openDial: a Dialogue Systems Toolkit based on Probabilistic Rules

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Introduction

- Statistical techniques are popular in spoken dialogue systems, but they also present a number of challenges, especially for complex, open-ended domains.
- One limitation is that the number of parameters to estimate often grows exponentially with the problem size, and can thus require large amounts of training data.
- For most dialogue domains, data is however scarce and expensive to acquire.
- One way to address this issue is to rely on more expressive representations, able to capture relevant aspects of the problem structure in a compact manner.

We describe here such an abstraction mechanism: probabilistic rules.

The rules are specifically devised to encode the kind of structure found in probabilistic models of dialogue (from understanding to management and to generation).

- To test these ideas, we are currently developing a software toolkit called openDial.
- openDial employs probabilistic rules as a unifying framework for encoding dialogue processing models and estimating their parameters from interaction data.

Statistical approaches for spoken dialogue systems

<table>
<thead>
<tr>
<th>Pros</th>
<th>Cons</th>
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<tbody>
<tr>
<td>Explicit account of uncertainties, increased robustness to errors (e.g. from ASR)</td>
<td>Limited to small, compact probabilistic models</td>
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<tr>
<td>More natural conversational behaviours, better domain- and user-adaptivity</td>
<td>Inability to handle complex knowledge structures</td>
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Approach

The architecture revolves around a shared dialogue state, encoded as a Bayesian Network (belief state $b$).

- At runtime, this dialogue state is continuously updated via the application of probabilistic rules.
- Each processing step (understanding, action selection, generation, etc.) is described by a distinct set of rules.
- Decision nodes trigger the execution of specific actions.
- External modules such as ASR or TTS can also connect to the shared dialogue state and read/write to it.

The rule-structured model of action selection against the plain & linear models is the same as the Bayesian Network.

- The rules take the form of structured mappings from conditions to (probabilistic) effects:
  
  \[ \begin{align*}
  & \text{if (condition \&\& \&\& $\theta_i$)} \text{ then } \text{effect } \theta_i \text{ holds} \\
  & \text{else if (condition)} \text{ then } \text{effect } \theta_i \text{ holds} \\
  & \text{else } \theta_i \text{ holds}
  \end{align*} \]

- Conditions are described as logical formulae grounded in a subset of state variables.
- Effects are defined similarly, and assign specific values to (new or existing) variables.
- For action-selection rules, the effect associates utilities to particular actions:
  
  \[ \begin{align*}
  & \text{if (condition \&\& \&\& $\theta_i$)} \text{ then } \text{effect } \theta_i \text{ holds} \\
  & \text{else if (condition)} \text{ then } \text{effect } \theta_i \text{ holds} \\
  & \text{else } \theta_i \text{ holds}
  \end{align*} \]

- Effect probabilities & action utilities are parameters which can be estimated from data.

Experiments

We have evaluated our approach in a human-robot interaction scenario.

- The objective was to learn the parameters of the action-selection model (i.e. the dialogue policy) from a small Wizard-of-Oz dataset with 1020 system turns.
- Each training sample in the dataset is a pair (dialogue state, action), representing a given (belief) state along with the action selected by the Wizard at that state.
- Parameter learning was performed with a Bayesian approach, using an initial prior which gradually narrows down to the values providing the best fit for the data:

  \[ P(b|D) = \frac{P(D|b)P(b)}{P(D)} \]

- Baseline: two «flattened» or rolled-out versions of the action selection model, with identical input and output variables, but without the intermediate rule structure.
- The empirical results demonstrate that the rule-structured model converges faster and with better generalization performance.

- The architecture revolves around a shared dialogue state, encoded as a Bayesian Network (belief state $b$).

Conclusions

- Probabilistic rules used to capture the underlying structure of dialogue models.
- Allow developers to exploit powerful generalisations and domain knowledge in the dialogue system design without sacrificing the probabilistic nature of the model.
- Very general framework that can express a wide spectrum of models.
- In the near future, we aim to extend our approach towards model-based Bayesian reinforcement learning, where the parameter distributions are directly updated in a fully online fashion, based on (real or simulated) interaction experience.

- On the practical side, we are also developing the openDial toolkit, which will enable developers to easily prototype dialogue systems based on probabilistic rules.
- The toolkit will include algorithms for efficient inference and parameter estimation, as well as development tools for designing dialogue domains and monitoring interactions.