Learning from My Friends: Few-Shot Personalized Conversation Systems via Social Networks

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Abstract

Personalized conversation models (PCMs) generate responses according to speaker preferences. Existing personalized conversation tasks typically require models to extract speaker preferences from user descriptions or their conversation histories, which are scarce for newcomers and inactive users. In this paper, we propose a few-shot personalized conversation task with an auxiliary social network. The task requires models to generate personalized responses for a speaker given a few conversations from the speaker and a social network. Existing methods are mainly designed to incorporate descriptions or conversation histories. Those methods can hardly model speakers with so few conversations or connections between speakers. To better cater for newcomers with few resources, we propose a personalized conversation model (PCM) that learns to adapt to new speakers as well as enabling new speakers to learn from resource-rich speakers. Particularly, based on a meta-learning based PCM, we propose a task aggregator (TA) to collect other speakers' information from the social network. The TA provides prior knowledge of the new speaker in its meta-learning. Experimental results show our methods outperform all baselines in appropriateness, diversity, and consistency with speakers.

Introduction

Recently, there has been a boom in research on neural conversation models (Shang, Lu, and Li 2015) due to the accessibility of vast conversational data on social media (e.g. Twitter). To generate appropriate and lively responses, researchers have proposed personalized conversation tasks that require models to customize responses for specific speakers, since different speakers tend to have different styles or preferences for their responses. There are two subtypes of such tasks. Description-conditioned tasks (Yang et al. 2017; Zhang et al. 2018b) require models to customize responses according to explicit speaker descriptions. These descriptions may come from human annotations (Zhang et al. 2018b) or user profiles in social media (Mazare et al. 2018). Speaker descriptions are not always available due to the cost of annotation and privacy concerns in social media. Conversation-conditioned tasks (Li et al. 2016b; Kottur, Wang, and Carvalho 2017) require models to generate personalized responses by exploiting speakers' preferences from their conversation histories. In reality, conversation histories may provide very few utterances of a particular speaker, which makes it hard to capture speaker preferences, especially for the newcomers or inactive users.

To better cater for newcomers, we propose a few-shot personalized conversation task with an auxiliary social network. The task has three characteristics: 1. During training, models cannot access information about the speakers in the testing set (i.e. newcomers); 2. During testing, there are only a few samples available for each speaker, which are collectively referred to as the support set; 3. There is a social network among all the speakers. Given the input query, our task requires a conversation model to generate a response for a new speaker with the help of the social network and a few (i.e. 10) past conversation samples from the speaker.

It is difficult to characterize the preferences of a new speaker from only a few conversation samples. Social networks can help here. In a social network, neighbors are users who follow each other, and they usually share interests and have similar chatting preferences. As our observation on our dataset, on average, the response similarity between two neighbors (0.47) is higher than that between two random speakers (0.38). [1] Consequently, we can utilize conversation histories of neighbors to help to determine preferences of a newcomer. In this way, we can handle newcomers even when there are no descriptions or a few conversations available.

Existing conversation-conditioned PCMs can be applied to our proposed task. Li et al. 2016b employ speaker embedding to capture speaker preferences. Based on this, Bak and Oh 2019 pre-built a conversation graph to describe speaker relations and learn node2vec embeddings (Grover and Leskovec 2016) over the graph. The node2vec embed-

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[1]The gap between 0.47 and 0.38 is quite large in this evaluation metric, as a contrast, the gap between similarity of two responses from one speaker (0.50) and 0.47 is only 0.03.