Abstract

Building unified conversational agents has been a long-standing goal of the dialogue research community. Most previous works only focus on a subset of various dialogue tasks. In this work, we aim to build a unified foundation model which can solve massive diverse dialogue tasks. To achieve this goal, we first collect a large-scale well-labeled dialogue dataset from 73 publicly available datasets. In addition to this dataset, we further propose two dialogue-oriented self-supervised tasks, and finally use the mixture of supervised and self-supervised datasets to train our foundation model. The supervised examples make the model learn task-specific skills, while the self-supervised examples make the model learn more general skills. We evaluate our model on various downstream dialogue tasks. The experimental results show that our method not only improves the ability of dialogue generation and knowledge distillation, but also the representation ability of models.

1 Introduction

Nowadays, dialogue systems are widely applied in various scenarios, such as intelligent personal assistants, customer service centers, smart speakers and so on. These applications have extensively promoted dialogue research, with various dialogue tasks being proposed, e.g. intent classification, dialogue state tracking, conversational question answering, and chit-chat. For each task, multiple dialogue datasets are collected and well labeled. With these datasets, we have witnessed rapid development of dialogue models and methods (Gao et al., 2019). However, most of them are targeted at a single task, sometimes even a single dataset. This phenomenon has limited the possibility to transfer knowledge between tasks and datasets hence undermined the development of a unified and well-generalized dialogue system.

Figure 1: The number distribution of the training samples on 73 dialog corpora, which span 15 supervised dialog-oriented tasks.

Thanks to the rapid development of pre-trained language models (PLMs) (Qiu et al., 2020), more and more research focus on building unified models for different natural language processing tasks. In the dialogue area, there are also some attempts to build unified dialogue models. However, previous works only focus on a small subset of dialogue tasks, e.g. dialogue understanding (Chen et al., 2022), and task-oriented dialogue (Su et al., 2021). Building unified dialogue models for massive diverse dialogue tasks has been a long-standing goal in the community.

In this paper, we aim to train a unified foundation model for a plethora of dialogue tasks. Such a model should be entitled to two types of skills: 1) Superb dialogue understanding capability, no matter the dialogue is a single utterance or long conversation with multi-turns. It should correctly extract useful information from the dialogue, e.g. entities, dialogue state, user’s intent and emotion. 2) Being able to leverage external knowledge, which can be plain text, semi-structured description, and structured knowledge graph (KG) or databases. These skills can not be achieved by traditional
self-supervised training. Therefore, we collect a large-scale well-labeled dialogue dataset from publicly available datasets. The dataset consists of 15 dialogue tasks, involving as many as 73 datasets. These tasks include intent detection, slot filling, dialogue state tracking, dialogue emotion recognition, KG-guided dialogue, Text-to-SQL, and so on. Both the input and output of these tasks are very diverse. The distribution of training samples supporting each task are shown in Figure 1.

In order to train a unified model, the primary prerequisite is to translate data in different tasks into a unified form. Motivated by previous work on instruction tuning (Wei et al., 2021) and prompt learning (Liu et al., 2021a), we split the input of each sample into three parts: dialogue content, external knowledge, and task description, and normalize all data into text-to-text format. Using this unified format, we can directly train the dialogue model initialized from a typical seq2seq model, e.g BART (Lewis et al., 2020) and T5 (Raffel et al., 2020). However, our preliminary experiments suggest that only using these supervised examples can not lead to stable training process. Therefore, we further propose two dialogue-oriented self-supervised tasks, and finally use the mixture of supervised and self-supervised methods to train our foundation model. The supervised learning paradigms enable the model learn task-specific skills, while the self-supervised tasks are tailored for dialog recovery skill. Upon the inclusion of multiple datasets and a mixture training procedure, our foundation model can be widely used in various downstream dialogue tasks. Extensive experimental results indicate that our model not only improve seq2seq generation performance, but also enhance language models’ the representation ability.

In summary, the contribution of this paper comes three folds:

- We collect a large-scale dialogue dataset (named DialogZoo dataset) across 15 dialogue tasks and 73 dialogue datasets, and normalize it with a unified text-to-text format. To the best of our knowledge, this is by far the largest form-unified dialogue dataset supporting as many as 15 dialogue tasks. We will make it publicly available.

