

# Planning for Artificial Intelligence



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Relaxation Heuristics

# Search, Heuristics

(revision)

# Informed Search

- Systematic (one-directional)
  - Greedy Best First Search (GBFS)
  - $A^*$
  - Weighted  $A^*$
- Systematic bidirectional
- Local
  - (Enforced) Hill Climbing

# Heuristic Function

- Let  $S$  be a set of states for a given planning task  $\Pi$ . A **heuristic function** (or **heuristics**) for  $\Pi$  is a function  $h:S \rightarrow \mathbb{N}_0 \cup \{\infty\}$
- The value  $h(s)$  **estimates** distance from  $s$  to the nearest goal state
- $h(s)$  is called **heuristic estimate** or **heuristic value** for  $s$
- A **perfect** (or optimal) **heuristics**, denoted as  $h^*$ , maps each state to the length (or cost) of the optimal plan to the nearest goal state
  - If  $h^*(s)=\infty$  then  $s$  is a dead-end state (no goal state is reachable from  $s$ )

# Properties of Heuristic Function

- Heuristic function  $h$  for  $\Pi$  (over  $S$ ) is
  - **safe** if for each  $s \in S$  s.t.  $h(s) = \infty$  it holds that  $s$  is a dead-end state (i.e,  $h^*(s) = \infty$ )
  - **goal aware** if  $h(s_G) = 0$  for each goal state  $s_G$
  - **admissible** if for each  $s \in S$  it holds that  $h(s) \leq h^*(s)$
  - **consistent** if goal aware and for each  $s, s' \in S$  s.t.  $s'$  is a successor of  $s$  it holds that  $h(s) \leq h(s') + \text{cost}(s, s')$

# Towards Good Heuristics

# Ideal Properties of Heuristics

- **Easy to compute** (at most in linear time)
- **Easy to implement**
- **Very informative** (close to the perfect heuristic)
  
- These properties often go against each other
  
- We consider STRIPS representation throughout this lecture

# Goal Count Heuristic

- The **Goal Count heuristic** represents how many goal atoms have yet to be achieved
- $h_G(s) = |G \setminus s|$
- **Easy to compute ?**



# Goal Count Heuristic

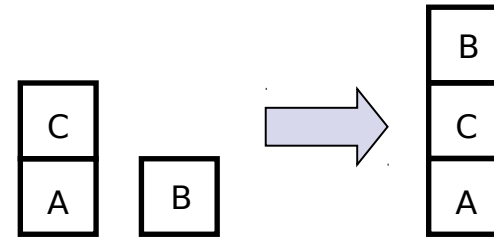
- The **Goal Count heuristic** represents how many goal atoms have yet to be achieved
- $h_G(s) = |G \setminus s|$
- Easy to compute ?
  - Yes
- Easy to implement ?

# Goal Count Heuristic

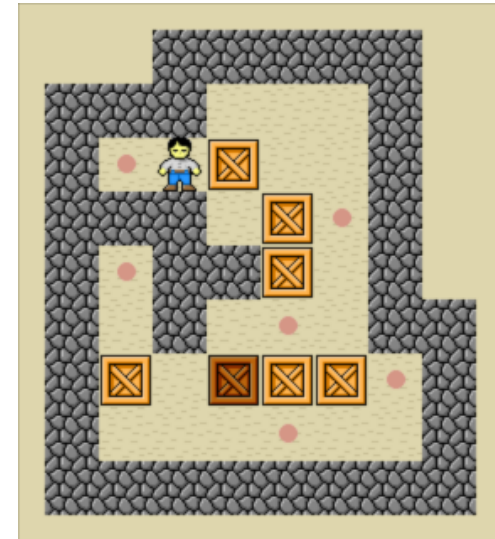
- The **Goal Count heuristic** represents how many goal atoms have yet to be achieved
- $h_G(s) = |G \setminus s|$
- Easy to compute ?
  - Yes
- Easy to implement ?
  - Yes
- Informative ?

# Goal Count Heuristic - Issues

- Some goals are achieved too early
  - Sussman anomaly (in BW)
- If the goal has only one atom
- It might take many steps to achieve one goal atom
  - e.g. Sokoban
- Not admissible
  - one action can achieve more goal atoms



The goal is to to build the A-B-C tower

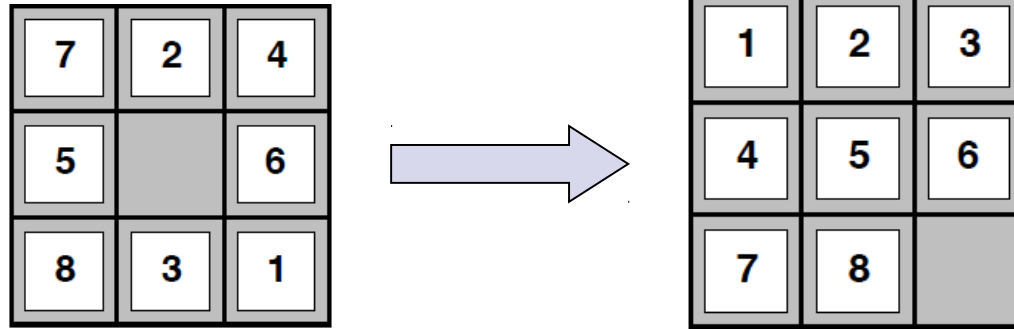


# How to effectively compute reasonably informative heuristics ?

- **Relax** some problem constraints
- **Abstract** the problem
- Leverage some **structural information**
  - **Landmarks**
  - **Potentials**
- ....

# Relaxation

# 8-puzzle example



- A tile can move from square A to B if **A is adjacent to B** and **B is free** →  $h^*$
- A tile can move from square A to B if **A is adjacent to B** →  $h^{MD}$  (Manhattan distance)
- A tile can move from square A to B →  $h^{MT}$  (Misplaced Tiles)
- $h^* \geq h^{MD} \geq h^{MT}$  (why?)

# Relaxation

- **Removing one or more constraints** from the problem
- **Solution** of the **original** problem is a **solution** of the **relaxed** problem
- If the **relaxed** problem is **unsolvable**, then the **original** problem is **unsolvable** too
- Solving the relaxed problem is at most as hard as solving the original problem

# Relaxation in planning

- How to relax planning tasks ?
  - **remove delete effects !**
  - in SAS, we don't remove variable assignment when its value changes (accumulate the values)
- We sometimes explicitly refer to such a relaxation as **delete-relaxation**



# Relaxed Planning Tasks

- The (delete-) **relaxation**  $a^+$  of an action  $a=(pre(a),del(a),add(a))$  is  $a^+=(pre(a),add(a))$
- The **result** of application of  $a^+$  in a state  $s$  (if possible) is  $s'=s \cup add(a)$
- Let  $\Pi=(P,A,I,G)$  be a planning task. The **relaxed planning task**  $\Pi^+$  for  $\Pi$  is  $\Pi^+=(P, \{a^+ \mid a \in A\}, I, G)$
- If  $\pi^+$  is a plan for  $\Pi^+$ , then  $\pi^+$  is a **relaxed plan** for  $\Pi$
- A **perfect** (or optimal) **relaxed heuristics**, denoted as  $h^+$ , maps each state to the length (or cost) of the optimal relaxed plan to the nearest goal state

$h^+$

- $h^+$  is **safe, goal aware, admissible and consistent**
- Finding optimal (delete-)relaxed plans is **NP-hard**
  - Not very practical to use  $h^+$
- **Any other idea ?**

# Greedy Algorithm for Relaxed Planning Tasks

$s := I$

$\pi^+ := \langle \rangle$

**while**  $G \not\subseteq s$  **do**

    select any  $a^+ \in A^+$  s.t.  $a^+$  is applicable in  $s$  and  $\text{add}(a^+) \not\subseteq s$

**if** no such  $a^+$  exists **then return** no solution

$s := s \cup \text{add}(a^+)$

$\pi^+ := \pi^+ . a^+$

**return**  $\pi^+$

# Properties of the Algorithm

- **sound**
  - returned plan is a relaxed plan for the planning task
  - if “unsolvable” is returned, then no action can add an atom to the state and hence some goal atoms cannot be achieved
- **complete**
  - the algorithm always terminates
    - each action can be applied at most once
    - at least one atom is added in each iteration
- **linear** time complexity

# Heuristic from the Greedy Algorithm

- The length or the cost of the relaxed plan (from the state  $s$ ) is the heuristic value for  $s$
- Such a heuristic is
  - **safe**
  - **goal aware**
- Often such relaxed plans are very suboptimal and such a heuristic is thus not very informative

# Two possibilities how to calculate relaxed heuristics

- Do not generate relaxed plans but **estimate difficulty** of a relaxed planning task
  - $h_{\max}$
  - $h_{\text{add}}$
- Generate “**reasonable**” relaxed plans
  - $h_{\text{FF}}$

# Optimistic and Pessimistic Assumptions of Task Difficulty

- The idea is to **estimate cost** of achieving an **atom** or of applying an **action**
- For each **atom** we look for the **cheapest action** to achieve it
- For each **action** we consider (either)
  - **sum** of the costs of the **atoms** in its precondition ( $h_{\text{add}}$ )
  - **maximum** of the costs of the **atoms** in its precondition ( $h_{\text{max}}$ )
- It can be observed that
  - $h_{\text{max}}$  provides an **optimistic** assumption for the relaxed plan cost
  - $h_{\text{add}}$  provides a **pessimistic** assumption for the relaxed plan cost
  - $h_{\text{max}} \leq h^+ \leq h_{\text{add}}$

