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Towards Online Planning for Dialogue Management with Rich Domain Knowledge

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IWSDS, November 29, 2012

Introduction

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Offline planning	Action selection is straightforward (and efficient)	• Must consider all possible situations • Policy must be recomputed after every model change
Online planning	• Must only plan for current situation • Easier to adapt to runtime changes	• Must meet real-time requirements

Approach

- To address these real-time constraints, we must ensure the planner concentrates on *relevant actions* and states
- **Intuition**: we can exploit *prior domain knowledge* to filter the space of possible actions and transitions
- We report here on our ongoing work with the use of *probabilistic rules* to encode the probability/reward models of our domain

Approach

- We represent the dialogue state as a **Bayesian Network**
- Probabilistic rules are applied upon this dialogue state to update / extend it

- Advantages:
  - (exponentially) fewer parameters to estimate
  - Can incorporate prior domain knowledge

[Pierre Lison, «Probabilistic Dialogue Models with Prior Domain Knowledge», SIGDIAL 2012]

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Probabilistic rules

- The rules 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 *rewards* to particular *actions*:

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

Rule examples

- Example r_1 (probability rule):

if (a_m = AskRepeat) **then**
  $P(a_u' = a_u) = 0.9$
  $P(a_u' \neq a_u) = 0.1$

- Example r2 (reward rule):

if ($a_u \neq$ None) **then**
  $R(a_m' = \text{AskRepeat}) = -0.5$

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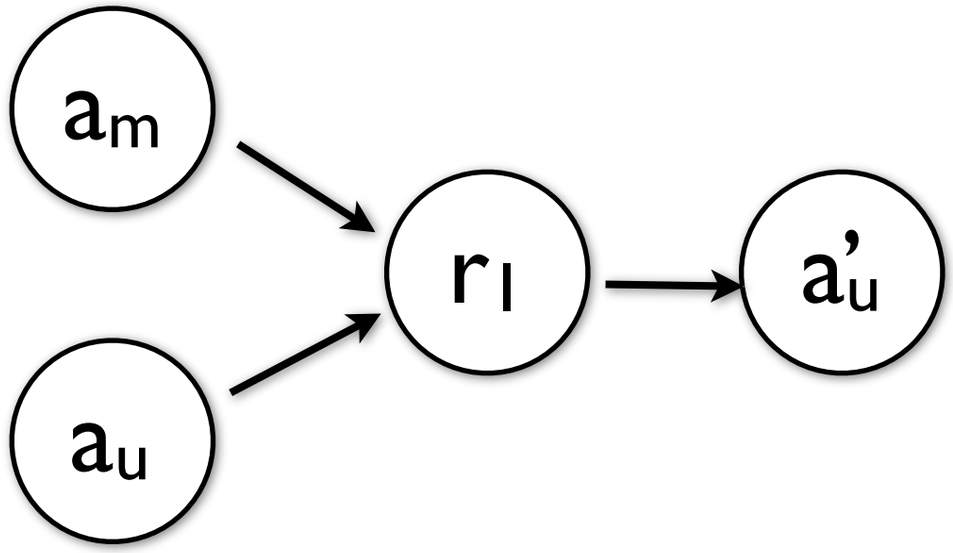

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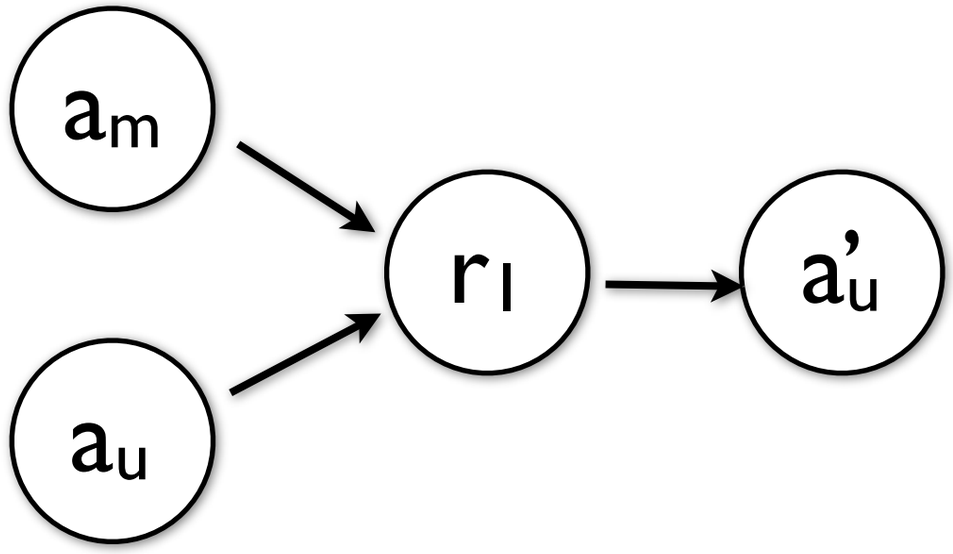

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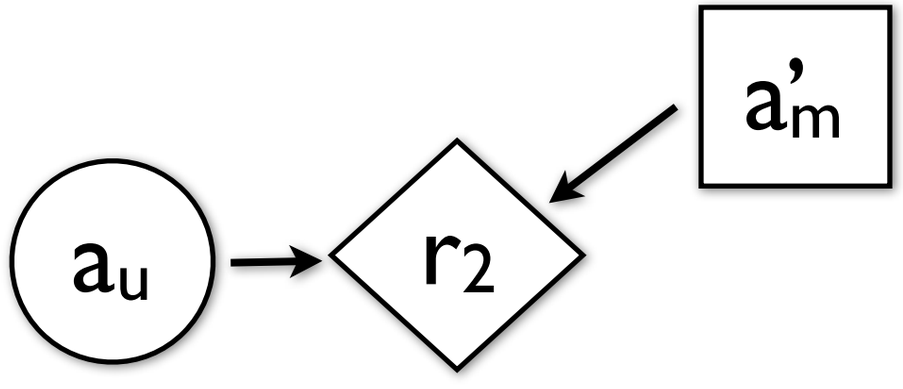

