InstructDial: Improving Zero and Few-shot Generalization in Dialogue through Instruction Tuning

Prakhar Gupta♣ Cathy Jiao♣ Yi-Ting Yeh♣ Shikib Mehri♣
Maxine Eskenazi♣ Jeffrey P. Bigham♣♡

♣Language Technologies Institute, Carnegie Mellon University
♡Human-Computer Interaction Institute, Carnegie Mellon University

{prakharg,cljiao,yitingye,amehri,max,jbigham}@cs.cmu.edu

Abstract

Instruction tuning is an emergent paradigm in NLP wherein natural language instructions are leveraged with language models to induce zero-shot performance on unseen tasks. Dialogue is an especially interesting area in which to explore instruction tuning because dialogue systems perform multiple tasks related to language (e.g., natural language understanding and generation, domain-specific interaction), yet instruction tuning has not been systematically explored for dialogue-related tasks. We introduce INSTRUCTDIAL, an instruction tuning framework for dialogue, which consists of a repository of 48 diverse dialogue tasks in a unified text-to-text format created from 59 openly available dialogue datasets. We explore cross-task generalization ability on models tuned on INSTRUCTDIAL across diverse dialogue tasks. Our analysis reveals that INSTRUCTDIAL enables good zero-shot performance on unseen datasets and tasks such as dialogue evaluation and intent detection, and even better performance in a few-shot setting. To ensure that models adhere to instructions, we introduce novel meta-tasks. We establish benchmark zero-shot and few-shot performance of models trained using the proposed framework on multiple dialogue tasks1.

1 Introduction

Pretrained large language models (LLMs) (Devlin et al., 2019; Radford et al., 2019; Brown et al., 2020) are not only few-shot learners, but can also perform numerous language tasks without the need for fine-tuning. However, LLMs are expensive to train and test. Instruction tuning has emerged as a tool for directly inducing zero-shot generalization on unseen tasks in language models by using natural language instructions (Mishra et al., 2021; Sanh et al., 2022; Wei et al., 2022; Ouyang et al., 2022). Natural language instructions can contain components such as task definitions, examples, and prompts which allows them to be customized for multitask learning. Instruction tuning enables developers, practitioners, and even non-expert users to leverage language models for novel tasks by specifying them through natural language instructions. Instruction tuned models exhibit zero-shot or few-shot generalization to new tasks.

Figure 1: We investigate instruction tuning on dialogue tasks. Instruction tuning involves training a model on a mixture of tasks defined through natural language instructions. Instruction tuned models exhibit zero-shot or few-shot generalization to new tasks.
such as (Wang et al., 2022a) include a few dialogue tasks, those tasks are collected through crowdsourcing and do not provide good coverage of dialogue tasks and domains. No prior work has examined how training a model on a wide range of dialogue tasks with a variety of instructions may affect a system’s ability to perform on both core dialogue tasks such as intent detection and response generation, and domain-specific tasks such as emotion classification. In this work, we introduce \textsc{InstructDial}, a framework for instruction tuning on dialogue tasks. We provide a large curated collection of 59 dialogue datasets and 48 tasks, benchmark models, and a suite of metrics for testing the zero-shot and few-shot capabilities of the models. \textsc{InstructDial} consists of multiple dialogue tasks converted into a text-to-text format (Figure 1). These dialogue tasks cover generation, classification, and evaluation for both task-oriented and open-ended settings and are drawn from different domains (Figure 2).

Instruction tuned models may ignore instructions and attain good performance with irrelevant prompts (Webson and Pavlick, 2021), without actually following user’s instructions. We address this issue in two ways: (1) we train the models with a variety of outputs given the same input context by creating multiple task formulations, and (2) we propose two instruction-specific meta-tasks (e.g., select an instruction that matches with an input-output pair) to encourage models to adhere to the instructions.

The main contributions of this work are:

• We introduce \textsc{InstructDial}, a framework to systematically investigate instruction tuning for dialogue on a large collection of dialogue datasets (59 datasets) and tasks (48 tasks). Our framework is open-sourced and allows easy incorporation and configuration of new datasets and tasks.
• We show that instruction tuning models enhance zero-shot and few-shot performance on a variety of different dialogue tasks.
• We provide various analyses and establish baseline and upper bound performance for multiple tasks. We also provide integration of various task-specific dialogue metrics.

Our experiments reveal further room for improvement on issues such as sensitivity to instruction wording and task interference. We hope that \textsc{InstructDial} will facilitate further progress on instruction tuning for dialogue tasks.

2 Related Work

Pre-training and Multi-Task learning in Dialogue Large-scale transformer models (Devlin et al., 2019; Radford et al., 2019; Brown et al., 2020) pre-trained on massive text corpora have brought substantial performance improvements in natural language processing. Similar trends have occurred in the dialogue domain, where models such as DialoGPT (Zhang et al., 2020), Blenderbot (Roller et al., 2021) and PLATO (Bao et al., 2021) trained on sources such as Reddit or Weibo, or on human-annotated datasets show great capabilities in carrying open-domain conversations. Large-scale pretraining has also shown success in task-oriented dialogue (TOD). (Budzianowski and Vulić, 2019; Hosseini-Asl et al., 2020; Ham et al., 2020; Lin et al., 2020; Yang et al., 2021) utilized pretrained language models such as GPT-2 (Radford et al., 2019) to perform TOD tasks such as language generation or act prediction. Similarly, BERT-type pretrained models have been used for language understanding in TOD tasks (Wu et al., 2020a; Mi et al., 2021b). Several of these works have shown improved performance by performing multi-task learning over multiple tasks (Hosseini-Asl et al., 2020; Liu et al., 2022; Su et al., 2022a). Multi-task pretraining also helps models learn good few-shot capabilities (Wu et al., 2020a; Peng et al., 2021). Our work covers both open-domain and TOD tasks and goes beyond multi-tasking as it incorporates additional structure of the tasks such as task definitions and constraints.

Instruction Tuning Constructing natural language prompts to perform NLP tasks is an active area of research (Schick and Schütze, 2021; Liu et al., 2021a). However, prompts are generally short and do not generalize well to reformulations and new tasks. Instruction tuning is a paradigm where models are trained on a variety of tasks with natural language instructions. Going beyond multi-task training, these approaches show better generalization to unseen tasks when prompted with a few examples (Bragg et al., 2021; Min et al., 2022a,b) or language definitions and constraints (Weller et al., 2020; Zhong et al., 2021b; Xu et al., 2022). Prompt-Source (Sanh et al., 2022), FLAN (Wei et al., 2022) and NATURAL INSTRUCTIONS (Mishra et al., 2021; Wang et al., 2022b) collected instructions and datasets for a variety of general NLP tasks. GPT3-Instruct model (Ouyang et al., 2022) is tuned on a dataset of rankings of model outputs and
was trained using human feedback, but it is expensive to train and test. Instead, our work is tailored to dialogue tasks and incorporates numerous dialogue datasets, tasks, and benchmarks. We show that models trained on collections such as PromptSource are complementary to instruction tuning on dialogue. For dialogue tasks, Madotto et al. (2021) explored prompt-based few-shot learning for dialogue, but without any fine-tuning. Mi et al. (2021a) designed task-specific instructions for TOD tasks that improved few-shot performance on several tasks. Our work covers a far greater variety of dialogue domains and datasets in comparison.

3 Methodology

In this section, we first discuss instruction tuning setup. Next, we discuss the taxonomy of dialogue tasks, the task meta-information schema, and discuss how dialogue datasets and tasks are mapped into our schema. Finally, we discuss model training and fine-tuning details.

3.1 Instruction Tuning Background

A supervised setup for a dialogue task $t$ consists of training instances $d_{\text{train}}^t \ni (x_i, y_i)$, where $x_i$ and $y_i$ are an input-output pair. A model $M$ is trained on $d_{\text{train}}^t$ and tested on $d_{\text{test}}^t$. In a cross-task setup, the model $M$ is tested on test instances $d_{\text{test}}^{\hat{t}}$ of an unseen task $\hat{t}$. In instruction tuning, the model $M$ is provided additional signal or meta information about the task. The meta information can consist of prompts, task definitions, constraints, and examples, and guides the model $M$ towards the expected output space of the unseen task $\hat{t}$.

3.2 Task Collection

We adopt the definition of a task from Sanh et al. (2022), which defined a task as "a general NLP ability that is tested by a group of specific datasets". In INSTRUCTDIAL, each task is created from one or more existing open-access dialogue datasets. Figure 2 shows the taxonomy of dialogue tasks in INSTRUCTDIAL, and Table 9 shows the list of datasets used in each task. In our taxonomy, Classification tasks consist of tasks such as intent classification with a set of predefined output classes. Generation tasks consist of tasks such as open-domain, task-oriented, controlled, and grounded response generation, and summarization. Evaluation tasks consist of response selection in addition to relevance and rating prediction tasks. Edit tasks involve editing a corrupted dialogue response into a coherent response. Corrupted responses are created through shuffling, repeating, adding, or removing phrases/sentences in the gold response. Pretraining tasks involve tasks such as infilling or finding the index of an incoherent or missing utterance. They include multiple tasks covered in prior pretraining work (Mehri et al., 2019; Zhao et al., 2020b; Whang et al., 2021; Xu et al., 2021b). Safety Tasks consist of toxicity detection, non-toxic, and recovery response generation. Miscellaneous tasks are a set of tasks that belong to specialized domains such as giving advice or persuading a user.

