State-based Systems

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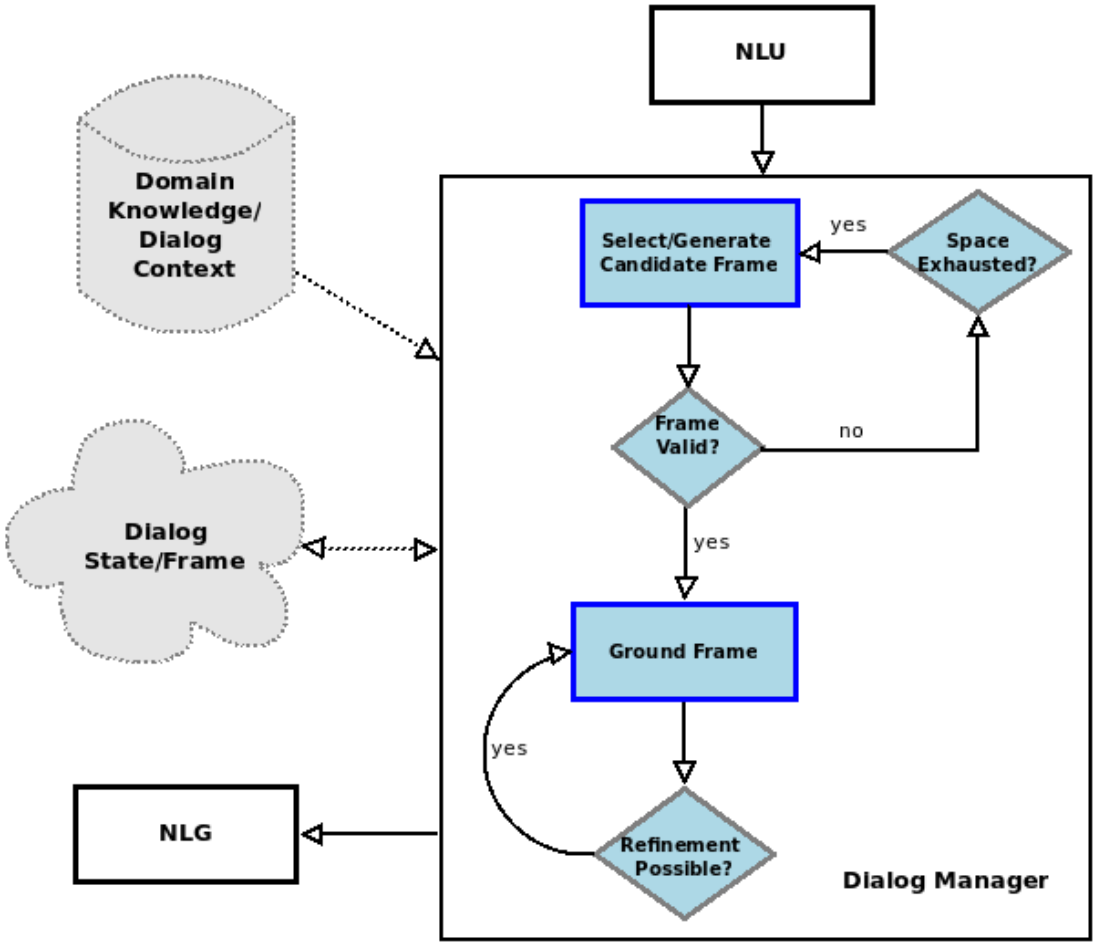
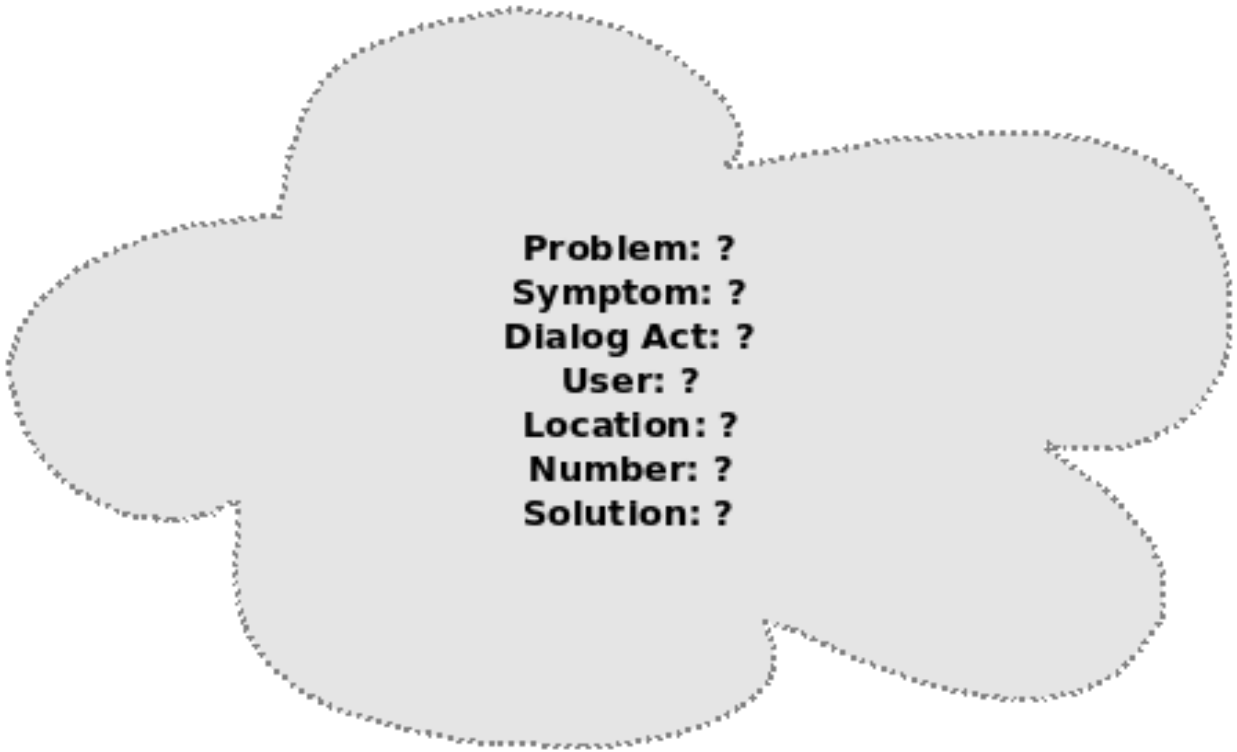
Outline

