UiO : University of Oslo

Probabilistic Dialogue Models with Prior Domain Knowledge

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SIGDIAL

Introduction

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- But scalability remains a challenge for many domains

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Better domain- and user-*adaptivity*, more *natural* and *flexible* conversational behaviours

Introduction

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- But scalability remains a challenge for many domains

Advantages	**Challenges**
Explicit account of *uncertainties*, increased *robustness* to errors	Good domain data is *scarce* and expensive to acquire!
Better domain- and user-*adaptivity*, more *natural* and *flexible* conversational behaviours	*Scalability* to complex domains (state space grows exponentially with the problem size)

Introduction (2)

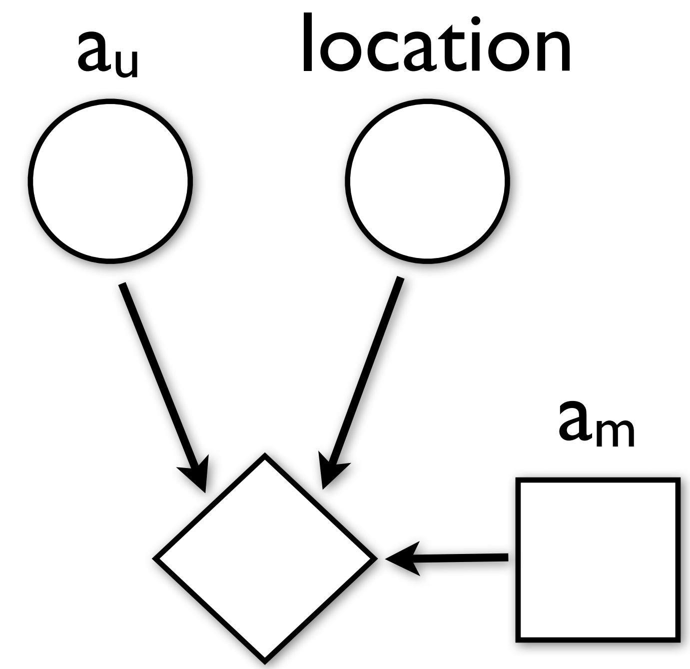
- Well-known problem in A.I. and machine learning
- Solutions typically involve the use of more *expressive representations*
    - Capturing relevant aspects of the *problem structure*
    - Taking advantage of hierarchical or relational abstractions
- We present here such an abstraction mechanism, based on the concept of *probabilistic rule*
- Goal: leverage our prior domain knowledge to yield structured, *compact* probabilistic models

Key idea

- Observation: dialogue models exhibit a fair amount of *internal structure*:
  - Probability (or utility) distributions can often be *factored*
  - Even if the full distribution has many dependencies, the probability (or utility) of a *specific outcome* often depends on only a small subset of variables
  - Finally, the values of the dependent variables can often be grouped into *partitions*

Example of partitioning

- Consider a dialogue where the user asks a robot yes/no questions about his location
- The state contains the following variables :
  - Last user dialogue act, e.g. $a_u = \text{AreYouIn(corridor)}$
  - The robot location, e.g. $\text{location} = \text{kitchen}$
- You want to learn the utility of $a_m = \text{SayYes}$



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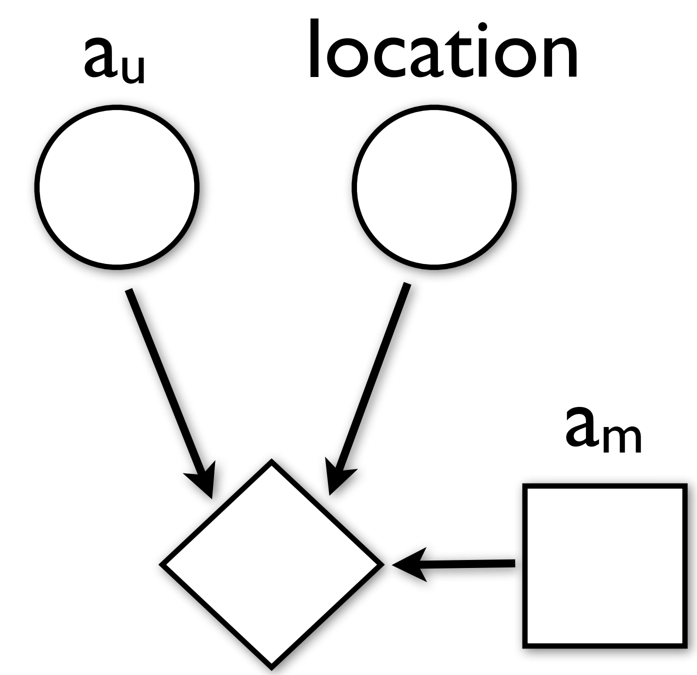
- You want to learn the utility of $a_m = \text{SayYes}$
- The combination of the two variables can take many values, but they can be partitioned in two sets:



$$a_u = \text{AreYouIn}(x) \wedge \text{location} = x \longrightarrow \text{positive utility}$$
$$a_u = \text{AreYouIn}(x) \wedge \text{location} \neq x \longrightarrow \text{negative utility}$$

Probabilistic rules

- Probabilistic rules attempt to capture such kind of structure
- They take the form of structured if...then...else cases, mappings from *conditions* to (probabilistic) *effects*:

> **if** (condition$_1$ holds) **then**
> P(effect$_1$)= θ_1, P(effect$_2$)= θ_2
> **else if** (condition$_2$ holds) **then**
> P(effect$_3$) = θ_3

- For action-selection rules, the effect associates utilities to particular actions:

> **if** (condition$_1$ holds) **then**
> Q(actions)= θ_1

Probabilistic rules (2)

- *Conditions* are arbitrary logical formulae on state variables
- *Effects* are value assignments on state variables
- Example of rule for action selection:

$$
\begin{aligned}
&\textbf{if } (\mathsf{a_u} = \mathsf{AreYouIn(x)} \land \mathsf{location} = \mathsf{x}) \textbf{ then} \\
&\qquad \{\mathsf{Q(a_m} = \mathsf{SayYes)} = 3.0\} \\
&\textbf{else if } (\mathsf{a_u} = \mathsf{AreYouIn(x)} \land \mathsf{location} \neq \mathsf{x}) \textbf{ then} \\
&\qquad \{\mathsf{Q(a_m} = \mathsf{SayNo)} = 3.0\}
\end{aligned}
$$

- Effect probabilities and utilities are *parameters* which can be estimated from data

Rule-based state update

- How are these rules applied in practice?
- The architecture revolves around a shared dialogue state, represented as a **Bayesian network**
- At runtime, the rules are *instantiated* in the network, updating and expanding it with new nodes and dependencies
- The rules thus function as *high-level templates* for a classical probabilistic model