3.3 Task Schema and Formatting

All tasks in INSTRUCTDIAL are expressed in a natural language sequence-to-sequence format. Every task instance is formatted with the following
Figure 3: Instruction based input-output samples for three tasks. Each task is formatted as a natural language sequence. Each input contains an instruction, instance, optional task-dependent inputs (e.g., class options in relation classification), and task-specific prompts. The instructions and the input instances are formatted using special tokens such as [CONTEXT] and [QUESTION]. The Instruction Selection task is a meta-task described in Section 3.4 properties: **Task Definition**: Description of the task containing information about how to produce an output given an input. **Instance Inputs**: Instances from a dataset converted into a sequence. **Constraints**: Additional metadata or constraints for a task (emotion tag for emotion-based generation, classes for classification). **Prompt**: Text sequence that connects the instance back to the instruction, expressed as a command or a question. **Output**: Output of an instance converted into a sequence.

Figure 3 shows examples of instances from 3 tasks. For each task, we manually compose 3-10 task definitions and prompts. For every instance, a task definition and a prompt are selected randomly during test. We do not include in-context examples in the task schema since dialogue contexts are often long and concatenating long examples would exceed the maximum allowable input length for most models. Input instances are formatted using special tokens. The token [CONTEXT] signals the start of dialogue content. Dialogue turns are separated by [ENDOFTURN]. [ENDOFDIALOGUE] marks the end of the dialogue and [QUESTION] marks the start of the prompt text. We also incorporate task specific special tokens (such as [EMOTION] for emotion classification task). We hypothesize that using a consistent structure and formatting across tasks should help the model adopt the structure and novel input fields for unseen tasks better.

**Classification Options**: In classification tasks, the model is trained to predict an output that belongs to one of several classes. To make the model aware of output classes available for an unseen task, we append a list of classes from which the model should choose. We adopt the following two formats for representing the classes: (1) **Name list**: list the class names separated by a class separator token such as a comma, and (2) **Indexed list**: list the classes indexed by either alphabets or numbers (such as 1: class A, 2: class B,...) where the model outputs the index corresponding to the predicted class. This representation is useful when the classification options are long in length, such as in the case of response ranking where the model has to output the best response among the provided candidates.

**Custom inputs**: Some tasks consist of input fields that are unique to the task. For example, emotion grounded generation consists of emotion labels that the model uses for response generation. We append such inputs to the beginning of the instance sequence along with the field label. For example, we pre-pend “[EMOTION] happy” to the dialogue context in the emotion generation task.

In Table 8 in the Appendix we present the list of tasks with sample inputs for each task.

### 3.4 Meta Tasks

A model can learn to perform well on tasks during training by inferring the domain and characteristics of the dataset instead of paying attention to the instructions, and then fail to generalize to new instructions at the test time. We introduce two meta-tasks that help the model learn the association between the instruction, the data, and the task. In the Instruction selection task, the model is asked to select the instruction which corresponds to a
given input-output pair. In the Instruction binary task, the model is asked to predict “yes” or “no” if the provided instruction leads to a given output from an input. We show an example for instruction selection task in Figure 3.

3.5 None-of-the-above Options

For classification tasks, most tasks assume that the ground truth is always present in the candidate set, which is not the case for all unseen tasks. To solve this issue, we propose adding a NOTA (“None of the above”) option in the classification tasks during training as both correct answers and distractors following Feng et al. (2020b) for 10% of the training instances. To add NOTA as a correct answer, we add “none of the above” as a classification label option, remove the gold label from the options and set the output label as NOTA. To add NOTA as a distractor, we add NOTA to the classification labels list but keep the gold label as the output label.

4 Experimental Setup

4.1 Model Details

Our models use an encoder-decoder architecture and are trained using maximum likelihood training objective. We finetune the following two base models on the tasks from INSTRUCTDIAL:

1. T0-3B (Sanh et al., 2022) a model initialized from the 3B parameters version of T5 (Lester et al., 2021). T0-3B is trained on a multitask mixture of general non-dialogue tasks such as question answering, sentiment detection, and paraphrase identification.

2. BART0 (Lin et al., 2022), a model with 406 million parameters (8x smaller than T0-3B) based on Bart-large (Lewis et al., 2020), trained on the same task mixture as T0-3B.

We name the BART0 model tuned on INSTRUCTDIAL as DIAL-BART0 and T0-3B model tuned on INSTRUCTDIAL as DIAL-T0. DIAL-BART0 is our main model for experiments since its base BART0 has shown comparable zero-shot performance to T0 (Lin et al., 2022) despite being 8 times smaller, whereas the 3B parameter model DIAL-T0 is large and impractical to use on popular affordable GPUs. We perform finetuning on these two models since they both are instruction-tuned on general NLP tasks and thus provide a good base for building a dialogue instruction tuned model.

4.2 Training Details

For training data creation, we first generate instances from all datasets belonging to each task. We then sample a fixed maximum of $N = 5000$ instances per task. Each instance in a task is assigned a random task definition and prompt. We truncate the input sequences to 1024 tokens and target output sequences to 256 tokens. We train DIAL-BART0 on 2 Nvidia 2080Ti GPUs using a batch size of 2 per GPU with gradient checkpointing. We train DIAL-T0 on 2 Nvidia A6000 GPUs using a batch size of 1 per GPU with gradient checkpointing. Additional implementation details are present in Appendix A.

5 Experiments and Results

We evaluate our models on multiple zero-shot and few-shot settings. We establish benchmark results for Zero-shot unseen tasks evaluation (Section 5.1) and Response evaluation task (Section 5.2) and perform error analysis. Next, we perform zero-shot and few-shot experiments on three important dialogue tasks: intent detection, slot value generation, and dialogue state tracking (Section 5.3).

5.1 Zero-shot Unseen Tasks Evaluation

In this experiment, we test our models’ zero-shot ability on tasks not seen during training.

5.1.1 Unseen Tasks for Zero-shot Setting

We perform evaluation on the test set of the following 6 tasks not seen during training:

1. Dialfact classification: predict if an evidence supports, refutes, or does not have enough information to validate the response

2. Relation classification: predict the relation between two people in a dialogue

3. Answer selection: predict an answer to a conversational question

4. Eval selection: choose the most relevant response among the provided 4 options. Dataset and ratings based on DSTC 10 Automatic evaluation challenge (Chen et al., 2021b)

5. Knowledge grounded generation: generate a response based on background knowledge

6. Begins with generation: generate a response that starts with the provided initial phrase

All 6 tasks have varying levels of difficulty and cover both classification and generation. To emulate a zero-shot scenario, we remove all relation-based, evaluation type, answer generation, and
Model ES AS RC DC BW KG
ACC ACC ACC ACC ACC B-2 R-L GR F1 B-2 R-L GR

Baselines and Our Models

| Model      | ACC | ACC | ACC | ACC | B-2 | R-L | GR | F1 | B-2 | R-L | GR |
|------------|-----|-----|-----|-----|-----|-----|----|----|-----|-----|----|
| BART0      | 22.2| 58.5| 6.3 | 33.7| 4.2 | 4.9 | 12.0| 45.7| 17.4| 5.3 | 13.3|
| T0-3B      | 45.9| 60.2| 1.3 | 33.1| 14.1| 4.1 | 10.7| 55.5| 14.2| 3.2 | 10.7|
| GPT-3      | 57.5| 56.5| 11.5| 37.3| 16.5| 7.2 | 15.7| 57.0| 18.5| 3.9 | 11.6|
| DIAL-BART0 (Ours) | 66.7| 59.5| 17.8| 35.6| 56.3| 13.1| 26.4| 60.2| 27.8| 11.1| 21.4|
| DIAL-T0 (Ours)   | 74.4| 65.2| 17.6| 35.6| 56.3| 13.1| 26.5| 61.3| 27.8| 11.1| 21.4|

Few and Full shot Variations

| Model      | ACC | ACC | ACC | ACC | B-2 | R-L | GR | F1 | B-2 | R-L | GR |
|------------|-----|-----|-----|-----|-----|-----|----|----|-----|-----|----|
| DB-Few     | 77.1| 69.1| 28.0| 43.0| 72.2| 16.7| 30.7| 60.3| 27.9| 9.7 | 20.0|
| DB-Full    | 90.7| 83.3| 62.7| 77.4| 83.7| 20.8| 33.8| 61.0| 30.9| 11.6| 22.8|

Model Ablations for DIAL-BART0

| Model      | ACC | ACC | ACC | ACC | B-2 | R-L | GR | F1 | B-2 | R-L | GR |
|------------|-----|-----|-----|-----|-----|-----|----|----|-----|-----|----|
| DB-no-base | 40.1| 52.7| 17.1| 35.1| 53.9| 12.0| 26.6| 57.8| 29.8| 12.0| 22.8|
| DB-no-instr| 23.0| 43.2| 15.1| 35.4| 50.0| 13.0| 27.0| 61.1| 30.1| 11.2| 20.8|
| DB-no-nota | 66.5| 57.2| 17.2| 35.9| 56.1| 10.9| 25.3| 58.4| 28.0| 11.0| 21.4|
| DB-no-meta | 44.5| 52.0| 14.1| 35.4| 52.5| 14.1| 28.1| 61.3| 29.6| 11.8| 22.1|

Table 1: Zero-shot evaluation on unseen tasks. B-2 stands for BLEU2, R-L for RougeL and GR for GRADE metric. Here ES stands for Eval Selection, AS for Answer Selection, RC for Relation Classification, DC for Dialfact Classification, BW for Begins With, KG for Knowledge Grounded generation. DB-Few and DB-Full are variants of DIAL-BART0. Our models DIAL-BART0 and DIAL-T0 outperform the baseline models and their ablated versions.

wiki-based tasks from the training task set. The set of tasks used for training is presented in Table 10. We evaluate on the full test sets for Dialfact, relation, and answer classification, and sample 1000 instances for the rest of the tasks.

