Natural Language Processing 365

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Data Science Natural Language Processing NLP Papers Summary

Day 127: NLP Papers Summary – Neural Approaches To Conversational AI – Introduction

By Ryan 6th May 2020 No Comments

Objective and Contribution

This is the first survey paper on neural methods for conversational AI. The contributions are:

1. Provide a comprehensive survey on neural methods for conversational AI, categorising existing work into three categories: question answering (QA), task-oriented, and social bots
2. Draw out the progression from traditional approaches to modern neural a ches, outlining how and why research has evolved that way and how we can move forwu d

3. Present both supervised and reinforcement learning to train SOTA dialogue agents
4. Draw out the conversational systems that are developed in both the research community and the industry, highlighting the progress and challenges of existing conversational systems

3 types of problems in Conversational AI (2 categories)

1. *QA (task-oriented)*. Using multiple data sources, the agent need to provide a direct and accurate answers to user queries (Turn 3 – 5)
2. *Task Completion (task-oriented)*. The agent is required to perform a specific task like reservation, or scheduling a meeting (Turn 6 – 7)
3. *Social Chat (chitchat)*. Provide smooth interactions with the user (Turn 1 – 2)

Turn	Dialogue
1	*usr:* Good morning!
	agt: Good morning, I hope you had a great weekend.
2	*usr:* not really.
	agt: You sound depressed. What can I do for you?
3	*usr:* I'd like to know where sales are lagging behind our forecast?
	agt: The worst region is [country], where sales are 15% below projections.
4	*usr:* Do you know why?
	agt: The forecast for [product] growth was overly optimistic.
5	*usr:* How can we turn this around?
	agt: Here are the 10 customers in [country] with the most growth potential, per our CRM model.
6	*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].
7	*usr:* Thanks!

Figure 1.1: A human-agent dialogue during the process of making a business decision. (*usr*: user, *agt*: agent) The dialogue consists of multiple segments of different types. Turns 1 and 2 are a social chat segment. Turns 3 to 5 are a QA segment. Turns 6 and 7 are a task-completion segment.

The typical architecture

Typically, task-oriented conversational AI has 4 main components:

1. *Natural Language Understanding*. Understanding the user's intent and extracting additional information
2. *State Tracker*. Tracking the state of the conversation and all essential information
3. *Dialog Policy*. Determine what's the next action based on the current state

4. *Natural Language Generation*. Converting agent actions / results into natural language responses

The figure below showcase the 4 components in a task-oriented conversational AI and how recent work has been using deep neural network to combine all these components together, developing a fully data-driven system.

