Open-Domain Neural Dialogue Systems

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1 Tutorial Overview

Until recently, the goal of developing open-domain dialogue systems that not only emulate human conversation but fulfill complex tasks, such as travel planning, seemed elusive. However, we start to observe promising results in the last few years as the large amount of conversation data is available for training and the breakthroughs in deep learning and reinforcement learning are applied to dialogue. In this tutorial, we start with a brief introduction to the history of dialogue research. Then, we describe in detail the deep learning and reinforcement learning technologies that have been developed for two types of dialogue systems. First is a task-oriented dialogue system that can help users accomplish tasks, ranging from meeting scheduling to vacation planning. Second is a social bot that can converse seamlessly and appropriately with humans. In the final part of the tutorial, we review attempts to developing open-domain neural dialogue systems by combining the strengths of task-oriented dialogue systems and social bots. The tutorial material is available at http://opendialogue.miulab.tw.

2 Outline

1. Introduction & Background [15 min.]
   - Brief history of dialogue research
   - Challenges of developing dialogue agents
   - Task-oriented dialogue systems
   - Social chat bots
   - How to evaluate dialogue systems
   - Neural network basics
   - Reinforcement learning (RL) basics
2. Task-Oriented Dialogue System [75 min.]
   - Natural language understanding (NLU)
     - Domain and intent classification
     - Slot tagging
   - Dialogue management (DM) – Dialogue state tracking (DST)
     - Neural belief tracker
     - Multichannel tracker
   - Dialogue management (DM) – Dialogue policy optimization
     - Dialogue RL signal
     - Deep Q-network for learning policy
     - Hierarchical RL for learning policy
   - Natural language generation (NLG)
     - Rule-based NLG
     - Learning-based NLG
     - Structural NLG
     - Contextual NLG
   - End-to-end task-oriented dialogue systems
     - Joint learning of NLU and DM
     - Supervised learning for dialogues
     - Memory networks for dialogues
     - RL-based InfoBot
     - LSTM-based dialogue control
     - RL-based task-completion bots
3. Social Chat Bots [75 min.]
   - Neural response generation models
   - Making the response diverse
   - Making the response consistent
   - Deep reinforcement learning for response generation
   - Image-grounded response generation
   - Knowledge-grounded response generation
   - Generative seq2seq for task-oriented dialogues
   - Combining task-oriented bots and social bots
4. Challenges & Conclusions [15 mins]
### 3 Task-Oriented Dialogue Systems

The architecture of a task-oriented dialogue system is illustrated in Figure 1 (Tur and De Mori, 2011). It consists of three components, natural language understanding (NLU), dialogue management (DM), and natural language generation (NLG) (Rudnicky et al., 1999; Zue et al., 2000; Zue and Glass, 2000).

#### Natural Language Understanding

NLU traditionally consists of domain identification and intent prediction, which are framed as utterance classification problems, and slot filling, framed as a sequence tagging task.

With the advances on deep learning, recent development has been focused on neural approaches. Ravuri and Stolcke (2015) proposed an RNN architecture for intent determination. Xu and Sarikaya (2013) incorporated features generated using neural approaches into the CRF framework for slot filling. Yao et al. (2013) and Mesnil et al. (2015) later employed the RNN-based sequence labeling model for slot filling. Such an architecture has been further extended to jointly model intent detection and slot filling in multiple domains (Hakkani-Tür et al., 2016; Jaech et al., 2016). End-to-end memory networks have shown to provide a good mechanism for integrating global knowledge context and local dialogue context into these models (Chen et al., 2016a,b). In addition, the importance of the NLU module is investigated in Li et al. (2017a), showing that different types of errors from NLU can degrade the whole system’s performance in a reinforcement learning setting.

#### Dialogue Management

DM plays two roles, tracking the dialogue state and performing the dialogue policy (i.e., telling the agent how to act given the dialogue state.)

The state-of-the-art dialogue managers monitor the dialogue progress (state) using neural dialogue state tracking models (Henderson et al., 2013). Recent work shows that that Neural Dialog Managers provide conjoint representations between the utterances, slot-value pairs as well as knowledge graph representations (Wen et al., 2016; Mrkšić et al., 2016; Liu and Lane, 2017), and thus make the deployment of large-scale dialogue systems for complex domain much easier.

A partially observable Markov decision process (POMDP) has been shown to be an effective mathematical framework for dialogue policy learning since it can model the uncertainty such as those caused by speech recognition errors and semantic decoding errors (Williams and Young, 2007; Young et al., 2013). Under POMDP, dialogue policy is trained using reinforcement learning (RL) where the agent learns how to act based on the reward signals received from the environment (Sutton and Barto, 1998).

#### Natural Language Generation

NLG approaches can be grouped into two categories, one focuses on generating text using templates or rules (linguistic) methods, the other uses corpus-based statistical methods (Oh and Rudnicky, 2002).

The RNN-based models have been applied to language generation for both social bots and task-orientated dialogue systems (Sordoni et al., 2015; Vinyals and Le, 2015; Wen et al., 2015b). The RNN-based NLG can learn from unaligned...
data by jointly optimizing sentence planning and surface realization, and language variation can be achieved by sampling from output candidates (Wen et al., 2015a). Moreover, Wen et al. (2015b) improved the prior work by adding a gating mechanism to control the dialogue act during generation in order to avoid repetition.

End-to-End Task-Oriented Dialogue System
Awareing the representation power of deep neural networks, there are more and more attempts to learning dialogue systems in an end-to-end fashion using different learning frameworks, including supervised learning and reinforcement learning (Yang et al., 2017).

Wen et al. (2016) and Bordes and Weston (2016) introduced a network-based end-to-end trainable task-oriented dialogue system. The authors treated training a dialogue system as learning a mapping from dialogue histories to system responses, and applied an encoder-decoder model. However, the system is trained in a supervised fashion that requires a lot of training data. Thus, the agent cannot learn a robust dialogue policy since it never explore the unknown space that is not covered by the limited training data.

Zhao and Eskenazi (2016) presented an end-to-end reinforcement learning (RL) approach to dialogue state tracking and policy learning. They show some promising results when applying the agent to the task of guessing the famous person a user is thinking of. Dhingra et al. (2017) proposed an end-to-end differentiable KB-Infobot for efficient information access. Li et al. (2017b) presented an end-to-end neural dialogue system for task completion. The agent can handle a wide variety of question types, including user-initiated request.

4 Social Chat Bots
Social bots are of growing importance in facilitating smooth interaction between humans and their electronic devices. Recently, researcher have begun to explore data-driven generation of conversational responses within the framework of neural machine translation (NMT) in the form of encoder-decoder or seq2seq models (Sordoni et al., 2015; Vinyals and Le, 2015; Li et al., 2016a), as illustrated in Figure 2.

However, the generated responses are often too general to carry meaningful information, such as “I don’t know.”, which can serve as a response to any user questions. A mutual information based model was proposed to address the issue, a mutual information model is proposed by Li et al. (2016a), and is later improved by using deep reinforcement learning (Li et al., 2016c). Furthermore, Li et al. (2016b) presented a persona-based model to address the issue of speaker consistency in neural response generation.

Although task-oriented dialogue systems and social bots are originally developed for different purposes, there is a trend of combining both as a step towards building an open-domain dialogue agent.

For example, on the one hand, Ghazvininejad et al. (2017) presented a fully data-driven and knowledge-grounded neural conversation model aimed at producing more contentful responses without slot filling. On the other hand, Zhao et al. (2017) proposed a task-oriented dialogue agented based on the encoder-decoder model with chatting capability.

5 Instructors
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