Example

Example

location

office	*[P=0.95]*
kitchen	*[P=0.05]*

a_u

AreYouIn(kitchen)	*[P=0.7]*
AreYouIn(corridor)	*[P=0.2]*
None	*[P=0.1]*

Example

Rule 1:

$$\textbf{if } (a_u = \text{AreYouIn}(x) \wedge \text{location} = x) \textbf{ then}$$
$$\{Q(a_m = \text{SayYes}) = 3.0\}$$
$$\textbf{else if } (a_u = \text{AreYouIn}(x) \wedge \text{location} \neq x) \textbf{ then}$$
$$\{Q(a_m = \text{SayNo}) = 3.0\}$$

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office	*[P=0.95]*
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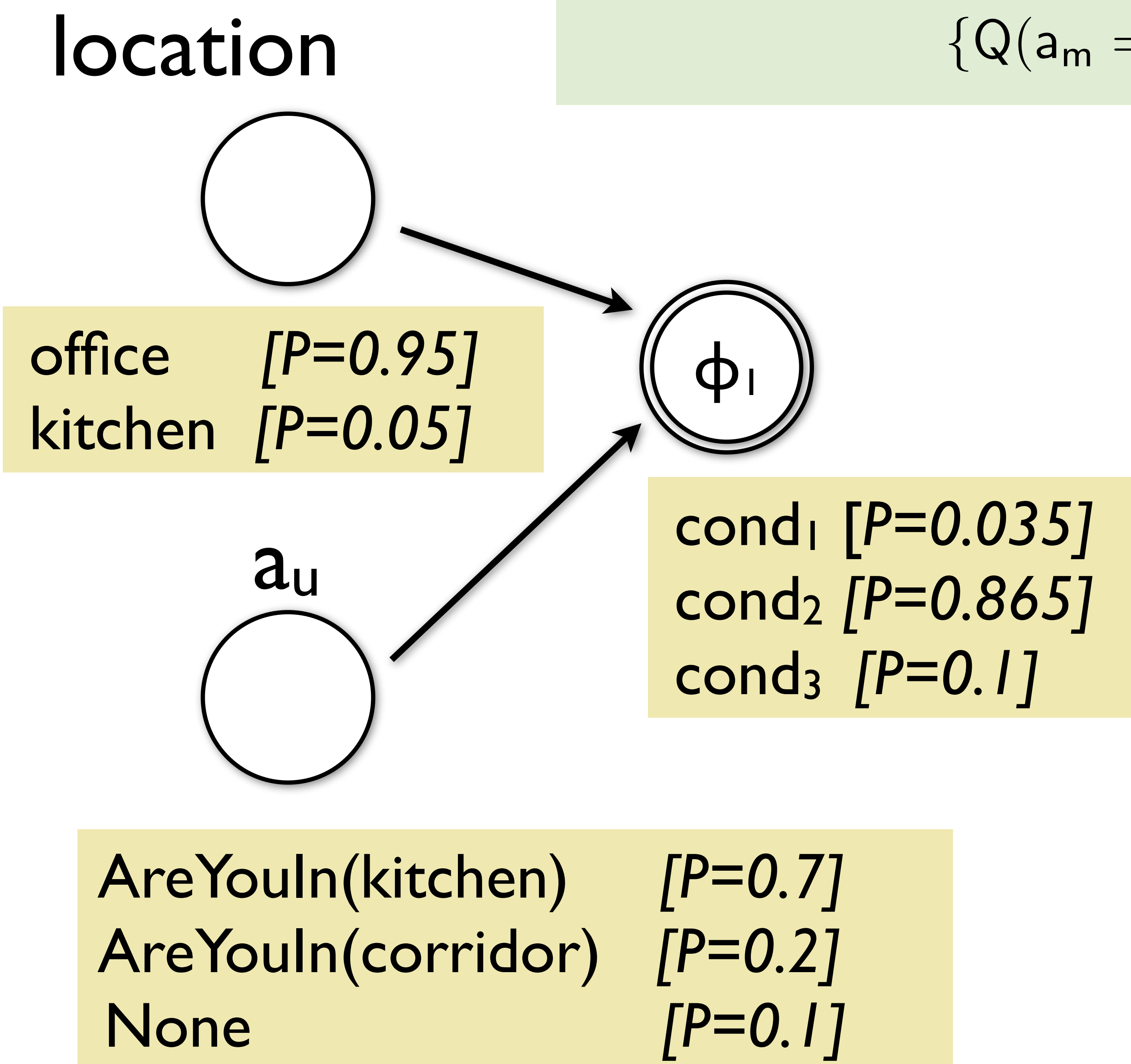

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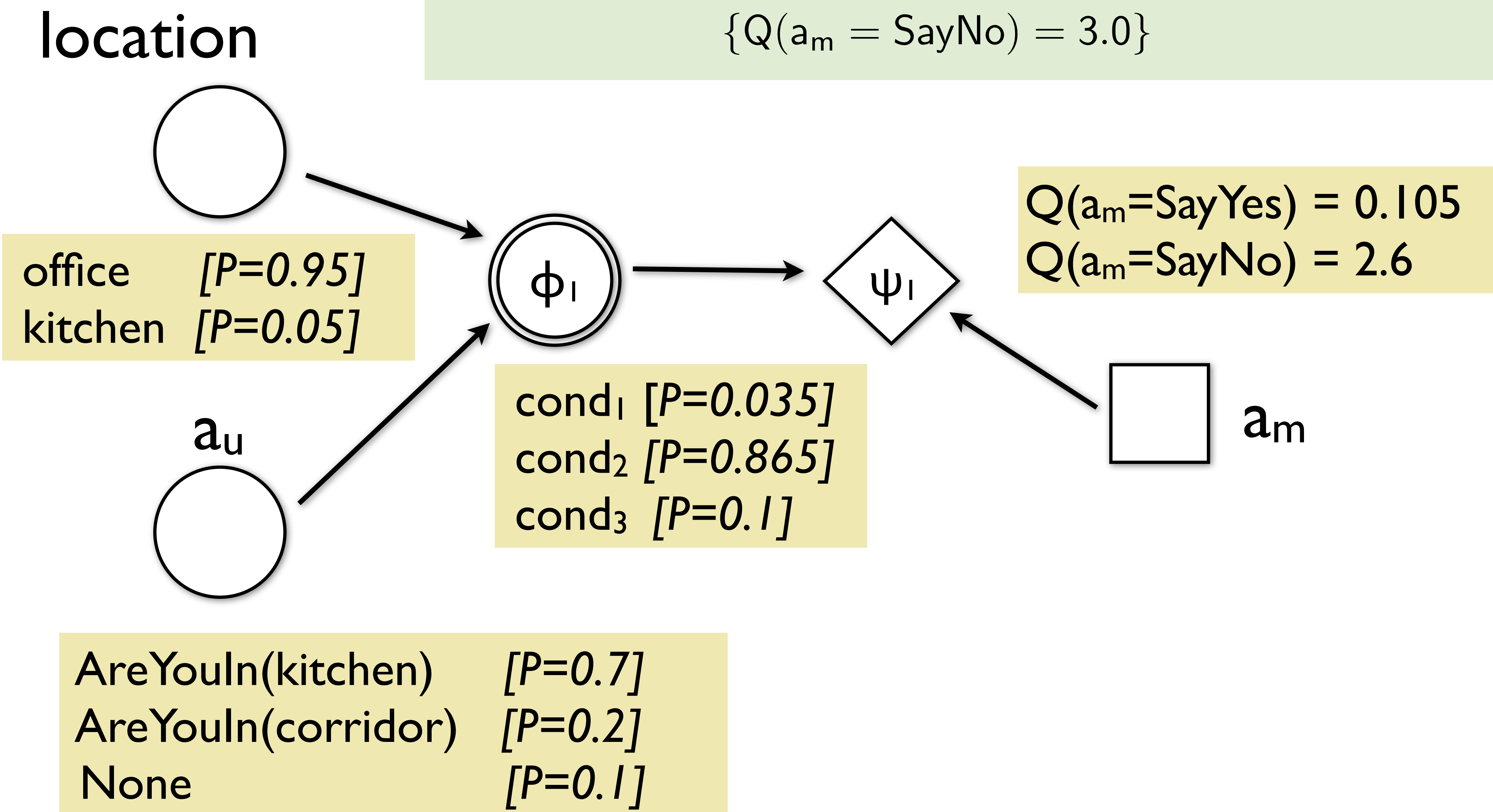

