

Finding Objects through Stochastic Shortest Path Problems

Manuela Veloso

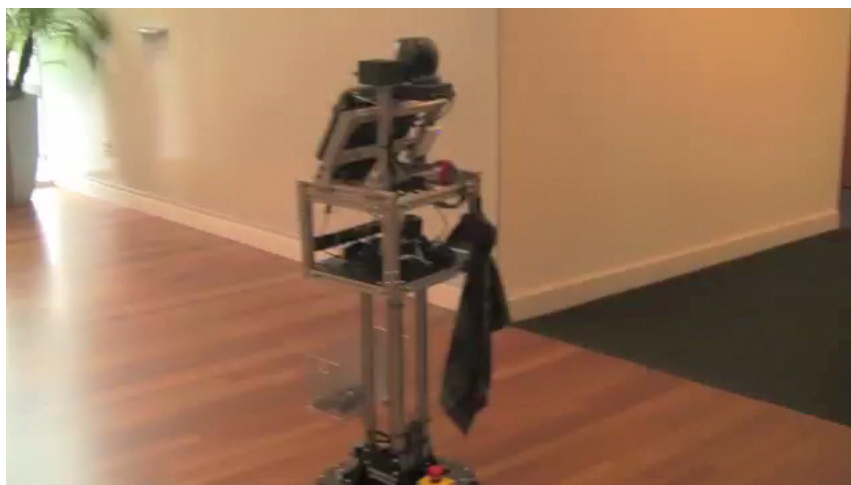
Thanks to Felipe Trevizan

School of Computer Science
Carnegie Mellon University

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CoBot: Autonomous Service Robot

Veloso, Biswas, Coltin, Rosenthal IJCAI'15



Motivation

- An autonomous agent moving in a **known environment** in order to **find an object** while **minimizing** the search **cost**, e.g.,
 - Taxi driver looking for passengers while minimizing the usage of gas
 - Software agent finding information about a product in the web while minimizing bandwidth
 - Service robot retrieving objects to users while minimizing the traveled distance

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Querying and Learning from the Web

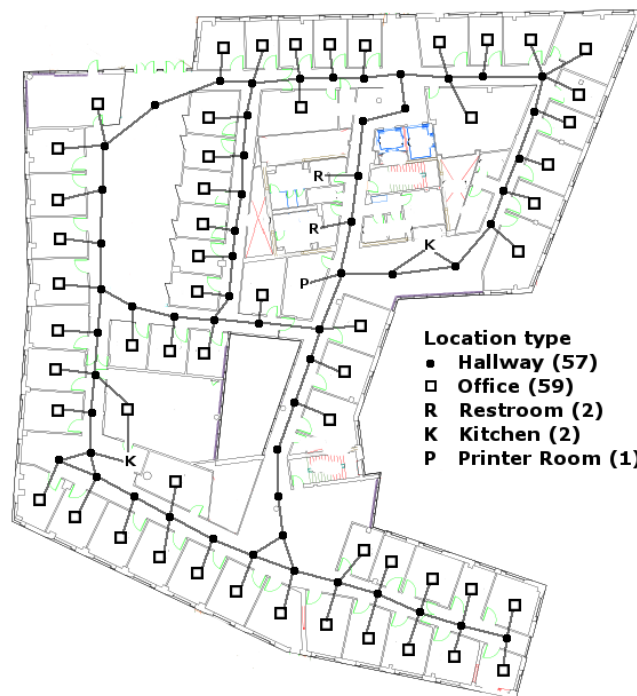


Search for Object Probabilistic Planning

- The probability of objects being in a given location type is obtained using **OpenEval** [Samadi et al, 2012].
- We compare 3 different probabilistic planners to find (also see paper):
 - **Coffee, Cup, Pen, Papers and Toner**