# Heuristic $h_{\text{add}}$

$$h_{\text{add}}(s) = h_{\text{add}}(G; s)$$

$$h_{\text{add}}(P; s) = \sum_{p \in P} h_{\text{add}}(p; s)$$

$$h_{\text{add}}(p; s) = 0, \text{ if } p \in s$$
$$= a_p(s), \text{ otherwise}$$

$$a_p(s) = \min_{a \in \{a' \mid p \in \text{add}(a')\}} h_{\text{add}}(a; s)$$

$$h_{\text{add}}(a; s) = c(a) + h_{\text{add}}(\text{pre}(a); s)$$

Note that  $s$  is a state,  $p$  is an atom,  $a$  is an action,  $G$  is a goal and  $P$  is a set of atoms



# Heuristic $h_{\max}$

$$h_{\max}(s) = h_{\max}(G; s)$$

$$h_{\max}(P; s) = \max_{p \in P} h_{\max}(p; s)$$

$$h_{\max}(p; s) = 0, \text{ if } p \in s$$

$$= a_p(s), \text{ otherwise}$$

$$a_p(s) = \min_{a \in \{a' \mid p \in \text{add}(a')\}} h_{\max}(a; s)$$

$$h_{\max}(a; s) = c(a) + h_{\max}(\text{pre}(a); s)$$

Note that  $s$  is a state,  $p$  is an atom,  $a$  is an action,  $G$  is a goal and  $P$  is a set of atoms

# Computation

- Basic idea – **value iteration**
- Set values of initial atoms to 0, and to  $\infty$  for other atoms and actions
- If a value of an atom changes, update the values of actions having it in precondition accordingly
- **Label-correcting** action selection method
  - select an **arbitrary** action to process (update the values of atoms in its add effects accordingly)
  - multiple updates per atom
- **Dijkstra** action selection method
  - select the **cheapest** action to process (update the values of atoms in its add effects accordingly)
  - single update per atom

# Reachability graph

- Also known as relaxed planning graph
- Consists of alternating layers of atoms and actions  $P_0, A_0, P_1, A_1, \dots$

