

# Dialogue management: discriminative approaches to belief tracking

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Discriminative models for belief tracking

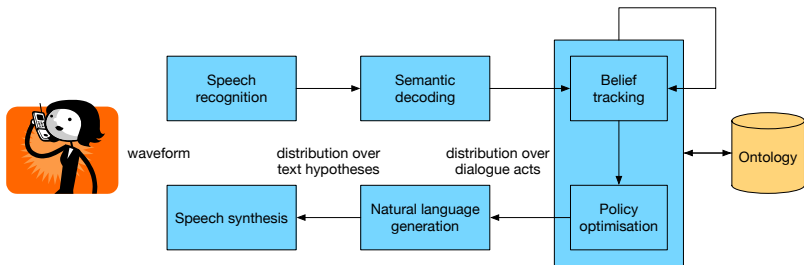
Ranking models

Deep neural network approaches to belief tracking

Recurrent neural network approaches to belief tracking

Integrated approaches to semantic decoding and belief tracking

# Dialogue management



# Generative vs discriminative models in belief tracking

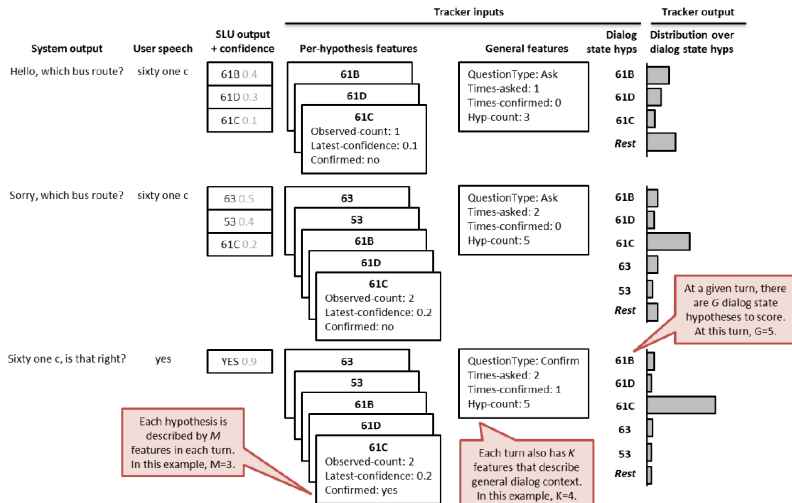
Discriminative models: the state depends on the observation

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

Generative models: the state generates the observation

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

# Advantage of discriminative belief tracking [Metallinou et al., 2013]



## Problems in generative belief tracking

- ▶ Generative models make assumption that observations at each turn are independent
- ▶ Discriminative models directly model the dialogue state given arbitrary and possibly correlated input features.

# Dialogue state tracking challenge (DSTC) problem formulation

Common dataset with tools to evaluate the performance of the tracker. The dialogue state consists of three components:

- goal** for each informable slot, e.g. pricerange=cheap.

- requested** slots by the user, e.g. phone-number.

- method** of search for the entities, e.g. *by constraints, by alternatives, by name.*

The belief state is then the distribution over possible slot-value pairs for goals, the distribution over possible requested slots and the distribution over possible methods.

# Evaluate the quality of the belief state tracker

**Accuracy** the fraction of turns where the top dialogue state hypothesis is correct

**L2 norm** is squared L2-norm of the hypothesised distribution  $\mathbf{p}$  and the true label

$$L2 = (1 - p_i)^2 + \sum_{j \neq i} p_j^2$$

where  $p_i$  is the probability assigned to the true label.



## Focus tracker

The focus tracker accumulates the evidence and changes the focus of attention according to the current observation.

$$b(s_t = s) = o(s) + \left(1 - \sum_{s'} o(s')\right) b(s_{t-1} = s)$$

## Class-based approaches to dialogue state tracking

Model the conditional probability distribution of dialogue state given all observations upto that turn in dialogue.

$$b(s_t) = p(s_t | o_0, \dots, o_t)$$

Features are extracted from  $o_0, \dots, o_t$  and include information about

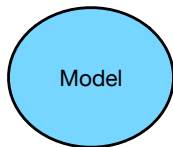
- ▶ latest turn
- ▶ dialogue history
- ▶ ASR errors

This allows a number of models to be used: maximum entropy linear classifiers, neural networks and ranking models.