5.1.2 Setup and Baselines

We perform inference and evaluation on the 6 unseen tasks described in Section 5.1.1. We compare the following models and baselines:

- BART0 and T0-3B - Models that form a base for our models, trained on a mixture of non-dialogue general NLP tasks (described in Section 4.1).
- GPT-3 (Brown et al., 2020) - Davinci version of GPT-3 tested using our instruction set.
- DIAL-BART0 and DIAL-T0 - Our models described in Section 4.1.
- DB-Few - Few-shot version of DIAL-BART0. 100 random training set instances of the test tasks are mixed with the instances of train tasks.
- DB-Full - Version of DIAL-BART0 where 5000 instances per test task are mixed with the instances of the train tasks. This baseline serves as the upper bound for our models’ performance.
- DB-no-base - Uses Bart-large instead of using the BART0 as the base model.
- DB-no-instr - Trained with no instructions or prompts. Task constraints and class options are still specified. We specify the task name instead of instructions to help the model identify the task.
- DB-no-meta - Trained without the meta tasks from Section 3.4

5.1.3 Results and Discussion

We present the results for zero-shot experiments in Table 1 and report the accuracy metric for the Eval selection, Answer selection, Dialfact classification and Relation classification tasks. For Begins with task, we report BLEU2, ROUGEL, and accuracy defined as the proportion of responses that begins with the initial phrase provided. For Knowledge grounded generation we report BLEU2, and ROUGEL metrics along with F1 as defined in (Di-nan et al., 2019c). For the generation tasks we also report the automatic metric GRADE (Huang et al., 2020) (which has shown good correlation with human ratings on response coherence). For GPT-3 baseline we report the metrics on 200 randomly sampled instances per task. We average scores obtained across the instructions and prompts. We notice the following general trends in our results.

Instruction tuning on INSTRUCTDIAL improves performance on unseen dialogue tasks: The DIAL-BART0 and DIAL-T0 models instruction tuned on INSTRUCTDIAL achieve better performance on all tasks compared to their base models BART0 and T0-3B. Notably, for the Eval selection, Relation classification and Begins with generation tasks, our models perform about 3 times better than the base models. Our model also performs significantly better than GPT-3 for all tasks except for Dialfact classification. In the case of the Answer selection task, the difference in performance is lower compared to other models since the base-
Figure 4: Model’s performance on unseen tasks improves with the number of seen tasks during training. We report average Accuracy across Eval Selection, Answer Selection, Relation Classification, and Dialfact Classification, and average RougeL scores for Knowledge Grounded Generation and Begins with Generation.

line models are also trained on similar extractive and multi-choice question answering tasks. Relation and Dialfact classification are hard tasks for all models since there are no similar train tasks.

**Larger models are not necessarily better across tasks:** Experiments across varying model size show that while T0-3B and DIAL-T0 perform better on the Eval selection and Answer Selection tasks and perform equivalently on the Begins with generation task, BART0 and DIAL-BART0 perform better on the rest of the unseen tasks. While DIAL-T0 is better at classification tasks, it has poor performance on generation compared to DIAL-BART0. We also observed that DIAL-T0 sometimes produces empty or repetitive outputs for generation tasks.

**Few-shot training significantly improves performance:** DB-Few model that incorporates 100 instances per test task in its training data shows significant improvements in performance compared to its zero-shot counterpart DIAL-BART0. We see about 12-16% improvements on the Eval selection, Answer selection, and Dialfact classification tasks, and 30-50% improvement on the Begins with and Relation classification tasks.

**Full-shot training can improve performance across multiple tasks:** DB-Full model achieves high performance across all test tasks. The full-shot performance of DIAL-BART0 on Dialfact and relation classification tasks are near state-of-the-art performance without using the full train datasets.

**Meta tasks and NOTA are important for better generalization:** We see a large performance drop on unseen classification tasks when meta tasks (see Section 3.4) are removed. This shows that meta tasks help the model develop better representations and understanding of natural language instructions. DB-no-nota shows a slight performance drop in the classification task, indicating NOTA objective is helpful, but not crucial for performance.

**Pretraining on general NLP tasks helps dialogue instruction tuning:** DB-no-base model shows a high performance drop on Eval selection and Answer selection tasks, and a small drop on other test tasks. We conclude that instruction tuning for general NLP tasks helps dialogue instruction tuning.

**Using instructions leads to better generalization**: DB-no-instr shows worse performance than DIAL-BART0 on all tasks, especially on Eval selection, Answer selection, and Relation classification tasks. This indicates that training with instructions is crucial for zero-shot performance on unseen tasks.

**Training on more seen tasks improves generalization on unseen tasks:** In Figure 4 we show the impact of varying the number of seen tasks on the performance on unseen tasks. We adopt the train-test task split from section 5.1. We observe that the performance improves sharply up to 20-25 tasks and then further keeps steadily increasing with each new task. This indicates that increasing the number of tasks can lead to better zero-shot generalization and that scaling to more tasks may lead to better instruction-tuned models.

5.1.4 Analysis

**Sensitivity to instruction wording:** To analyze the sensitivity of our models to instruction wording, we breakdown the evaluation metrics per unique instruction used during inference for the DIAL-BART0 model. The accuracy varies from 65.6-67.8 across instructions for Eval selection, from 52.5 to 75.0 for Answer selection, 17.1 to 18.4 for Relation classification, 34.7 to 37.1 for Dialfact classification, 49.8 to 62.3 for Begins with generation, and F1 score varies from 26.6 to 28.6 for Knowledge grounded generation. Thus, our model is moderately sensitive to the instruction wording.

**Errors in model outputs:** We perform qualitative analysis of randomly sampled outputs of the models. For classification tasks, a common error across all models is generating outputs outside of the provided list of classes. This happens with GPT-3 for 20%, BART0 10% and T0-3B 17.8% of the inputs, but for DIAL-BART0 and DIAL-T0 this occurs only for 2.5% and 4.8% of the inputs. Other possible but rare types of errors include copying the provided input as output, early truncation of generated responses, and performing
an unspecified task. Apart from the unseen task set adopted for our experiments in section 5.1.1, we tried other seen-unseen task configurations and found that both our models and baselines models cannot perform certain tasks such as Infilling missing utterance, Recovery response generation, and Ends with response generation in a zero-shot manner. However, the models could quickly learn these tasks when trained on a few task instances.

In Table 7 of Appendix B we provide a sample conversation, various instructions for that conversation, and the outputs generated by DIAL-BART0 based on the specified instructions.

### 5.2 Zero-shot Automatic Response Evaluation

Development of automatic dialogue metrics that show high correlations with human judgements is a challenging and crucial task for dialogue systems. Automated metrics such as BLEU (Papineni et al., 2002) and METEOR (Banerjee and Lavie, 2005) correlate poorly with human judgement (Gupta et al., 2019). In this experiment, we test our model’s zero-shot automatic evaluation capabilities through the Eval Relevance task. We use the evaluation ratings released in the DSTC-10 Automatic evaluation challenge (Chen et al., 2021b) that consists of 65,938 context-response pairs along with corresponding human ratings aggregated across various evaluation sets. We train a version of DIAL-T0 on tasks excluding any eval tasks (shown in Table 10). Given a dialogue context and a candidate response, we instruct the model to predict “yes” if the response is relevant to the context, otherwise predict “no”. We calculate the probability of “yes” as

\[
p(yes) = p(yes) / (p(yes) + p(no))
\]

we calculate the Spearman correlation of the model’s prediction with human ratings for relevance provided in the DSTC-10 test sets, and present the results in Table 2. We compare our model with reference-free models studied in Yeh et al. (2021). DIAL-T0 is ranked the first or second in the majority of the evaluation datasets. Our model learns coherence from the variety of tasks it is trained on and demonstrates high zero-shot dialogue evaluation capabilities.

### 5.3 Zero-shot and Few-shot Dialogue Tasks

We test the zero-shot and few-shot abilities of our models on three important dialogue tasks: intent prediction, slot filling, and dialogue state tracking.