$$P_0 = I$$

$$A_i = \{a \mid \text{pre}(a) \subseteq P_i\}$$

$$P_{i+1} = P_i \cup \bigcup_{a \in A_i} \text{add}(a)$$

- Terminate when  $G \subseteq P_i$  or  $P_{i+1} = P_i$

# Running Example (relaxed planning task)

$P = \{a,b,c,d,e,f,g,h\}$

$I = \{a\}$

$G = \{c,d,e,f,g\}$

$a_1 = (\{a\}, \{b,c\})$

$a_2 = (\{a,c\}, \{d\})$

$a_3 = (\{b,c\}, \{e\})$

$a_4 = (\{b\}, \{f\})$

$a_5 = (\{d\}, \{e,f\})$

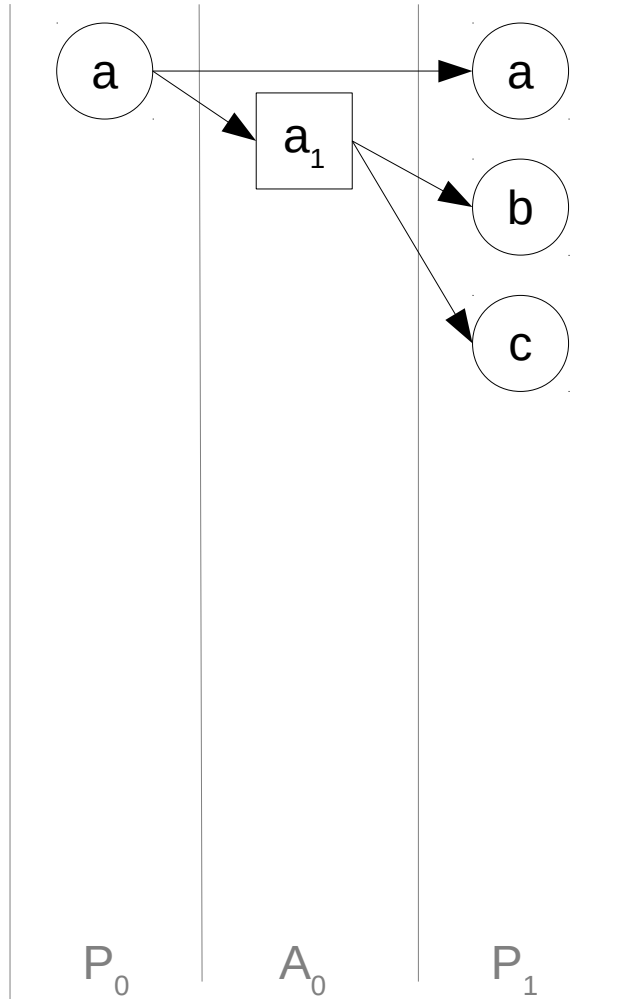
$a_6 = (\{d\}, \{g\})$

# Running Example: Reachability Graph

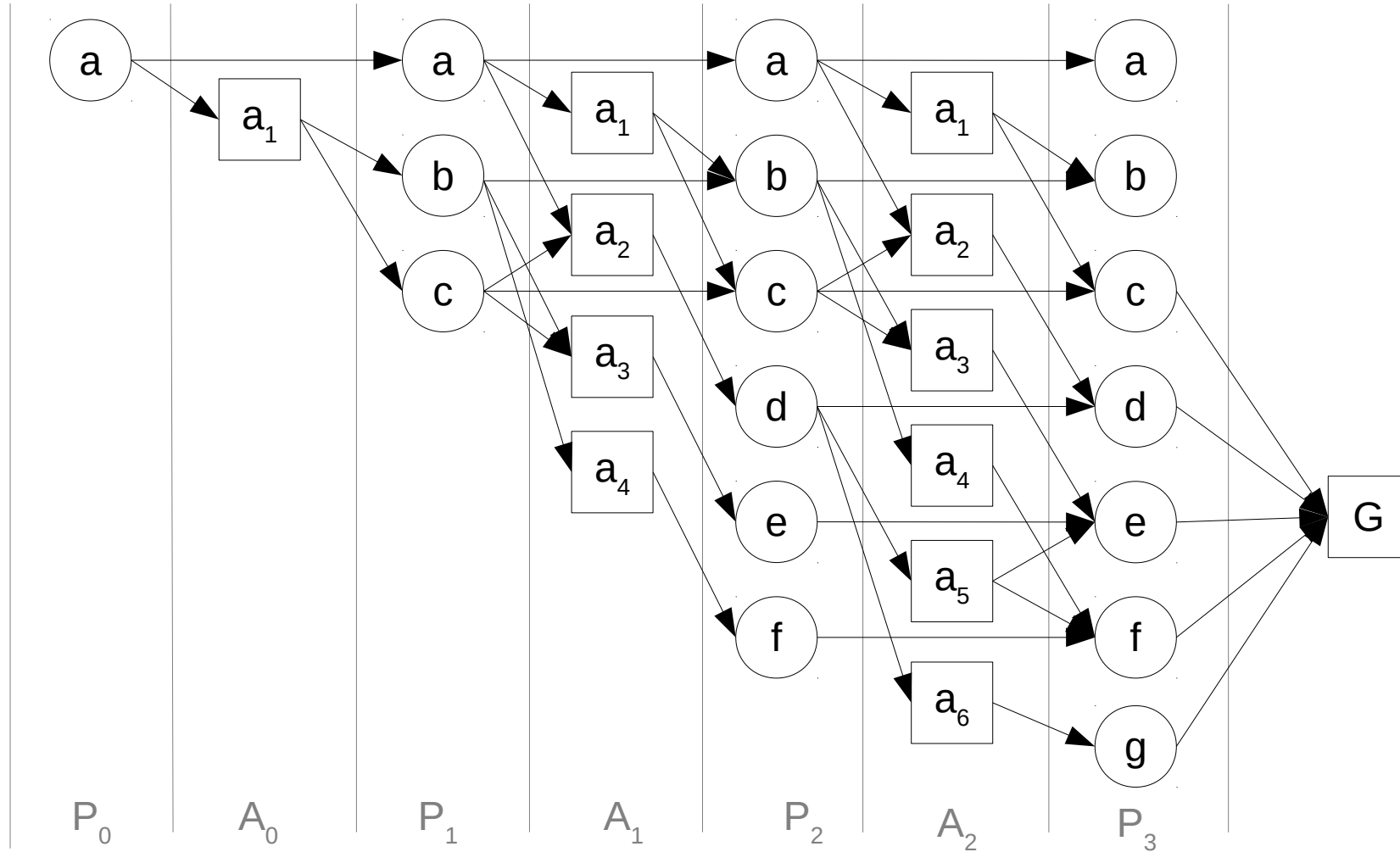
a

$P_0$

# Running Example: Reachability Graph



# Running Example: Reachability Graph

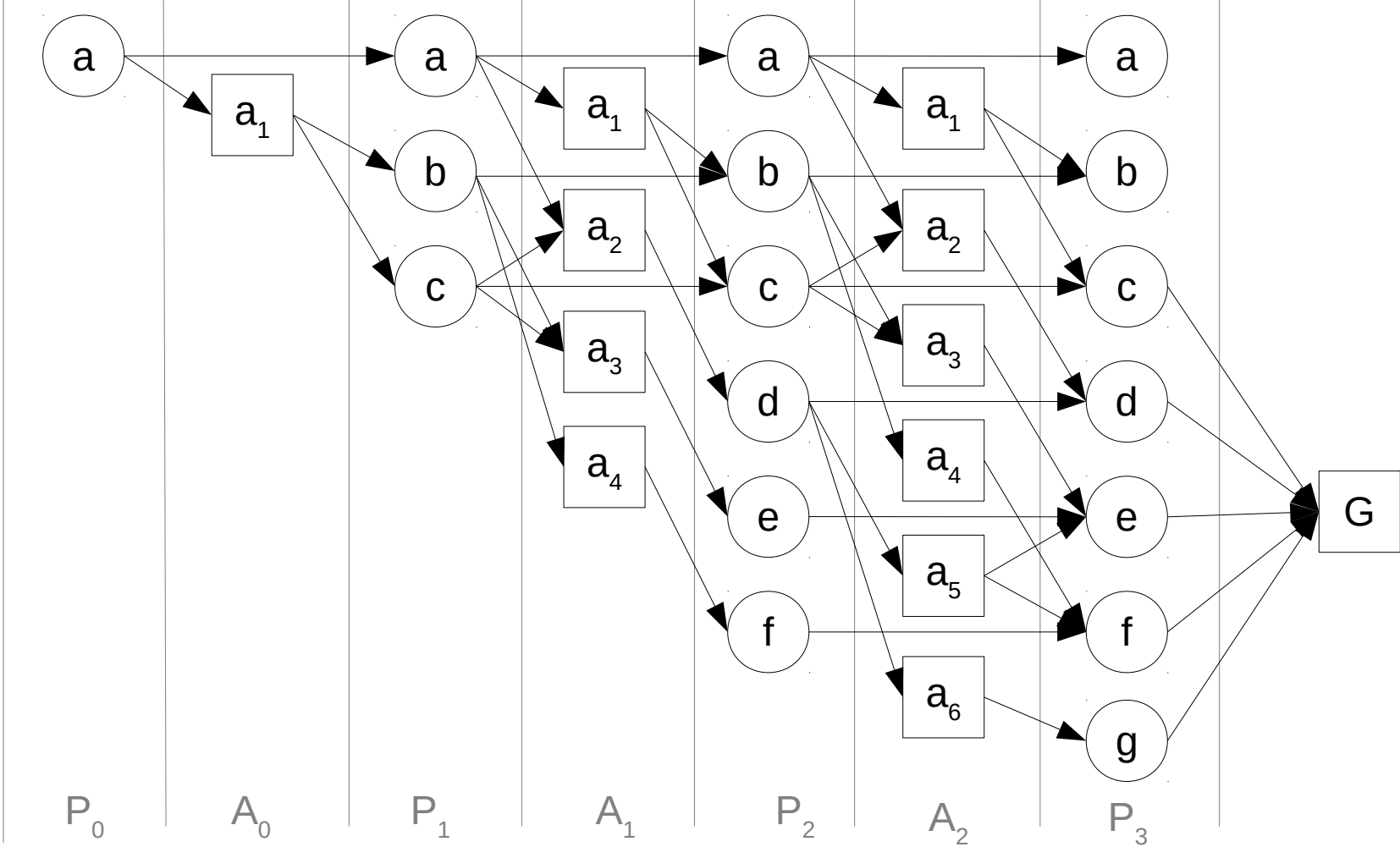


## Using Reachability Graph for computing $h_{\max}$ and $h_{\text{add}}$

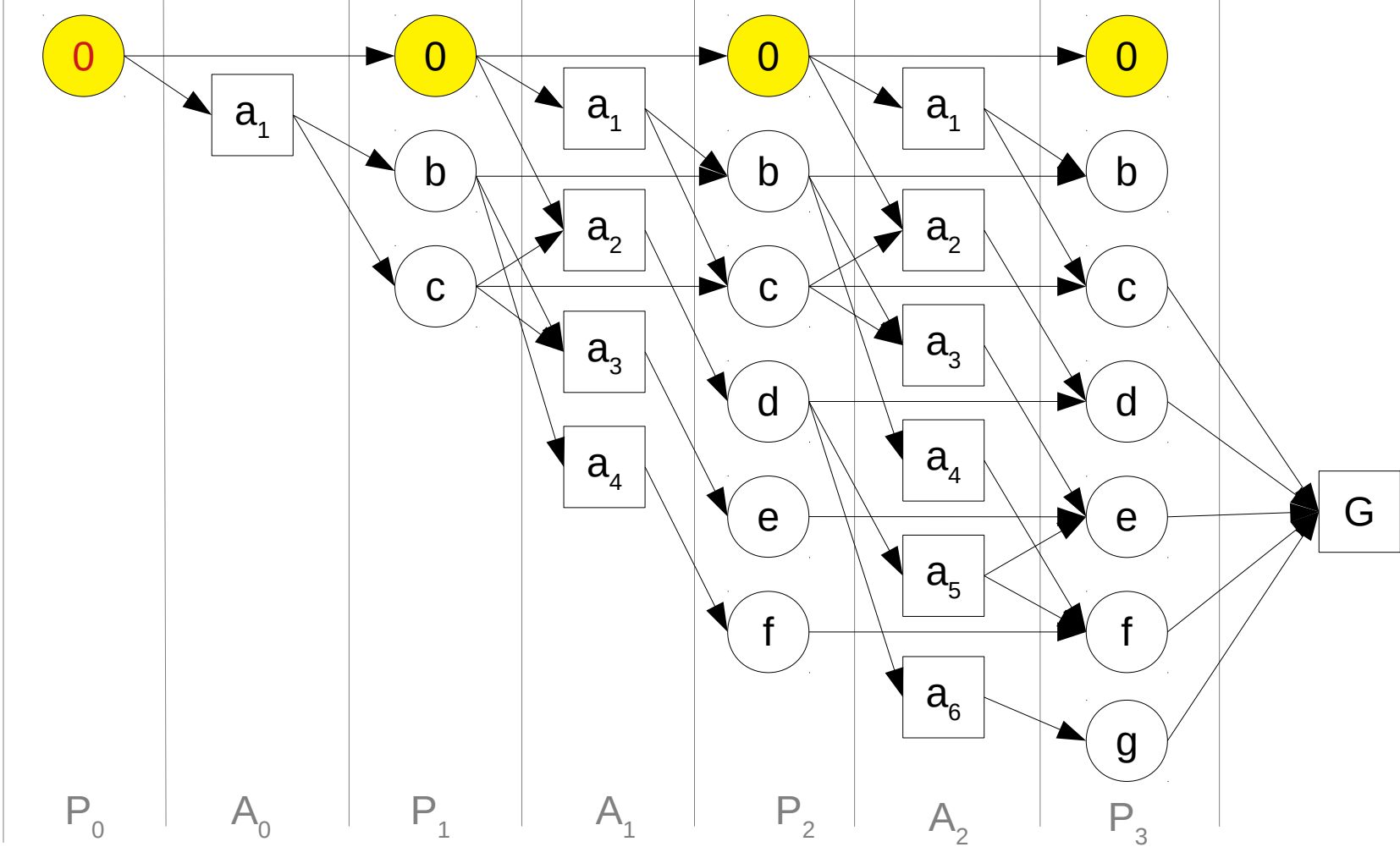
- For **uniform cost** planning tasks we can leverage reachability graph
  - It's a special case of the **Dijkstra action selection method**
- Initially, the reachability graph is constructed from  $I$  (or any state  $s$ )
  - If a fixed point is reached, i.e.,  $P_{i+1}=P_i$ , then  $h_{\max}(I)=h_{\text{add}}(I)=\infty$
- Then actions are processed layer by layer (from  $A_0, A_1, \dots$ ) until  $G$  is reached
  - The value in  $G$  is the value of the heuristic for  $I$  (or  $s$ )