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Map



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Probabilistic Planners

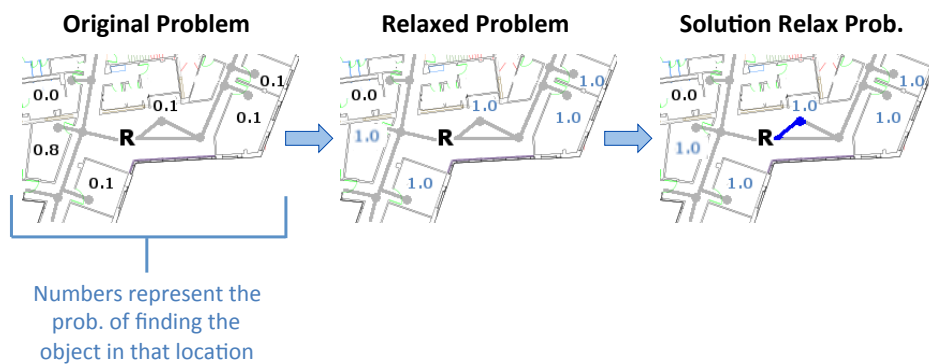
- We compared the following planners:
 - **FF-Replan** [Yoon et al, 2007]
 - **UCT** [Kocsis and Szepesvári, 2006]
 - **SSiPP** [Trevizan and Veloso, 2012]

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FF-Replan

[Yoon et al, 2007]

- Main idea: simplify the problem by **removing the probabilities** from actions

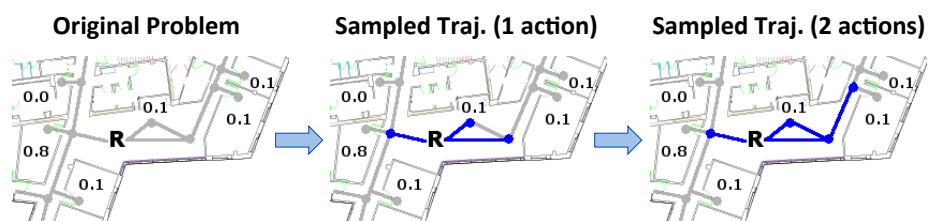


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UCT

[Kocsis and Szepesvári, 2006]

- Main ideas:
 - **Limit** the maximum **number of actions** that can be applied to reach the goal
 - Use sparse **sampling** to search for a solution

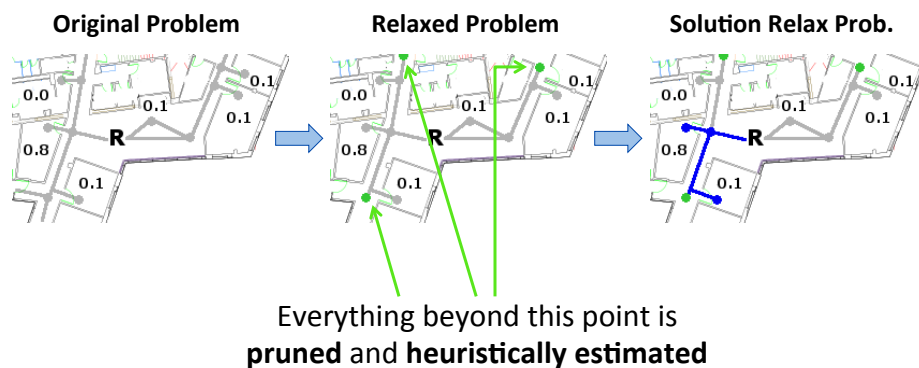


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SSiPP

[Trevizan and Veloso, 2012]

- Main idea: **prune** states reachable only in the **far future**



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Results: Finding a Pen



Probability of finding the a pen at:

Restroom	Kitchen	Office	Printer R.
0.15	0.23	0.35	0.27

Avg and 95% conf. int. of the cost to find a pen:

l_0	FF-Replan	UCT ($c = 8$)	SSiPP ($t = 20$)
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			