Reasoning Systems



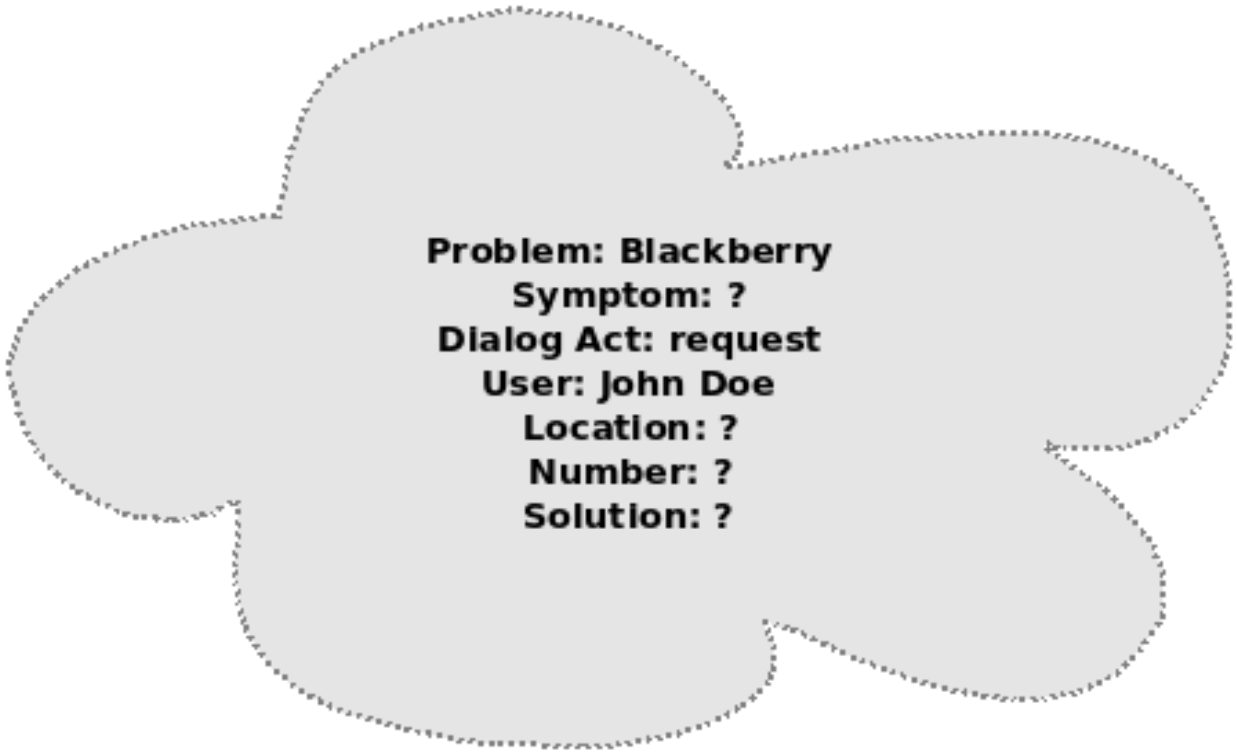
planner

Dialog States



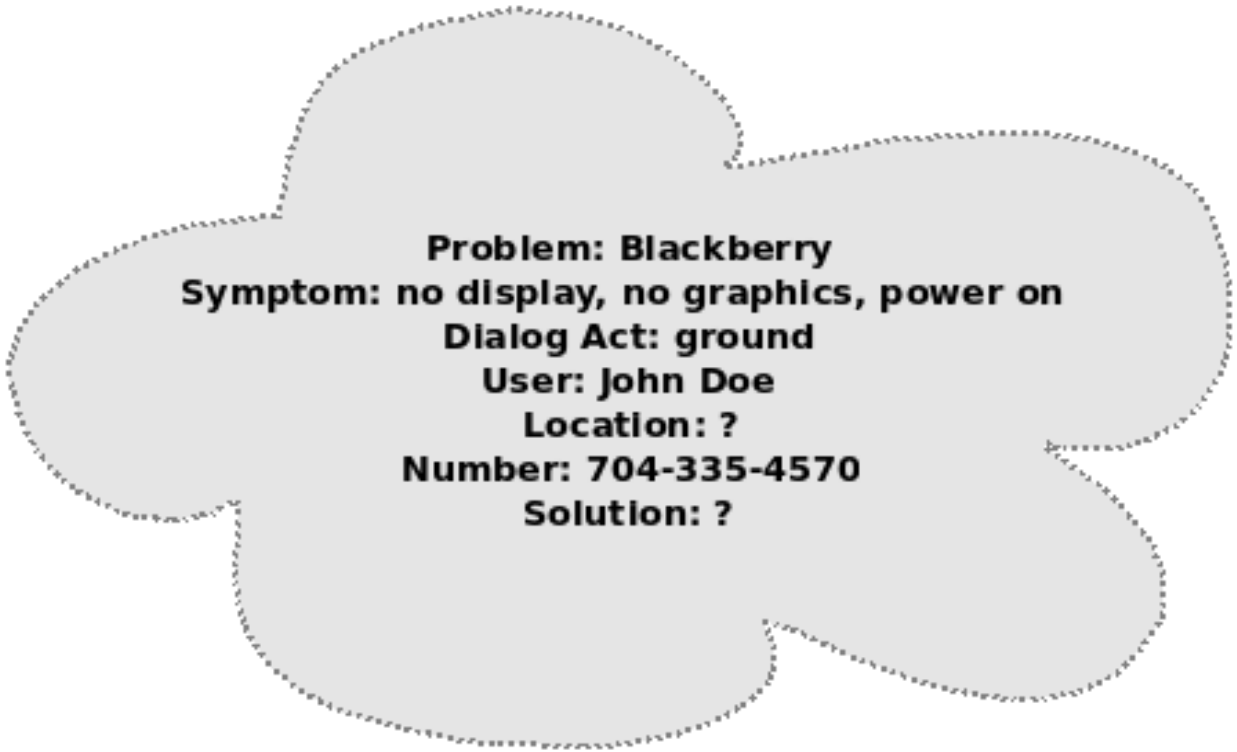
⇒ At the beginning, the frame/state is empty (greet)

Dialog States



$\Rightarrow$ The user request induces a candidate problem (request)

