Lazy is Efficient
(in plan recognition)

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Abstract Mind Architecture
(in artificial intelligence)

Two Processes

Perception/World Modeling:	Action Selection/Decision Making:
Vision, sensor processing, sensor fusion, ...	Planning, plan execution, goal deliberation, reacting...

My Scientific Problem:

The Nature of the Social Mind

The computational mechanisms that allow the mind to reason about, and interact with, others?

(differently than *about* or *with* inanimate objects)

Abstract Mind Architecture
(in artificial intelligence)

Two Processes

Perception/World Modeling:	Action Selection/Decision Making:
Theory of Mind: Intents, plans of other minds (in AI: Plan Recognition)	**Coordination:** Manipulating, acting w.r.t other minds

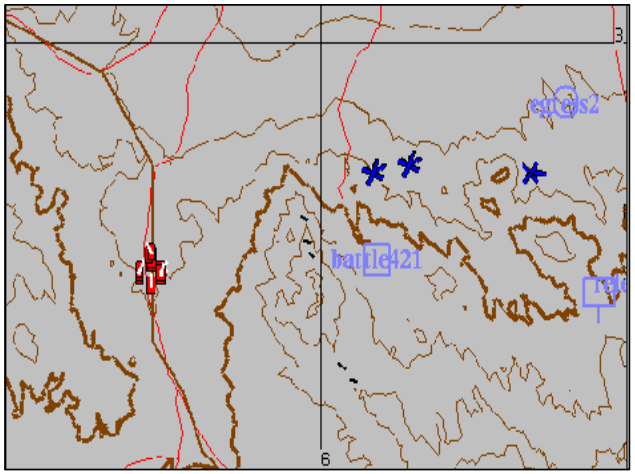
This talk

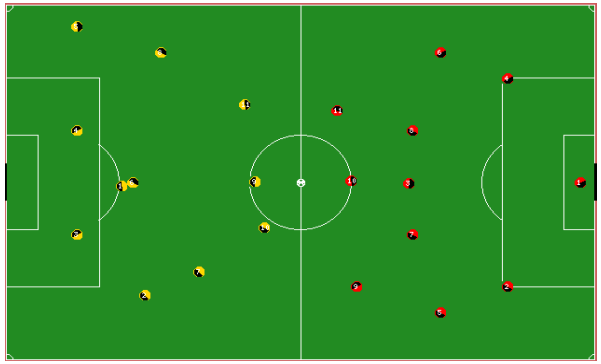
Since 1995….

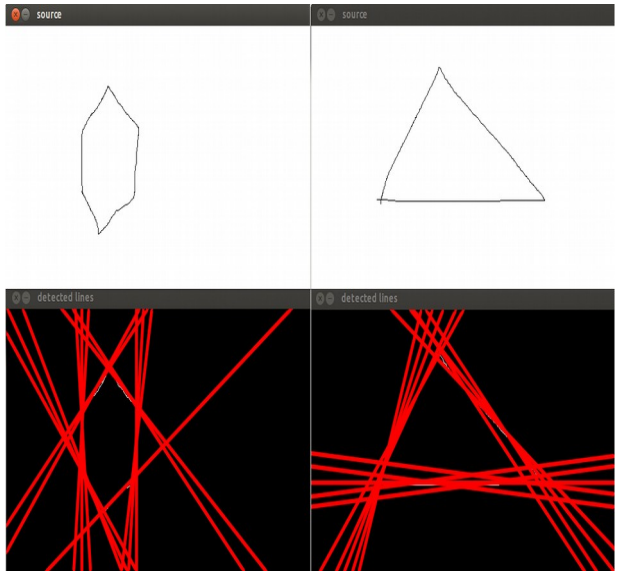
- Tracking teammates (RESL, w/ Tambe)
- Overhearing teams (YOYO, YOYO*, w/ Tambe, Pynadath)
- Overhearing using Colored Petri-nets (w/ Gutnik)
- **Symbolic Recognition (SBR, w/ Avrahami-Zilberbrandt)**
- Decision-theoretic rec. (UPR, w/ Avrahami-Zilberbrandt)
- Intent detection (w/ Bochek-Dokow)
- **Mirroring (w/ Vered)**

See: www.cs.biu.ac.il/~galk/publications/class_rescat.html

Dynamic, Continuous, Multi-Agent







Recognition Challenges

- Online: Observations incrementally received
- Complex state observations
  - Observe state, not agent actions
  - State is factored (composed of multiple features)
- Situated (reactive)
  - Observed agents react, deviate from own plans
  - What goal/plan is true <u>now</u>
- Observations stem from continuous world
  - Sensitivity to discretization (loss of information)

SBR: Symbolic Behavior Recognition [IJCAI 2005, MOO 2004-2005]

- Online, keyhole recognition, discrete observations
- Applied to vision tracker data (e.g., airport security)

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[IJCAI 2005, MOO 2004-2005]

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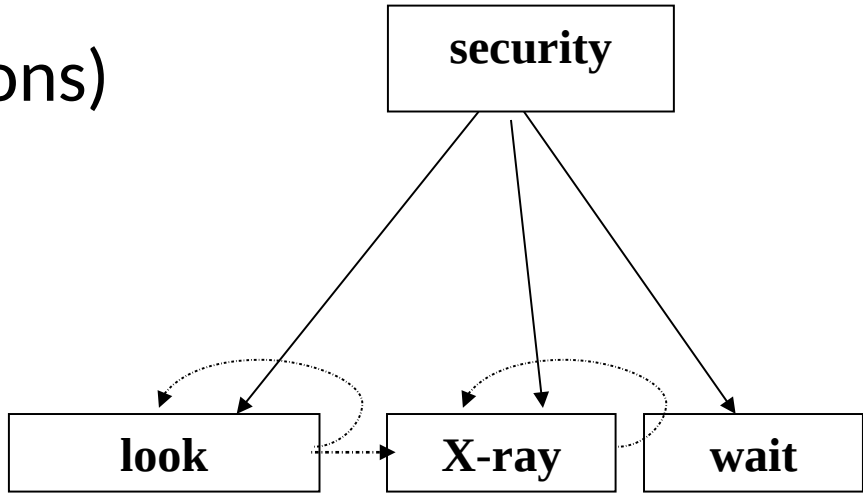
What is agent doing?

Is its behavior anomalous?

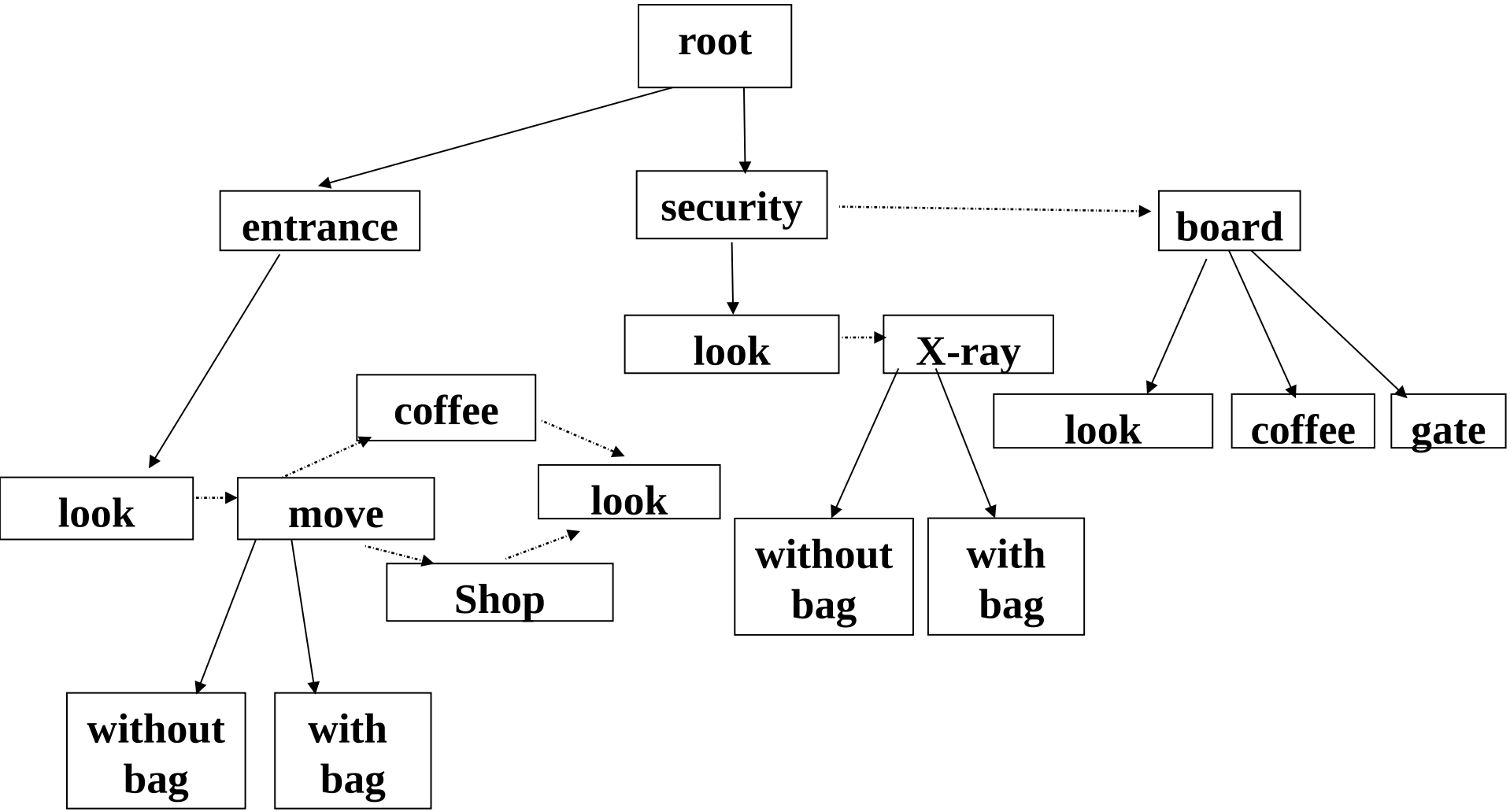
SBR Plan Library: Layered, Durative Actions

