Current research topics in spoken dialogue systems

Milica Gašić

Dialogue Systems Group, Cambridge University Engineering Department

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Open domain dialogue systems

Incremental dialogue
Statistical spoken dialogue systems

- So far we focused on limited-domain spoken dialogue systems
- These are slot filling dialogues of relatively small ontologies $\sim 1000$ entities $\sim 20$ slots
- Provided we have data each dialogue system module can be described with a statistical model and trained
Dialogue system architecture

I’m looking for a restaurant inform(type=restaurant)

Speech recognition -> Semantic decoding

Dialogue management

Speech synthesis -> Natural language generation

Waveform -> Text -> Dialogue acts

Ontology

What kind of food do you have in mind? request(food)
Ontology

- Speech recognition
- Semantic decoding
- Dialogue management
- Natural language generation
- Speech synthesis
- Ontology

*waveform* → *text* → *dialogue acts* → *Ontology*
Extending dialogue system coverage

- Limited domain dialogue systems
- Multi domain dialogue systems
- Open domain dialogue systems

Knowledge graph
Objectives

▶ Allow the user to reference multiple domains within a single conversation
▶ Support natural conversation even for domains which have been rarely visited
▶ Learns automatically through interaction with the user
Example dialogue

Hello, how can I help you?

What appointments do I have tomorrow?

You have a meeting at 10am with John and a teleconf at noon with Bill.

I need to go to London first thing, can you reschedule the meeting with John?

John is free tomorrow at 3pm, is that ok?

Yes, that's fine. I also need a taxi to the station.

Meeting with John at 15.00 is confirmed. What time do you need the taxi?

When does the train depart to London?

The 9.15am gets in at 10.06.

When is the one before that?

The train before that leaves at 8.45am and arrives at 9.40.

Ok I will take that, book the taxi for 8.15am from my house.

Ok, I will book the taxi for 8.15am, is that correct?

Yes that's right.

Ok. Do you need anything else?

Not for now thanks.
Reuse of data

- Each element of a dialogue system is data driven and depends on the ontology
- If we want to build a dialogue system to operate on multiple domains it is essential there is reuse of knowledge
Delexicalisation for domain-independent belief tracking

- Idea: replace all occurrences of slot values in data with generic symbols (tags) and train a general belief tracker

  \[ I \text{ want Chinese food} \quad \rightarrow \quad I \text{ want VALUE SLOT} \]

  \[ I \text{ want cheap price range} \]

- This captures dialogue dynamics and facilitate generalisation to unseen slots and domains
Initialising belief tracking models for new domains [Mrkšić et al., 2015]

- **Out-of-domain Initialisation**
- **In-domain Initialisation**

**Graphs:**
- Accuracy vs. Number of training dialogues
- In-domain: Michigan Restaurants
  - Out-of-domain: Other restaurant domains, Tourist Information, Hotels
- In-domain: Laptops
  - Out-of-domain: Restaurants, Tourism, Hotels
Committee of dialogue policies
Bayesian committee machine for distributed dialogue management

- Each dialogue manager operates independently, receives speech, tracks its own beliefs and proposes system actions
- Each domain policy is modelled as a Bayesian estimator, e.g. Gaussian process with posterior mean $\bar{Q}_i$ and covariance $\Sigma_i$
- Committee of dialogue policies is then also a Bayesian estimator

$$\bar{Q}(b, a) = \Sigma(b, a) \sum_{i=1}^{M} \Sigma_i(b, a)^{-1} \bar{Q}_i(b, a)$$

$$\Sigma(b, a)^{-1} = -(M-1) \times k(((b, a), (b, a))^{-1} + \sum_{i=1}^{M} \Sigma_i(b, a)^{-1}$$
Results [Gašić et al., 2015]

![Graph showing moving average reward over dialogues for single domain policy and committee policy.](image-url)
But that is not all...

- Semantic decoder needs to share data for new domains
- Dialogue manager must be able to talk about different things at the same time
- Natural language generator needs also to be able to generate responses for new domains
- ...
Towards more natural interaction

- So far we assumed strict turn taking mechanism
- Humans interrupt each other, talk at the same time and hesitate during conversation

U: I’m looking for an Italian restaurant in the north
S: Cocum is a nice Indian restaurant in the north
U: Italian, please
S: Margarita is a nice Italian restaurant
U: I’m looking for umm...
S: Yes?
U: ...an Italian restaurant in the north
S: Cocum is a nice Indian ...
U: Italian, please
S: Margarita is a nice Italian restaurant
Incremental dialogue architecture allow next component to start processing before the previous one has completed.
Why incremental dialogue?

The main benefits of incremental dialogue are:

▶ reduced latency
▶ increased system efficiency
▶ increased user satisfaction
▶ increase user fluency

Open questions

▶ What is the best architecture?
▶ Which machine learning methods to use to find optimal behaviour?
Incremental speech recognition and semantic decoder [Paetzel et al., 2015]
Incremental dialogue manager apart from making high level decisions also needs to make low level decisions (micro-turns):

- speak
- be silent
- back-channel

How to learn these decisions?
Learning micro-turn decisions

- States and decisions
- States and rewards
- States and decisions

Data

Model

Predictions

- Supervised learning model
- Reinforcement learning model
- Inverse reinforcement learning model

- Decisions that mimic the data
- Decisions that maximise the reward
- Decisions that mimic the data and maximise the reward
Inverse reinforcement learning (IRL) recovers the model and then learns the optimal policy.
Learn optimal decisions from human-human data by using Gaussian process IRL which assumes a non-parametric (and non-linear) model for the unknown reward.
Difficulty of evaluation

What to measure?
- Log likelihood of the micro-turn
- Length of dialogue
- User satisfaction

Remaining problems
- Effectively incorporate semantics into the incremental decision making process
IRL for micro-turn management – results

- Cross-validation log-likelihood results of each micro-turn
- Reward can depend only on state $R(s)$ or both state and action $R(s, a)$
- Supervised learning for $\gamma = 0$
Summary

- End-to-end statistical dialogue is feasible for and can match or exceed hand-crafted systems in limited domains
- Reuse of data is crucial for modelling open-domain systems and avoiding unacceptable user experience
- Incremental dialogue produces more natural interaction by increasing system efficiency, user satisfaction and user fluency