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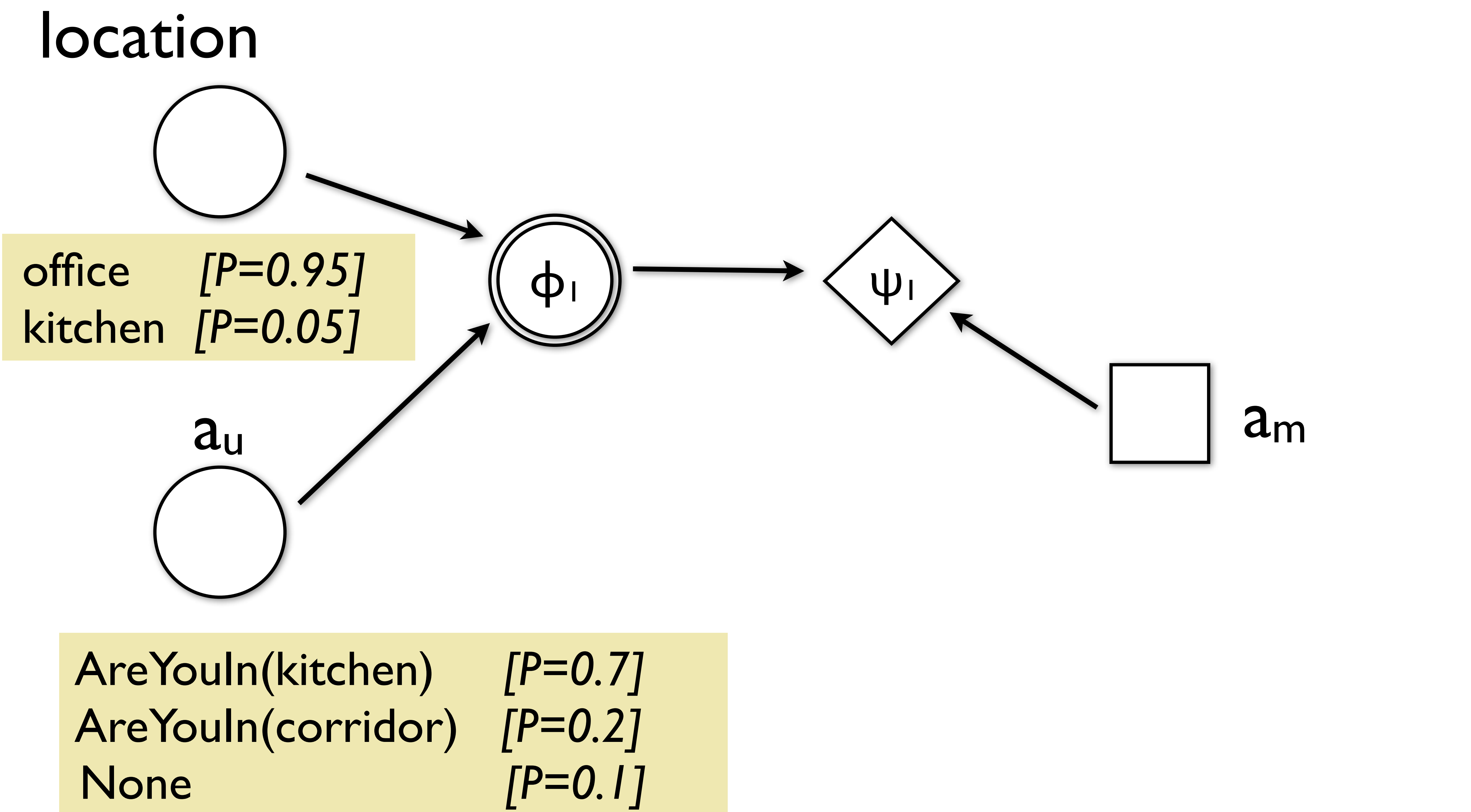
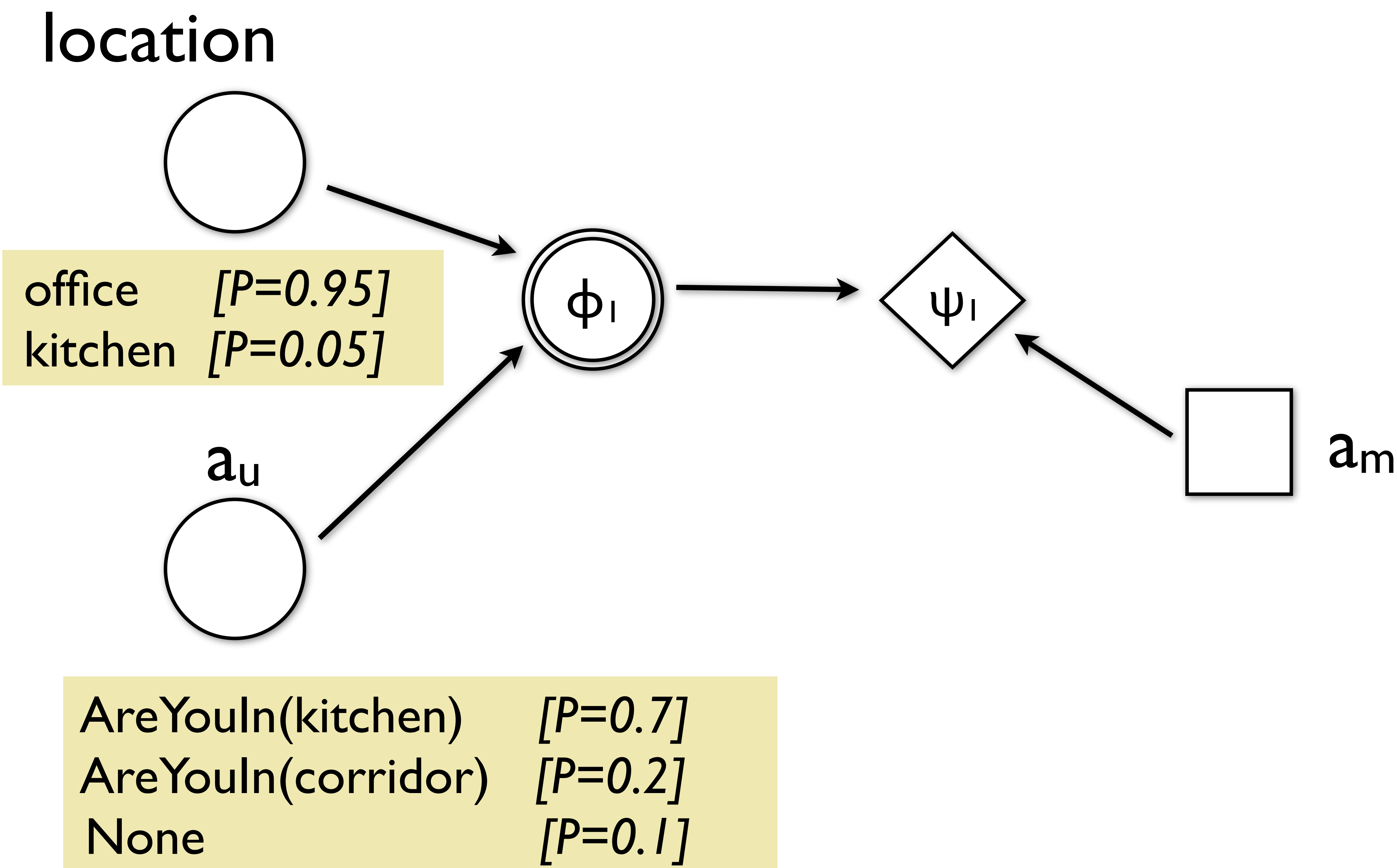