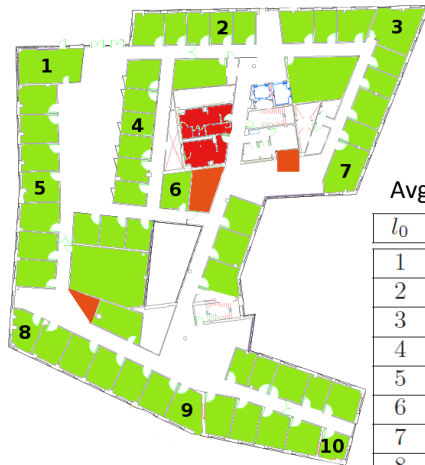
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Results: Finding a Pen (All parameters)

	l_0	UCT $w = 1000$				SSiPP					
		FF-Replan	$c = 2$	$c = 4$	$c = 8$	$t = 10$	$t = 12$	$t = 14$	$t = 16$	$t = 18$	$t = 20$
pen	1	9.4 \pm 2	9.1 \pm 3	8.7 \pm 3	9.3 \pm 4	9.0 \pm 2	10.2 \pm 2	8.7 \pm 2	8.5 \pm 2	9.1 \pm 2	8.4 \pm 1
	2	8.8 \pm 2	8.9 \pm 4	9.0 \pm 2	8.7 \pm 3	9.8 \pm 2	9.2 \pm 2	9.8 \pm 2	8.5 \pm 1	8.9 \pm 2	8.9 \pm 2
	3	8.5 \pm 1	10.8 \pm 3	10.8 \pm 3	12.0 \pm 3	9.5 \pm 2	8.2 \pm 2	9.5 \pm 2	8.9 \pm 2	8.7 \pm 2	7.8 \pm 1
	4	8.2 \pm 2	9.6 \pm 3	10.4 \pm 3	9.1 \pm 3	9.2 \pm 2	8.3 \pm 2	9.0 \pm 2	8.7 \pm 3	9.0 \pm 2	8.5 \pm 2
	5	8.7 \pm 2	9.6 \pm 3	8.6 \pm 2	9.7 \pm 5	9.6 \pm 1	9.9 \pm 2	8.8 \pm 2	9.0 \pm 2	9.4 \pm 2	9.1 \pm 2
	6	11.1 \pm 3	11.0 \pm 3	11.7 \pm 2	10.8 \pm 3	11.0 \pm 2	10.7 \pm 1	10.6 \pm 2	10.0 \pm 2	10.1 \pm 2	10.0 \pm 2
	7	10.9 \pm 2	11.7 \pm 3	11.9 \pm 3	11.4 \pm 4	11.4 \pm 2	11.1 \pm 2	11.2 \pm 2	11.3 \pm 2	11.2 \pm 2	11.5 \pm 2
	8	10.7 \pm 2	10.4 \pm 3	10.9 \pm 2	10.5 \pm 3	10.1 \pm 2	11.8 \pm 2	8.6 \pm 2	10.8 \pm 2	10.4 \pm 2	10.2 \pm 2
	9	11.3 \pm 2	10.4 \pm 3	10.6 \pm 3	10.9 \pm 4	10.2 \pm 2	10.9 \pm 2	10.8 \pm 2	10.9 \pm 2	10.0 \pm 2	10.9 \pm 2
	10	9.7 \pm 2	9.3 \pm 2	9.9 \pm 2	9.7 \pm 2	9.4 \pm 2	9.8 \pm 2	9.5 \pm 2	9.6 \pm 2	9.9 \pm 2	9.5 \pm 2

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Results: Finding Papers



Probability of finding papers at:

Restroom	Kitchen	Office	Printer R.
0.00	0.13	0.70	0.17

Avg and 95% conf. int. of the cost to find papers:

l_0	FF-Replan	UCT ($c = 8$)	SSiPP ($t = 20$)
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			

