Neural Approaches to Conversational AI

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ABSTRACT

This tutorial surveys neural approaches to conversational AI that were developed in the last few years. We group conversational systems into three categories: (1) question answering agents, (2) task-oriented dialogue agents, and (3) social bots. For each category, we present a review of state-of-the-art neural approaches, draw the connection between neural approaches and traditional symbolic approaches, and discuss the progress we have made and challenges we are facing, using specific systems and models as case studies.

CCS CONCEPTS

• **Computing methodologies** → **Discourse, dialogue and pragmatics**; • **Information systems** → Document representation; Information retrieval query processing; Users and interactive retrieval;

KEYWORDS

Conversation, dialogue, question answering, task-oriented dialogue, social chat bot

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1 MOTIVATION AND OBJECTIVES

Developing an intelligent dialogue system that not only emulates human conversation, but also can answer questions of topics ranging from latest news of a movie star to Einstein's theory of relativity, and fulfill complex tasks such as travel planning, has been one of the longest running goals in AI. The goal remains elusive until recently when we started observing promising results in both the research community and industry as the large amount of conversation data is available for training and the breakthroughs in deep learning (DL) and reinforcement learning (RL) are applied to conversational AI.

This tutorial presents a review of state of the art neural approaches to conversational AI that were developed in the last few years, draws the connection between neural approaches and traditional symbolic approaches, and discusses the progress we have made and challenges we are facing, using specific systems and models as case studies.

Table 1: A human-agent dialogue during a process of making a business decision. (*usr*: user, *agt*: agent)

usr:	Where are sales lagging behind our forecast?
agt:	The worst region is [country], where sales are 15% below projections.
usr:	Do you know why?
agt:	The forecast for [product] growth was overly optimistic.
usr:	How can we turn this around?
agt:	Here are the 10 customers in [country] with the most growth potential, per our CRM model.
usr:	Can you set up a meeting with the CTO of [company]?
agt:	Yes, I've set up a meeting with [person name] for next month when you are in [location].
usr:	Thanks.

This tutorial is a valuable resource for students, researchers, and the software developers, providing a detailed presentation of the important ideas and insights needed to understand and create modern dialogue agents that are instrumental to making the world knowledge and services accessible to millions of users in the most natural way.

2 THE TUTORIAL

In this tutorial, we start with a brief introduction to the recent progress on DL and RL that is related to natural language processing (NLP), information retrieval (IR) and conversational AI. Then, we describe in detail the state-of-the-art neural approaches developed for three types of dialogue systems. The first is a question answering (QA) agent. Equipped with rich knowledge drawn from various data sources including Web documents and pre-complied knowledge graphs (KG's), the QA agent can provide concise direct answers to user queries. The second is a task-oriented dialogue system that can help users accomplish tasks ranging from meeting scheduling to vacation planning. The third is a social chat bot which can converse seamlessly and appropriately with humans, and often plays roles of a chat companion and a recommender. In the final part of the tutorial, we review attempts to developing open-domain conversational AI systems that combine the strengths of different types of dialogue systems.

2.1 A Unified View: Dialogue as Optimal Decision Making

The example dialogue presented in Table 1 can be formulated as a sequential decision making process. It has a natural hierarchy: a top-level process selects what agent to activate for a particular subtask (e.g., answer a question, schedule a meeting, give a recommendation or just have a chat etc.), and a low level process, perform by the selected agent, chooses primitive actions to complete the subtask.

Such hierarchical decision making processes can be formulated in the mathematical framework of *options over Markov Decision*

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Table 2: Reinforcement Learning for Dialogue.

dialogue	state	action	reward
QA	understanding of user query intent	clarification questions or answers	relevance of answer # of dialogue turns
task-oriented	understanding of user goal	dialogue-act and slot/value	task success rate # of dialogue turns
chatbot	conversation history and user intent	response	user engagement
top-level bot	understanding of user top-level intent	options	daily/monthly usage

Processes (MDPs) [14], where options generalize primitive actions to higher-level actions. This is an extension to the traditional MDP setting where an agent can only choose a primitive action at each time step, with options the agent can choose a multi-step action which for example could be a sequence of primitive actions for completing a subtask.