Dialog States

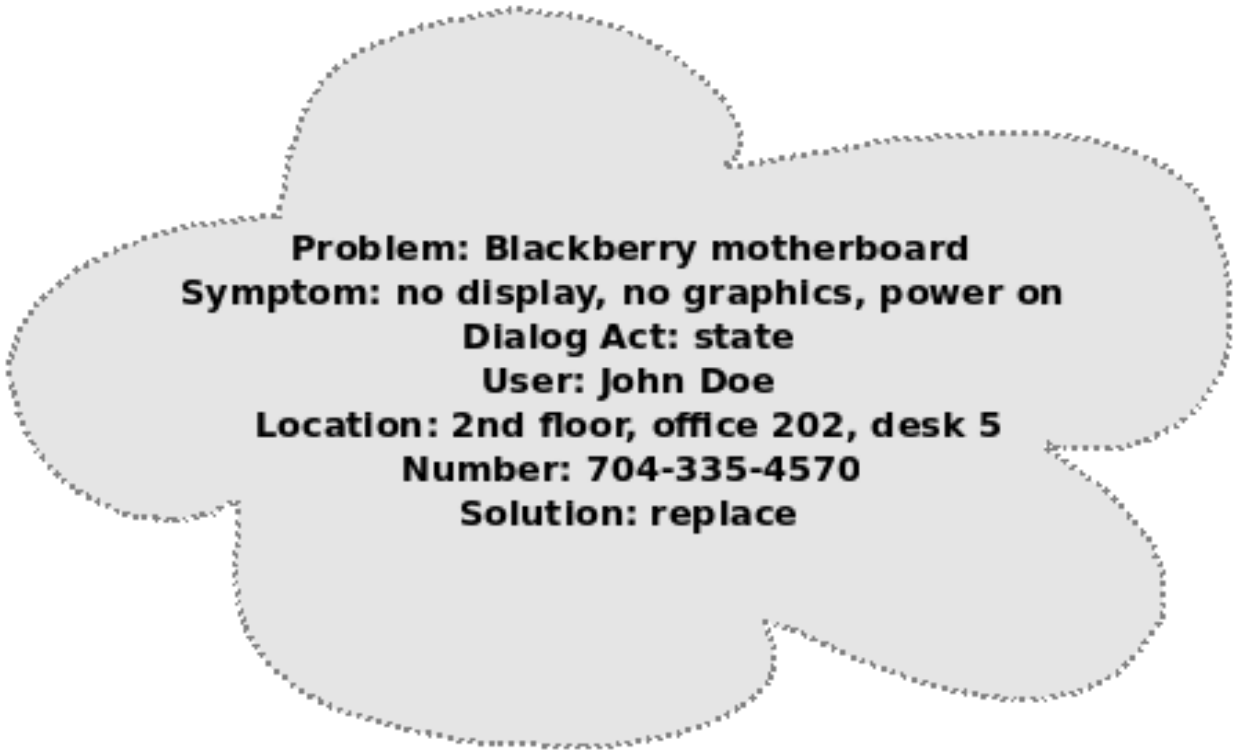


$\Rightarrow$ A conversation is engaged to gather more information (ground)

Dialog States

$\Rightarrow$ We continue until we fill the frame (ground)

Dialog States



$\Rightarrow$ A solution is determined and the dialog ends (state + greet)

Rule-based Management [JM09]

A rule is an expression of the form

```
GREET(u,p,a):
  PRE:
        User(u), Problem(p), DA(a), a=request
  POST:
        AddProblem(p), AddDA(a), AddUser(u),
        Reply("Thank you for choosing to
        chat with IT...")
```

such that if Boolean conditions

```
  User(u), Problem(p), DA(a), a=request
```

are satisfied, a number of actions are triggered

```
  KeepProblem(p), KeepDA(a), KeepUser(u),
  Reply("Thank you for choosing to chat with IT...")
```

Dialog State Update [JM09]

- Preconditions check for the current state S of the dialog
- Actions induce a change in S', giving rise to a new state S'

