# Dialogue management: discriminative approaches to belief tracking

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Discriminative models for belief tracking

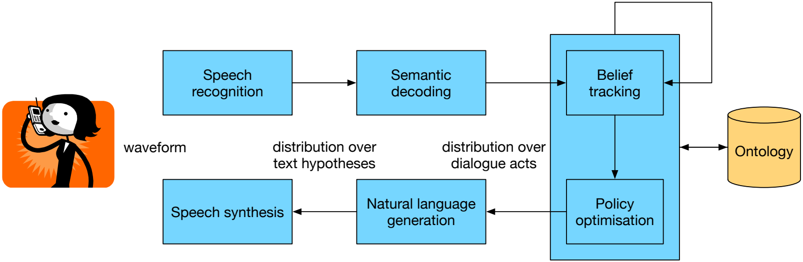
Ranking models

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

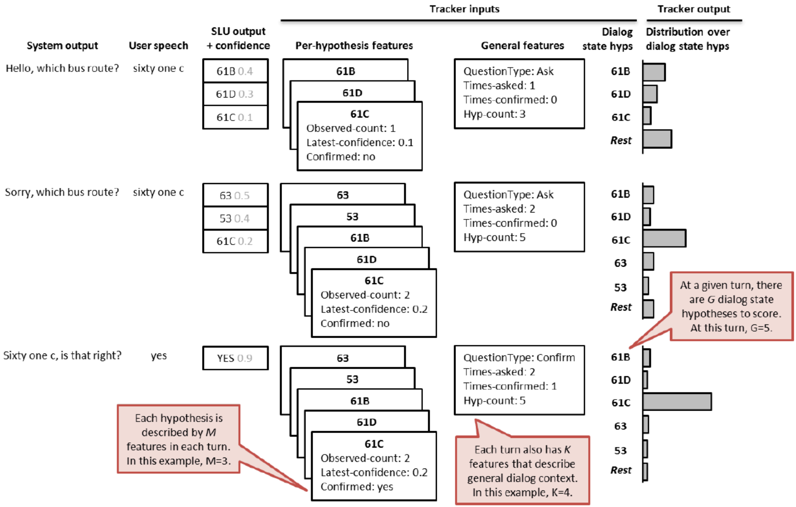
Discriminative models: the state depends on the observation

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

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 **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.

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

# Class-based approaches to dialogue state tracking

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

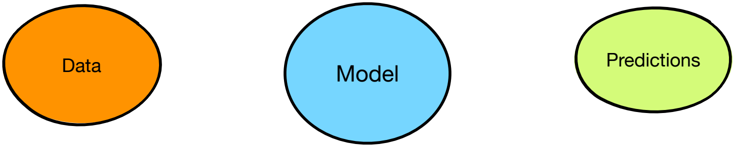
$$b(s_t) = p(s_t | o_0, \cdots, o_t)$$

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

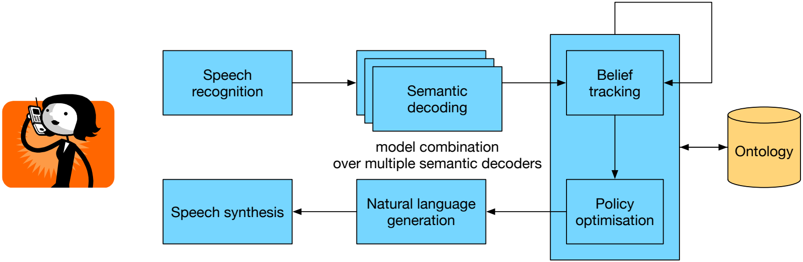



- Observations labelled with dialogue states

- 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

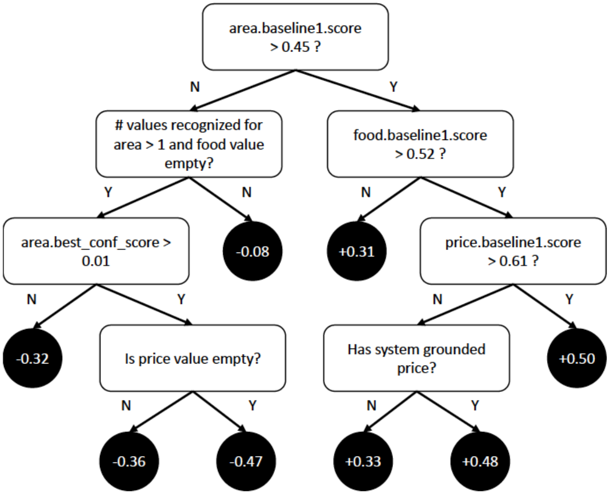
- Enumerate possible dialogue states
- Extract features
- Scoring

