



A hybrid approach to dialogue management based on probabilistic rules

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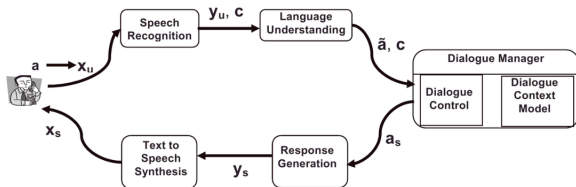
Outline

1. Motivation
2. Probabilistic rules
3. Evaluation
4. Conclusion



Motivation

Dialogue Management [1]



Proper solutions:

- ▶ Hand-crafted / rule-based models (e.g. ISU)
- ▶ Statistical models (e.g. POMDP)



Motivation

Bottlenecks

- ▶ Hand-crafted / rule-based models
 - ▶ assume complete observability
 - ▶ no errors and uncertainty
 - ▶ knowledge base has to be completely specified beforehand

- ▶ Statistical models
 - ▶ depend on large amount of data leading to high costs for data acquisition
 - ▶ have a huge state space



Motivation

Target: Combine advantages into a hybrid system

- ▶ Hand-crafted / rule-based models
 - ▶ precisely tailored for various behaviour

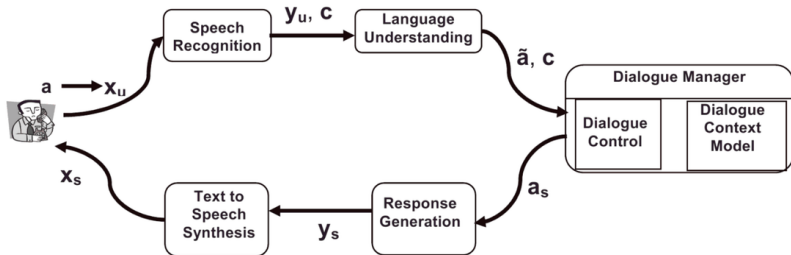
- ▶ Statistical models
 - ▶ handle errors and uncertainty

Approach: Pierre Lison, 2014, “A hybrid approach to dialogue management based on **probabilistic rules**” [2]



Probabilistic rules

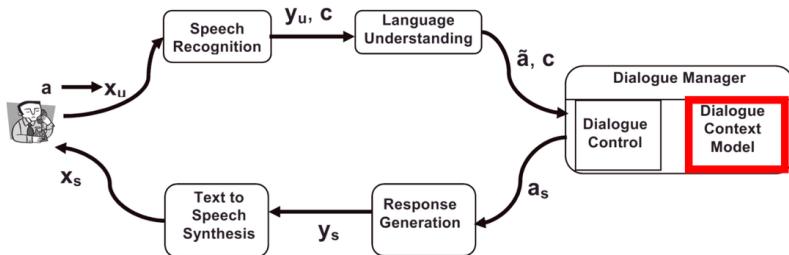
Dialogue Management [1]



Probabilistic rules

Dialogue Management [1]

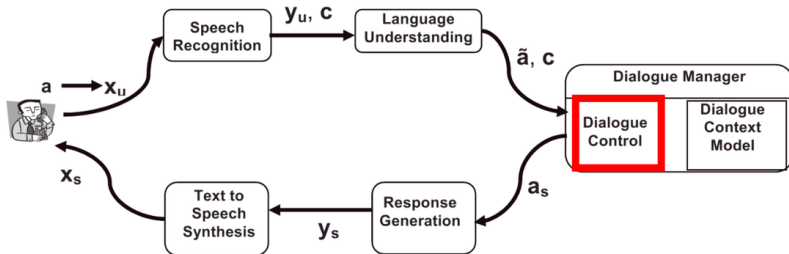
- ▶ Dialogue Context Model → **Probability rules**



Probabilistic rules

Dialogue Management [1]

- ▶ Dialogue Context Model → **Probability rules**
- ▶ Dialogue Control → **Utility rules**







Probability rules

 $\forall \mathbf{x},$
if (c_1) **then**

$$\left\{ \begin{array}{l} P(E_1 = e_{1,1}) = \theta_{1,1} \\ \dots \\ P(E_1 = e_{1,m_1}) = \theta_{1,m_1} \end{array} \right.$$

else if (c_2) **then**

$$\left\{ \begin{array}{l} P(E_2 = e_{2,1}) = \theta_{2,1} \\ \dots \\ P(E_2 = e_{2,m_2}) = \theta_{2,m_2} \end{array} \right.$$

