

Advanced MDP Algorithms

Mausam


VI → Asynchronous VI

- Is backing up *all* states in an iteration essential?
 - No!
- States may be backed up
 - as many times
 - in any order
- If no state gets starved
 - convergence properties still hold!!

Residual wrt Value Function V (Res^V)

- Residual at s with respect to V
 - magnitude($\Delta V(s)$) after one Bellman backup at s

$$Res^V(s) = \left| V(s) - \min_{a \in \mathcal{A}} \sum_{s' \in \mathcal{S}} \mathcal{T}(s, a, s') [\mathcal{C}(s, a, s') + V(s')] \right|$$

- Residual wrt respect to V
 - max residual
 - $Res^V = \max_s (Res^V(s))$  $Res^V < \epsilon$
(ϵ -consistency)

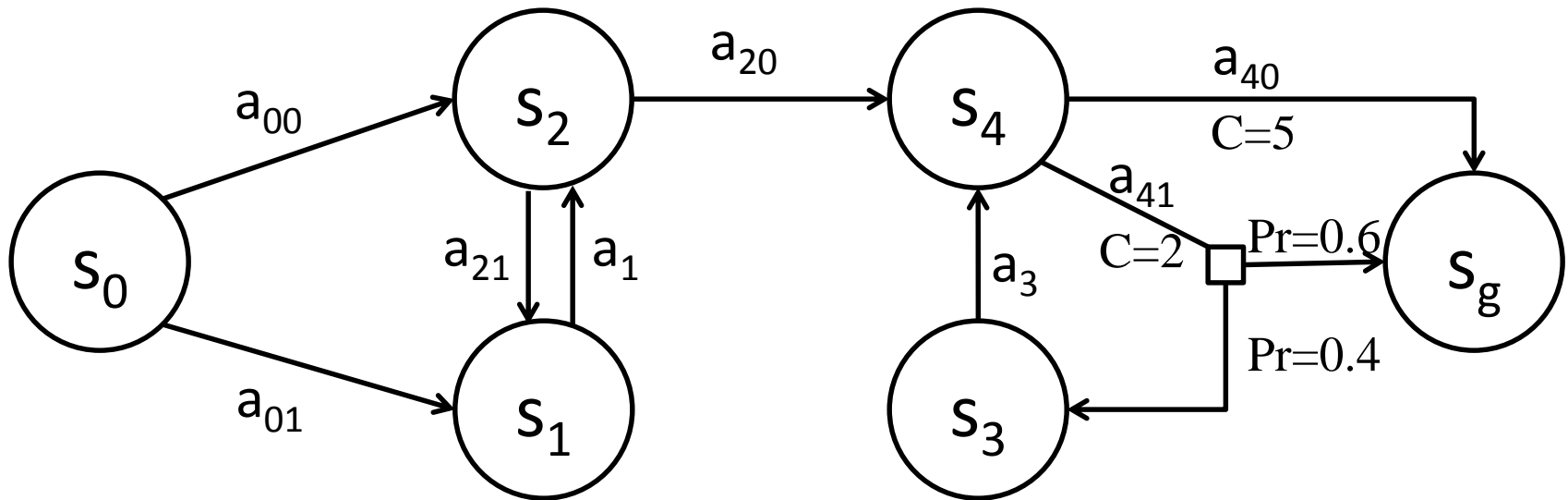
(General) Asynchronous VI

```
1 initialize  $V$  arbitrarily for each state
2 while  $Res^V > \epsilon$  do
3   | select a state  $s$ 
4   | compute  $V(s)$  using a Bellman backup at  $s$ 
5   | update  $Res^V(s)$  REVISE
6 end
7 return greedy policy  $\pi^V$ 
```

Prioritization of Bellman Backups

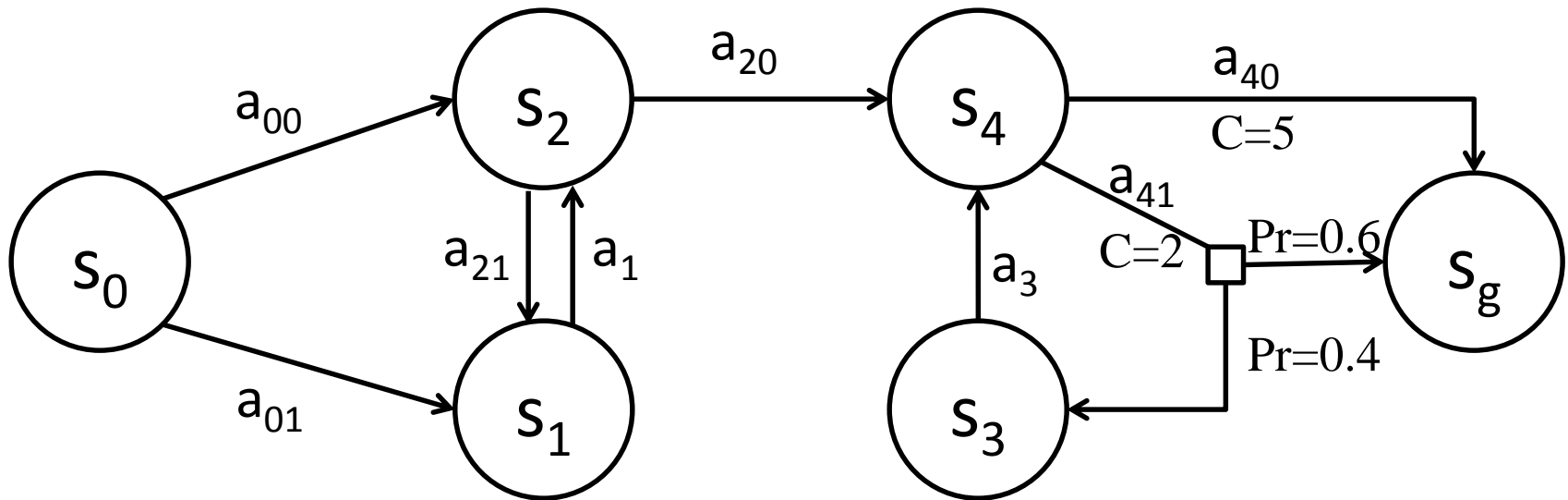
- Are all backups equally important?
- Can we avoid some backups?
- Can we schedule the backups more appropriately?

Useless Backups?



n	$V_n(s_0)$	$V_n(s_1)$	$V_n(s_2)$	$V_n(s_3)$	$V_n(s_4)$
0	3	3	2	2	1
1	3	3	2	2	2.8
2	3	3	3.8	3.8	2.8
3	4	4.8	3.8	3.8	3.52
4	4.8	4.8	4.52	4.52	3.52
5	5.52	5.52	4.52	4.52	3.808
20	5.99921	5.99921	4.99969	4.99969	3.99969

Useless Backups?

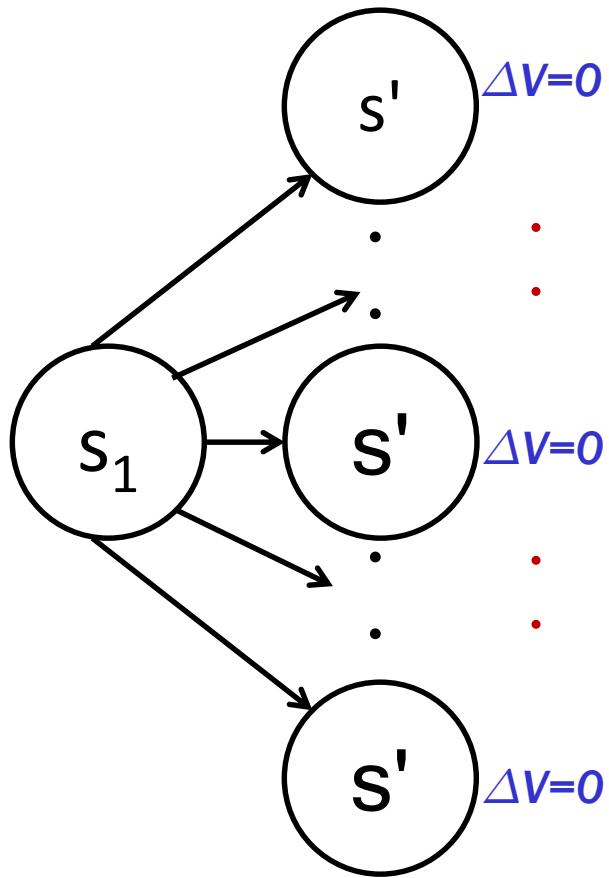


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1	3	3	2	2	2.8
2	3	3	3.8	3.8	2.8
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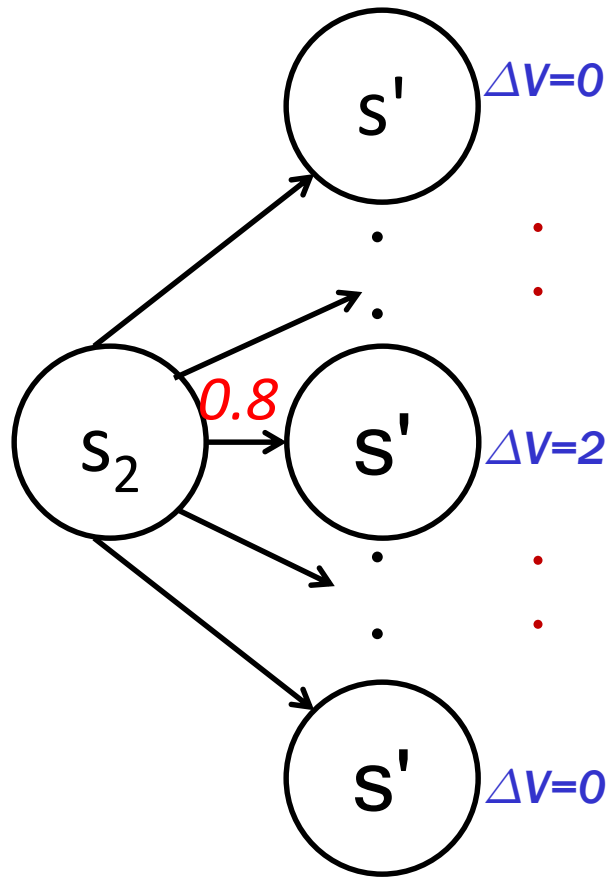
Asynch VI \rightarrow Prioritized VI

```
1 initialize  $V$ 
2
3 repeat
4   |   select state  $s'$ 
5   |   compute  $V(s')$  using a Bellman backup at  $s'$ 
6   |   foreach predecessor  $s$  of  $s'$ , i.e.,  $\{s | \exists a [\mathcal{T}(s, a, s') > 0]\}$  do
7   |   |   compute priority( $s$ )
8   |   |    $q.push(s, \text{priority}(s))$ 
9   |   end
10 until termination;
11 return greedy policy  $\pi^V$ 
```

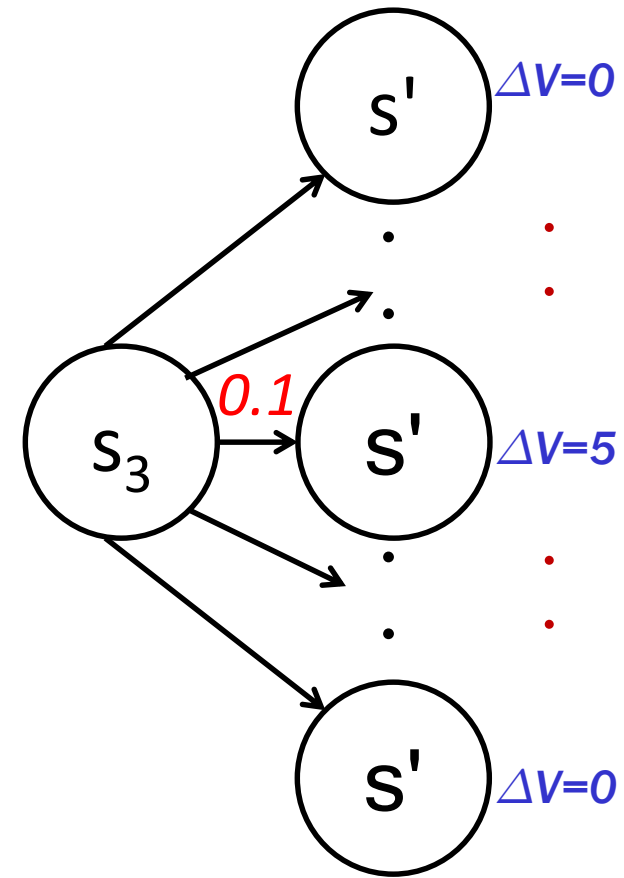

Which state to prioritize?



