Dialogue management: generative approaches to belief tracking

Milica Gašić

Dialogue Systems Group, Cambridge University Engineering Department

February 7, 2017
In this lecture...

Dialogue management architecture

Need for belief tracking

Generative approaches to belief tracking

Hidden Information State (HIS) dialogue model

Bayesian Update of Dialogue State (BUDS) model
Example dialogue

Hello, how may I help you?

I’m looking for a Thai restaurant.

What part of town do you have in mind?

Something in the centre.

Bangkok city is a nice place, it is in the centre of town and it serves Thai food.

What’s the address?

Bangkok city is a nice place, their address is 24 Green street.

Thank you, bye.
Spoken dialogue systems architecture

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

Flow diagram:
- Waveform
- Distribution over text hypotheses
- Distribution over dialogue acts
- Ontology
Dialogue management

- Speech recognition
- Semantic decoding
- Natural language generation
- Speech synthesis
- Belief tracking
- Policy optimisation
- Ontology

Waveform distribution over text hypotheses, distribution over dialogue acts.
Example: 1-best input and no belief tracking

1. I'm looking for a Thai restaurant.
   - **hi(type=restaurant)**: 0.6
   - **inform(type=restaurant, food=Thai)**: 0.4

2. Thai.
   - **hi()**: 0.5
   - **inform(food=Turkish)**: 0.3
   - **inform(food=Thai)**: 0.2

You are looking for a restaurant right?

You are looking for a restaurant right?
Example: N-best input and no belief tracking

1. I'm looking for a Thai restaurant.

   - hello(type=restaurant) 0.6
   - inform(type=restaurant, food=Thai) 0.4

2. Thai.

   - hello() 0.5
   - inform(food=Turkish) 0.3
   - inform(food=Thai) 0.2

What kind of food would you like?

What kind of food would you like?
**Example: N-best input with belief tracking**

<table>
<thead>
<tr>
<th>Turn</th>
<th>Observations</th>
<th>Belief States</th>
<th>Actions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td><em>I’m looking for a Thai restaurant.</em></td>
<td></td>
<td><em>What kind of food would you like?</em></td>
</tr>
<tr>
<td></td>
<td><strong>hello(type=restaurant)</strong> 0.6</td>
<td><strong>R</strong> 0.6</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>inform(type=restaurant, food=Thai)</strong> 0.4</td>
<td><strong>O</strong> 0.4</td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td><em>Thai.</em></td>
<td></td>
<td><em>Did you say Thai or Turkish?</em></td>
</tr>
<tr>
<td></td>
<td><strong>hello()</strong> 0.5</td>
<td><strong>R</strong> 0.8</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>inform(food=Turkish)</strong> 0.3</td>
<td><strong>O</strong> 0.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>inform(food=Thai)</strong> 0.2</td>
<td><strong>TH</strong> 0.4</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>TR</strong> 0.3</td>
<td><strong>O</strong> 0.3</td>
<td></td>
</tr>
</tbody>
</table>
Elements of dialogue management

What the system says:

actions

a1 a2 a3 aT-1

What the user wants:

states

S1 S2 S3 ST-1 ST

What the system hears:

observations

O1 O2 O3 OT-1 OT

dialogue turns

Challenges in dialogue modelling

- How to define the state space?
- How to tractably maintain the dialogue state?
- Which actions to take?

Solution: Define dialogue as a control problem where the behaviour can be automatically learned.
Dialogue management as Markov decision process

- Dialogue states
- Reward – a measure of dialogue quality
- Markov decision process
- Optimal system actions
Theory: Bayesian networks

- Bayesian network is a directed acyclic graph where nodes represent random variables and the arrows represent conditional independence assumption.
- Dynamic Bayesian network is a Bayesian network which repeats its structure at each point in time.
Theory: Markov decision process

\[ s_t \] dialogue states
\[ a_t \] system actions
\[ r_t \] rewards
\[ p(s_{t+1}|s_t, a_t) \] transition probability
Dialogue as a Markov decision process?

1. I’m looking for an Italian restaurant.

   - `inform(type=restaurant, food=Indian)` with probability 0.6
   - `inform(type=restaurant, food=Italian)` with probability 0.4

2. Something in the north.

   - `inform(area=north)` with probability 1.0

What part of town do you have in mind?

Cocum is a nice Indian restaurant in the north.
Dialogue management as partially observable Markov decision process

- Noisy observations of dialogue state
- Reward – a measure of dialogue quality
- Partially observable Markov decision process
- Distribution over possible dialogue states – belief state
- Optimal system actions
Generative vs discriminative models in belief tracking

Discriminative models: the state depends on the observation

\[ b(s_t) = p(s_t | o_t) \]

Generative models: the state generates the observation

\[ b(s_t) = \frac{p(s_t, o_t)}{\sum_{s_t} p(s_t, o_t)} \propto p(o_t | s_t) p(s_t) \]
Partially observable Markov decision process

- State generates a noisy observation: $p(o_t|s_t)$ — the observation probability.