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

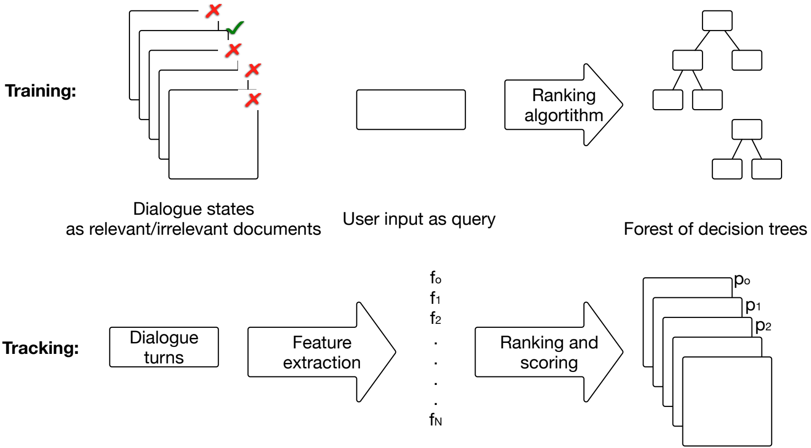
# Theory: Decision trees

- 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

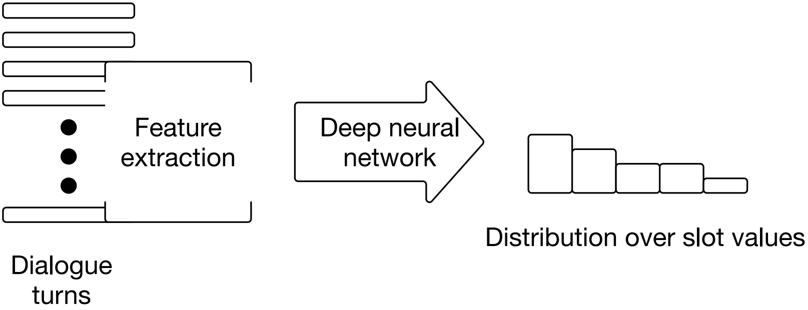
$$\mathbf{h}_0 = g_0(W_0\mathbf{x}^\mathsf{T} + b_0)$$
$$\mathbf{h}_i = g_i(W_i\mathbf{h}_{i-1}^\mathsf{T} + b_i), 0 < i < m$$
$$\mathbf{y} = \text{softmax}(W_m\mathbf{h}_{m-1}^\mathsf{T} + b_m)$$
$$\text{softmax}(\mathbf{h})_i = \exp(h_i)/(\sum_j \exp(h_j))$$

where

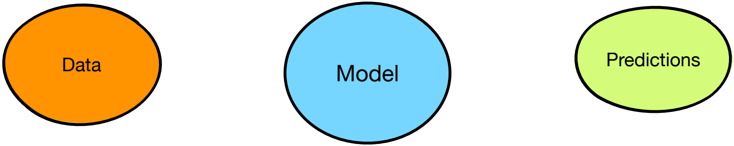
- $g_i$ (differentiable) activation functions hyperbolic tangent tanh or sigmoid $\sigma$
- $W_i, b_i$ parameters to be estimated

# 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



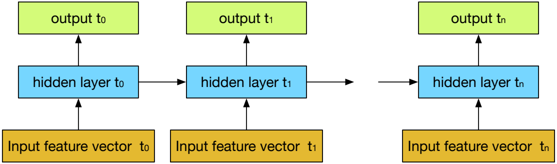

- Sequence of observations labelled with dialogue states

- Recurrent neural networks

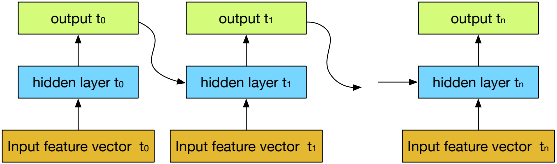
- Distribution over possible dialogue states – **belief state**