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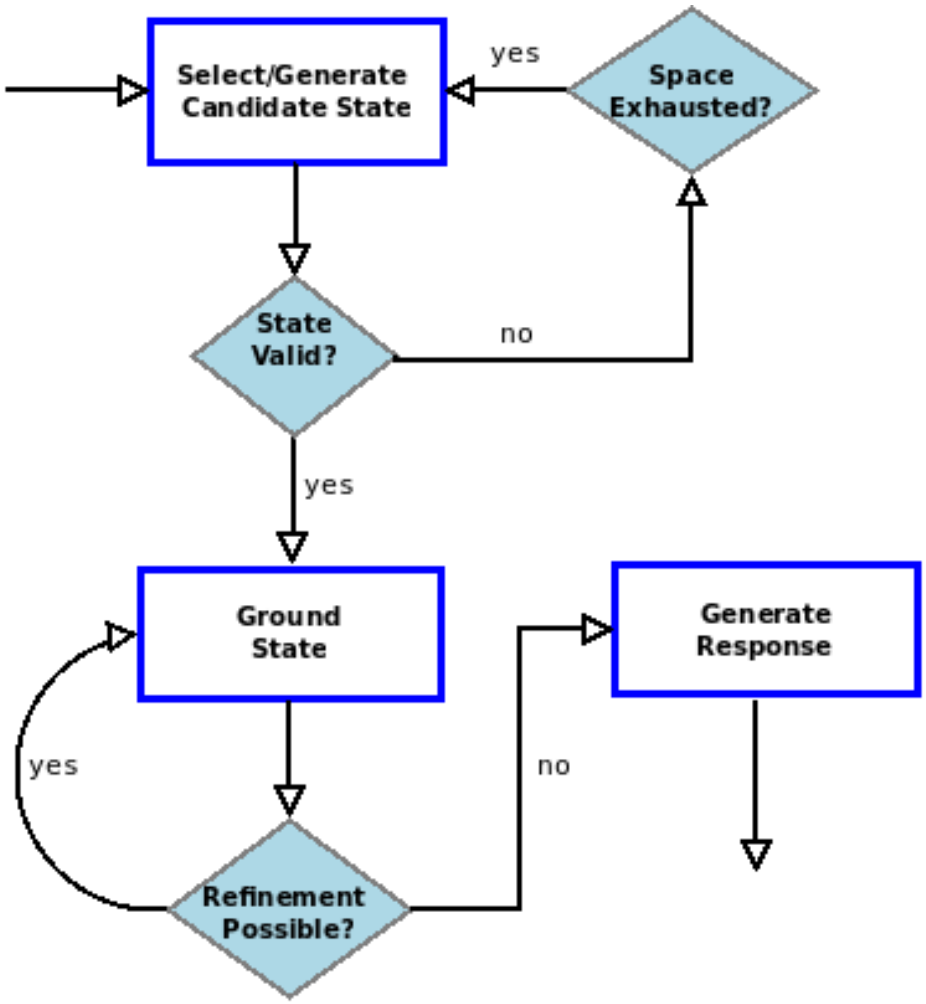
- Via side effects many more operations are possible