- State is unobservable and depends on the previous state and the action: $p(s_{t+1}|s_t, a_t)$ — the transition probability.
Theory: Belief propagation

Probabilities conditional on the observations

Interested in marginal probabilities $p(x|O), O = O_a \cup O_b$

$$p(x|O_b, O_a) \propto p(x, O_b|O_a) = p(O_b|x, O_a)p(x|O_a) = p(O_b|x)p(x|O_a)$$
Split $O_b$ further into $O_c$ and $O_d$

$$p(x|O_a, O_c, O_d) \propto p(O_c, O_d|x)p(x|O_a) = p(O_c|x)p(O_d|x)p(x|O_a)$$
Theory: Belief propagation

\[
p(c|O_a, O_b) = \sum_{a,b} p(a|O_a)p(b|O_b)p(c|a, b)
\]

\[
p(O_c, O_b|a) \propto \sum_{b,c} p(O_c|c)p(b|O_b)p(c|a, b)
\]
Theory: Belief propagation

\[ p(b|O_a) = \sum_a p(a|O_a)p(b|a) \]

\[ p(O_b|a) = \sum_b p(O_b|b)p(b|a) \]
Belief state tracking

\[ b(s_{t+1}) \propto p(o_{t+1}|s_{t+1}) \sum_{s_t} p(s_{t+1}|a_t, s_t) b(s_t) \]

Requires summation over all possible states at every dialogue turn – **intractable!**
Practical examples of POMDP systems

- POMDPs are normally intractable for everything but very simple cases
- However there are approximations which enable their use for real-world dialogue domains
  
  Hidden Information State (HIS) system [Young et al., 2010]
  Bayesian Update of Dialogue State (BUDS) system [Thomson and Young, 2010]
Requirements for belief tracking

Dialogue history  The system needs to keep track of what happened so far in the dialogue. This is normally done via the **Markov property**.

Task-orientated dialogue  The system needs to know what the user wants. This is modelled via the **user goal**.

Robustness to errors  The system needs to know what the user says. This is modelled via the **user act**.
Dialogue state factorisation

Decompose dialogue state into conditionally independent elements
- user goal $g_t$
- user action $u_t$
- dialogue history $d_t$
Belief update

\[
b(g_{t+1}, u_{t+1}, d_{t+1}) = 
\begin{align*}
& p(o_{t+1}|u_{t+1}) \cdot \\
& p(u_{t+1}|g_{t+1}, a_t) \cdot \\
& \sum_{g_t} p(g_{t+1}|a_t, g_t) \cdot \\
& \sum_{d_t, u_t} p(d_{t+1}|d_t, g_{t+1}, u_{t+1}, a_t) \cdot \\
& b(g_t, u_t, d_t)
\end{align*}
\]

- Requires summation over all possible goals – **intractable!**
- Requires summation over all possible histories and user actions – **intractable!**
Hidden Information State (HIS) dialogue state

**Observation:**
N-best list of user acts

**User Goal:**
Partitions of the goal space built according to ontology

**Dialogue history:**
Grounding states

**Hypotheses:**
Every combination of user act, partition and history

**Belief state:** Distribution over most likely hypotheses
System: How may I help you?
request(task)
User: I’d like a restaurant in the centre.
inform(entity=venue,type=restaurant, area centre)
Pruning
Pruning
Bayesian update of dialogue state model

- Further decomposes the dialogue state
- Produces tractable belief state update
- Transition and observation probability distributions can be parametrised and their shape learned
Bayesian network in the BUDS model
Belief tracking in the BUDS model

For each node $x$

- Start on one side and keep getting $p(x|O_a)$
- Then start on the other side and keep getting $p(O_b|x)$
- To get a marginal simply multiply these
Simple example

\[
p(o|g) & o: \text{Thai} & o: \text{Turk.} \\
g: \text{Thai} & 0.8 & 0.2 \\
g: \text{Turk.} & 0.2 & 0.8 \\
\]

\[
p(g'|g) & g': \text{Thai} & g': \text{Turk.} \\
g: \text{Thai} & 0.9 & 0.1 \\
g: \text{Turk.} & 0.1 & 0.9 \\
\]

\[
\begin{align*}
p(g'|g) &= p(o'|g')b(g') \\
p(o|g) &= 0.8*0.9+0.2*0.1=0.74 \\
p(o'|g') &= 0.8*0.1+0.2*0.9=0.26 \\
\end{align*}
\]

\[
\begin{align*}
p(g'|g) &= 0.8*0.4+0.2*0.6=0.44 \\
p(o|g) &= 0.2*0.4+0.8*0.6=0.56 \\
\end{align*}
\]
Learning of the shape of distributions

Expectation propagation

- Allows parameter tying
- Handles factorised hidden variables
- Handles large state spaces
- Does not require annotations but uses the output of the semantic decoder
Properties of belief tracking for dialogue management include Markov assumption, being able to model the user goal and being robust to speech recognition errors.

Generative models for belief tracking are based on partially observable Markov decision processes.

Hidden Information State (HIS) model decomposes the dialogue state into the user goal, the user action and the dialogue history. Transitions are hand-crafted and the goals are grouped together to allow tractable belief tracking.

Bayesian Update of Dialogue State (BUDS) model further factorises the state which allows tractable belief tracking but also learning of the shapers of distributions via Expectation propagation.