Learning to Prune Dominated Action Sequences in Online Black-box Planning

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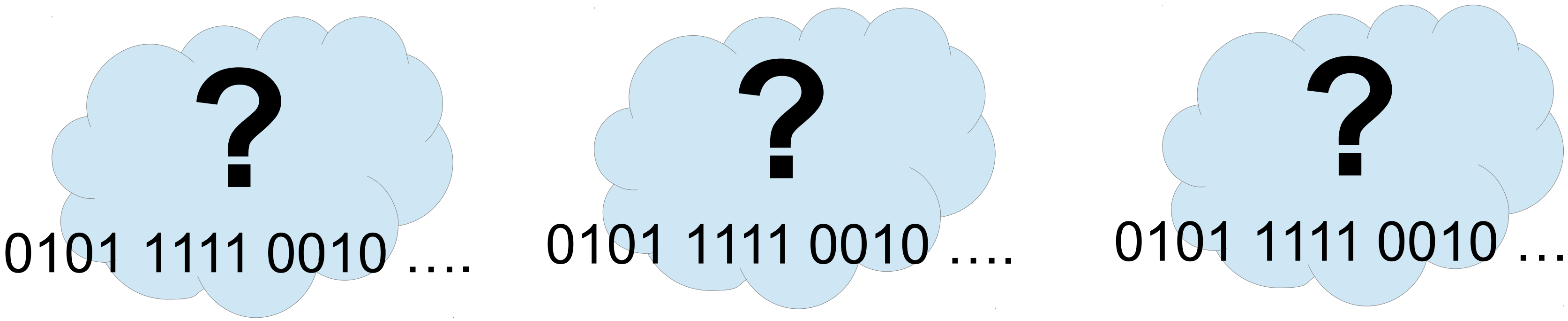
Black-box Planning in Arcade Learning Environment

- What a human sees

Arcade Learning Environment
(Bellemare et al. 2013)

Black-box Planning in Arcade Learning Environment

- What the computer sees



Arcade Learning Environment
(Bellemare et al. 2013)

General-purpose agents have many irrelevant actions

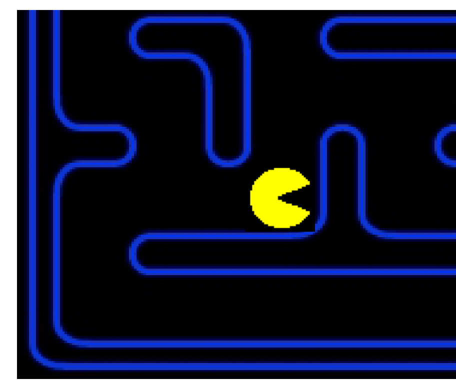
- The set of actions which are “useful” in each environment (= game) is a subset of the available action set in the ALE
- Yet an agent has no prior knowledge regarding which actions are relevant to the given environment in black-box domain

Neutral	Neutral + fire
Up	Up + fire
Up-left	Up-left + fire
Left	Left + fire
Down-left	Down-left + fire
Down	Down + fire
Down-right	Down-right + fire
Right	Right + fire
Up-right	Up-right + fire

Available action set in the ALE
(18 actions)

Neutral
Up
Left
Down
Right

Actions which are useful
in the environment



State Space Planning Problem

Two ways of domain description

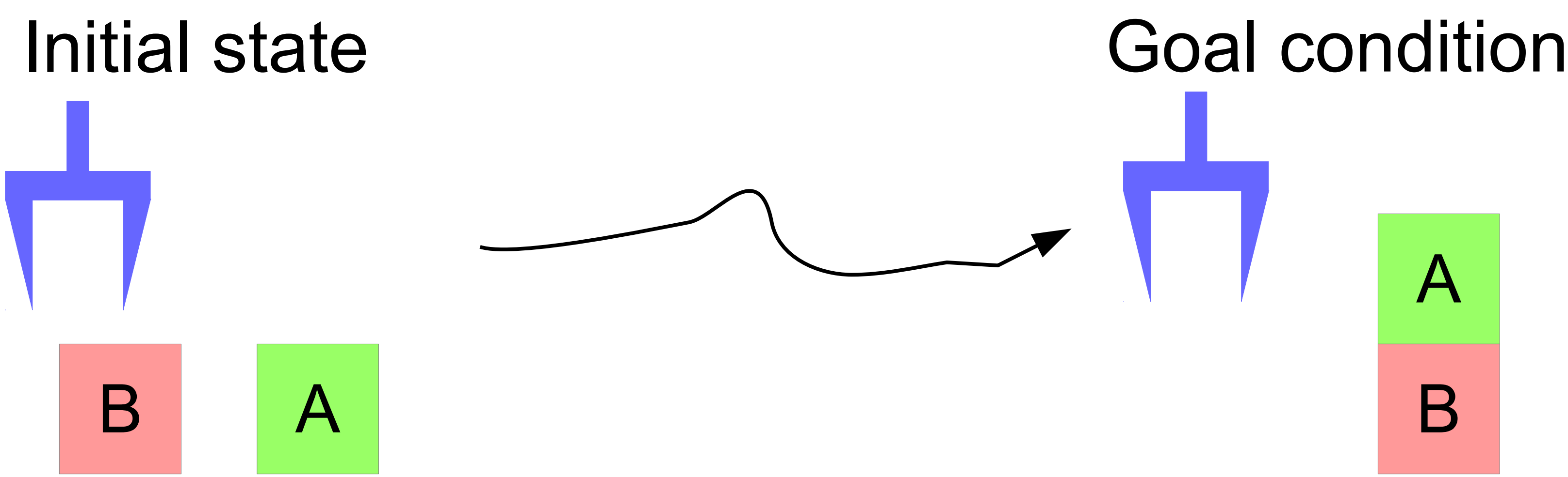
- Transparent model domain (e.g. PDDL)
- Black-box domain

Transparent Model Domain

Input: initial state, goal condition, action set is described in logic (e.g. PDDL)

- Easy to compute relevant action
- Possilble to deduce which actions are useful

```
Init: ontable(a),ontable(b),clear(a),clear(b)
Goal: on(a,b)
Action:
   Move(b,x,y)
      Precond: on(b,x),clear(x),clear(y)
      Effect:  on(b,y),clear(x),¬on(b,x),¬clear(y)
```



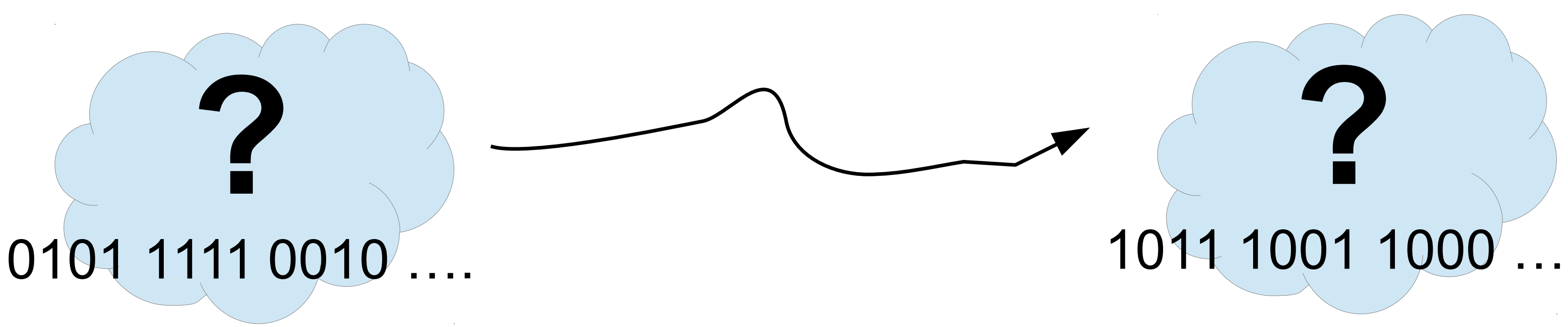
Example: blocks world

Black-box Domain

- Domain description in Black-box domain:
  - s_0: initial state (bit vector)
  - $suc(s, a)$: (black-box) successor generator function returns a state which results when action a is applied to state s
  - $r(s, a)$: (black-box) reward function (or goal condition)

  →**No description of which actions are valid/relevant**

Initial state | Goal condition



Arcade Learning Environment (ALE): A Black-box Domain (Bellemare et al. 2013)

- Domain description in the ALE:
  - State: RAM state (bit vector of 1024 bits)
  - Successor generator: Complete emulator
  - Reward function: Complete emulator

Arcade Learning Environment

Arcade Learning Environment (ALE): A Black-box Domain (Bellemare et al. 2013)

- Domain description in the ALE:
  - 18 available actions for an agent
  - **No description of which actions are relevant/required**
  - Node generation is the main bottleneck of walltime (requires running simulator)

Arcade Learning Environment

Two Lines of Research in the ALE
(Bellemare et al. 2013)

- Online planning setting (e.g. Lipovetzky et al. 2015)

  An agent runs a simulated lookahead each k (= 5) frames and chooses an action to execute next (**no prior learning**)

- Learning setting (e.g. Mnih et al. 2015)