- Using the newly-proposed dataset as well as two dialogue-oriented self-supervised tasks, a unified dialogue foundation model (named DialogZoo model) is trained with multi-task learning.

- Extensive experimental results show that our pre-trained foundation model outperforms the state-of-the-art models on three aspects including representation, knowledge distillation and generation.

2 Related Work

2.1 Pre-trained Dialogue Models

Pre-trained dialogue models are pretrained language models (PLMs) designed for dialogue tasks. Recent years have witnessed remarkable progress in pre-trained dialogue models. Most of them fall into three categories. The first is training language models on large-scale dialogue corpus using typical self-supervised objects, i.e. mask language modeling (MLM) (Devlin et al., 2019) and autoregressive generation (Brown et al., 2020). Representative works that fall into this category include Meena (Adiwardana et al., 2020), Blender (Roller et al., 2020), and DialoGPT (Zhang et al., 2020), which utilize large-scale open-domain dialogues as the training corpus, and TOD-BERT (Wu et al., 2020), and ConvBERT (Mehri et al., 2020), which use task-oriented dialogues as the training corpus. The utilization of dialogue corpus significantly boosts the dialogue understanding and generation ability of language models. The second category is training language models on well-labeled dialogues using task-specific supervised objects. Most works that fall into this category focus on the task-oriented dialogue area, such as SOLOIST (Peng et al., 2021), PPTOD (Su et al., 2021), and GALAXY (He et al., 2022). The usage of dialogue annotations not only improves the performance of related downstream tasks but also improves the transferability of dialogue models in few-shot scenarios. The third is to design dialogue-oriented self-supervised training objectives (Bao et al., 2020; Xu and Zhao, 2021). These works try to minimize the gap between downstream tasks and self-supervised tasks.

Different from the above works, we collect a large scale well-labeled dialogue corpus of diverse dialogue tasks and formulate them into a unified text-to-text format. With this supervised corpus, we further propose two dialogue-oriented self-supervised tasks to jointly pre-train our unified dialogue model.
Table 1: The detailed introduction of 15 dialog-oriented tasks (DOTs) under the unified generative framework. “#Dataset” means the number of datasets used in corresponding task.

| DOTs | Dialog Content | External Knowledge | Output Format | #Dataset |
|------|----------------|--------------------|---------------|----------|
| REW  | Multiple Turns | None               | Single Utterance | 3        |
| NLG  | None           | Semi-structured Description | Single Utterance | 5        |
| SUM  | Multiple Turns | None               | Unstructured Text | 3        |
| FILL | Single Turn    | Semi-structured Description | Structured Knowledge | 7        |
| INTENT | Single Turn  | Semi-structured Description | Unstructured Text | 4        |
| DST  | Multiple Turns | Semi-structured Description | Structured Knowledge | 6        |
| COMM | Single Turn    | Unstructured Text   | Unstructured Text | 5        |
| EMO  | Single Turn    | Semi-structured Description | Unstructured Text | 5        |
| DOCQA| Multiple Turns | Unstructured Text   | Unstructured Text | 7        |
| DIALQA| Multiple Turns | Unstructured Text   | Unstructured Text | 6        |
| CHAT | Multiple Turns | Unstructured Text   | Single Utterance | 5        |
| KGDIAL | Multiple Turns | Structured Knowledge | Single Utterance | 2        |
| TXT2SQL | Multiple Turns | Structured Knowledge | Structured Knowledge | 3        |
| SIM  | Multiple Turns | Semi-structured Description | Single Utterance | 6        |
| TOD  | Multiple Turns | Semi-structured Description | Single Utterance | 6        |

2.2 Multi-task Learning for Pre-trained Language Models

Recently, multi-task learning of pre-trained language models has attracted spotlight research interest. Aghajanyan et al. (2021) proposes the concept of pre-finetuning, which is massive multi-task learning on 50 tasks. They show that pre-finetuning consistently improves performance for pre-trained models on various classification and generation tasks. FLAT (Wei et al., 2021) and T0 (Sanh et al., 2021) scale to more tasks (i.e. 62 and 171 respectively) for multi-task learning, and translate all samples to text-to-text formats based on task instructions. The most recent proposed ExT5 (Aribandi et al., 2021) is a model pre-trained using multi-task learning of self-supervised span denoising and supervised datasets.

