Dialog Router: Automated Dialog Transition via Multi-Task Learning

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Abstract

Dialog Router is a general paradigm for human-bot symbiosis dialog systems to provide friendly customer care service. It is equipped with a multi-task learning model to automatically capture the underlying correlation between multiple related tasks, i.e. dialog classification and regression, and greatly reduce human labor work for system customization, which improves the accuracy of dialog transition. In addition, for learning the multi-task model, the training data and labels are easy to collect from human-to-human historical dialog logs, and the Dialog Router can be easily integrated into the majority of existing dialog systems by calling general APIs. We conduct experiments on real-world datasets for dialog classification and regression. The results show that our model achieves improvements on both tasks, which benefits the dialog transition application. The demo illustrates our method's effectiveness in a real customer care service.

Introduction

In customer care services, such as robo-sales and after-sales, building a human-bot symbiosis dialog system is a low-cost way to meanwhile make the service quality remain at a high level. If not, massive human agents should be hired. In such a human-bot symbiosis dialog system, usually bot agents can handle easy questions while human agents are responsible for difficult ones. On the other hand, unsuitable human agent would also be replaced by more suitable ones. Therefore, when to trigger the dialog transition among bot and humans is a significant application-driven problem.

To address the problem of dialog transition, an intuitive solution is via handcrafted rules (Jiang et al. 2019a). However, large human labor work is required for system customization, and the scalability and flexibility are unsatisfactory. Learning based models can overcome the drawbacks (Jiang et al. 2019b). By our observations, we leverage Net Promoter Score (NPS)[1], which is a widely-used metric to evaluate the degree of users' satisfaction in existing dialog systems, to monitor users along with dialog turns. Low NPS may suggest that the dialog should be transited from bot to human agent or from an unqualified human agent to another. However, at the beginning stage of dialogs, we find that the textual information is limited to train a good model for NPS regression prediction. Moreover, correctly classifying the current dialog's category to a suitable human agent is the following important task. To improve the performance of both tasks, the underlying correlation between the two tasks should be leveraged and modeled.

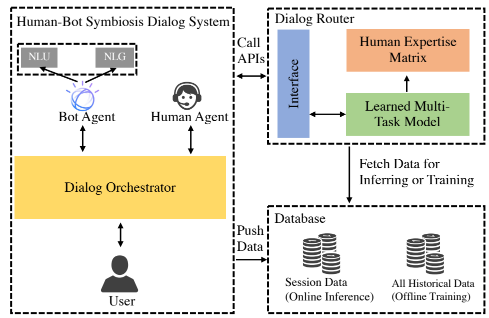

Figure 1: Architecture of a human-bot symbiosis dialog system which integrates Dialog Router with general APIs

To model the correlation between multiple tasks, multi-task learning is the natural choice, because the related tasks can be modeled by the explicit formation of parameters sharing. We propose a multi-task learning model which leverages the latest pre-trained model BERT (Devlin et al. 2018) to encode conversations and an efficient and easy-to-deploy multi-task learning framework (Arora et al. 2018) to implement our system. As shown in Figure 1, it is a whole picture of human-bot symbiosis dialog system which integrates the Dialog Router via multi-task learning. The architecture supports real-time monitoring for dialog transition and is flexible to add Dialog Router into the majority of existing dialog systems via calling general APIs. In the followings, we will introduce how the dialog system generally integrates the Dialog Router for dialog transition application, and some quantitative experiments are conducted to prove performance improvement. The supplementary video demo shows the effectiveness of our method in real industrial environment.

System Overview

A human-bot symbiosis dialog system with dialog transition is composed of, as Figure 1 illustrates, Dialog Orchestra-

*This work was done when he was in IBM Research-China.

[1]https://www.bernardmarr.com/default.asp?contentID=1393

tor, Natural Language Understanding (NLU), Natural Language Generation (NLG), Dialog Router which includes the Interface, a Learned Multi-Task Model and Human Expertise Matrix, and a dialog database.

Dialog Orchestrator, NLU and NLG Parts

In most human-bot symbiosis systems, the Dialog Orchestrator is responsible for dispatching who will deliver the service for users. As to our architecture, this part can call the APIs of Dialog Router to make decision of which agent is competent. Also, this part should push every utterance from both sides to the database for later online model inference and offline model training.

