DialogStudio: Towards Richest and Most Diverse Unified Dataset Collection for Conversational AI

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Abstract

Despite advancements in conversational AI, language models encounter challenges to handle diverse conversational tasks, and existing dialogue dataset collections often lack diversity and comprehensiveness. To tackle these issues, we introduce DialogStudio: the largest and most diverse collection of dialogue datasets, unified under a consistent format while preserving their original information. Our collection encompasses data from open-domain dialogues, task-oriented dialogues, natural language understanding, conversational recommendation, dialogue summarization, and knowledge-grounded dialogues, making it an incredibly rich and diverse resource for dialogue research and model training. To further enhance the utility of DialogStudio, we identify the licenses for each dataset and design domain-aware prompts for selected dialogues to facilitate instruction-aware finetuning. Furthermore, we develop conversational AI models using the dataset collection, and our experiments in both zero-shot and few-shot learning scenarios demonstrate the superiority of DialogStudio. To improve transparency and support dataset and task-based research, as well as language model pre-training, all datasets, licenses, codes, and models associated with DialogStudio are made publicly accessible¹.

1 Introduction

Recent years have seen remarkable progress in Conversational AI, primarily driven by the advent of language models (Longpre et al., 2023; Zhang et al., 2022b; Brown et al., 2020; Touvron et al., 2023). Despite the advancements, these models often fall short when handling various tasks in a conversation due to the lack of comprehensive and diverse training data. Current dialogue datasets (Lin et al., 2021; Asri et al., 2017) are typically limited in size and task-specific, which thus results in suboptimal ability in task-oriented model performance. Additionally, the lack of dataset standardization impedes model generalizability.

A few recent works (Longpre et al., 2023; Gupta et al., 2022; Ding et al., 2023) have introduced a large collection of datasets, which includes diverse tasks based on public datasets. For instance, FlanT5 (Longpre et al., 2023) presents the flan collections with a wide array of datasets and tasks. However, only a few of them are relevant to conversational AI. Although OPT (Iyer et al., 2022) have incorporated collections with several dialogue datasets, these collections remain inaccessible to the public. Other efforts like InstructDial (Gupta et al., 2022) and ParlAI (Miller et al., 2017) consist of more dialogue datasets, but they lack diversity and comprehensiveness. For instance, ParlAI mainly

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¹https://github.com/salesforce/DialogStudio

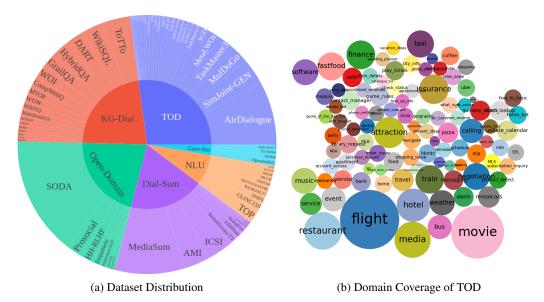


Figure 1: (a) is the distribution of all datasets in DialogStudio. The outer and inner circle list names of datasets and the associated categories, respectively. (b) illustrates covered domains of Task-Oriented Dialogues in DialogStudio.

includes open-domain dialogue datasets, which are exclusively accessible through their platform. These collections often process datasets into a sequence-to-sequence format to support language model training, featuring input-output pairs such as dialogue context and system response. However, they often overlook other crucial dialogue information, constraining their utility for research interest on individual datasets, tasks, and broader applications.

To overcome the aforementioned challenges, we introduce DialogStudio, the most comprehensive and diverse collection of publicly available dialogue datasets, unified under a consistent format. By aggregating dialogue from various sources, DialogStudio promotes holistic analysis and the development of models adaptable to a variety of conversational scenarios. The collection spans an extensive range of domains, aspects, and tasks, and it is inclusive of several categories: Open-Domain Dialogues, Task-Oriented Dialogues, Natural Language Understanding, Conversational Recommendation, Dialogue Summarization, and Knowledge-Grounded Dialogues. Thus, it can provide support for research in both individual dialogue tasks and large-scale language pre-training.