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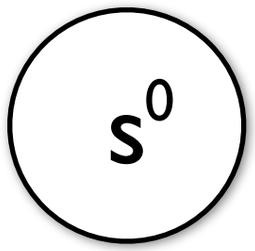
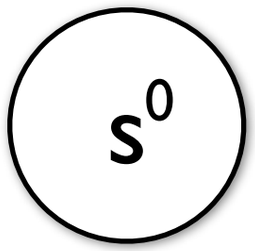
  - samples a collection of **trajectories** (sequence of actions) starting from the current state, until a specific horizon is reached
  - and records the **return** obtained for each trajectory
- The algorithm then searches for the action sequence with highest average return, and executes the first action in this sequence

Planning algorithm

Planning algorithm

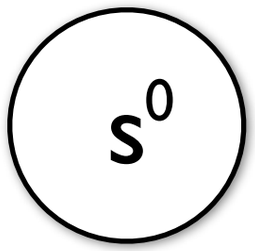


Planning algorithm



Loop (for each trajectory):

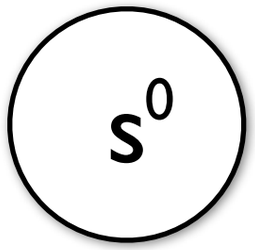
Planning algorithm



Loop (for each trajectory):

Q = 0

Planning algorithm



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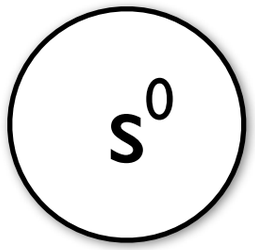
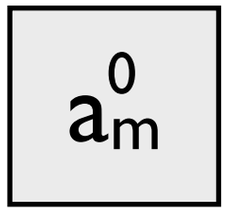




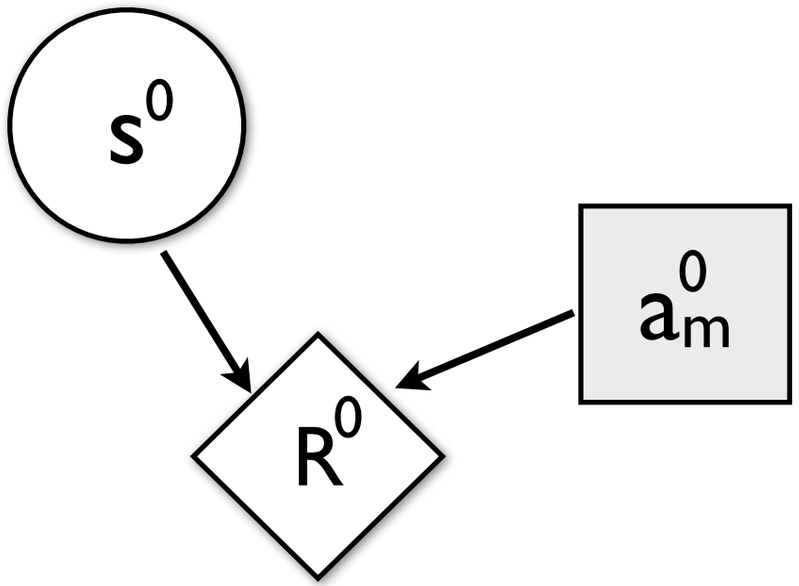
Loop (for each trajectory):

Q = 0

Loop (until horizon reached):

Sample system action a_m

Planning algorithm



Loop (for each trajectory):

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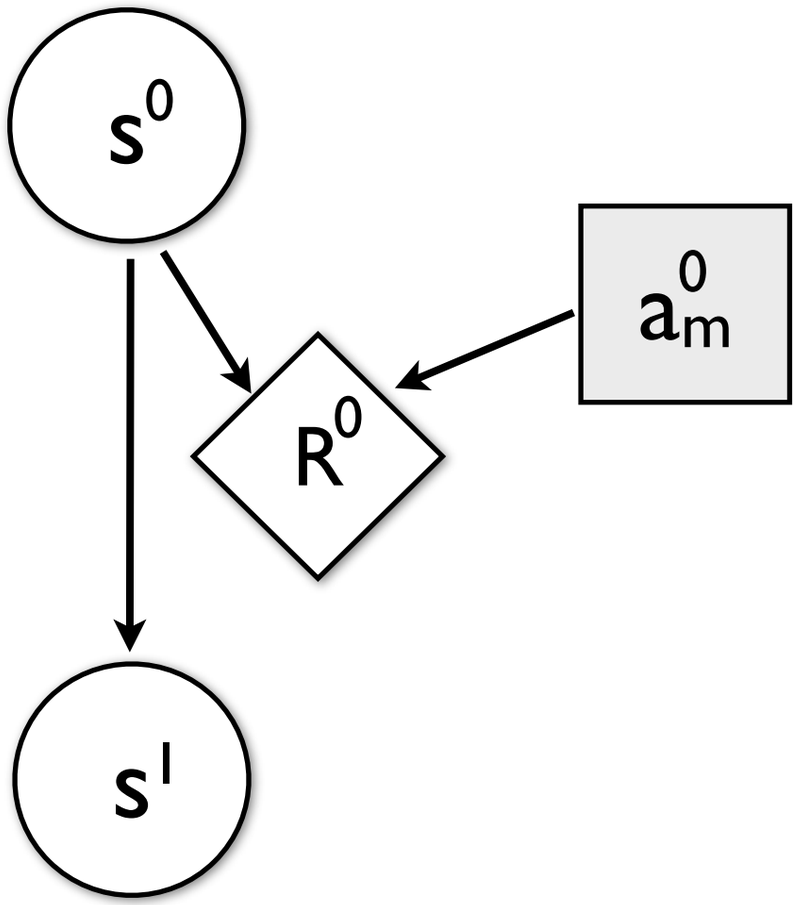
Sample system action a_m