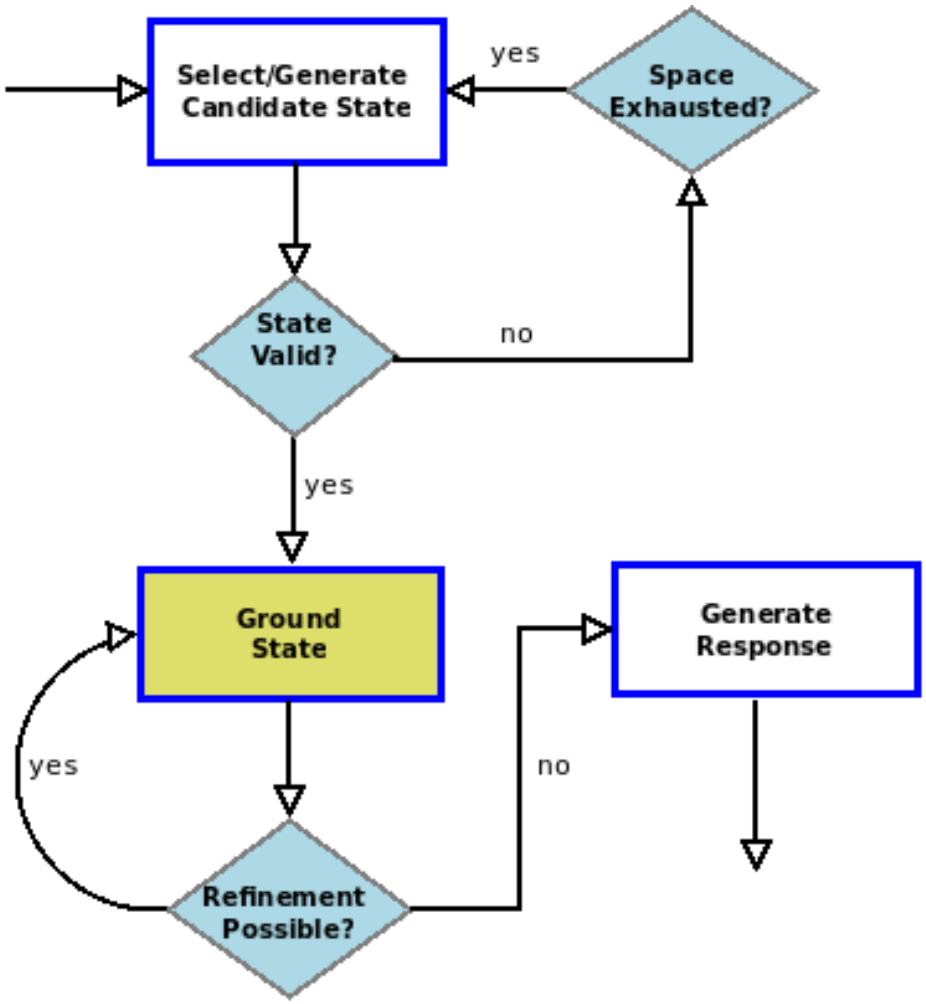
Dialog State Update (ctd.)



More in general, rule-based updates are iteratively executed until a complete DS, the goal state is reached

The grounding module is usually responsible for this task

Dialog State Update (ctd.)



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Examples of State-based Systems

System	Internal State	Manager Type	Domain	Domain Context	Initiative	Anaphora