  An agent generates a reactive controller for mapping states into actions

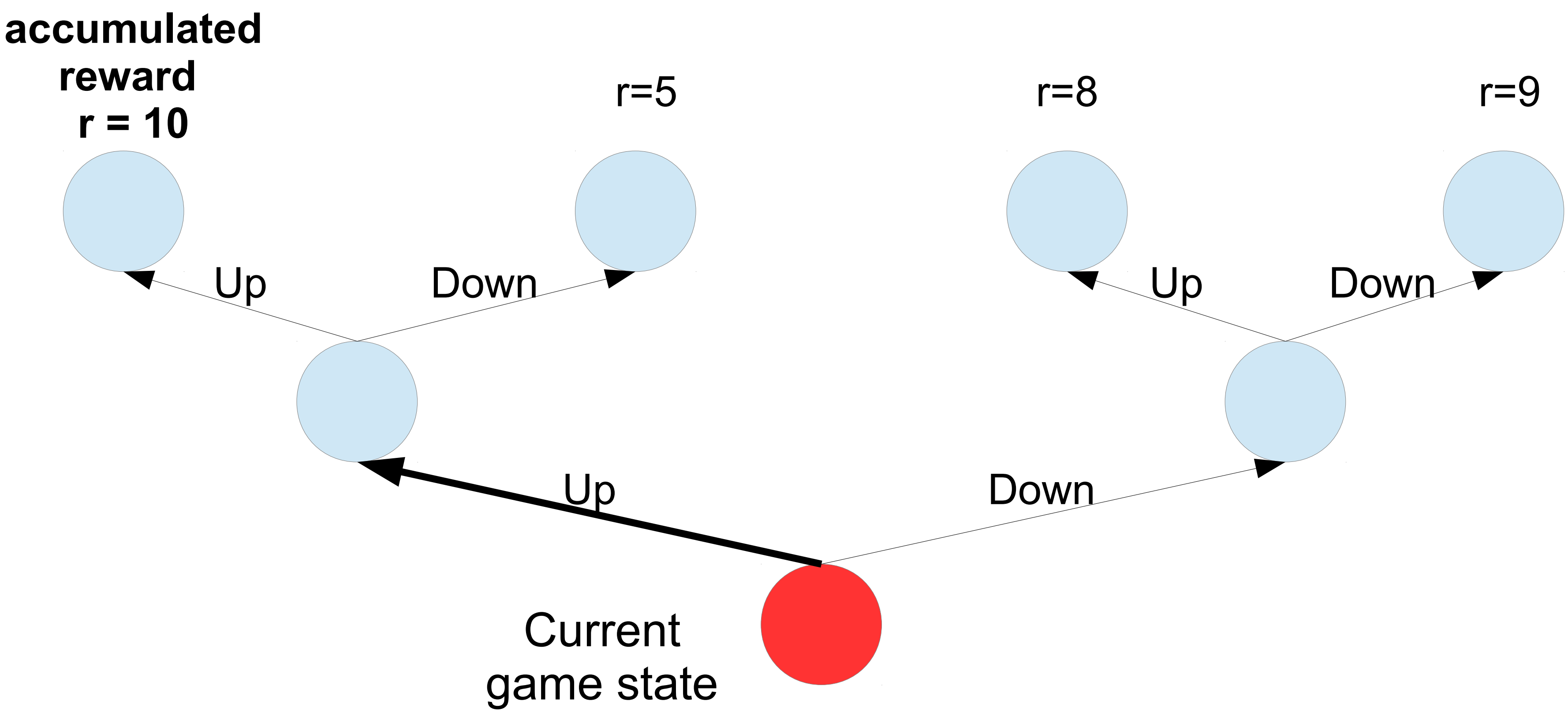
We focus on Online planning setting for this talk
(applying our method to RL is future work)

Online Planning on the ALE

(Bellemare et al 2013)

For each planning iteration (= planning episode)

1. Run a simulated lookahead with a limited amount of computational resource (e.g. # of simulation frames)
2. Choose an action which leads to the best accumulated reward



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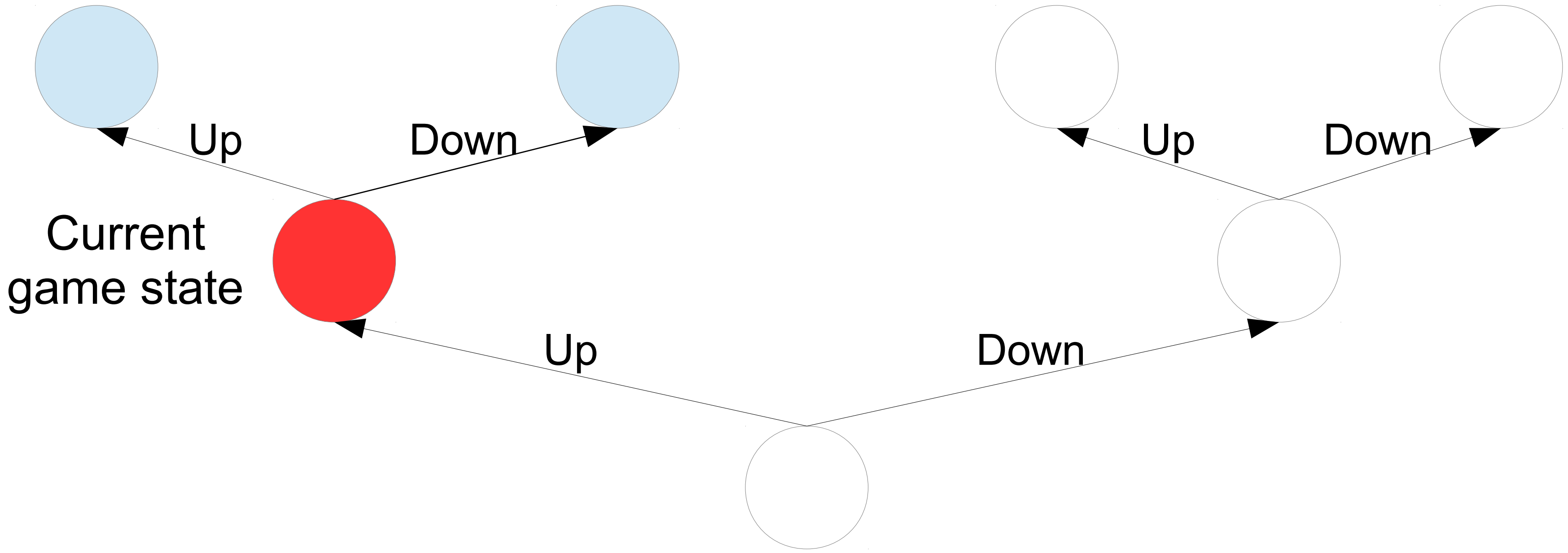

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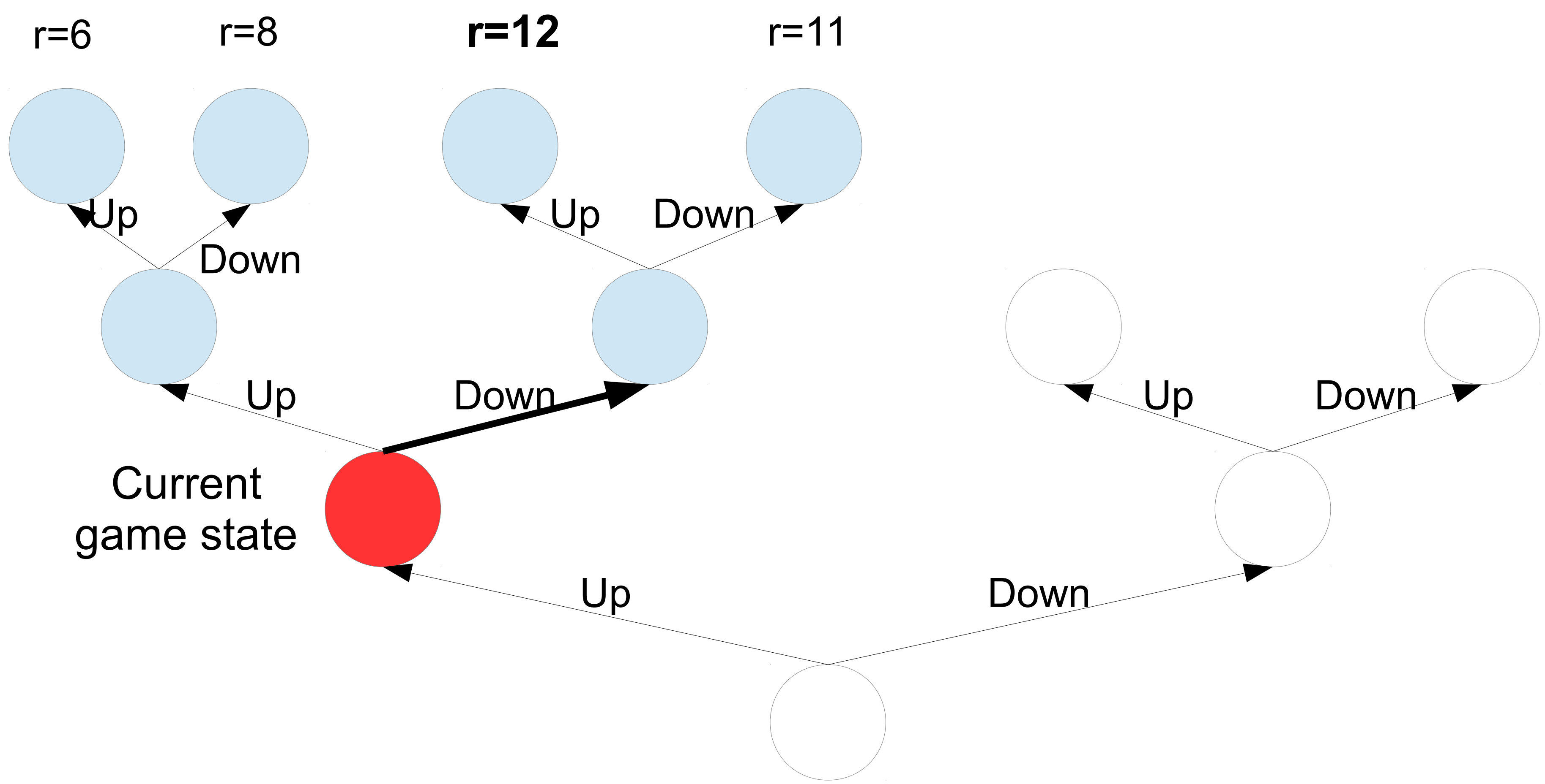