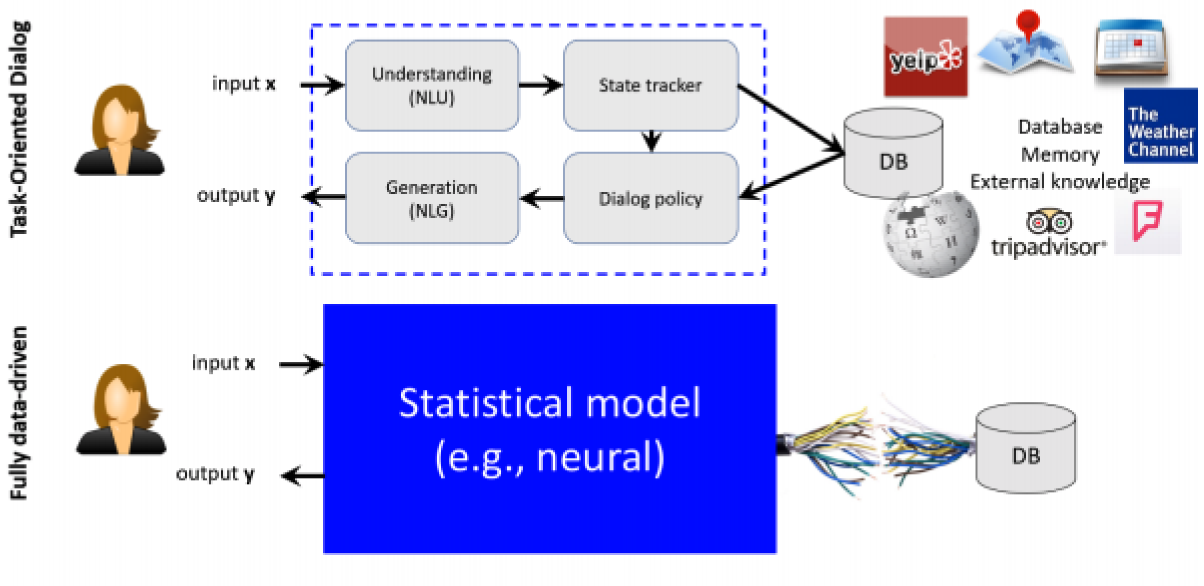


Figure 1.2: Two architectures of dialogue systems for (Top) traditional task-oriented dialogue and (Bottom) fully data-driven dialogue.

Task-oriented agents have access to external database whereas social chatbots do not since they aren't required to use external sources to complete a specific task. Therefore, social chatbots are usually trained using human-to-human conversational data. However, recent work has begun to explore how to connect chitchat using world knowledge and images to make the conversation more contentful and interesting.

A Unified View: Dialogue as Optimal Decision Making

The idea behind a unified view for conversational AI is that conversations can be viewed as a decision making process whereby there's a natural hierarchy of top-level process to select which agent we should use to solve a particular subtask (the 3 types of problems) and low-level process, where the selected agent performs actions to complete the subtask. This can be formulated using Markov Decision Processes (MDPs) and both top- and low-level pro can be captured using the reinforcement learning (RL) framework. The agent would navigate in a

MDP, where by at each step, the agent would observes the current state and choose an action based on the dialog policy. The agent then receives a reward and observes a new state, repeating the cycle until the end. The objective of the agent is to find optimal policies that maximise the expected rewards. The table below showcase this unified view of RL, where state-action space is map to different reward functions.

Table 1.1: Reinforcement Learning for Dialogue. CPS stands for Conversation-turns Per Session, and is defined as the average number of conversation-turns between the bot and the user in a conversational session.

dialogue	**state**	**action**	**reward**
QA	understanding of user query intent	clarification questions or answers	relevance of answer, (min) CPS
task-oriented	understanding of user goal	dialogue-act and slot/value	task success rate, (min) CPS
chitchat	conversation history and user intent	responses	user engagement, measured in CPS
top-level bot	understanding of user top-level intent	options	user engagement, measured in CPS

Two large-scale open-domain dialogue systems have already been developed with this unified view in mind: Sounding Board and Microsoft XiaoIce. The reward functions in the table above seems contradictory in terms of CPS between task-oriented and chitchat. Microsoft XiaoIce is optimised for expected CPS meaning it is optimised for maximising long-term engagement.

All in all, RL allows us to build a unified dialogue system, however, it often requires the agent to train in an interactive environment with real users across multiple domains. In practice, agents are first train using machine learning methods before continuous learning through RL.

The transition of NLP to Neural Approaches

The development of neural methods means that we are relying less and less on human engineered features. Neural methods in machine reading comprehension (MRC) and dialogue usually consists of three steps as shown below:

1. *Encoding* user input and knowledge into neural semantic representations (embeddings)
2. *Reasoning* in the neural space to generate answer vector
3. *Decoding* the neural response into natural language output in the symbolic space

