

# Dialogue management: generative approaches to belief tracking

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# 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.

**inform(type=restaurant, food=Thai)**

What part of town do you have in mind?

Something in the centre.

**inform(area=centre)**

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

What's the address?

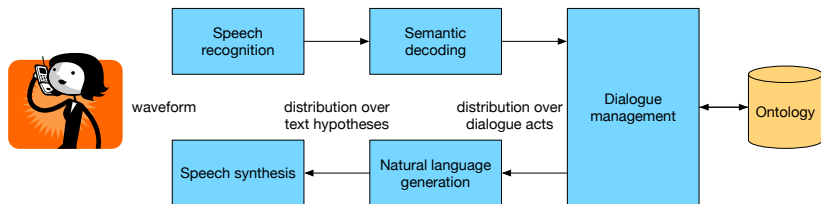
**request(address)**

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

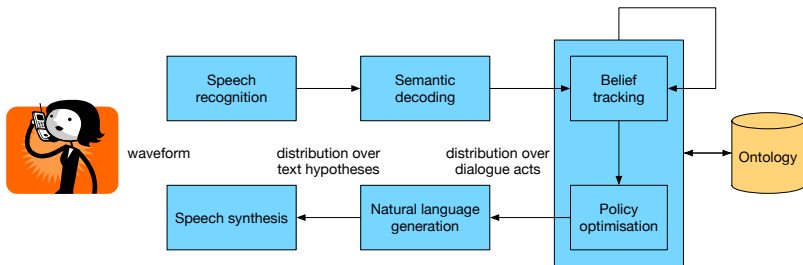
Thank you, bye.

**bye()**

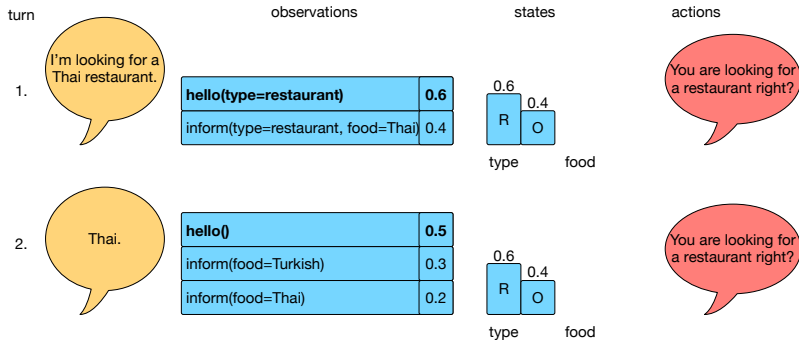
# Spoken dialogue systems architecture



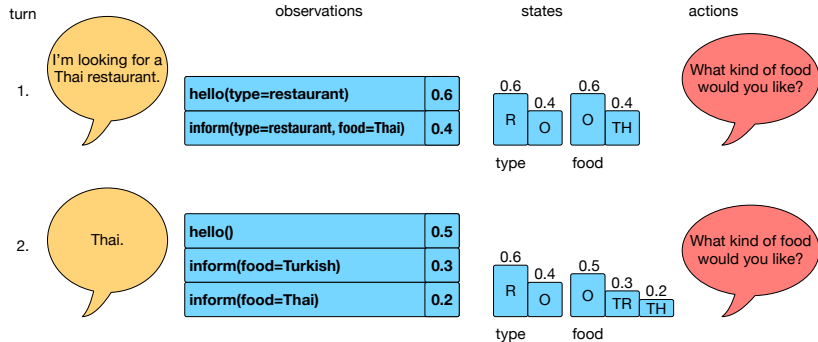
# Dialogue management



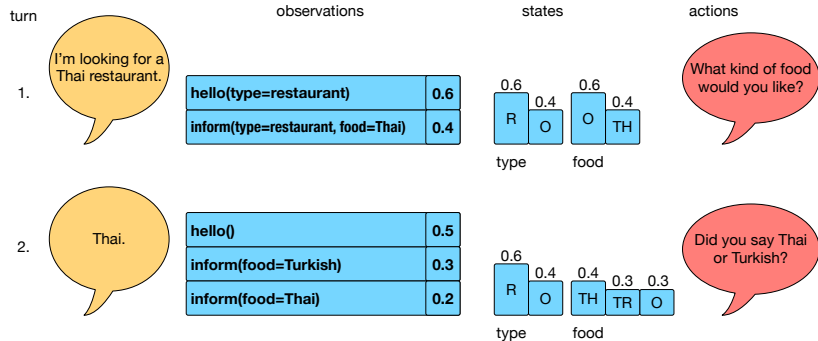
# Example: 1-best input and no belief tracking