- Directed acyclic connected graph
- Vertices denote plan steps (actions)
- Edges
  - Vertical (decomposition) edges
  - Horizontal (sequential) edges

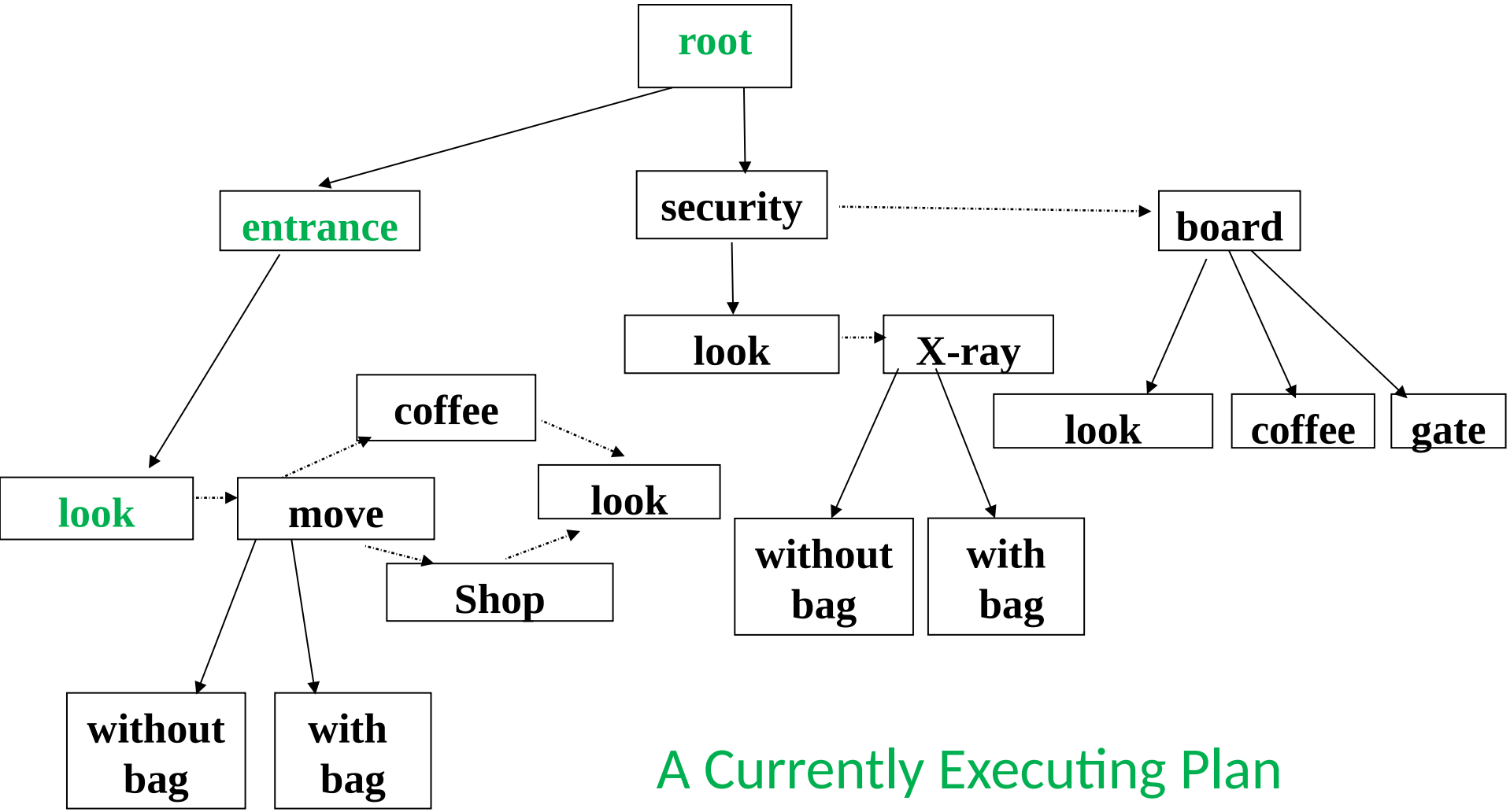


- <u>Every</u> vertex may generate obs, have duration (cycles)
- "Or"-graph (edges denote ordered choices)