If we view each option as an action, both top-level and low-level processes can be naturally mapped to the reinforcement learning (RL) framework as follows. The dialogue agent navigates a MDP, interacting with its environment over a sequence of discrete steps. At step, the agent observes the current state, and chooses an action a according to a policy. The agent then receives reward and observe a new state, continuing the cycle until the episode terminates. The goal of dialogue learning is to find optimal policies to maximize expected rewards. Table 2 summarizes all dialogue agents using a unified view of RL.

Although RL provides a unified machine learning (ML) framework for building dialogue agents, applying RL requires training a dialogue agent by interacting with real users, which can be very expensive for many domains. Thus, in practice we often use RL together with supervised learning especially in the cases where there is a large amount of human-human conversational data. In the rest of the tutorial, we will survey these ML approaches.

2.2 Question Answering and Machine Reading Comprehension

Recent years have witnessed an increasing demand for question answering (QA) dialogue agents that allow users to query large scale knowledge bases (KB) or document collections via natural language. The former is known as KB-QA agents and the latter text-QA agents. KB-QA agents are superior to traditional SQL-like systems in that users can query a KB interactively without composing complicated SQL-like queries. Text-QA agents are superior to traditional search engines, such as Bing and Google, in that they provide concise direct answers to user queries.

In this part, we start with a review of traditional symbolic approaches to KB-QA based on semantic parsing. We show that a symbolic system is hard to scale because the keyword-matching-based inference used by the system is inefficient for a big KB, and is not robust to paraphrasing. To address these issues, neural approaches are developed to represent queries and KB using continuous semantic vectors so that the inference can be performed at the semantic level in a compacted neural space. We use ReasoNet with shared memory [11] as an example to illustrate the implementation details. We also review different dialogue policies for multi-turn KB-QA agents.

We then discuss neural text-QA agents. The heart of such systems is a neural Machine Reading Comprehension (MRC) model that generates an answer to an input query based on a set of passages. After reviewing popular MRC datasets, we describe the technologies developed for state-of-the-art MRC models in two dimensions: (1) the methods of encoding query and passages as vectors in a neural space, and (2) the methods of performing inference in the neural space to generate the answer.

We end this section by outlining our effort of turning Microsoft Bing from a Web search engine into an open-domain QA engine.

2.3 Task-Oriented Dialogue Systems

In this part, we first introduce the architecture of a typical task-oriented dialogue system. It consists of (1) a natural language understanding (NLU) module for identifying intents of user utterances; (2) a state tracker for tracking conversation state; (3) a dialogue policy which selects the next action based on the current state; and (4) a natural language generator (NLG) for converting the agent action to a natural language response. While traditionally these modules are often implemented and optimized individually using statistical models and/or hand-craft rules [15, 19], there is a growing interest in applying deep learning and reinforcement learning to automate the optimization of a dialogue system.

We describe state-of-the-art approaches in two frontiers. The first is end-to-end (E2E) learning where these modules are implemented using differentiable models like neural networks, so that they can be jointly optimized from user feedback signals using backpropagation and RL. The second is the use of advanced RL techniques to optimize dialogue policies in more complex scenarios. Examples include improved efficiency of exploration for faster learning, and hierarchical problem solving for composite-task dialogues where the reward signal is particularly sparse. We review several recent proposals, including the ones based on Bayesian models, curiosity-driven strategy, hierarchical reinforcement learning, adversarial learning, and the Dyna framework [8, 13] to integrate planning and learning, etc.

We end this section by presenting a few example task-oriented systems from some of the leading players in the industry, including Microsoft's Cortana, Amazon's Alexa and Google's Assistant.

2.4 Fully Data-Driven Conversation Models and Social Bots

Social bots (also known as chatbots) are of growing importance in facilitating smooth interaction between humans and their electronic devices. Recently, researchers have begun to explore fully data-driven generation of conversational responses within the framework of neural machine translation (NMT) in the form of encoder-decoder or seq2seq models [10, 12, 16]. Such end-to-end models have been particularly successful with social bot scenarios, as they require little interaction with the user's environment (no need for API calls) and such models cope well with free-form and open domain texts.