DialogStudio stands out not only for its comprehensive coverage but also for its accessibility. It offers easy access with a unified format and documents. A straightforward load_dataset() command through HuggingFace allows users to seamlessly interact with the collection, and we have included documentation for each dataset to enhance usability. We anticipate that this collection will enable comprehensive and standardized training and evaluations of dialogue models, fostering fair comparisons and propelling further advancements in Conversational AI.

Furthermore, we identify dialogue domains for each dialogue and create tailored prompts for selected datasets accordingly. Leveraging these datasets from DialogStudio, we have constructed instruction-aware models, with capacities ranging from 770M to 3B parameters. These models have the ability to handle various external knowledge and are adept at both response generation and general tasks, demonstrating the benefits of DialogStudio. The main contributions of this paper are as follows:

- We introduce DialogStudio, a meticulously curated collection of dialogue datasets. These datasets
 are unified under a consistent format while retaining their original information. We incorporate
 domain-aware prompts and identify dataset licenses, making DialogStudio an exceptionally rich
 and diverse resource for dialogue research and model training.
- To promote transparency and facilitate research, we made our collected datasets publicly accessible. Moreover, we have made concerted efforts to enhance DialogStudio's usability and will continue refining it for optimal user experience.

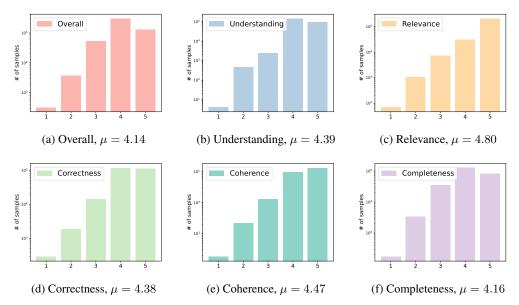


Figure 2: The score distribution for the dialogue quality.

• We train conversational AI models based on DialogStudio, and these models have demonstrated superior performance over strong baselines in both zero-shot and few-shot learning scenarios.

2 Data analysis

2.1 Data Visualization

The dialogue datasets are compartmentalized into several categories: *Open-Domain Dialogues*, *Task-Oriented Dialogues* (*TOD*), *Natural Language Understanding Dialogues* (*NLU*), *Conversational Recommendation* (*Conv-Rec*), *Dialogue Summarization* (*Dial-Sum*), and *Knowledge-Grounded Dialogues* (*KG-Dial*). Figure 1a presents an overview of DialogStudio's dataset categories. Note that the category boundaries are fuzzy as some datasets span multiple categories. For instance, SalesBot (Chiu et al., 2022) contains both casual and task-oriented conversations. Analogously, MultiWOZ (Budzianowski et al., 2018), a task-oriented dialogue corpus, incorporates knowledge bases and dialogue acts to enhance knowledge-grounded generation. Additionally, DialogStudio demonstrates its diversity by covering a wide range of domains, part of which is shown in Figure 1b.

2.2 Data Quality Investigation

Due to the existence of noise in dialogue, we develop a simple yet effective way to verify the quality of the datasets. Specifically, we employ ChatGPT (GPT-3.5-turbo) to evaluate the quality of system responses based on severall perspectives (Mehri et al., 2022; Kim et al., 2022a), *i.e.*, Understanding, Relevance, Correctness, Coherence, Completeness and Overall quality. Understanding assesses whether the model's responses accurately reflect the meaning and intent of the user's inputs. Relevance demonstrates whether the generated response should be directly related and appropriate to the preceding user input and the context of the conversation. Coherence measures the logical consistency of the model's responses within the context of the conversation. Completeness refers to whether the system's responses fully address the user's queries or tasks. Overall quality comprehensively rates the quality of dialogue. All scores are in the range of 1-5, and higher scores should only be given to truly exceptional examples. We delicately design the prompt and ask the ChatGPT model to *strictly* rate the score. After aligning ChatGPT and human verification on sampled dialogues, we view a score greater than 3 as a good quality dialog. Since there are a lot of datasets in DialogStudio, we select 33 datasets and the distributions of those scores are illustrated in Figure 2.1.

