

# Zero Shot Task Oriented Dialog

Anonymous ACL submission

## Abstract

This document is a supplement to the general instructions for \*ACL authors. It contains instructions for using the L<sup>A</sup>T<sub>E</sub>X style file for ACL 2023. The document itself conforms to its own specifications, and is, therefore, an example of what your manuscript should look like. These instructions should be used both for papers submitted for review and for final versions of accepted papers.

## 1 Introduction

## 2 Methodology

Steps: Pretraining(CE Loss), Training (loss on target only)

Context: Dialog History like SimpleTOD DST instead of dialog history

Additional info Schema List of system actions  
User actions Service Results

Contrastive Loss User action, System action System Action, NLG

## 3 Experimental Setup

### 3.1 Datasets

We use the SGD (Rastogi et al., 2020) and SGD-X (Lee et al., 2022) datasets to conduct experiments. Seen domains are obtained from the train schema file and unseen domains from the eval and test schema files. The models are trained on seen domains and inference is performed on all, seen and unseen domains.

To evaluate the performance of the models, we use metrics from SGD, MultiWoz 2.0 benchmark (Ramadan et al., 2018) and introduce 2 novel metrics: Average Action Accuracy, Joint Action Accuracy. These new metrics are similar to the goal metrics in SGD, but are performed on the actions. For response generation, we report the ROUGE-2 (Lin and Och, 2004) score and GLEU (Wu et al., 2016) instead of BLEU as it performs better on

individual sentence pairs. The combined score is calculated as suggested in (Mehri et al., 2019) with  $(\text{Inform} + \text{Success}) \times 0.5 + \text{GLEU}$ .

## 4 Related Works

### 4.1 Supervised End to End Models

Pretrained language models like BERT (Devlin et al., 2019), GPT-2 (Radford et al., 2019) and T5 (Raffel et al., 2019) have been used extensively in the literature for End to End models for TOD systems (Hosseini-Asl et al., 2020), (Peng et al., 2021), (Lee et al., 2020), (Yang et al., 2020), (Jeon and Lee, 2021), (Sun et al., 2022), (Yang et al., 2022), (Noroozi et al., 2020). In these models, the context consists of user and system utterance, whereas in our model we use the last user utterance and the previous state DST as context. Moreover, most of these models have the best performance in supervised settings and do not have the primary focus on zero-shot generalization.

### 4.2 Zero Shot End to End Models

Zero Shot DST models (Feng et al., 2020), (Zhao et al., 2022) incorporate schema as part of the context and generalize well for DST, however these models do not focus on system actions and response generation.

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