In the dialogue research field, there are also a few works on multi-task learning of pre-trained language models. Su et al. (2021) proposes a multi-task pre-training framework that allows a unified dialogue model to solve different sub-tasks in task-oriented dialogue systems. Chen et al. (2022) investigates different multi-task training strategies for a set of dialogue understanding tasks. Our work distinguishes from the above by not limiting to a subset of dialogue tasks. We explore large-scale multi-task learning of enormous yet diverse supervised dialogue tasks as well as two dialogue-oriented self-supervised tasks.

3 DialogZoo Dataset

As mentioned in Section 1, the research in dialogue area faces the problem of having difficulty in reusing labeled corpus from other dataset, other domain or other task. To solve this, we try to build a unified dialogue dataset containing multiple dialogue tasks and various domains. Instead of collecting large scale unlabeled corpus from internet to pretrain language model like T5 (Raffel et al., 2020), we choose those carefully annotated dialogue data from previous work, which will be described in next section.

3.1 Tasks and datasets in DialogZoo

In this section, we describe the tasks and datasets in DialogZoo. Our principle is to collect those dataset with high quality annotation and already studied by some researchers to ensure the quality of unified dataset. At last, We collected dataset from 15 tasks and 73 datasets in total. We summarize these tasks in Table 1, and corresponding datasets in Table 5.

3.2 Dialogue understanding and Knowledge understanding

Smith et al. (2020) propose a 4-part blended skill requirement for open-domain dialogue agent, which puts emphasis on agent’s conversational ability. Beyond that, we introduce the ability requirement on agent’s understanding in external knowledge as dialogue system is knowledge-intensive, the agent has to process complicated information like dialogue
Figure 2: All the collected dialog datasets in DialogZoo. The upper right means that the dialog tasks need stronger understanding ability on both dialog and knowledge levels.

A unified dialogue model normally needs to equip with the ability in two aspects: **dialogue understanding** and **knowledge understanding**. It must do well in understanding a long dialogue history. It must extract keywords, entities, speaker’s intent correctly, detect speaker’s emotion properly, and take speaker’s personal background and conversation scene into consideration to avoid malicious response. Apart from that, it must be able to understand different knowledge source to help model construct a helpful response to speaker. It must extract information related to user’s utterance from a long wiki article or structured dialogue states. More specifically, we set different levels of ability in these two dimensions.

- **Dialogue understanding**: Basic requirement for dialogue understanding is to extract answer directly from single-turn utterance. The next level is to abstractly classify or generate response to single-turn utterance. Further, it extracts answer from multi-turn dialogues. The most difficult level is to abstractly classify, summarize or generate response to multi-turn dialogues.

- **Knowledge understanding**: There’re many different formats of external knowledge and they differ in knowledge understanding ability. No external knowledge is the start point of knowledge understanding, then keywords like conversation topic or speaker’s emotion. Simple structured knowledge like dialogue states or system act are the next level. Further, unstructured long text from sentence-level dialogue background to a full wiki article pose new challenges. Beyond that is world knowledge that is not contained in any text.

All the collected datasets are shown in Figure 2, which are used to pre-train our unified DiaogZoo model. The number distribution of training samples on 73 dialog corpora is shown in Figure 1.

### 4 DialogZoo Model

In this section, we first describe our framework to formulate all the dialog-oriented tasks into text-to-text format. To enhance representation ability of DialogZoo model, we further design two self-supervised tasks (named REO and CLO). Last but not least, we introduce our training strategy of large-scale dialog-oriented tasks, where the distribution of training samples among different tasks are unbalance.

#### 4.1 Unified Generative Framework

As shown in Figure 3, dialog corpora always connect with the diverse external knowledge. For example, the external knowledge of QA data is normally sourced from document and the task-oriented dialog (TOD) is corresponding to a database, which is defined by the expert-designed dialog ontology. In DialogZoo, all dialog types are included in the dialog content, e.g., single turn QA, sequential QA (SQA), task-oriented dialog (TOD) and chitchat (Chat). The types of corresponding external knowledge are also diversified, including unstructured document, semi-structured scene description, structured database etc..