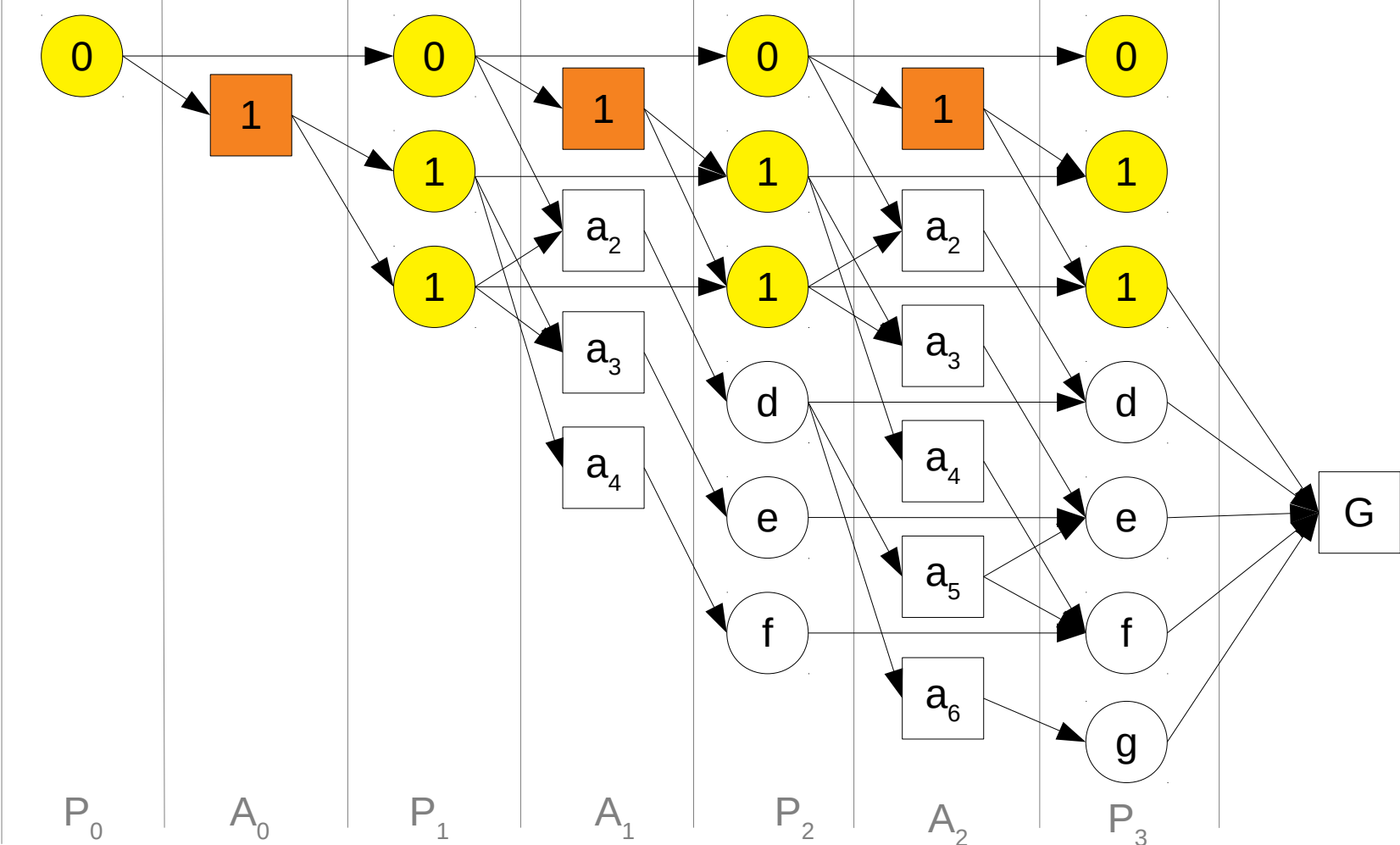
# Running Example: $h_{\max}$



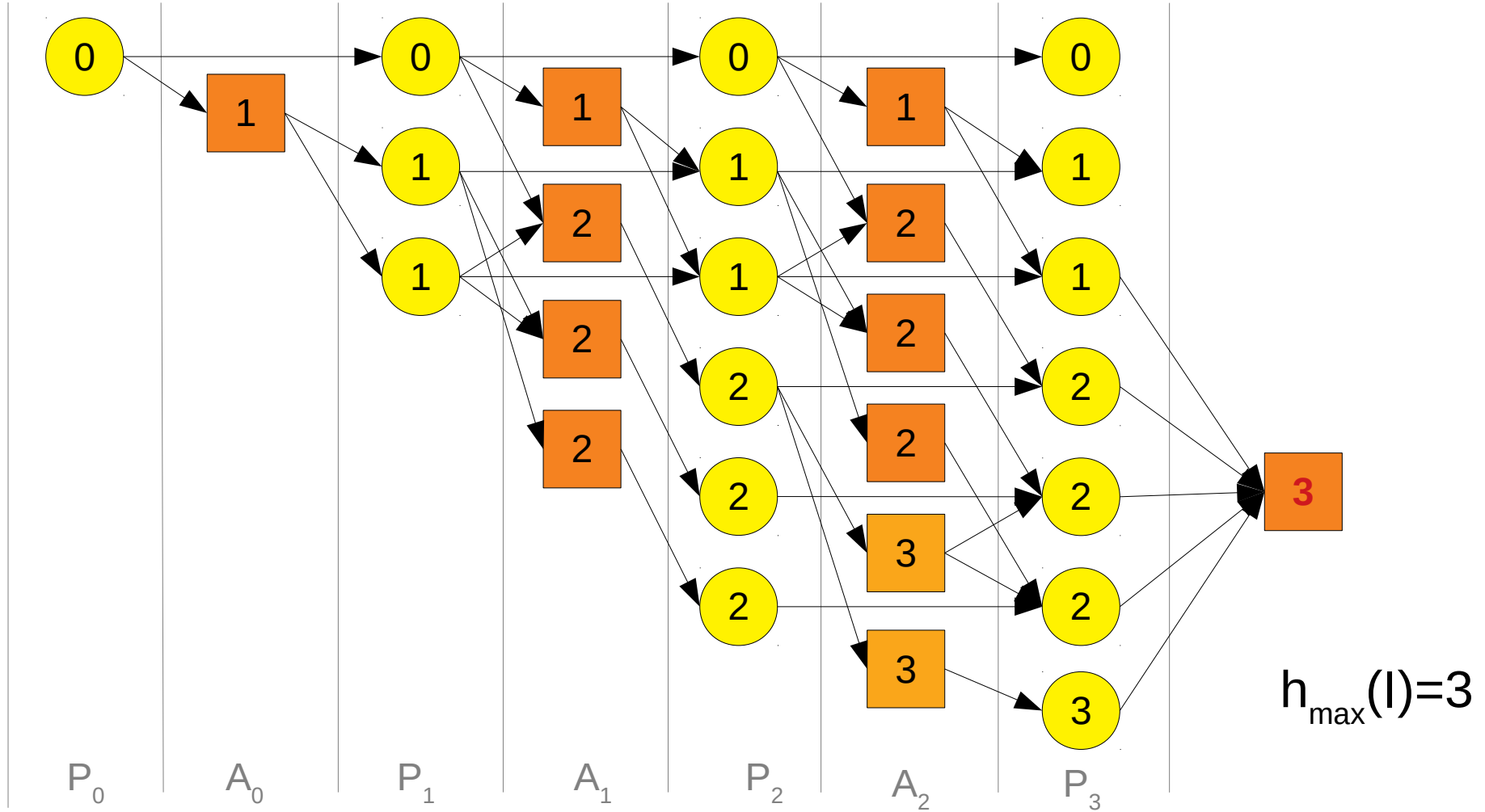
# Running Example: $h_{\max}$



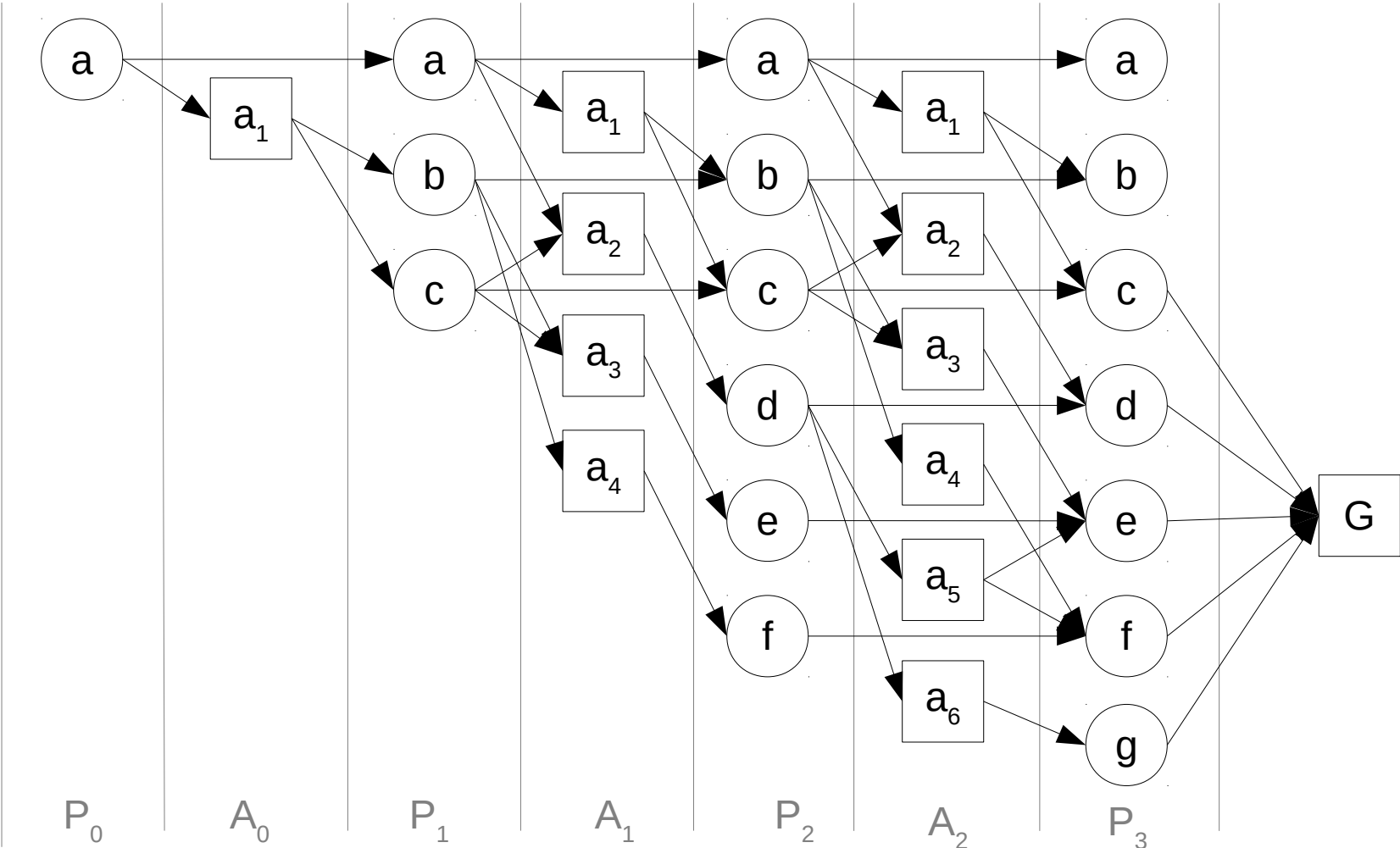
# Running Example: $h_{\max}$



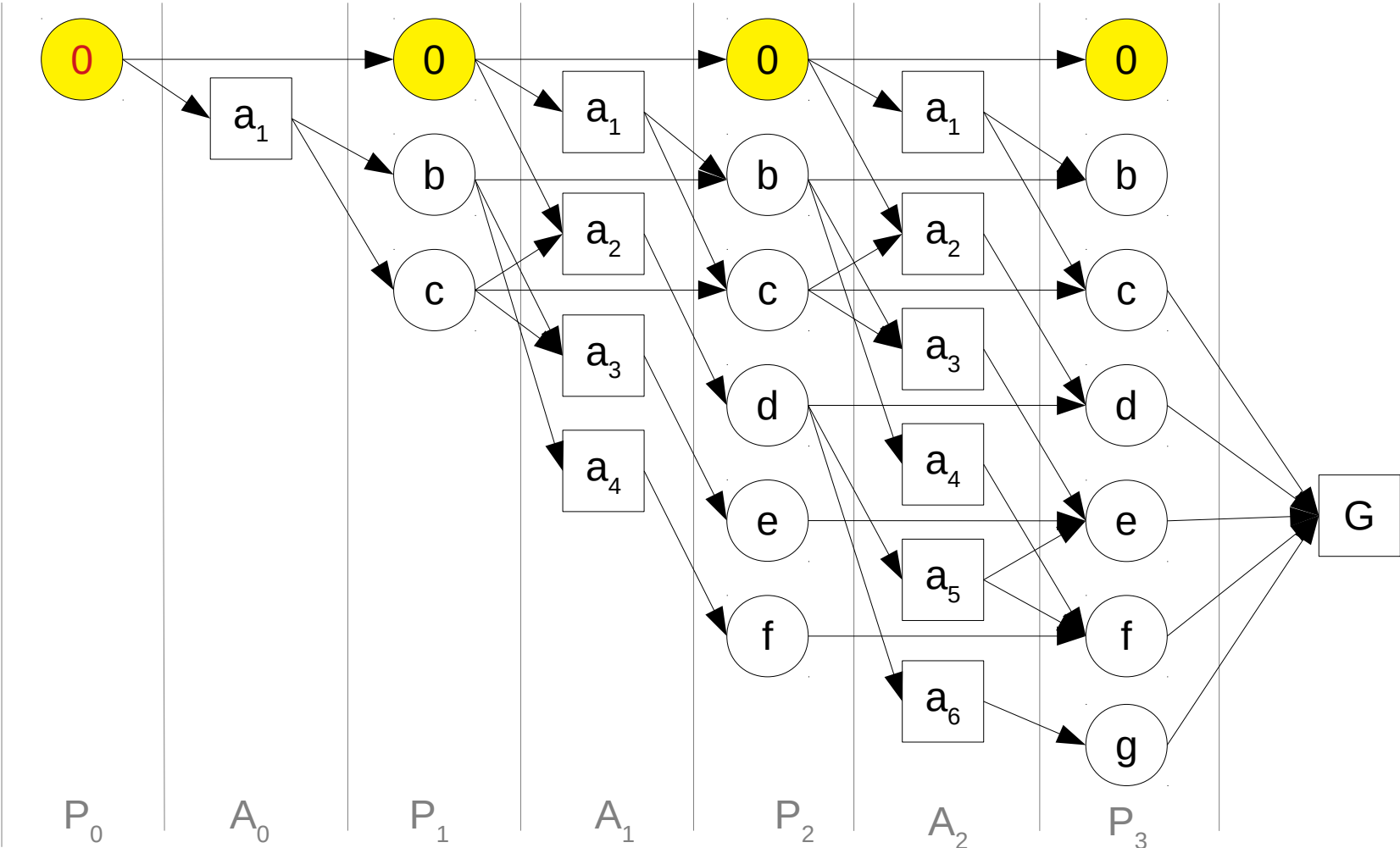
# Running Example: $h_{\max}$



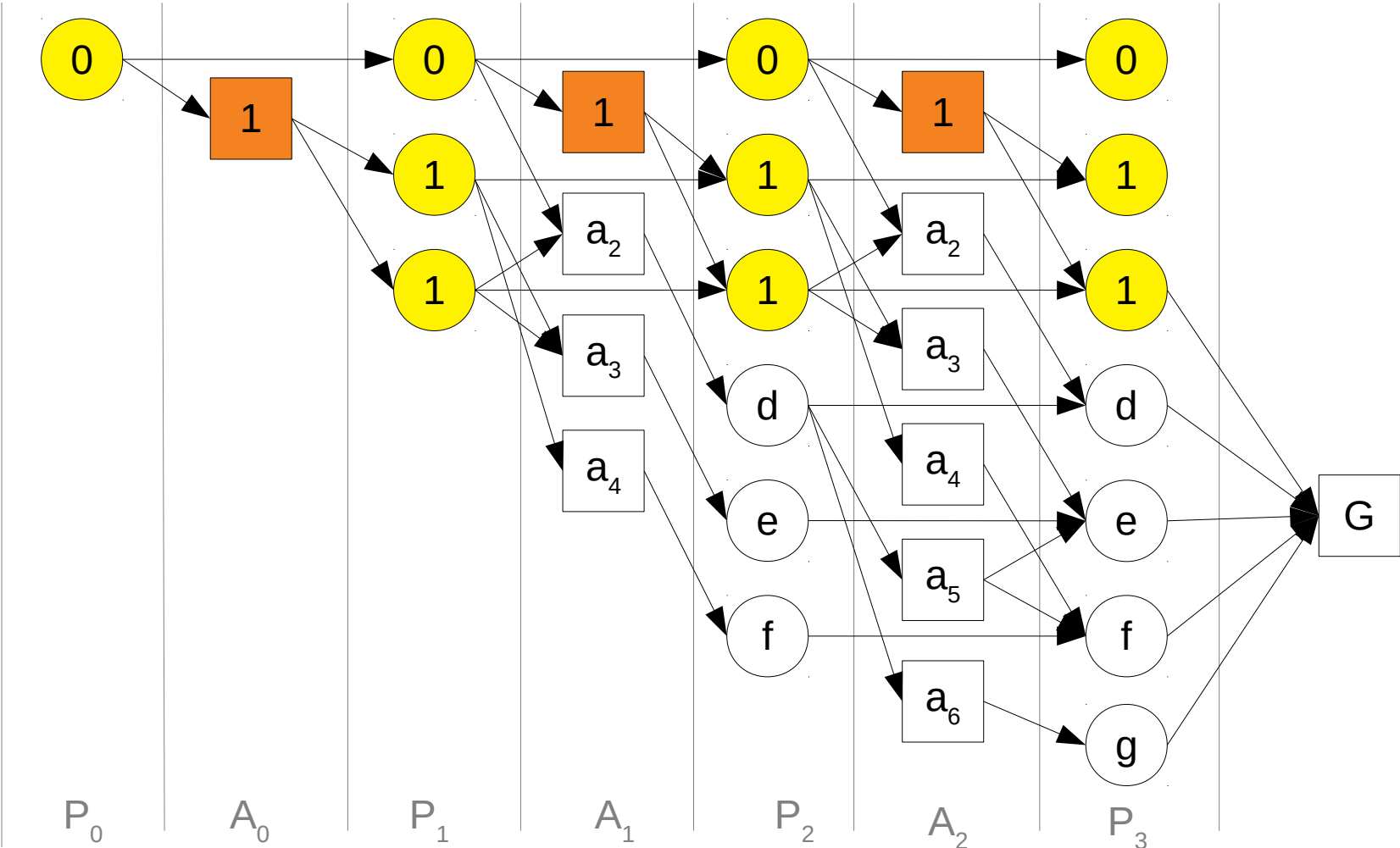
# Running Example: $h_{\text{add}}$



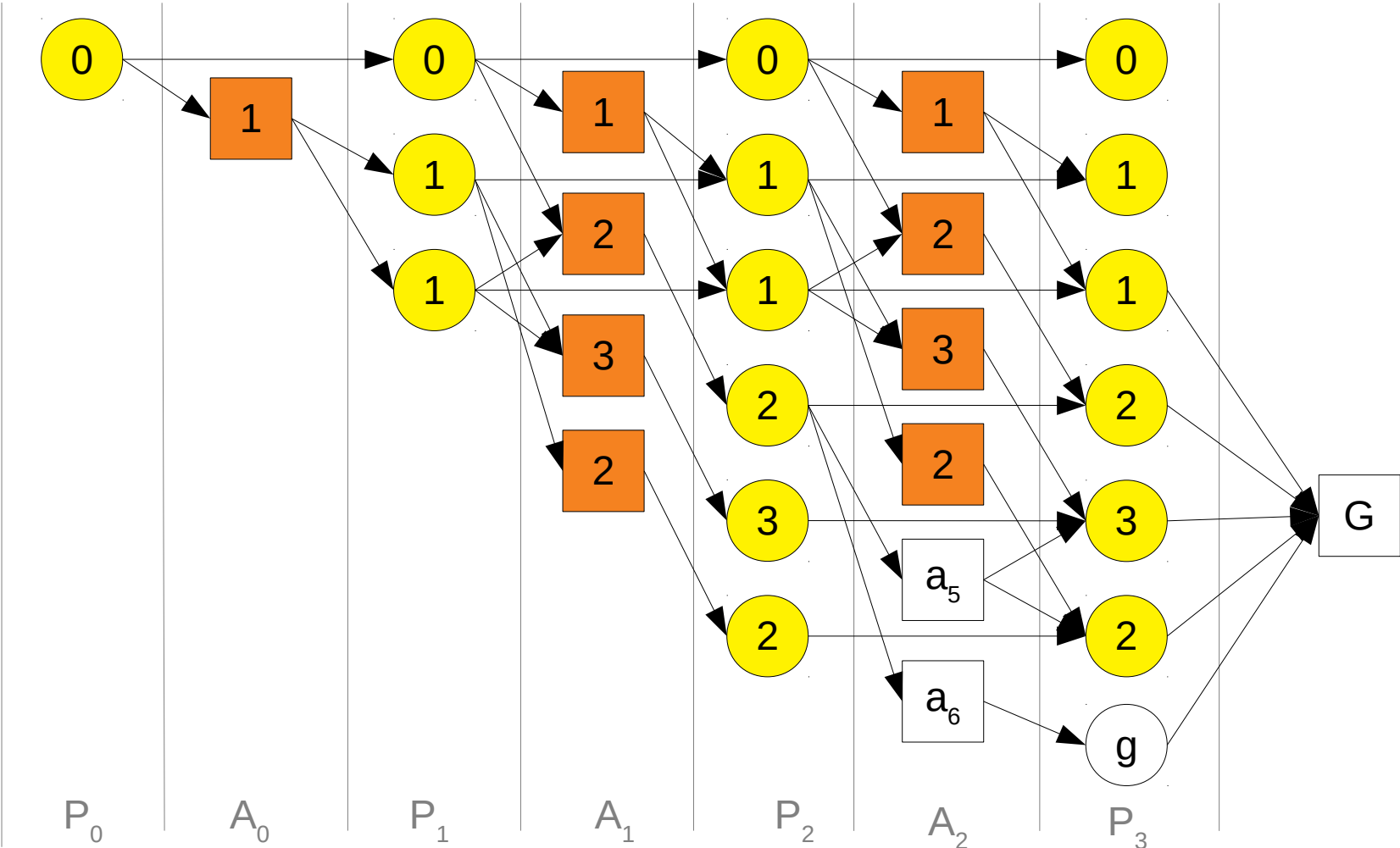
# Running Example: $h_{\text{add}}$



# Running Example: $h_{\text{add}}$

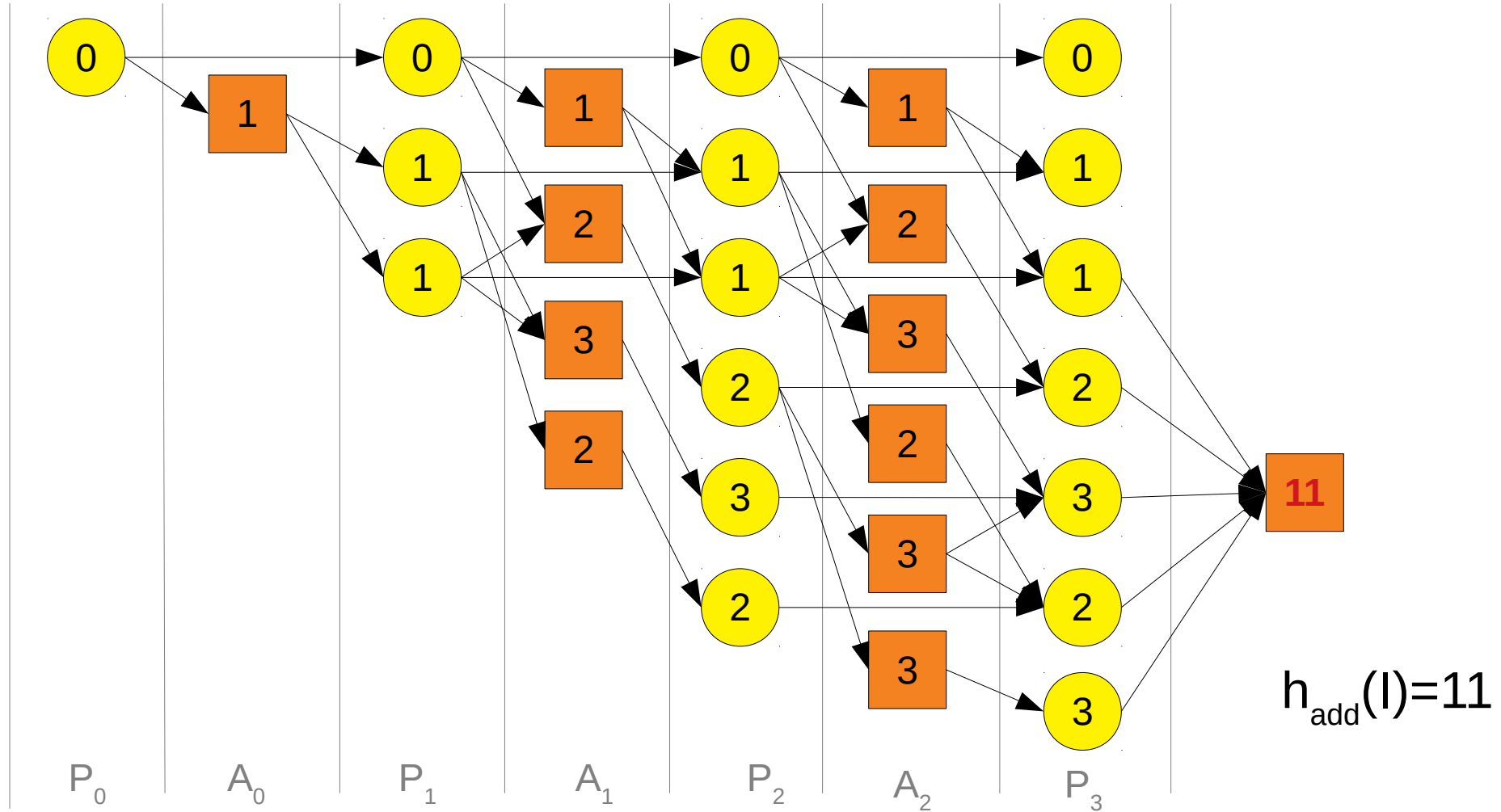


