. Since real-world instructions are quite diverse and hard to annotate their formats, we instead focus on instructions that describe NLP tasks to rigorously study the effects of instruction format. We believe the derived findings can potentially be applied to real-world instructions in the future.

Synthetic Data Denoising Generative models are commonly utilized for data augmentation (Taori et al., 2023). However, these synthetic datasets are not always as reliable as those human-annotated ones, and filtering out noisy examples can boost the model performance (Le Bras et al., 2020). Recent studies have suggested different approaches for denoising. For instance, Yang et al. (2020); Fang et al. (2022) adopted influence functions (Koh & Liang, 2017) to evaluate the quality of the synthetic data; Wang et al. (2022c) employ the NLU Consistency Filtering (Anaby-Tavor et al., 2020) to filter out low-quality samples. In our research, we utilized LLMs for instruction format transfer, which may introduce noise throughout the process.

To overcome this challenge, we adopted a simple and effective perplexity scoring strategy to denoise our auto-constructed dataset (section 5).

3 Instruction Format Inconsistency

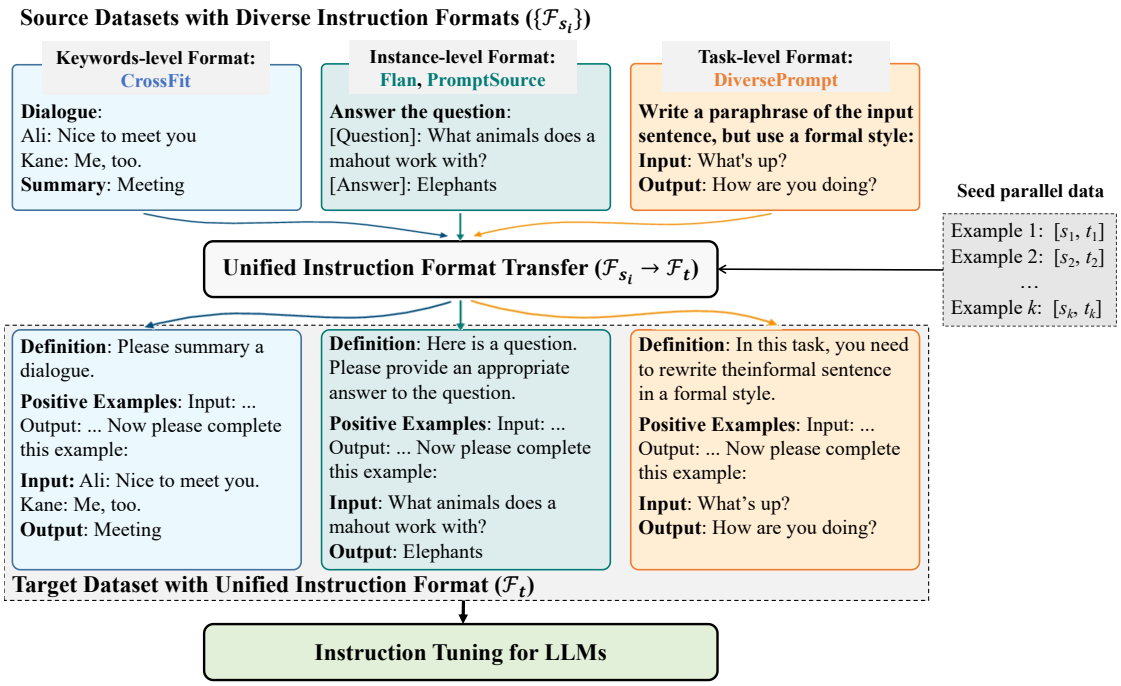

Figure 2: Transferring instruction formats with UIT. The existing instruction formats exhibit variations across different datasets, which can be classified into three distinct hierarchical formats: Task level, Instance level, and Keywords level. UIT leverages seed parallel data to conduct format transfer across different formats automatically.

As outlined in Iyer et al. (2022), existing instruction formats exhibit variations across different datasets, which can be classified into three distinct hierarchical levels: Task-level format, Instance-level format, and Keywords-level format (as illustrated in Figure 2). We present an overview of existing instruction tuning datasets based on instruction formats in Table 1.