$Q = Q + \gamma^t R$

Planning algorithm



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Predict next state s

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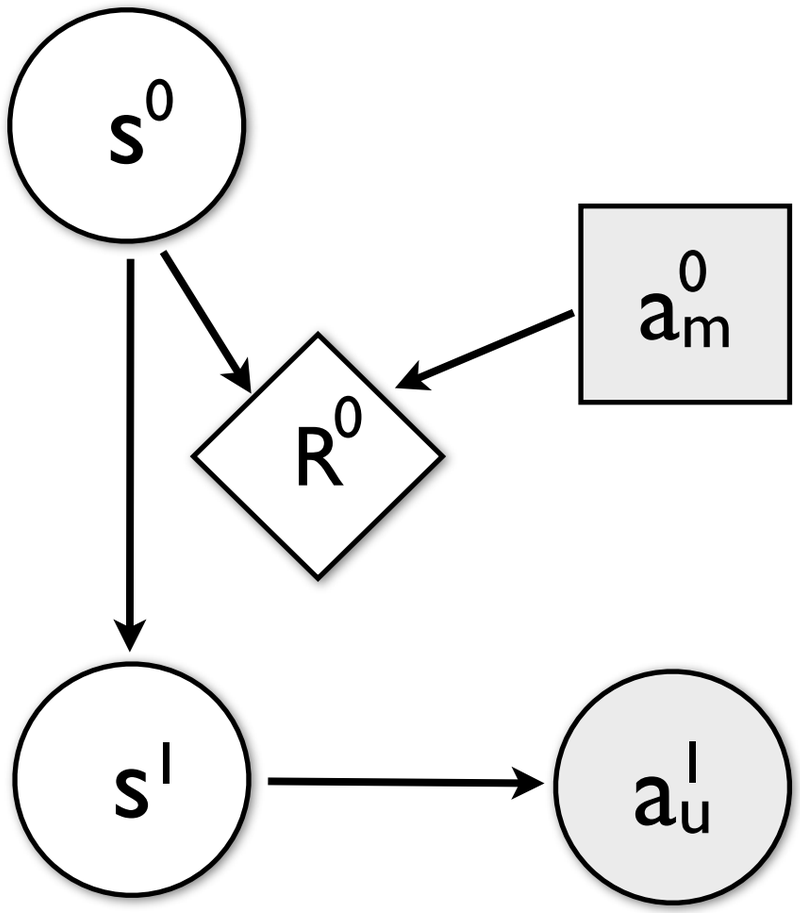

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Sample next user action a_u

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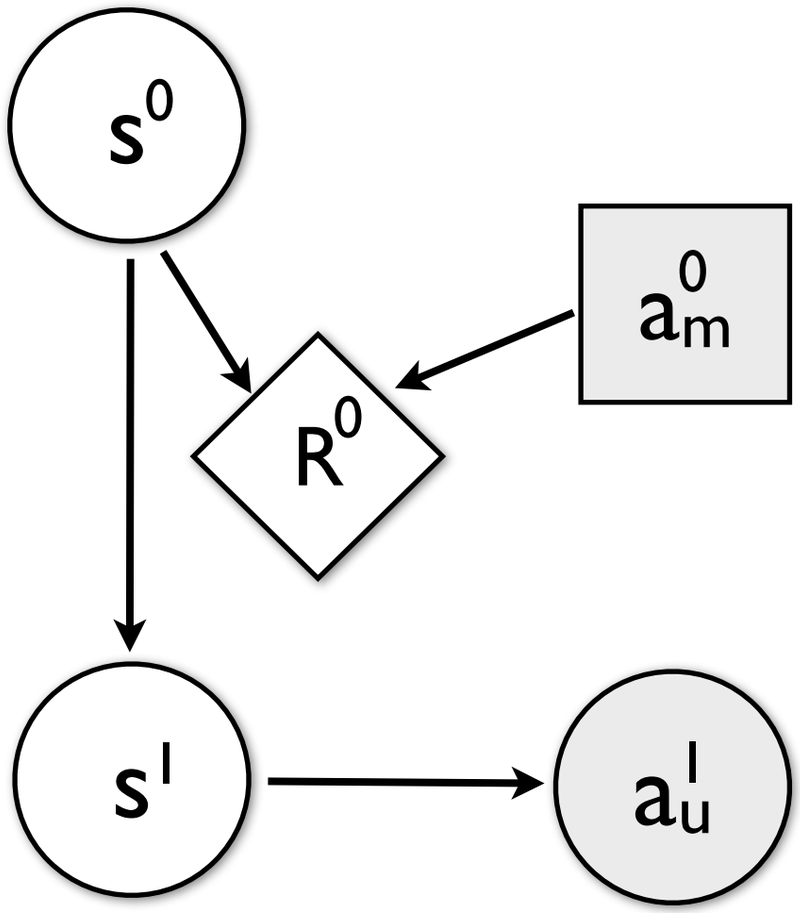