# Running Example: $h_{\text{add}}$





# Running Example: $h_{\text{add}}$



# Remarks

- $h_{\max}$  is sometimes too optimistic as it assumes that some (parallel) actions count as one
  - e.g. loading and unloading multiple packages into/from the truck
- $h_{\text{add}}$  is sometimes too pessimistic as it assumes that each atom is achieved by a separate process
  - e.g. moving a block from a tower can both place the block in the right place and clears the block underneath
- Generally,  $h_{\text{add}}$  is more informative than  $h_{\max}$  albeit being inadmissible

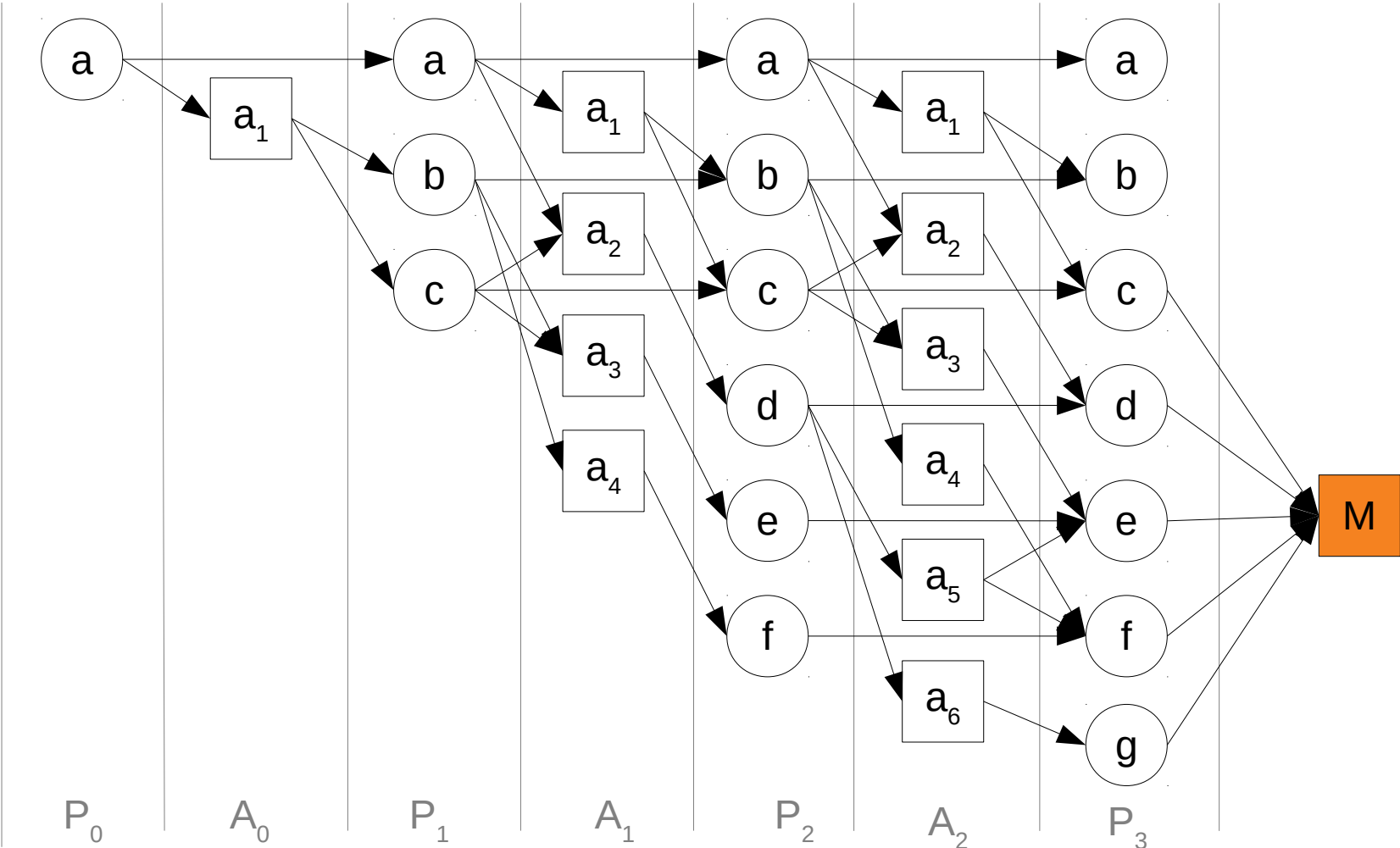
$h_{FF}$ 

- Generates whole relaxed plans (suboptimal but often reasonable)
- Reachability graph is initially generated and the **goal node is marked**
  - If, however, a fixed point is reached, i.e.,  $P_{i+1}=P_i$ , then  $h_{FF}(I)=\infty$
- Each action or atom node can be either **marked** or **unmarked**
- A **marked action node** is **justified** if all its predecessors (atom nodes) are **marked**
- A **marked atom node** is **justified** if at least one of its predecessors is **marked**