## Class-based approaches to dialogue state tracking



- ▶ Observations labelled with dialogue states

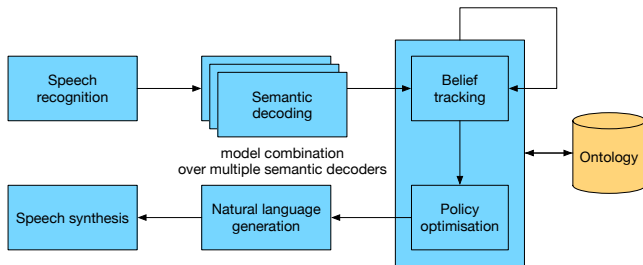


- ▶ Neural networks
- ▶ Ranking models



- ▶ Distribution over possible dialogue states – **belief state**

# Dialogue management with multiple semantic decoders



# Ranking approach to dialogue state tracking

Dialogue state tracking of the user goal consists of the following three steps

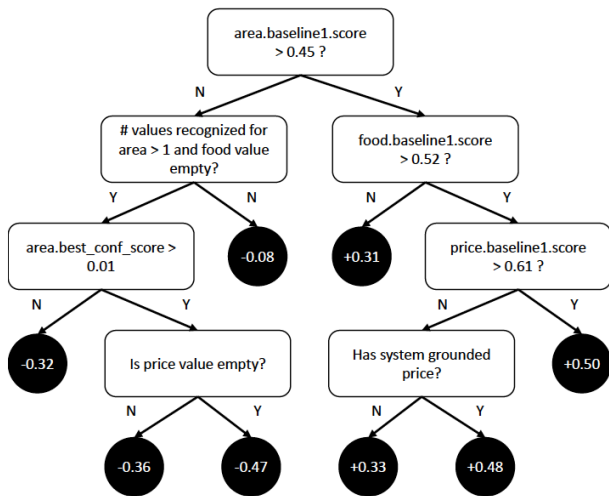
- ▶ Enumerate possible dialogue states
- ▶ Extract features
- ▶ Scoring

Using multiple semantic decoders trained on different datasets can produce a richer set of possible dialogue states.

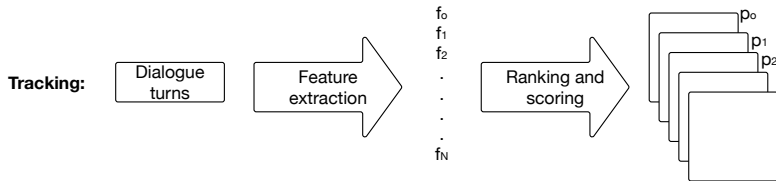
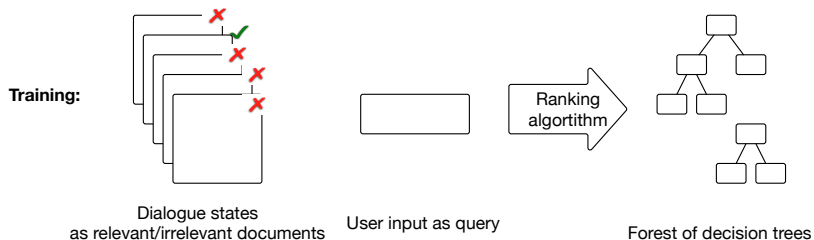
## Theory: Decision trees

- ▶ For a set of input data points  $\mathbf{x}_1, \dots, \mathbf{x}_N$  and target values  $t_1, \dots, t_N$  find partitioning of the input space and the set of questions so that the sum-of-squares (in the regression case) or the cross entropy (in the classification case) is minimal.
- ▶ Random forests are a way of averaging multiple decision trees trained on different parts of the same training set.