location
office [P=0.95]
kitchen [P=0.05]
ϕ_1
ψ_1
a_u
a_m
AreYouIn(kitchen) [P=0.7]
AreYouIn(corridor) [P=0.2]
None [P=0.1]

Example

<u>Rule 2:</u> $\textbf{if}\ (a_u \neq \text{None})\ \textbf{then}$

$$\{Q(a_m = \text{AskRepeat}) = 0.5\}$$



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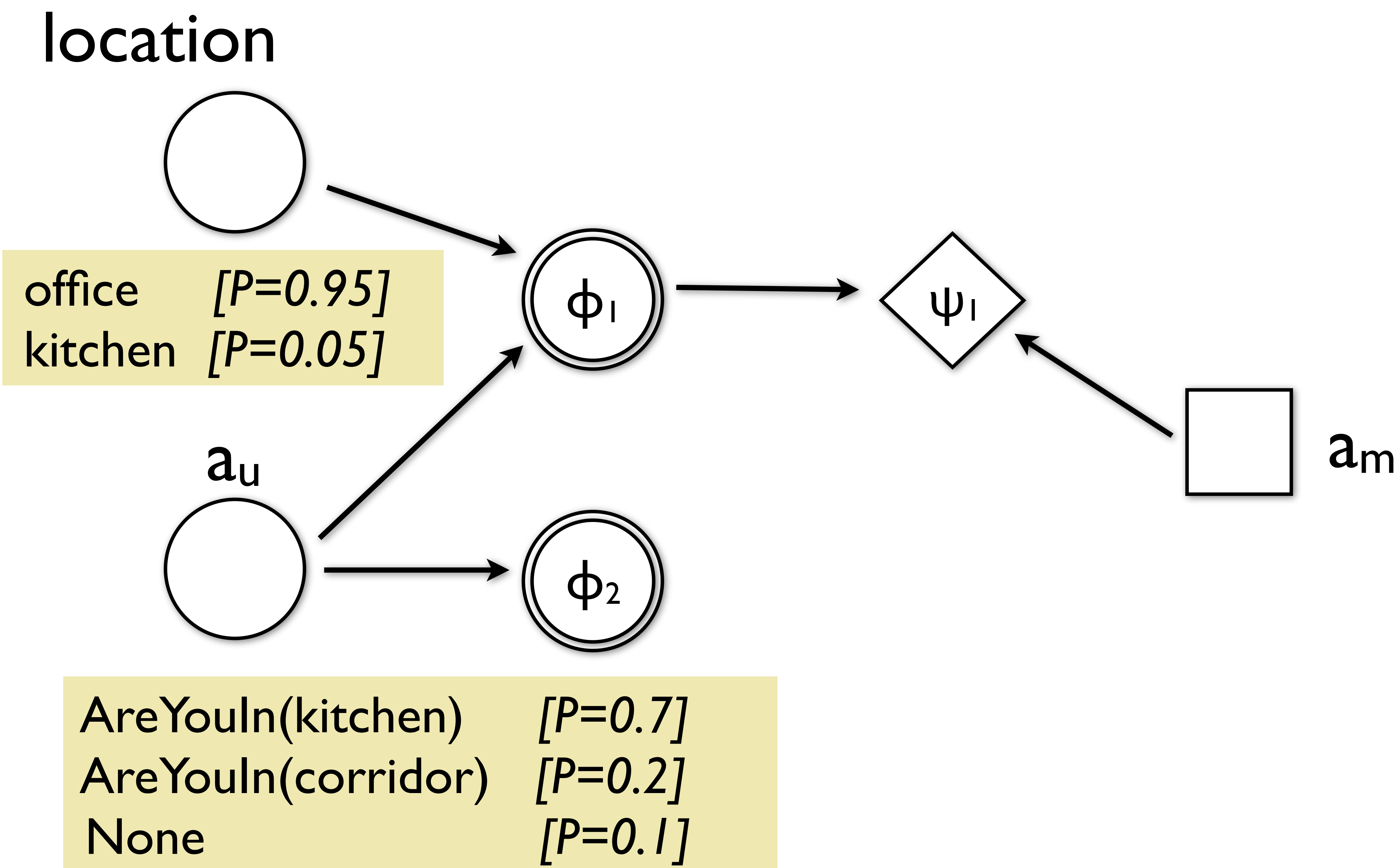