Given this circumstance, we split the input of dialog-oriented tasks (DOTs) into three components: **dialog content**, **connected external knowledge** and **task definition**. The output format under the unified generative framework is dependent on the task definition. The unified generative template of DialogZoo is as below:

where “[TI]” is the special token of dialog-oriented tasks, e.g., “[rew]” represents the task identification of dialog rewrite (REW) task. The dialog content
and the corresponding external knowledge have various input formats across 15 dialog-oriented tasks. The input dialog content consists of three categories: single turn, multiple turns and “None”, where “None” dialog content exists in NLG task, whose input is the logical form. The external knowledge span four categories: unstructured text, semi-structured description, structured knowledge and “None”. Here, the special case “None” exists in the general dialog-oriented tasks, e.g. dialog summary. The task definition is the custom description with only one sentence. The output formats are also diversity, which consist of unstructured text (e.g., in INTENT and SUM), single utterance (e.g., in REW and NLG), structured knowledge (e.g., in TXT2SQL). Note that the output does not include the completed dialog in supervised dialog-oriented tasks. The detailed introduction of the input and output on all DOTs are shown in Table 1, with specific instances shown in Appendix.

4.2 Self-supervised Tasks

As discussed in Section 4.1, the completed dialog does not exist in the output of all supervised dialog-oriented tasks. Due to this fact, DialogZoo model’s decoder could never see the completed dialog during training, largely restricting its representation capability. To alleviate this problem, we design two self-supervised tasks: REO and CLO, which are both dialog denoising tasks.

**REO Task** Under our unified generative framework, the dialog content in REO is aggregation of the multiple-turn dialog data in all supervised corpora. We randomly permute the order of multiple-turn dialog at turn level. The REO task aims to recover the original order of permuted dialog. The input external knowledge of REO is “None”.

**CLO Task** Similarly, the dialog content in CLO is aggregation of the single-turn and multiple-turn dialog data in all the supervised corpora. We leverage...
Algorithm 1: Task-iterative Training Strategy

Input: Iteration Step: $S$, Dialog-Oriented Tasks: $T$, Training Samples: $C = \{c_0, \ldots, c_T\}$, Epoch: $E$.

Initialize training step: $i = 0$;

for $e$ in range($E$) do

\[ M = \max(|C|) \% S \]

for $m$ in range($M$) do

for $t$ in range($T$) do

\[ t_i = i \% |c_t| \]

\[ L(\theta) = \text{NLLLoss}(c[t_i : t_i + S]) \]

Update $\theta$

end

$i += S$

end

end

the entity extraction tool (spaCy)\(^1\) to extract all meaningful entities in the dialog content. The extracted entities are replaced by masking tokens in the dialog content and the set of extracted entities are permuted, working as external knowledge. The CLO task aims to recover the masked dialog content according to the given entities from external knowledge.

4.3 Task-iterative Training Strategy

As shown in Figure 1, the distribution of training samples is extremely unbalanced. Our preliminary results show that direct mix-up training makes the unified DialogZoo model converge to the high-proportion tasks, e.g., dialog state tracking (DST).

Therefore, we apply a task-iterative training strategy, where a hyperparameter is added to control the task iteration step (e.g., 512 samples in our experiment). In the multitask training process, we iterate the dialog-oriented tasks (including supervised and self-supervised tasks) at each 512 samples. The epoch ends until the most samples of the task meet the final 512 samples. The rest tasks may be trained more than one time. This task-iterative training strategy can guarantee that every DOT is trained by the same steps at each epoch, purposefully applied to achieve comparable results on all DOTs. The detailed training strategies are shown in Algorithm 1, where $\theta$ is shared parameters of unified DialogZoo model and NLLLoss is negative log likelihood loss.