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Predict next state s

Sample next user action a_u

Do belief update

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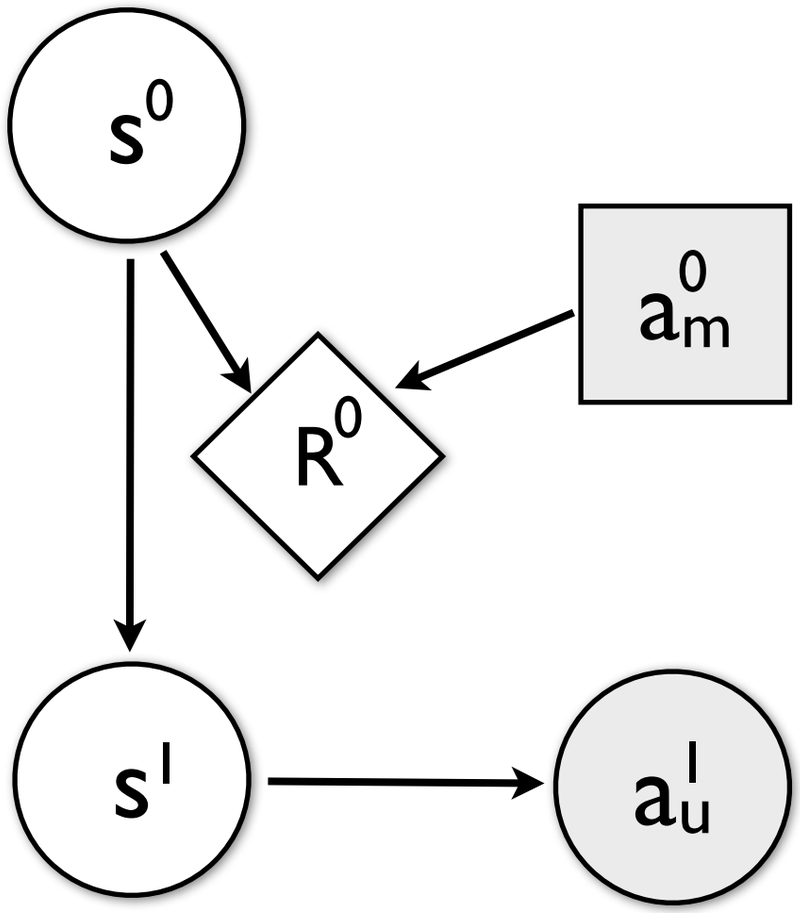

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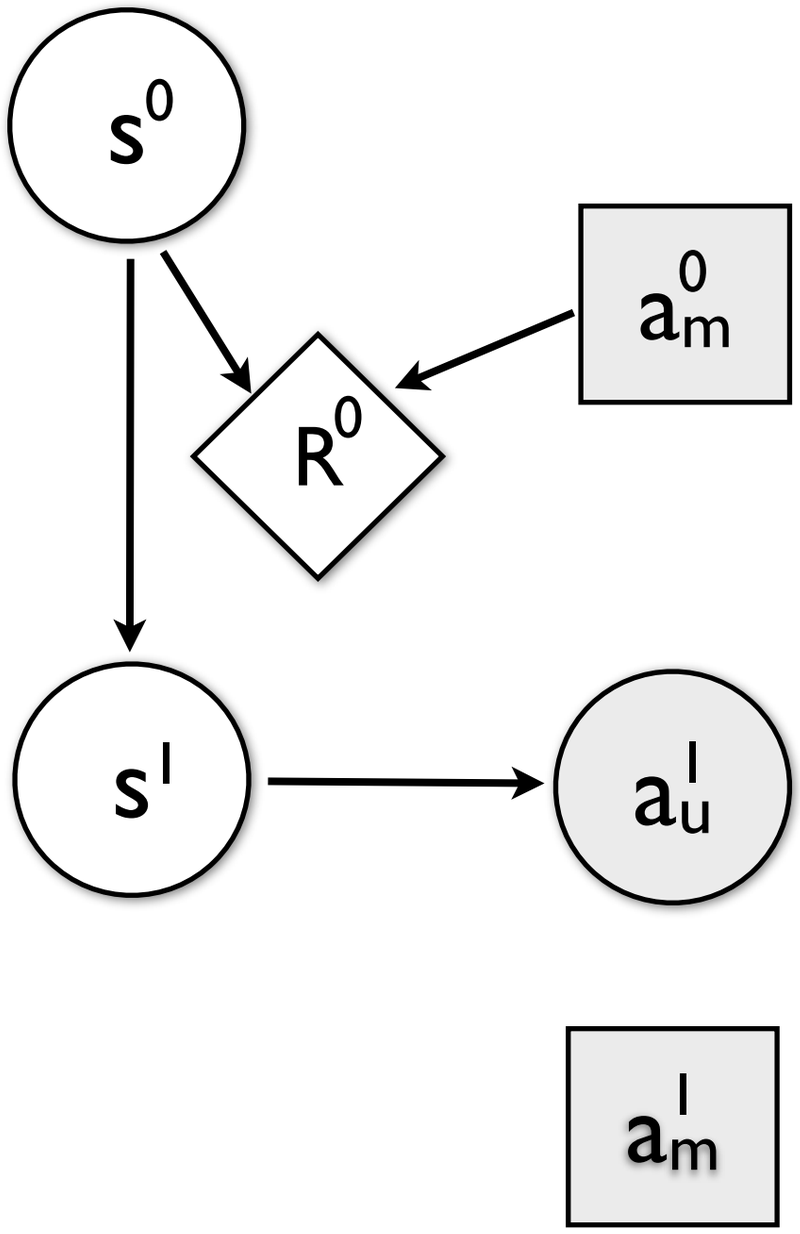