s_1 is zero priority



s_2 is higher priority



s_3 is low priority

Prioritized Sweeping

$$\text{priority}_{PS}(s) = \max \left\{ \text{priority}_{PS}(s), \max_{a \in \mathcal{A}} \{ \mathcal{T}(s, a, s') Res^V(s') \} \right\}$$

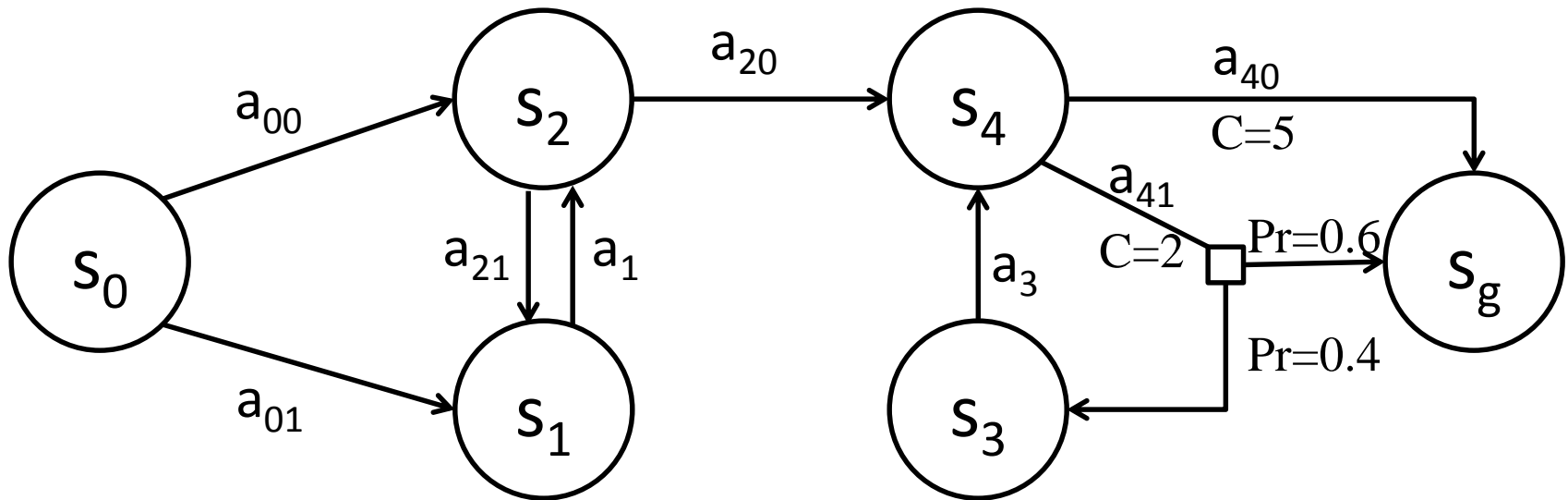
- **Convergence** [Li&Littman 08]

Prioritized Sweeping converges to optimal in the limit,

if all initial priorities are non-zero.

(does not need synchronous VI iterations)

Prioritized Sweeping



	$V(s_0)$	$V(s_1)$	$V(s_2)$	$V(s_3)$	$V(s_4)$
Initial V	3	3	2	2	1
	3	3	2	2	2.8
Priority	0	0	1.8	1.8	0
Update	3	3	3.8	3.8	2.8
Priority	2	2	0	0	1.2
Update	3	4.8	3.8	3.8	2.8

Limitations of VI/Extensions

- Scalability
 - Memory linear in size of state space
 - Time at least polynomial or more
- Polynomial is good, no?
 - state spaces are usually huge.
 - if n state vars then 2^n states!
- Curse of Dimensionality!

Heuristic Search

- Insight 1
 - knowledge of a start state to save on computation
~ (all sources shortest path \rightarrow single source shortest path)
- Insight 2
 - additional knowledge in the form of heuristic function
~ (dfs/bfs \rightarrow A*)

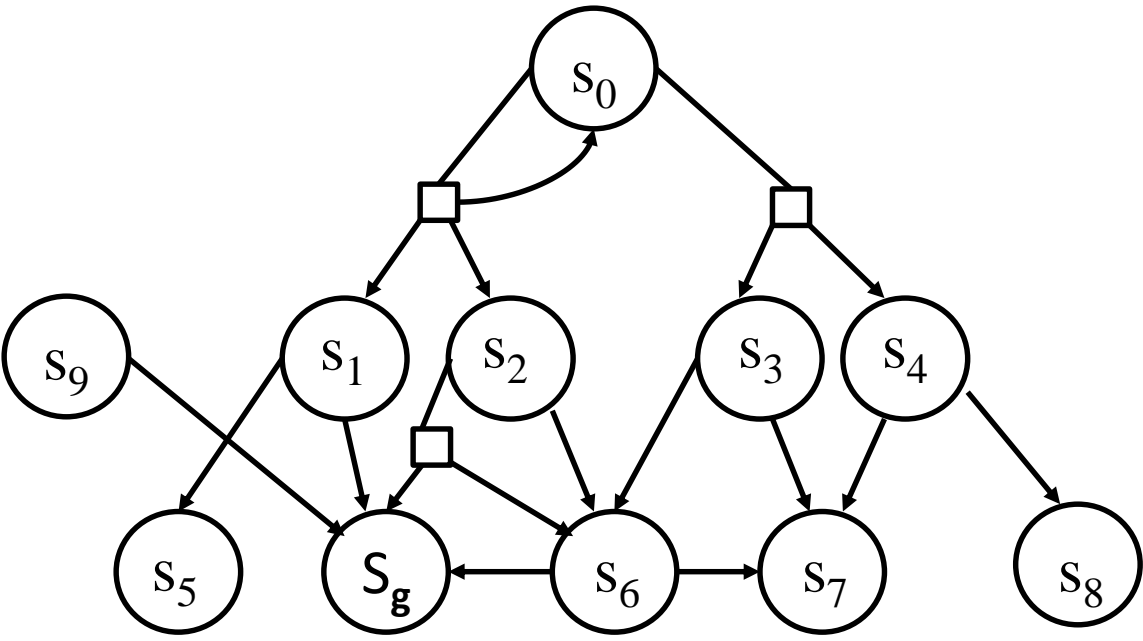
Model

- MDP with an additional start state s_0
 - denoted by MDP_{s_0}
- What is the solution to an MDP_{s_0}
- Policy ($S \rightarrow A$)?
 - are states that are not reachable from s_0 relevant?
 - states that are never visited (even though reachable)?

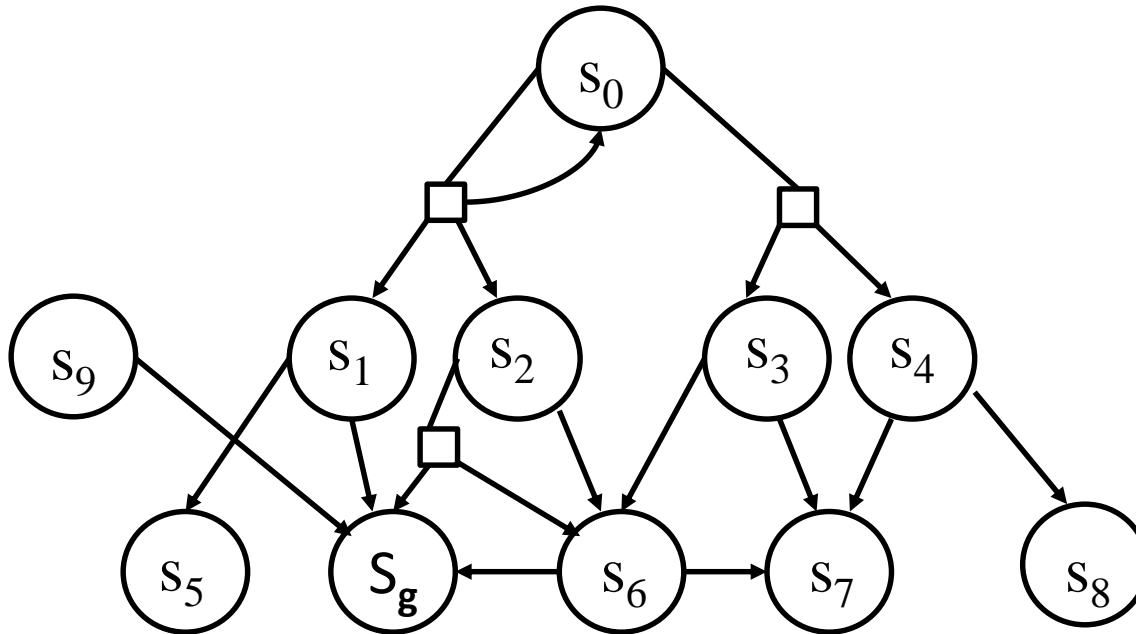
Partial Policy

- Define *Partial policy*
 - $\pi: S' \rightarrow A$, where $S' \subseteq S$
- Define *Partial policy closed w.r.t. a state s* .
 - is a partial policy π_s
 - defined for all states s' reachable by π_s starting from s

Partial policy closed wrt s_0



Partial policy closed wrt s_0



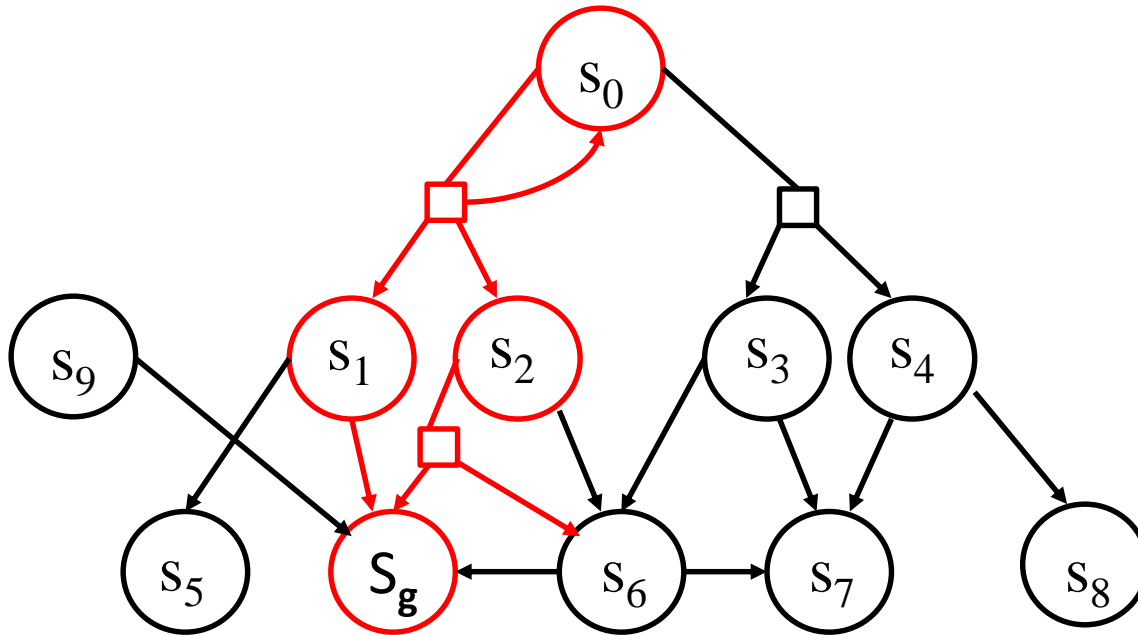
Is this policy closed wrt s_0 ?