5 Experiments

We train our unified DialogZoo model on 73 dialog corpora, which span 15 supervised dialog-oriented tasks and 2 self-supervised tasks. Our DialogueZoo model mainly support three main usages: representation, knowledge-distillation and generation. Representation means that the unified model can be directly initialized as dialog encoding model and then fine-tuned in downstream tasks. Knowledge-distillation indicates that DialogZoo model can directly used as understanding model under the unified generative framework. Generation means that it is also a dialog response model, which can generate fluent and reasonable expression. Compared with previous dialog pre-trained models, our model is the only one that can achieve strong performance on all three aspects. To sum up, our DialogZoo contributes the first multi-purposed cross-domain pretrained model with superior performance on numerous downstream tasks.

5.1 Baselines & Benchmarks

In our experiments, we respectively use BART-Base (Lewis et al., 2020) and T5-Base (Raffel et al., 2020) as the backbone of DialogZoo model. These intuitive baselines are the corresponding PLMs while other baselines are pre-trained dialog models, including ConvBERT (Mehri et al., 2020) and Span-ConveRT (Coope et al., 2020b), which are both trained by MLM loss (Devlin et al., 2019). We further include SOLOIST (Peng et al., 2021) and PPTOD (Su et al., 2021), the two pre-trained end-to-end TOD models fine-tuned on the existed task-oriented dialog corpora. The rest baselines are the well-designed models for the corresponding dialog-oriented tasks.

We evaluate our unified DialogZoo model on DialogGLUE (Mehri et al., 2020) benchmark, which consists of four dialog-oriented tasks: slot filling (FILL), intent detection (INTENT), semantic parsing and dialog state tracking (DST). TOP (Gupta et al., 2018) is semantic parsing task in DialogGLUE, which is unseen in DialogZoo.

5.2 Implementation

All the Transformer-based pre-trained language models are loaded from HuggingFace library (Wolf et al., 2019). We train our unified DialogZoo model on 8 V100 GPUs with 32G memory. The batch size is 256 with gradient accumulation strategy (updated per 8 steps). The max token length of input

\(^1\)https://github.com/explosion/spaCy
Table 2: The representation ability of six different pre-trained language models on DialoGLUE benchmark. All metrics are the higher the better.

| Intent Detection | ConvBERT | ConvBERT* | BART_{base} | DialogZoo_{bart} | T5_{base} | DialogZoo_{t5} |
|------------------|----------|-----------|-------------|------------------|-----------|----------------|
| BANKING77 (ACC.) | 92.89    | 92.08     | 93.15       | **93.32**        | 92.31     | 93.02          |
| CLINIC150 (ACC.)| 97.04    | 95.58     | 96.20       | **97.33**        | 96.49     | 97.31          |
| HWU64 (ACC.)    | 91.82    | 90.89     | 91.17       | **94.42**        | 91.26     | 93.16          |

| Slot Filling | RESTUARANT8k (F1) | 96.04 | 95.29 | 92.29 | 93.89 | 95.98 | **96.07** |
|             | DSTC8 (F1)         | 89.45 | 86.71 | 86.77 | 88.53 | 90.56 | **90.76** |

| Semantic Parsing | TOP (EM) | 81.43 | 80.80 | 80.71 | 81.24 | 81.81 | **82.04** |

| Dialog State Tracking | MULTIWOZ2.1 (JGA) | 58.11 | 56.21 | 56.57 | 59.19 | 57.21 | **60.58** |
|-----------------------|-------------------|-------|-------|-------|-------|-------|-----------|
| Average Score         | 86.68             | 85.37 | 85.27 | 86.85 | 86.73 | **87.56** |

Figure 4: The proportion of the training samples on unsupervised tasks and supervised tasks. The top 4 supervised tasks that have more training samples are DST, CHAT, TOD and SIM.

and output sets as 350. The learning rate is 1e-5 with AdamW optimizer. The unified DialogZoo models are trained with 200K steps, which takes around 72 hours. We finally involved 10,661,579 samples in total to train the unified model, including supervised instances and unsupervised instances. The detailed proportion of training samples is illustrated in Figure 4.

5.3 Usage 1: Representation

We conduct all the representation experiments on the standard DialoGLUE benchmark. The strong baseline model ConvBERT is pre-trained on over 70 million Reddit data with MLM method. To fairly compare with our proposed DialogZoo model, we also pre-train the comparable ConvBERT* with our collected dialog corpora. The 4.6 million DialogZoo data used to train ConvBERT* is substantially less than the original corpus in ConvBERT. We rerun ConvBERT and ConvBERT* on DialoGLUE with their released source code. All the test results are based on the checkpoints that achieve the best evaluate performance on development set. As shown in Table 2, we can see that the representation ability of ConvBERT* is absolutely worse than the ConvBERT. The main reason is that the scale of pre-training corpus is less in an order of magnitude, which is the main factor affecting unsupervised learning performance.