We also reveal the average score as the μ in each sub-caption. In general, the dialogues show high qualities.

3 Datasets Unification and Access

We collect and process a wide range of datasets, involving different domains, types, and tasks. Since these datasets originally contain various information and format, we propose a unification strategy to process all the datasets such that they can be loaded in the same data loader.

3.1 Unification

Before unifying the format of those datasets, we fixed several issues as follows: 1) we remove those dialogues labeled as multi-turn dialogues, but actually with only one turn and miss either user utterance or system utterance. 2) We manually check the individual dialogues. If one dialogue contains one or more empty user or system utterances, we fill utterances based on corresponding dialogue contexts, dialogue acts, and dialogue information.

Additionally, we recognize the success of instruction tuning for dialogue models and thus we manually pre-define five different prompt templates for multi-turn dialogue datasets, such as *This is a bot helping users to {Task_Domain}*. *Given the dialogue context and external database, please generate a relevant system response for the user.* The *{Task_Domain}* is associated with the dialogue domain and we manually create a corresponding description. For example, if a dialogue is of domain *travel*, we set *{Task_Domain}* as *book a trip*. A concrete example of the prompt is demonstrated in Figure 3.

```
"FRAMES--train--1":
"dialogue id": "train 1",
                                                                                               "original dialog id": "train 1",
                                                                                               "dialog index": 1
"num_utterances": 14,
                                                                                                original dialog info": {
"utterances": [
                                                                                                    scenario": {
   "db_id": "U22HTHYNP",
                                                                                                    "db_type": "booking",
"task": "book"}}
      "text": "I'd like to book a trip to Atlantis from Caprica on
               Saturday, August 13, 2016 for 8 adults.",
      "ap_label": "".
     "da_label": "inform"
                                                                                                     "turn id": 1,
                                                                                                     "user utterance": "I'd like to book a trip to Atlantis from Caprica on Saturday
                                                                                                                           August 13, 2016 for 8 adults. I have a tight budget of 1700."
                                                                                                     "system response": "Hi...I checked a few options for you, and we do not currently
      "speaker": "USR"
                                                                                                                            have any trips that meet this criteria."
     "text": "I have a tight budget of 1700.", "ap_label": "",
                                                                                                     "dialog history": "",
                                                                                                    "original user side information": {
   "da_label": "inform"
     "da label": "inform"
      "speaker": "SYS",
                                                                                                        "da label": "sorry",
     "text": "Hi...I checked a few options for you, and we do
                                                                                                         slots": {
  "dst_city": "Atlantis",
  "or_city": "Caprica",
  "str_date": "Saturday, August 13, 2016",
  "n_adults": "8",
               not currently have any trips that meet this criteria.",
      "da label": "sorry".
      "slots": {
                                                                                                          "budget": "1700"
         "dst_city": "Atlantis",
        "or_city": "Caprica",
"str_date": "Saturday, August 13, 2016",
         "n_adults": "8",
                                                                                                    "dst": "book dst_city Atlantis, book or_city Caprica, book str_date Saturday, August 13, 2016, book n_adults 8, book budget 1700"
         "budget": "1700"
                                                                                                'external knowledge": "( travel : (( trip : ( returning : ( duration : ( hours : 0 | min : 51...'
                                                                                              "dst knowledge": "(book: (dst_city: (Indianapolis | St. Loius | Le Paz | ...) | or_city: (PUebla | sf | toluca | San Francisco...",
scenario": {
  "db id": "U22HTHYNP",
                                                                                               "intent knowledge": "( book : ( null | negate | request | goodbye | affirm))...",
   "db_type": "booking",
  "task": "book"
                                                                                                     This is a bot helping users to book a trip. Given the dialog context and external
                                                                                                     database, please generate a relevant system response for the user.'
            (a) Original Data
                                                                                                                               (b) DialogStudio Data
```

Figure 3: A dialogue format example. Left: original example, right: converted example. Here We only show the first turn and partial information.