# Example decision tree for belief tracking [Williams, 2014]



# Web-style ranking [Williams, 2014]





## Theory: Deep neural networks

$$\mathbf{h}_0 = g_0(W_0\mathbf{x}^T + b_0)$$

$$\mathbf{h}_i = g_i(W_i\mathbf{h}_{i-1}^T + b_i), 0 < i < m$$

$$\mathbf{y} = \text{softmax}(W_m\mathbf{h}_{m-1}^T + b_m)$$

$$\text{softmax}(\mathbf{h})_i = \exp(h_i) / \left( \sum_j \exp(h_j) \right)$$

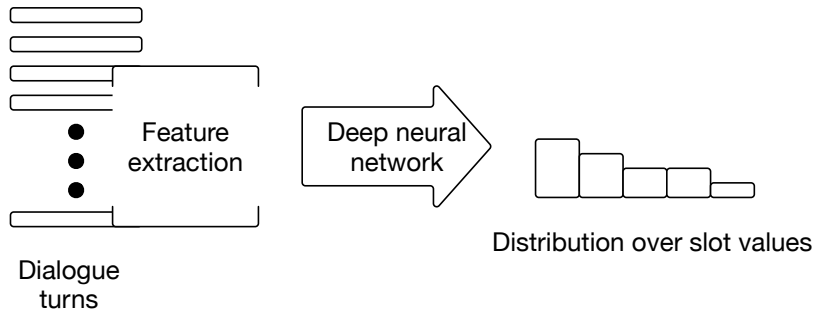
where

$g_i$  (differentiable) activation functions hyperbolic tangent tanh or sigmoid  $\sigma$

$W_i, b_i$  parameters to be estimated

## Deep neural networks for belief tracking [Henderson et al., 2013]

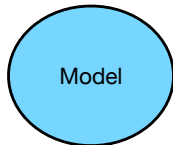
- ▶ Outputs a sequence of probability distributions over an arbitrary number of possible values
- ▶ Learns tied weights using a single neural network
- ▶ Uses a form of sliding window for feature extraction



# Sequence-to-sequence approaches to dialogue state tracking



- ▶ Sequence of observations labelled with dialogue states



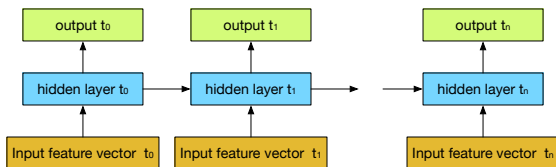
- ▶ Recurrent neural networks



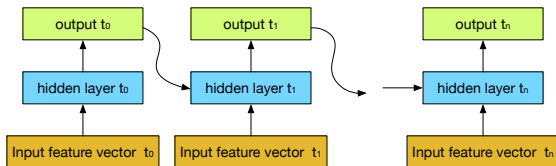
- ▶ Distribution over possible dialogue states – **belief state**

# Theory: Recurrent neural networks

## Elman-type



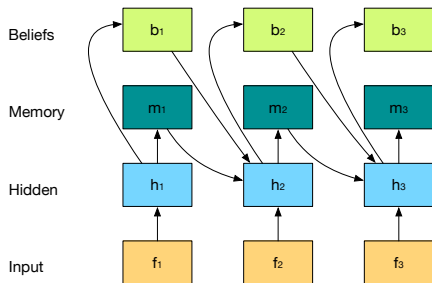
## Jordan-type



## Recurrent neural network based belief tracking [Henderson, 2015]

- ▶ Contains internal memory which represents dialogue context
- ▶ Structurally a combination of Elman and Jordan types
- ▶ Takes the most recent dialogue turn and last machine dialogue act as input, updates its internal memory and calculates distribution over slot values.