We directly replace the ConvBERT model with the DialogZoo model, where we do not adjust any hyper-parameters during the fine-tuning process. The designed models for downstream tasks in DialoGLUE are also unchanged, e.g. DST used Trippy model (Heck et al., 2020). DialogZoo_{bart} and DialogZoo_{t5} means that the backbones of DialogZoo are BART-Base and T5-Base, respectively. Compared with original backbones, two DialogZoo models achieved better performance on all
Knowledge Distillation Methods

### Intent Detection

| Method       | SOTA (ACC.) | DialogZoo\textsubscript{t5} w/ FT |
|--------------|-------------|----------------------------------|
| BANKING77    | 93.86       | 92.82                            |
| CLINC150     | 97.16       | 100.00                           |
| HWU64        | 92.94       | 98.70                            |

### Slot Filling

| Method       | Score   |
|--------------|---------|
| RESTUARANT8K | 98.00   |
| DSTC8\textdagger{1} | 89.45   |

### Dialog State Tracking

| Method       | Score   |
|--------------|---------|
| MULTIW2Z2.2  | 57.70   |

### Text to SQL

| Method       | Score   |
|--------------|---------|
| SPARC\textdagger{2} | 51.70   |

Table 3: The performance on knowledge distillation tasks. \textdagger{1} means the corresponding dataset on slot filling task is unseen in DialogZoo. \textdagger{2} means the results on development set.

DialogGLUE tasks. DialogZoo\textsubscript{t5} enjoys the best performance on intent detection tasks. However, there is a large performance decrease in slot filling tasks compared to ConvBERT. DialogZoo\textsubscript{t5} surpasses ConvBERT on all tasks, where the average score gets absolute 0.88 points gain. It indicates that the multitask learning method is another way to enhance the representation ability of the pre-trained model with the same scale corpus.

**Ablation Study** We remove two self-supervised tasks in DialogZoo to investigate their effects on representation ability. As shown in Figure 5, “w/o SST” means the unified model is trained on only supervised dialog-oriented tasks with backbone of BART-Base. We can see that the average scores on DialoGLUE are unstable during the training process. DialogZoo with two unsupervised tasks can achieve stable growth on average score.

### Usage 2: Knowledge-Distillation

In addition to using DialogZoo model as representation model, we can also leverage DialogZoo model as knowledge distillation model to directly parse the structured knowledge in a generative way. As shown in Table 3, DialogZoo\textsubscript{t5} can achieve new state-of-the-arts on three knowledge distillation tasks. On CLINC15, DialogZoo\textsubscript{t5} even reaches 100% accuracy. “w/ FT” means that DialogZoo\textsubscript{t5} continues to be fine-tuned on the corresponding tasks. The fine-tuned DialogZoo\textsubscript{t5} achieve another two SOTA performance on the distillation tasks. Note that DSTC8 on slot filling task is unseen on DialogZoo, which is a zero-shot setting. DialogZoo\textsubscript{t5} can get 47.85 F1 score. It indicates that DialogZoo model has strong generalization capability.

### Usage 3: Generation

Different from structured semantic space in knowledge distillation, generation tasks support free and large output space, where our DialogZoo model also shows splendid efficiency. As shown in Table 4, DialogZoo\textsubscript{t5} achieves comparable performance on dialog generation tasks, which include three typical dialog systems (Chitchat, QA and TOD). In user simulation task, the user’s intent is given as the external knowledge in DialogZoo model. DialogZoo\textsubscript{t5} arrives at exciting performance with 28.97 R-L score. The fine-tuned DialogZoo\textsubscript{t5} reaches 43.07 R-L score. DialogZoo\textsubscript{t5} also outperforms SOTA on two general dialog understanding tasks (dialog summary and dialog rewrite).