Next, we construct a uniform JSON dictionary format to store all relevant information of each dialogue as illustrated in Figure 3. Compared with existing works, DialogStudio covers more dialogue information and is easier to retrieve the information for arbitrary dialogue-related tasks. Concretely, we include all dialogue-related information, such as the dialogue ID, data split label, domain, task,

and content. Additionally, we identify the external knowledge, dialogue state tracking (DST) knowledge, and intent knowledge in the dialogue, which are the most beneficial knowledge for a dialogue.

Regarding external knowledge, we construct it based on information such as databases and dialogue acts. Since each dialogue dataset focuses on specific tasks or domains and has a different database and annotation schema, we unify such information into *external knowledge*. For example, if the user is looking for a hotel and asking for its address, the system response should be based on both the search results from the database and the dialogue context. To simulate the realistic situation and avoid directly providing the model with the ground truth resulting hotel, we also randomly sample four other candidate results and mix them with the ground truth result. All information is flattened and converted into a string as external knowledge.

To complete tasks and generate coherent responses, a dialogue system needs to track users' requirements for the task. Those requirements are usually represented as dialogue states. For example, regarding the hotel booking task, a dialogue system needs to extract information such as price range and locations to enable searching hotels in the database. The type of dialogue states varies across different tasks and datasets. As such, it is hard for dialogue systems to predict the values of those dialogue states if unknowing the specific dialogue states the task covers. Therefore, we propose to insert the schema, consisting of pre-defined dialogue state types and values for each task, into the input sequence. For datasets like SGD (Rastogi et al., 2020), which already provides annotation schema, we directly convert the dictionary-structured schema into a string. For the rest datasets that have no such schema file, we iterate over all dialogues and collect potential state annotations to construct a schema. We provide domains, slot types, and slot values in the schema string. For those categorized dialogue slots like "hotel star-ratings", which have a fixed number of candidate values, we provide all possible values. For others that have unlimited possible values, e.g. "stay night", we randomly sample ten values, such that a model can learn what slot values are relevant to these slot types. We put the turn-level ground-truth DST information in "dst", and the general DST information under "dst knowledge", as presented in Figure 3.

Analogously, intent prediction also requires models to know all possible intent types for each task. Therefore, we extract the schema directly from the schema file if it exists. As to datasets without schema, we also iterate over all dialogue in the dataset to collect all potential intents. Then, we put the turn-level ground-truth intent information into "intent", and the general intents under "intent knowledge", as presented in Figure 3. Note that not all datasets provide detailed annotation for dialogue states, intents, or even databases. For dialogue state tracking and intent classification tasks, we only process dialogues with corresponding annotations. Since all data is used for response generation, we leave the external knowledge value for the database blank if there is no related database in the original dataset.

3.2 Access and Ethics

As aforementioned in the format, our DialogStudio data is easy to access via the JSON files. To make DialogStudio more maintainable and accessible, we publish datasets on both GitHub and HuggingFace. GitHub mainly stores selected dialogue examples and relevant documents. We sample 5 original dialogues and 5 converted dialogues for each dataset to facilitate users in comprehending our format and examining the contents of each dataset. The complete DialogStudio dataset is maintained in our HugginFace repository, where all the datasets can be directly downloaded or loaded with the HuggingFace load_dataset() API. We will continuously maintain and update both GitHub and HuggingFace.

DialogStudio is built upon public research datasets, and we believe it is important to clearly present the license associated with each of these datasets. Consequently, we have included the original licenses for all datasets. All these datasets are supportive of academic research, and some of them also endorse commercial usage. The code that we employ falls under the widely accepted Apache 2.0 license.

Regarding the ethical concerns, we admit that DialogStudio is collected by the authors of this work and we did not hire external annotators. Since it contains unified datasets across several categories, it supports various research purposes from individual tasks and datasets to language model pretraining.