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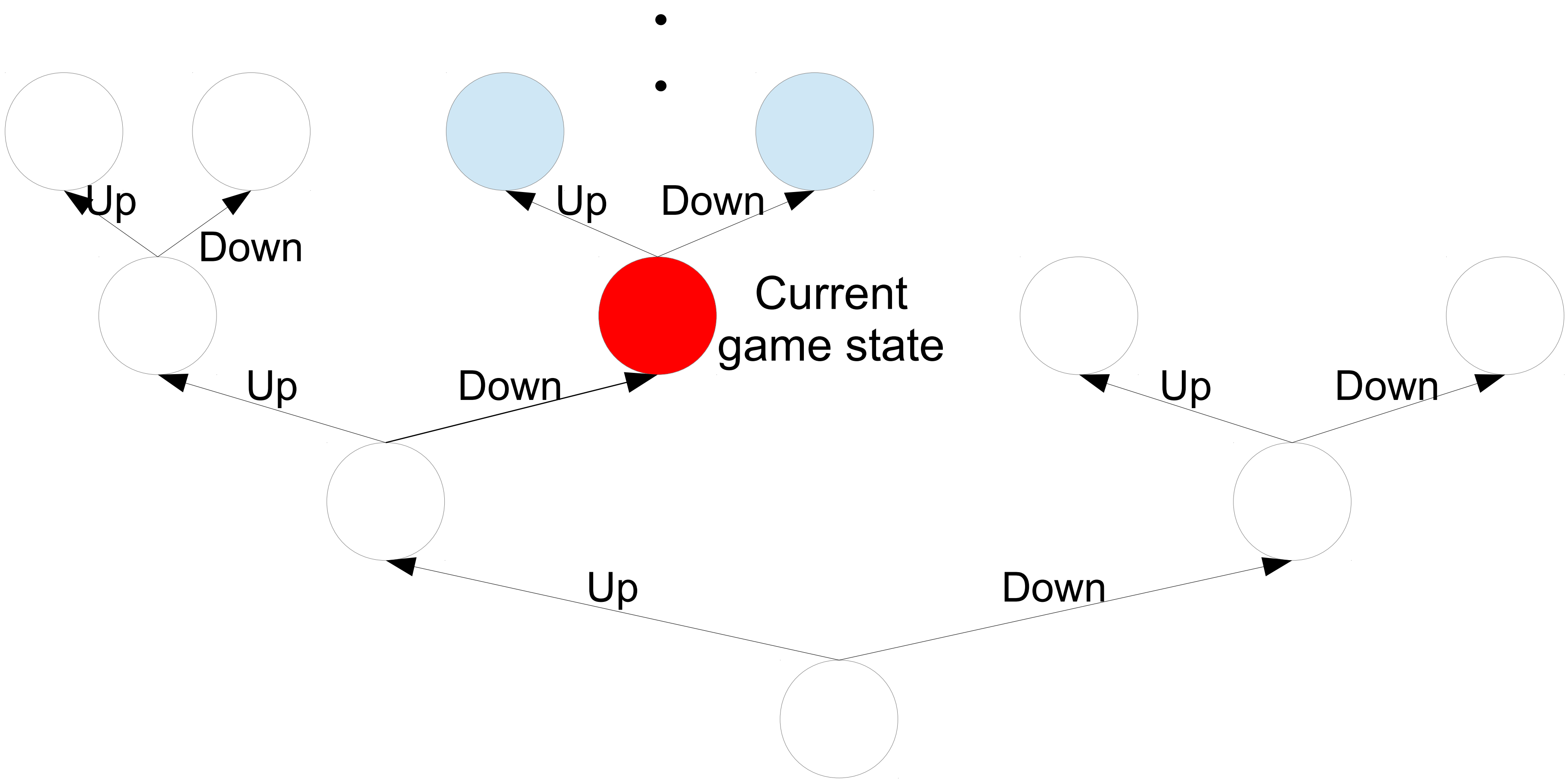

General-purpose agents have many irrelevant actions

- The set of actions which are "useful" in each environment (= game) is a subset of the available action set in the ALE

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(18 actions)

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Actions which are useful
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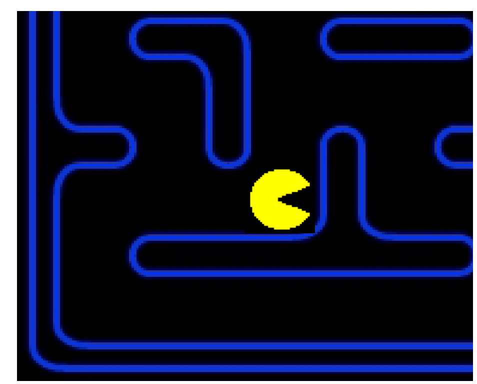


General-purpose agents have many irrelevant actions

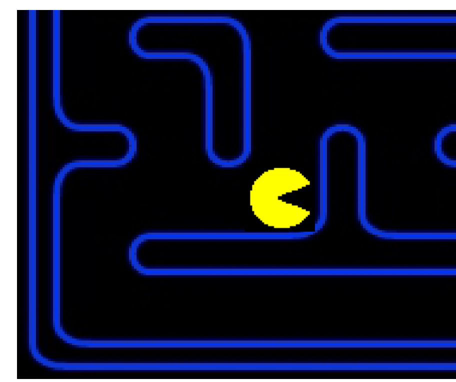
- The set of actions which are “useful” in each environment (= game) is a subset of the available action set in the ALE
- The set of actions which are “useful” in each state in the environment is a smaller subset

Neutral	Neutral + fire
Up	Up + fire
Up-left	Up-left + fire
Left	Left + fire
Down-left	Down-left + fire
Down	Down + fire
Down-right	Down-right + fire
Right	Right + fire
Up-right	Up-right + fire

Available action set in the ALE (18 actions)

Neutral
Up
Left
Down
Right

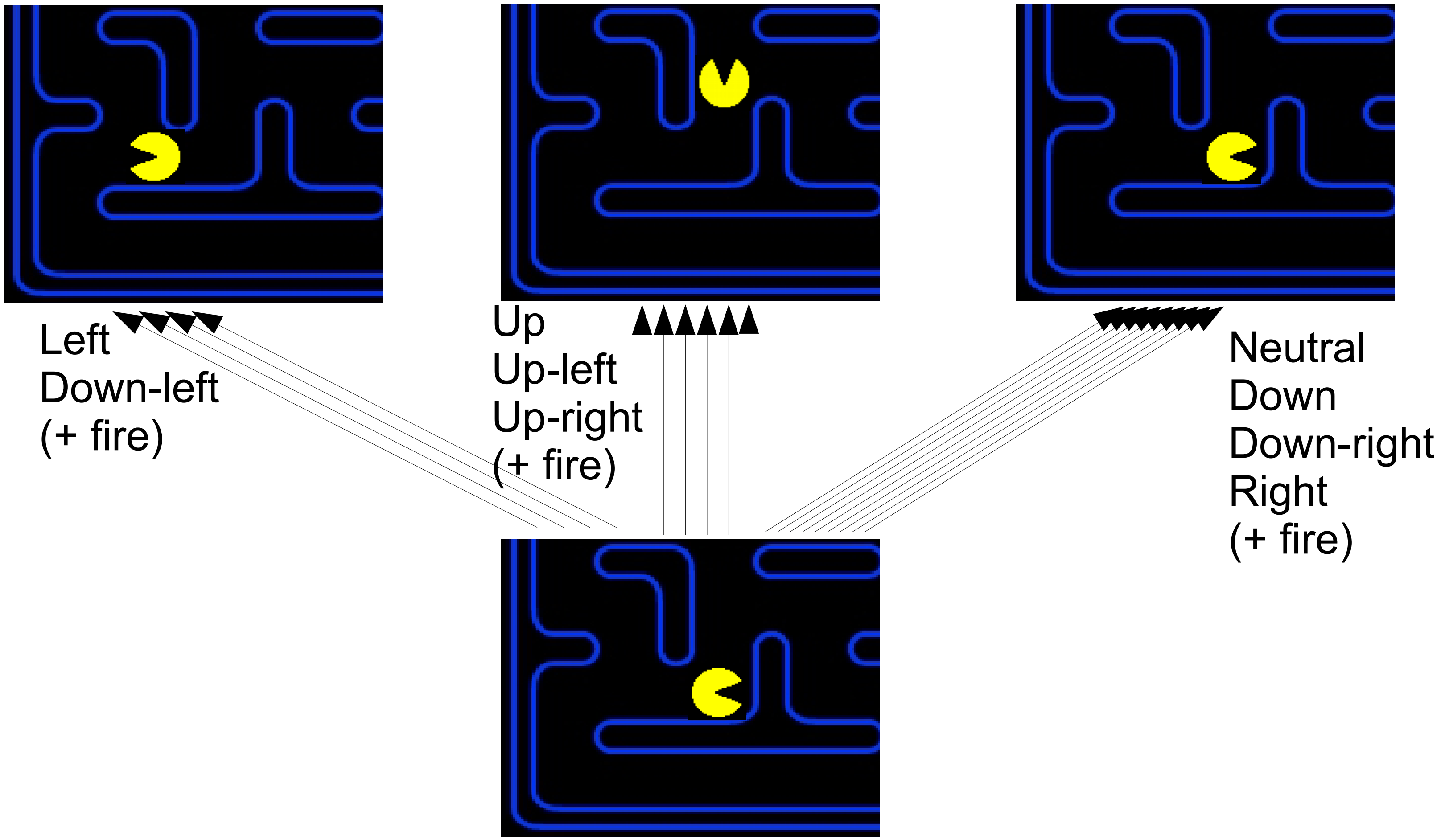
Actions which are useful in the environment



