Accurate Probability Estimation of Hypothesised User Acts for POMDP Approaches to Dialogue Management

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12th annual research colloquium of the special-interest group for computational linguistics in the UK and Ireland
CLUKI 2009, Dublin
Outline

1. Background
   - End-to-End Statistical Spoken Dialogue Systems
   - Dialogue Management
   - Learning Frameworks for Statistical Spoken Dialogue Systems

2. Experiment
   - Methodology
   - Results
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This work should be seen as a contribution to a much large project.

Aim is to build end-to-end statistical spoken dialogue systems.

This on going work at the University of Edinburgh.

Originally funded by the EPSRC (project EP/E019501/1).

Now with various partners in EU project CLASSiC.
My work is specifically focused on Dialogue Management for Statistical Spoken Dialogue Systems.

So what is a Spoken Dialogue System?

What is Dialogue Management?

What are the issues in Dialogue Management?
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What is a Spoken Dialogue System?

**Legend:**

- **ASR:** Automatic Speech recognition
- **NLU:** Natural Language Understanding
- **DM:** Dialogue Management
- **NLG:** Natural Language Generation
- **TTS:** Text To Speech
- **s_t:** Speech Signal from user
- **u_t:** Utterance Hypotheses
- **h_t:** Conceptual Interpretation Hypotheses
- **a_t:** Action Hypotheses
- **w_t:** Output Hypotheses
Typical Dialogue

System: Hello how may I help?

User: I’m after an expensive French restaurant.

System: You’re looking for French food. In what area of the city do you want to eat?

User: Expensive French in the centre please.

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What is Dialogue Management?

Dialogue Management is deciding what the Spoken Dialogue System should do next, e.g.

- greet the user,
- request information,
- seek clarification,
- confirm an item,
- search the database,
- present items,
- give up and pass the call to a human,
- close the dialogue,
- etc.
Issues in Dialogue Management?

Issues with current Dialogue Management:
- The problem space is very large.
- Hand-coded solutions are difficult to design and are not guaranteed to be “good”.
- Systems are fragile, and Users are frustrated!

Research opportunity:
- Can we automatically learn good solutions in this space?
- Optimising our dialogue management?
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Single View of a Dialogue

This view lends itself to learning Dialogue Management as a Markov Decision Process (MDP).

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s_i: Speech Signal from user
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Maintaining Multiple Views of the Current Dialogue's State

- Maintaining Multiple Views of the Current Dialogue's State

the Partially Observable Markov Decision Process (POMDP) framework is a natural extension of MDPs that can be applied in this situation.
A POMDP maintain a probability distribution over all possible states of the system, known as its *belief*. In this case a distribution is maintained over all possible states of the conversation (a factorised or tree representation is typically used to provide a compact representation... but still not compact enough for learning).

For each *observation* the POMDP receives it updates its belief space.

In the case of Spoken Dialogue System the observation is typically the parsed utterance.

The standard POMDP belief update equation is of the form: 
\[ b'(s') = \sum_{s \in S} P(o|s')P(s'|s, a)b(s) \]
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For Spoken Dialogue Systems the standard POMDP belief update equation is typically re-factored as:

\[
b'(p', a'_u, s'_d) = kP(o'|a'_u)P(a'_u|p', a_m) \\
\sum_{s_d} P(s'_d|p', a'_u, s_d, a_m)P(p'|p)b(p, s_d)
\]

- \(b'(p, a'_u, s'_d)\) is the updated belief space,
- \(k\) is a normalisation constant,
- \(P(o'|a'_u)\) is the observation model,
- \(P(a'_u|p', a_m)\) is the user action model,
- \(P(s'_d|p', a'_u, s_d, a_m)\) is the dialogue model,
- \(P(p'|p)\) and \(b(p, s_d)\) together form a belief refinement step.
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For this paper the term we are focusing on observation model, \( P(o'|a'_u) \).

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Parsed the human transcription of each utterance using Spoken Language Understanding (SLU) parsers; GF Parser and Beast Parser.

The resulting user semantic acts are taken as being the correct interpretation of the user’s utterance.

Against these we compare the outputs of the automatic speech recogniser and parser (ASL-SLU).
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Use the Automatic Speech Recogniser HTK/ATK.
Fed the audio files of each utterance to ATK.
for each utterance ATK produces an ordered N-best list (where N=3) of strings with an associated confidence score.

1st “want an expensive french” 0.92
2nd “want want a french” 0.67
3rd “want an expensive restaurant” 0.32
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ATK can use output two different confidence score measures for each word string;

- a tradition average word confidence (of all words in the string), and
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We examined both these metrics to see if either provides a good approximation for the observation model.
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- Metric: average word confidence, inference evidence score
- The hypothesis position in the N-best list.

As a reminder, the hypothesis we are testing is whether the approximation that: \( P(o|a_u) \approx ASR \text{ confidence score} \).
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Average Word Confidence

1st hypothesis, average word confidence

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3rd hypothesis, average word confidence

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Accurate Probability Estimation of Hypothesised User Acts
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However the graphs do suggest a simple linear regression could be used to improve the approximation for the application covered by this corpus.

With Pearson’s correlation suggesting that inference evidence scores should be preferred.

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- The results also suggest inference evidence scores should be preferred for POMDP Spoken Dialogue Systems.

Future Work
- Test the effectiveness of the linear remapping with real users.
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Thank you.

http://homepages.inf.ed.ac.uk/pacrook
Summed counts of matching and non-matching parsed hypotheses

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