4 Experiments

In this section, we present the pre-training details, methodologies, and metrics used to assess the performance of our DialogOhana model. The evaluation process aims to measure the model's ability to both solve task-oriented dialogues and understand general prompt-based instruction.

4.1 DialogOhana Pre-training

In this section, we introduce more details about how we conduct our pre-training. In regards of training DialogOhana, we mix several datasets from DialogStudio.

For task-oriented and conversational recommendation datasets, we selected dialogues from a range of sources including KVRET (Eric et al., 2017), AirDialogue (Wei et al., 2018), DSTC2-Clean (Mrkšić et al., 2017), CaSiNo (Chawla et al., 2021), FRAMES (El Asri et al.), WOZ2.0 (Mrkšić et al., 2017), CraigslistBargains (He et al., 2018), Taskmaster1-2 (Byrne et al., 2019), ABCD (Chen et al., 2021a), MulDoGO (Peskov et al., 2019), BiTOD (Lin et al., 2021), SimJoint (Shah et al., 2018), STAR (Mosig et al., 2020), SGD (Rastogi et al., 2020), OpenDialKG (Moon et al., 2019) and DuRecDial-2.0 (Liu et al., 2021).

Meanwhile, for knowledge-grounded dialogues, we drew upon dataset from SQA (Iyyer et al., 2017), SParC (Yu et al., 2019b), FeTaQA (Nan et al., 2022), MultiModalQA (Talmor et al., 2021), CompWebQ (Talmor & Berant, 2018), CoSQL (Yu et al., 2019a).

For open-domain dialogues, we sample dialogues from SODA (Kim et al., 2022a), ProsocialDialog (Kim et al., 2022b), Chitchat (Myers et al., 2020).

For each dialogue dataset, we sample at most 11k dialogues. Additionally, we extracted around 11k dialogue turns from question-answering dialogues featured in RACE (Lai et al., 2017), NarrativeQA (Kočiskỳ et al., 2018), SQUAD (Rajpurkar et al., 2018), MCtest (Richardson et al., 2013), OpenBookQA (Mihaylov et al., 2018), MultiRC (Khashabi et al., 2018). Here, a dialogue turn refers to a pair consisting of a dialogue context and its corresponding system response. The rest datasets in DialogStudio are preserved for future evaluations and downstream fine-tuning.

We follow the public HuggingFace transformer code (Wolf et al., 2020; Wang et al., 2022) to train the model. For initializing our models, we adopt T5 (Raffel et al., 2020) and Flan-T5 (Longpre et al., 2023) as starting points to respectively establish DialogStudio-T5 and DialogStudio-Flan-T5. For the training of DialogStudio-Flan-T5, we exclude all translation-oriented tasks, limiting the sample size for each Flan task to a maximum of 150 examples. This leads to a cumulative total of 140,000 samples. We train the model up to 3 epochs with bfloat16 precision, a total batch size of 64. We set a constant learning rate 5e-5 and 3e-5 for the large model and the 3B model, respectively. Experiments are conducted using 16 A100 GPUs, each with 40GB of GPU memory.

4.2 Evaluation for Response Generation

Settings. We evaluate the performance on CoQA (Reddy et al., 2019) and MultiWOZ 2.2 (Zang et al., 2020). CoQA is a multi-turn conversational question answering dataset with 8k conversations about text passages from seven diverse domains. MultiWOZ 2.2 is one of the largest and most widely used multi-domain task-oriented dialogue corpora with more than 10000 dialogues. Each dialogue involves with one or more domains such as *Train, Restaurant, Hotel, Taxi*, and *Attraction*. The dataset is challenging and complex due to the multi-domain setting and diverse linguistic styles. Note that we exclude these two datasets during the pre-training stage in case of data leakage.