- **Task-level Format** encompasses a comprehensive definition of a task and may include supplementary information such as positive or negative examples and explanations of the examples. Representative datasets are Ni-v2 (Wang et al., 2022b), Unnatural Instructions (Honovich et al., 2022a), and Alpaca (Taori et al., 2023).
- **Instance-level Format** employs succinct templates that are customized for each individual example and is occasionally structured in a cloze-style format to elicit the intended output. Representative datasets are Flan (Wei et al., 2021) and PromptSource (Bach et al., 2022).
- **Keywords-level Format** closely resembles the instance-level format, but it limits the instruction templates exclusively to keywords. CrossFit (Ye et al., 2021b) serves as a representative example of a keywords-level dataset.

Compared with task diversity, the effect of format consistency is poorly understood in instruction tuning. We contend that successful instruction understanding and generalization are influenced by both task diversity and format consistency. Task diversity can be enhanced by incorporating as many tasks into the training

Example 1
Source Instruction: Translate to Spanish
Target Instruction: In this task, you are given a sentence in the English language. Your job is to translate the English sentence into the Spanish language.

Example 2
Source Instruction: output the opposite of
Target Instruction: Given an adjective, generate its antonym. An antonym of a word is a word opposite in meaning to it.

Example 3
Source Instruction: Output whether the sentiment of the input sentence is positive or negative.
Target Instruction: Given a review, you need to predict whether the review is good or bad. A negative review is a bad review, and positive/neutral reviews are good reviews.

Example 4
Source Instruction: Rate from 0 (definitely not) to 5 (perfectly) the degree in which both sentences describe the same event.

Target Instruction: Given two sentences related to a specific event or scenario, assign a score from 0 (definitely not) to 5 (perfectly) to indicate the degree in which both sentences describe the same event.

Figure 3: An example of format transfer using GPT3.5, where we prompt the model with 3 parallel examples to generate the target instruction for the 4-th example.

data (e.g., merging existing instruction tuning datasets) as possible. However, it is crucial to note that when merging different datasets for training, the training data originating from different sources often present variations in the instruction formats. When confronted with instructions of unseen inconsistent formats at the test time, the trained model may fail to generalize well and comprehend the intent behind different instructions, showing poor OOD generalization.

4 Framework and Experiments

To mitigate format inconsistency, we propose a format transfer framework, *Unified Instruction Tuning* (UIT), to convert the instruction formats of existing datasets into a unified format.

4.1 Unified Instruction Format Transfer

Denote the target unified instruction format as $\mathcal{F}_t$ and the original instruction format of a source dataset as $\mathcal{F}_s$, we aim to convert $\mathcal{F}_s$ into $\mathcal{F}_t$ to alleviate the OOD generalization in the instruction format. Taking inspiration from Honovich et al. (2022a), we rely on the LLM's in-context learning ability to conduct format transfer in an automatic manner. Specifically, we manually select k seed parallel data $\{[s_1, t_1], \cdots, [s_k, t_k]\}$, where s_i and t_i are the same instance (task) expressed in format $\mathcal{F}_s$ and $\mathcal{F}_t$ respectively. Given a new instance s_{new} with format $\mathcal{F}_s$, we transfer its instruction format into the unified instruction format $\mathcal{F}_t$ via in-context learning as follows:

$$t_{new} = \text{LLM}\left(s_{new}, [s_1, t_1], \cdots, [s_k, t_k]\right), \tag{1}$$

where t_{new} refers to the transferred instance with $\mathcal{F}_t$. We choose `text-davinci-003` (GPT3.5) as the LLM for format transfer. Details of the prompt for format transfer are shown in Figure 3.

4.2 Experiments

Settings To simulate the format inconsistency problem, we design two experimental settings:

- **Testing-time Format Transfer**: the training data is formatted in $\mathcal{F}_t$, while the test data is formatted in $\mathcal{F}_s$. To mitigate the format inconsistency, we convert the instruction format of the test data into $\mathcal{F}_t$, without modifying the training data. This setting is designed to explore the format inconsistency impact between training data and the test data in the inference phase.

- **Training-time Format Transfer**: the training data is mixed with different formats (e.g., both $\mathcal{F}_s$ and $\mathcal{F}_t$), and the testing data is in the format of $\mathcal{F}_t$. Instead of modifying the testing data, here

we convert the training data from format $\mathcal{F}_s$ to $\mathcal{F}_t$. This setting is designed to simulate the format inconsistency of different sources of the training data.