$$\pi_{s_0}(s_0) = a_1$$

$$\pi_{s_0}(s_1) = a_2$$

$$\pi_{s_0}(s_2) = a_1$$

Partial policy closed wrt s_0



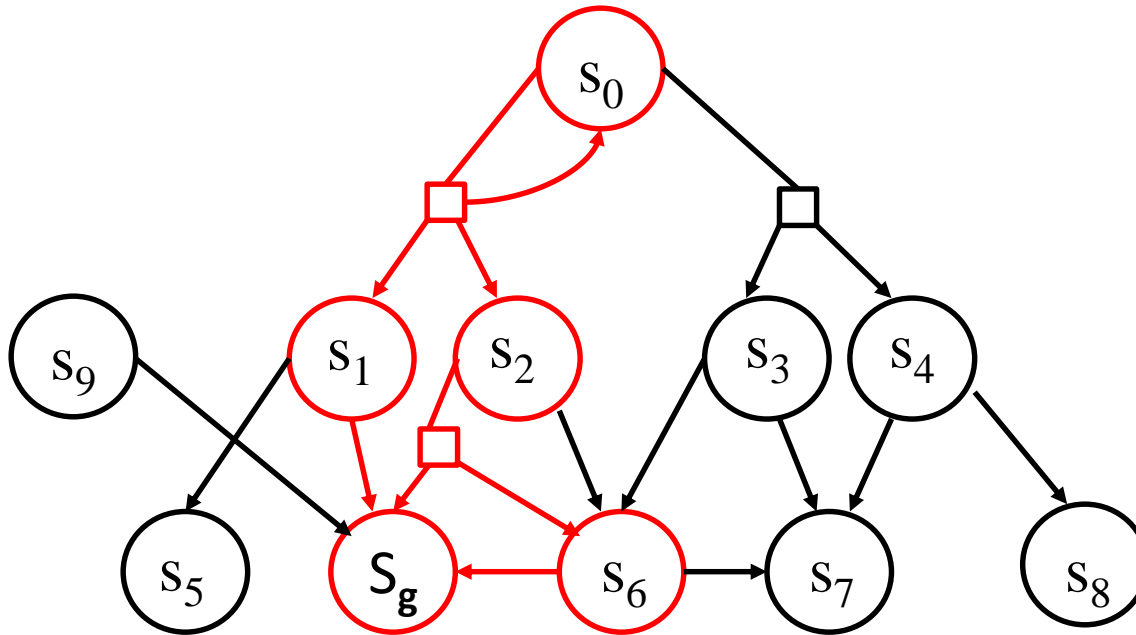
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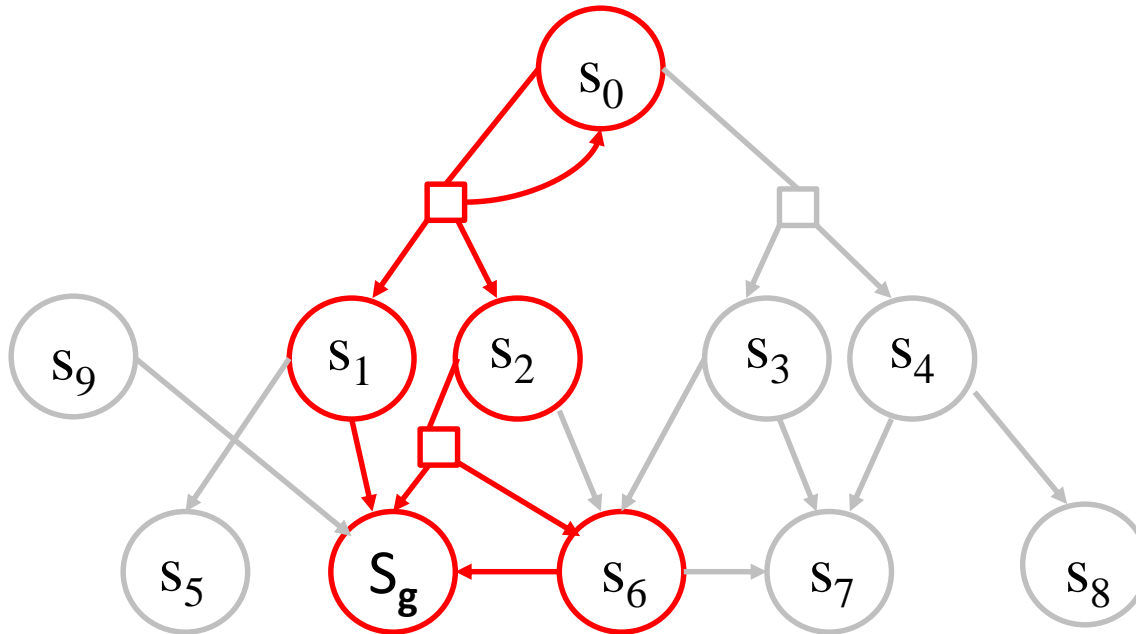
Partial policy closed wrt s_0



Is this policy closed wrt s_0 ?

$\pi_{s_0}(s_0) = a_1$
 $\pi_{s_0}(s_1) = a_2$
 $\pi_{s_0}(s_2) = a_1$
 $\pi_{s_0}(s_6) = a_1$

Policy Graph of π_{s_0}



$$\pi_{s_0}(s_0) = a_1$$

$$\pi_{s_0}(s_1) = a_2$$

$$\pi_{s_0}(s_2) = a_1$$

$$\pi_{s_0}(s_6) = a_1$$

Greedy Policy Graph

- Define *greedy policy*. $\pi^V = \operatorname{argmin}_a Q^V(s,a)$
- Define *greedy partial policy rooted at s_0*
 - Partial policy rooted at s_0
 - Greedy policy
 - denoted by $\pi_{s_0}^V$
- Define *greedy policy graph*
 - Policy graph of $\pi_{s_0}^V$: denoted by $G_{s_0}^V$

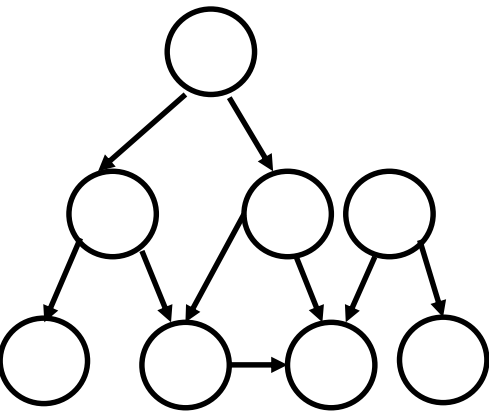
Heuristic Function

- $h(s): S \rightarrow \mathbb{R}$
 - estimates $V^*(s)$
 - gives an indication about “goodness” of a state
 - usually used in initialization $V_0(s) = h(s)$
 - helps us avoid seemingly bad states
- Define *admissible* heuristic
 - optimistic
 - $h(s) \leq V^*(s)$

A General Scheme for Heuristic Search in MDPs

- Two (over)simplified intuitions
 - Focus on states in greedy policy wrt V rooted at s_0
 - Focus on states with residual $> \epsilon$
- Find & Revise:
 - repeat
 - find a state that satisfies the two properties above
 - revise: perform a Bellman backup
 - until no such state remains

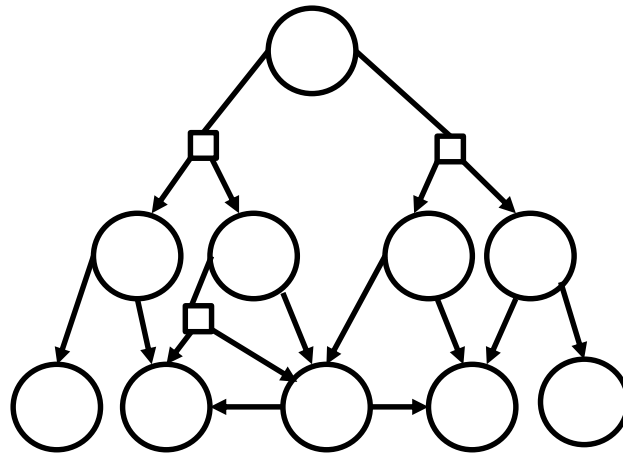
A* → LAO*



regular graph

soln:(shortest) path

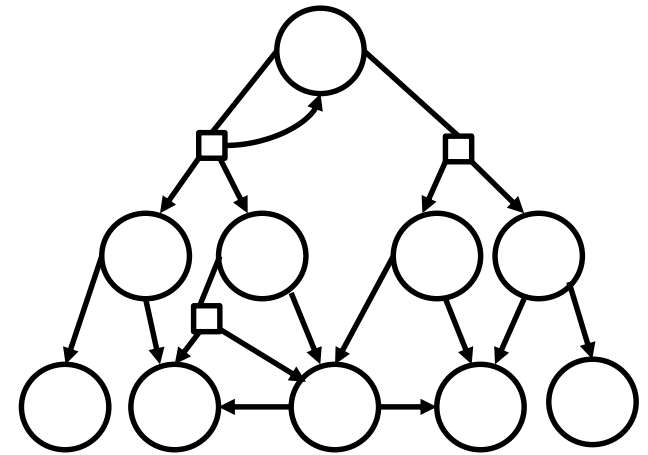
A*



acyclic AND/OR graph

soln:(expected shortest)
acyclic graph

AO* [Nilsson'71]



cyclic AND/OR graph

soln:(expected shortest)
cyclic graph

LAO* [Hansen&Zil.'98]

All algorithms able to make effective use of reachability information!

LAO* Family

add s_0 to the fringe and to greedy policy graph

repeat

- FIND: expand **some** states on the fringe (in greedy graph)
- initialize all new states by their heuristic value
- **choose** a subset of affected states
- REVISE: **perform** some Bellman backups on this subset
- recompute the greedy graph

until greedy graph has no fringe & residuals in greedy graph small

output the greedy graph as the final policy

LAO*

add s_0 to the fringe and to greedy policy graph

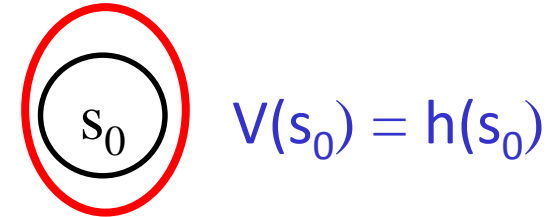
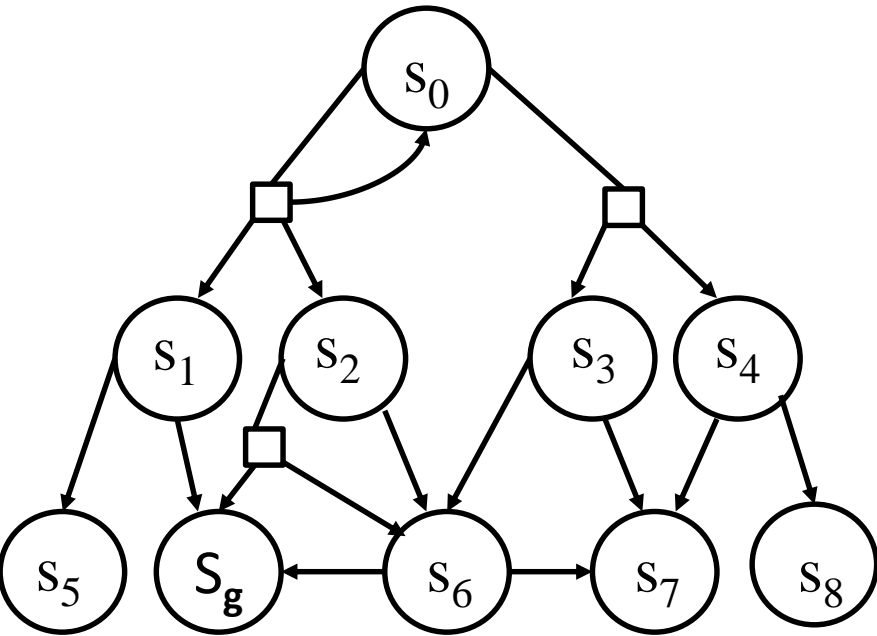
repeat