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Results: Finding Papers (All parameters)

	l_0	FF-Replan	UCT $w = 1000$			SSiPP					
			$c = 2$	$c = 4$	$c = 8$	$t = 10$	$t = 12$	$t = 14$	$t = 16$	$t = 18$	$t = 20$
papers	1	3.3 ±1	3.2 ±1	3.9 ±1	3.9 ±2	3.2 ±0	3.6 ±1	3.2 ±0	3.8 ±1	3.3 ±0	3.6 ±1
	2	3.7 ±1	3.7 ±1	3.1 ±1	4.4 ±1	4.0 ±1	3.7 ±1	4.2 ±1	3.5 ±1	3.8 ±1	3.4 ±1
	3	4.4 ±1	4.9 ±1	4.4 ±1	4.8 ±1	3.7 ±1	3.5 ±1	3.8 ±1	3.8 ±1	3.5 ±1	3.6 ±1
	4	4.4 ±1	4.3 ±1	4.7 ±1	4.9 ±3	3.6 ±1	3.7 ±1	3.5 ±1	3.5 ±1	3.6 ±1	3.7 ±1
	5	3.5 ±1	3.4 ±1	3.9 ±1	3.3 ±1	3.7 ±1	3.9 ±1	3.4 ±1	3.9 ±1	3.5 ±1	3.4 ±1
	6	3.6 ±1	3.7 ±1	3.9 ±1	3.8 ±1	3.5 ±1	3.5 ±1	3.9 ±1	3.6 ±1	3.4 ±1	3.6 ±1
	7	5.9 ±1	6.4 ±1	6.2 ±1	6.0 ±1	6.0 ±1	6.1 ±1	6.0 ±1	5.8 ±1	6.2 ±1	5.8 ±1
	8	4.7 ±1	3.9 ±1	3.5 ±1	3.8 ±1	4.4 ±1	3.5 ±1	3.9 ±1	3.6 ±1	3.6 ±1	3.7 ±1
	9	4.8 ±1	3.5 ±1	3.7 ±1	4.0 ±1	4.0 ±1	3.5 ±1	3.9 ±1	3.8 ±1	3.8 ±1	3.8 ±1
	10	3.4 ±0	3.3 ±1	4.1 ±2	3.5 ±1	3.2 ±1	3.3 ±0	3.5 ±1	3.4 ±1	3.7 ±1	3.5 ±1

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Results: Finding a Toner



Probability of finding a toner at:

Restroom	Kitchen	Office	Printer R.
0.05	0.02	0.06	0.87

Avg and 95% conf. int. of the cost to find a pen:

l_0	FF-Replan	UCT ($c = 8$)	SSiPP ($t = 20$)
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			

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Results: Finding a Toner (All parameters)