For both settings, we choose T5-LM-xl [2] as our model and use Exact Match (EM) and Rouge-L as evaluation metrics.

Datasets For the testing-time setting, we select Ni-v2 (Wang et al., 2022b) as the training dataset and use DiversePrompt (Honovich et al., 2022b), Flan (Wei et al., 2021), CrossFit (Ye et al., 2021a), and PromptSource (Bach et al., 2022) as the test dataset. We evaluate the tasks that do not appear in the training stage. These tasks are the same as or similar to those in Ni-v2 test set. In Ni-v2, the instruction format incorporates four components: (1) task definition (**D**), (2) positive example (**P**) for demonstration instances with the ground-truth label, (3) negative examples (**N**) for demonstration instances with a false label, and (4) explanations (**E**) that provide detailed explanations for the examples. Different formats refer to distinct combinations of the above components. For example, the **DP** format includes the task definition and positive examples information. In our experiments, we consider four primary formats, namely **DP**, **DPN**, **DPE**, and **DPNE** as the unified instruction format, respectively.

For the training-time setting, we use the training set of Ni-v2 together with Flan, CrossFit, and P3 respectively for training and use the test set of Ni-v2 for evaluation. As Flan, CrossFit, and P3 may contain instances that exist in the test set of Ni-v2, to prevent data leakage, we filter the overlapped data in Flan, CrossFit, and P3 and use the remaining data for training. In this setting, we choose **DP** as the unified instruction format.

Baselines We construct two baselines: (1) **Raw** does not involve any modifications on the instruction format for both training and testing. For instance, we directly test an instance from Flan in its original format using a model trained with Ni-v2 in **DPN** format. (2) **Heuristic** applies manually-designed rules to transfer different instruction formats into the unified one. If the information from the original format matches the corresponding field in the unified format, we fill the unified format with that information. Otherwise, we leave the respective field in the unified format blank. For instance, an instance from Flan can be transferred to the **DPE** format by leaving the *Definition* and *Explanations* fields blank and filling the *Positive Examples* field with randomly selected instances from the Flan training set.

Table 2: Testing-time format transfer experiment with four target unified instruction formats (**DP**, **DPE**, **DPN**, **DPNE**), respectively. We evaluate three methods: (1) raw instructions, transferred instructions based on (2) heuristic rules and (3) our proposed UIT. The training is conducted on Ni-v2 while the testing is conducted on DiversePrompt, FLAN, CrossFit, and PromptSource, respectively.

Format	Method	DiversePrompt		FLAN		CrossFit		PromptSource		Average	
		EM	Rouge-L	EM	Rouge-L	EM	Rouge-L	EM	Rouge-L	EM	Rouge-L
DP	raw	0.1	4.7	11.6	20.8	0.2	3.9	6.6	13.6	4.6	10.8
DPE	raw	0.1	5.0	18.1	27.8	0.3	4.4	14.4	19.2	8.2	14.1
DPN	raw	0.2	5.5	12.0	22.6	0.2	4.5	5.3	11.6	4.4	11.1
DPNE	raw	0.1	5.2	15.2	25.3	0.2	3.8	19.2	23.7	8.7	14.5
DP	heuristic	**34.7**	45.1	31.4	44.8	43.7	56.0	27.3	32.7	34.3	44.6
DPE	heuristic	32.5	43.4	32.0	45.3	41.3	54.2	26.6	31.1	33.1	43.8
DPN	heuristic	30.6	43.5	31.9	45.3	43.5	55.5	29.0	33.9	33.9	44.8
DPNE	heuristic	30.6	43.4	30.7	43.6	42.8	54.6	29.1	33.7	33.4	44.1
DP	unified	34.2	**45.4**	32.6	46.3	49.1	60.1	29.2	34.7	36.3	46.6
DPE	unified	32.9	44.8	33.5	46.9	46.9	58.4	27.8	32.8	35.5	46.0
DPN	unified	31.5	44.3	34.8	**48.3**	**50.3**	**60.4**	**32.4**	**38.3**	**37.5**	**48.2**
DPNE	unified	32.2	43.4	**35.0**	48.0	48.6	59.3	29.8	34.9	36.6	46.7

[2] https://huggingface.co/google/t5-xl-lm-adapt

Table 3: Training-time format transfer experiment with **DP** format. We compare our UIT with two baselines: raw instructions and instructions transferred by the heuristic rule. The training dataset is Ni-v2 combined with CrossFit, Flan, or P3.