Neutral
Up
Left

Actions which are useful in the state

General-purpose agents have many irrelevant actions

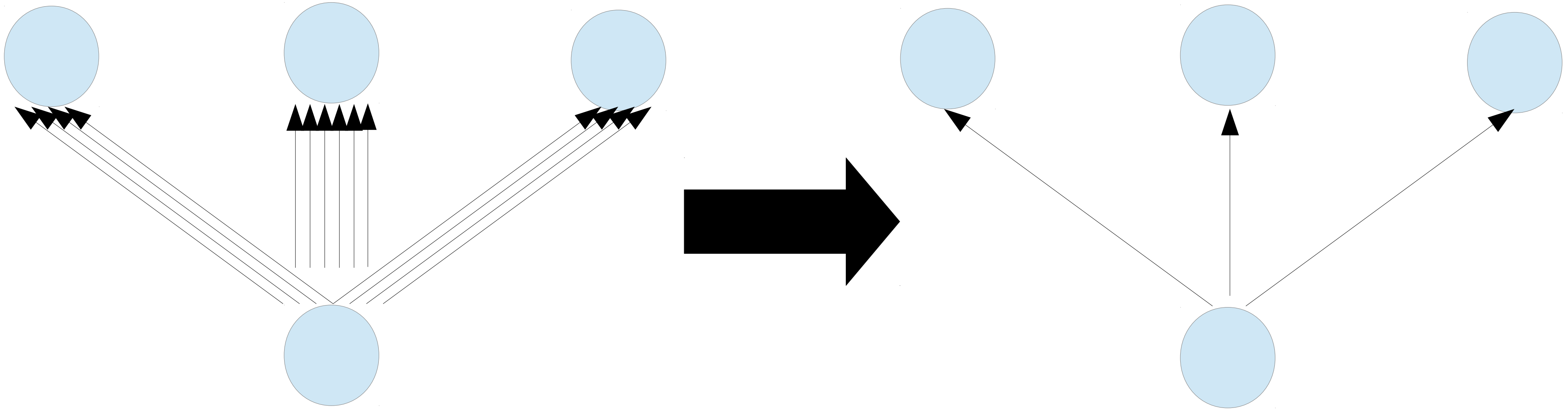


- Generated duplicate nodes can be pruned by duplicate detection
- However, **in simulation-based black-box domain node generation is the main bottleneck of the walltime performance**

→ **By pruning irrelevant actions we should make use of the computational resource more efficiently**

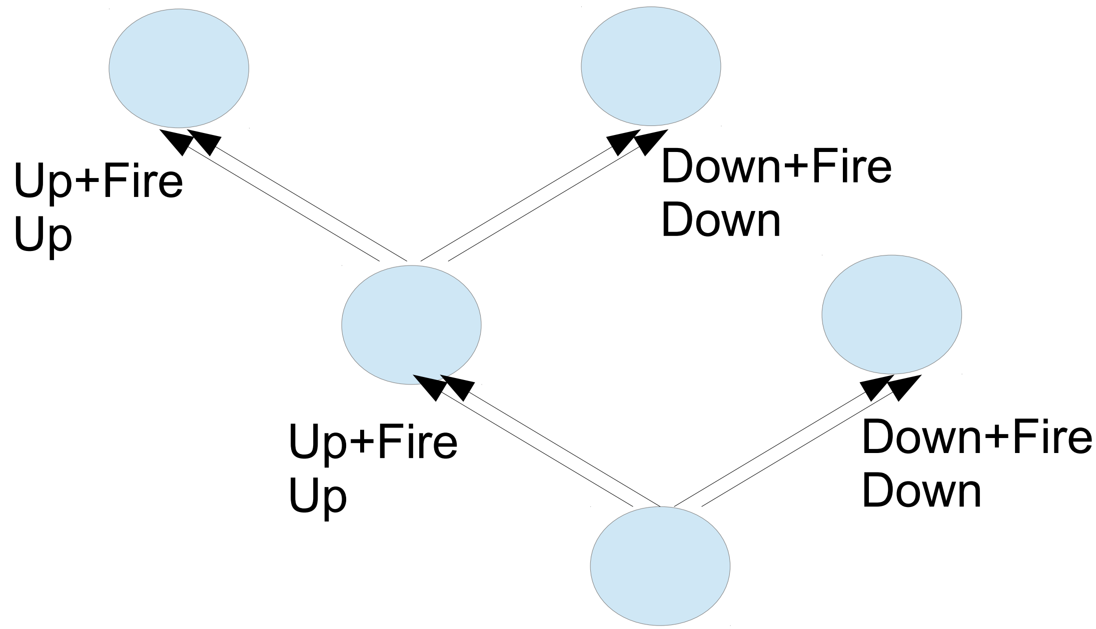
Dominated action sequence pruning (DASP)

- Goal: Find action sequences which are useful in the environment
  (for simplicity we explain using action sequence of length=1)
- Prune redundant actions in the course of online planning
- Find a minimal action set which can reproduce previous search graphs and use the action set for the next planning episode

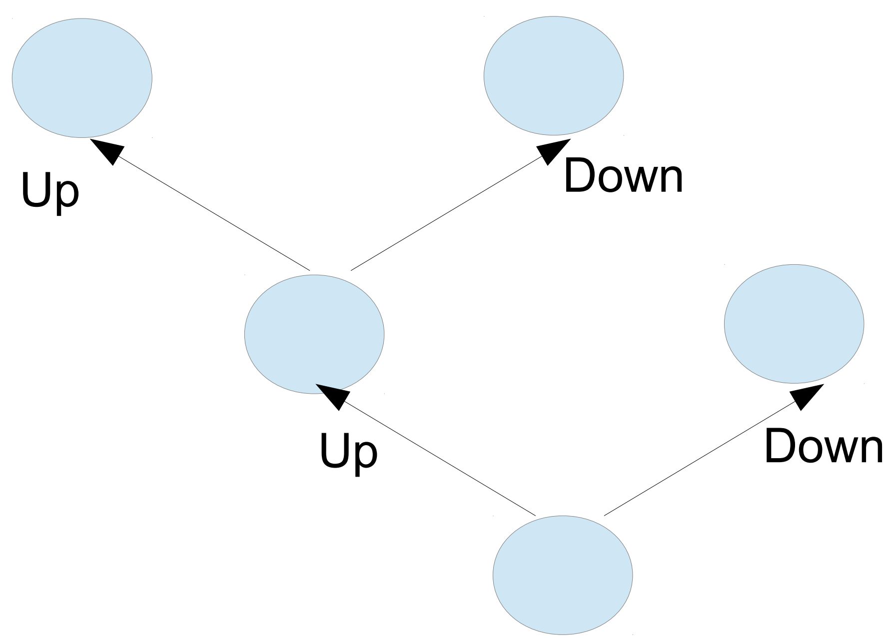


Dominated action sequence pruning (DASP)