- FIND: expand **best state s** on the fringe (in greedy graph)
- initialize all new states by their heuristic value
- subset = **all states in expanded graph that can reach s**
- REVISE: perform **VI** on this subset
- recompute the greedy graph

until greedy graph has no fringe & ~~residuals in greedy graph small~~

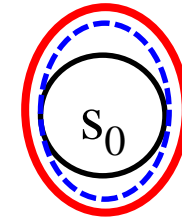
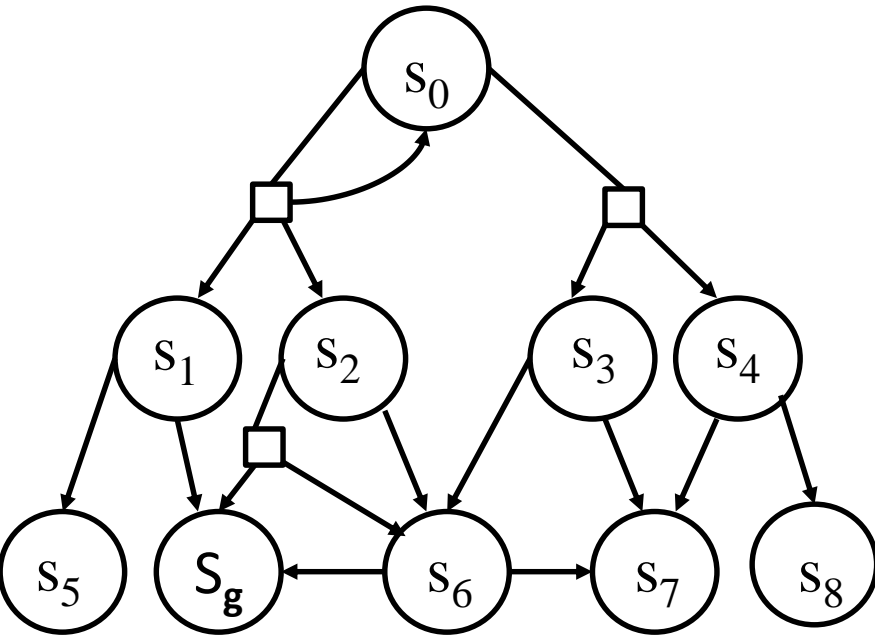
output the greedy graph as the final policy

LAO*



add s_0 in the fringe and in greedy graph

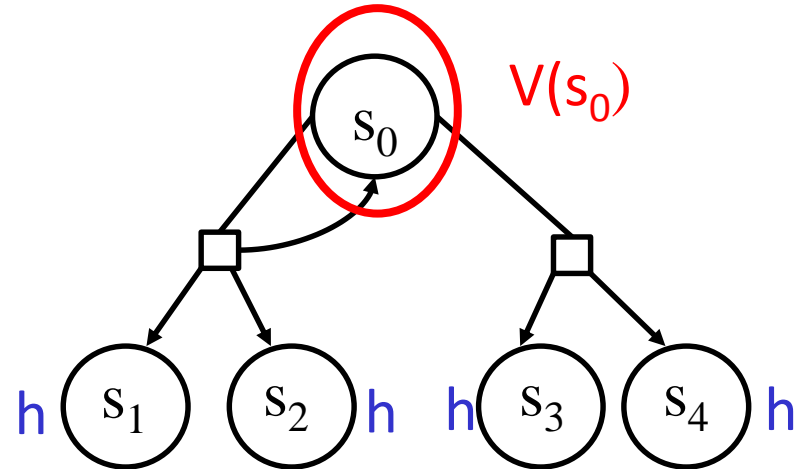
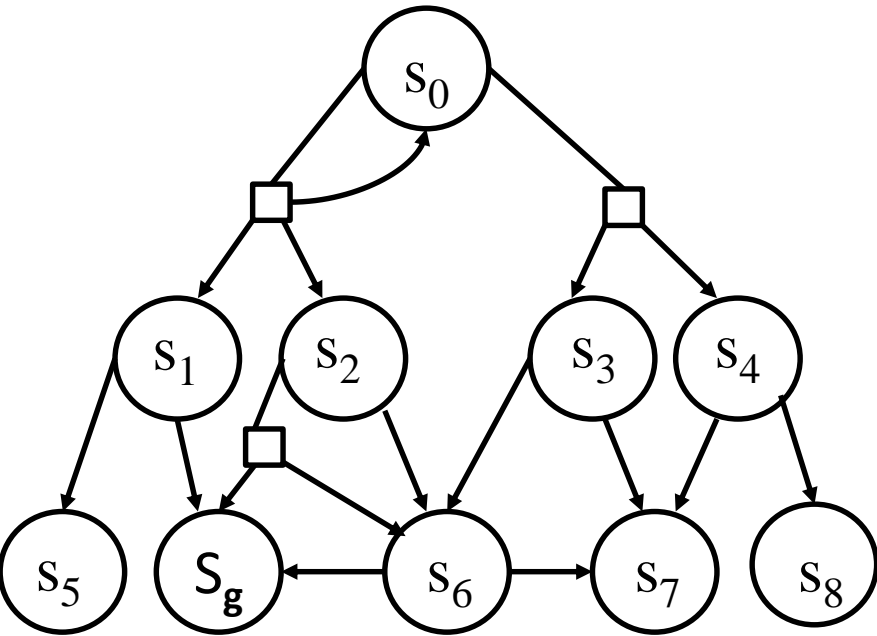
LAO*



$$V(s_0) = h(s_0)$$

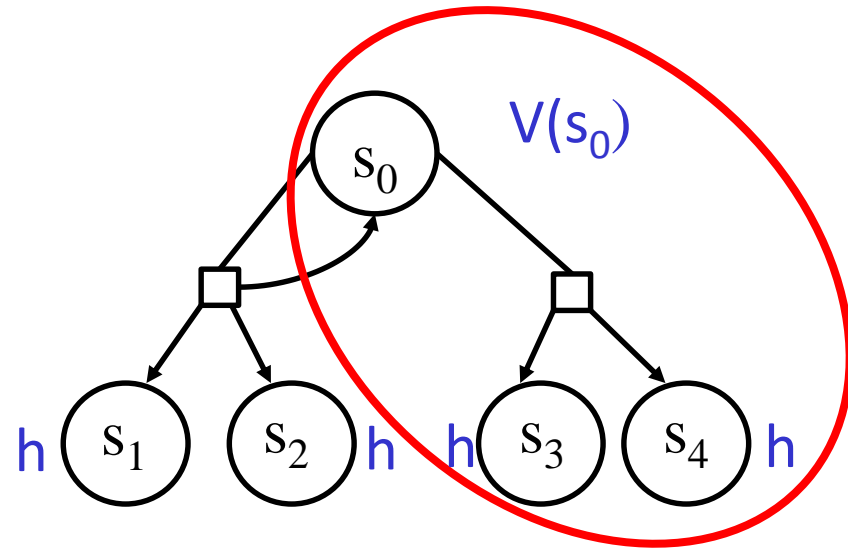
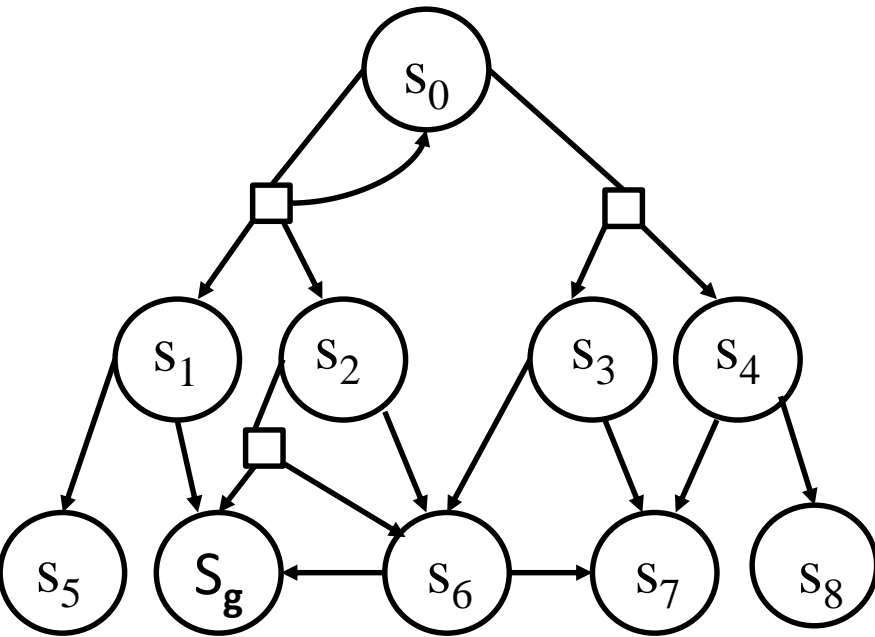
FIND: expand some states on the fringe (in greedy graph)

LAO*



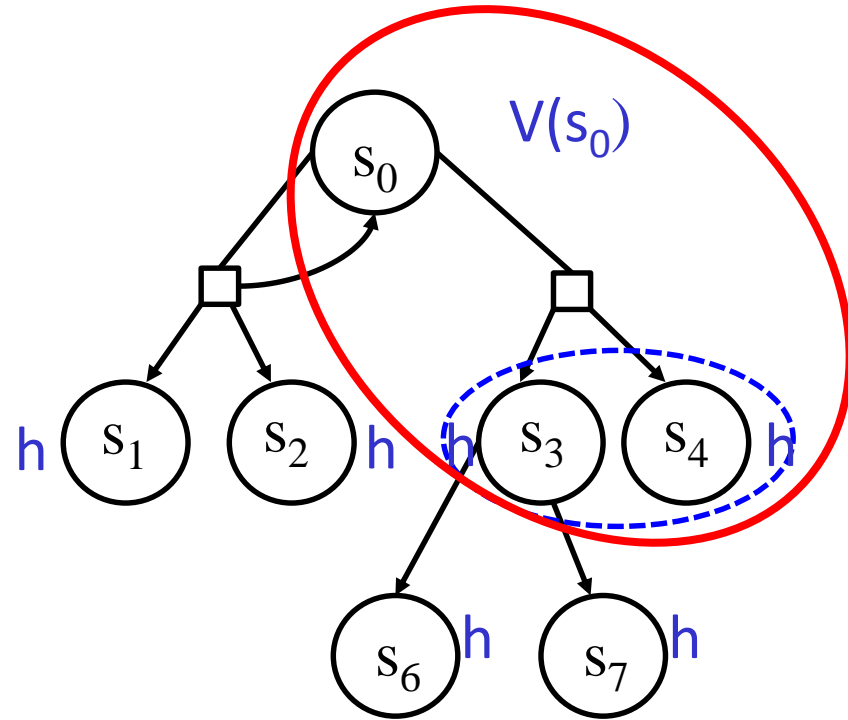
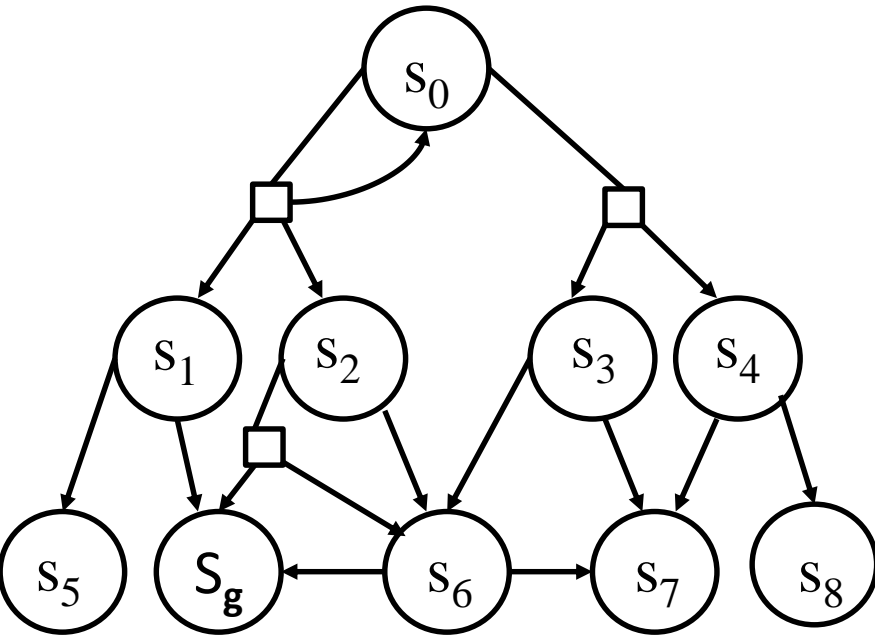
FIND: expand some states on the fringe (in greedy graph)
initialize all new states by their heuristic value
subset = all states in expanded graph that can reach s
perform VI on this subset