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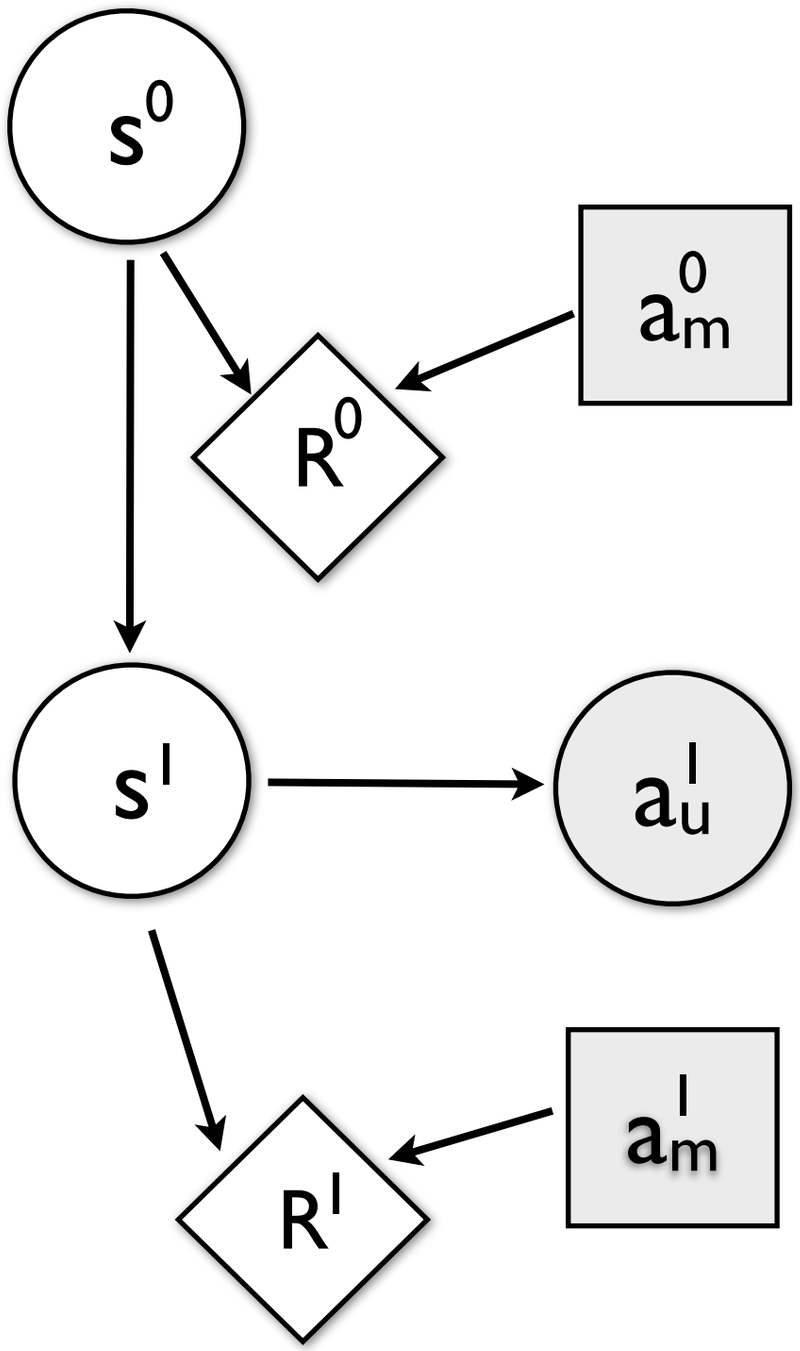

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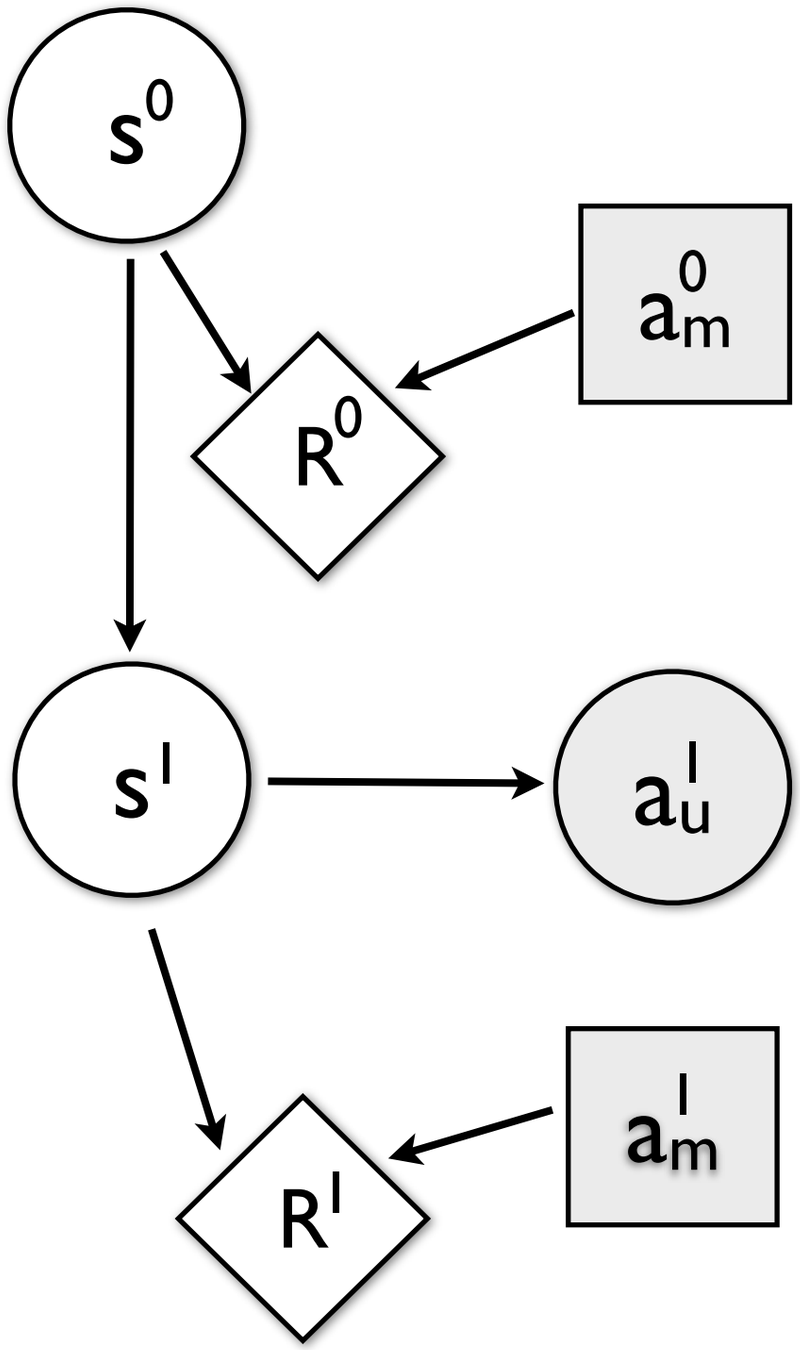