For building the bot agent, we leverage a conversational platform by defining intents and entities for NLU[2]. Given an utterance, the platform can output a list of identified intents, entities and corresponding confidence scores.

For the NLG part, we use a well-trained attention-based model with our data (Bordes, Boureau, and Weston 2017). Given identified intents, entities and historical utterances within a session together as input, the model can output an utterance. Note that the Orchestrator, NLU and NLG parts are not our highlights in this paper.

Dialog Router

Dialog Router contains 3 modules and 3 APIs for generally integrating this part in existing systems.

Interface This module is responsible for receiving calls from Dialog Orchestrator and returning the decision on whether to transit the dialog by calling the learned multi-task model. This module also interacts with the Database to fetch data for online model inferring or offline model training and updating. When to update the multi-task model can be freely set as automatically or manually.

Multi-Task Model We leverage BERT, which is dominant in most NLP tasks (Devlin et al. 2018), and the similar process with deep neural network (Cohan et al. 2019) to encode each utterance in a conversation. As Figure 2 shows, in the Dialog Encoder layer, we connect all the utterances of a dialog session like BERT, and an additional transformer layer over all the $T_{[SEP]}$ vectors outputs the $conv$ vector which is a contextualized representation of all utterances. Then to fully leverage the BERT's encoding ability at different levels, the $conv$ vector is connected with Dialog Category Classification task and the $T_{[CLS]}$ vector is used to predict NPS. The predicted distribution of dialog categories by the model and a human expertise matrix are multiplied to obtain the most suitable agent which has the highest weight.

Human Expertise Matrix We particularly design a matrix to store the relationship between agents and their expertise aspects, which plays the role of translator from predicted category distribution to expertise distribution. The matrix is easy to build just by statistics from the historical records. We count the frequency between an agent and an aspect of expertise as the matrix value. The matrix can be dynamically updated along with the increasing of historical data.

[2]https://www.ibm.com/cloud/watson-assistant/

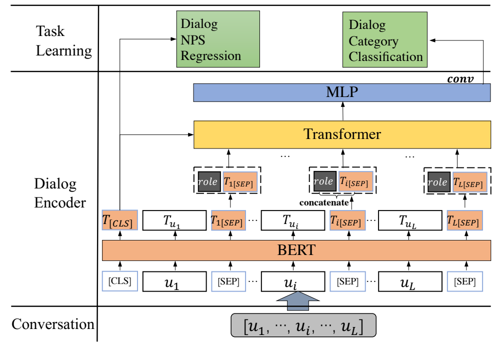

Figure 2: Multi-Task Model

Models	micro-F1	RMSE
textCNN (Zhang and Wallace 2015)	77.81	0.9787
textRNN (Wang et al. 2018)	77.77	0.9801
CNN-BiRNN (Wang, Jiang, and Luo 2016)	78.61	0.9867
textReg (Dereli and Saraclar 2019)	77.98	0.9689
BERT (Devlin et al. 2018)	80.04	0.9702
Ours (using [CLS] only)	80.47	0.9519
Ours (using [CLS] and conv)	**81.88**	**0.9302**

Table 1: Comparison with baselines.

Database

The Database stores every historical dialog utterance, which is already deployed in most existing systems. Only two APIs should be additionally designed to fetch data for runtime model inference and offline model updating.

Demonstration

Results

In our experiments, we collect 22,897 training records among 7 different categories and the NPS ranges from 1 to 10 from a real industrial dialog system. The NPS labelled by user to indicate for user satisfaction feedback. The dataset is split to 8:1:1 for training, validating and testing. The results in Table 1 show our model achieves performance improvement over several state-of-the-art baselines, which can provide more accurate dialog transition.

Case Studies

We deploy our Dialog Router to a real-world online dialog system for educational QA. The demo video demonstrates that our human-bot symbiosis system can greatly monitor the real-time dialog state and timely transit the dialog to a suitable agent when the predicted NPS is low.

Conclusion

In this paper, we propose an paradigm for dialog transition in human-bot symbiosis dialog systems via multi-task learning. We make the state-of-the-art learning based method grounded. Our experiments and demo video show the effectiveness of our Dialog Router. The system can automatically learn from historical data, and is flexible enough to be integrated into the majority of existing dialog systems which provide friendly customer care service.

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