# RNN structure

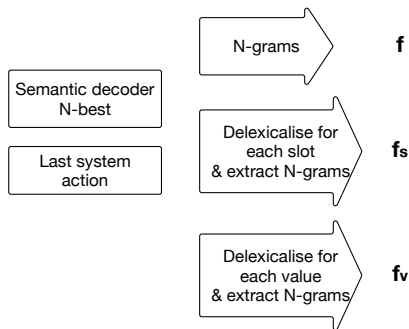


**Beliefs** a probability distribution over the available slot values (the belief state) for each slot in the ontology.

**Memory** a continuous vector representing dialogue context.

**Input** features extracted from the current user utterance, previous system act, belief state and the memory layer.

# Feature engineering



- ▶ For the same input feature vectors will be different for different slots and values
- ▶ These inputs then query different recurrent neural networks to produce distribution over slot value pairs

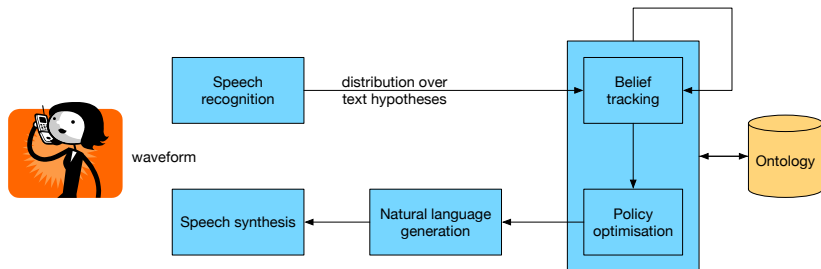
## Results from dialogue state tracking challenge

Taking into account only semantic decoding features:

	Goals		Method		Requested	
	Acc.	L2	Acc.	L2	Acc.	L2
Focus	0.719	0.464	0.867	0.210	0.879	0.206
RNN	0.742	0.387	0.922	0.124	0.957	0.069
Web-style ranking	0.775	0.758	0.944	0.092	0.954	0.073



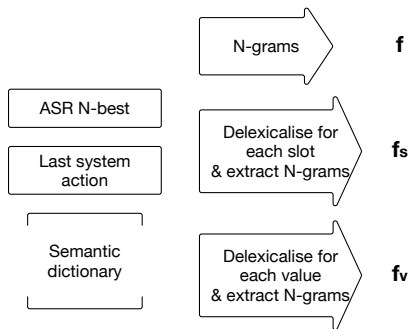
# Alternative dialogue system architecture



## Integrated approaches to semantic decoding and belief tracking [Henderson et al., 2014]

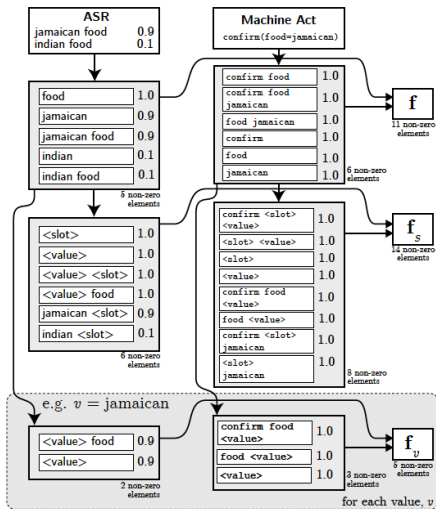
- ▶ Instead of extracting features from semantic decoding hypotheses extract features from ASR hypotheses
- ▶ Apply the same neural network structure
- ▶ Avoids information loss resulting from compact semantic representation of traditional approach
- ▶ Output: distribution over slot-value pairs

# Feature extraction from ASR hypotheses



- ▶ For limited vocabulary dialogue system possible to extract N-gram features from ASR
- ▶ In order to deal with data sparsity need to delexicalise input
- ▶ Unlike for semantic decoding output, here it is not obvious which word corresponds to which slot and value
- ▶ Semantic dictionary is therefore needed to define possible values

# Example input features



## Results from dialogue state tracking challenge

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Taking into account only ASR features:

	Goals		Method		Requested	
	Acc.	L2	Acc.	L2	Acc.	L2
RNN	0.768	0.346	0.940	0.095	0.978	0.035



## Delexicalisation - elephant in the room

- ▶ Most of the performance gain comes from delexicalised features
- ▶ This requires a separate semantic dictionary which for all values from ontology defines their possible realisations, for example expensive → luxurious, upmarket, pricey
- ▶ In real systems this poses a major problem

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