Method	**+CrossFit**		**+FLAN**		**+P3**	
	EM	Rouge-L	EM	Rouge-L	EM	Rouge-L
raw	37.5	**56.0**	38.4	56.9	38.8	56.7
heuristic	37.7	55.9	**38.9**	57.4	**39.9**	**58.1**
unified	**37.9**	**56.0**	**38.9**	**57.5**	39.4	57.3

Results and Analyses Testing-time format transfer results are shown in Table 2, and we find that: (1) transferring the instruction format either through the heuristic rule or our UIT significantly improves the performance than the vanilla baseline (i.e., raw), demonstrating the necessity of maintaining format consistency in instruction tuning; (2) our UIT consistently outperforms the heuristic method across all benchmarks and almost all formats in Ni-v2. Compared with the heuristic method, UIT fully utilizes the semantic understanding and generation abilities of GPT3.5 to derive better transferred instructions; (3) the **DPN** format demonstrates the highest average performance and exhibits the largest improvements with UIT.

Training-time format transfer results are shown in Table 3, which shows that format transfer also brings performance improvements compared to raw baseline and performs slightly better than the heuristic method. This again demonstrates that UIT can improve the generalization performance by unifying the instruction format. However, the improvements in the training-time setting are not as significant as that in the testing-time setting. We conjecture this may be because the format inconsistency issue is more evident in our testing-time setting than the training-time setting. Overall, the results under both settings validate our hypothsis that mitigating the instruction format conduces to improved generalization.

Limitations in Practice Despite the favorable performance, the proposed framework still has some limitations: first, automatic format transfer sometimes involves noises or even errors in the generated data, which may produce adverse effects; second, the proposed method heavily relies on OpenAI API calls, which entail substantial costs especially for large-scale instruction datasets. Both issues would limit UIT's real-world deployment. In the following, we discuss potential solutions for the above limitations by proposing a denoising strategy (section 5) and training an offline transfer model (section 6), respectively.

5 Denoising for Format Transfer

Empirically, transferring format via LLMs will introduce noises unavoidably. The transferred instances may contain errors like critical changes to task definition or hallucinatory restrictions. Intuitively, utilizing erroneous instructions would impair the model's generalization performance. To the end, we propose a perplexity-based denoising strategy to filter low-quality instances.

Perplexity-based Denoising Strategy Perplexity (PPL) is a widely used metric for evaluating the semantic coherence and certainty of language models. We assume that noisy instructions can reduce the certainty of LLMs in accurately predicting the correct output token sequence[3], leading to higher perplexity. As a result, perplexity serves as a useful metric for assessing the quality of transferred instructions. Hence, we propose to sample multiple times from LLM to obtain multiple transferred instructions. Then we calculate the perplexity for each instruction. Specifically, we concatenate the transferred instruction and the input query, then predict the annotated label and calculate its perplexity, and filter those with high perplexity.

We employ GPT3.5 with temperature 1.0 to perform sampling for N times with different random seeds, where N is chosen from $\{1, 2, 4, 8, 16, 32\}$. Then, we sort the generated instructions based on perplexity using GPT-J (Wang & Komatsuzaki, 2021) and select the sample with the lowest perplexity. We compare

[3]We merely use the positive example (**P**) as mentioned in section 4.2 for noise assessment.

Table 4: The performance of the denoising strategy at the testing and training time with different number of samples.

Sample Num	Testing time		Training time	
	EM	Rouge-L	EM	Rouge-L
1	32.4	38.3	37.4	56.1
2	33.0	38.9	**39.4**	**57.6**
4	33.5	39.4	38.2	56.5
8	33.7	39.7	38.8	57.0
16	**33.8**	**39.8**	38.5	56.3

our method with the baseline that only samples once from GPT3.5. Without loss of generality, we conduct experiments on Ni-v2 and PromptSource under both the testing-time and training-time settings. For the former, we select the transferred instruction sample with the lowest perplexity; while for the latter, we incorporate multiple transferred instructions with lower perplexity as the training data.

Results As shown in Table 4, our proposed denoising strategy significantly improves the performance at the testing time, and this improvement continues to increase when more instructions are sampled, which shows our method can successfully filter out those low-quality instructions to reduce noises during format transfer. In addition, the method can also improve performance in the training-time setting but the improvement is not more evident when more transferred instructions are included in the training data. It reveals that the model is less sensitive to noises during the training phase.