OpenDial [Lis15]	yes	rule-based/ probabilistic	several	no	double	?
AIDA [BJK+13]	yes	rule-based	several	DB	?	?
Roundtable [FKM+13]	yes	rule-based	several		?	?
Boye et al. [Boy07]	yes	planning	technical	KB	?	?
Chakrabarti et al. [CL12]	yes	rule-based	technical	KB	system	?

⇒ In what follows, we will illustrate the theory using P. Lison's OpenDial system

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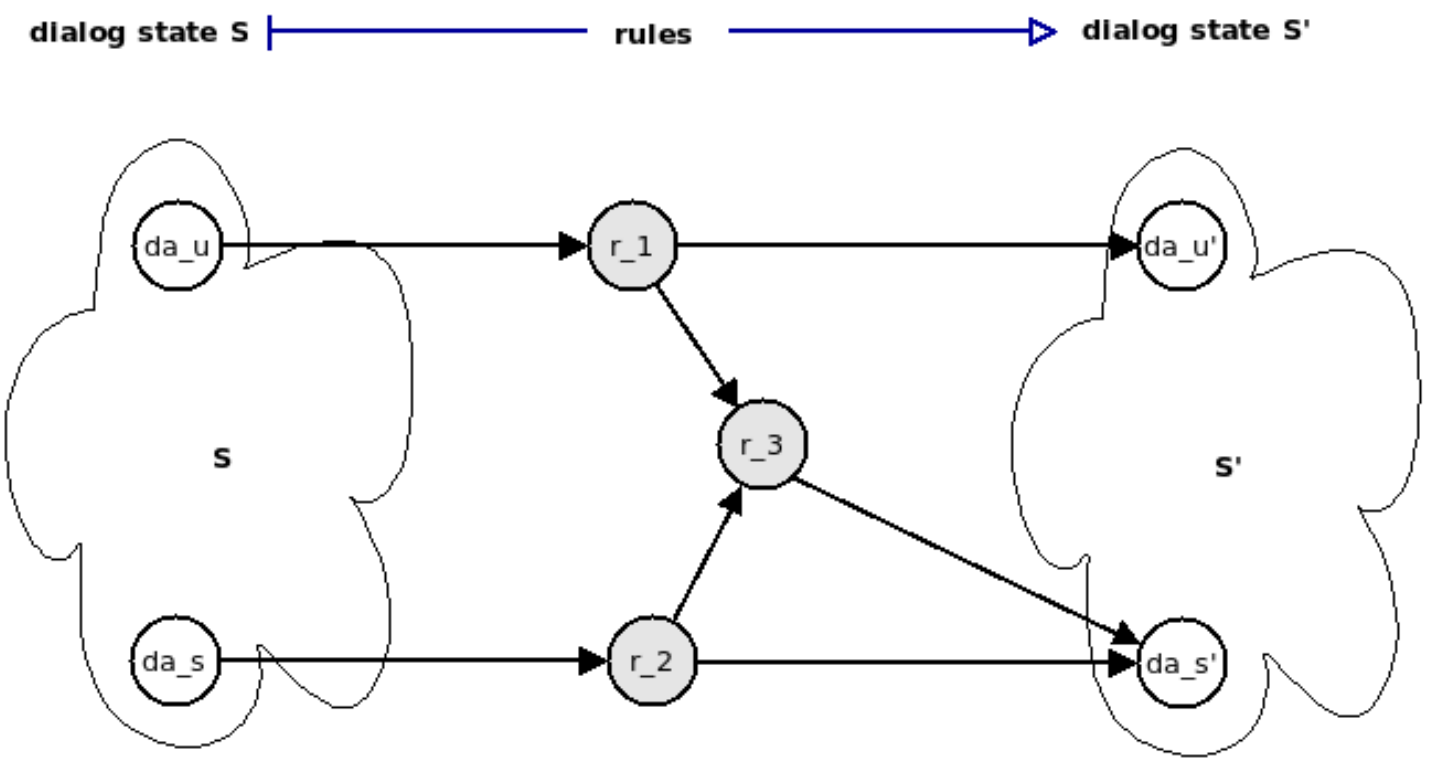
Graph-based Representation [Lis15]



