Dialogue management: discriminative approaches to belief tracking

Milica Gašić

Dialogue Systems and Machine Learning Group,
Heinrich Heine University Düsseldorf

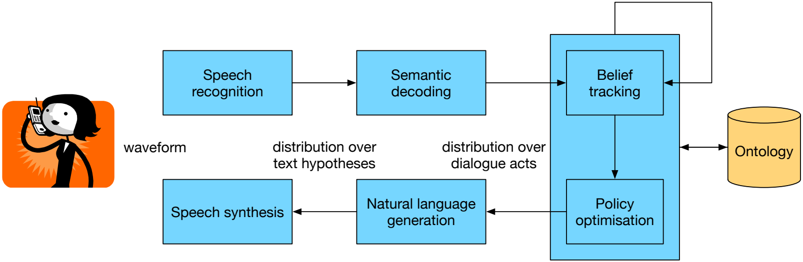
Discriminative models for belief tracking

Ranking models

Deep neural network approaches to belief tracking

Recurrent neural network approaches to belief tracking

Dialogue management



Generative vs discriminative models in belief tracking

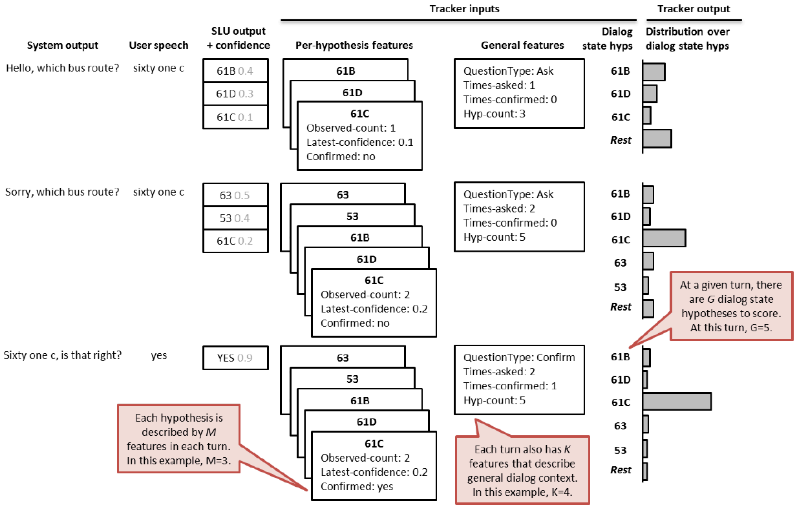
Discriminative models: the state depends on the observation

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

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 conditionally 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 **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.

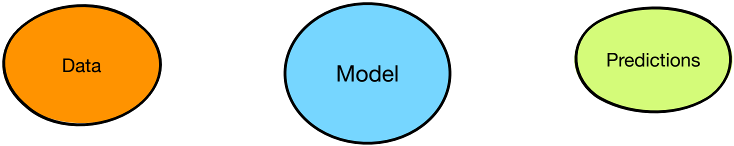
$$b(s_t) = p(s_t | o_0, \cdots, o_t)$$

Features are extracted from $o_0, \cdots, o_t$ 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

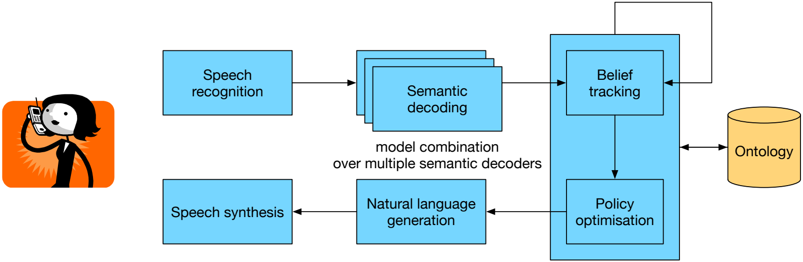


- Observations labelled with dialogue states

- 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

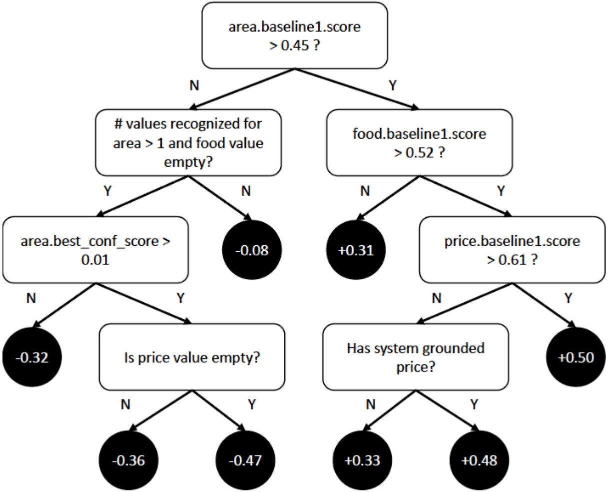
- Enumerate possible dialogue states
- Extract features
- Scoring