6 Training Offline Model for Format Transfer

Converting large-scale instructions via OpenAI API can cause substantial costs for API calls. To alleviate the reliance on OpenAI API, it is necessary to derive an offline model that has comparable format transfer performance than GPT3.5 but involves fewer costs. Hence we propose to distill the format transfer ability of GPT3.5 into small-scale models.

Fine-tuned Offline Model with Knowledge Distillation Compared with larger models, small offline models are less capable to complete format transfer directly through in-context learning without training. Therefore, we strive to enhance small-scale models via knowledge distillation (Hinton et al., 2015). In pursuit of higher quality, we always make GPT3.5 convert the relatively complex and informative instruction format (e.g., Ni-v2) into a simpler and less informative one (e.g., PromptSource). In this way, we obtain parallel data and use it to fine-tune GPT-J for format transfer. Without loss of generality, we use the generated PromptSource-style instructions as the source and the original Ni-v2 instructions as the target to construct a dataset of approximately 3,000 instances. To assess the quality of GPT-J's transfer results, we compare them with the heuristic baseline and GPT3.5's conversion results in the testing-time setting with two formats (**DP** and **DPN**).

Results As exhibited in Table 5, the fine-tuned GPT-J performs much better than the heuristic baseline but slightly worse than GPT3.5. This shows that our method can well distill the format transfer ability into small-scale models, which saves the costs in practice. Additionally, the performance is highly correlated with the similarity of the source and target formats. For instance, for DiversePrompt whose instruction format is similar to the target format, the transfer process is less challenging. As a result, the fine-tuned model demonstrates comparable or even superior performance than GPT3.5. Conversely, for CrossFit which only describes keywords and lacks natural language instructions, it is more difficult for small models to produce high-quality instructions, resulting in inferior performance.

Table 5: Results of training an offline model (GPT-J) for format transfer at testing time. We compare the transferred instructions using heuristic rules, GPT3.5, or our fine-tuned GPT-J. Other settings are similar to those in Table 2.

Format	Method	DiversePrompt		Flan		CrossFit		PromptSource		Average	
		EM	Rouge-L	EM	Rouge-L	EM	Rouge-L	EM	Rouge-L	EM	Rouge-L
DP	heuristic	34.7	45.1	31.4	44.8	43.7	56.0	27.3	32.7	34.3	44.6
DPN	heuristic	30.6	43.5	31.9	45.3	43.5	55.5	29.0	33.9	33.9	44.8
DP	GPT3.5	34.2	45.4	32.6	46.3	49.1	60.1	29.2	34.7	36.3	46.6
DPN	GPT3.5	31.5	44.3	**34.8**	48.3	**50.3**	**60.4**	30.8	36.1	**37.1**	**47.6**
DP	GPT-J	**35.2**	45.6	33.5	46.6	43.6	54.5	**31.6**	36.4	36.0	45.8
DPN	GPT-J	34.7	**45.7**	**34.8**	**48.4**	46.0	55.5	31.4	**36.5**	36.7	46.5

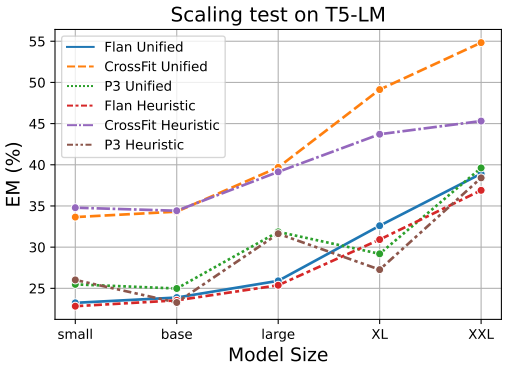

Figure 4: Results of T5-LM of different model sizes on the testing-time transfer setting.

Table 6: Testing time transfer experiment results when Flan is selected as the target dataset and Ni-v2 as the source dataset. Transferring Ni-v2 to the target format brings significant performance improvements during inference when training is conducted with target format.