Example: Plans and Hypotheses

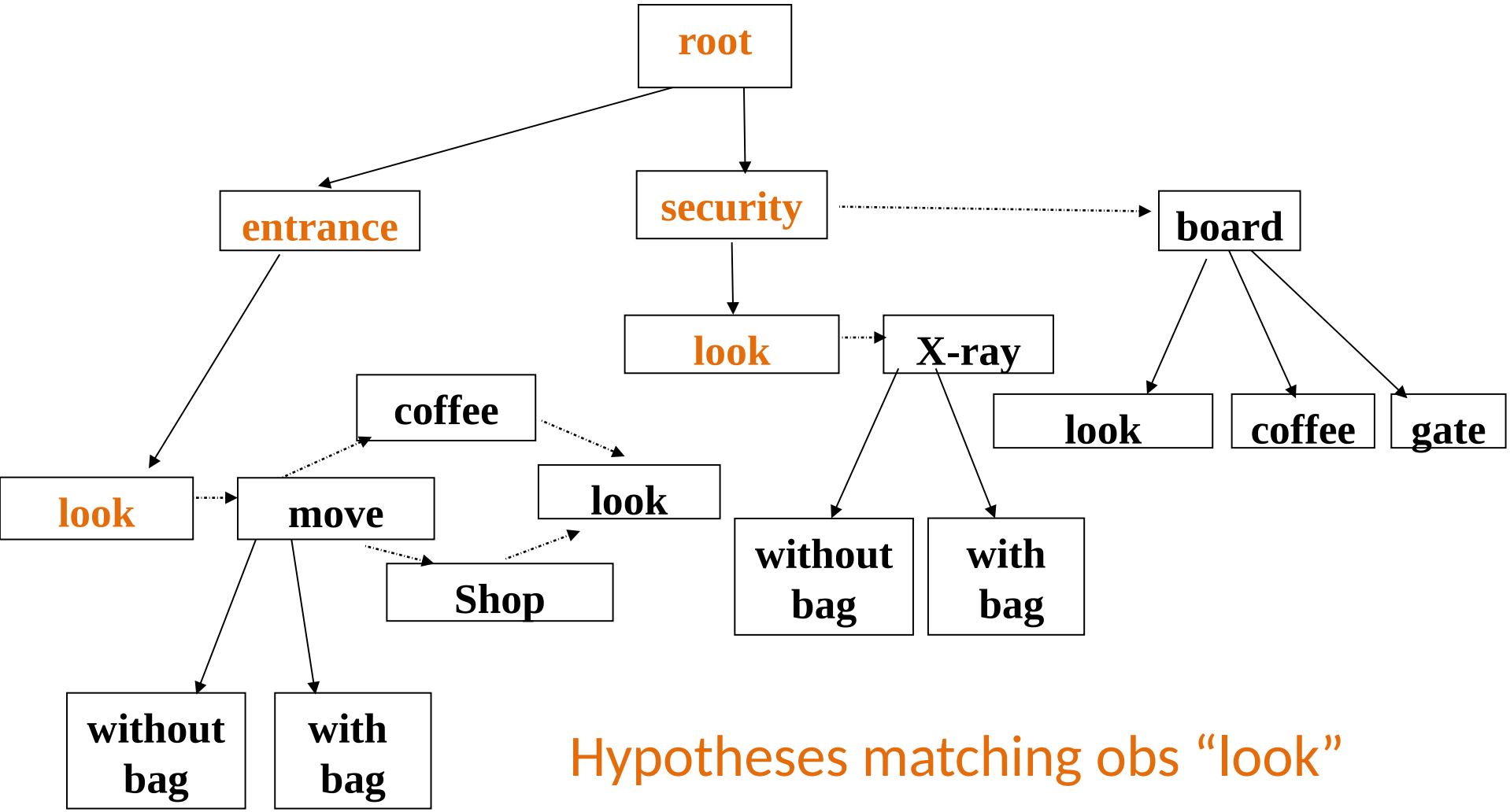


Example: Plans and Hypotheses



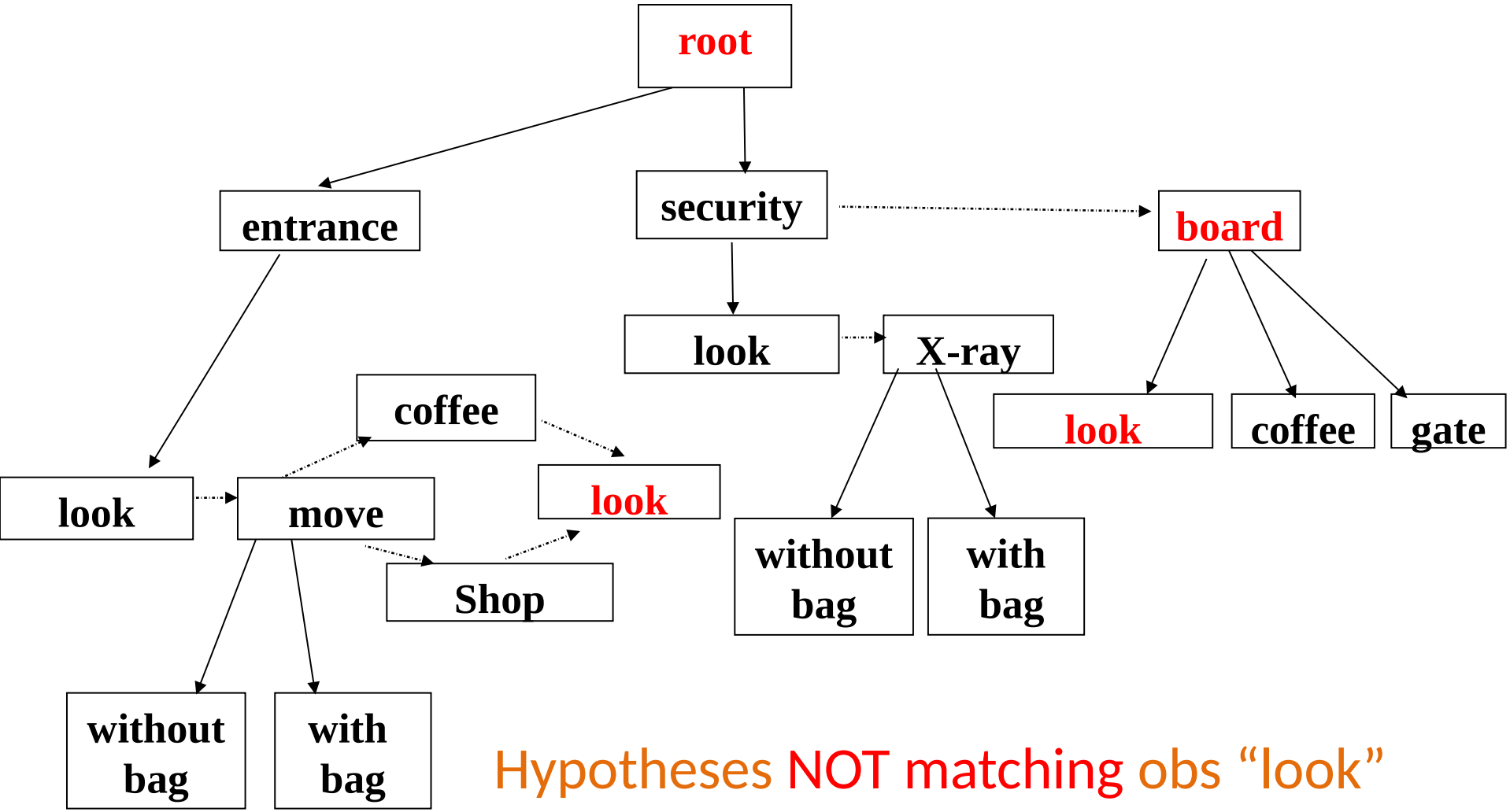
A Currently Executing Plan

Example: Plans and Hypotheses



Hypotheses matching obs “look”

Example: Plans and Hypotheses



Hypotheses NOT matching obs “look”

SBR Key Ideas

- Sacrifice memory to gain speed
  - Entire grounded library in memory, in advance
  - Auxiliary data structures to support fast queries
- Distinguish recognition queries
  - Given last observation, what might be true now
  - Given history of observations, what might have been true

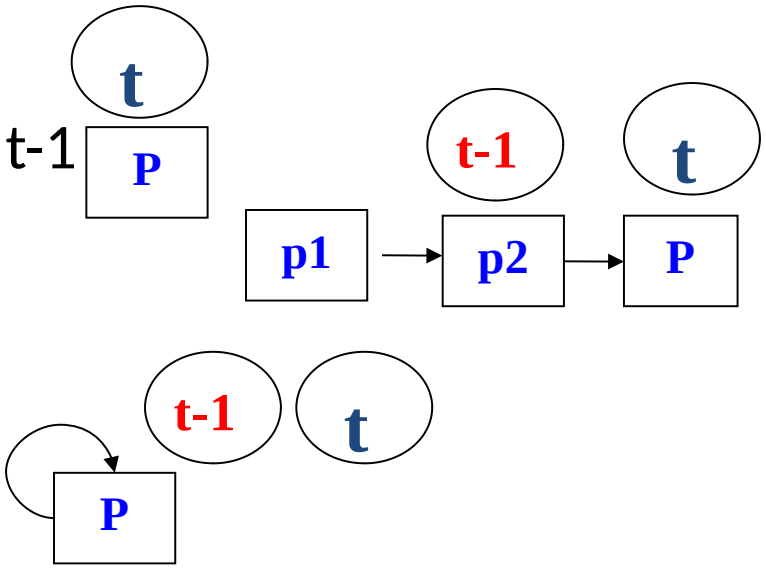
SBR Key Ideas

- Sacrifice memory to gain speed
  - Entire grounded library in memory, in advance
  - Auxiliary data structures to support fast queries
- **Distinguish recognition queries**
  - **Given last observation, what might be true now**
  - **Given history of observations, what might have been true**

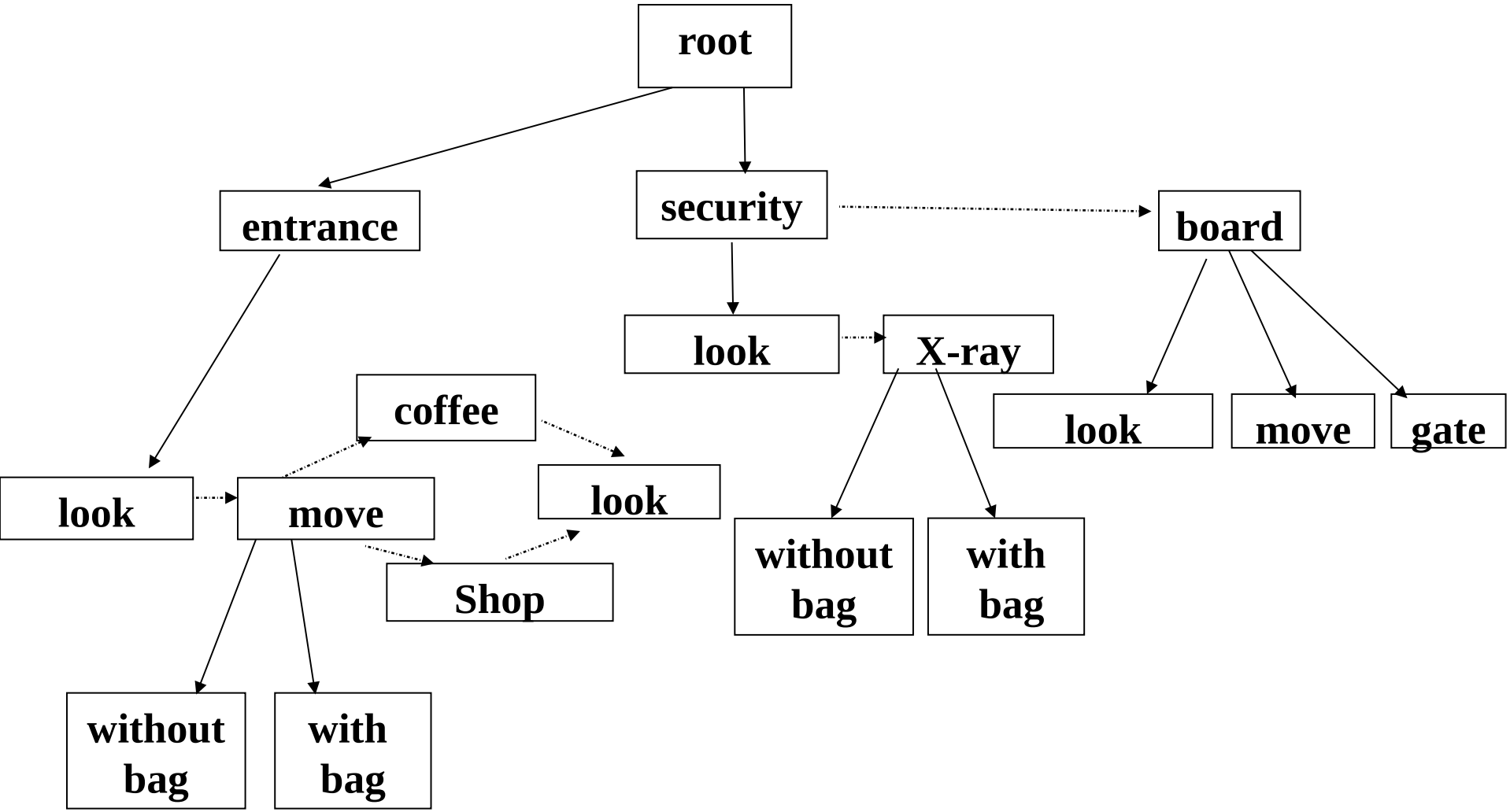
This allows computing only what is needed!