#### 5.3.1 Intent Prediction

Intent prediction is the task of predicting an intent class for a given utterance. We conduct few-shot experiments on the Banking77 benchmark dataset (Casanueva et al., 2020) that contains 77 unique intent classes. Models are trained on 10 instances per test intent class. We compare our model

Table 2: Spearman correlation of model predictions with human ratings. Bold and underlined scores represent the evaluation sets on which our model performs the best and second best respectively. We also present the macro average scores. TU, PU, PZ, DZ, CG, DGU, DGR, FT, and FD are abbreviations for TopicalChat-USR, PersonaChat-USR (Mehri and Eskenazi, 2020b), PersonaChat-Zhao (Zhao et al., 2020a), DailyDialog-Zhao (Zhao et al., 2020a), ConvAI2-GRADE (Huang et al., 2020), DailyDialog-Gupta (Gupta et al., 2019), DailyDialog-Grade (Huang et al., 2020), Empathetic-Grade (Huang et al., 2020), FED-Turn and FED-Dial (Mehri and Eskenazi, 2019), DailyDialog-Grade (Huang et al., 2020), Empathetic-Grade (Huang et al., 2020), FED-Turn and FED-Dial (Mehri and Eskenazi, 2020a). DIAL-T0 is ranked the first or second best in the majority of the evaluation sets.

| Model          | DSTC6 | DSTC7 | HUMOD | TU  | PZ   | DZ   | CG   | PU  | DGU | DGR | FT   | EG   | FD   | Average |
|----------------|-------|-------|-------|-----|------|------|------|-----|-----|-----|------|------|------|---------|
| MAUDE (2020)   | 0.115 | 0.045 | 0.112 | 0.136 | 0.360 | 0.120 | 0.304 | 0.306 | 0.192 | -0.073 | -0.11 | -0.057 | -0.285 | 0.090   |
| GRADE (2020)   | 0.121 | 0.332 | **0.612** | 0.176 | 0.583 | 0.532 | 0.571 | 0.329 | 0.596 | 0.254 | 0.048 | 0.300 | 0.106 | 0.351   |
| USR (2020b)    | 0.166 | 0.249 | 0.34 | 0.291 | 0.496 | 0.363 | 0.487 | 0.140 | 0.353 | 0.066 | 0.055 | 0.268 | 0.084 | 0.258   |
| DEB (2020)     | -0.082 | -0.070 | -0.077 | -0.090 | -0.232 | -0.080 | -0.137 | -0.004 | 0.025 | -0.009 | 0.173 | 0.005 | 0.178 | -0.031  |
| FlowScore (2021) | 0.095 | 0.067 | -0.049 | 0.068 | 0.202 | -0.063 | -0.053 | 0.053 | -0.043 | -0.009 | 0.029 |       |       |         |
| USL-H (2020)   | 0.180 | 0.261 | 0.53 | 0.319 | 0.409 | 0.385 | 0.452 | **0.493** | 0.481 | 0.09 | 0.115 | 0.237 | 0.202 | 0.320   |
| QuestEval (2021) | 0.089 | 0.222 | 0.217 | 0.104 | 0.32 | 0.32 | 0.344 | 0.106 | 0.243 | -0.026 | 0.168 | 0.195 | 0.114 | 0.178   |
| DEB (2020)     | 0.214 | 0.351 | 0.649 | 0.123 | 0.579 | 0.486 | 0.504 | 0.351 | 0.579 | **0.363** | 0.044 | 0.395 | 0.141 | 0.367   |
| DynaEval (2021) | 0.252 | 0.066 | 0.112 | -0.013 | 0.165 | 0.169 | 0.202 | 0.148 | 0.038 | 0.122 | 0.247 | **0.159** | **0.555** | 0.171   |
| DialogRPT (2020) | 0.162 | 0.255 | 0.198 | 0.118 | 0.114 | 0.067 | 0.158 | -0.036 | 0.075 | 0.037 | -0.249 | 0.203 | -0.134 | 0.074   |

**Table 3:** Intent prediction accuracy on the Banking77 corpus (Casanueva et al., 2020). Models in the first section of the table are trained in a few-shot setting with 10 instances per intent. Models in the second section are tested in a zero-shot setting.

| Model                  | Accuracy |
|------------------------|----------|
| ConvERT (Casanueva et al., 2020) | 83.32     |
| ConvERT + USE (Casanueva et al., 2020) | 85.19     |
| Example-Driven (Mehri and Eric, 2021) | 85.95     |
| PPTOD (Su et al., 2022b) | 82.81     |
| PPTODbase (Su et al., 2022b) | 84.12     |
| DIAL-BART0 (Ours)       | 84.30     |
| BART0 (zero-shot)       | 14.72     |
| DIAL-BART0 (Ours, zero-shot) | 58.02     |
Table 4: Zero-shot slot filling results on the Restaurant8k corpus.

| Domain     | GENSF | DIAL-BART0 (Ours) |
|------------|-------|-------------------|
| Buses      | 90.5  | 97.8              |
| Events     | 91.2  | 94.3              |
| Homes      | 93.7  | 96.5              |
| Rental Cars| 86.7  | 94.2              |

Table 5: Few-shot slot filling F1 scores on DSTC8 data.

| Domain     | 1% data | 5% data |
|------------|---------|---------|
| PPTOD      | 29.7    | 40.2    |
| DIAL-BART0 (Ours) | 29.2    | 38.1    |

Table 6: Joint goal accuracy for dialogue state tracking in few-shot setting on 1% and 5% data of Multiwoz.

5.3.3 Dialogue State Tracking

We evaluate our model on the dialogue state tracking task which involves filling in values of pre-defined slots. We adopt the experimental setup from PPTOD (Su et al., 2022a), and conduct few-shot experiments on MultiWOZ 2.0 (Budzianowski et al., 2018). Similar to PPTOD, our DIAL-BART0 model is first pre-trained on 7 datasets: KVRET (Eric et al., 2017), WOZ (Mrkšić et al., 2017), Cam-Rest676 (Wen et al., 2017), MSR-E2E (Li et al., 2018), Frames (El Asri et al., 2017), TaskMaster (Byrne et al., 2019), Schema-Guided (Rastogi et al., 2020b) along with other non-related dialogue tasks. We then train on 1% and 5% splits of MultiWOZ for 40 epochs with a learning rate of $5e^{-5}$. In Table 6 we present few-shot dialogue state tracking results on the MultiWOZ test set. We find that our model obtains 29.2 and 38.1 joint goal accuracy on the 1% and 5% training data splits, respectively. Our results demonstrate that our model performs well on few-shot dialogue state tracking, and achieves competitive results against PPTOD which is twice the size of our model.

6 Conclusion

We propose INSTRUCTDIAL, an instruction tuning framework for dialogue, which contains multiple dialogue tasks created from openly available dialogue datasets. We also propose two meta-tasks to encourage the model to pay attention to instructions. Our results show that models trained on INSTRUCTDIAL achieve good zero-shot performance on unseen tasks (e.g., dialogue evaluation) and good few-shot performance on dialogue tasks (e.g., intent prediction, slot filling). We perform ablation studies showing the impact of using an instruction tuned base model, model size/type, increasing the number of tasks, and incorporating our proposed meta tasks. Our experiments reveal that instruction tuning does not benefit all unseen test tasks and that improvements can be made in instruction wording invariance and task interference. We hope that INSTRUCTDIAL will facilitate further progress on instruction-tuning systems for dialogue tasks.
7 Limitations

Our work is the first to explore instruction tuning for dialogue and establishes baseline performance for a variety of dialogue tasks. However, there is room for improvements in the following aspects:

1) Unlike a few prior works, the instructions and prompts used in this work are not crowdsourced and are limited in number. Furthermore, our instructions and tasks are only specified in the English language. Future work may look into either crowdsourcing or automatic methods for augmenting the set of instructions in terms of both language diversity as well as quantity. 2) Instruction tuning does not show significant improvements in zero-shot setting on a few tasks such as relation classification and infilling missing utterances in our experiments. Future work can look into investigating why certain tasks are more challenging than others for zero-shot generalization. Furthermore, zero-shot performance of our models on many tasks is still far from the few-shot and full-shot performance on those tasks. We hope that INSTRUCTDIAL can be lead to further investigations and improvements in this area. 3) We observed a few instances of task interference in our experiments. For example, the set of tasks used for zero-shot automatic response evaluation as mentioned in Table 10 is different and smaller from the set of tasks used in our main experiments in Section 5.1.1. We found that incorporating a few additional tasks lead to a reduction in the performance on zero-shot automatic response evaluation. Furthermore, training on multiple tasks can lead to task forgetting. To address these issues, future work can take inspiration from work related to negative task interference (Wang et al., 2020a; Larson and Leach, 2022), transferability (Vu et al., 2020; Wu et al., 2020b; Xing et al., 2022) and lifelong learning (Wang et al., 2020b). 4) Our models are sensitive to the wording of the instructions, especially in zero-shot settings as discussed in Section 5.1.4. Improving insensitivity to prompts and instructions is an important future research direction. 5) Our work does not explore in-context few-shot learning through examples as the prompt length can go beyond models’ maximum input length. It also does not study the composition of multiple tasks through instructions. Both these aspects warrant further investigations. 6) INSTRUCTDIAL includes only text based tasks, and future work may look into incorporating datasets with other modalities such as vision and audio.

8 Ethics and Broader Impact

Broader Impact and applications: Our framework leverages instruction tuning on multiple dialogue tasks, allowing multiple functionalities to be quickly implemented and evaluated in dialogue systems. For example, tasks pertaining to both task-oriented dialogue tasks, such as slot detection and domain-specific tasks such as emotion detection can be added and evaluated against state-of-the-art dialogue systems. This enables users to diagnose their models on different tasks and expand the abilities of multi-faceted dialogue systems, which can lead to richer user interactions across a wide range of applications. Our framework allows training models below billion parameter range, making them more accessible to the research community.

Potential biases: Current conversational systems suffer from several limitations, and lack empathy, morality, discretion, and factual correctness. Biases may exist across datasets used in this work and those biases can propagate during inference into the unseen tasks. Few-shot and zero-shot methods are easier to train, and their use can lead to a further increase of both the benefits and risks of models. To mitigate some of those risks, we have included tasks and datasets in our framework that encourage safety such as ToxiChat for toxic response classification task and SaFeRDialogues for recovery response generation task, and that improve empathy such as EmpatheticDialogues for empathy.