	l_0	FF-Replan	UCT $w = 1000$			SSiPP					
			$c = 2$	$c = 4$	$c = 8$	$t = 10$	$t = 12$	$t = 14$	$t = 16$	$t = 18$	$t = 20$
toner	1	54.1 \pm 9	43.2 \pm 10	41.9 \pm 11	41.3 \pm 11	42.8 \pm 7	29.5 \pm 7	27.2 \pm 5	37.9 \pm 7	27.1 \pm 6	27.9 \pm 6
	2	56.8 \pm 9	41.9 \pm 10	45.7 \pm 12	40.3 \pm 11	41.5 \pm 5	19.0 \pm 5	18.3 \pm 5	18.7 \pm 5	18.5 \pm 6	18.3 \pm 6
	3	50.1 \pm 9	56.6 \pm 12	55.3 \pm 11	53.1 \pm 13	38.5 \pm 5	33.1 \pm 6	25.3 \pm 6	22.4 \pm 4	23.4 \pm 9	21.2 \pm 5
	4	61.3 \pm 9	59.3 \pm 10	58.0 \pm 12	42.2 \pm 11	30.2 \pm 9	20.7 \pm 6	20.5 \pm 6	19.1 \pm 7	21.3 \pm 7	19.3 \pm 7
	5	39.3 \pm 6	38.9 \pm 10	31.5 \pm 10	36.5 \pm 12	30.2 \pm 7	31.8 \pm 8	23.9 \pm 5	23.2 \pm 6	25.0 \pm 7	23.6 \pm 7
	6	53.3 \pm 6	37.5 \pm 11	29.8 \pm 7	23.1 \pm 6	18.6 \pm 6	19.6 \pm 4	19.0 \pm 5	18.9 \pm 6	18.4 \pm 4	18.6 \pm 6
	7	45.5 \pm 7	26.4 \pm 10	20.7 \pm 8	21.2 \pm 7	18.3 \pm 5	17.9 \pm 5	18.0 \pm 6	18.4 \pm 7	17.6 \pm 7	17.9 \pm 5
	8	33.9 \pm 8	21.5 \pm 10	19.8 \pm 12	18.7 \pm 9	23.4 \pm 10	19.7 \pm 9	18.8 \pm 6	16.7 \pm 8	16.2 \pm 8	17.1 \pm 7
	9	36.8 \pm 8	29.9 \pm 10	25.9 \pm 10	23.6 \pm 9	18.5 \pm 8	17.6 \pm 6	18.8 \pm 7	18.3 \pm 9	16.6 \pm 6	16.2 \pm 5
	10	54.5 \pm 8	31.5 \pm 9	29.5 \pm 7	27.6 \pm 10	27.8 \pm 6	25.1 \pm 6	23.0 \pm 6	24.1 \pm 7	22.6 \pm 7	22.1 \pm 6

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Search for Object

- We showed
 - how to model object finding as **probabilistic planning** problems
 - that **domain-independent probabilistic planners** offer framework which:
 - is **extremely flexible** (e.g., *makeCoffee*, *buyCoffee*)
 - represents a **well defined** optimization problem
- We empirically compared FF-Replan, UCT and **SSiPP** for the obtained class of problems

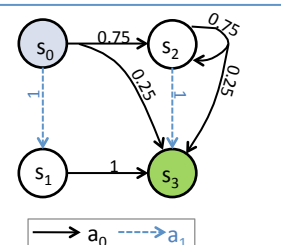
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Stochastic Shortest Path Problems

An SSP is the tuple $\langle S, s_0, G, A, P, C \rangle$:

- Set of states S
- Initial state s_0
- Set of goal states $G \subseteq S$
- Set of actions A
- Transition probability $P(s' | s, a)$
- Cost $C(s, a, s') > 0$
 - defined when $P(s' | s, a) > 0$

Example



$G = \{s_3\}$

$C(, a_0,)$:

s'/s	s_0	s_1	s_2
s_2	1	--	1
s_3	2	2	2

$C(, a_1,)$:

s'/s	s_0	s_2
s_1	2	--
s_3	--	7

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Solutions for SSPs

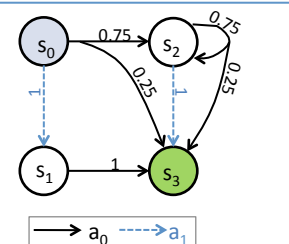
- The **solution** for an SSP is a policy, i.e., a **mapping from states to actions**.
- An **optimal** policy π^* minimizes $V^*(s_0)$, i.e., the expected cost to reach a goal state from s_0 .

$$V^*(s) = \begin{cases} 0 & \text{if } s \in G \\ \min_{a \in A} \sum_{s' \in S} P(s'|s, a) [C(s, a, s') + V^*(s')] & \text{otherwise} \end{cases}$$

- In the example:

	s_0	s_1	s_2
π^*	a_1	a_0	a_0

Example



$G = \{s_3\}$

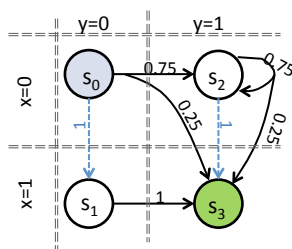
s'/s	s_0	s_1	s_2
s_2	1	--	1
s_3	2	2	2

s'/s	s_0	s_2
s_1	2	--
s_3	--	7

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Factored Representation

- Use **state variables** to represent the state space S :
 - $F: \{f_1, \dots, f_k\}, f_i \text{ in } \{0, 1\}$
 - $S = \{0, 1\}^k$
- Benefit:** compact representation
- In the example, two state variables: x and y