Action set available to the agent
{Up,
Down,
Up+Fire,
Down+Fire}

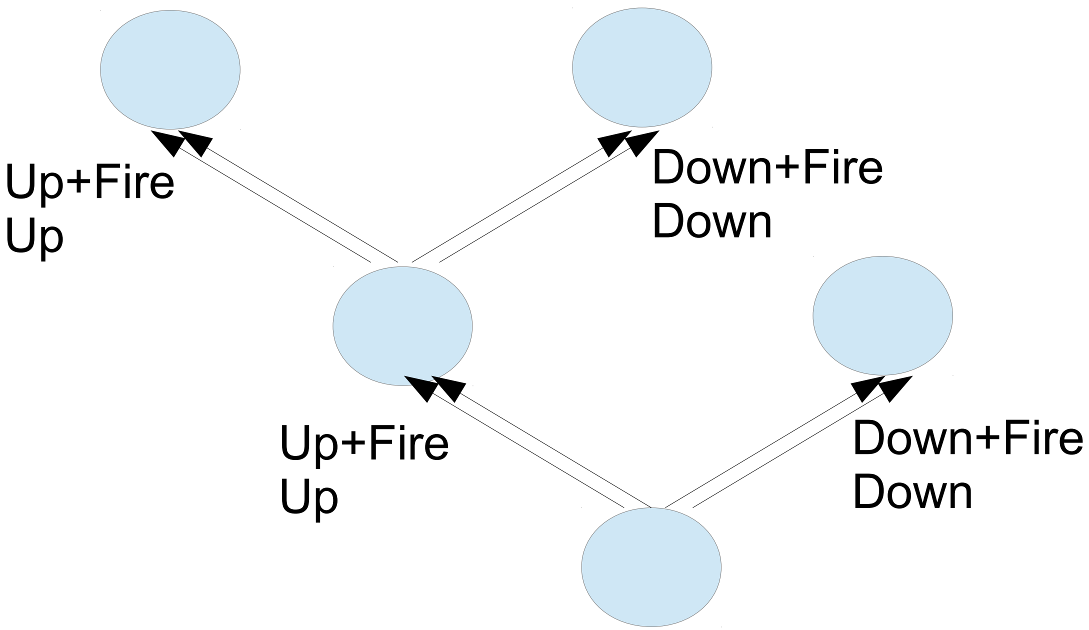


Minimal action set
{Up,
Down}



DASP: Find a minimal action set

- Algorithm: Find a minimal action set A

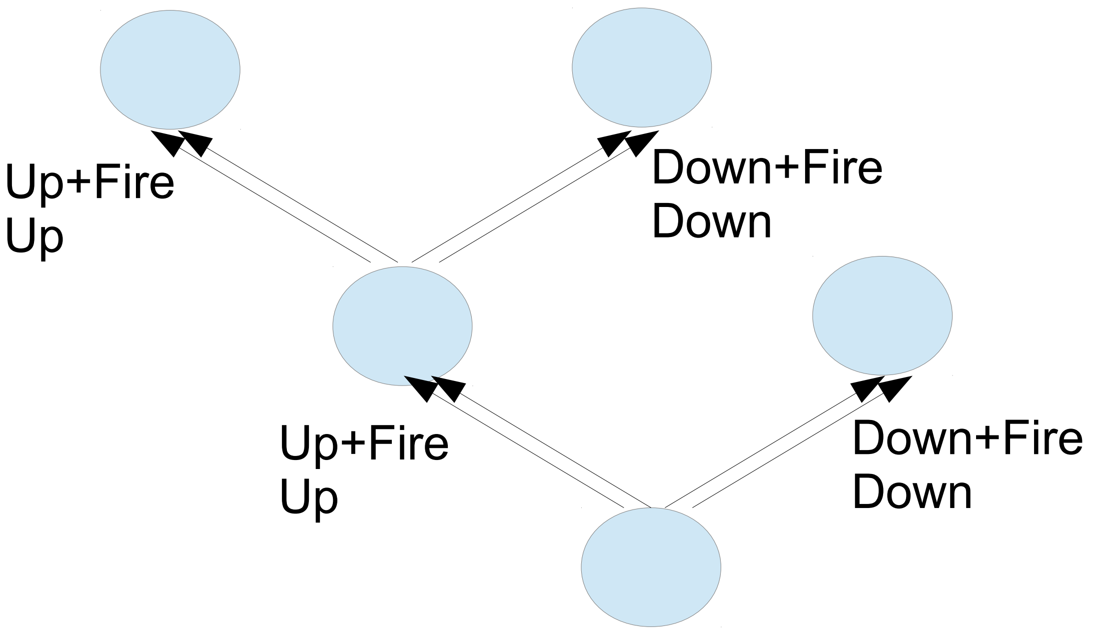


search graphs in previous episodes

DASP: Find a minimal action set

- Algorithm: Find a minimal action set A

1. $v_i \in V$ corresponds to action *i* in hypergraph $G = (V, E)$.



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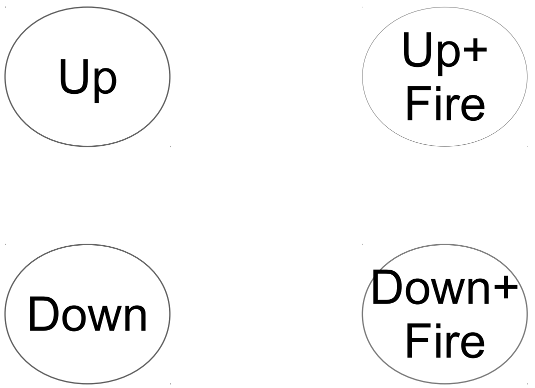
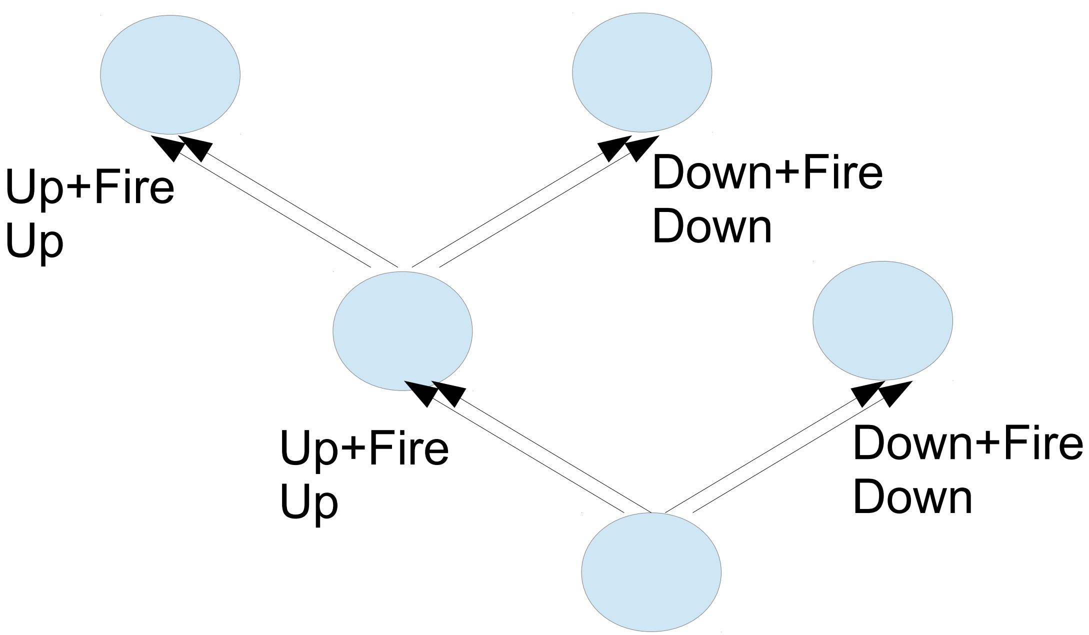


Hypergraph G

DASP: Find a minimal action set

- Algorithm: Find a minimal action set A

1. $v_i \in V$ corresponds to action *i* in hypergraph $G = (V, E)$.
   $e(v_0, v_1, \ldots, v_n) \in E$ iff there is one or more duplicate search nodes generated by all of $v_0, v_1, \ldots, v_n$ but not by any other actions.



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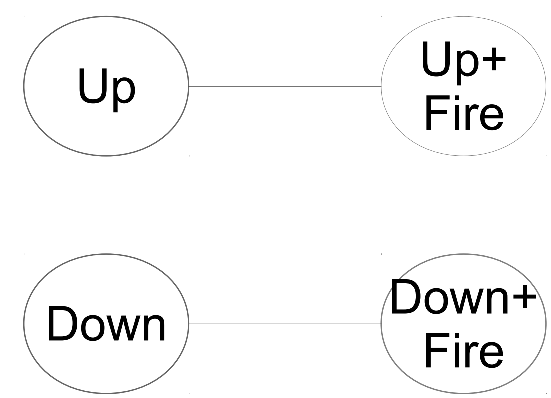

Hypergraph G

DASP: Find a minimal action set

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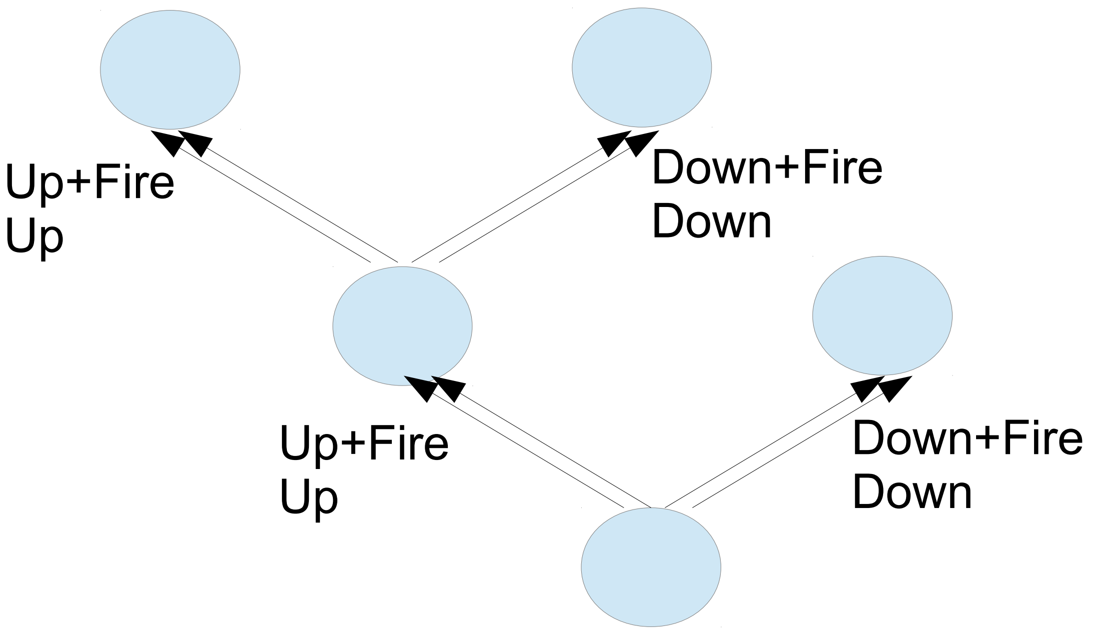
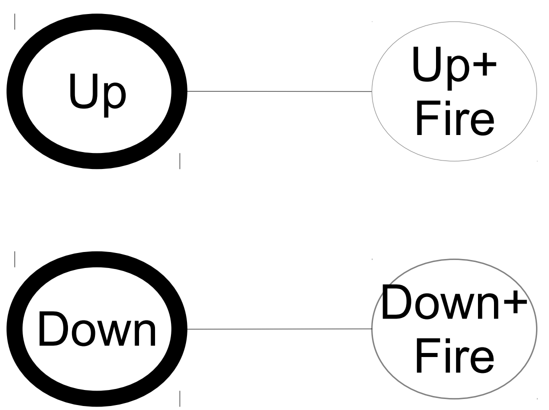
2. Add the minimal vertex cover of G to A