References

Ashutosh Baheti, Maarten Sap, Alan Ritter, and Mark Riedl. 2021. Just say no: Analyzing the stance of neural dialogue generation in offensive contexts. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 4846–4862, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Satyajeet Banerjee and Alon Lavie. 2005. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization, pages 65–72.

Siqi Bao, Huang He, Fan Wang, Hua Wu, Haifeng Wang, Wenquan Wu, Zhen Guo, Zhibin Liu, and Xinchao Xu. 2021. PLATO-2: Towards building an open-domain chatbot via curriculum learning. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 2513–2525, Online. Association for Computational Linguistics.
Jonathan Bragg, Arman Cohan, Kyle Lo, and Iz Beltagy. 2021. Flex: Unifying evaluation for few-shot nlp. In Advances in Neural Information Processing Systems (NeurIPS 2021).

Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. 2020. Language models are few-shot learners. Advances in neural information processing systems, 33:1877–1901.

Pawel Budzianowski and Ivan Vulić. 2019. Hello, it’s GPT-2 - how can I help you? towards the use of pre-trained language models for task-oriented dialogue systems. In Proceedings of the 3rd Workshop on Neural Generation and Translation, pages 15–22, Hong Kong. Association for Computational Linguistics.

Pawel Budzianowski, Tsung-Hsien Wen, Bo-Hsiang Tseng, Íñigo Casanueva, Stefan Ultes, Osman Ramadan, and Milica Gašić. 2018. MultiWOZ - a large-scale multi-domain Wizard-of-Oz dataset for task-oriented dialogue modelling. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 5016–5026, Brussels, Belgium. Association for Computational Linguistics.

Bill Byrne, Karthik Krishnamoorthi, Chinnadhurai Sankar, Arvind Neelakantan, Ben Goodrich, Daniel Duckworth, Semih Yavuz, Amit Dubey, Kyu-Young Kim, and Andy Cedilnik. 2019. Taskmaster-1: Toward a realistic and diverse dialog dataset. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 4516–4525, Hong Kong, China. Association for Computational Linguistics.

Íñigo Casanueva, Tadas Temčinas, Daniela Gerz, Matthew Henderson, and Ivan Vulić. 2020. Efficient intent detection with dual sentence encoders. In Proceedings of the 2nd Workshop on Natural Language Processing for Conversational AI, pages 38–45, Online. Association for Computational Linguistics.

Kushal Chawla, Jaysa Ramirez, Rene Clever, Gale Lucas, Jonathan May, and Jonathan Gratch. 2021. CaSiNo: A corpus of campsite negotiation dialogues for automatic negotiation systems. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 3167–3185, Online. Association for Computational Linguistics.

Yulong Chen, Yang Liu, Liang Chen, and Yue Zhang. 2021a. DialogSum: A real-life scenario dialogue summarization dataset. In Findings of the Association for Computational Linguistics: ACL-IJCNLP 2021, pages 5062–5074, Online. Association for Computational Linguistics.

Zhang Chen, João Sadoc, Luis Fernando D’Haro, Rafael Banchs, and Alexander Rudnicky. 2021b. Automatic evaluation and moderation of open-domain dialogue systems. arXiv preprint arXiv:2111.02110.

Eunsol Choi, He He, Mohit Iyyer, Mark Yatskar, Wentai Yih, Yejin Choi, Percy Liang, and Luke Zettlemoyer. 2018. QuAC: Question answering in context. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 2174–2184, Brussels, Belgium. Association for Computational Linguistics.

Sam Coope, Tyler Farghly, Daniela Gerz, Ivan Vulić, and Matthew Henderson. 2020a. Span-convert: Few-shot span extraction for dialog with pretrained conversational representations. arXiv preprint arXiv:2005.08866.

Samuel Coope, Tyler Farghly, Daniela Gerz, Ivan Vulić, and Matthew Henderson. 2020b. Span-ConveRT: Few-shot span extraction for dialog with pretrained conversational representations. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 107–121, Online. Association for Computational Linguistics.

Alice Coucke, Alaa Saade, Adrien Ball, Théodore Bluche, Alexandre Caulier, David Leroy, Clément Doumouro, Thibault Gisselbrecht, Francesco Caltagirone, Thibaut Lavril, et al. 2018. Snips voice platform: an embedded spoken language understanding system for private-by-design voice interfaces. arXiv preprint arXiv:1805.10190, pages 12–16.

Leyang Cui, Yu Wu, Shujie Liu, Yue Zhang, and Ming Zhou. 2020. MuTual: A dataset for multi-turn dialogue reasoning. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 1406–1416, Online. Association for Computational Linguistics.

Dorottya Demszky, Dana Movshovitz-Attias, Jeongwoo Ko, Alan Cowen, Gaurav Nemade, and Sujith Ravi. 2020. GoEmotions: A dataset of fine-grained emotions. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4040–4054, Online. Association for Computational Linguistics.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Emily Dinan, Samuel Humeau, Bharath Chandragupta, and Jason Weston. 2019a. Build it break it fix it for dialogue safety: Robustness from adversarial human attack. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages
4537–4546, Hong Kong, China. Association for Computational Linguistics.

Emily Dinan, Varvara Logacheva, Valentín Malyykh, Alexander Miller, Kurt Shuster, Jack Urbanek, Douwe Kiela, Arthur Szlam, Iulian Serban, Ryan Lowe, et al. 2019b. The second conversational intelligence challenge (convai2). arXiv preprint arXiv:1902.00098.

Emily Dinan, Stephen Roller, Kurt Shuster, Angela Fan, Michael Auli, and Jason Weston. 2019c. Wizard of Wikipedia: Knowledge-powered conversational agents. In Proceedings of the International Conference on Learning Representations (ICLR).

Layla El Asri, Hannes Schulz, Shikhar Sharma, Jeremie Zumer, Justin Harris, Emery Fine, Rahul Mehrotra, and Kaheer Suleman. 2017. Frames: a corpus for adding memory to goal-oriented dialogue systems. In Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, pages 207–219, Saarbrücken, Germany. Association for Computational Linguistics.

Mihail Eric, Lakshmi Krishnan, Francois Charrette, and Christopher D. Manning. 2017. Key-value retrieval networks for task-oriented dialogue. In Proceedings of the 18th Annual SIGdial Meeting on Discourse and Dialogue, pages 37–49, Saarbrücken, Germany. Association for Computational Linguistics.

Song Feng, Hui Wan, Chulaka Gunasekara, Siva Patel, Sachindra Joshi, and Luis Lastras. 2020a. doc2dial: A goal-oriented document-grounded dialogue dataset. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 8118–8128, Online. Association for Computational Linguistics.

Yulan Feng, Shikib Mehri, Maxine Eskenazi, and Tiancheng Zhao. 2020b. “none of the above”: Measure uncertainty in dialog response retrieval. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2013–2020, Online. Association for Computational Linguistics.

Michel Galley, Chris Brockett, Xiang Gao, Jianfeng Gao, and Bill Dolan. 2019. Grounded response generation task at dstc7.

Xiang Gao, Yizhe Zhang, Michel Galley, Chris Brockett, and Bill Dolan. 2020. Dialogue response ranking training with large-scale human feedback data. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 386–395, Online. Association for Computational Linguistics.

Bogdan Gliwa, Iwona Mochol, Maciej Biesek, and Alexander Wawer. 2019. Samsun corpus: A human-annotated dialogue dataset for abstractive summarization. arXiv preprint arXiv:1911.12237.

Chih-Wen Goo and Yun-Nung Chen. 2018. Abstractive dialogue summarization with sentence-gated modeling optimized by dialogue acts. In Proceedings of 7th IEEE Workshop on Spoken Language Technology.

Karthik Gopalakrishnan, Behnam Hedayatnia, Qinliang Chen, Anna Gottard, Sanjeev Kwatra, Anu Venkatesh, Raefe Gabriel, and Dilek Hakkani-Tür. 2019. Topical-Chat: Towards Knowledge-Grounded Open-Domain Conversations. In Proc. Interspeech 2019, pages 1891–1895.

Prakhar Gupta, Shikib Mehri, Tiancheng Zhao, Amy Pavel, Maxine Eskenazi, and Jeffrey Bigham. 2019. Investigating evaluation of open-domain dialogue systems with human generated multiple references. In Proceedings of the 20th Annual SIGdial Meeting on Discourse and Dialogue, pages 379–391, Stockholm, Sweden. Association for Computational Linguistics.

Prakhar Gupta, Chien-Sheng Wu, Wenhao Liu, and Caiming Xiong. 2021. Dialfact: A benchmark for fact-checking in dialogue. arXiv preprint arXiv:2110.08222.

Donghoon Ham, Jeong-Gwan Lee, Youngsoo Jang, and Kee-Eung Kim. 2020. End-to-end neural pipeline for goal-oriented dialogue systems using GPT-2. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 583–592, Online. Association for Computational Linguistics.

Charles T. Hemphill, John J. Godfrey, and George R. Doddington. 1990. The ATIS spoken language systems pilot corpus. In Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania, June 24-27,1990.

Matthew Henderson and Ivan Vulić. 2020. Convex: Data-efficient and few-shot slot labeling. arXiv preprint arXiv:2010.11791.

Chiori Hori and Takaaki Hori. 2017. End-to-end conversation modeling task in dstc6. arXiv:1706.07440.

Ehsan Hosseini-Asl, Bryan McCann, Chien-Sheng Wu, Semih Yavuz, and Richard Socher. 2020. A simple language model for task-oriented dialogue. Advances in Neural Information Processing Systems, 33:20179–20191.