Representation of $P(s' | s, a_0)$

Explicit:

s/s'	s_0	s_1	s_2	s_3
s_0	0	0	.75	.25
s_1	0	0	0	1
s_2	0	0	.75	.25
s_3	0	0	0	1

Factored:

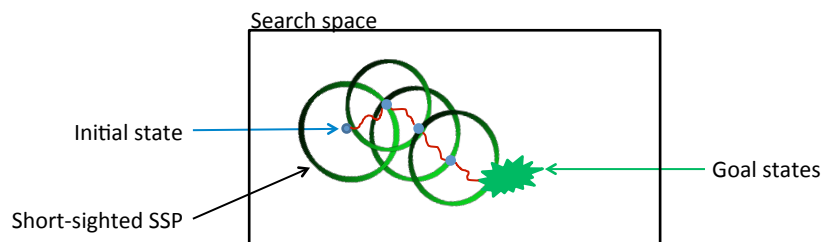
x/x'	0	1
0	.75	.25
1	0	1
y/y'	0	1
0	0	1
1	0	1

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Planner: SSiPP

[Trevizan and Veloso, 2012]

- Generate a *short-sighted SSP*:
 - **Prune** the state space
 - Heuristically **estimate the cost** of pruned states
- Solve the subproblems and execute this solution
- Repeat until goal is reached



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Short-Sighted SSPs: Definition

- Given:
- an SSP $\langle S, s_0, G, A, P, C \rangle$,
 - $s \in S$
 - $t > 0$ and
 - a heuristic function H

$\delta(s, s')$: minimum number of actions to reach s' from s

the (s, t) -short-sighted SSP is $\langle S', s, G', A, P, C' \rangle$:

- $S' = \{s' \in S \mid \delta(s, s') \leq t\}$
- $G' = \{s' \in S \mid \delta(s, s') = t\} \cup (G \cap S')$
- $C'(s, a, s') = \begin{cases} C(s, a, s') + H(s') & \text{if } s' \in G' \\ C(s, a, s') & \text{otherwise} \end{cases}$

States reachable using **up to t** actions

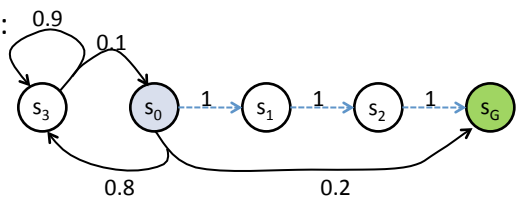
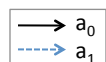
Artificial goal: states reachable using **exactly t** actions

If s' is an artificial goal, then its cost is incremented by its heuristic value

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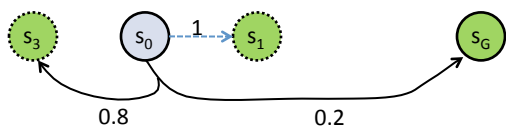
Short-Sighted SSPs: Example

- Original problem:

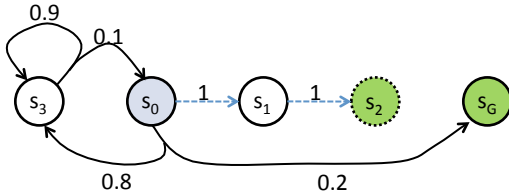


	$\delta(a_0, s)$
s_0	0
s_1	1
s_2	2
s_3	1
s_G	1

- $(s_0, 1)$ -short-sighted:



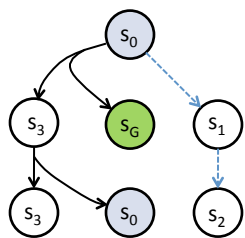
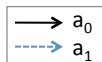
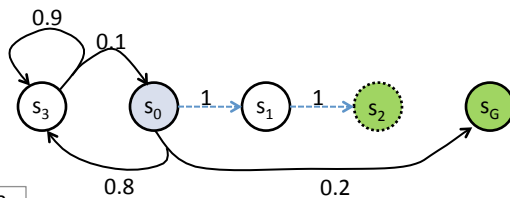
- $(s_0, 2)$ -short-sighted



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Short-Sighted SSPs and Look-ahead

Theorem: the optimal value-function for an (s, t) -short-sighted SSP is at least as good as the t -look-ahead value of s .

Look-ahead/UCT ($t=2$)Short-sighted SSP ($t=2$)

- Short-sighted SSPs preserve the action structure, e.g., self-loop actions and loops of actions

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Short-Sighted Probabilistic Planner (SSiPP)

```

begin
   $s \leftarrow s_0$ 
  while  $s \notin G$  do
     $\langle S', s, G', A, P, C' \rangle \leftarrow \text{GENERATE-SHORT-SIGHTED-SSP}(S, s, H)$ 
     $\hat{\pi}^* \leftarrow \text{OPTIMAL-SSP-SOLVER}(\langle S', s, G', A, P, C' \rangle, H)$ 
    while  $s \notin G'$  do
       $s \leftarrow \text{execute-action}(\hat{\pi}^*(s))$ 
  end
end

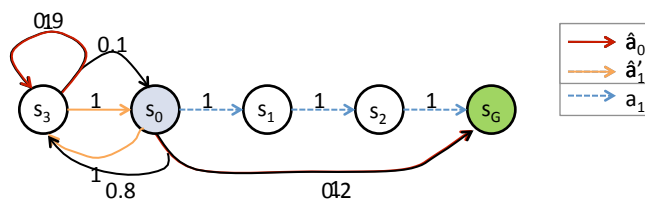
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Since short-sighted SSPs are much smaller than the original problem, we can compute a complete policy for them.

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Planner: FF-Replan

[Yoon et al, 2007]

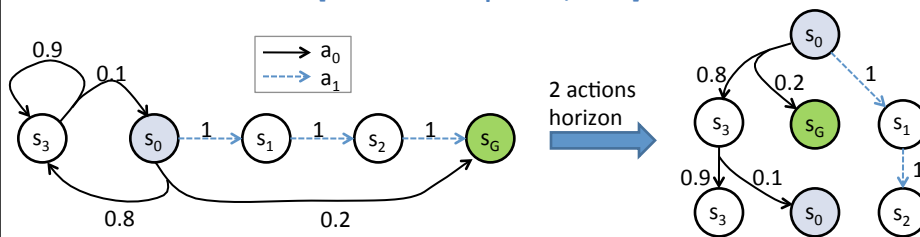


- Relax probabilistic actions into deterministic actions (**determinization**)
- **Pro:** scales up
- **Cons:** oblivious to probabilities

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Planner: UCT

[Kocsis and Szepesvári, 2006]



- Relaxes a given SSP by a sequence of **finite-horizon** problems
- Uses sparse sampling to efficiently explore the search tree
- **Pro:** scales up
- **Con:** can't represent loops

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Conclusion – Related Work

- [Aydemir et al, 2011]
 - MDP in the belief space of relational descriptions
 - Solved using greedy search over finite horizon
- [Velez et al, 2011]
 - Maps objects while moving
 - Minimizes traveled distance and false positives
 - Solved using sampling over finite horizon
- [Kollar and Roy, 2009]
 - Finds objects using co-location data (label comparison on Flickr)
 - Minimizes expected plan size over a posteriori prob. of finding the object.
 - Solved using breath-first search with additional constraints
- [Samadi et al, 2012]
 - Finds object by querying Google to obtain prior probability
 - Maximizes utility function based on probability of finding object, cost of obtaining object and feedback about the object
 - Solved using beam search

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