Current State Query
What <u>is</u> True

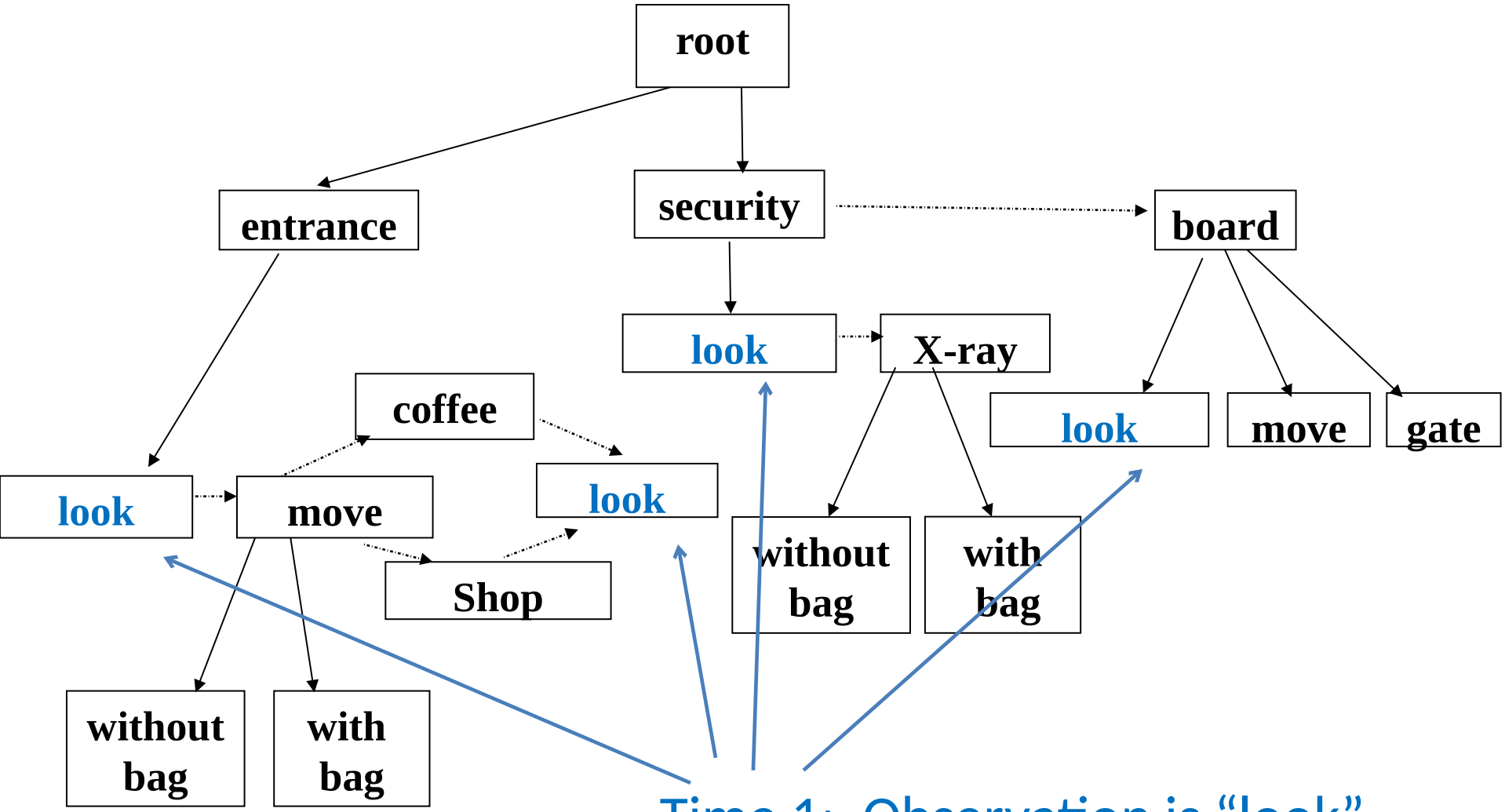
- Generating plan-path hypotheses:
  - Tag matching plans by observation time
  - Propagate tags up/down according to <u>temporal consistency</u>
- Plan P is <u>temporally consistent</u> in time-stamp t if:
  - No incoming sequential edges
  - OR: Exist previous plan tagged with t-1
  - OR: Tagged with t-1
- Efficient: O(M log L)
  - M number of matching plan steps
  - L size of library