search graphs in previous episodes

A = {Up, Down}



Hypergraph G

DASP: Find a minimal action set

- Algorithm: Find a minimal action set A

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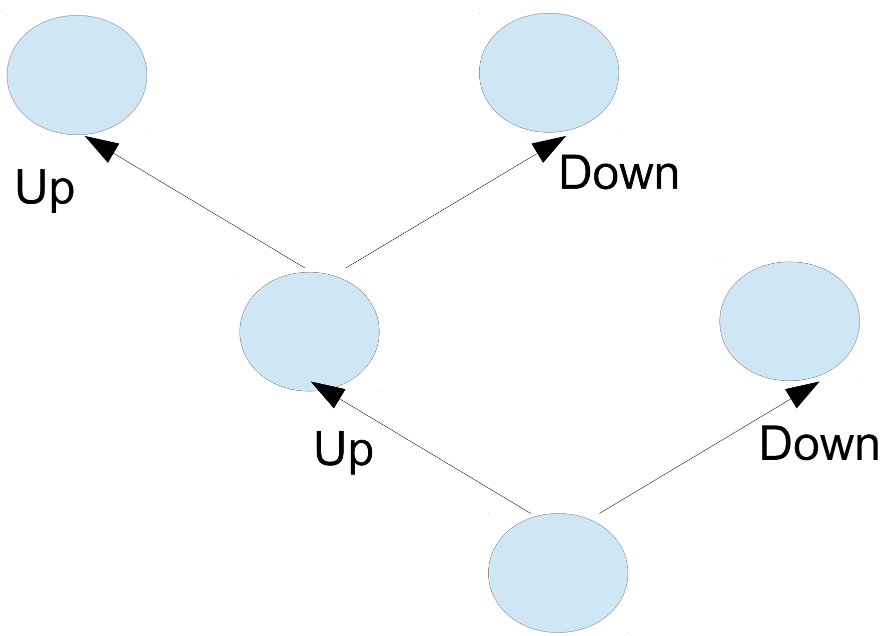
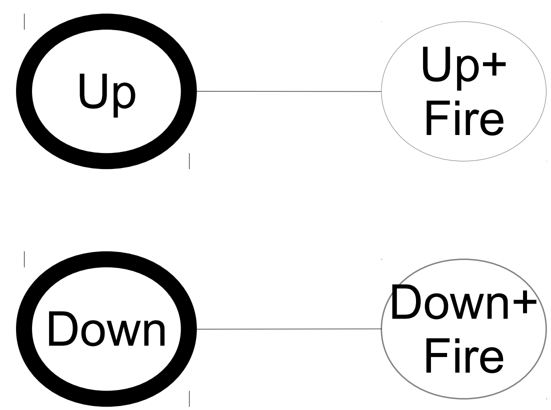
2. Add the minimal vertex cover of G to A



search graph using A

A = {Up, Down}

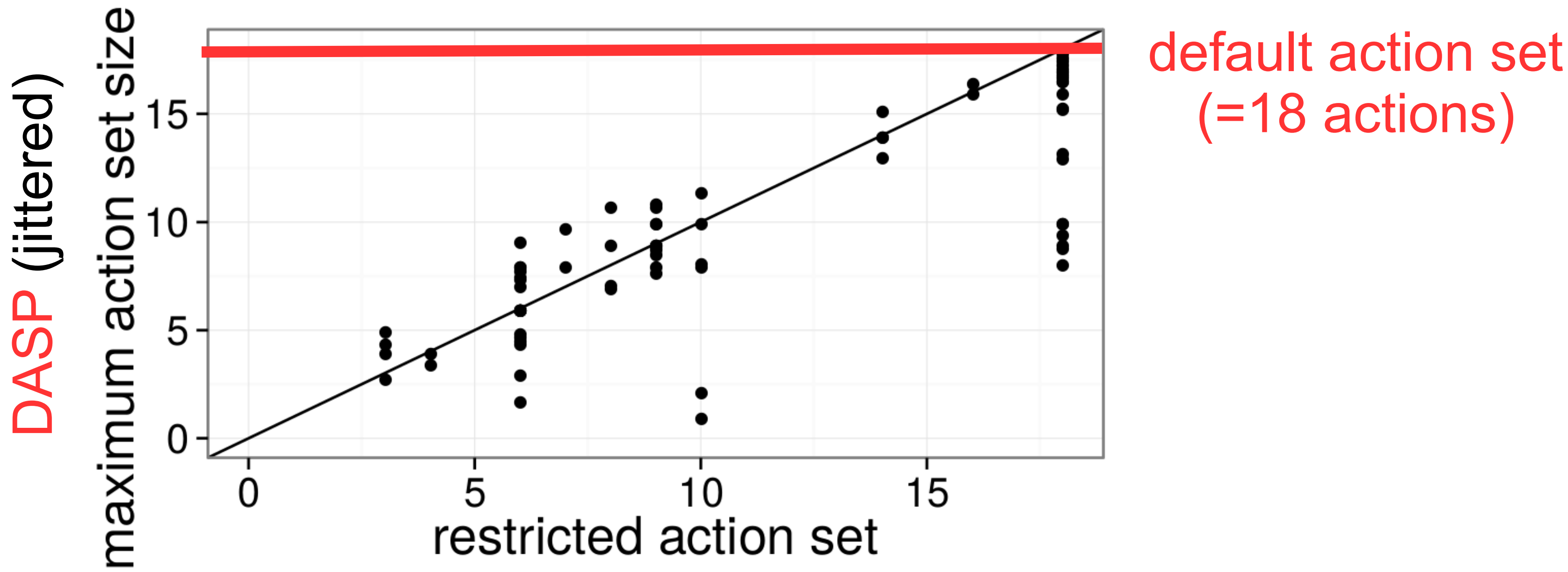


Hypergraph G

Experimental Result: acquired minimal action set

- DASP finds and uses a minimal action set at each planning epsiode except for the first 12 planning episodes
- Restricted action set:

  hand-coded set of minimal actions for each game



Problem of DASP

- DASP is a binary classifier: to prune or not to prune
- Most of the actions are only **conditionally effective**

1. FIRE action may be useful only if the agent has a sword or a bomb.

   Such actions may be preemptively pruned before encountering a context it becomes useful. DASP only guarantees that the action set reproduce search graphs of **previous** planning episodes.

2. LEFT action may be meaningless if there is a wall on the left of the agent

   DASP may not prune conditionally ineffective actions

→Should prune actions in the context of the current planning episode !

Dominated action sequence avoidance (DASA)

- Goal: Find actions which are useful **in the planning episode**
- Let $p(a, t)$ be the ratio of new nodes action a generated at t-th planning episode.
- From $p(a, t)$ we estimate $p^*(a, t)$: probability of action a generating a new node at $t+1$-th planning episode.

$$p^*(a, 0) = 1$$

$$p^*(a, t+1) = \frac{p(a, t) + \alpha p^*(a, t)}{1+\alpha}$$

- At t-th planning episode, for each node expansion, agent applies action a with probability $P(a, t)$

$$P(a, t) = (1-\epsilon) s(p^*(a, t)) + \epsilon$$

where s is a smoothing function (e.g. sigmoid),
ε is a minimal probability to apply action a.

Experimental Evaluation

- Compared scores achieved on 53 games in the ALE
- Applied DASP and DASA to breadth-first search variants
  - p-IW(1) (Shleyfman et al. 2016), IW(1) (Lipovetzky et al. 2012), BrFS (breadth-first search)
- Limited the number of node generation per planning episode to 2000 (excluding "reused" nodes generated in previous planning episode)

- DASA2: DASA applied to action sequence of length = 2
- DASA1: DASA applied to action sequence of length = 1
- DASP1: DASP applied to action sequence of length = 1
- default: Use all available actions in the ALE (18 actions)
- restricted: A minimal action set required to solve the game (hard-coded by a human for each game)

Experimental result: Score

- **DASA2 had the best coverage for all five settings**
- p-IW(1) (400gend) configuration:
  - Limited the number of node generation to 400. DASA2 outperformed the other methods.
- p-IW(1) (extend) configuration:
  - Added two spurious buttons with no effect. DASA2 outperformed the other methods.

	DASA2	DASA1	DASP1	default	restricted
p-IW(1)	**22**	10	4	6	10
p-IW(1) (400gend)	**24**	14	6	5	7
IW(1)	**22**	9	7	7	8
BrFS	**18**	11	11	6	11
p-IW(1) (extend)	**39**	22	19	16	-

Coverage = #Games where each method (column) scored the best among the methods (in each row/configuration)

Experimental Results: Depth of the search

- Compared the number of node expansion and the depth of the search tree using p-IW(1)
- The result indicates that DASA2 is successfully exploring larger and deeper state-space

	DASA2	DASA1	DASP1	default	restricted
Expanded	**254.9**	191.1	119.9	119.6	234.0
Depth	**82.8**	59.5	34.6	34.1	40.8

Expanded = the average number of node expansion
Depth = the depth of the search tree

Conclusion

- Proposed DASP and DASA, methods to avoid redundant actions in Black-box Domain
- We experimentally evaluated DASP and DASA in the ALE
- Showed that by avoiding redundant actions an agent can search deeper and achieved higher score

Lesson:

- Avoiding redundant action sequences avoids generating duplicate states, a bottleneck in simulation-based black-box domains