# Example: N-best input and no belief tracking

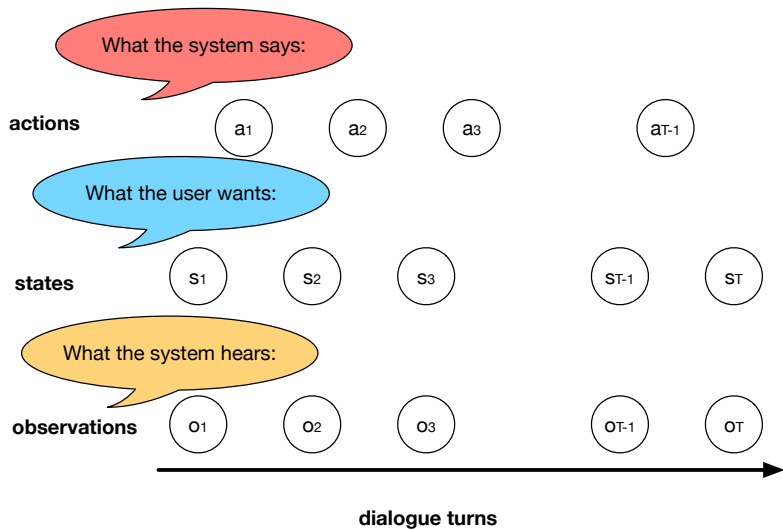


# Example: N-best input with belief tracking





# Elements of dialogue management



# Challenges in dialogue modelling

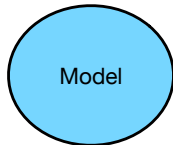
- ▶ How to define the state space?
- ▶ How to tractably maintain the dialogue state?
- ▶ Which actions to take?

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.

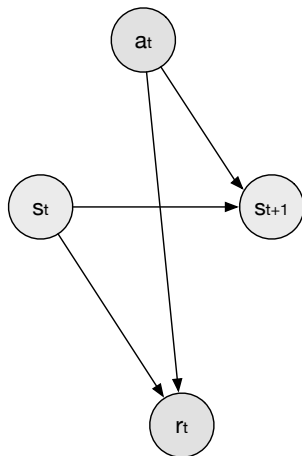
# Theory: Markov decision process

$s_t$  dialogue states

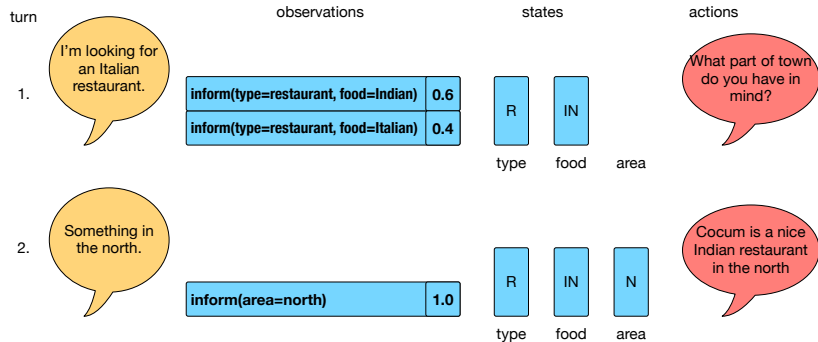
$a_t$  system actions

$r_t$  rewards

$p(s_{t+1}|s_t, a_t)$  transition  
probability



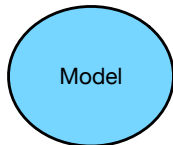
# Dialogue as a Markov decision process?



# 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

$$b(s_t) = p(s_t|o_t)$$

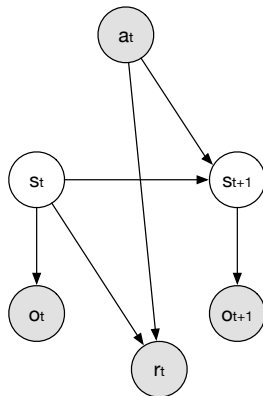
Generative models: the state generates the observation

$$b(s_t) = \frac{p(s_t, o_t)}{\sum_{s_t} p(s_t, o_t)} \propto p(o_t|s_t)p(s_t)$$



# Partially observable Markov decision process

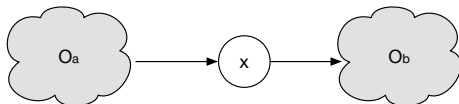
- ▶ State generates a noisy observation  
 $p(o_t | s_t)$  – the **observation probability**