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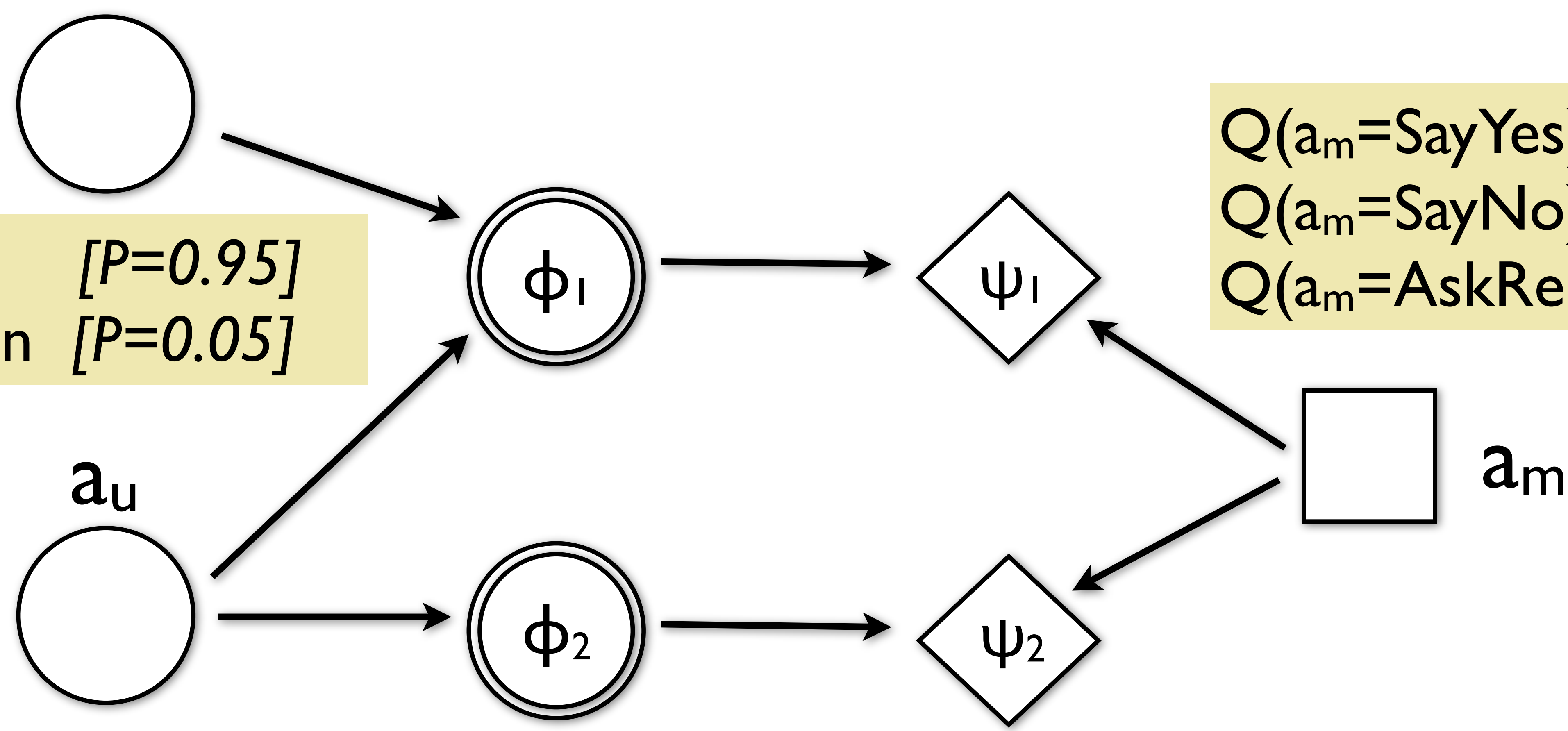
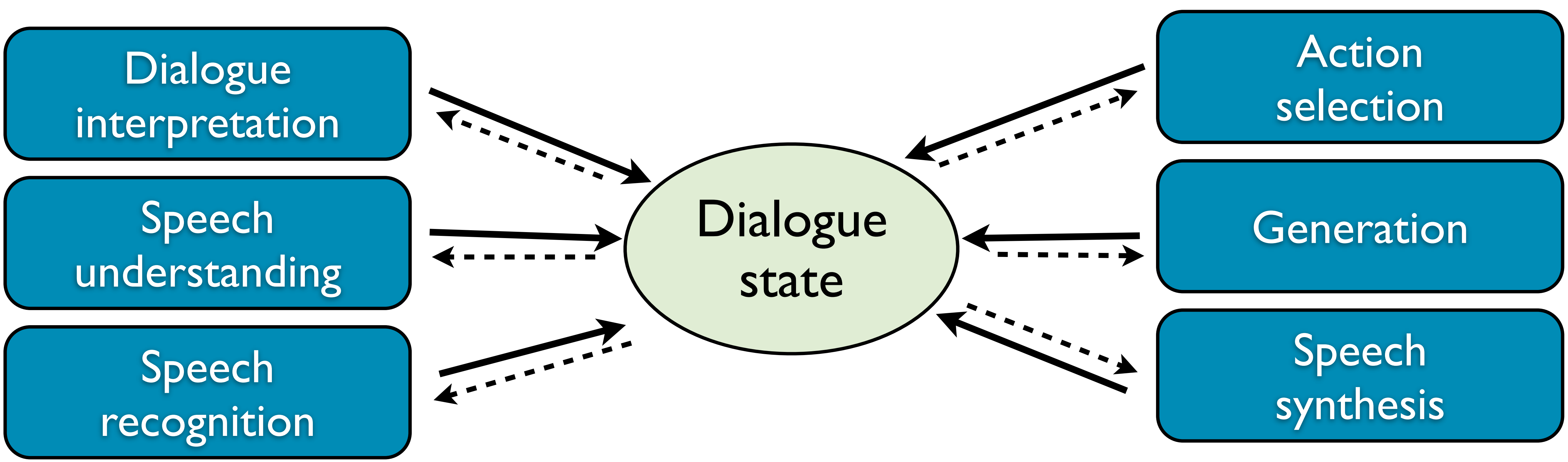


Q(a_m=SayYes) = 0.105
Q(a_m=SayNo) = 2.6
Q(a_m=AskRepeat)=0.45

AreYouIn(kitchen)	*[P=0.7]*
AreYouIn(corridor)	*[P=0.2]*
None	*[P=0.1]*

Processing workflow

- The dialogue state, encoded as a Bayesian Network, is the central, shared information repository
- Each processing task (understanding, management, generation, etc.) read and write to it
- Many of these tasks are expressed in terms of collections of probabilistic rules



Parameter learning

- The rule parameters (probabilities or utilities) must be estimated from empirical data
- We adopted a Bayesian approach, where the parameters are themselves defined as variables
- The parameter distributions will then be modified given the evidence from the training data