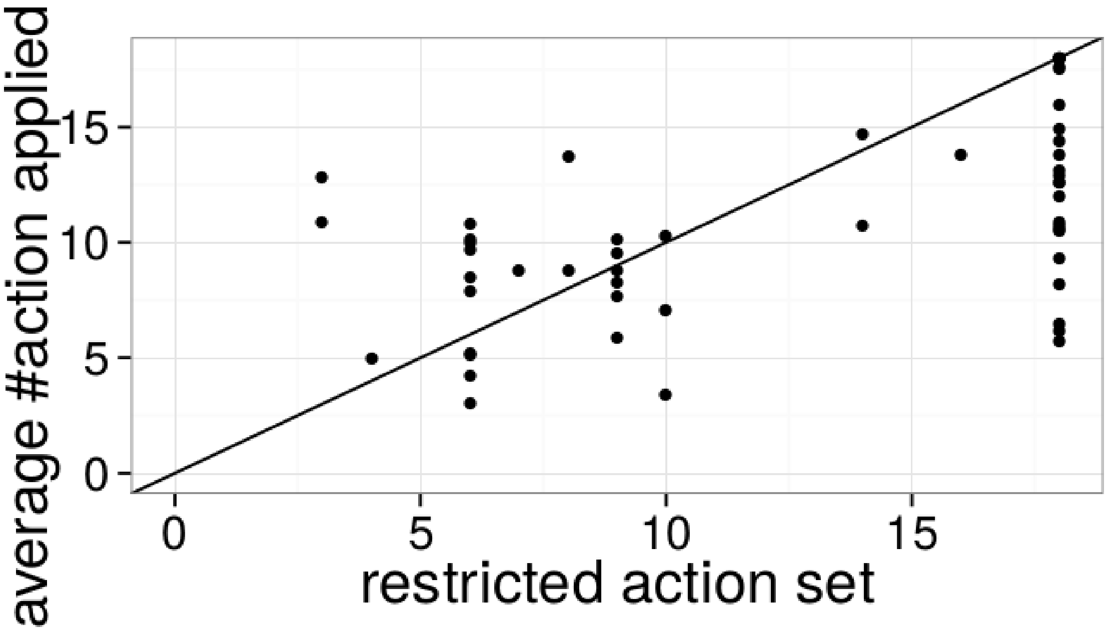
Future Work

- Apply DASA in RL (currently working on this)
- Extract more information from the domain

Appendix slides

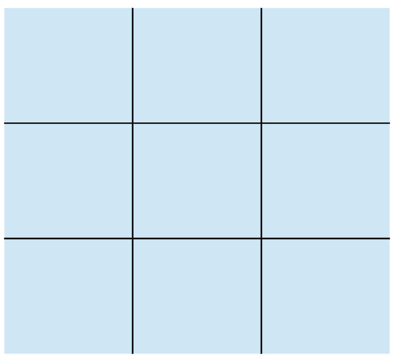
Experimental Result: number of pruned actions

- Pruned many actions (#available action = 18)
- Restricted action set: a minimal action set required
  (hard-coded by a human for each game)



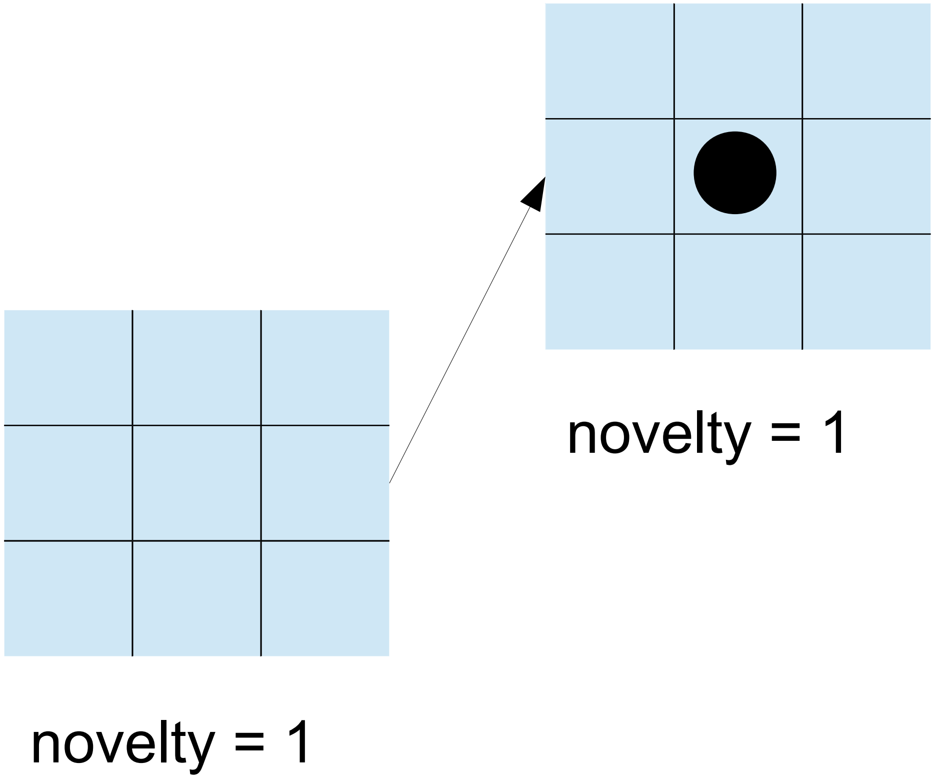
DASA2

IW(1) Example: Tick-Tack-Toe



novelty = 1

IW(1) Example: Tick-Tack-Toe



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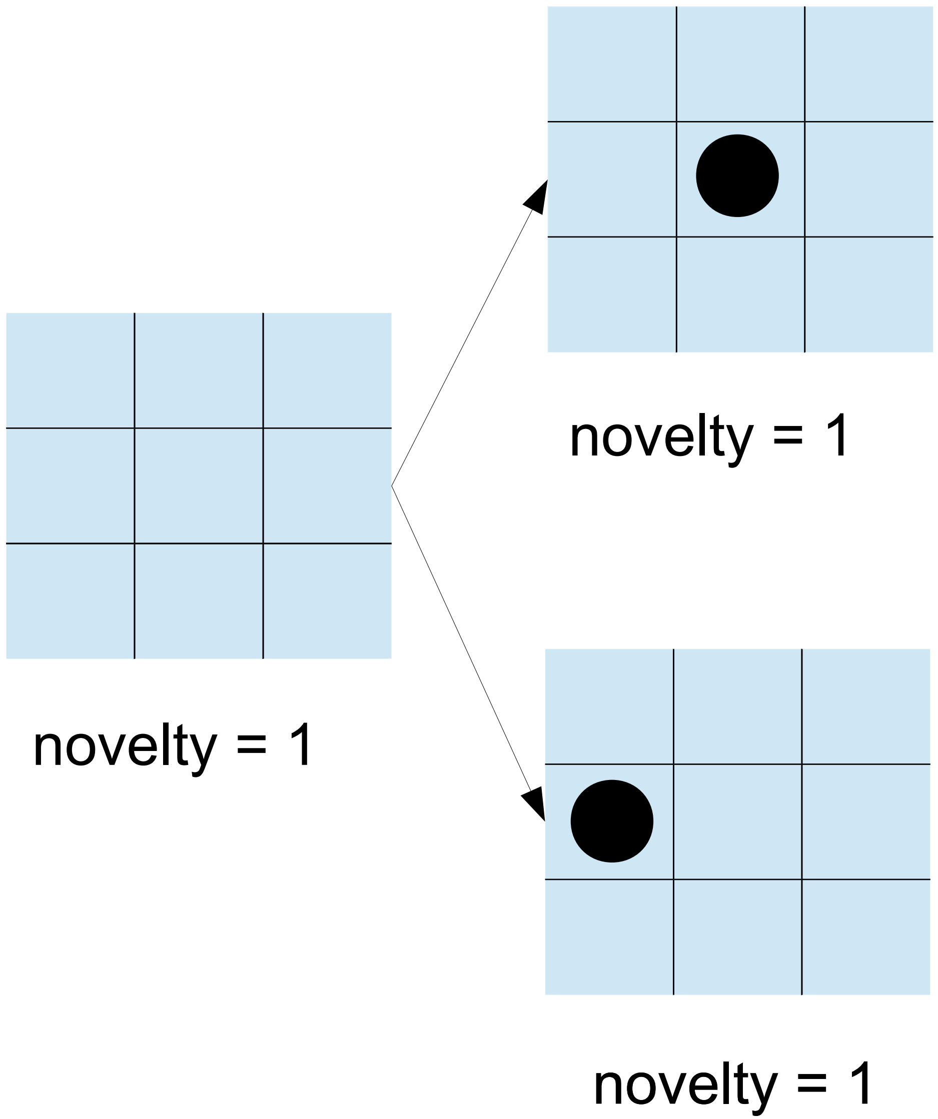