LAO*



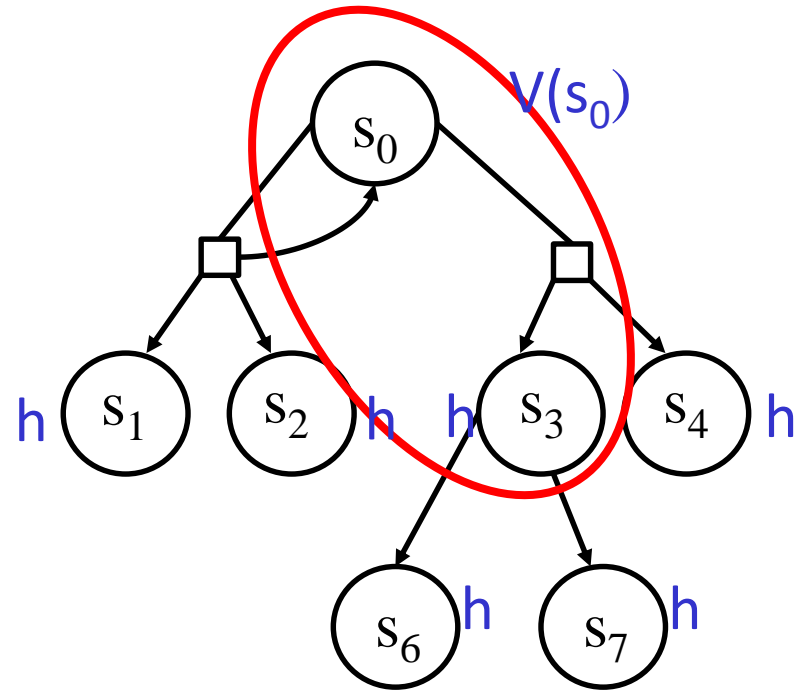
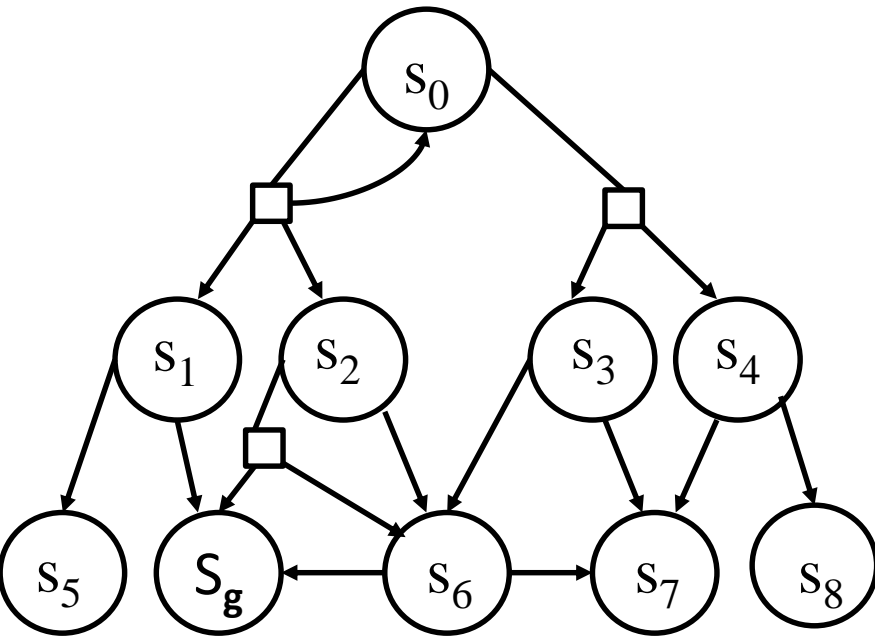
- FIND: expand some states on the fringe (in greedy graph)
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- perform VI on this subset
- recompute the greedy graph

