Current research topics in spoken dialogue systems

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March 3, 2016

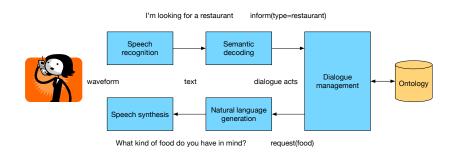
Open domain dialogue systems

Incremental dialogue

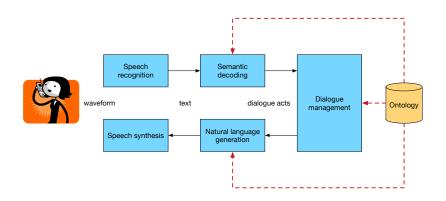
Statistical spoken dialogue systems

- ▶ 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

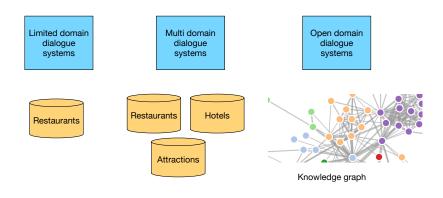
Dialogue system architecture



Ontology



Extending dialogue system coverage

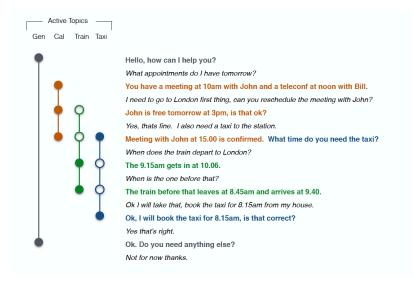


Objectives

- 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



Reuse of data

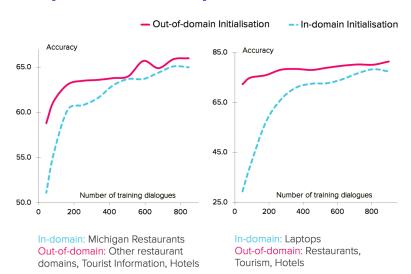
- ► Each element of a dialogue system is data driven and depends on the ontology
- ▶ If we want to build a dialogue system to operate on multiple domains it is essential there is reuse of knowledge

Delexicalisation for domain-independent belief tracking

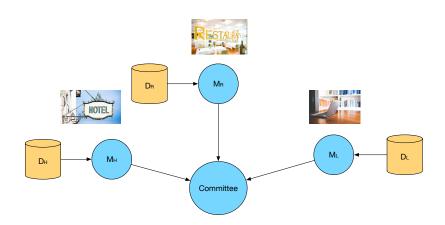
▶ Idea: replace all occurrences of slot values in data with generic symbols (tags) and train a general belief tracker

► This captures dialogue dynamics and facilitate generalisation to unseen slots and domains

Initialising belief tracking models for new domains [Mrkšić et al., 2015]



Committee of dialogue policies



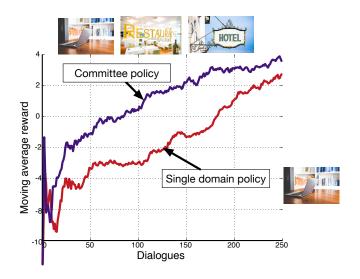
Bayesian committee machine for distributed dialogue management

- 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 \overline{Q}_i and covariance Σ_i
- Committee of dialogue policies is then also a Bayesian estimator

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

$$\Sigma(\boldsymbol{b},a)^{-1} = -(M-1) * k((\boldsymbol{b},a),(\boldsymbol{b},a))^{-1} + \sum_{i=1}^{M} \Sigma_{i}(\boldsymbol{b},a)^{-1}$$

Results [Gašić et al., 2015]



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

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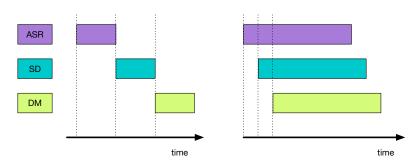
Towards more natural interaction

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



Incremental dialogue

Incremental dialogue architecture allow next component to start processing before the previous one has completed.



Why incremental dialogue?

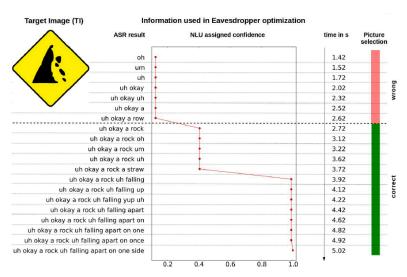
The main benefits of incremental dialogue are:

- 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

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

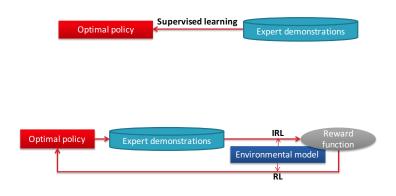


- Supervised learning model
- Reinforcement learning model
- Inverse reinforcement learning model



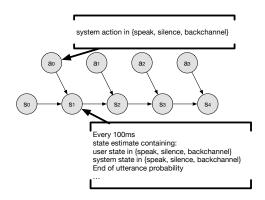
- Decisions that mimic the data
- Decisions that maximise the reward
- Decisions that mimic the data and maximise the reward

Supervised vs inverse reinforcement learning



► Inverse reinforcement learning (IRL) recovers the model and then learns the optimal policy

Micro-turn management as an IRL task [Kim et al., 2014]



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?

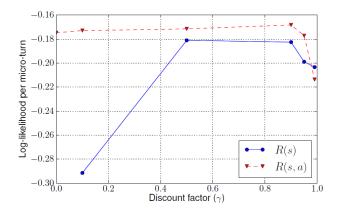
- Log likelihood of the micro-turn
- Length of dialogue
- User satisfaction

Remaining problems

 Effectively incorporate semantics into the incremental decision making process

IRL for micro-turn management – results

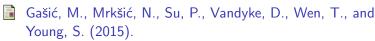
- Cross-validation log-likelihood results of each micro-turn
- ▶ Reward can depend only on state R(s) or both state and action R(s, a)
- ▶ Supervised learning for $\gamma = 0$



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

References I



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References II



Paetzel, M., Manuvinakurike, R., and DeVault, D. (2015). "so, which one is it?" the effect of alternative incremental architectures in a high-performance game-playing agent. In *Proceedings of the 16th Annual Meeting of the Special Interest Group on Discourse and Dialogue*, pages 77–86, Prague, Czech Republic. Association for Computational Linguistics.