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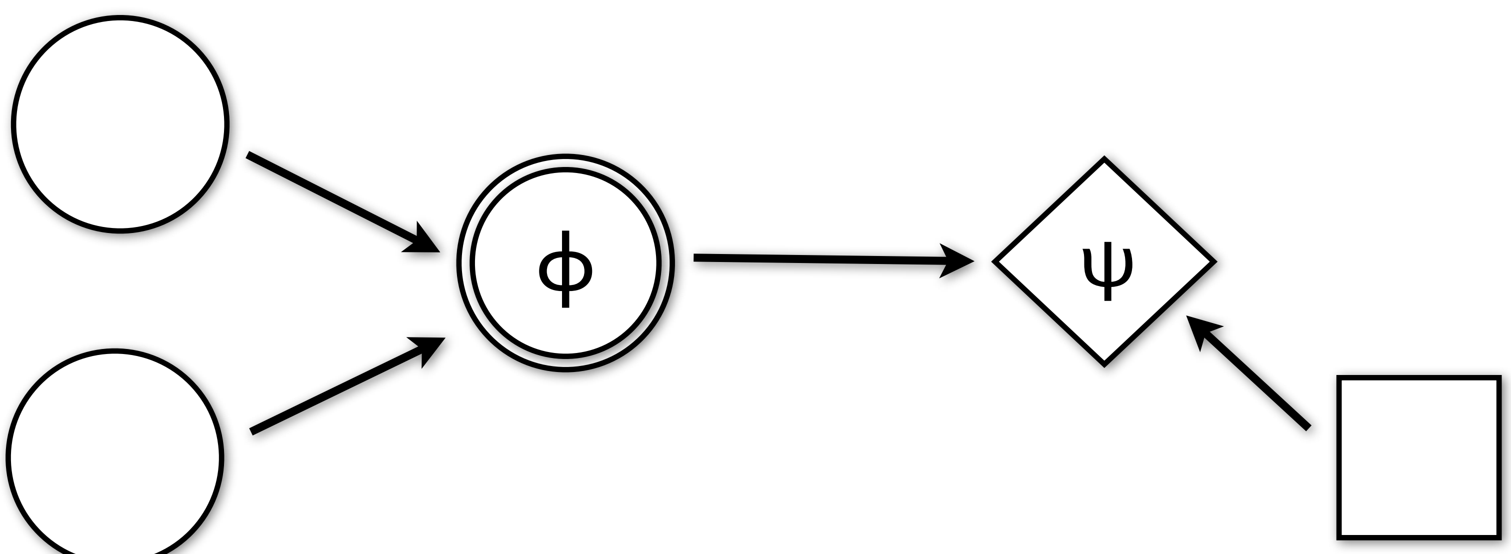

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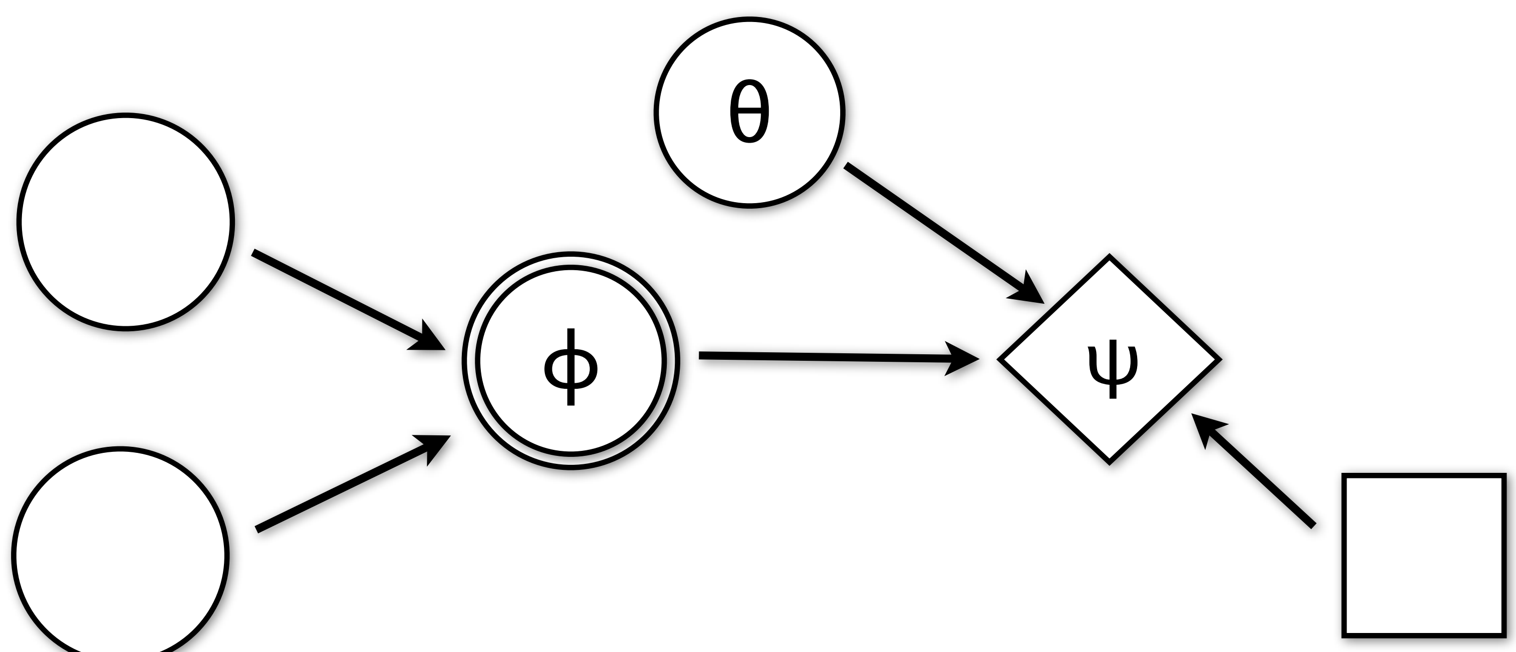

Evaluation

- Policy learning task in a human-robot interaction scenario, based on Wizard-of-Oz training data
- Objective: estimate the utilities of possible system actions
- Baselines: «rolled-out» versions of the model
  - «plain» probabilistic models with identical input and output variables, but without the condition and effect nodes as intermediary structures

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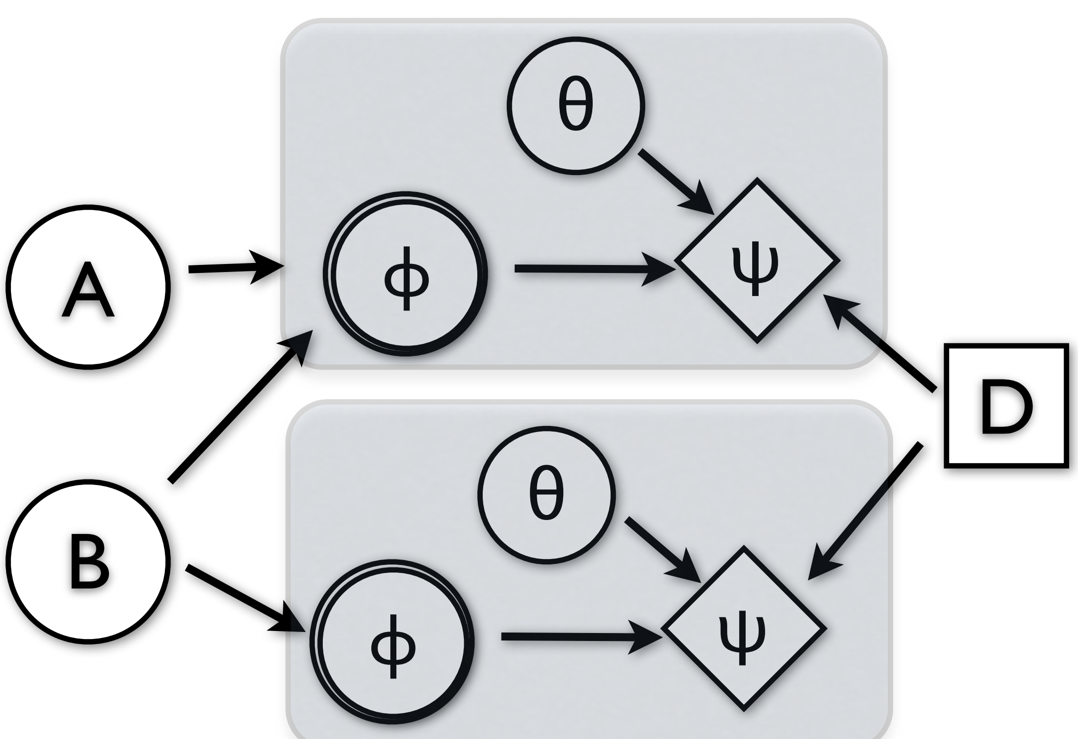