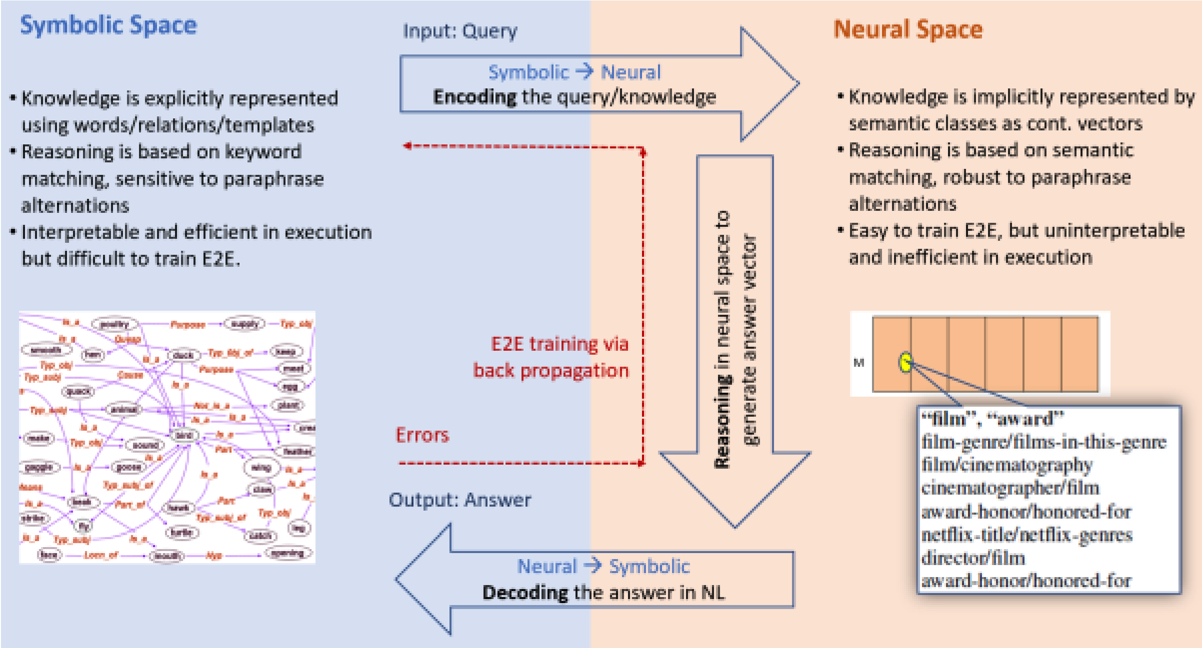
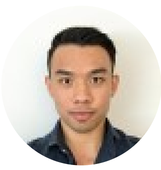


Figure 1.4: Symbolic and Neural Computation.

End-to-end training has yielded many SOTA results in conversational AI, however, they are often weak in execution efficiency and interpretability, whereas symbolic traditional approaches are the opposite. Existing works have been to develop a hybrid methods of the two, to capture the strengths of both neural and symbolic methods.

Source: https://arxiv.org/pdf/1809.08267.pdf



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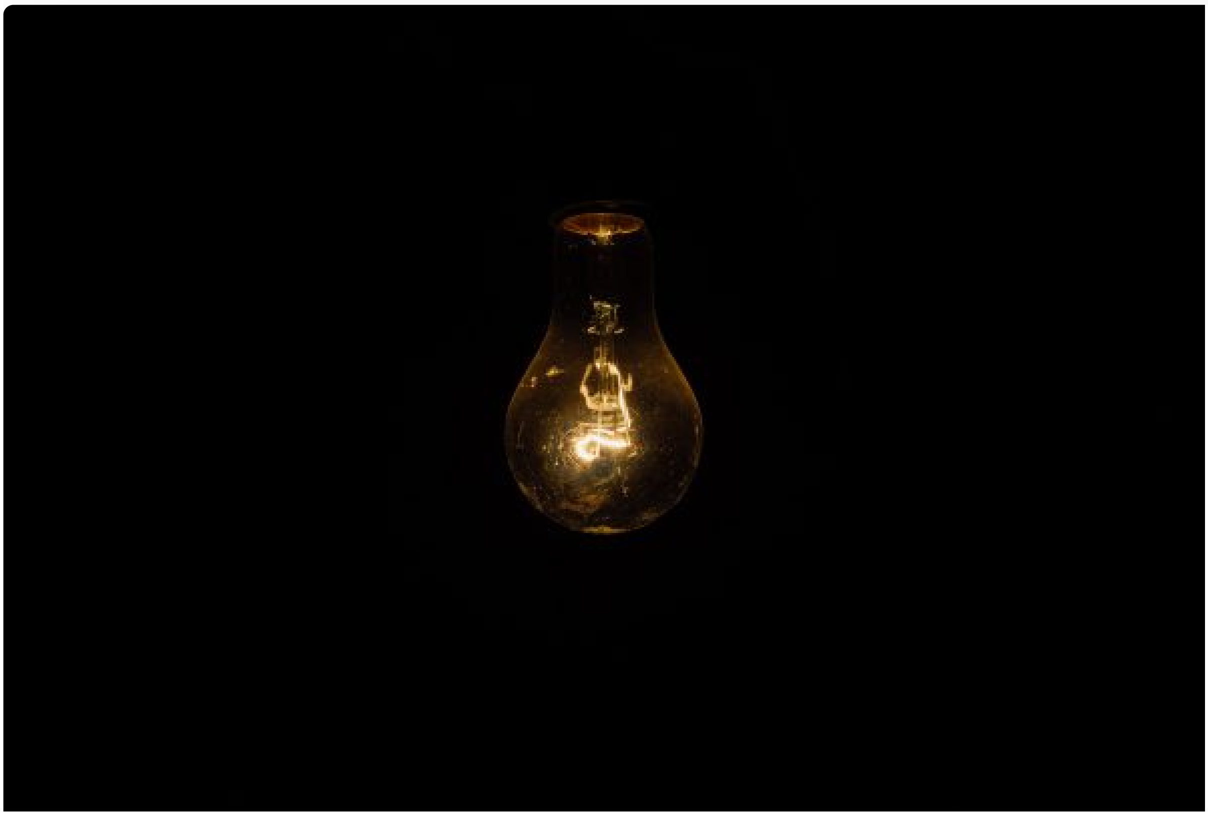