 \dots
 c_j : Condition

 E_j : Random variable

 $e_{i,j}$: Effect

 $\theta_{i,j}$: Probability



Conditions

- ▶ Input variables (ASR/SLU or internal state)
- ▶ Predicate logic (e.g. conjunction) and binary relations (e.g. equality)
- ▶ Free variables (universally quantified)

Example:

$$\begin{aligned}
 \forall x, \quad & \mathbf{if} (a_u = \text{RequestAction}(x) \wedge a_m = \text{Do}(x)) \mathbf{then} \\
 & \left\{ P(a'_u = \text{Confirm}) = 0.2 \right. \\
 & \mathbf{else if} (a_u \neq \text{RequestAction}(x) \wedge a_m = \text{Do}(x)) \mathbf{then} \\
 & \left\{ \begin{array}{l} P(a'_u = \text{Disconfirm}) = 0.5 \\ P(a'_u = \text{RequestAction}(\text{Stop})) = 0.3 \end{array} \right.
 \end{aligned}$$

[2]



Effects

- ▶ An effect assigns values to a set of output variables
- ▶ e.g., $e_{i,j} = \{a'_u = x\}$
- ▶ Each effect is assigned a probability $P(E_i = e_{i,j}) = \theta_{i,j}$

Example:

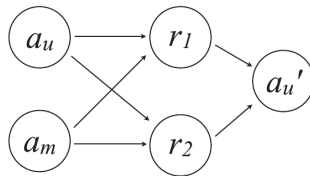
$\forall x,$ **if** $(a_u = \text{RequestAction}(x) \wedge a_m = \text{Do}(x))$ **then**
 $\{ P(a'_u = \text{Confirm}) = 0.2$
else if $(a_u \neq \text{RequestAction}(x) \wedge a_m = \text{Do}(x))$ **then**
 $\left\{ \begin{array}{l} P(a'_u = \text{Disconfirm}) = 0.5 \\ P(a'_u = \text{RequestAction}(\text{Stop})) = 0.3 \end{array} \right.$

[2]

Instantiation

r1: $\forall x,$
 if $(a_u = x \wedge a_m = AskRepeat)$ then
 $\{ P(a_u' = x) = 0.9$

r2: $\forall x,$
 if $(a_u = RequestAction(x) \wedge a_m = Do(x))$ then
 $\{ P(a_u' = Confirm) = 0.2$
 else if $(a_u \neq RequestAction(x) \wedge a_m = Do(x))$ then
 $\{ P(a_u' = Disconfirm) = 0.5$
 $\{ P(a_u' = RequestAction(Stop)) = 0.3$


 input
 variables

 probability
 rules

 output
 variables

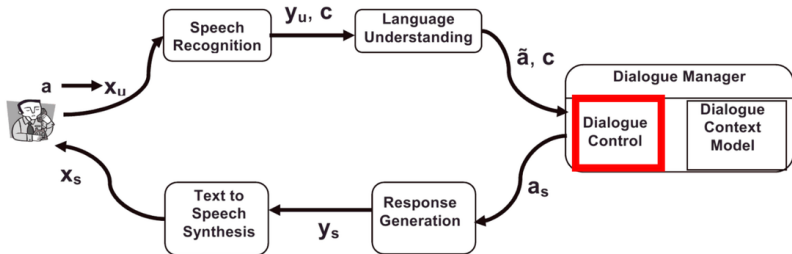
[2]



Probabilistic rules

Dialogue Management [1]

- ▶ Dialogue Context Model → **Probability rules**
- ▶ Dialogue Control → **Utility rules**





Utility rules

 $\forall \mathbf{x},$
if (c_1) **then**

$$\begin{cases} U_1(d_{1,1}) = \theta_{1,1} \\ \dots \\ U_1(d_{1,m_1}) = \theta_{1,m_1} \end{cases}$$

else if (c_2) **then**

$$\begin{cases} U_2(d_{2,1}) = \theta_{2,1} \\ \dots \\ U_2(d_{2,m_2}) = \theta_{2,m_2} \end{cases}$$