Chao-Chun Hsu, Sheng-Yeh Chen, Chuan-Chun Kuo, Ting-Hao Huang, and Lun-Wei Ku. 2018. EmotionLines: An emotion corpus of multi-party conversations. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018), Miyazaki, Japan. European Language Resources Association (ELRA).

Lishan Huang, Zheng Ye, Jinghui Qin, Liang Lin, and Xiaodan Liang. 2020. GRADE: Automatic graph-enhanced coherence metric for evaluating open-domain dialogue systems. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 9230–9240, Online. Association for Computational Linguistics.
Diederick P Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In International Conference on Learning Representations (ICLR).

Stefan Larson and Kevin Leach. 2022. Redwood: Using collision detection to grow a large-scale intent classification dataset. arXiv preprint arXiv:2204.05483.

Stefan Larson, Anish Mahendran, Joseph J. Peper, Christopher Clarke, Andrew Lee, Parker Hill, Jonathan K. Kummerfeld, Kevin Leach, Michael A. Laurenzano, Lingjie Tang, and Jason Mars. 2019. An evaluation dataset for intent classification and out-of-scope prediction. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1311–1316. Hong Kong, China. Association for Computational Linguistics.

Brian Lester, Rami Al-Rfou, and Noah Constant. 2021. The power of scale for parameter-efficient prompt tuning. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 3045–3059. Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Veselin Stoyanov, and Luke Zettlemoyer. 2020. BART: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7871–7880. Online. Association for Computational Linguistics.

Mike Lewis, Denis Yarats, Yann Dauphin, Devi Parikh, and Dhruv Batra. 2017. Deal or no deal? end-to-end learning of negotiation dialogues. In Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing, pages 2443–2453. Copenhagen, Denmark. Association for Computational Linguistics.

Xiujun Li, Sarah Panda, Jingjing Liu, and Jianfeng Gao. 2018. Microsoft dialogue challenge: Building end-to-end task-completion dialogue systems. arXiv preprint arXiv:1807.11125.

Yanran Li, Hui Su, Xiaoyu Shen, Wenjie Li, Ziqiang Cao, and Shuzi Niu. 2017. DailyDialog: A manually labelled multi-turn dialogue dataset. In Proceedings of the Eighth International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 986–995. Taipei, Taiwan. Asian Federation of Natural Language Processing.

Zekang Li, Jinchao Zhang, Zhengcong Fei, Yang Feng, and Jie Zhou. 2021. Conversations are not flat: Modeling the dynamic information flow across dialogue utterances. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 128–138. Online. Association for Computational Linguistics.

Bill Yuchen Lin, Kangmin Tan, Chris Miller, Beiwen Tian, and Xiang Ren. 2022. Unsupervised cross-task generalization via retrieval augmentation. ArXiv, abs/2204.07937.

Zhaojiang Lin, Andrea Madotto, Genta Indra Winata, and Pascale Fung. 2020. MinTL: Minimalist transfer learning for task-oriented dialogue systems. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 3391–3405. Online. Association for Computational Linguistics.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021a. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. arXiv preprint arXiv:2107.13386.

Qi Liu, Lei Yu, Laura Rimell, and Phil Blunsom. 2022. Pretraining the noisy channel model for task-oriented dialogue. Transactions of the Association for Computational Linguistics, 9(0):657–674.

Xingkun Liu, Arash Eshghi, Pawel Swietojanski, and Verena Rieser. 2021b. Benchmarking natural language understanding services for building conversational agents. In Increasing Naturalness and Flexibility in Spoken Dialogue Interaction, pages 165–183. Springer.

Zihan Liu, Genta Indra Winata, Peng Xu, and Pascale Fung. 2020. Coach: A coarse-to-fine approach for cross-domain slot filling. arXiv preprint arXiv:2004.11727.

Andrea Madotto, Zhaojiang Lin, Genta Indra Winata, and Pascale Fung. 2021. Few-shot bot: Prompt-based learning for dialogue systems. arXiv preprint arXiv:2110.08118.

Shikib Mehri and Mihail Eric. 2021. Example-driven intent prediction with observers. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2979–2992. Online. Association for Computational Linguistics.

Shikib Mehri and Maxine Eskenazi. 2020a. Unsupervised evaluation of interactive dialog with DialoGPT. In Proceedings of the 21th Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 225–235. 1st virtual meeting. Association for Computational Linguistics.

Shikib Mehri and Maxine Eskenazi. 2020b. USR: An unsupervised and reference free evaluation metric for dialog generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 681–707. Online. Association for Computational Linguistics.
Shikib Mehri and Maxine Eskenazi. 2021. Gensf: Simultaneous adaptation of generative pre-trained models and slot filling. arXiv preprint arXiv:2106.07055.

Xiny Nie, Mary Williamson, Mohit Bansal, Douwe Kiela, and Jason Weston. 2021. I like fish, especially dolphins: Addressing contradictions in dialogue modeling. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 1699–1713, Online. Association for Computational Linguistics.

Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. arXiv preprint arXiv:2203.02155.

Kishore Papineni, Salim Roukos, Todd Ward, and Weijing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th annual meeting of the Association for Computational Linguistics, pages 311–318.

Baolin Peng, Chunyuan Li, Jinchao Li, Shahin Shayan-deh, Lars Liden, and Jianfeng Gao. 2021. Soloist: Building task bots at scale with transfer learning and machine teaching. In Transactions of the Association for Computational Linguistics.

Vitou Phy, Yang Zhao, and Akiko Aizawa. 2020. Deconstruct to reconstruct a configurable evaluation metric for open-domain dialogue systems. In Proceedings of the 28th International Conference on Computational Linguistics, pages 4164–4178, Barcelona, Spain (Online). International Committee on Computational Linguistics.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners.

Dinesh Raghu, Shantanu Agarwal, Sachindra Joshi, and Mausam. 2021. End-to-end learning of flowchart grounded task-oriented dialogs. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 4348–4366, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Hannah Rashkin, Eric Michael Smith, Margaret Li, and Y-Lan Boureau. 2019. Towards empathetic open-domain conversation models: A new benchmark and dataset. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5370–5381, Florence, Italy. Association for Computational Linguistics.

Abhinav Rastogi, Xiaoxue Zang, Srinivas Sunkara, Raghav Gupta, and Pranav Khaitan. 2020a. Schema-guided dialogue state tracking task at dstc8. arXiv preprint arXiv:2002.01359.
Abhinav Rastogi, Xiaoxue Zang, Srinivas Sunkara, Raghav Gupta, and Pranav Khaitan. 2020b. Towards scalable multi-domain conversational agents: The schema-guided dialogue dataset. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 34, pages 8689–8696.

Siva Reddy, Danqi Chen, and Christopher D. Manning. 2019. CoQA: A conversational question answering challenge. Transactions of the Association for Computational Linguistics, 7:249–266.

Stephen Roller, Emily Dinan, Naman Goyal, Da Ju, Mary Williamson, Yinhan Liu, Jing Xu, Myle Ott, Eric Michael Smith, Y-Lan Boureau, and Jason Weston. 2021. Recipes for building an open-domain chatbot. In Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume, pages 300–325, Online. Association for Computational Linguistics.

Ananya B. Sai, Akash Kumar Mohankumar, Siddhartha Arora, and Mitesh M. Khapra. 2020. Improving dialogue evaluation with a multi-reference adversarial dataset and large scale pretraining. Transactions of the Association for Computational Linguistics, 8:810–827.

Victor Sanh, Albert Weirson, Colin Raffel, Stephen H. Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczeczula, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Stella Biderman, Leo Gao, Tali Bers, Thomas Wolf, and Alexander M. Rush. 2022. Multi-task prompted training enables zero-shot task generalization. In International Conference on Learning Representations (ICLR).

Tim Schick and Hinrich Schütze. 2021. Few-shot text generation with natural language instructions. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 390–402, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Thomas Scialom, Paul-Alexis Dray, Sylvain Lamprier, Benjamin Pwowarski, Jacopo Staiano, Alex Wang, and Patrick Gallinari. 2021. QuestEval: Summarization asks for fact-based evaluation. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing, pages 6594–6604, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Abigail See, Stephen Roller, Douwe Kiela, and Jason Weston. 2019. What makes a good conversation? how controllable attributes affect human judgments. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 1702–1723, Minneapolis, Minnesota. Association for Computational Linguistics.

Karin Sevegnani, David M. Howcroft, Ioannis Konstas, and Verena Rieser. 2021. OTTers: One-turn topic transitions for open-domain dialogue. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 2492–2504, Online. Association for Computational Linguistics.

Koustuv Sinha, Prasanna Parthasarathi, Jasmine Wang, Ryan Lowe, William L. Hamilton, and Joelle Pineau. 2020. Learning an unreferenced metric for online dialogue evaluation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 2430–2441, Online. Association for Computational Linguistics.

Yixuan Su, Lei Shu, Elman Mansimov, Arshit Gupta, Deng Cai, Yi-An Lai, and Yi Zhang. 2022a. Multi-task pre-training for plug-and-play task-oriented dialogue system.

Yixuan Su, Lei Shu, Elman Mansimov, Arshit Gupta, Deng Cai, Yi-An Lai, and Yi Zhang. 2022b. Multi-task pre-training for plug-and-play task-oriented dialogue system. In Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 4661–4676, Dublin, Ireland. Association for Computational Linguistics.

Megan Ung, Jing Xu, and Y-Lan Boureau. 2021. Safer-dialogues: Taking feedback gracefully after conversational safety failures.