Current State Query: Example

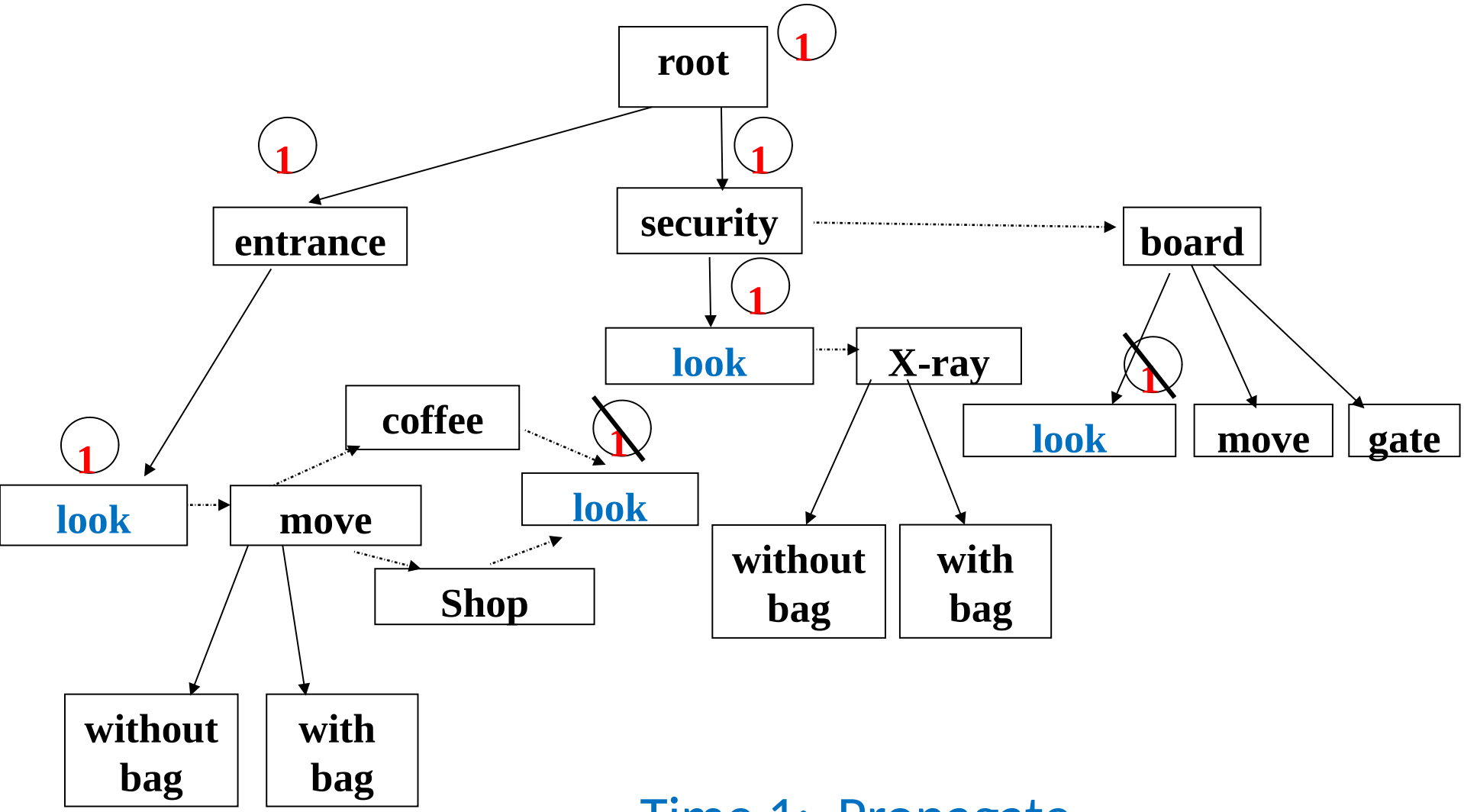


Current State Query: Example



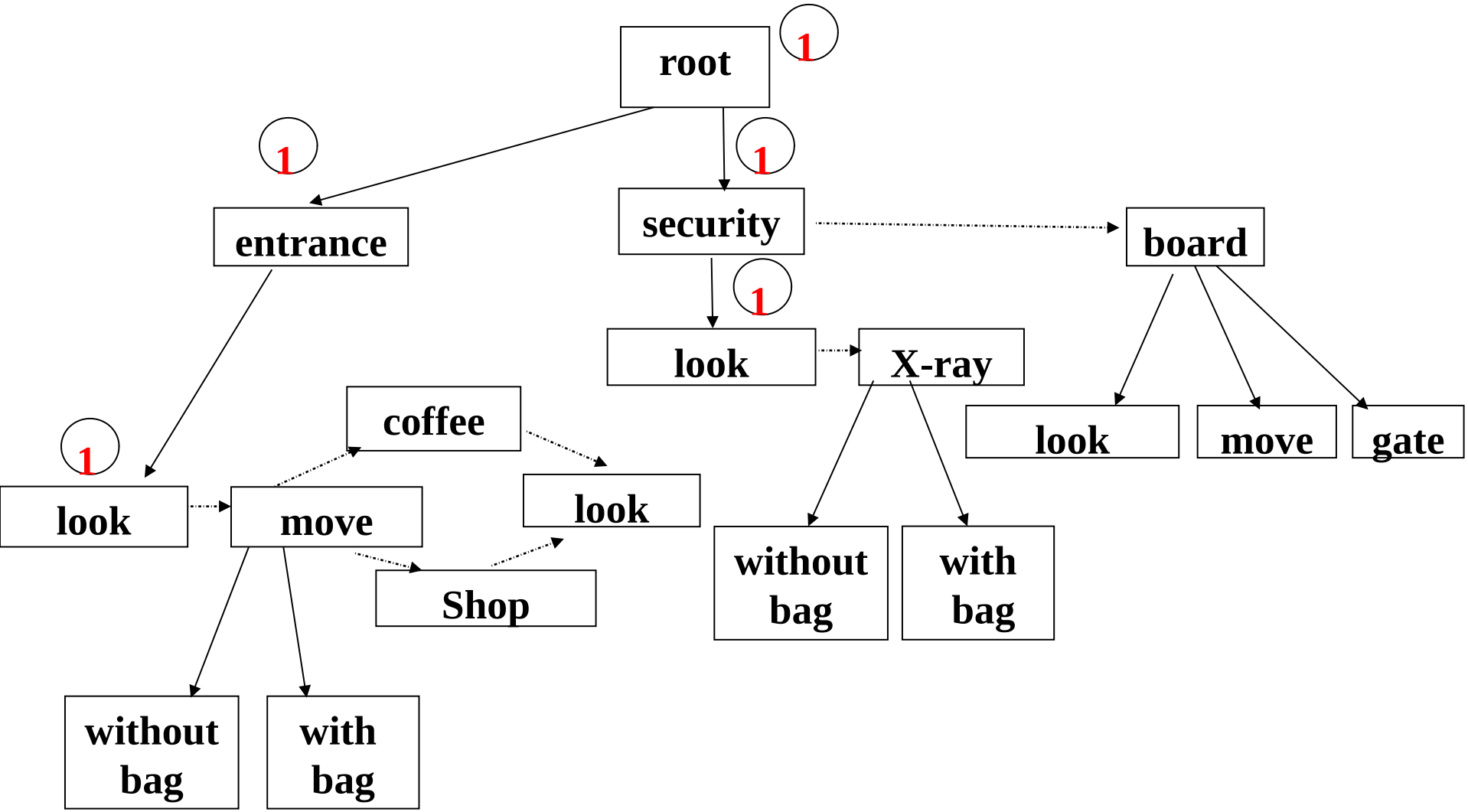
Time 1: Observation is “look”