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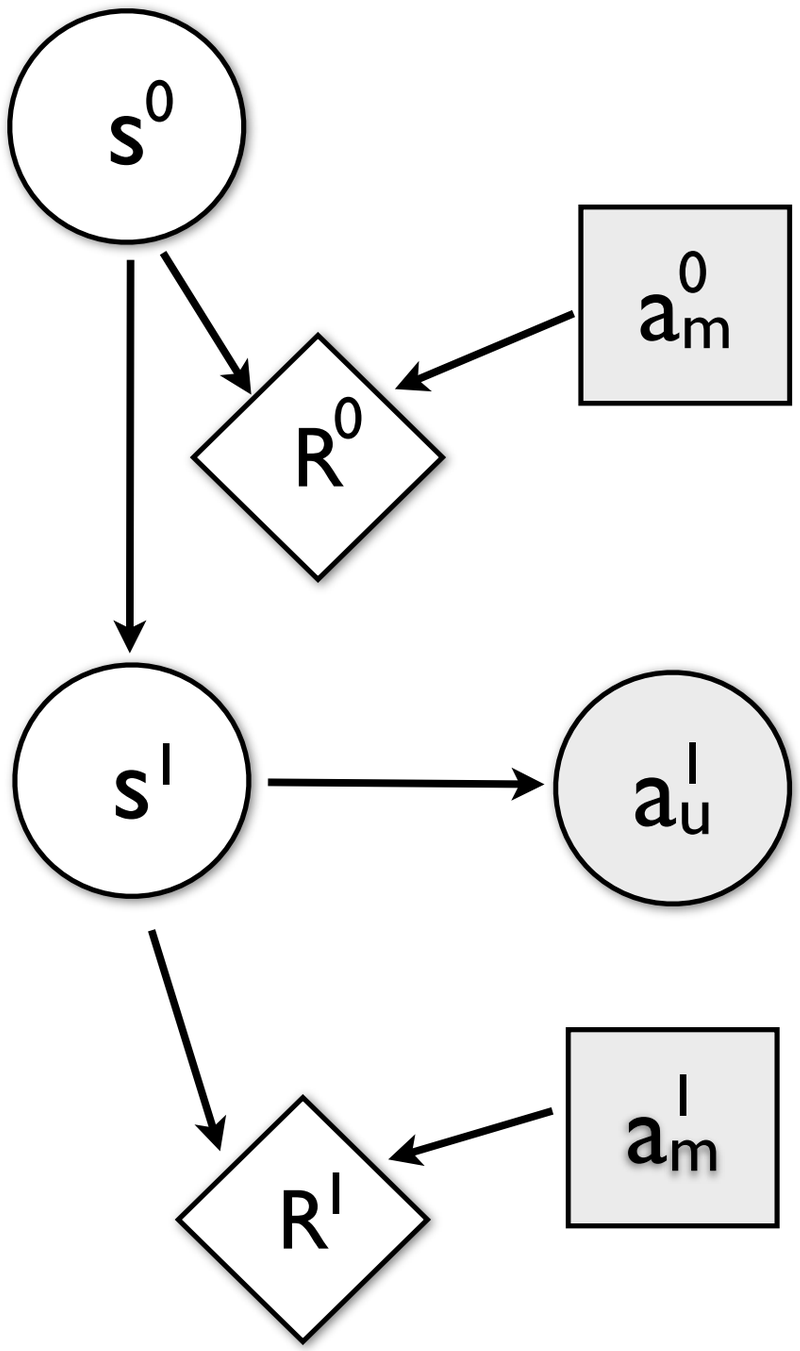