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

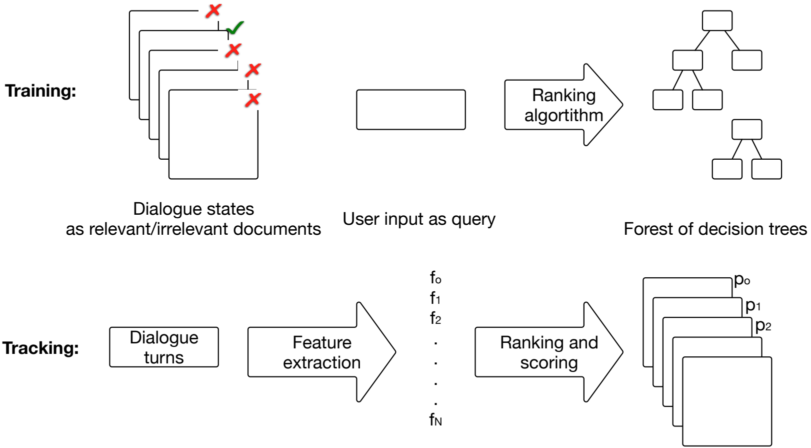
Theory: Decision trees

- For a set of input data points $\mathbf{x}_1, \cdots, \mathbf{x}_N$ and target values $t_1, \cdots, t_N$ 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

$$
\begin{aligned}
\mathbf{h}_0 &= g_0(W_0 \mathbf{x}^\mathsf{T} + b_0) \\
\mathbf{h}_i &= g_i(W_i \mathbf{h}_{i-1}^\mathsf{T} + b_i), 0 < i < m \\
\mathbf{y} &= \mathrm{softmax}(W_m \mathbf{h}_{m-1}^\mathsf{T} + b_m) \\
\mathrm{softmax}(\mathbf{h})_i &= \exp(h_i) / (\sum_j \exp(h_j))
\end{aligned}
$$

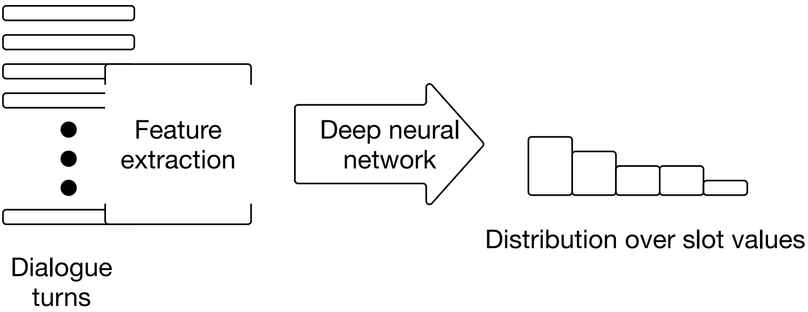
where

g_i (differentiable) activation functions hyperbolic tangent tanh or sigmoid σ

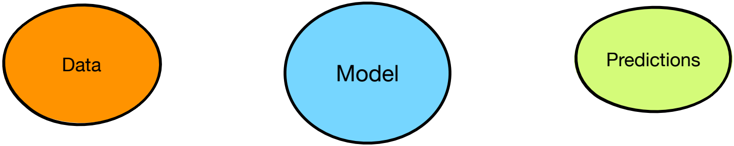
W_i, b_i parameters to be estimated

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



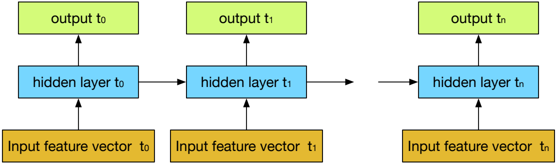
Sequence-to-sequence approaches to dialogue state tracking



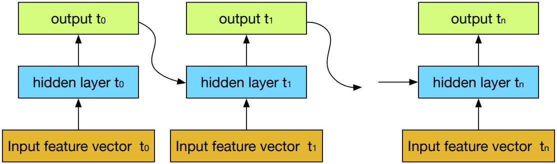
- Sequence of observations labelled with dialogue states
- Recurrent neural networks
- Distribution over possible dialogue states – **belief state**

Theory: Recurrent neural networks

Elman-type



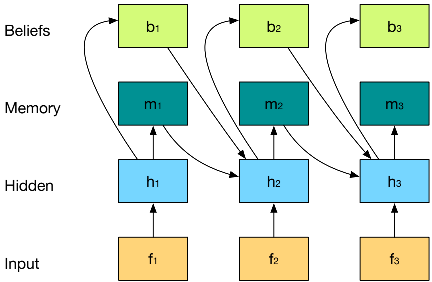
Jordan-type



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

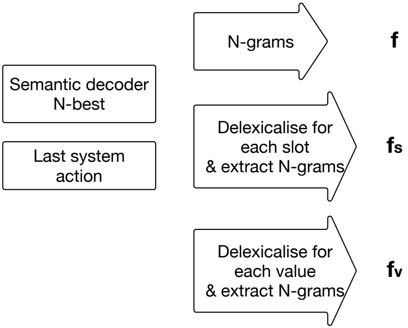


Beliefs a probability distribution over the available slot values (the belief state) for each slot in the ontology.

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

Summary

- Generative models require modeling of the observation probability and they assume that the features between subsequent turns are conditionally independent given the underlying states.
- Discriminative models model directly dependence of states on the observed features which can be correlated between the turns. Due to this they are more accurate.
- Discriminative methods can be class-based (random forests or DNNs) or sequence-to-sequence-based (RNNs).
- The belief tracker can be evaluated using accuracy or L2 norm and depending on how the tracker is optimised it would score differently on different models.

References I

Henderson, M. (2015).
Discriminative Methods for Statistical Spoken Dialogue Systems.
PhD thesis, University of Cambridge.

Henderson, M., Thomson, B., and Young, S. J. (2013).
Deep Neural Network Approach for the Dialog State Tracking Challenge.
In *Proceedings of SIGdial*.

Metallinou, A., Bohus, D., and Williams, J. D. (2013).
Discriminative state tracking for spoken dialog systems.
In *Proceedings of Annual Meeting of the Association for Computational Linguistics (ACL), Sofia, Bulgaria*. Association for Computational Linguistics.

References II

Williams, J. D. (2014).
Web-style ranking and slu combination for dialog state tracking.
In *Proceedings of SIGDIAL*. ACL Association for Computational Linguistics.