Current State Query: Example

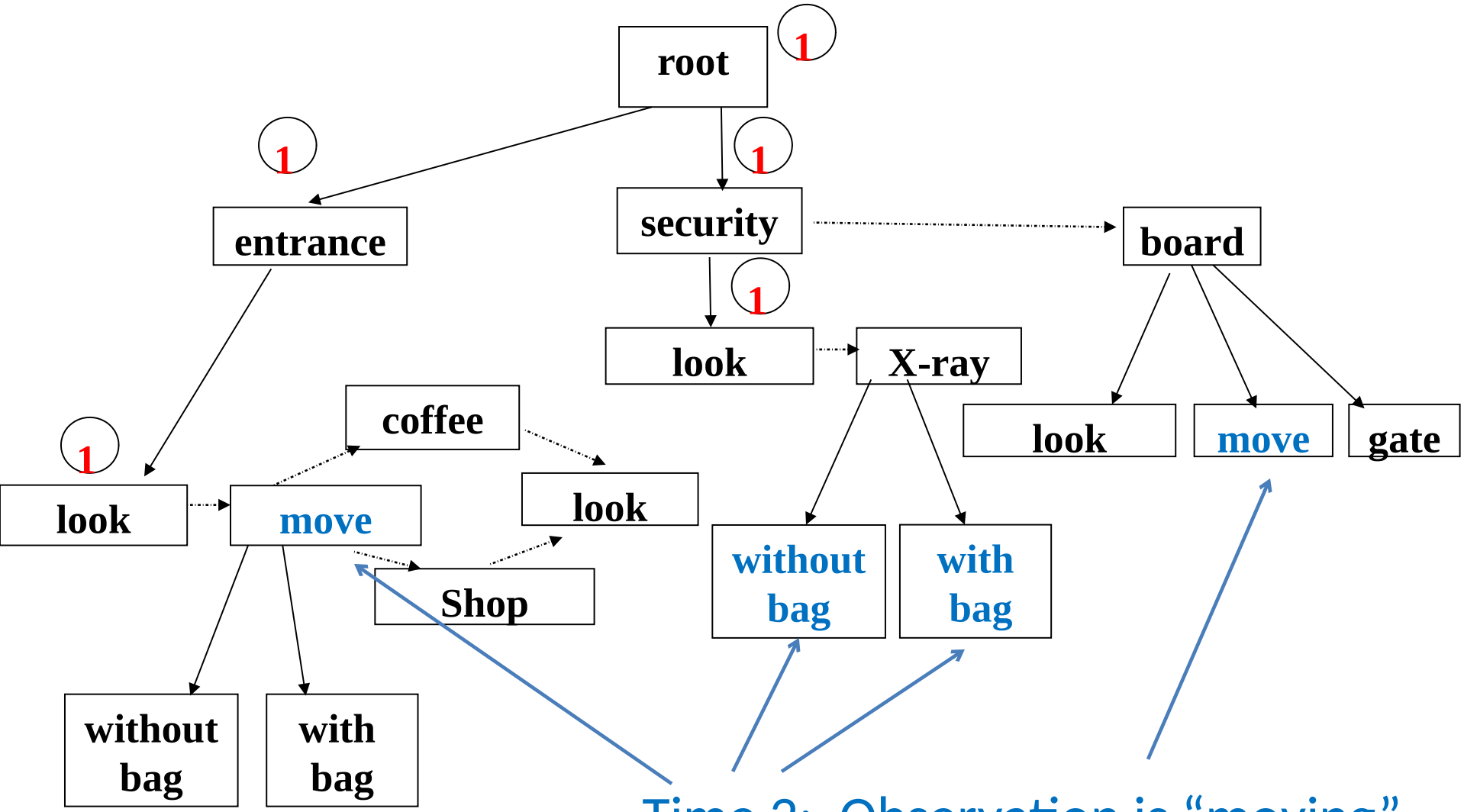


Time 1: Propagate

Current State Query: Example

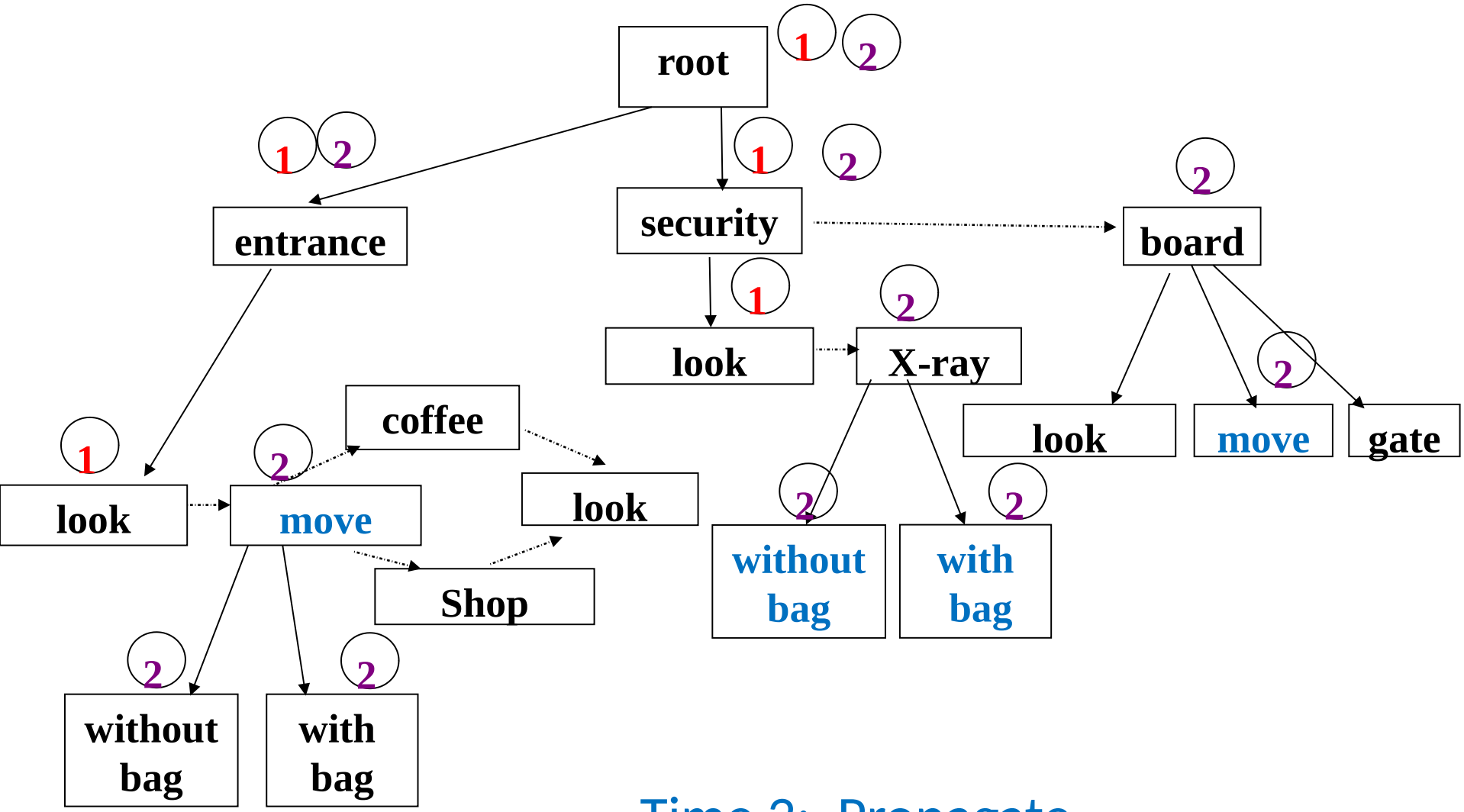


Current State Query: Example



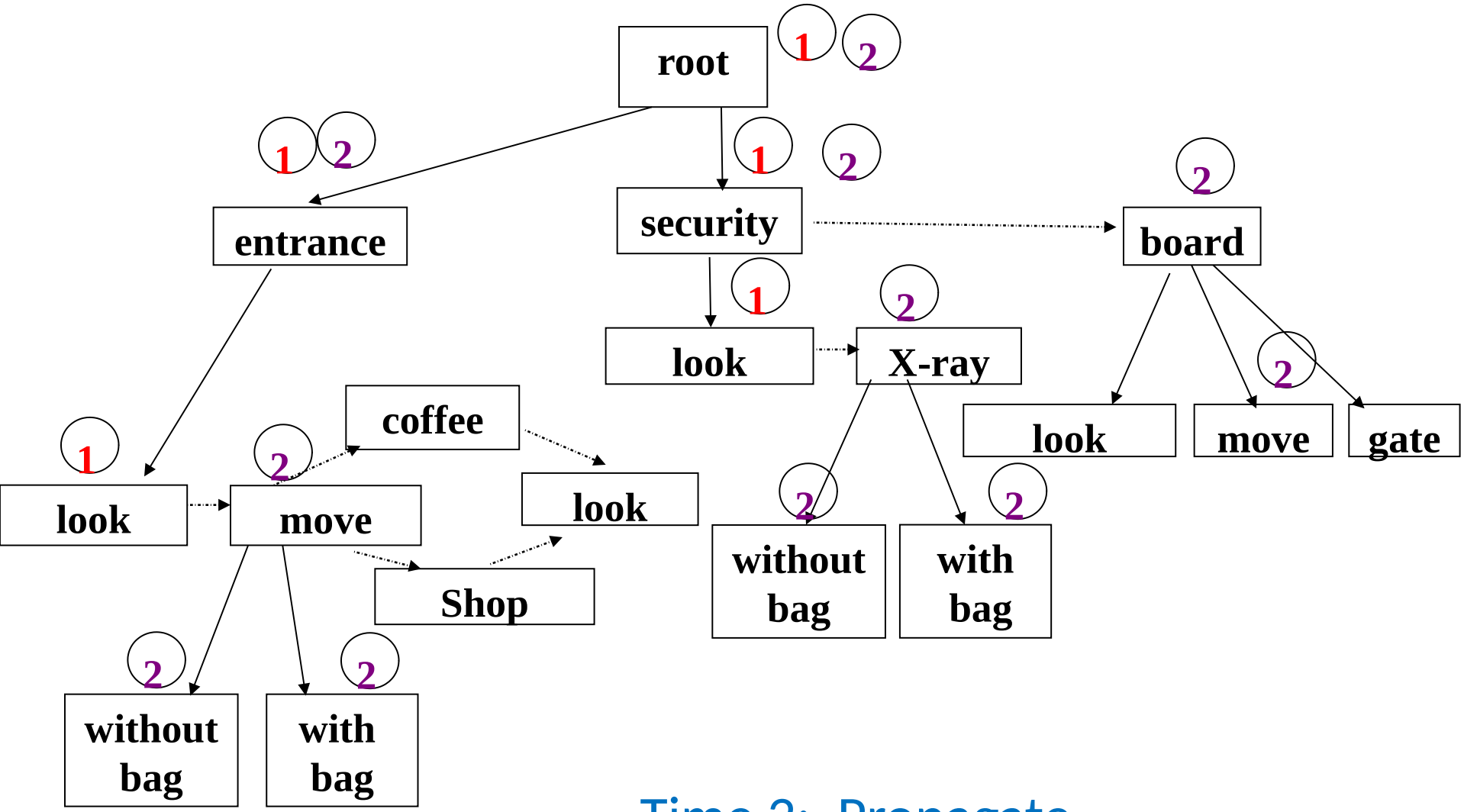
Time 2: Observation is “moving”

