Prompt Conditioned VAE: Enhancing Generative Replay for Lifelong Learning in Task-Oriented Dialogue

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Abstract

Lifelong learning (LL) is vital for advanced task-oriented dialogue (ToD) systems. To address the catastrophic forgetting issue of LL, generative replay methods are widely employed to consolidate past knowledge with generated pseudo samples. However, most existing generative replay methods use only a single task-specific token to control their models. This scheme is usually not strong enough to constrain the generative model due to insufficient information involved. In this paper, we propose a novel method, *prompt conditioned VAE for lifelong learning* (PCLL), to enhance generative replay by incorporating tasks' statistics. PCLL captures task-specific distributions with a conditional variational autoencoder, conditioned on natural language prompts to guide the pseudo-sample generation. Moreover, it leverages a distillation process to further consolidate past knowledge by alleviating the noise in pseudo samples. Experiments on natural language understanding tasks of ToD systems demonstrate that PCLL significantly outperforms competitive baselines in building lifelong learning models. We release the code and data at GitHub.

1 Introduction

Task-oriented dialogue (ToD) systems are of great importance in advanced AI applications (Zhang et al., 2020b; Dai et al., 2020, 2021; He et al., 2022a,b,c). However, most existing ToD systems are developed under the assumption that the data distribution remains unchanged (Zhu et al., 2022). Unless the entire system is retrained, this setup may not be realistic when the ToD system deployed in practice needs to support new features and provides more services over time based on user demands. Without incurring the high cost of retraining, Lifelong Learning (LL) is able to acquire new knowledge continuously while preserving previously learned knowledge (Delange et al., 2021). Hence, it's crucial to equip natural language understanding (NLU) modules, the vital components of ToD systems, with the lifelong learning ability.

The main issue for lifelong learning is *catastrophic forgetting* (McClelland et al., 1995; Parisi et al., 2019), which refers to the phenomenon that a model forgets previously learned tasks when learning new tasks. Various approaches have been proposed to alleviate this issue (Schwarz et al., 2018; Aljundi et al., 2018; Rusu et al., 2016; Aljundi et al., 2017). The replay-based methods are among the most effective and widely used ones (Rebuffi et al., 2017; Shin et al., 2017; Dai et al., 2022). The main idea of replay-based methods is to retrain samples or representations from already seen tasks when learning new tasks (Mundt et al., 2020). Some methods explicitly store previously seen real samples for replaying (*experience replay*) (Rebuffi et al., 2017; Chaudhry et al., 2019). However, this setting will be infeasible when data from previous tasks is unavailable due to data security concerns. Other methods try to generate pseudo samples using a generative model (*generative replay*). This variant relieves the burden of storing previously seen data and has been widely adopted in previous studies (Delange et al., 2021; Shin et al., 2017; Kemker and Kanan, 2018).

The key to generative replay is to produce pseudo samples to approximate the real data distribution of previous tasks. Intuitively, higher quality pseudo samples can better preserve learned tasks and lead to less forgetting in LL. However, the generation of pseudo samples for each seen task in previous studies (Sun et al., 2020; Chuang et al., 2020) is usually controlled by a single task-specific token. It has been observed that this scheme is usually insufficient to constrain the PLM (Sun et al., 2020), due to limited information involved. Consequently, the generated pseudo samples suffer from

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