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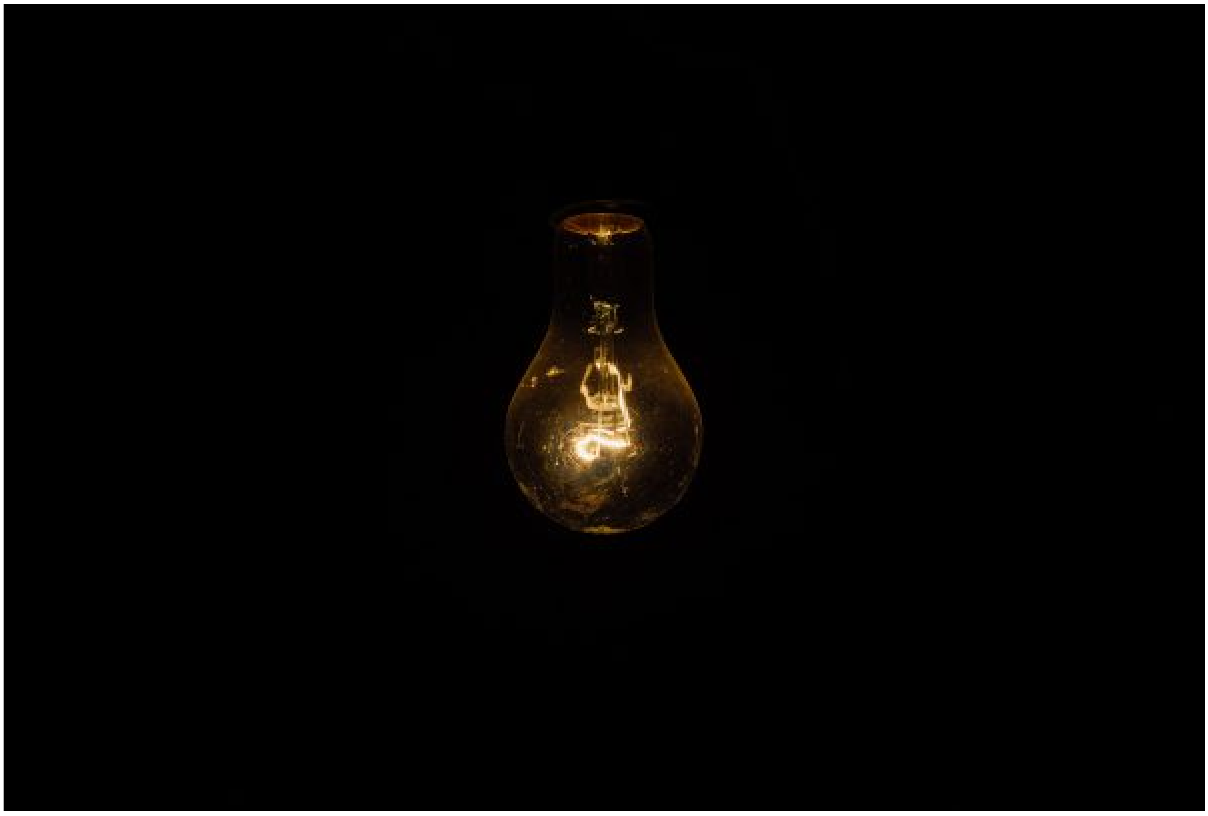

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