⇒ nodes denote rules and DAs

⇒ incoming edges denote preconditions

⇒ outgoing edges denote actions

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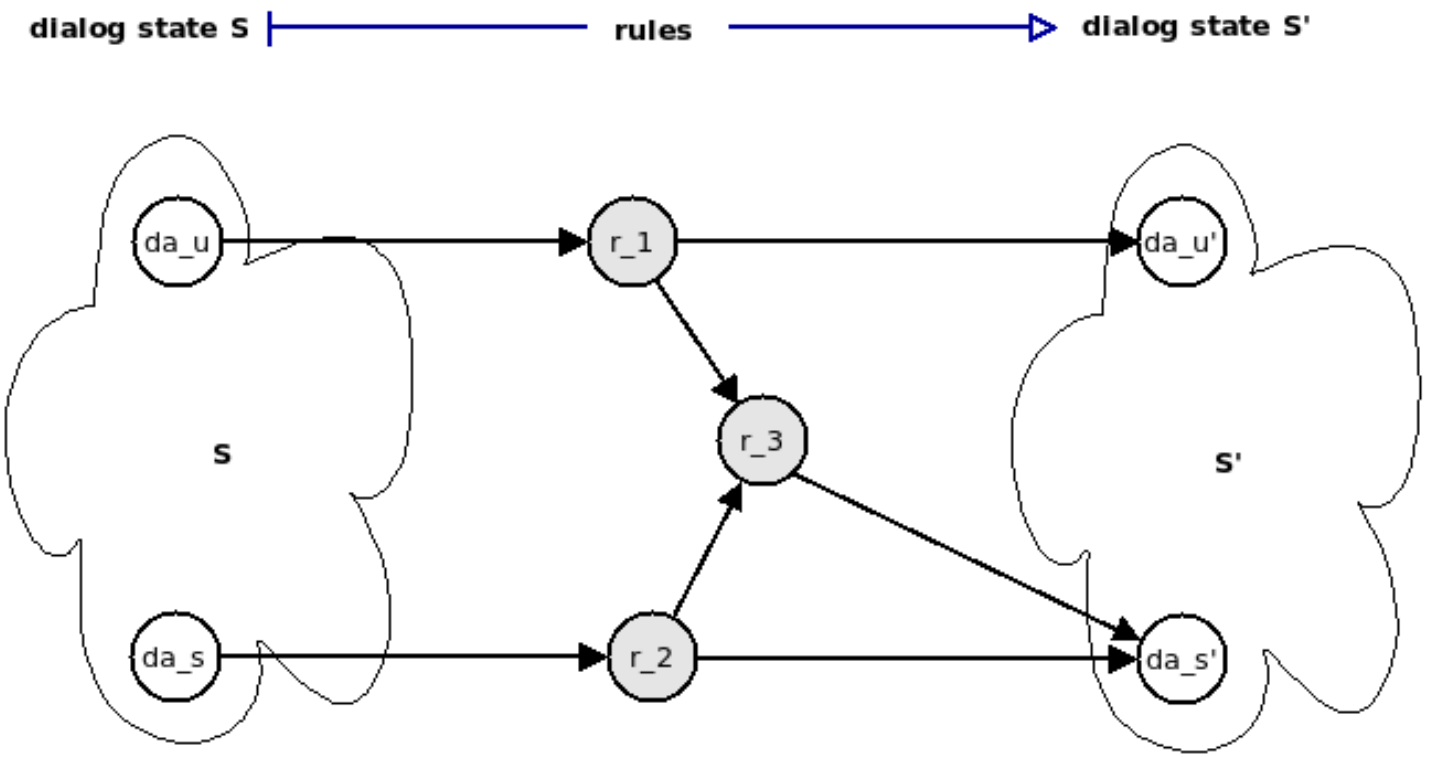