 \dots
 c_j : Condition

 U_i : Utility table

 $d_{i,j}$: Decision

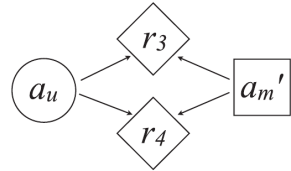
 $\theta_{i,j}$: Utility value



Instantiation

r3: $\forall x,$
if ($a_u = \text{RequestAction}(x)$) **then**
 $\{ U(a'_m = \text{Do}(x)) = 5$
else
 $\{ U(a'_m = \text{Do}(x)) = -5$

r4: $\forall x,$
if ($a_u = \text{RequestAction}(x) \vee a_u = \text{Ask}(x)$) **then**
 $\{ U(a'_m = \text{AskRepeat}) = 1$



input
variables

utility
rules

decision
variables

[2]



Parameter estimation

Probabilistic **rule structure** is **hand-crafted** by system designer.

Parameters like effect probabilities and utilities are **estimated** by learning:

- ▶ Supervised learning (Wizard-of-Oz data)
- ▶ Reinforcement learning (real or simulated interactions)

In both cases, Bayesian inference to estimate best values for parameters

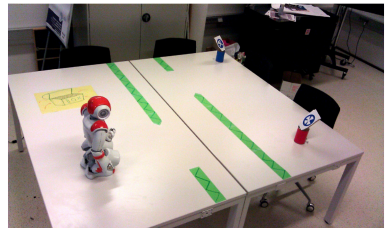


Evaluation

Test scenario

Tasks:

1. Walk to the other end of the table considering walls
2. Pick up a certain object
3. Bring the object back to the start point
4. Release the object on the landmark



[2]



Evaluation

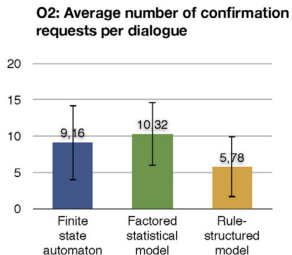
Comparison

- ▶ Finite-state automation
- ▶ Factored statistical model
- ▶ Probabilistic rule model

Evaluation

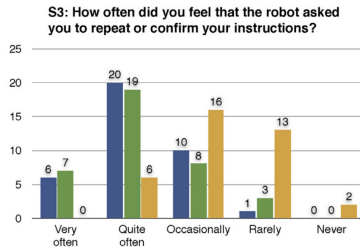
Metrics

Objective



[2]

Subjective





Evaluation

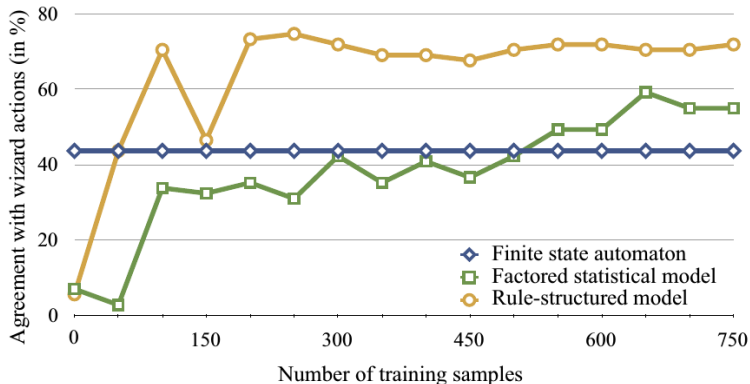
Results

- ▶ 15 metrics in total (9 objective, 6 subjective)
- ▶ 7 metrics show **significantly higher** results for the probabilistic rule model
- ▶ 6 metrics show **higher** results for the probabilistic model



Evaluation

Learning Curve [2]





Conclusion

Probabilistic rule model...

- ▶ ...combines advantages of hand-crafted and statistical model
- ▶ ...uses probability rules for dialogue context model
- ▶ ...uses utility rules for dialogue control
- ▶ ...partitions the state space by conditions
- ▶ ...has distributions over possible effects
- ▶ ...uses parameters estimated by learning
- ▶ ...outperforms hand-crafted and statistical model in the (simple) test scenario



[1] **Kristiina Jokinen and Michael F. McTear.**

Spoken Dialogue Systems, volume 5 of *Synthesis Lectures on Human Language Technologies*.

Morgan & Claypool, San Rafael, CA, 2010.

[2] **Pierre Lison.**

A hybrid approach to dialogue management based on probabilistic rules.

Comput. Speech Lang., 34(1):232–255, November 2015.