For CoQA, we follow the original paper setting to answer question based on external passage. For MultiWOZ 2.2, we consider the lexicalized dialogue-act-to-response generation task where the model needs to consider both the dialogue context and the dialogue acts during generation. We

	CoQA		MultiWOZ	
	ROUGE-L	F1	ROUGE-L	F1
Flan-T5-3B (Longpre et al., 2023)	37.1	37.2	7.0	7.4
Flan-T5-Large (Longpre et al., 2023)	22.5	22.3	15.9	17.6
GODEL-Large (Peng et al., 2022)	43.2	43.3	18.5	19.3
DialogStudio-T5-Large	61.2	61.5	32.4	$\bar{34.5}$
DialogStudio-Flan-T5-Large	63.3	63.5	33.7	35.9

Table 1: Zero-shot results on CoQA and MultiWOZ 2.2.

	CR (14 tasks)	DAR (7 tasks)	TE (27 tasks)	avg. (48 tasks)
OPT-30B (Zhang et al., 2022b)	21.3/1.1	35.2/4.1	40.3/0.9	32.3/2.0
OPT-IML-30B (Iyer et al., 2022)	37.4/41.6	51.4/51.8	54.7/47.8	47.9/47.1
OPT-175B (Zhang et al., 2022b)	21.0/4.2	37.1/16.8	41.6/2.2	33.3/7.7
OPT-IML-175B (Iyer et al., 2022)	39.0/49.8	61.2 /60.2	54.3/51.0	51.5 /53.6
Tk-INSTRUCT-11B (Wang et al., 2022)	32.3/ 62.3	51.1/ 69.6	55.0/64.1	46.1/ 65.3
Tk-INSTRUCT-3B (Wang et al., 2022)	38.4/51.3	45.7/58.5	48.4/52.8	44.2/54.2
DialogStudio-NIV2-T5-3B	41.3 /59.8	57.5/63.7	52.3/55.1	50.4/59.5

Table 2: 0-shot/2-shot/5-shot ROUGE-L testing results on unseen datasets and unseen tasks. Results of baselines are reported by original papers. CR, DAR, and TE, avg. are abbreviations for Coreference Resolution, Dialogue Act Recognition, Textual Entailment, and average results, respectively.

follow the prompt from (Bang et al., 2023) to instruct models, i.e., Continue the dialogue as a task-oriented dialogue system called SYSTEM. The answer of SYSTEM should follow the ACTION provided next while answering the USER's last utterance.

We focus on zero-shot evaluation and report the ROUGE-L and F1 score (Miller et al., 2017), where ROUGE-L measures the longest common subsequence and F1 measures the Unigram F1 overlap between the prediction and ground-truth response.

Baselines. We consider GODEL (Peng et al., 2022) and Flan-T5 (Longpre et al., 2023) as our baselines. GODEL is a T5-based large pre-trained model for goal-oriented dialogues. It is pre-trained with 551M multi-turn Reddit dialogues and 5M knowledge-grounded and question-answering dialogues. Flan-T5 is an instruction-aware model. It is also initialized from T5 and pre-trained on the Flan collection, which consists of more than 1800 tasks and 400 datasets, including dialogue datasets.

Results. Table 1 depicts the results from both zero-shot and few-shot testing. Evidently, DialogStudio considerably surpasses the baseline models in terms of zero-shot learning, exhibiting a robust generalized ability for response generation in a zero-shot scenario.

Flan-T5-3B, on the other hand, underperforms in the task of generating responses from dialog-acts. This model tends to produce incorrect dialog acts, unnatural utterances, or terminates with an empty end token. One explanation for this is that Flan-T5 models did not receive sufficient dialogue training during the instruction-training phase on the Flan collections.

4.3 Evaluation on Super-NaturalInstructions

Settings. NIV2 (Wang et al., 2022) introduces an instruction-tuning benchmark with more than 1600 tasks. We select 3 categories with 44 tasks from the held-out test set, which consists of 154 tasks, i.e., Coreference Resolution, Dialogue Act Recognition, and Textual Entailment. The selected tasks and datasets are unseen in the training stage. Specifically, we follow all settings including metrics in Wang et al. (2022), i.e., we train the model with instructions + 2 positive demonstrations and no negative demonstrations. We fine-tune DialogStudio-T5-3B on the 756 training tasks.