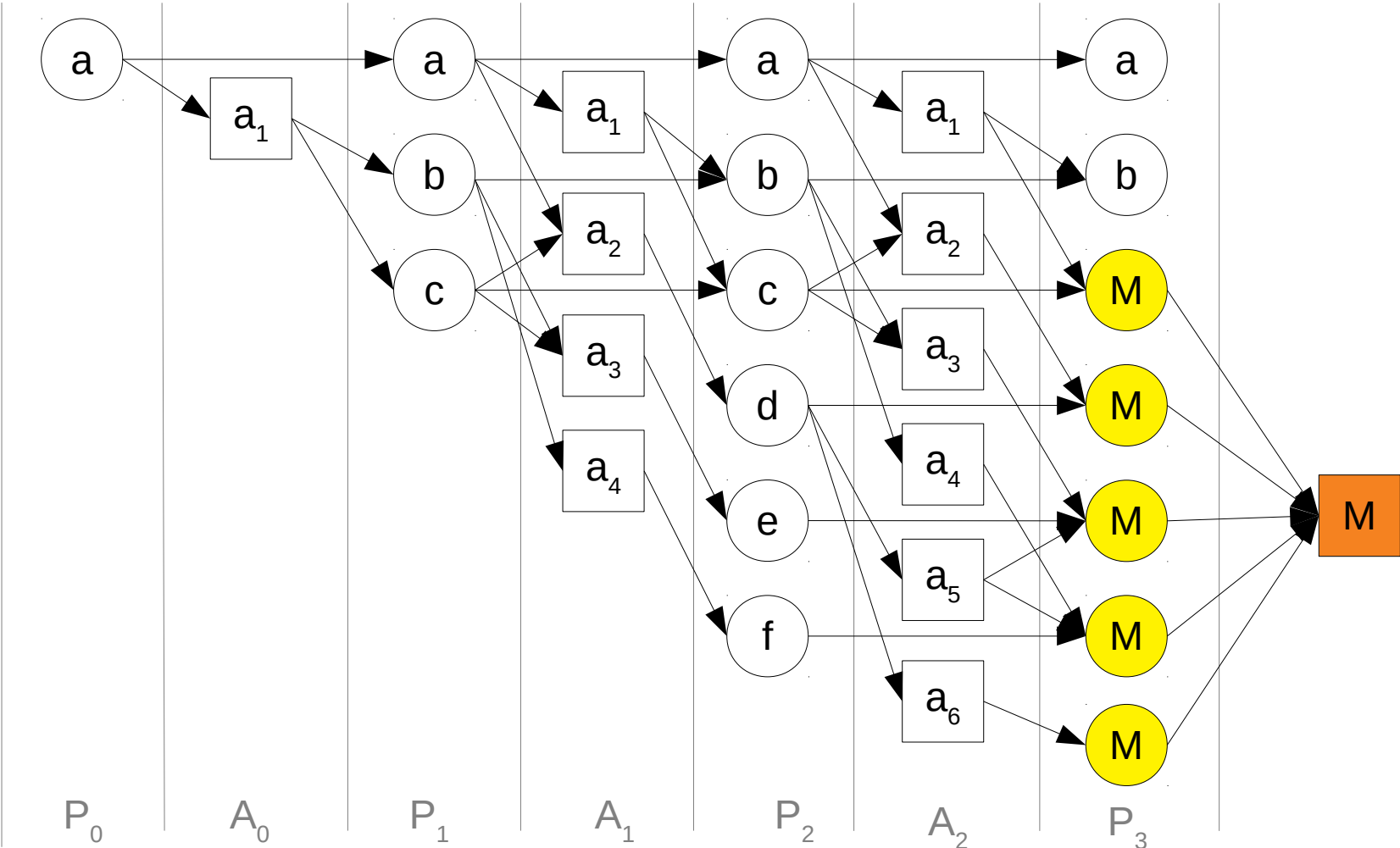
$h_{FF}$ 

- Starting with marked goal node, apply the following rules **layer by layer** until **all marked nodes are justified**
  - 1) Mark all immediate predecessors of a marked unjustified action node
  - 2) Mark the immediate predecessor of a marked unjustified atom node with only one immediate predecessor
  - 3) Mark an immediate predecessor of a marked unjustified atom node connected via an idle arc (to the same atom in the previous layer)
  - 4) Mark any immediate predecessor of a marked unjustified atom node
- The rules are applied in a **priority order** (earlier first if applicable)
- The **number** (or the **total cost**) of **marked action nodes** is the  $h_{FF}$  **value**