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Predict next state s

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Do belief update

Record Q for trajectory

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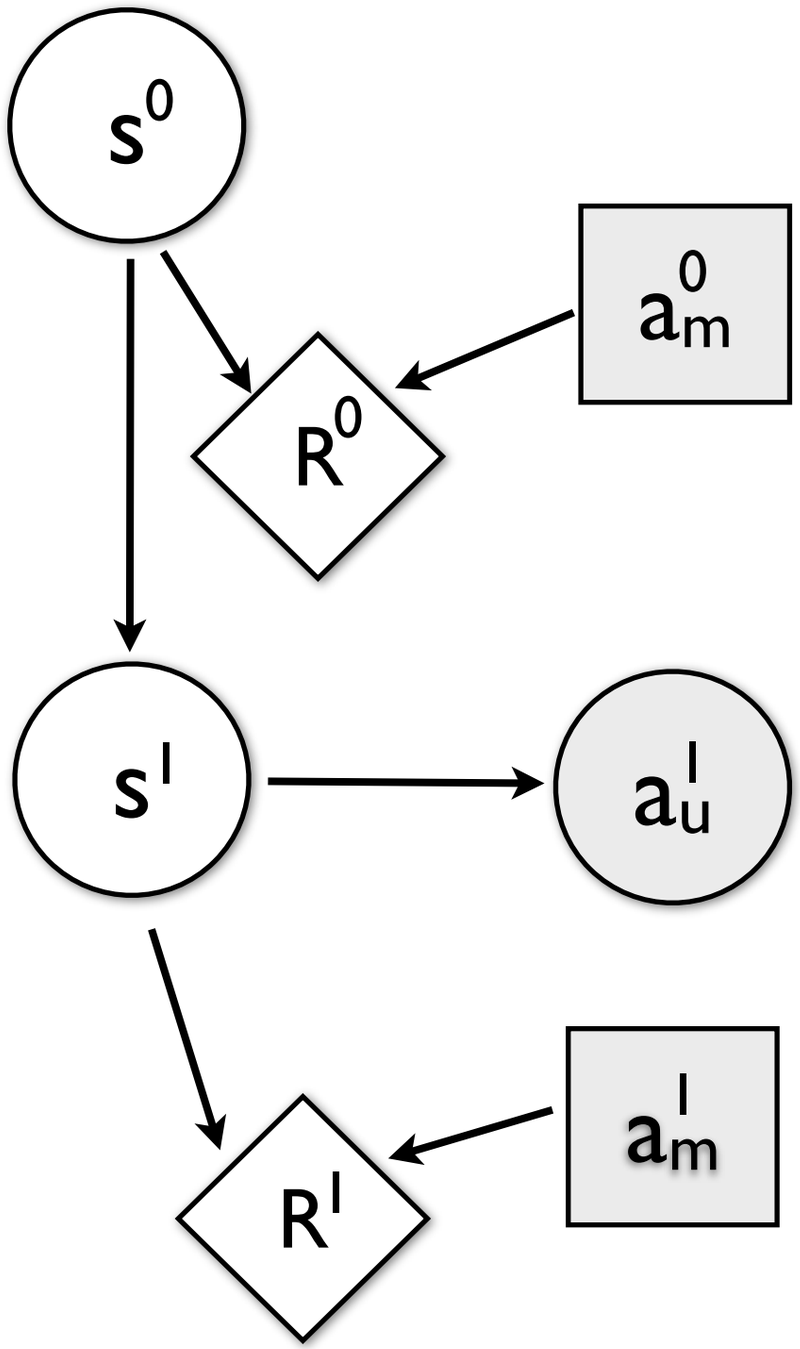

Repeat until enough trajectories are collected

Loop (for each trajectory):

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Loop (until horizon reached):

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Do belief update

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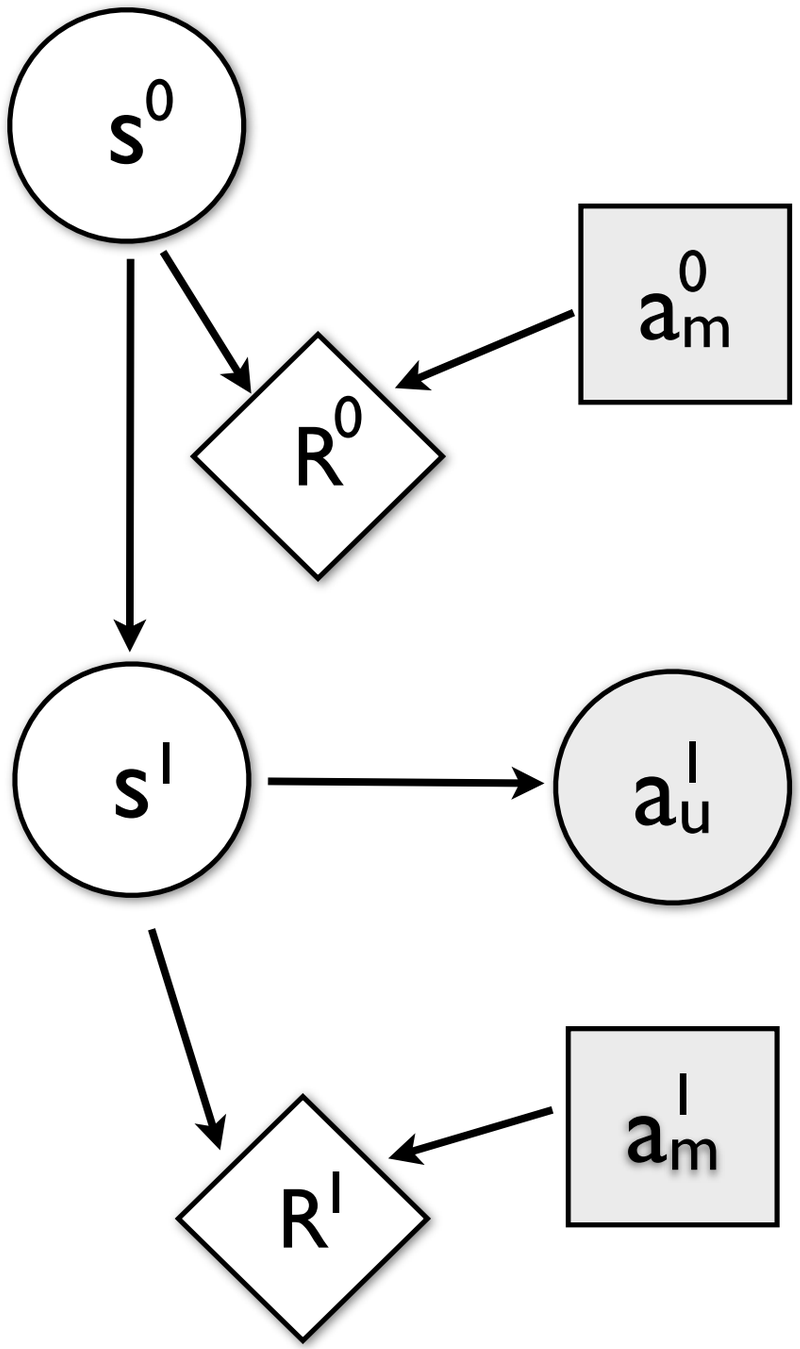