### Conclusion

In this paper, we collect 73 dialog datasets across 15 supervised dialog-oriented tasks to pre-train a unified DialogZoo model. To enhance the representation ability of DialogZoo model, we further propose two unsupervised dialog denoising tasks to jointly pre-train the DialogZoo model with multitask learning. The experimental results show that our pre-trained DialogZoo model can obtain strong performance on three aspects: representation, knowledge distillation and generation.
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A Appendix
| DOT   | Datasets                                                                 |
|-------|--------------------------------------------------------------------------|
| **REW** | Task (Quan et al., 2019), Canard (Elgohary et al., 2019), Mudoco (Martin et al., 2020) |
| **NLG** | Sclstm (Wen et al., 2015), E2E (Novikova et al., 2017), Rnnlg (Wen et al., 2016), E2E-challenge (Li et al., 2018), Google-SIM (Shah et al., 2018) |
| **SUM** | Samsun (Gliwa et al., 2019), Dialogsum (Chen et al., 2021), ReadingComprehension (Ma et al., 2018) |
| **FILL** | Restaurant8k (Coope et al., 2020a), Snips (Coucke et al., 2018), HWU64 (Liu et al., 2021b), MAMS (Jiang et al., 2019), ASTE (Xu et al., 2021), Sentihood (Saeidi et al., 2016) |
| **INTENT** | Banking77 (Casanueva et al., 2020), Snips (Coucke et al., 2018), HWU64 (Liu et al., 2021b), Clinic (Larson et al., 2019) |
| **DST** | SGD (Rastogi et al., 2020), TaskMaster2 (Byrne et al., 2019), WOZ (Mrkšić et al, 2016), MultiWOZ2.2 (Zang et al., 2020), MultiDogo (Peskov et al., 2019), DSTC2 (Henderson et al., 2014a), DSTC3 (Henderson et al., 2014b) |
| **COMM** | Alphanli (Bhagavatula et al., 2019), Commonsense-qa (Talmor et al., 2018), Cosmosqa (Huang et al., 2019), Csqqa2 (Talmor et al., 2022), SocialQA (Sap et al., 2019) |
| **EMO** | Emory (Goodfellow et al., 2013), Go-emotion (Demszky et al., 2020), Meld (Poria et al., 2018), Recon (Poria et al., 2021) |
| **DOCQA** | CoQA (Reddy et al., 2018), CMUDoG (Zhou et al., 2018), DoQA (Campos et al., 2019), NarrativeQA (s Ko’ciský et al., 2018), QuAC (Choi et al., 2018), Race (Lai et al., 2017), Squad (Rajpurkar et al., 2018) |
| **DIALQA** | DDrel (Jia et al., 2020), FriendsQA (Yang and Choi, 2019), Molweni (Li et al., 2020), DialogRE (Yu et al., 2020), Mutual (Cui et al., 2020), Dream (Sun et al., 2019) |
| **CHAT** | DailyDialog (Li et al., 2017), PersonaChat (Zhang et al., 2018), Metal-WOZ (Shulz et al., 2019), EmpatheticDialog (Rashkin et al., 2019), CommonsenseDialog (Zhou et al., 2021) |
| **KG DIAL** | Soccer-kgdial, Incar-kgdial (Chaudhuri et al., 2019) |
| **TXT2SQL** | Spider (Yu et al., 2018), Sparc (Yu et al., 2019b), CoSQL (Yu et al., 2019a) |
| **SIM** | SGD (Rastogi et al., 2020), Task-master2 (Byrne et al., 2019), WOZ (Mrkšić et al., 2016), MultiWOZ2.2 (Zang et al., 2020), MultiDogo (Peskov et al., 2019), DSTC2 (Henderson et al., 2014a), DSTC3 (Henderson et al., 2014b) |
| **TOD** | SGD (Rastogi et al., 2020), Task-master2 (Byrne et al., 2019), WOZ (Mrkšić et al., 2016), MultiWOZ2.2 (Zang et al., 2020), MultiDogo (Peskov et al., 2019), DSTC2 (Henderson et al., 2014a), DSTC3 (Henderson et al., 2014b) |

Table 5: Datasets in DialogZoo, for those datasets with annotations for more than one tasks, we put it in all related tasks.