Current State Query: Example



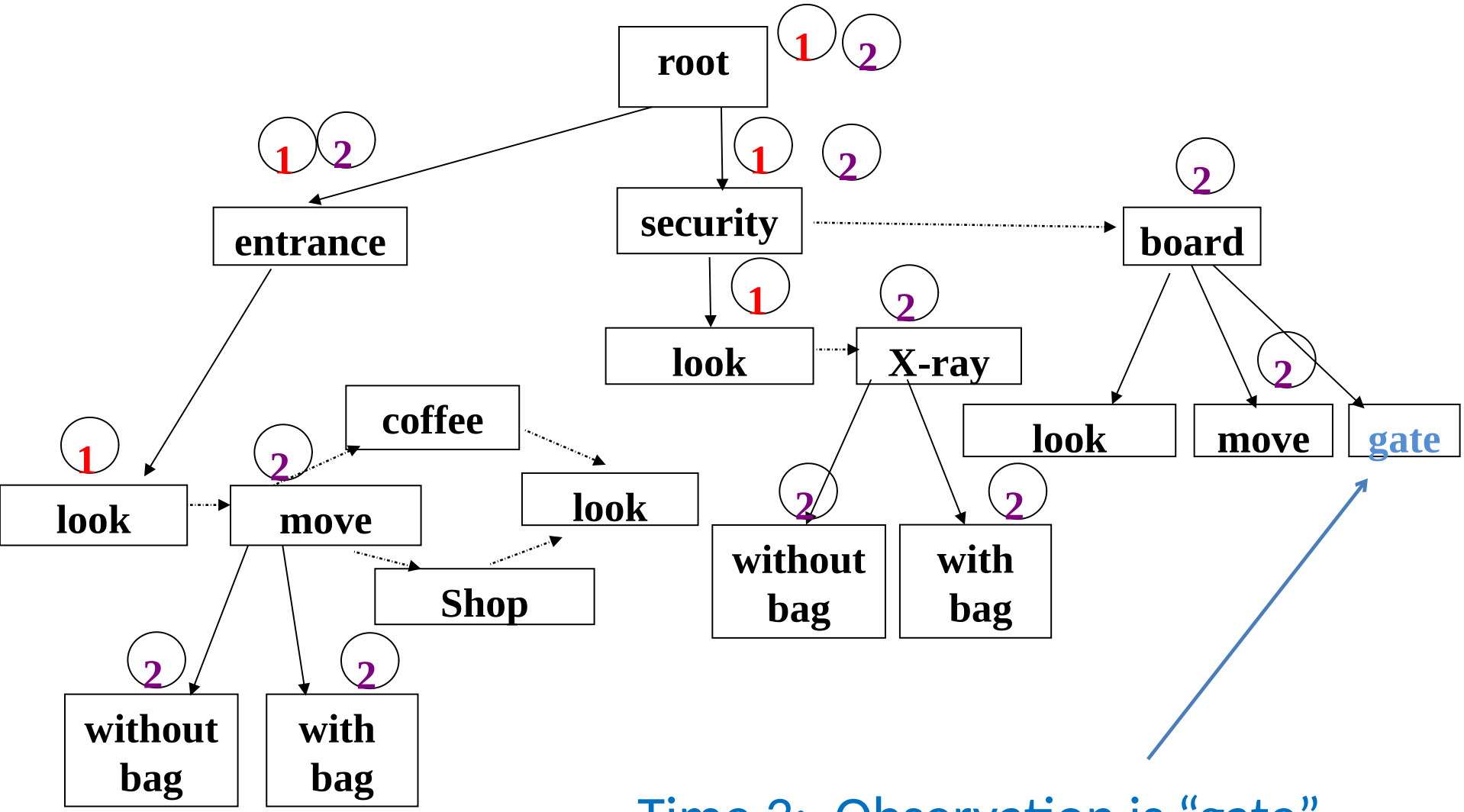
Time 2: Propagate

Current State Query: Example



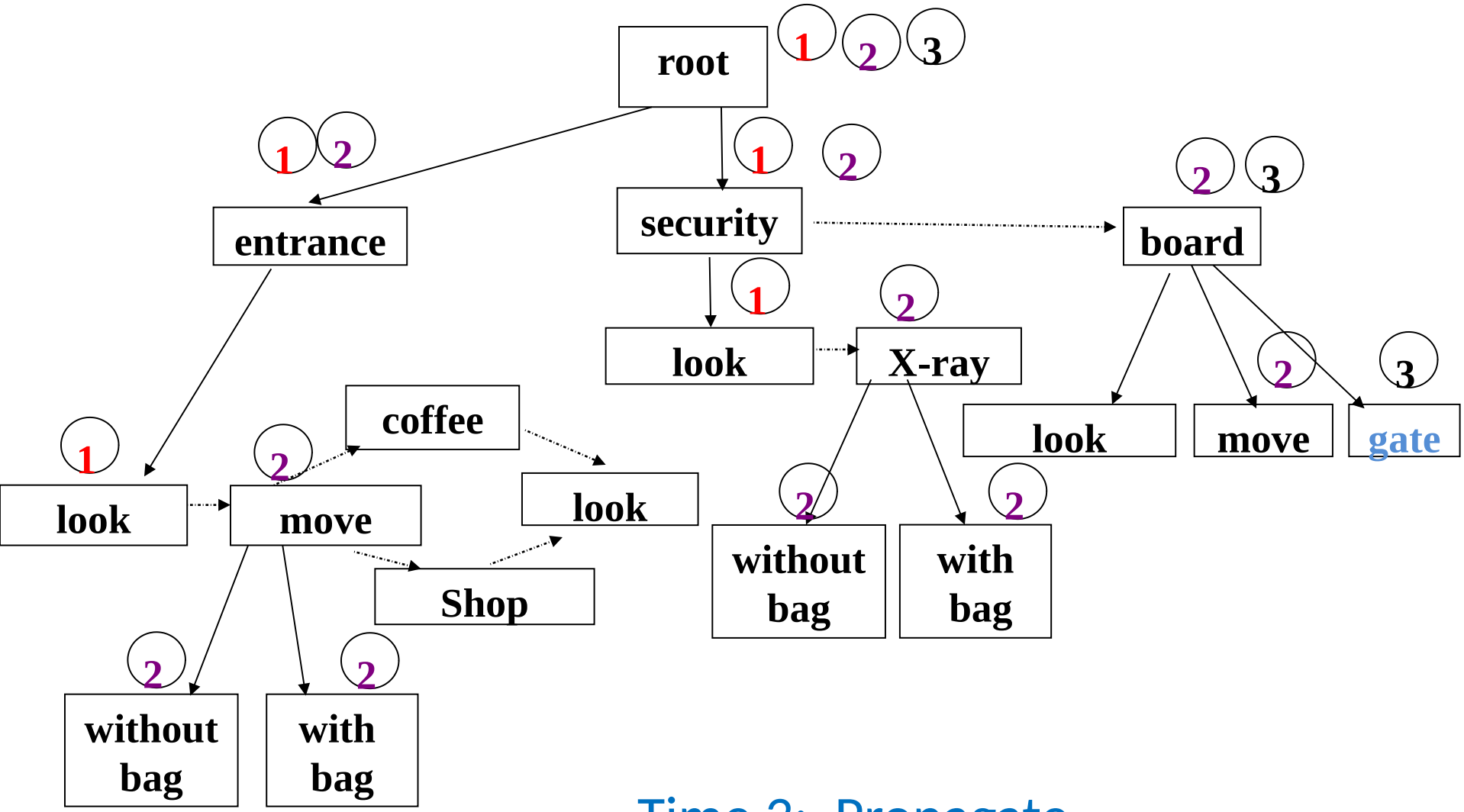
Time 2: Propagate

Current State Query: Example



Time 3: Observation is “gate”