- ▶ 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

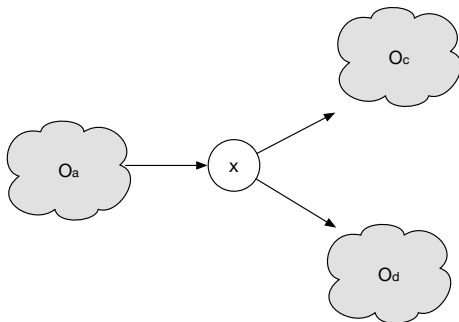


Interested in marginal probabilities  $p(x|O)$ ,  $O = O_a \cup O_b$

$$p(x|O_b, O_a) \propto p(x, O_b|O_a) = p(O_b|x, O_a)p(x|O_a) = p(O_b|x)p(x|O_a)$$

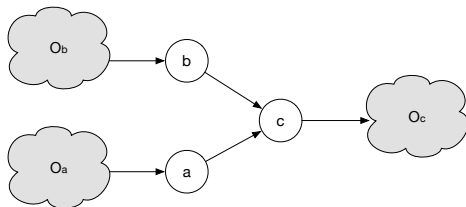
## Theory: Belief propagation

Split  $O_b$  further into  $O_c$  and  $O_d$



$$p(x|O_a, O_c, O_d) \propto p(O_c, O_d|x)p(x|O_a) = p(O_c|x)p(O_d|x)p(x|O_a)$$

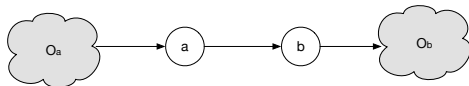
## Theory: Belief propagation



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

$$p(O_c, O_b|a) \propto \sum_{b,c} p(O_c|c)p(b|O_b)p(c|a, b)$$

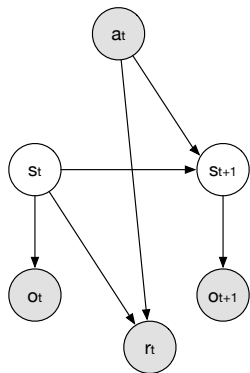
## Theory: Belief propagation



$$p(b|O_a) = \sum_a p(a|O_a)p(b|a)$$

$$p(O_b|a) = \sum_b p(O_b|b)p(b|a)$$

## 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**.



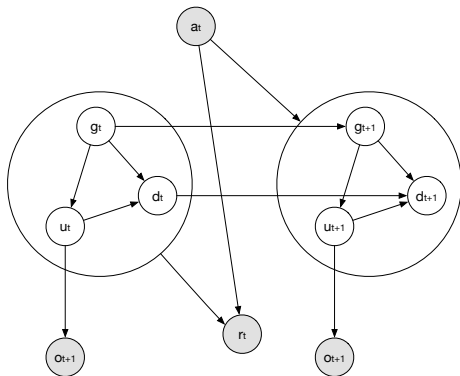
# Dialogue state factorisation

Decompose  
dialogue state into  
conditionally  
independent  
elements

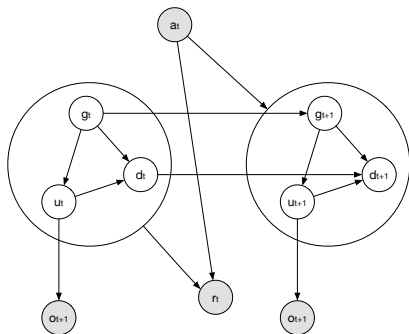
user goal  $g_t$

user action  $u_t$

dialogue history  $d_t$



## Belief update



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

- ▶ 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

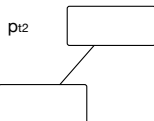
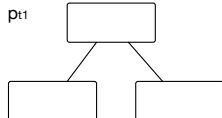
O<sub>t1</sub>