⇒ nodes denote rules and DAs

⇒ incoming edges denote preconditions Bayesian network!

⇒ outgoing edges denote actions

Beliefs, Desires & Intentions

- A planning dialog system can
  1. decide a course of action ⇒ intention
  2. based on its communicative goal/DA ⇒ desire
  3. and background knowledge/context/DS ⇒ belief

- At each step i the DM will
  1. observe the current state S_i of the DS
  2. access the background knowledge (context)
  3. set itself a goal expressed as a system DA
  4. do forward chaining of rules until either the goal or failure is reached

Remark: it is possible to implement a DM using a planning blackbox and dialog rules using rule languages such as the Planning Domain Definition Language (PDDL)

Probabilistic Dialog Management

Probablistic dialog management is based on Markov decision procedures (MDPs) defined at time (= turn) t

- Given

  1. S a sequence $s_0, \ldots, s_t$ of states (= history of DSs at t)
  2. A a sequence $a_0, \ldots, a_t$ of actions (= history of DM actions at t)
  3. transition assignment $b : S \times A \times S \rightarrow [1, 0]$ s.t.

$$b(s_i, a_i, s_{i+1}) = P(S = s_{i+1} \mid S = s_i, A = a_i)$$

  4. $r : S \times A \times S \rightarrow \mathbb{R}$ a reward assignment

- Find the policy $\pi : S \rightarrow A$ that maximizes expected cumulative reward:

$$\pi^* = \arg\max_{\pi} E[\sum_{i=0}^{t} r(s_i, a_i, s_{i+1}) \mid \pi]$$

$\Rightarrow$ If partially observable: add a sequence $O = o_0, \ldots, o_t$ of observations and a belief state b and use them to define r and π

A Simple Exercise

user:	blackberry problem
rep.:	what kind of problem?
user:	black screen
rep.:	anything else?
user:	keyboard unresponsive
rep.:	I'll pass you to the technician
user:	thanks!
rep.:	bye

EXO: How do we implement this Dialog in OpenDial?

Conclusions

1. Reasoning-based dialog systems incorporate rules, a DS and possibly background knowledge
2. They are in principle better at dealing with grounding than chatterbots
3. Their DM can be extended into a full-scale planner and support side-effects
4. Rules can incorporate probabilities to model ambiguity and uncertainty
5. But: most implementations understand only the vocabulary of their domain


Thank You!!!

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Appendix - Computing π^*

To compute π^* it is sufficient to solve the Bellman recurrence

$$V(s) := \begin{cases} 0 & \text{if } s = s_0 \\ \sum_i b(s_i, \pi^*(s_i), s_{i+1}) \times [r(s_i, \pi^*(s_i), s_{i+1}) + V(s_{i+1})] & \text{otherwise} \end{cases} \quad (1)$$

for every state s, where

- $V(s)$ is the cum. reward ("utility") at state s
- $\pi^*(s) := \arg\max_a \Phi$ (Φ is the body of equation 1)

$\Rightarrow$ It can be solved efficiently using dynamic programming