Baselines. OPT (Zhang et al., 2022b) is a set of open decoder-only transformer models pre-trained on 180B tokens. OPT-IML (Iyer et al., 2022) is an instruction meta-learning model based on the OPT-IML bench with more than 1500 tasks. Tk-INSTRUCT (Wang et al., 2022) is initialized from

	MMLU		BBH
	0-SHOT	5-SHOT	3-SHOT
TK-INSTRUCT 11B (Wang et al., 2022)	-	41.1	32.9
LLAMA 13B (Touvron et al., 2023)	-	46.2	37.1
Vicuna 13B (Chiang et al., 2023)	-	49.7	37.1
Flan-T5-Large (Longpre et al., 2023)	41.5	41.9	37.1
Flan-T5-XL (Peng et al., 2022)	48.7	49.3	40.2
OPT-IML-Max 30B (Iyer et al., 2022)	46.3	43.2	31.3
DialogStudio-Flan-T5-Large	40.1	40.9	$ -34.\bar{2} $
DialogStudio-Flan-T5-3B	48.3	47.8	40.3
	I		ı

Table 3: Test results on MMLU and BBH. Results come from original papers and InstructEval (Chia et al., 2023)

T5 and further pre-trained based on NIV2 collections. Note that we neglect Flan-T5 because it trains with all the downstream datasets and tasks.

Results. Table 2 shows the 0-shot and 2-shot results on unseen datasets and unseen tasks. Based on the average performance on 48 tasks, DialogStudio-NIV2-T5-3B outperforms OPT-IML-175B by 5.9% on 2-shot learning with more than 50 times fewer model parameters, and it surpasses Tk-INSTRUCT-11B by 4.3% on 0-shot learning with more than 3 times fewer parameters. The performance demonstrates the strong generalization ability of DialogStudio model. Compared with Tk-INSTRUCT-3B, DialogStudio-NIV2-T5-3B achieves 6.2% and 5.3% improvements on 0-shot and 2-shot learning respectively. Given that both Tk-INSTRUCT and our DialogStudio-NIV2-T5-3B are fine-tuned from the T5 model, this improvement indicates the effectiveness of pre-training with our dialogue collection, DialogStudio.

4.4 Evaluation on MMLU and BBH

Table 3 presents results on MMLU (Hendrycks et al., 2020) and Big Bench Hard (BBH) (Srivastava et al., 2022). When comparing the performance of DialogStudio-Flan-T5 with Flan-T5, we observe a minor decrease. However, this is accompanied by a significant improvement in dialogue capabilities.

5 CONCLUSION

In this paper, we introduce DialogStudio, a unified and diverse collection of 80 dialogue datasets, retaining their original information. Utilizing DialogStudio, we developed the DialogOhana models, demonstrating superior performance in both zero-shot and few-shot learning scenarios. We release both DialogStudio and DialogOhana to foster transparency and support research into datasets, tasks, and pre-training models for conversational AI.