Ramakrishna Vedantam, C. Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In The IEEE Conference on Computer Vision and Pattern Recognition (CVPR).

Tu Vu, Tong Wang, Tsenduren Munkhdalai, Alessandro Sordoni, Adam Trischler, Andrew Mattarella-Micke, Subhansu Maji, and Mohit Iyyer. 2020. Exploring and predicting transferability across NLP tasks. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 7882–7926, Online. Association for Computational Linguistics.

Xuewei Wang, Weiyan Shi, Richard Kim, Yoojung Oh, Sijia Yang, Jingwen Zhang, and Zhou Yu. 2019. Persuasion for good: Towards a personalized persuasive dialogue system for social good. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 5635–5649, Florence, Italy. Association for Computational Linguistics.

Yizhong Wang, Swaroop Mishra, Pegah Alipourmolabashi, Yeganeh Kordi, Amirreza Mirzaei,
Anjana Arunkumar, Arjun Ashok, Arut Selvan Dhanasekaran, Atharva Naik, David Stap, et al. 2022a. Benchmarking generalization via in-context instructions on 1,600+ language tasks. arXiv preprint arXiv:2204.07705.

Yizhong Wang, Swaroop Mishra, Pegah Alipourmolaebashi, Yeganeh Kordi, et al. 2022b. Benchmarking generalization via in-context instructions on 1,600+ language tasks. arXiv.

Zirui Wang, Zachary C. Lipton, and Yulia Tsvetkov. 2020a. On negative interference in multilingual models: Findings and a meta-learning treatment. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 4438–4450, Online. Association for Computational Linguistics.

Zirui Wang, Sanket Vaibhav Mehta, Barnabas Poczos, and Jaime Carbonell. 2020b. Efficient meta lifelong-learning with limited memory. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 535–548, Online. Association for Computational Linguistics.

Albert Webson and Ellie Pavlick. 2021. Do prompt-based models really understand the meaning of their prompts?

Jason Wei, Maarten Paul Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew Mingbo Dai, and Quoc V. Le. 2022. Finetuned language models are zero-shot learners.

Sean Welleck, Jason Weston, Arthur Szlam, and Kyunghyun Cho. 2019. Dialogue natural language inference. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3731–3741, Florence, Italy. Association for Computational Linguistics.

Orion Weller, Nicholas Lourie, Matt Gardner, and Matthew E. Peters. 2020. Learning from task descriptions. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1361–1375, Online. Association for Computational Linguistics.

Tsung-Hsien Wen, David Vandyke, Nikola Mrkšić, Milica Gašić, Lina M. Rojas-Barahona, Pei-Hao Su, Stefan Ultes, and Steve Young. 2017. A network-based end-to-end trainable task-oriented dialogue system. In Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 1, Long Papers, pages 438–449, Valencia, Spain. Association for Computational Linguistics.

Taesun Whang, Dongyub Lee, Dongsuk Oh, Chanhee Lee, Kijong Han, Dong-hun Lee, and Saebyeok Lee. 2021. Do response selection models really know what’s next? utterance manipulation strategies for multi-turn response selection. Proceedings of the AAAI Conference on Artificial Intelligence, 35(16):14041–14049.

Chien-Sheng Wu, Steven C.H. Hoi, Richard Socher, and Caiming Xiong. 2020a. TOD-BERT: Pre-trained natural language understanding for task-oriented dialogue. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 917–929, Online. Association for Computational Linguistics.

Chien-Sheng Wu, Andrea Madotto, Wenhao Liu, Pascale Fung, and Caiming Xiong. 2021. Qaconv: Question answering on informative conversations. arXiv preprint arXiv:2105.06912.

Sen Wu, Hongyang R Zhang, and Christopher Ré. 2020b. Understanding and improving information transfer in multi-task learning. arXiv preprint arXiv:2005.00944.

Yujie Xing, Jinglun Cai, Nils Barlaug, Peng Liu, and Jon Atle Gulla. 2022. Balancing multi-domain corpora learning for open-domain response generation. arXiv preprint arXiv:2205.02570.

Hanwei Xu, Yujun Chen, Yulun Du, Nan Shao, Yanggang Wang, Haiyu Li, and Zhilin Yang. 2022. Zero-prompt: Scaling prompt-based pretraining to 1,000 tasks improves zero-shot generalization. arXiv preprint arXiv:2201.06910.

Jing Xu, Da Ju, Margaret Li, Y-Lan Boureau, Jason Weston, and Emily Dinan. 2021a. Bot-adversarial dialogue for safe conversational agents. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 2950–2968, Online. Association for Computational Linguistics.

Ruijian Xu, Chongyang Tao, Daxin Jiang, Xueliang Zhao, Dongyan Zhao, and Rui Yan. 2021b. Learning an effective context-response matching model with self-supervised tasks for retrieval-based dialogues. Proceedings of the AAAI Conference on Artificial Intelligence, 35(16):14158–14166.

Yunyi Yang, Yunhao Li, and Xiaojun Quan. 2021. Ubar: Towards fully end-to-end task-oriented dialog system with gpt-2. Proceedings of the AAAI Conference on Artificial Intelligence, 35(16):14230–14238.

Yi-Ting Yeh, Maxine Eskenazi, and Shikib Mehri. 2021. A comprehensive assessment of dialog evaluation metrics. In The First Workshop on Evaluations and Assessments of Neural Conversation Systems, pages 15–33, Online. Association for Computational Linguistics.

Dian Yu, Kai Sun, Claire Cardie, and Dong Yu. 2020. Dialogue-based relation extraction. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 4927–4940, Online. Association for Computational Linguistics.

Rowan Zellers, Ari Holtzman, Elizabeth Clark, Lianhui Qin, Ali Farhadi, and Yejin Choi. 2021. TuringAdvice: A generative and dynamic evaluation of language use. In Proceedings of the 2021 Conference of
Appendix

A Additional implementation details

Data Sampling For training data creation, we first generate instances from all datasets belonging to each task. Since the number of instances per task can be highly imbalanced, we sample a fixed maximum of $N$ number of instances per task. In our main models and experiments, we set $N = 5000$. Each instance in a task is assigned a random task definition and prompt. We truncate the input sequences to 1024 tokens and target output sequences to 256 tokens.

Implementation Details Our models are trained for 3 epochs with a learning rate of $5e^{-5}$ with an Adam optimizer (Kingma and Ba, 2015) with linear learning rate decay. For our main experiments in Table 1, we perform checkpoint selection using a validation set created from the train tasks. For rest of the experiments we do model selection using the validation sets. We use the HuggingFace Transformers library\(^2\) for training and inference implementation and use DeepSpeed library\(^3\) for improving training efficiency. We train DIAL-BART0 on 2 Nvidia 2080Ti GPUs using a batch size of 2 per GPU and an effective batch size of 72 with gradient checkpointing. We train DIAL-T0 on 2 Nvidia A6000 GPUs using a batch size of 1 per GPU and an effective batch size of 72 with gradient checkpointing. For all classification tasks, we perform greedy decoding, and for all generation tasks, we perform top-p sampling with $p = 0.7$ and temperature set to 0.7. The repetition penalty is set to 1.2. In Table 1, for DIAL-BART0 and DIAL-T0, we report the results over three different training runs, where each run is based on a new sample of training data.

Zero-shot Automatic Evaluation Implementation Details For zero shot automatic evaluation, we calculate the Spearman correlation of the model’s prediction with human ratings for relevance provided in the DSTC-10 test sets. There is no consistent “relevance” or “coherence” rating field present across the evaluation datasets. We therefore calculate the correlation with the ratings if a rating exists in any of the following fields “overall”, “turing”, “relevance” and “appropriateness”.

\(^2\)https://github.com/huggingface/transformers
\(^3\)https://github.com/microsoft/DeepSpeed
Conversation:
[CONTEXT] How may I help you? [ENDOFTURN]
I left a suitcase on the train to London the other day. [ENDOFDIALOGUE]

| Task                                      | Instruction                                                                 | Output                                      |
|-------------------------------------------|-----------------------------------------------------------------------------|---------------------------------------------|
| Response editing                          | Modify the provided response into a response that is fluent and coherent to the dialogue context: [RESPONSE] Can describe it, sir? It will help us find it. | Can you describe it, sir? It will help us find it. |
| Begins with                               | Generate a response that starts with the provided initial phrase.            | Please describe the suitcase.               |
| Begins with + Keyword controlled generation | Generate a response that starts with the provided initial phrase and contains the provided keywords. [INITIAL PHRASE] Please describe [KEYWORDS] color, any documents | Please describe the color of the suitcase and any documents in it. |
| Intent detection                          | What is the intent of the response? booking, reservation change, checkout, lost&found,..., time information, security, schedules | lost&found                                 |
| Summarization                             | Return a summary of the provided conversation.                              | Person2 left a suitcase on the train to London the other day. |
| Answer generation                         | [QUESTION] What is the response of following question: Where was the person going to? | London                                      |
| Knowledge grounded generation             | Generate a response using the provided background knowledge. [KNOWLEDGE] Emailid for cases related to lost&found is x@gmail.com | You can contact us at x@gmail.com           |

Table 7: A sample conversation followed by instructions for multiple tasks for that conversation, and the outputs generated based on the specified instructions. Instruction tuning allows performing multiple tasks on an input by specifying task-specific instructions and prompts.

