Declarative Design of Spoken Dialogue Systems with Probabilistic Rules

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Introduction

- Spoken dialogue systems typically rely on pipeline architectures with «black-box» components developed separately

- Each component employs ad-hoc encoding formats for their inputs/outputs and internal parameters

- Formats rarely compatible with one another!
  - Difficult to derive a semantic interpretation as a whole
  - Difficult to perform joint optimisations
  - Domain- or task-specific knowledge often «hardwired»
Introduction

• We adopt an alternative approach:
  • Declarative specification of all domain- & task-specific knowledge via a common representation formalism
  • System architecture «stripped down» to a core set of algorithms for probabilistic inference

• Advantages:
  • Domain portability
  • More transparent semantics
  • More flexible workflow
General architecture

• **Blackboard architecture** revolving around a shared dialogue state

  • Dialogue models are attached to this dialogue state, and listen for relevant changes appearing on it
  
  • When triggered, they read/write to this state, creating and updating the state variables

• Dialogue state encoded as a **Bayesian Network**

  • Each network node represents a distinct state variable, possibly connected to other variables
General architecture

Dialogue Interpretation

Speech understanding

Speech recognition

Extra-linguistic environment

Dialogue state \( \vec{b} \)

User intention \( \vec{i}_u \)

Perceived context \( \vec{c} \)

Intended response \( \vec{a}_m^* \)

Utterance to synthesise \( \vec{u}_m^* \)

Recognition hypotheses \( \vec{u}_u \)

Dialogue act \( \vec{a}_u \)

Action selection

Generation

Speech synthesis

User

input speech signal (user utterance)

output speech signal (machine utterance)
Dialoge models

• The dialogue models are all expressed in terms of probabilistic rules

• Probabilistic rules are *high-level templates* for constructing probabilistic models

• Why use this representation formalism?
  - Take advantage of the *internal structure* of the problem while retaining the stochastic modelling
  - Abstraction mechanism (reduced set of parameters)
Probabilistic rules

• Probabilistic rules take the form of structured if...then...else cases

• Mapping from conditions to (probabilistic) effects:

\[
\begin{align*}
\text{if (condition}_1 \text{ holds) then} \\
P(\text{effect}_1) &= \theta_1, \quad P(\text{effect}_2) = \theta_2, \quad \ldots \\
\text{else if (condition}_2 \text{ holds) then} \\
P(\text{effect}_3) &= \theta_3, \quad \ldots \\
\ldots \\
\text{else} \\
P(\text{effect}_n) &= \theta_n, \quad \ldots
\end{align*}
\]
Probabilistic rules

- **Conditions** are (arbitrarily complex) logical formulae on state variables
- **Effects** are value assignments on state variables
- Effect probabilities are parameters that can be estimated from data

Example:

\[
\text{if } (a_m = \text{AskRepeat}) \text{ then} \\
P(a_u' = a_u) = 0.9 \\
P(a_u' \neq a_u) = 0.1
\]
Utility rules

- The formalism can also describe *utility models*
- In this case, the rule maps each condition to an assignment of *utility values* for particular actions:

\[
\begin{align*}
\text{if} \ (\text{condition}_1 \ \text{holds}) \ & \text{then} \\
Q(\text{actions}_1) &= \theta_1, \ Q(\text{actions}_2) = \theta_2, \ldots \\
\text{else if} \ (\text{condition}_2 \ \text{holds}) \ & \text{then} \\
Q(\text{actions}_3) &= \theta_3, \ldots \\
\ldots \\
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Rule instantiation

• How are the rules applied to the dialogue state?
• The rules are instantiated in the Bayesian Network, expanding it with new nodes and dependencies
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\[ r_1: \]

\[
\text{if } (X = ... \lor Y \neq ...) \text{ then } \\
P(V = ... \land W = ...) = 0.6
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(The ... dots in \( r_1 \) should be replaced by concrete values)
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\[ r_2: \]

\[
\text{if } (X = \ldots \lor Y \neq \ldots) \text{ then } \\
Q(A_1 = \ldots \land A_2 = \ldots) = 3
\]
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Processing workflow

• To ease the domain design, the rules are grouped into models

• Each model is associated with a trigger variable causing its activation

• When a model is activated:
  • A rule node is created for each rule, conditionally dependent on the variables used in the conditions
  • Nodes corresponding to the output variables of the rule are also created/updated, and connected to the rule node
Processing workflow (example)
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Processing workflow (example)
Processing workflow (example)
Processing workflow (example)
Processing workflow (example)

etc.
Processing workflow

• Additional details

• No pipeline restriction: processing flow is possible

• Decision nodes require a decision to be made, by selecting the value with maximum utility

• Once the dialogue state is «stable» (no more model can be triggered), it is pruned to reduce it to a minimal size, retaining only the necessary nodes

• The rules update existing variables or create new ones
Experiments

- The described formalism was implemented and tested in a simple human-robot interaction scenario.
- The models for NLU, DM and NLG were encoded as probabilistic rules (total of 68 rules).
Experiments

• The utilities for the action selection rules were learned from Wizard-of-Oz data

• The other rules (NLU and NLG) were deterministic

• System also included a speech recogniser, TTS, and libraries for controlling the physical actions of the robot

Examples

• Dialogue act recognition rule:

\[ r_1 : \text{if} (u_u \text{ matches } \text{“left arm down”}) \]
\[ \lor (u_u \text{ matches } \text{“lower * left arm”}) \]
\[ \lor (u_u \text{ matches } \text{“down * left arm”}) \text{ then} \]
\[ \{ P(a_u' = \text{LeftArmDown}) = 1.0 \} \]

• Prediction of next user action:

\[ r_2 : \text{if} (a_m = \text{AskRepeat}) \text{ then} \]
\[ \{ P(a_u' = a_u) = 0.9 \} \]
Examples

• Action selection rules:

\[ r_3 : \text{if } (i_u = \text{RequestMovement}(X)) \text{ then } \{Q(a'_m = \text{DoMovement}(X)) = 3.0\} \]

\[ r_4 : \text{if } (\text{true}) \text{ then } \{Q(a'_m = \text{AskRepeat}) = 1.2\} \]

• Natural language generation rule:

\[ r_5 : \text{if } (a_m = \text{Ack}) \text{ then } \{Q(u'_m = \text{“ok”}) = 1.0 \land \\
Q(u'_m = \text{“great”}) = 1.0 \land \\
Q(u'_m = \text{“thanks”}) = 1.0\} \]
Conclusions

• Dialogue system design based on the specification of probabilistic rules

• «Hybrid» approach combining domain knowledge and stochastic modelling

• Step towards a cleaner separation between system architecture and domain-and task-specific knowledge?
Future work

• Online estimation of the rule parameters (e.g. model-based Bayesian reinforcement learning)

• Joint optimisations of the parameters for NLU, DM and NLG models

• Incremental processing
Next interaction domain
Next interaction domain