O<sub>t2</sub>



O<sub>tN</sub>

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



**Dialogue  
history:**  
Grounding  
states

d<sub>t1</sub>

d<sub>t2</sub>



d<sub>tD</sub>

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

$h_{1=(O_{t1}, p_{t1}, d_{t1})}$

$h_{2=(O_{t2}, p_{t1}, d_{t2})}$



$h_{1=(O_{tN}, p_{tP}, d_{tD})}$

**Belief state:** Distribution over most likely hypotheses

# HIS partitions

**System:** How may I help you?

**request(task)**

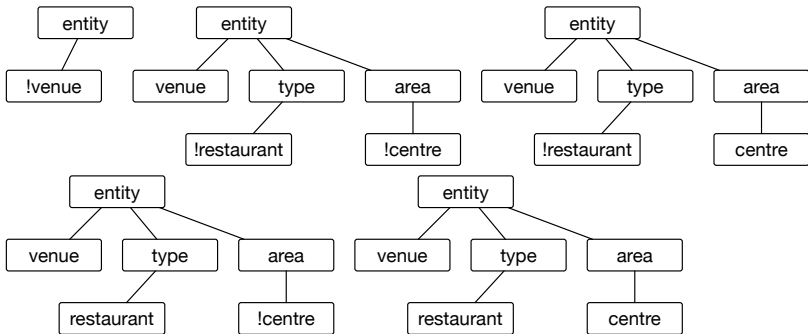
**User:** I'd like a restaurant in the centre.

**inform(entity=venue,type=restaurant, area centre)**

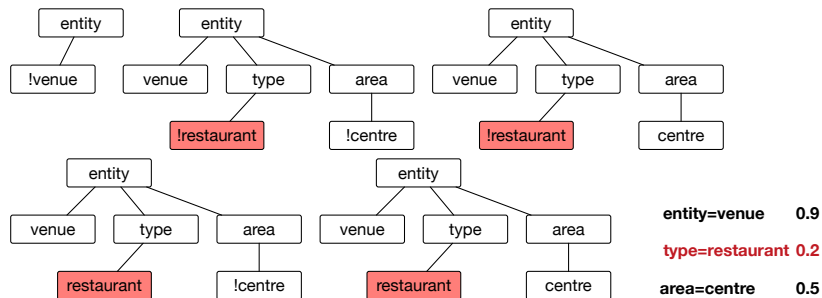
**entity=venue**

**area=centre**

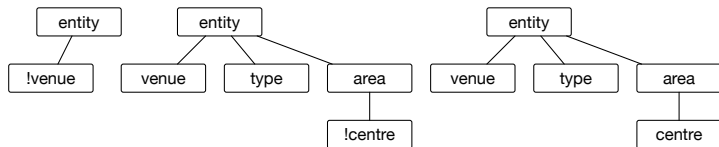
**type=restaurant**



# Pruning



# Pruning



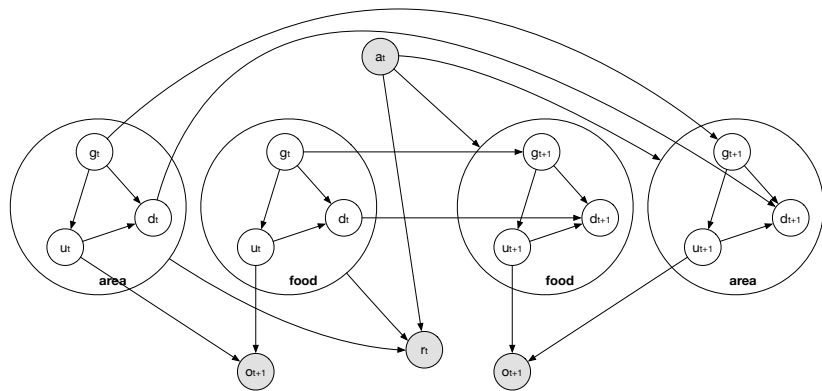
**entity=venue 0.9**

**area=centre 0.5**

## 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

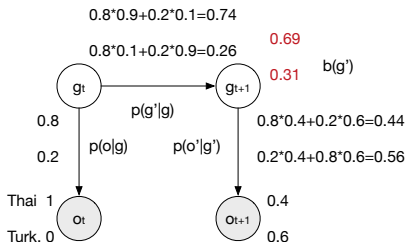
For each node  $x$

- ▶ 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

$p(o g)$	$o$ : Thai	$o$ : Turk.
$g$ : Thai	0.8	0.2
$g$ : Turk.	0.2	0.8

$p(g' g)$	$g'$ : Thai	$g'$ : Turk.
$g$ : Thai	0.9	0.1
$g$ : Turk.	0.1	0.9



# 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

## Summary

- ▶ 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

# References

-  Thomson, B. and Young, S. (2010).  
Bayesian update of dialogue state: A POMDP framework for spoken dialogue systems.  
*Computer Speech and Language*, 24(4):562–588.
-  Young, S., Gašić, M., Keizer, S., Mairesse, F., Schatzmann, J., Thomson, B., and Yu, K. (2010).  
The Hidden Information State model: A practical framework for POMDP-based spoken dialogue management.  
*Computer Speech and Language*, 24(2):150–174.