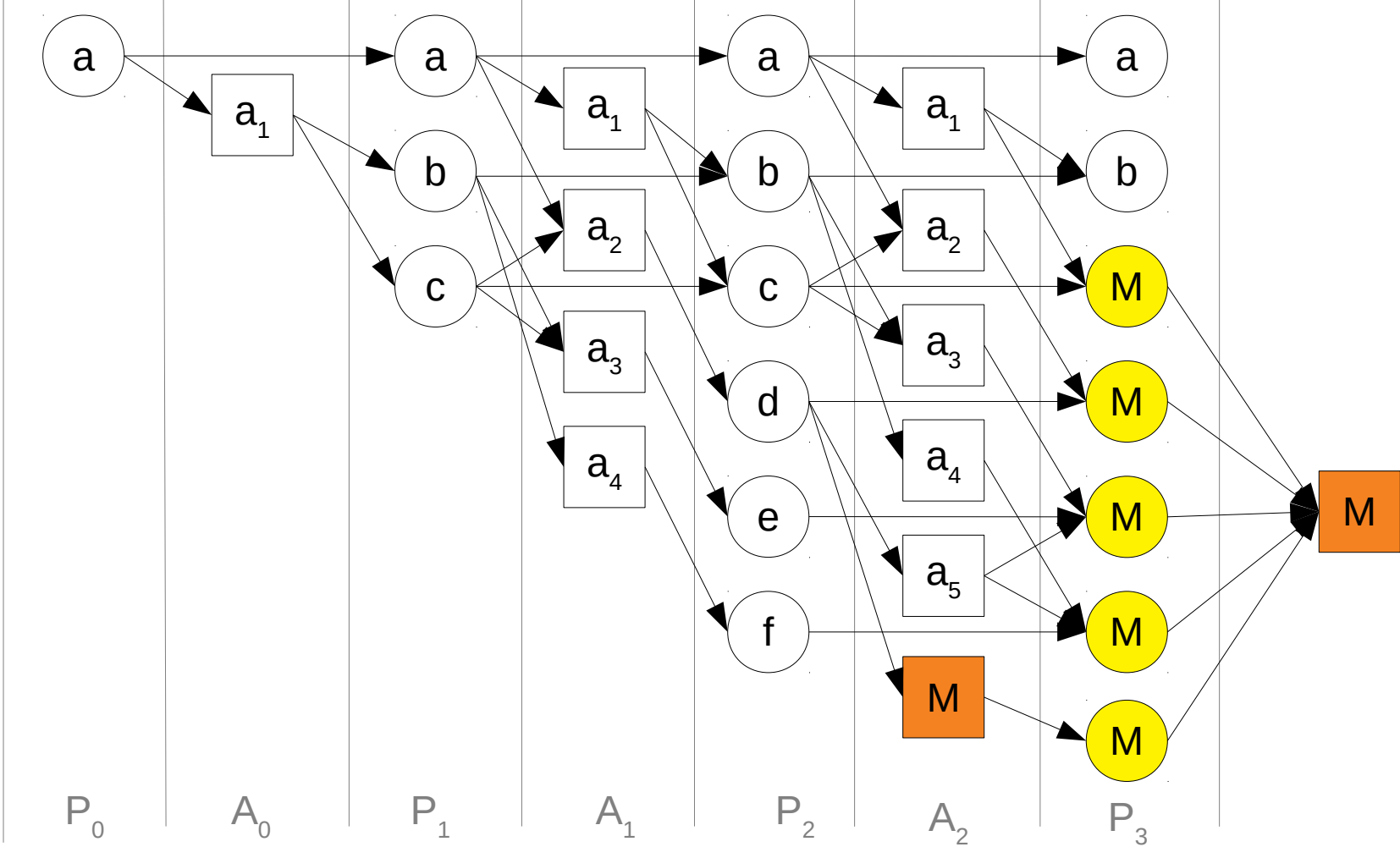
# Running Example: $h_{FF}$



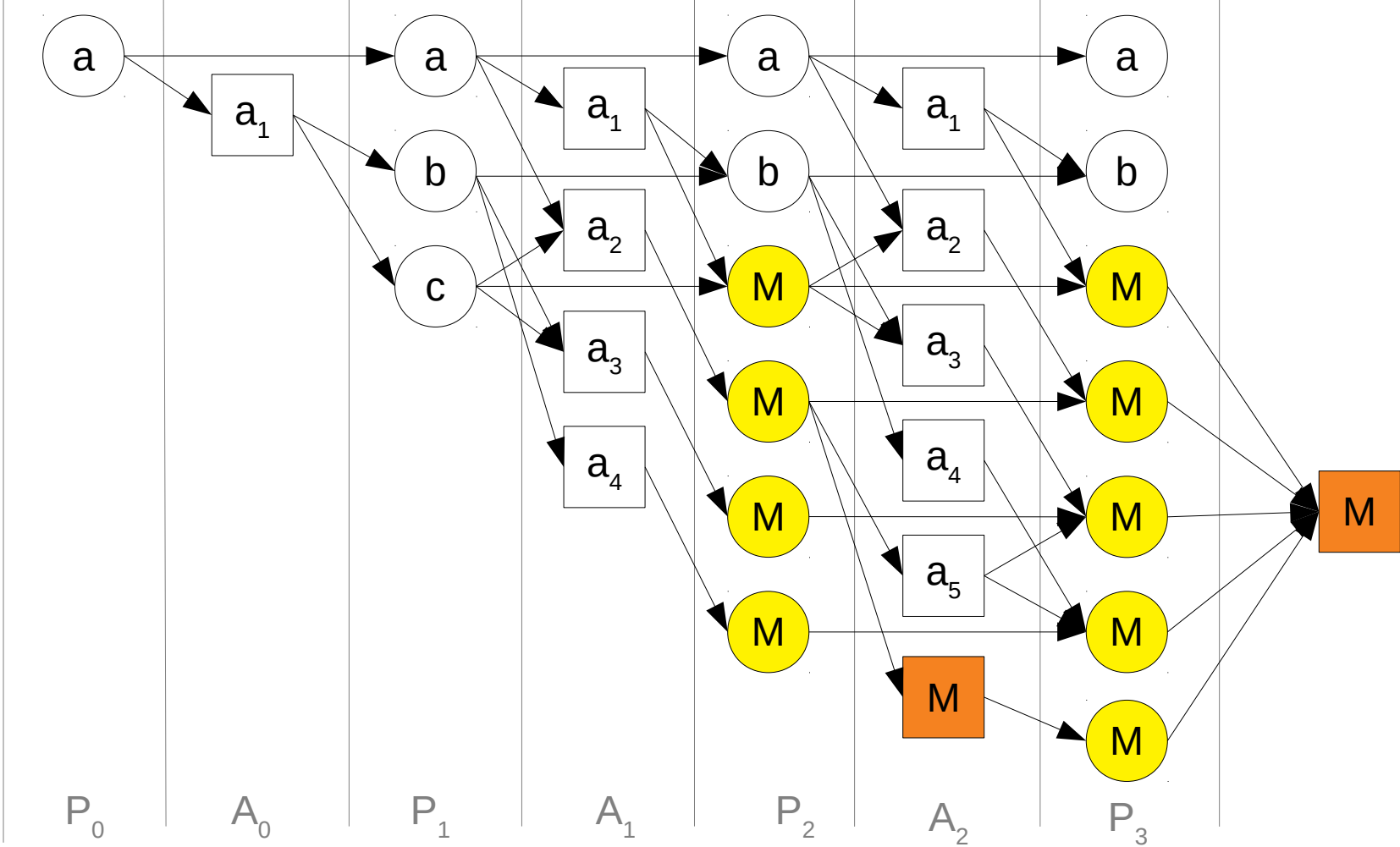
# Running Example: $h_{FF}$



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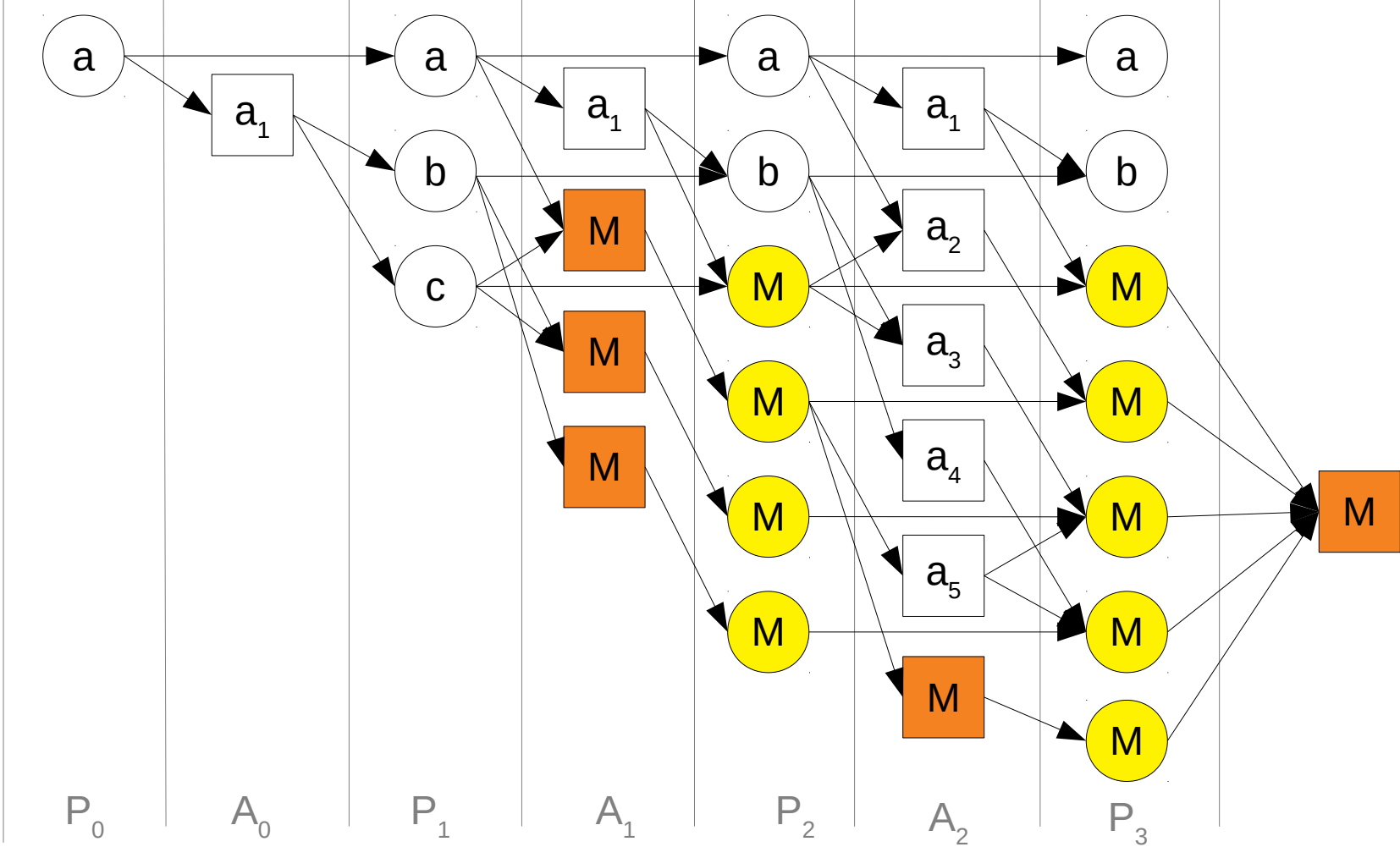


# Running Example: $h_{FF}$

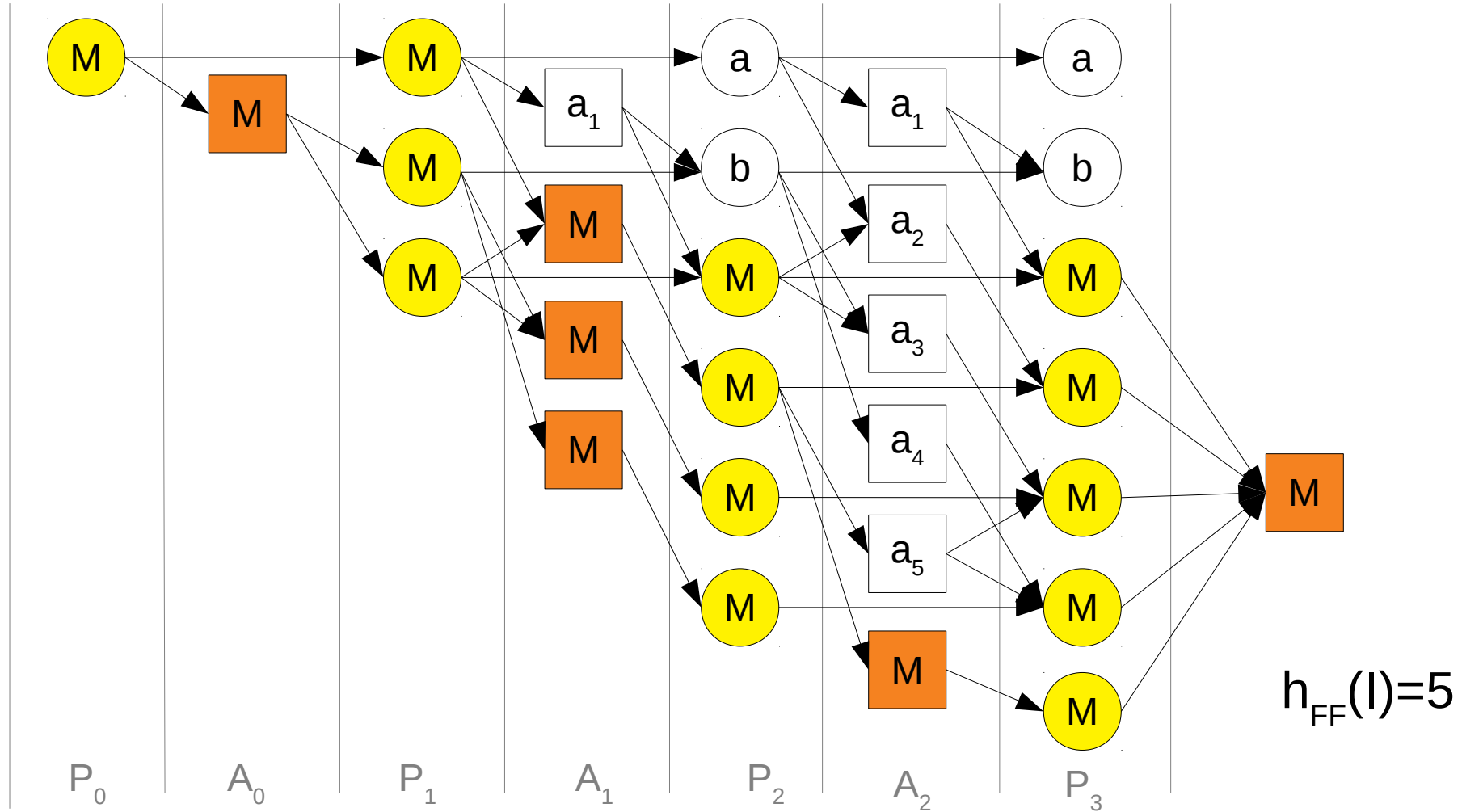




# Running Example: $h_{FF}$



# Running Example: $h_{FF}$



## $h_{FF}$ Remarks

- $h_{FF}$  is not well defined as tie-breaking might lead to different values
- $h_{\max} \leq h^+ \leq h_{FF} \leq h_{\text{add}}$
- FF planner won the second IPC (in 2000)
- Note that delete-relaxation has some drawbacks (e.g. some non-detected dead-ends)