# Theory: Recurrent neural networks

## Elman-type



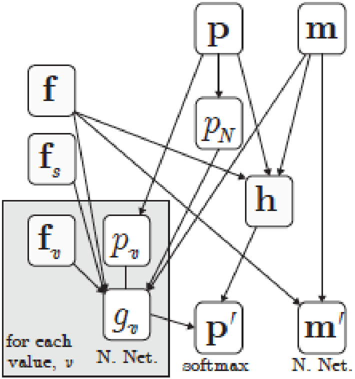

## Jordan-type



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

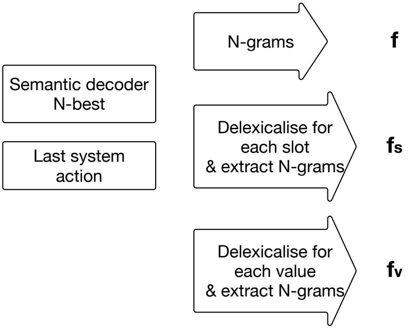
- Contains internal memory which represents dialogue context
- Structurally a combination of Elman and Jordan types
- Takes the most recent dialogue turn and last machine dialogue act as input, updates its internal memory and calculates distribution over slot values.

# RNN structure




- **f** slot independent features, $\mathbf{f}_s$ are slot dependent features and $\mathbf{f}_v$ are value dependent features
- **m** is the internal memory from the previous time step and **m**′ is the memory in the next step
- **p** is the distribution over slot value pairs from the previous time step and **p**′ is the estimated distribution
- **h** and $\mathbf{g}_v$ are estimated with Neural network with one hidden layer and sigmoid activation function

# Feature engineering



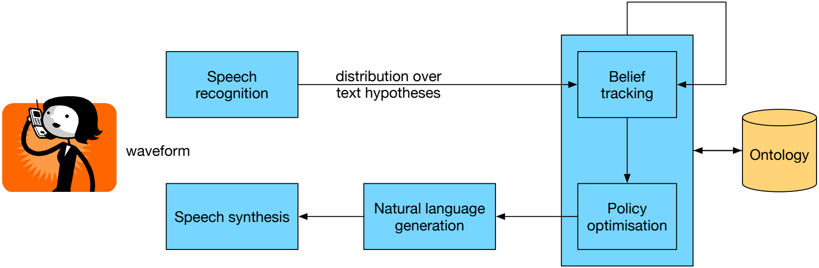

- For the same input feature vectors will be different for different slots and values
- These inputs then query different recurrent neural networks to produce distribution over slot value pairs

# 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 |

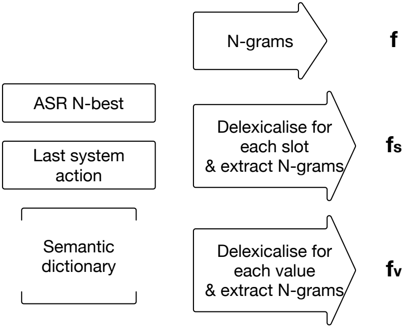
# Alternative dialogue system architecture



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

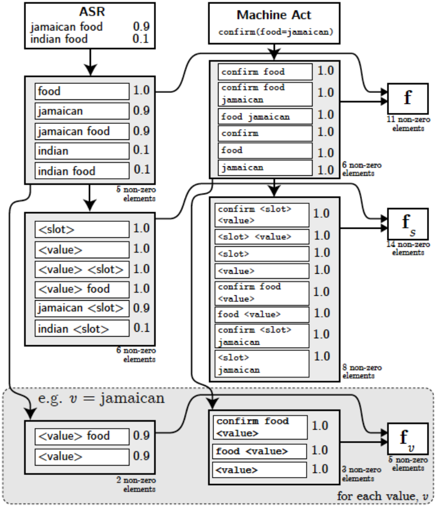
- Instead of extracting features from semantic decoding hypotheses extract features from ASR hypotheses
- Apply the same neural network structure
- Avoids information loss resulting from compact semantic representation of traditional approach
- Output: distribution over slot-value pairs

# 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



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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 $\rightarrow$ luxurious, upmarket, pricey
- In real systems this poses a major problem

# 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*.

Henderson, M., Thomson, B., and Young, S. J. (2014).
Word-based Dialog State Tracking with Recurrent Neural Networks.
In *Proceedings of SIGdial*.

# References II


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.

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