However, neural responses are often too general to carry meaningful information, e.g., with the common response "I don't know" which can serve as a reply to most user questions. A mutual information model is proposed by [5], and is later improved by using deep reinforcement learning [7]. Furthermore, Li et al.[6] 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, [4] 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. [20] proposed a task-oriented dialogue agented based on the encoder-decoder model with chatting capability. These works represent steps toward end-to-end dialogue systems that are useful in scenarios beyond chitchat.

We end this section by presenting a few examples of chatbots that have been made available to the public, including Microsoft's XiaoIce, Replika and Alexa Prize systems.

3 RELEVANCE TO THE IR COMMUNITY AND RELATED TUTORIALS

Conversational AI, which aims to develop intelligent agents for QA, social chat and task-completion, as presented in this tutorial, is a rapidly growing field, attracting many researchers in the IR community. As a result, SIGIR 2018 creates a new track of *Artificial Intelligence, Semantics, and Dialog* to bridge research in AI and IR, especially toward QA, deep semantics and dialogue with intelligent agents.

Recently, there have been related tutorial and survey papers on deep learning and dialogue systems. [3, 17, 18] reviewed deep learning approaches to a wide range of IR and NLP tasks, including dialogue. [2] is a recent tutorial on dialogue mainly focusing on task-oriented agents. [9] gave a good survey of public dialogue datasets that can used to develop dialogue agents. [1] reviewed popular deep neural network models for dialogue, focusing only on supervised learning approaches.

This tutorial expands the scope of [1] and [9] by going beyond data and supervised learning. To the best of our knowledge, it is also the first tutorial on neural approaches to conversational AI targeting IR audiences.

The contributions of this tutorial include:

(1) We provide a comprehensive survey on neural approaches to conversational AI that were developed in the last few years, covering QA, task-oriented and social bots with a unified view of optimal decision making.
(2) We draw connections between modern neural approaches and traditional symbolic approaches, allowing us to better understand why and how the research has been evolved and shed light on how we move forward.
(3) We present state-of-the-art approaches to training dialogue agents using both supervised learning and reinforcement learning methods.
(4) We picture the landscape of conversational systems developed in research communities and released in industry, demonstrating via case studies the progress we have made and the challenges we are facing.

4 FORMAT AND DETAILED SCHEDULE

The tutorial consists of four parts. The detailed schedule is as follows.

(1) Part 1 (15 minutes): Introduction
  - Who should attend this tutorial?
  - Dialogue: what kinds of problem?
  - A unified view: dialogue as optimal decision making
  - Machine learning basics
  - Deep learning leads to paradigm shift in NLP and IR
  - Reinforcement learning
(2) Part 2 (45 minutes): QA and MRC
  - The KB-QA task
  - Semantic parsing
  - Embedding-based KB-QA
  - Multi-turn KB-QA agents
  - Machine reading for Text-QA
  - Neural MRC models
  - QA in Bing
(3) Part 3 (50 minutes): Task-oriented dialogue
  - Overview and architecture
  - Review of traditional approaches
  - Natural language understanding and dialogue state tracking
  - Evaluation and user simulator
  - Neural approaches and E2E learning
  - RL for dialogue policy learning
  - Task-oriented bots in industry
(4) Part 4 (50 minutes): Fully data-driven conversation models and chatbots
  - E2E neural conversation models, e.g., seq2seq, HRED, etc.
  - Challenges and remedies
  - Grounded conversation models
  - Beyond supervised learning
  - Data and evaluation
  - Chatbots in public
  - Future work: toward more goal-oriented E2E conversational systems

5 TYPE OF SUPPORT MATERIALS TO BE SUPPLIED TO ATTENDEES

We will make the slides deck of the tutorial available for all attendees to download one or two weeks before the conference, and will make the full and technical report available for download around one month after the conference.

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