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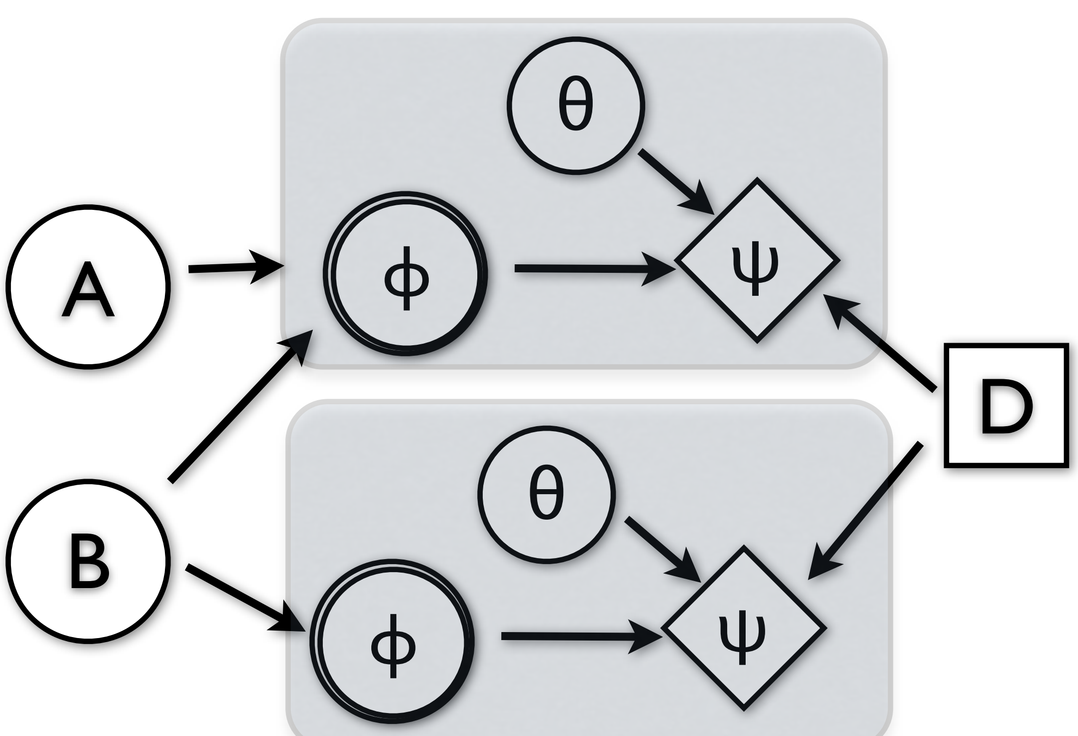

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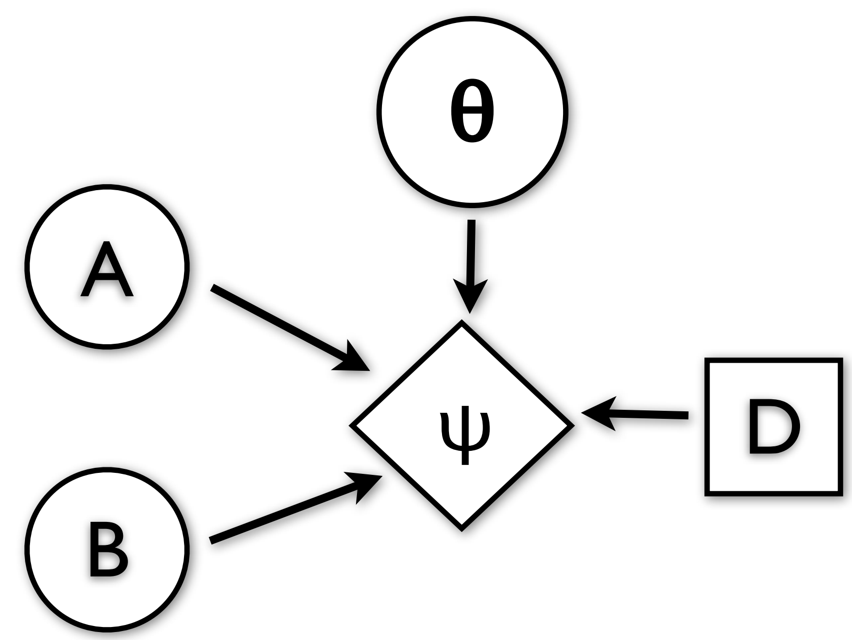


Experimental setup

- Interaction scenario: users instructed to teach the robot a sequence of basic movements (e.g. a small dance)
- Dialogue system comprising ASR and TTS modules, shallow components for understanding and generation, and libraries for robot control
- The Wizard had access to the dialogue state and took decisions based on it (among a set of 14 alternatives)
- 20 interactions with 7 users, for a total of 1020 turns

Each sample *d* in the data set is a pair (b_d, t_d):