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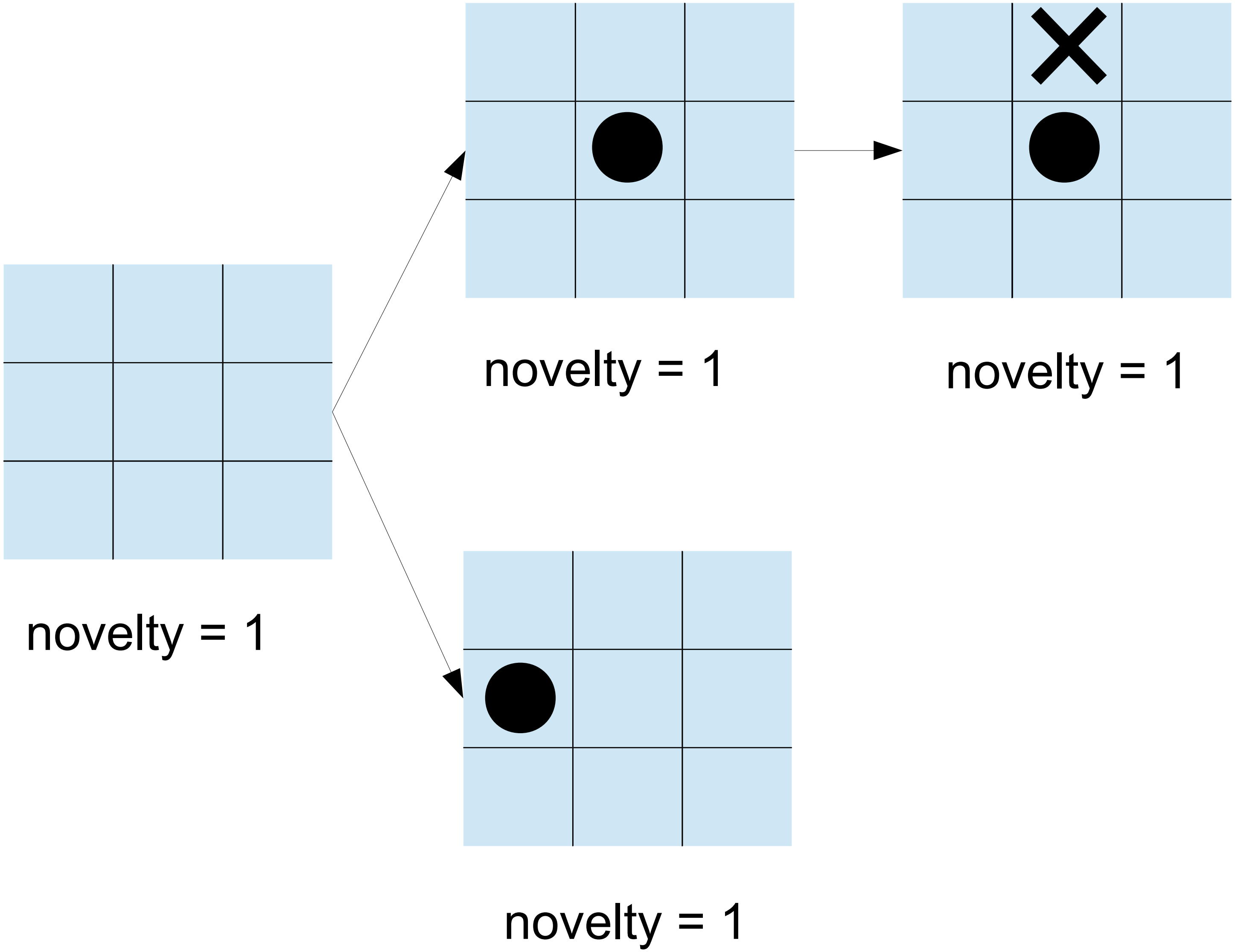

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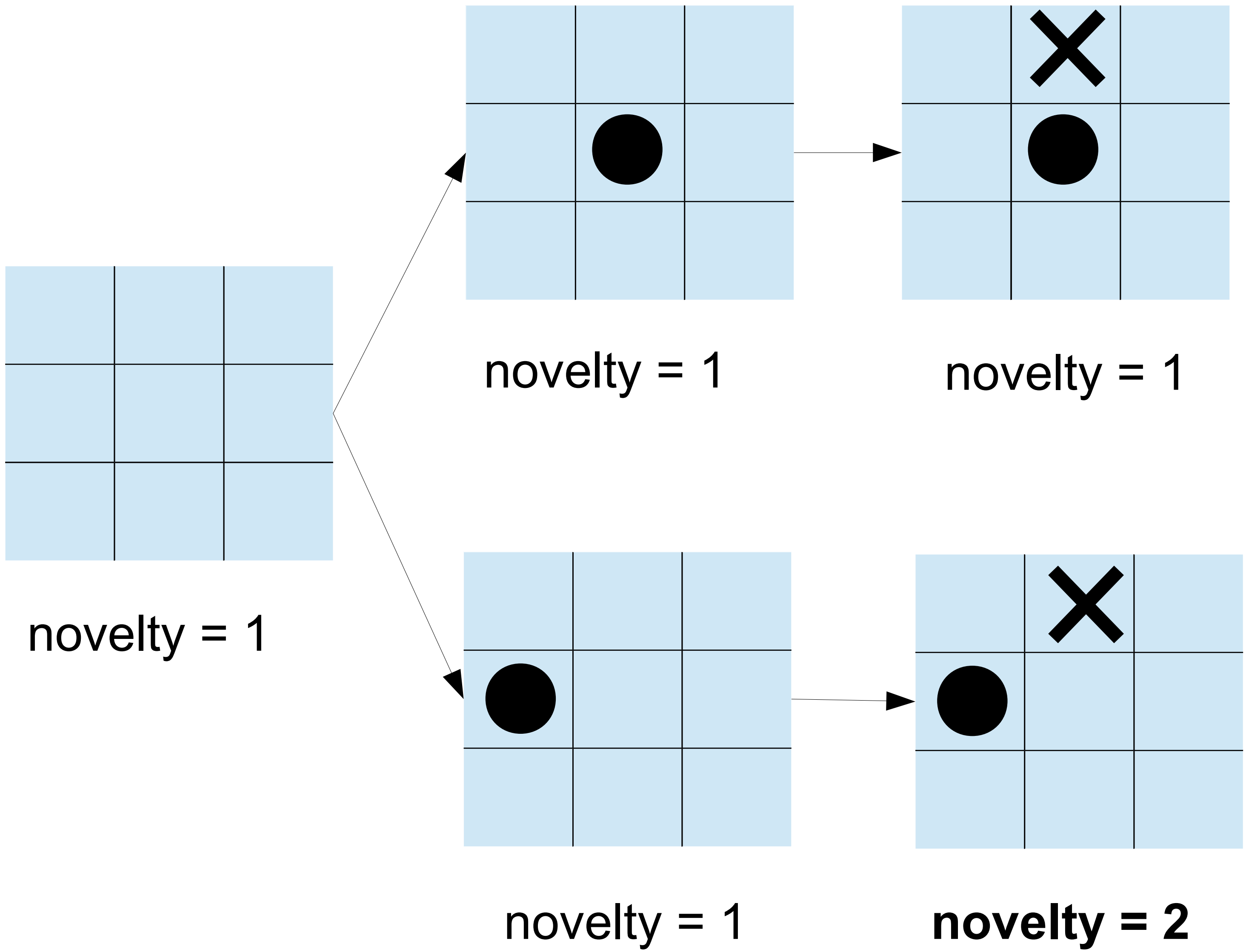

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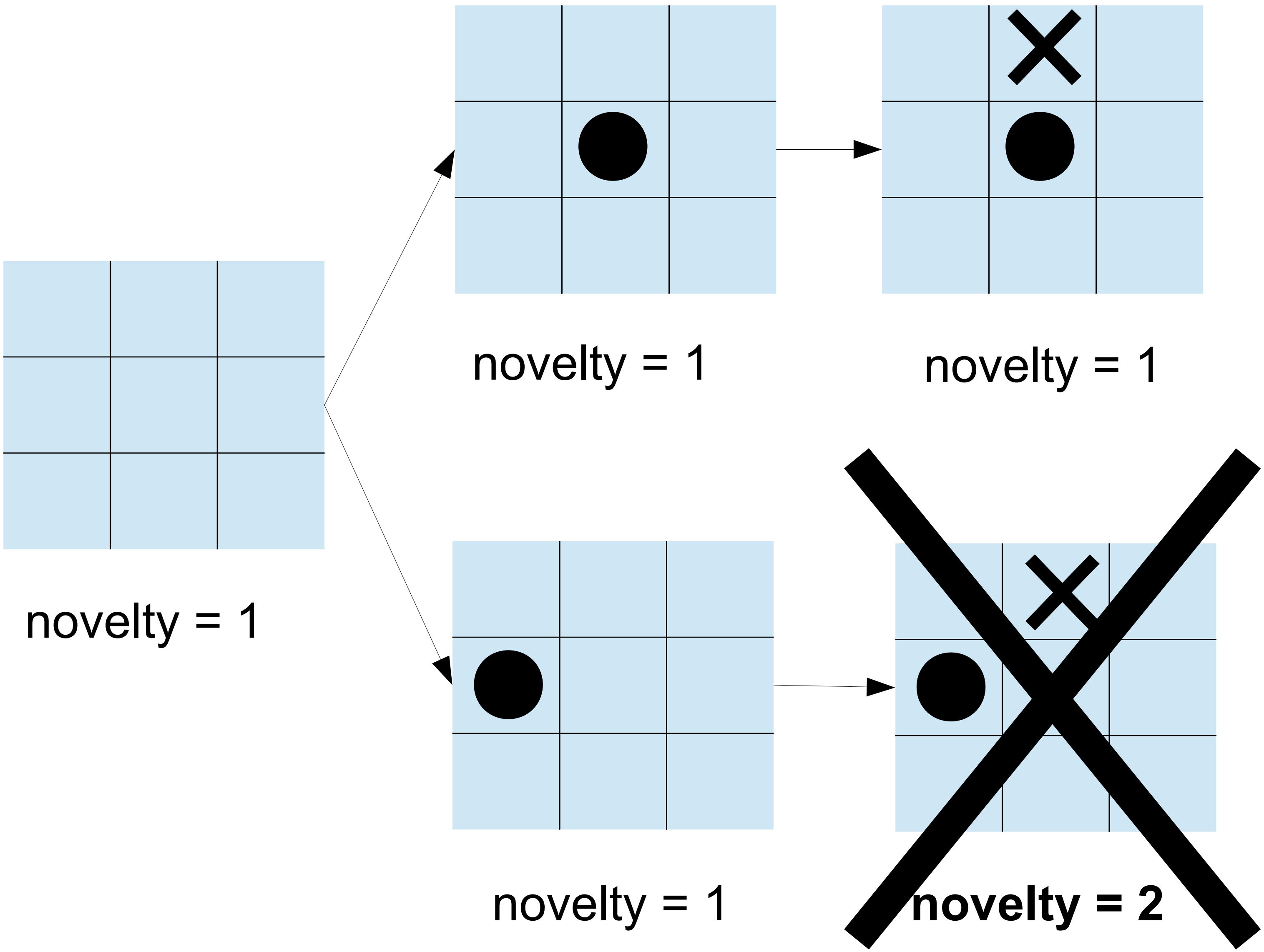

- **Aggressive pruning strategy**