Source	Target	Method	EM	Rouge-L
Ni-v2	Flan	heuristic	18.4	28.3
Ni-v2	Flan	unified	**29.3**	**43.0**

7 Further Analysis

Effects of the Target Unified Format In previous experiments, we mainly use Ni-v2 as the target instruction format. To verify the versatility of UIT for various target instructions formats, we select Flan, an instance-level dataset as the target dataset and conduct testing-time transfer experiments. Results are shown in Table 6, from which we find that testing-time format transfer brings even more significant performance improvements than the scenario when Ni-v2 is selected as target dataset. This again validates our hypothesis that format consistency is essential to OOD generalization for instruction tuning, no matter which target format is.

Effects of Model Scaling As observed in previous works (Iyer et al., 2022), larger models tend to perform better in following human instructions. We also conduct model scaling experiments in the testing-time setting with T5 (Raffel et al., 2020), with the model size ranging from 5 million (T5-small) to 10 billion (T5-XXL). Results presented in Figure 4 demonstrate that in general, the performance tends to improve as the model

Table 7: Experiments for task diversity and format consistency. For task diversity, we set the training dataset to `src+same`, `src+diff` or `src+same+diff`. For format consistency, we either use the raw format or use the unified format.

Method	`src+same`		`src+diff`		`src+same+diff`	
	EM	Rouge-L	EM	Rouge-L	EM	Rouge-L
raw	29.3	46.3	28.3	45.3	29.1	45.8
unified	30.8	47.6	30.7	47.7	**31.0**	**47.8**

size increases. These findings suggest that instruction format consistency is consistently essential to language models of various sizes.

Task Diversity v.s. Format Consistency We show that both task diversity and format consistency have impacts on the generalization performance for instruction tuning. As task diversity can only be a variable during the training stage, we only conduct training-time transfer experiments. Specifically, we choose Ni-v2 as the target dataset with **DP** as target format and P3 as the source dataset. We first randomly select 20 tasks from Ni-v2 (denoted as `src`). Then we choose the same 20 training tasks from P3, denoted as `same`, and 20 different tasks from P3, which is denoted as `diff`. We treat whether to integrate `same` or `diff` to the training set (`src`) as a variable and evaluate on the original Ni-v2 test set.

As shown in Table 7, no matter which tasks are chosen as the training data, our UIT always performs better than the vanilla baseline (raw), which again demonstrates the importance of format consistency. We can also observe that without format unification, `src+same` performs better than `src+diff`, which indicates that increasing task diversity may be inferior without format consistency. Besides, `source+same+diff` with UIT performs the best among all combinations, suggesting that increasing task diversity and maintaining format consistency at the same time is the best practice for merging datasets in instruction tuning. We believe this finding can guide practitioners to better prepare the datasets for insturction tuning in the future.

8 Conclusion

In this paper, our unified instruction-tuning framework (UIT) provides a standardized approach to enhancing the generalization ability for instruction tuning by unifying the format of existing instruction tuning datasets and enabling format transfer between them. Our approach has been tested on various datasets and has shown improvements in model performance. We also propose a denoising method and an offline model training method to make our UIT more feasible in practice. In general, we study an under-explored facet, i.e., the format consistency, for instruction tuning, and we hope our work could facilitate more attempts in relevant areas.

9 Limitation

While our proposed UIT framework and format transferer offer a promising approach to enhancing the generalization performance of instruction-tuned LLMs, there are several limitations that should be acknowledged. Firstly, our method relies on the assumption that the user knows the target instruction format in advance, which may not always be the case. Secondly, we focus on instruction tuning for NLP tasks, instead of broader settings (e.g., real-world instructions (Taori et al., 2023; Chiang et al., 2023)) where formats are hard to define. We expect future works to explore whether our UIT framework can be applied to broader scenarios.

Appendices

A Case Study

We list some examples of our format transfer process in this section.

Transferring from P3 to Ni-v2 (Task: trec):
Instruction: You are given a sentence which contains a question and a possible answer type. Your task is to identify the correct answer type from the suggested options. You may need to read the sentence and its context carefully in order to determine the correct answer type.
Positive Examples:
Input: What do bee hives do in cranberry bogs ?\nIs this asking about Description, Entity, Abbreviation, Person, Quantity, Location?
Output: Description
Explanation: The question is asking for a description of what bee hives do in cranberry bogs. So the correct answer type is Description.
Negative Examples:
Input: What golfing accessory was patented by George Grant on December 12\nIs this asking about Description, Entity, Abbreviation, Person, Quantity, Location?
Output: Quantity
Explanation: The sentence is asking about a golfing accessory. These types of questions typically require an answer about an entity (i.e. a specific object or thing), so the correct answer type is 'Entity' rather than 'Quantity'.