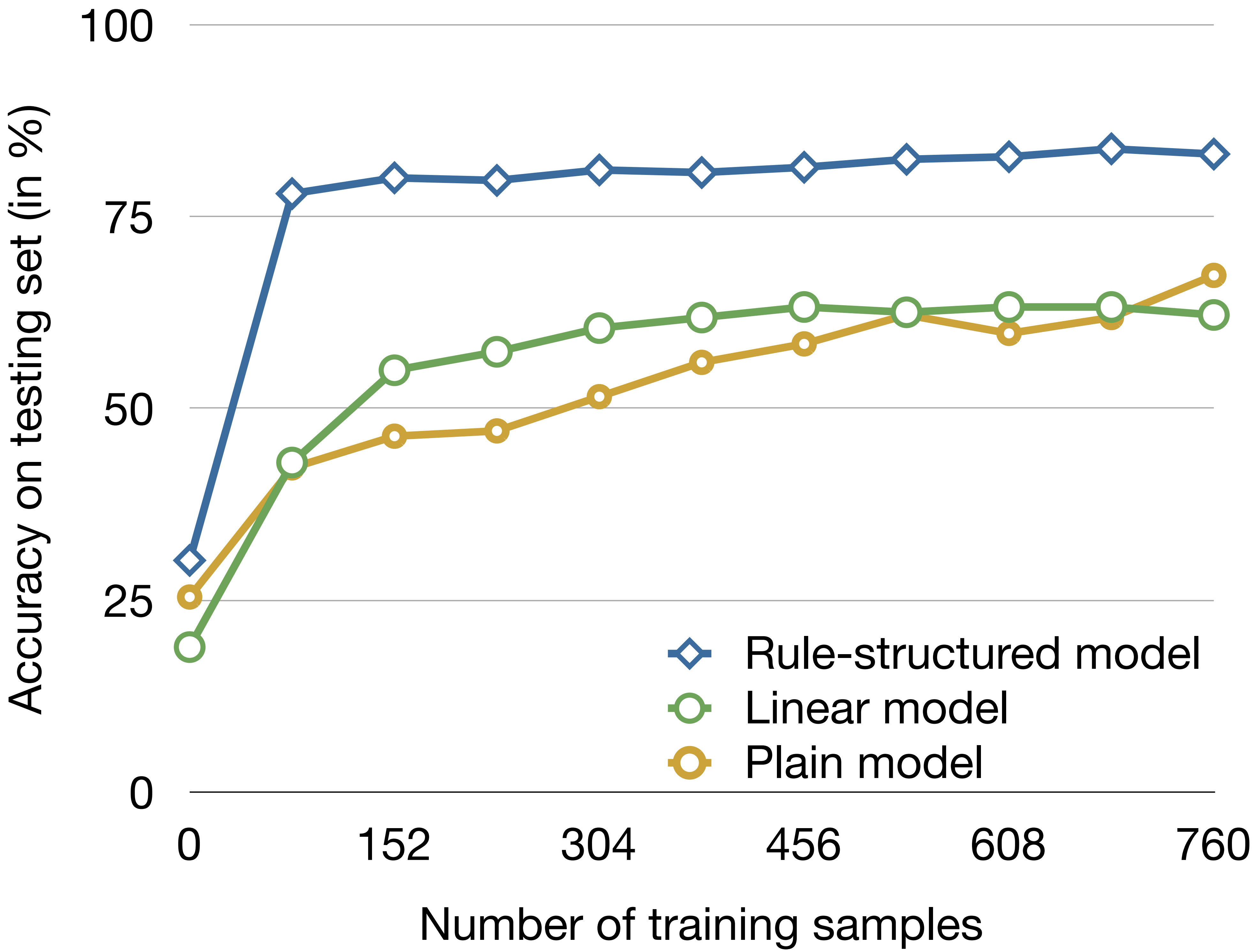
- b_d is a recorded dialogue state
- t_d is the «gold standard» system action selected by the Wizard at the state b_d

Empirical results

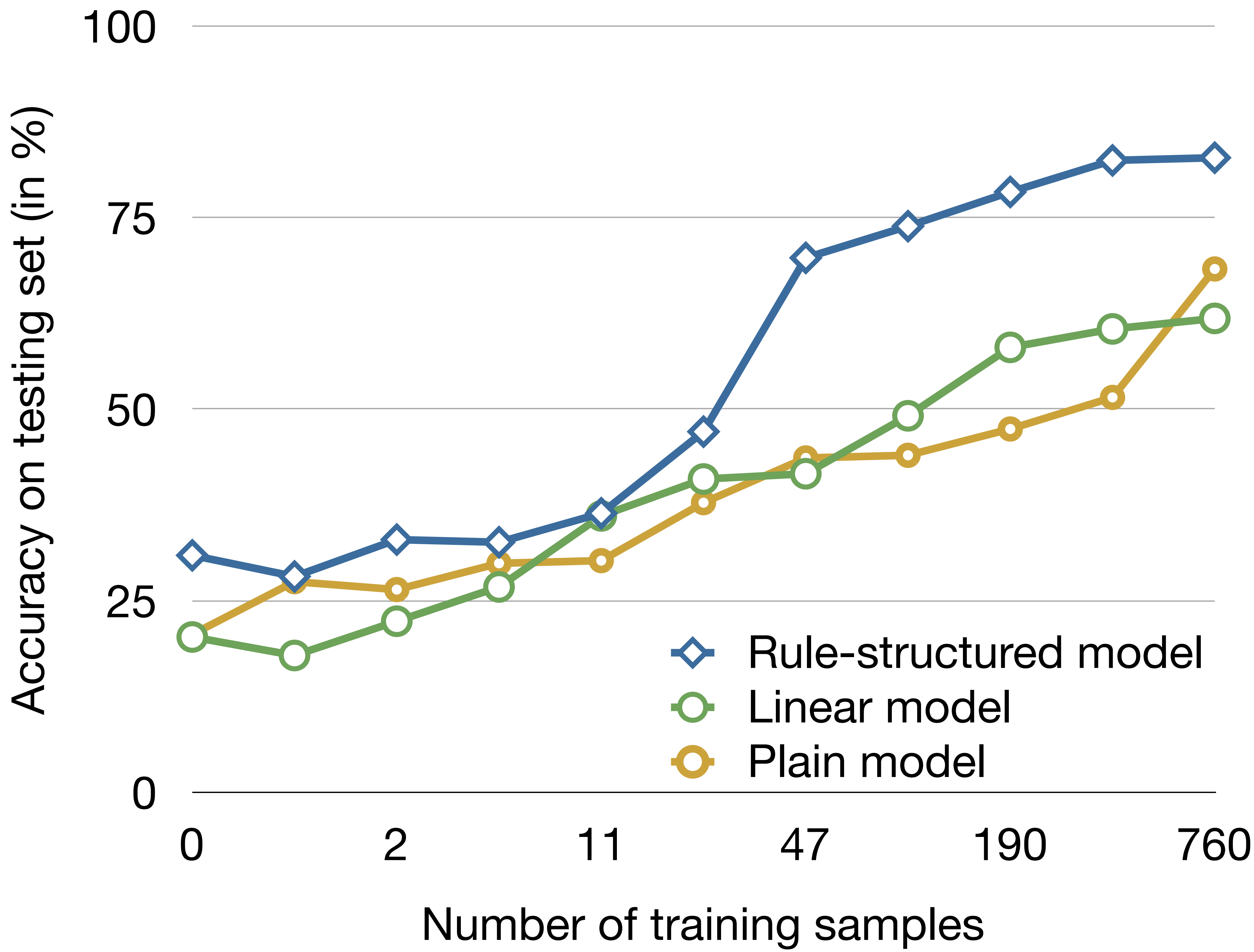
- Data set split into training (75%) and testing (25%)
- Accuracy measure: percentage of actions corresponding to the ones selected by the Wizard
  - But Wizard sometimes inconsistent / unpredictable
- The rule-structured model outperformed the two baselines in accuracy and convergence speed

Type of model	Accuracy (in %)
Plain model	67.35
Linear model	61.85
Rule-structured model	**82.82**

Learning curve (linear scale)



Learning curve (log-2 scale)



Conclusions

- **Probabilistic rules** used to capture the underlying structure of dialogue models
- Allow developers to exploit powerful generalisations and domain knowledge without sacrificing the probabilistic nature of the model
- Framework validated on a policy learning task based on a Wizard-of-Oz dataset
- Future work: extend the approach towards model-based Bayesian *reinforcement learning*