LAO*



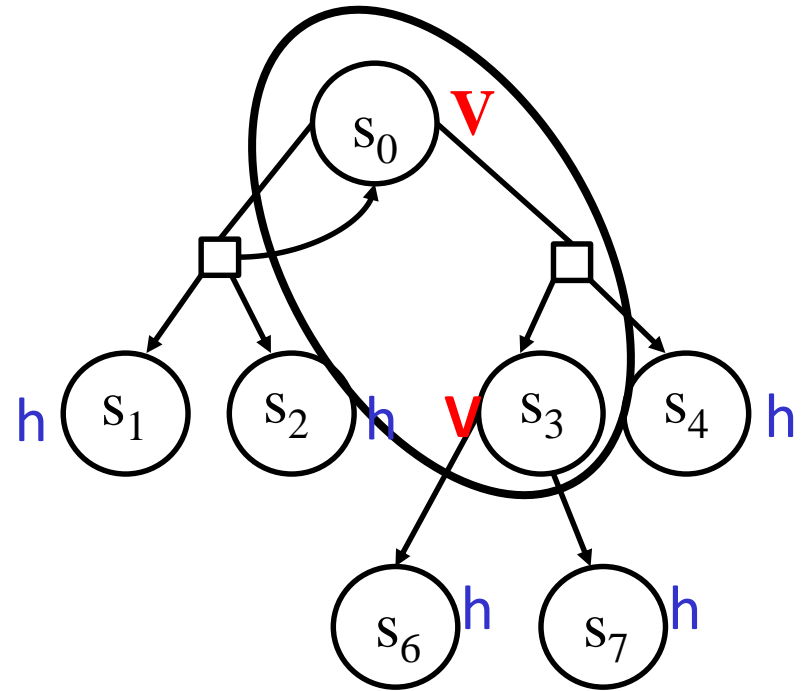
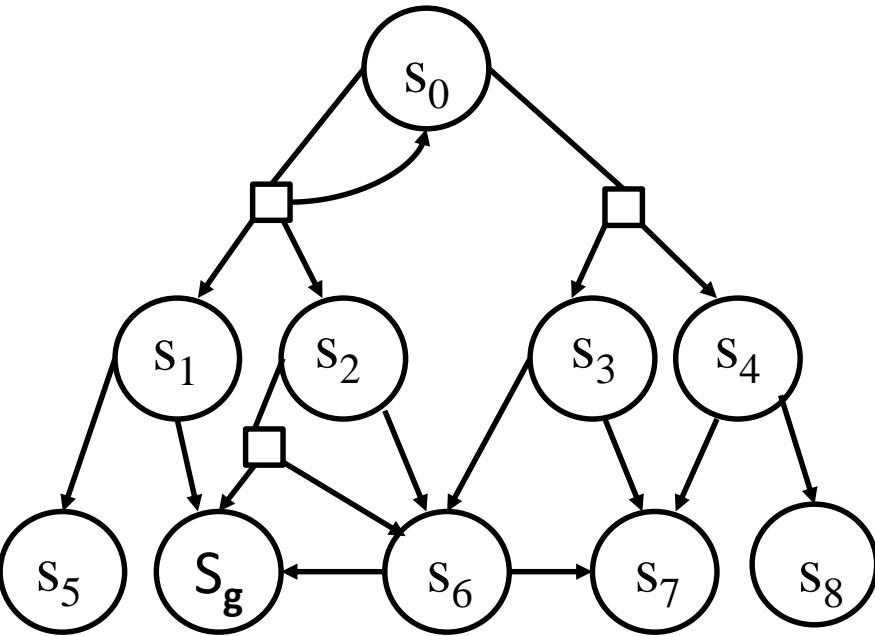
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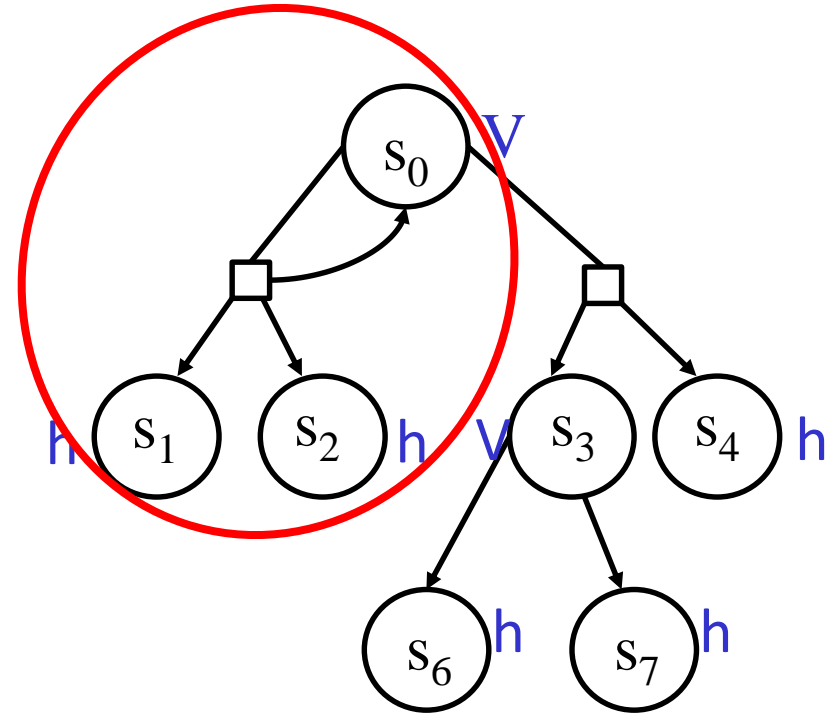
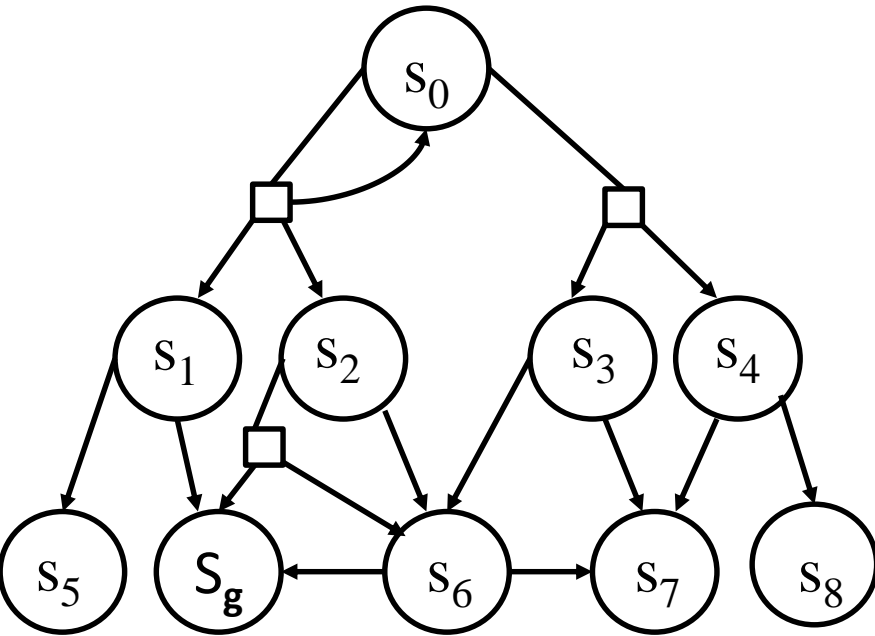
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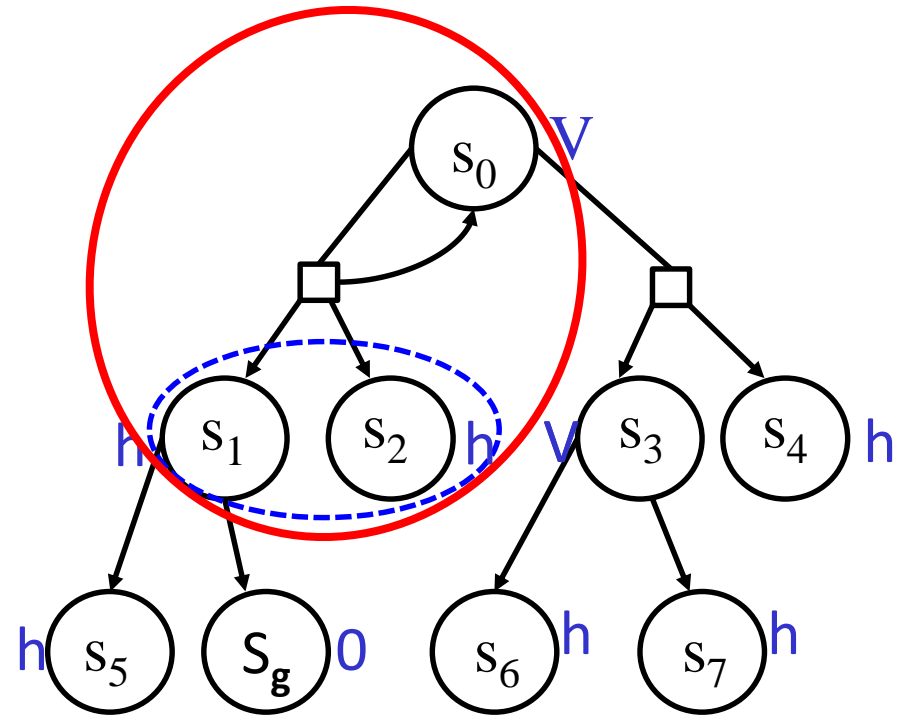
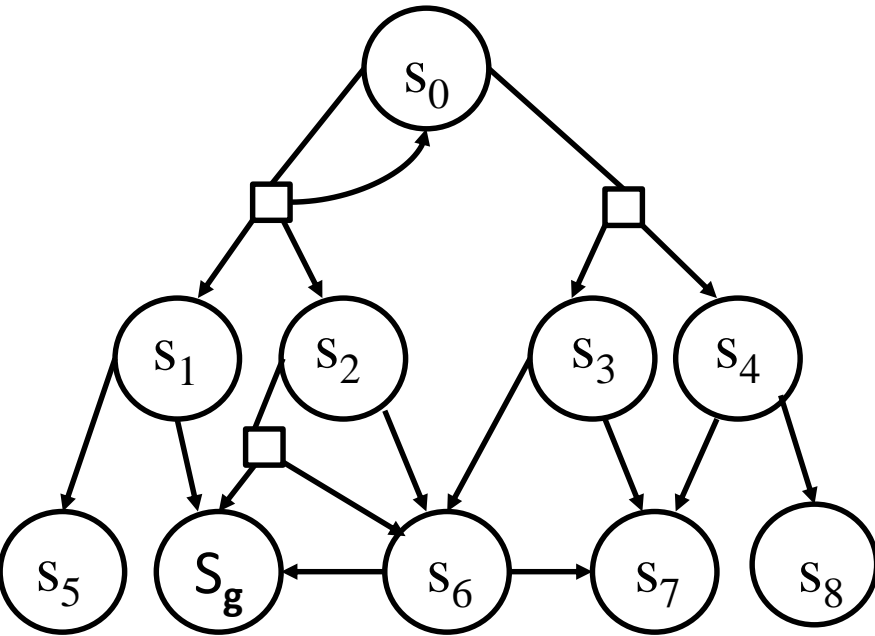
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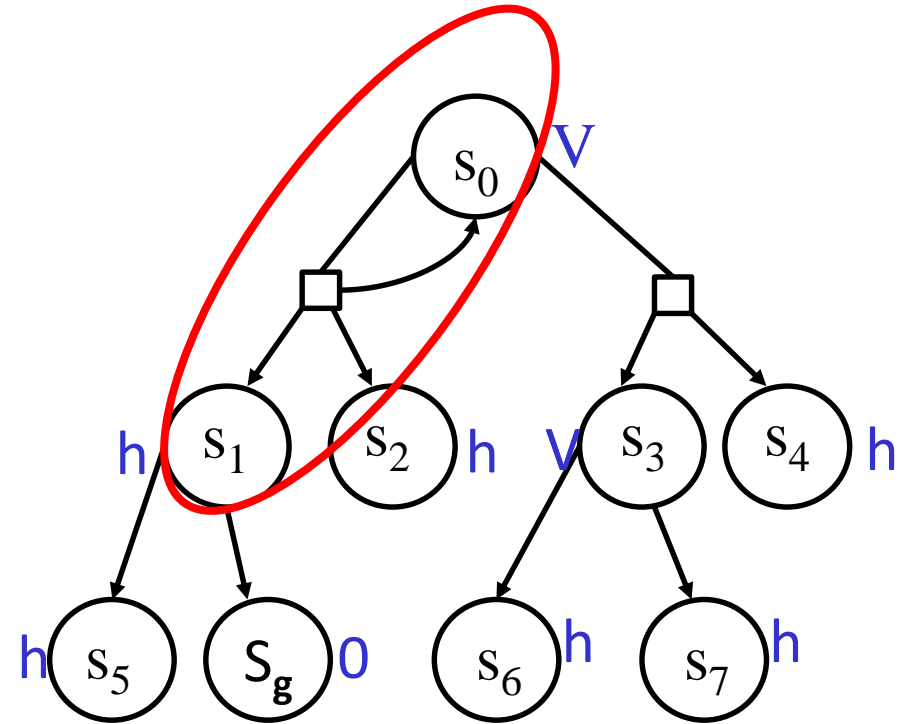
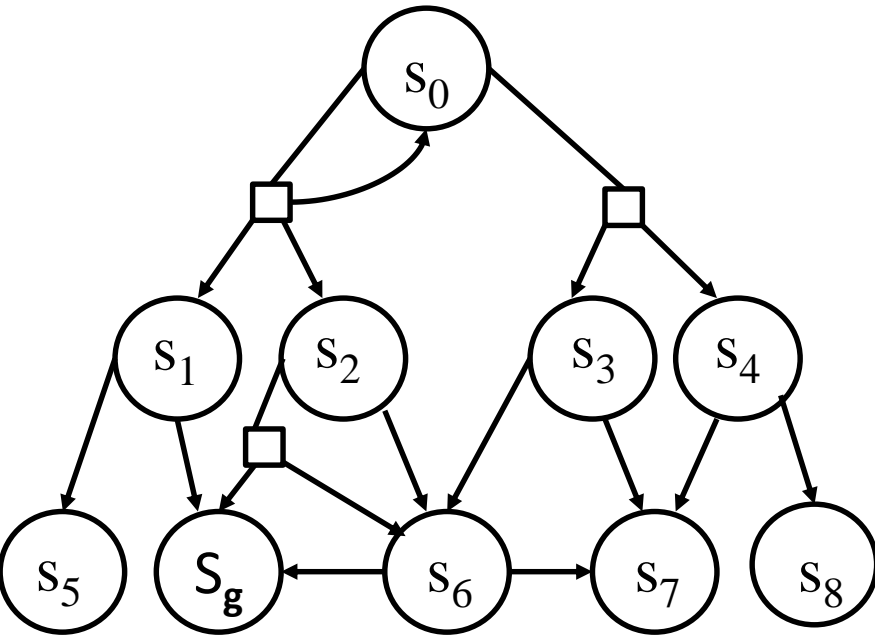
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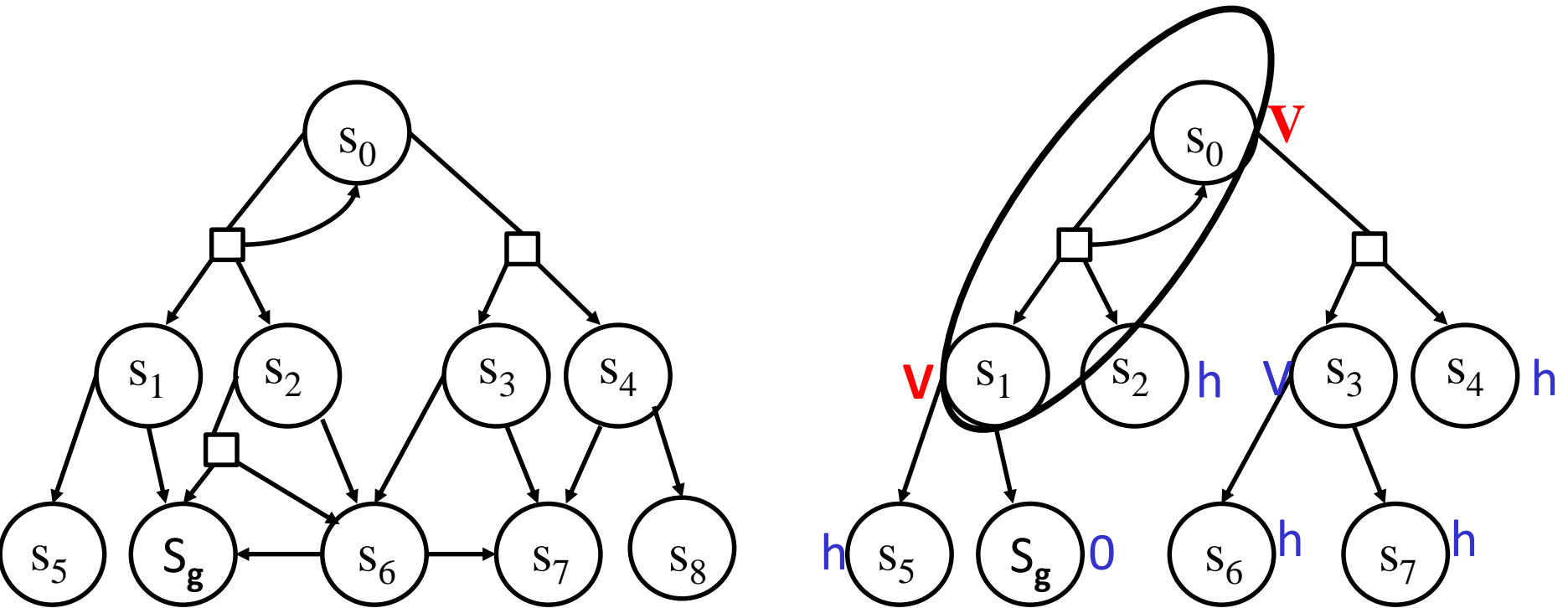
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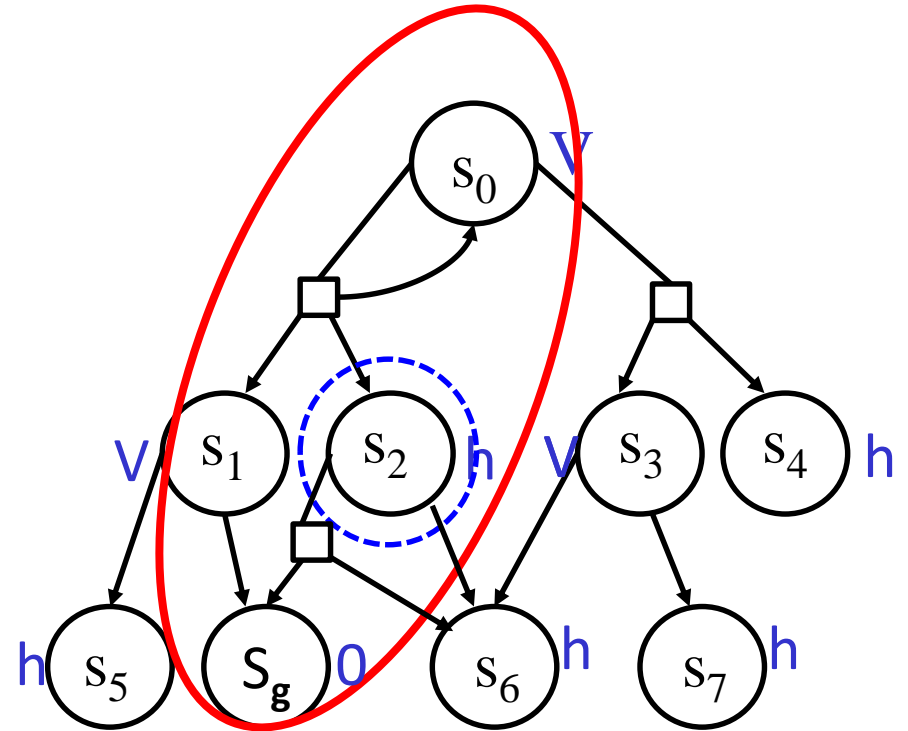
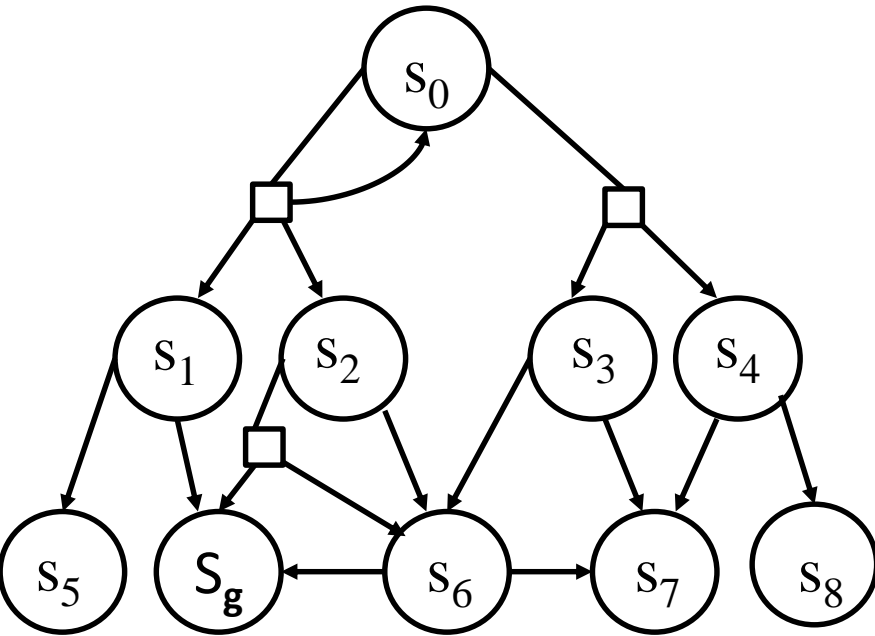
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LAO*