Original P3(trec):
Instruction: {Input}\n\nDescriptors: Description, Entity, Abbreviation, Person, Quantity, Location\n\nBest Descriptor?\n
Positive Examples:
Input: What do bee hives do in cranberry bogs ?\n
Output: \nDescription

Transferring from Flan to Ni-v2 (Task: wsc):
Instruction: In this task, you are given two sentences (sentence 1 and sentence 2). If sentence 1 implies that sentence 2 is true, answer "Yes", otherwise "No".
Positive Examples:
Input: sentence 1: As Ollie carried Tommy up the long winding steps, his legs ached. sentence 2: Tommy's legs ached. options: - no - yes.
Output: no
Explanation: The sentence 1 does not imply that Tommy's legs ached. So, the output should be "No".
Negative Examples:
Input: Sentence 1: Paul couldn't find his car keys, so he had to walk. Sentence 2: Paul had to walk.
Output: Yes
Explanation: Sentence 1 implies that sentence 2 is true, so the correct output should be "Yes".

Original Flan(wsc):
Instruction: If "{sentence1}", can we conclude that "{sentence2}"\n{options_}
Positive Examples:
Input: If "As Ollie carried Tommy up the long winding steps, his legs ached.", can we conclude that "Tommy's legs ached."\n\nOPTIONS:\n- no\n- yes.
Output: no

Transferring from CrossFit to Ni-v2 (Task: imdb):
Instruction: You are given a sentence or a paragraph describing a particular topic. Your task is to classify the sentiment of the sentence/paragraph as either negative or positive. Label the sentiment in the output as per the given parameters without incorporating any additional information into your answer.
Positive Examples:
Input: I am a big fan a Faerie Tale Theatre and I've seen them all and this is one of the best! It's funny, romantic, and a classic. I recommend this for all ages. It's great for little kids because it's well, Cinderella and great for adults and teen because it's funny and not over the top. I watched it when I was little and I still watch it now. It has great lines that my family and I quote all the time. The acting is great and it never gets old. If you like fairy tales and romances you will love this. I've watched many a Cinderella movie in my time and this is the best of them all. (Sorry Disney) I highly recommend this movie and all the Faerie Tale Theatre shows. They all appeal to all ages and are all unique and very entertaining.
Output: positive
Explanation: The sentence describes a very positive opinion on the chosen topic. The opinion is supported by facts, like the uniqueness of the show, its lasting values, great acting, and so on. Hence, the sentiment of the sentence is classified as positive.
Negative Examples:
Input: I know a few things that are worst. A few. It had a couple of funny scenes. It is a movie not appropriate for kids but, only a child would find this movie hilarious. This is definetly a movie that you would like to use a free rental coupon for. Don't waste your money just to laugh a couple of times.
Output: Positive
Explanation: The given sentence is mainly negative in nature as it suggests not to waste money on the movie. The word \"definetly\" and \"a couple of funny scenes\" are used in the sentence to provide a bit of contrast, yet it does not make the overall sentiment of the sentence positive. Therefore, the correct answer should be \"negative\" instead of \"positive\".

Original CrossFit(imdb):
Instruction:
Positive Examples:
Input: I am a big fan a Faerie Tale Theatre and I've seen them all and this is one of the best! It's funny, romantic, and a classic. I recommend this for all ages. It's great for little kids because it's well, Cinderella and great for adults and teen because it's funny and not over the top. I watched it when I was little and I still watch it now. It has great lines that my family and I quote all the time. The acting is great and it never gets old. If you like fairy tales and romances you will love this. I've watched many a Cinderella movie in my time and this is the best of them all. (Sorry Disney) I highly recommend this movie and all the Faerie Tale Theatre shows. They all appeal to all ages and are all unique and very entertaining.
Output: positive

Transferring from Ni-v2 to Flan (Task: dialogre):
Instruction: {input} Identify the name of one of the speakers in the given dialog.

Original Ni-v2(dialogre):
Instruction: You are given a dialog between 2 or more individuals. Within the dialog, there will be clues as to the names of the speakers. You will be asked at the end of the dialog to identify the name of one of the speakers.

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