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Appendix

Table 4 and Table 5 lists datasets included in DialogStudio. Initially, we present a partial list of these datasets. For more comprehensive and up-to-date information, please refer to our GitHub page.

```
NLU++ (Casanueva et al., 2022)
       BANKING77-OOS (Zhang et al., 2022a)
       BANKING77 (Casanueva et al., 2020)
       RESTAURANTS8K (Coope et al., 2020)
       CLINC150 (Larson et al., 2019)
       CLINC-Single-Domain-OOS-banking (Zhang et al., 2022a)
       CLINC-Single-Domain-OOS-credit_cards (Zhang et al., 2022a)
       HWU64 (Liu et al., 2019)
NLU
       SNIPS (Coucke et al., 2018)
       SNIPS-NER (Coucke et al., 2018)
       DSTC8-SGD (Coope et al., 2020)
       TOP (Gupta et al., 2018)
       TOP-NER (Gupta et al., 2018)
       ATIS-NER (Hemphill et al., 1990)
       ATIS (Hemphill et al., 1990)
       MIT-MOVIE (Liu et al., 2013)
       MIT-RESTAURANT (Liu et al., 2013)
       KVRET (Eric et al., 2017)
       AirDialogue (Wei et al., 2018)
       DSTC2-Clean (Mrkšić et al., 2017)
       CaSiNo (Chawla et al., 2021)
       FRAMES (El Asri et al.)
       WOZ2.0 (Mrkšić et al., 2017)
       CraigslistBargains (He et al., 2018)
       Taskmaster1 (Byrne et al., 2019)
       Taskmaster2 (Byrne et al., 2019)
       Taskmaster3 (Byrne et al., 2019)
       ABCD (Chen et al., 2021a)
       MulDoGO (Peskov et al., 2019)
       BiTOD (Lin et al., 2021)
TOD
       SimJointGEN (Shah et al., 2018)
       SimJointMovie (Shah et al., 2018)
       SimJointRestaurant (Shah et al., 2018)
       STAR (Mosig et al., 2020)
       SGD (Rastogi et al., 2020)
       MultiWOZ2_1 (Eric et al., 2020)
       MultiWOZ2_2 (Zang et al., 2020)
       HDSA-Dialog (Chen et al., 2021a)
       MS-DC (Li et al., 2018b)
       GECOR (Quan et al., 2019)
       Disambiguation (Qian et al., 2022)
       MetaLWOZ (Lee et al., 2019)
       KETOD (Chen et al., 2022b)
       MuDoCo (Martin et al., 2020)
```

Table 4: List of datasets included in DialogStudio (a).

	SQA (Iyyer et al., 2017)
	SParC (Yu et al., 2019b)
	FeTaQA (Nan et al., 2022)
	MultiModalQA (Talmor et al., 2021)
	CompWebQ (Talmor & Berant, 2018)
	CoSQL (Yu et al., 2019a)
	CoQA (Reddy et al., 2019)
	Spider (Yu et al., 2018)
	ToTTo (Parikh et al., 2020)
KG-Dial	WebQSP (Yih et al., 2016)
	WikiSQL (Zhong et al., 2017)
	WikiTQ (Pasupat & Liang, 2015)
	DART (Nan et al., 2021)
	GrailQA (Gu et al., 2021)
	HybridQA (Chen et al., 2020)
	MTOP (Chen et al., 2020)
	UltralChat-Assistance (Ding et al., 2023)
	Wizard_of_Wikipedia (Dinan et al., 2018)
	Wizard_of_Internet (Komeili et al., 2022)
	TweetSumm (Feigenblat et al., 2021)
	SAMSum (Gliwa et al., 2019)
	DialogSum (Chen et al., 2021b)
	AMI (Kraaij et al.)
	ICSI (Janin et al., 2003)
Dial-Sum	QMSum (Zhong et al., 2021)
	MediaSum (Zhu et al., 2021)
	ECTSum (Mukherjee et al., 2022)
	SummScreen_ForeverDreaming (Chen et al., 2022a)
	SummScreen_TVMegaSite (Chen et al., 2022a)
	CRD3 (Rameshkumar & Bailey, 2020)
	ConvoSumm (Fabbri et al., 2021)
	ChitCHAT (Myers et al., 2020)
	SODA Kim et al. (2022a)
	Prosocial (Kim et al., 2022b)
Onen Demein	HH-RLHF (Bai et al., 2022)
Open-Domain	Empathetic (Rashkin et al., 2019)
	ConvAI2 (Dinan et al., 2019)
	AntiScam (Li et al., 2020)
	PLACES3.5 (Chen et al., 2023)
	SalesBot (Chiu et al., 2022)
Conv-Rec	Redial (Li et al., 2018a)
	Inspired (Hayati et al., 2020)
	DuRecDial 2.0 (Liu et al., 2021)
	OpendialKG (Moon et al., 2019)
	Toble 5: List of detects included in DielogStudie

Table 5: List of datasets included in DialogStudio (b).