FIND: expand some states on the fringe (in greedy graph)
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subset = all states in expanded graph that can reach s
perform VI on this subset
recompute the greedy graph

LAO*



FIND: expand some states on the fringe (in greedy graph)

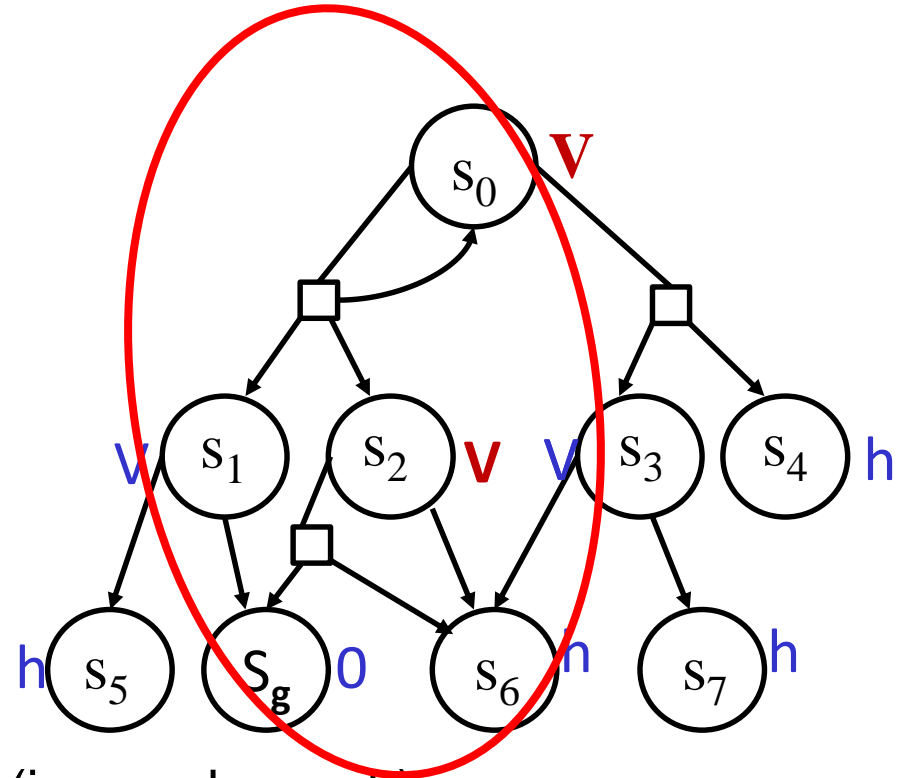
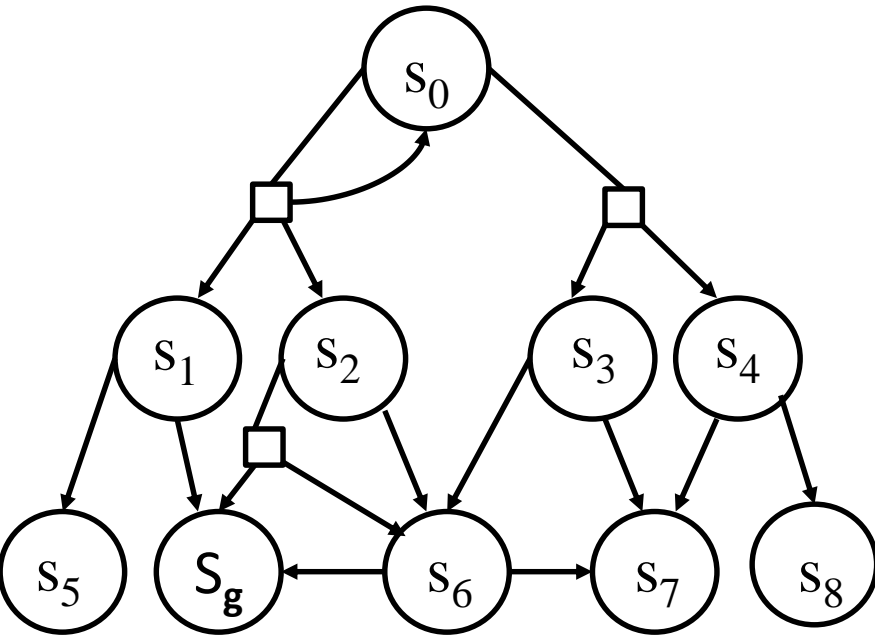
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subset = all states in expanded graph that can reach s

perform VI on this subset

recompute the greedy graph

LAO*



FIND: expand some states on the fringe (in greedy graph)

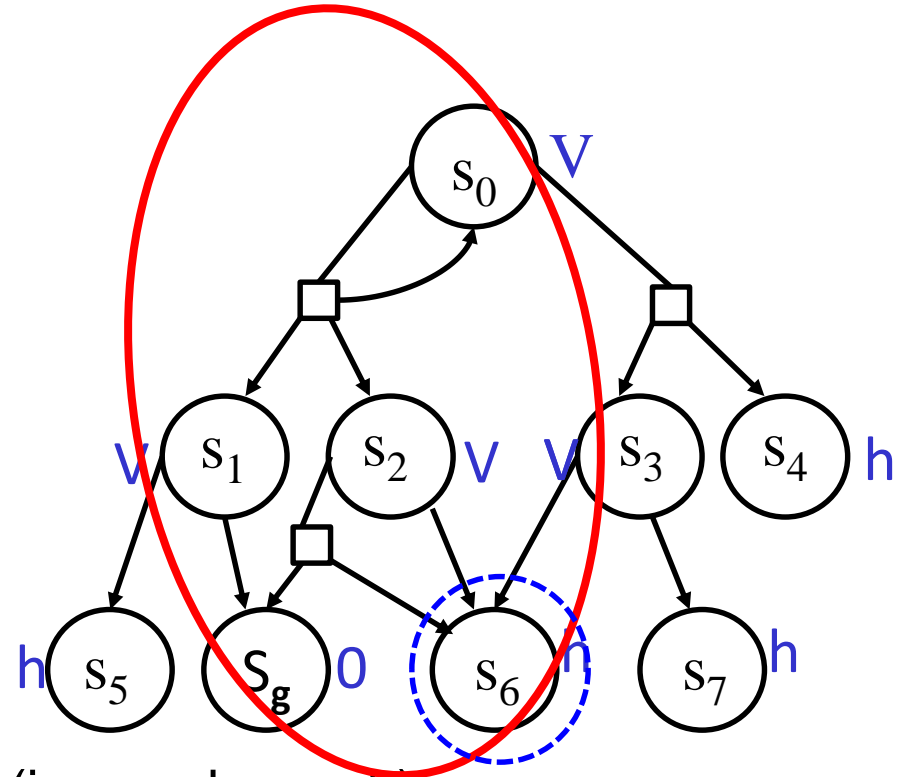
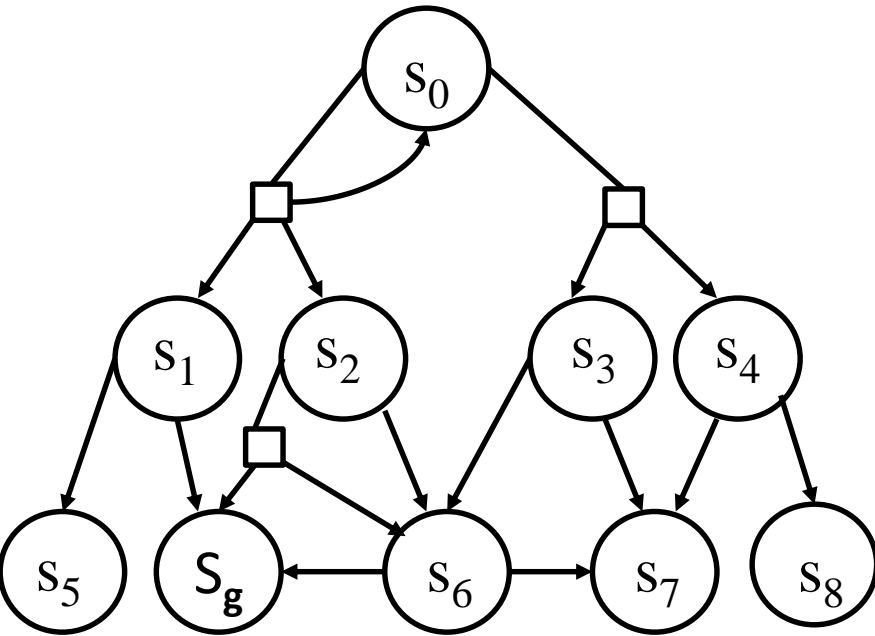
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LAO*