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Loop (until horizon reached):

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Predict next state s

Sample next user action a_u

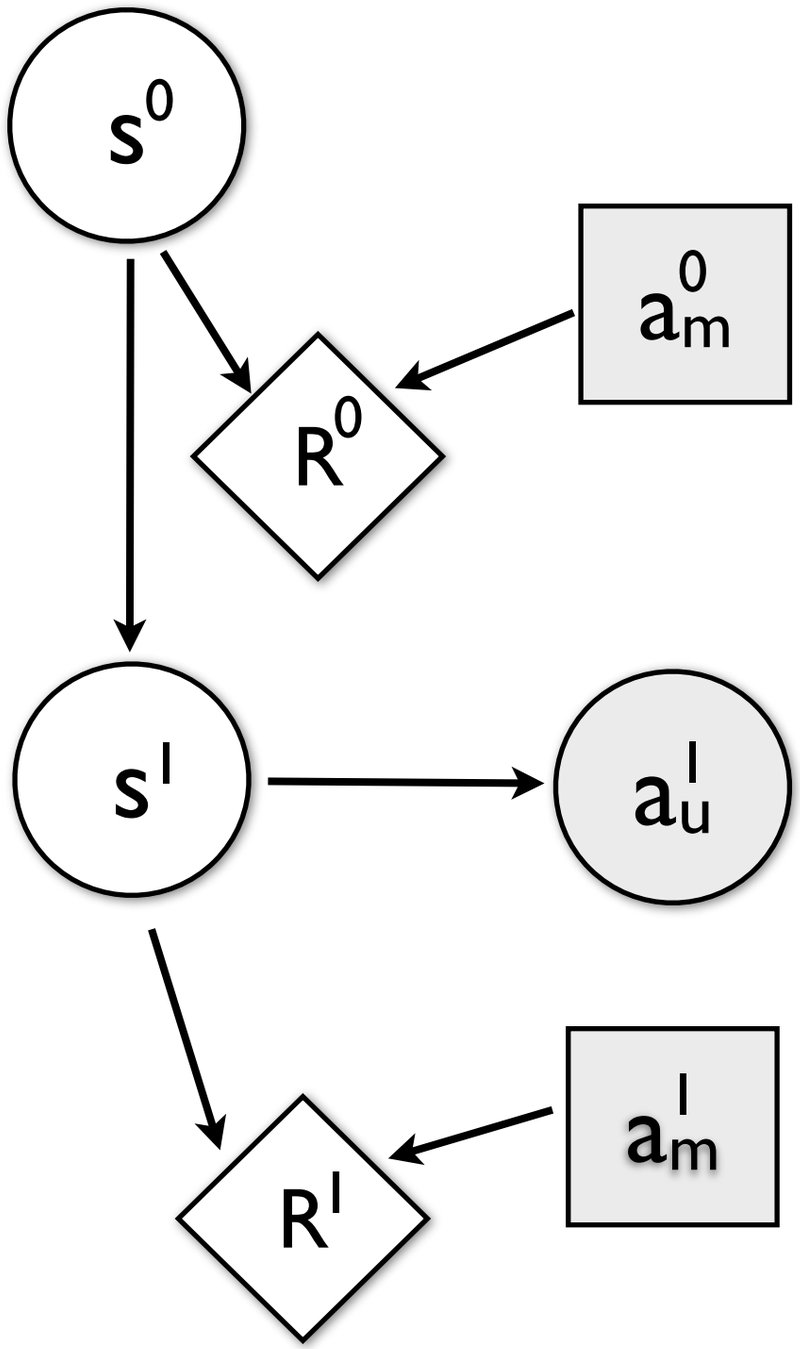
Do belief update

Record Q for trajectory

∀ trajectory, calculate average Q

⋮ until horizon is reached

Planning algorithm



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Loop (for each trajectory):

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Loop (until horizon reached):

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Predict next state s

Sample next user action a_u

Do belief update

Record Q for trajectory

∀ trajectory, calculate average Q

Return trajectory with max. Q

⋮ until horizon is reached

Discussion

- What is original in our approach?
  - The rules provide high-level constraints on the relevant actions (and subsequent future states)
  - For instance, if the user intention is `Want(Mug)`, the rules will provide utilities for the actions `PickUp(Mug)` or `AskRepeat`, but will consider `PickUp(Box)` as irrelevant
  - In other words, they enable the algorithm to quickly focus the search towards high-utility regions
  - ... and discard irrelevant actions and predictions

Discussion

- We did some preliminary experiments with an implementation of this algorithm
  - The rules did make a difference in guiding the search for «relevant» trajectories
  - But unfortunately, the algorithm doesn't yet scale to real-time performance (sorry)
  - Need to find better *heuristics* to aggressively *prune* the applied rules, improve action sampling and the performance of the inference algorithm

Conclusions

- Online planning can help us build more **adaptive** dialogue systems
  - Can be combined with offline planning, using a precomputed policy to guide the search of an online planner!
  - Using *prior domain knowledge* (encoded with e.g. *probabilistic rules*) should help the planner focus on relevant actions and filter out irrelevant ones
- More work needed to find tractable planning techniques, and collect empirical results

Online reinforcement learning

- Links with the reinforcement learning literature:
  - Our approach can be seen as a *model-based* approach to reinforcement learning, where a model is learned and then used to plan the best actions
  - Most other approaches rely on a *model-free* reinforcement learning paradigm, and try to learn the optimal action directly from experience, without trying to estimate explicit models (and plan over them)