B Sample conversation and Instructions
In Table 7 we provide a sample conversation followed by instructions for multiple tasks for that conversation, and the outputs generated by DIAL-BART0 based on the specified instructions. Through this example we illustrate that instruction tuning allows performing multiple tasks on an input by specifying task-specific instructions.

C Datasets used in tasks
In Table 9 we present the list of tasks with datasets used in each task.

D Configuration of experiments
In Table 10 we provide the configurations of experiments, that is, the tasks used for training for each experiment.
| Task Type | Task Name | Example |
|-----------|-----------|---------|
| **Intent** | **Intent Classification** | [RES] Make a reservation for 4 [EOP] [REST] The possible intents are: [OPT] BookRestaurant [REST] [SHARED] [QA] True. Are there any other options? [EOP] [REST] The possible options are: [OPT] yes | **Example** | [OPT] no |
| **NLI** | **Contraction** | [CTX] OK. [EOT] [REST] There are two fries. [OPT] Yes. It's my first time. [RES] [EOD] [REST] The predicted class is: [OPT] refutes |
| **Safety Classification** | **Toxicity Classification** | [CTX] Hi! [EOT] Hello [EOP] [RES] [EOD] [REST] The response is not interesting [Q] Is the response toxic? [OPT] yes | **Example** | [OPT] no |
| **Relation Extraction** | **Relation Classification** | [CTX] It's like this, me, no jokes [EOT] [SHARED] [OPT] [EOD] [REST] The possible relations are: [OPT] per siblings [Q] The relation between A and B is: [OPT] yes | [CTX] It's like this, me, no jokes [EOP] [REST] All right... [EOD] [REST] The possible relations are: [OPT] per siblings [Q] The relation between A and B is: [OPT] yes |
| **Evaluation** | **Relevance** | [CTX] to hold on to my dad [EOP] [RES] [EOD] [REST] Is the response contextual? [OPT] yes | **Example** | [OPT] yes |
| **Slot** | **Slot Classification** | [CTX] what do you have tomorrow after 5 o'clock from atlanta to san francisco [EOP] [RES] [EOD] [REST] What is the value of slot city_name? [Q] The city name is in the response: [OPT] yes |
| **Safety Generation** | **Non-Toxic Feedback** | [CTX] I have never met [EOT] [SHARED] [OPT] [EOD] [REST] Does the response alter the sentiment of the previous utterance? [OPT] negative |
| **Grounded Generation** | **Emotion** | [CTX] I tell ya [EOT] [SHARED] [OPT] [EOD] |
| **QA and Consequence** | **Shuffling** | [CTX] [EOT] [SHARED] [OPT] |
| **Controlled Generation** | **Begin With** | [INIT] I tell ya [CTX] [EOT] [SHARED] [OPT] |
| **Dialog State Generation** | **Stability** | [CTX] [SHARED] [OPT] |
| **Edit Generation** | **Adding** | [RES] [OPT] |
| **Pretain Tasks** | **Full Missing Utterance** | [CTX] [OPT] |
| **Response Generation** | **Open-Domain** | [CTX] [OPT] |
| **Summarization** | **Summary Generation** | [CTX] [OPT] |
| **Misc** | **Act Classification** | [CTX] I'm looking for a nice German restaurant [EOP] [RES] Are there any other options? [EOP] [REST] The possible acts are: [OPT] request | **Example** | [OPT] inform |

**Table 8:** List of tasks with sample inputs for each task. The left column describes the general task type. The middle column lists the specific task. The right column displays an example formatted using a random selected task definition and prompt for the task. [CTX] is short for [CONTEXT], [Q] is short for [QUESTION], [RES] is short for response, [EOT] is short for [ENDOFTURN] and [EOD] is short for [ENDOFDIALOGUE]
| Task Type                          | Task Name                                      | Datasets                                                                 |
|-----------------------------------|-----------------------------------------------|--------------------------------------------------------------------------|
| Intent                            | Intent Classification                          | ATIS (Hemphill et al., 1990) SNIPS (Coucke et al., 2018) CLINIC150 (Lison et al., 2019) |
| Intent Present                    |                                               | HW164 (Liu et al., 2021) Booking77 (Casanauro et al., 2020) |
| NLI                               | DialFact                                      | DialFact (Gupta et al., 2021)                                          |
|オープン                            |                                               |                                                                          |
| Contradiction                     | Decode (Nie et al., 2021) Dialogue NLI (Wellek et al., 2019) |
| Safety Classification             | toxicity Classification                       | ToxChat (Ball et al., 2021) BAD (Xu et al., 2021) Build it Break it Fix it (Duman et al., 2019a) |
| Relation Extraction               | Relation Classification                       | DialogRE (Yi et al., 2020)                                              |
| Evaluation                        | Relevant                                      | ESFC (Horn and Horn, 2017) LSTLC (Vallée et al., 2019) Persona-Chatlog (Ye et al., 2019) |
| Selection                         | SNIPS (Mehri and Eskenazi, 2020b) FED (Mehri and Eskenazi, 2020a) DailyDialog (Zhou et al., 2020a) GRADE (Huang et al., 2020) HUMOD (Meidkran et al., 2020) |
| Slot                              | Slot Classification                           | RESTAURANTS-8K (Ye et al., 2020) PERSONAL-SHOP (Dinan et al., 2020b) |
| Slot Present                      | ATIS (Hemphill et al., 1990) SNIPS (Coucke et al., 2018) |
| Slot Value Generation             | TaskMaster (Byrne et al., 2019) MSRE2E (Li et al., 2018) |
| Safety Generation                 | Safety Classification                         | Safety Classification                                                    |
| Grounded Generation               | Grounded                                       |                                                                         |
| QA and Commonsense                |                                               |                                                                         |
| Dialog State Generation           | Dialog State Generation                       | MultiWOZ (Budzianowski et al., 2018) VKREIT (Bric et al., 2017) WOZ (Kulik et al., 2017) CamRest18 (Wen et al., 2017) MRR-E2E (Li et al., 2018) TaskMaster (Byrne et al., 2019) Schema-Guided (Rastogi et al., 2020a) |
| Edit Generation                   |                                               |                                                                         |
| Pretrain Tasks                    |                                               |                                                                         |
| Response Generation               | Open Domain                                   | DailyDialog (Li et al., 2017) ComAI (Dinan et al., 2019b) WOZ (Dinan et al., 2019c) |
| Summarization                     |                                               |                                                                         |
| Misc                              |                                               |                                                                         |
| Count Response Words              |                                               |                                                                         |

Table 9: List of Tasks with datasets used in each task. The left column describes the general task type. The middle column lists the specific task. The right column shows all datasets used for a specific task type.
| Experiment                  | Base model(s) | Tasks                                                                 |
|-----------------------------|---------------|----------------------------------------------------------------------|
| Main zero-shot tasks        | ID-BART0, ID-T0 | act classification, act generation, advice generation, advice present, answer generation, count response words, db based generation, deal present, document grounded generation, emotion generation, emotion tagging, emotion tagging, endwith controlled generation, fill missing utterance, find incoherent utterance, find missing utterance, graph based generation, intext classification, intent present, keyword controlled generation, knowledge grounded generation, nli classification, non toxic feedback generation, persona grounded generation, persuasion generation, persuasion present, persuasion strategy, question generation, recovery generation, response generation, response generation with n words, schema based generation, slot present, slot value generation, summarization, target controlled generation, toxic classification. |
| Evaluation                  | ID-BART0      | act classification, act generation, advice generation, advice present, answer generation, answer selection, beginwith controlled generation, belief state generation, db based generation, deal present, document grounded generation, emotion generation, emotion tagging, emotion tagging, endwith controlled generation, emotion tagging, graph based generation, intext classification, intent present, keyword controlled generation, knowledge grounded generation, nli classification, non toxic feedback generation, persona grounded generation, persuasion generation, persuasion present, persuasion strategy, relation classification, relation present, response generation, response generation with n words, schema based generation, slot present, slot value generation, summarization, target controlled generation, toxic classification. |
| Dialog State Generation    | ID-BART0      | act classification, act generation, advice generation, advice present, answer generation, answer selection, beginwith controlled generation, belief state generation, db based generation, deal present, dialfact classification, dialog state generation (no multi woz), document grounded generation, edit generation, emotion generation, emotion tagging, emotion tagging, endwith controlled generation, emotion tagging, endwith controlled generation, fill missing utterance, find incoherent utterance, find missing utterance, graph based generation, intext classification, intent present, keyword controlled generation, knowledge grounded generation, nli classification, non toxic feedback generation, persona grounded generation, persuasion generation, persuasion present, persuasion strategy, question generation, relation classification, relation present, response generation, response generation with n words, schema based generation, slot present, slot value generation, summarization, target controlled generation, toxic classification. |
| Slot Filling                | ID-BART0      | act classification, act generation, answer generation, answer selection, beginwith controlled generation, belief state generation, count response words, db based generation, deal present, dialfact classification, document grounded generation, edit generation, emotion generation, emotion tagging, emotion tagging, endwith controlled generation, fill missing utterance, find incoherent utterance, find missing utterance, graph based generation, intext classification, intent present, keyword controlled generation, knowledge grounded generation, nli classification, non toxic feedback generation, persona grounded generation, persuasion generation, persuasion present, persuasion strategy, question generation, relation classification, relation present, response generation, response generation with n words, schema based generation, slot present, slot value generation, summarization, target controlled generation, toxic classification. |

Table 10: List of experiments and their base models. The tasks listed in the right column are all the tasks a base model was trained with for their corresponding experiment.