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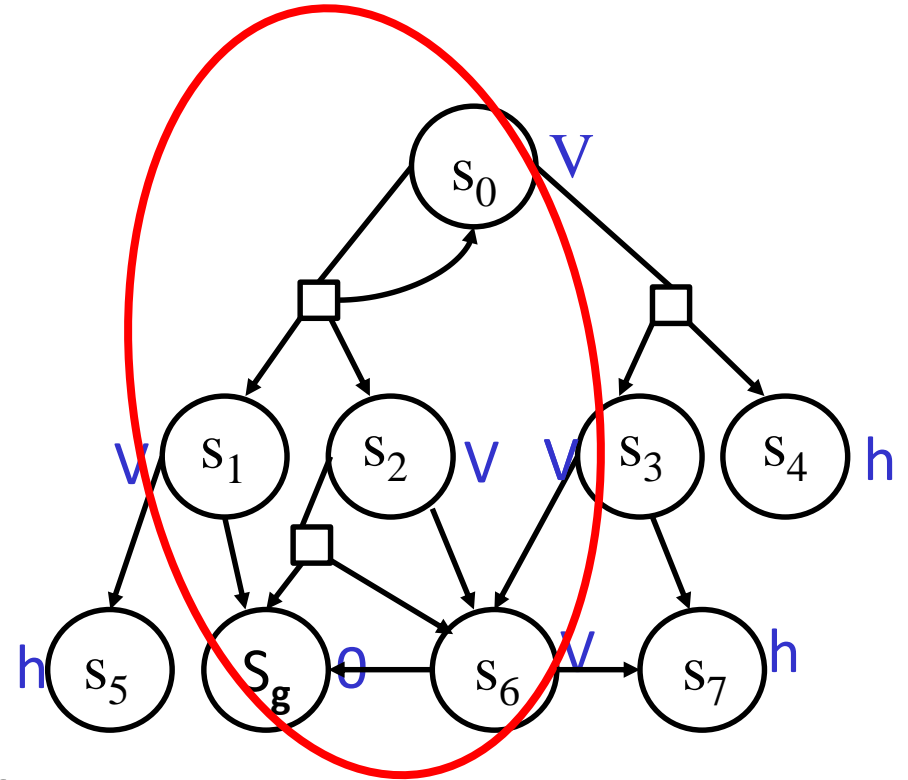
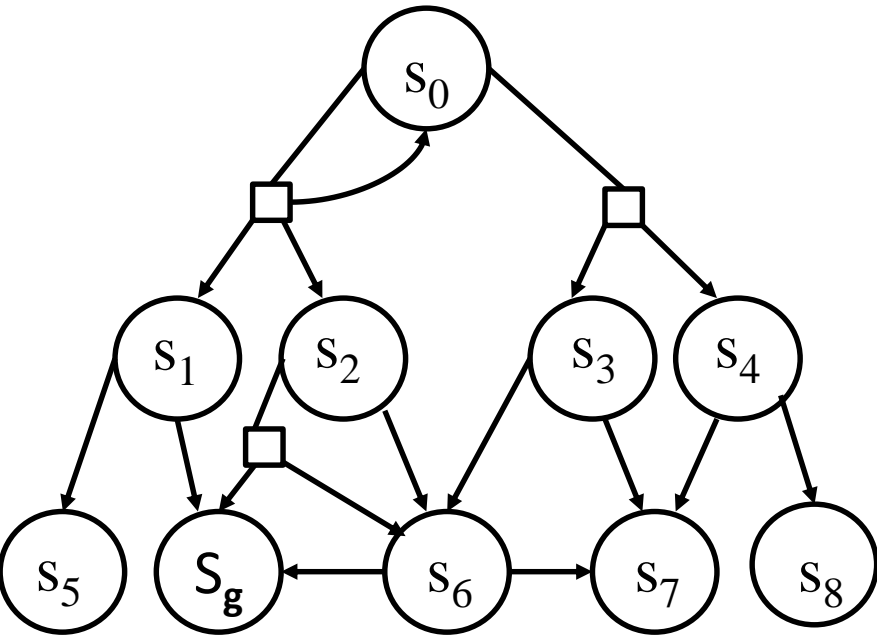
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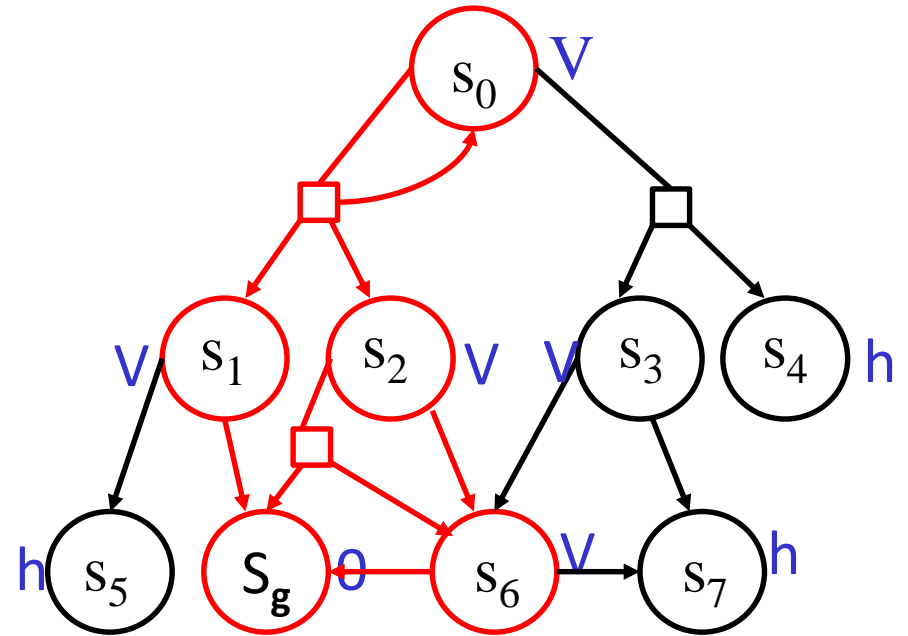
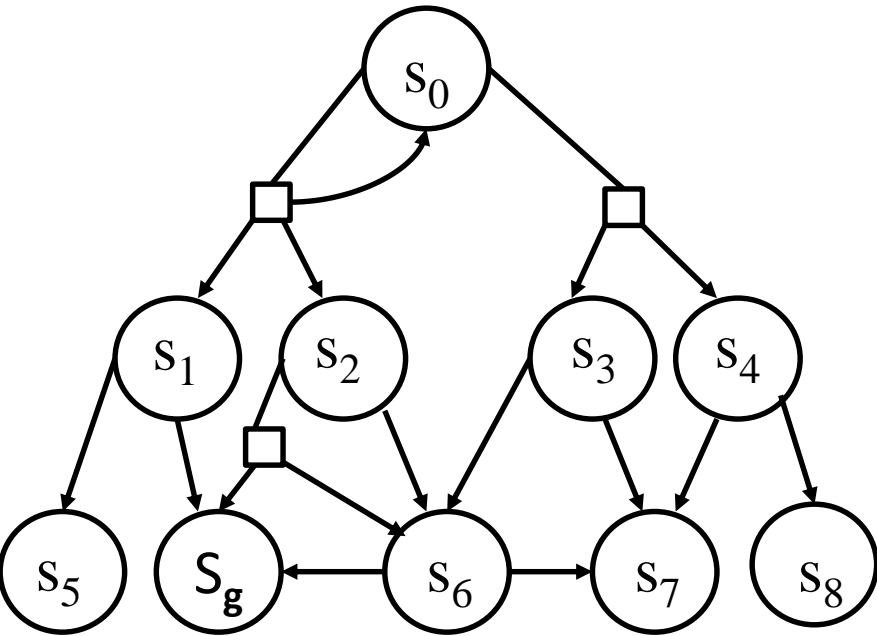
recompute the greedy graph

LAO*



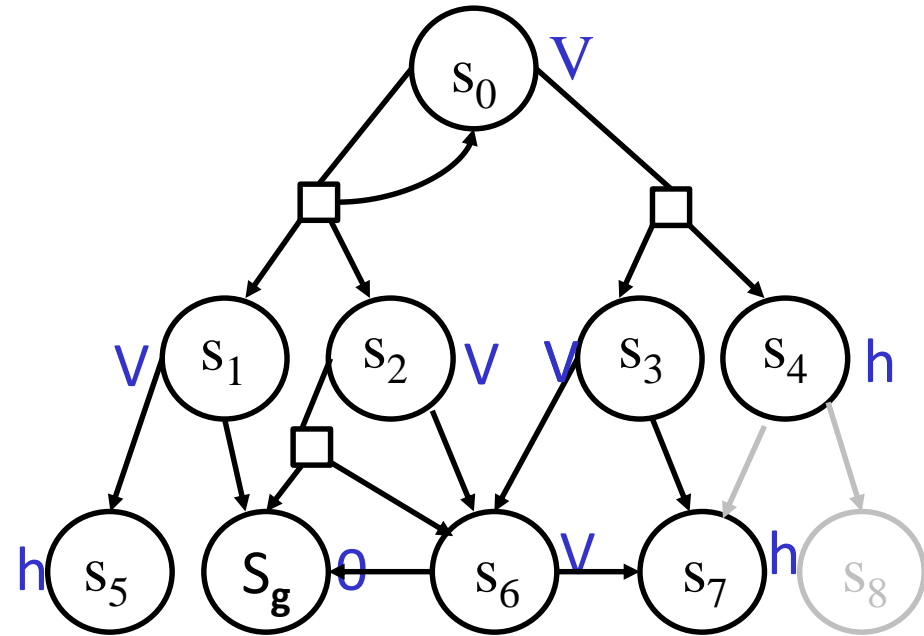
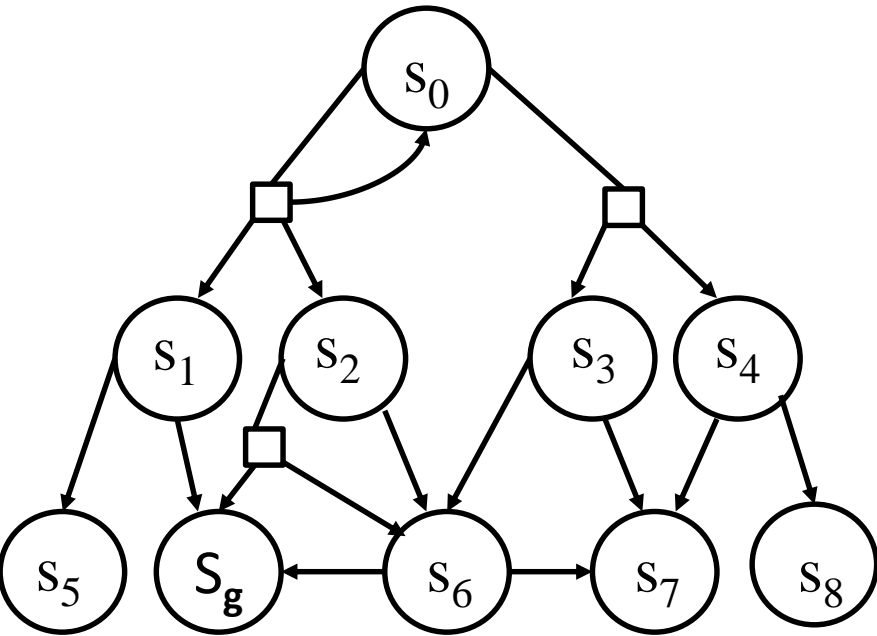
output the greedy graph as the final policy

LAO*



output the greedy graph as the final policy

LAO*



*s_4 was never expanded
 s_8 was never touched*

LAO*

add s_0 to the fringe and to greedy policy graph

one expansion

repeat

- FIND: expand best state s on the fringe (in greedy graph)
- initialize all new states by their heuristic value
- subset = all states in expanded graph that can reach s
- REVISE: perform VI on this subset
- recompute the greedy graph

until greedy graph has no fringe

lot of computation

output the greedy graph as the final policy

Optimizations in LAO*

add s_0 to the fringe and to greedy policy graph

repeat

- FIND: expand best state s on the fringe (in greedy graph)
- initialize all new states by their heuristic value
- subset = all states in expanded graph that can reach s
- VI iterations until greedy graph changes (or low residuals)
- recompute the greedy graph

until greedy graph has no fringe

output the greedy graph as the final policy

Optimizations in LAO*

add s_0 to the fringe and to greedy policy graph

repeat

- FIND: **expand all states in greedy fringe**
- initialize all new states by their heuristic value
- subset = all states in expanded graph that can reach s
- VI iterations until greedy graph changes (or low residuals)
- recompute the greedy graph

until greedy graph has no fringe

output the greedy graph as the final policy

iLAO*

add s_0 to the fringe and to greedy policy graph


repeat

- FIND: **expand all states in greedy fringe**
- initialize all new states by their heuristic value
- subset = all states in expanded graph that can reach s
- **only one backup per state in greedy graph**
- recompute the greedy graph

until greedy graph has no fringe

output the greedy graph as the final policy

*in what order?
(fringe \rightarrow start)
DFS postorder*



Extensions

- Heuristic Search + Dynamic Programming
 - AO*, LAO*, RTDP, ...
- Factored MDPs
 - add planning graph style heuristics
 - use goal regression to generalize better
- Hierarchical MDPs
 - hierarchy of sub-tasks, actions to scale better
- Reinforcement Learning
 - learning the probability and rewards
 - acting while learning - connections to psychology
- Partially Observable Markov Decision Processes
 - noisy sensors; partially observable environment
 - popular in robotics