Current State Query: Example

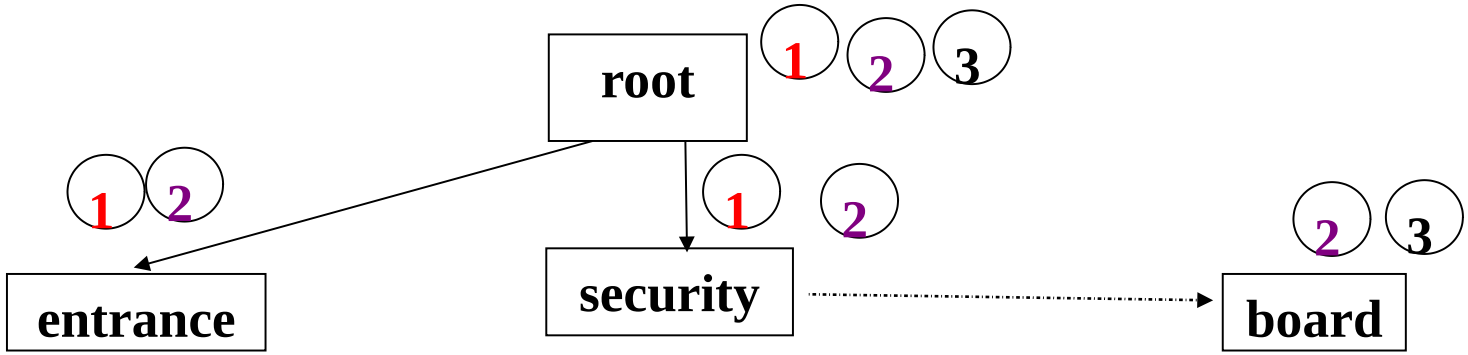


Time 3: Propagate

History of States Query

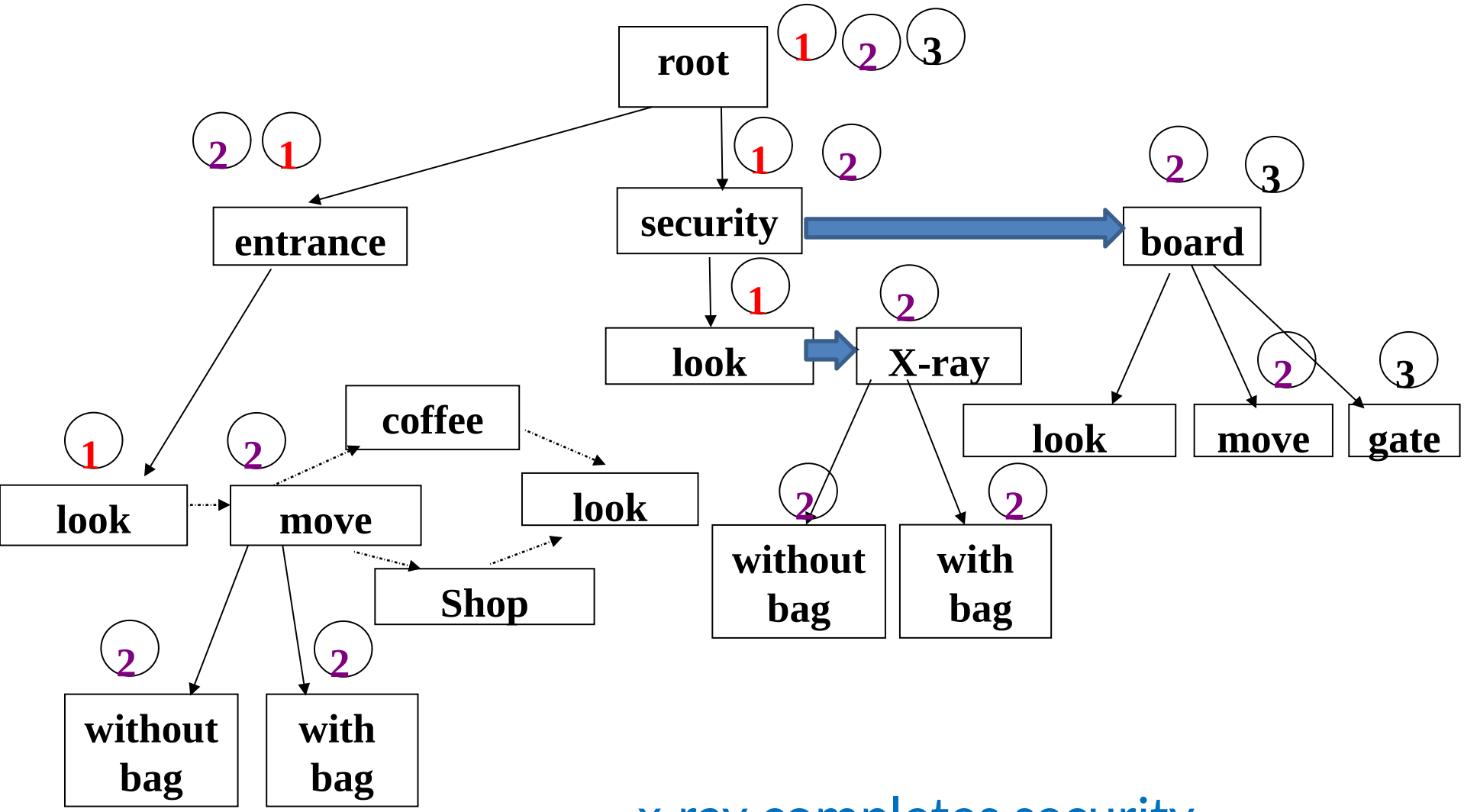
What <u>was</u> True

- CSQ is <u>situated</u>: only hypothesizes as to current state
- Does not explain complete sequences



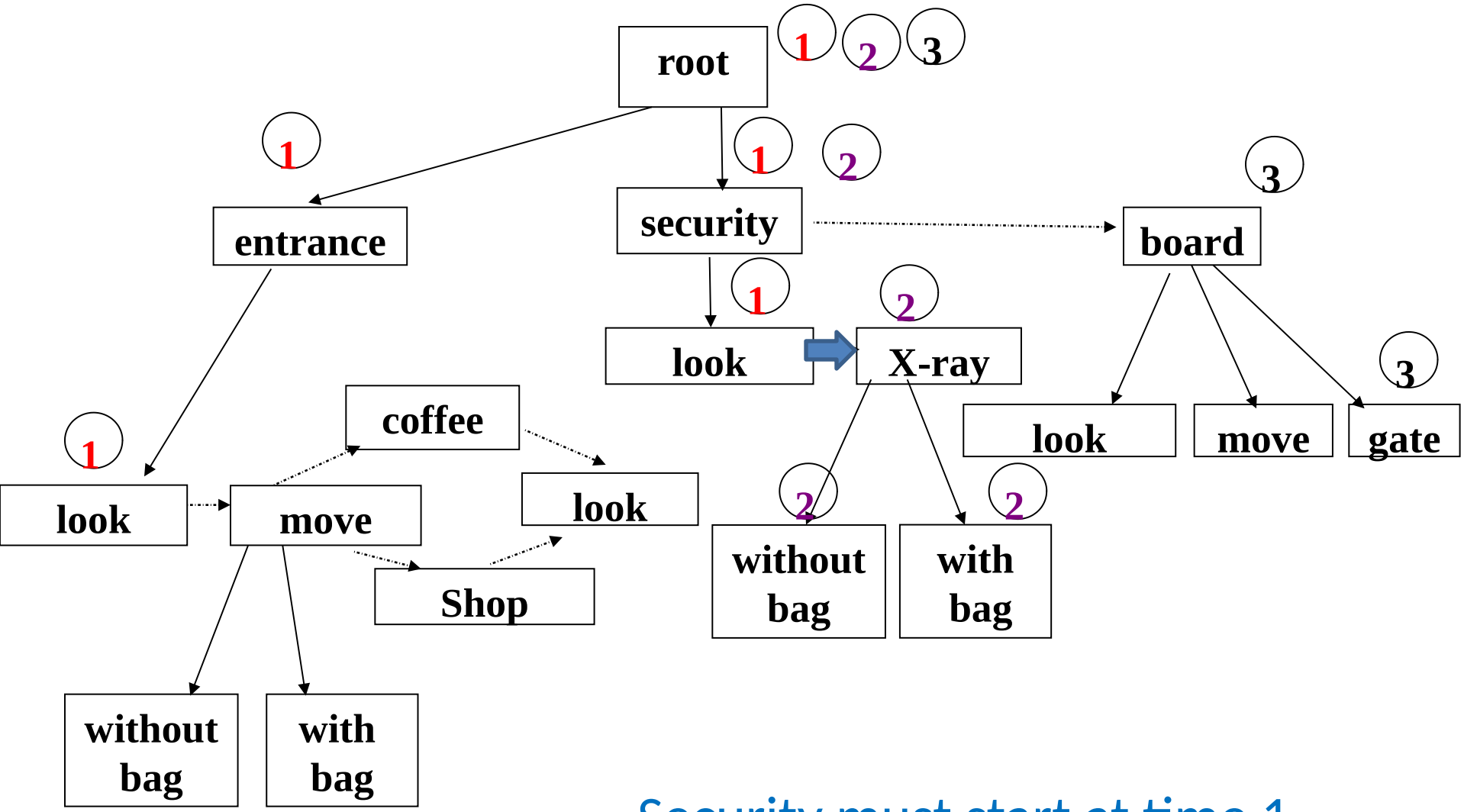
All possible sequences (1,2,3)? **No.**

History of States



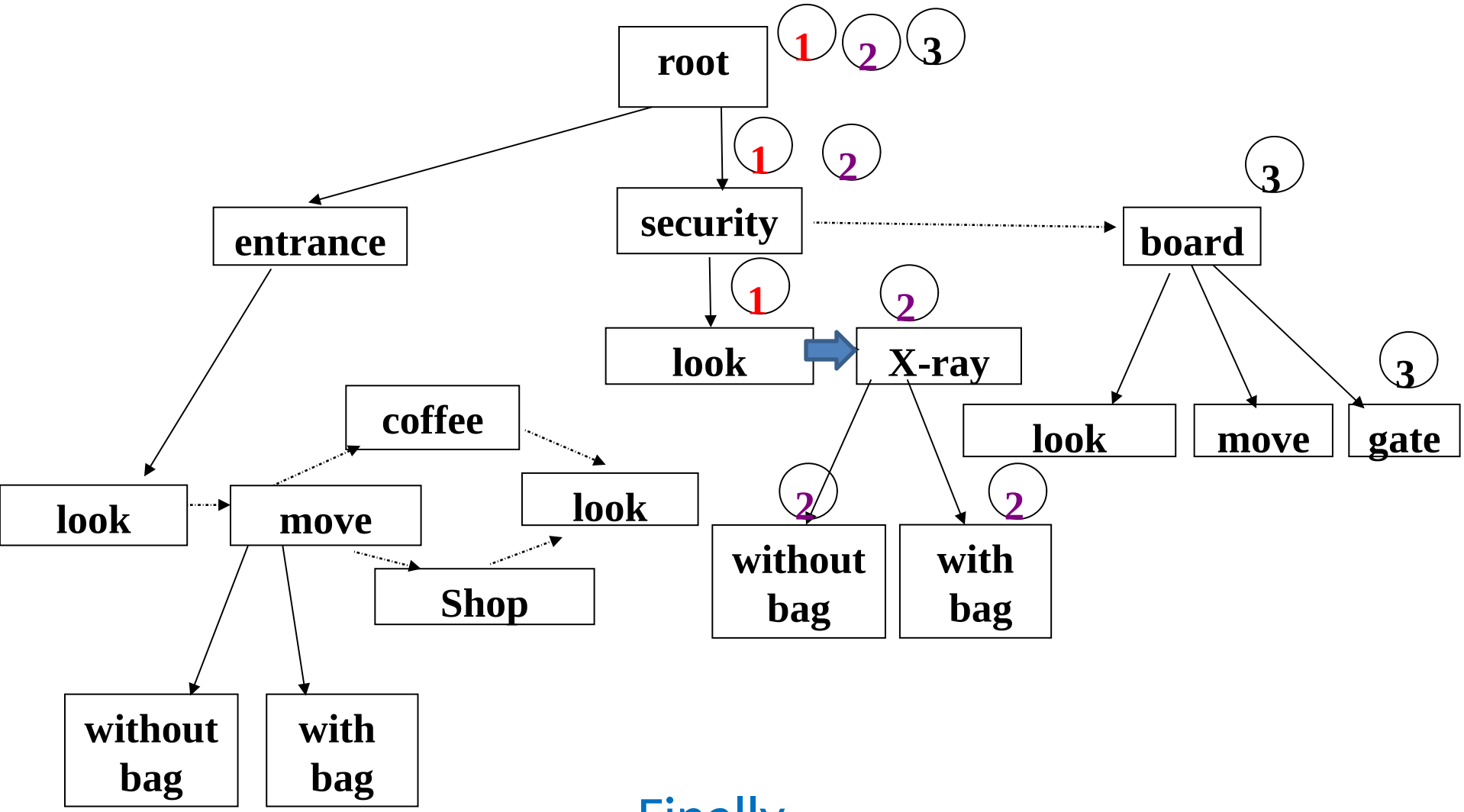
x-ray completes security
Security terminates at time 2

History of States



Security must start at time 1

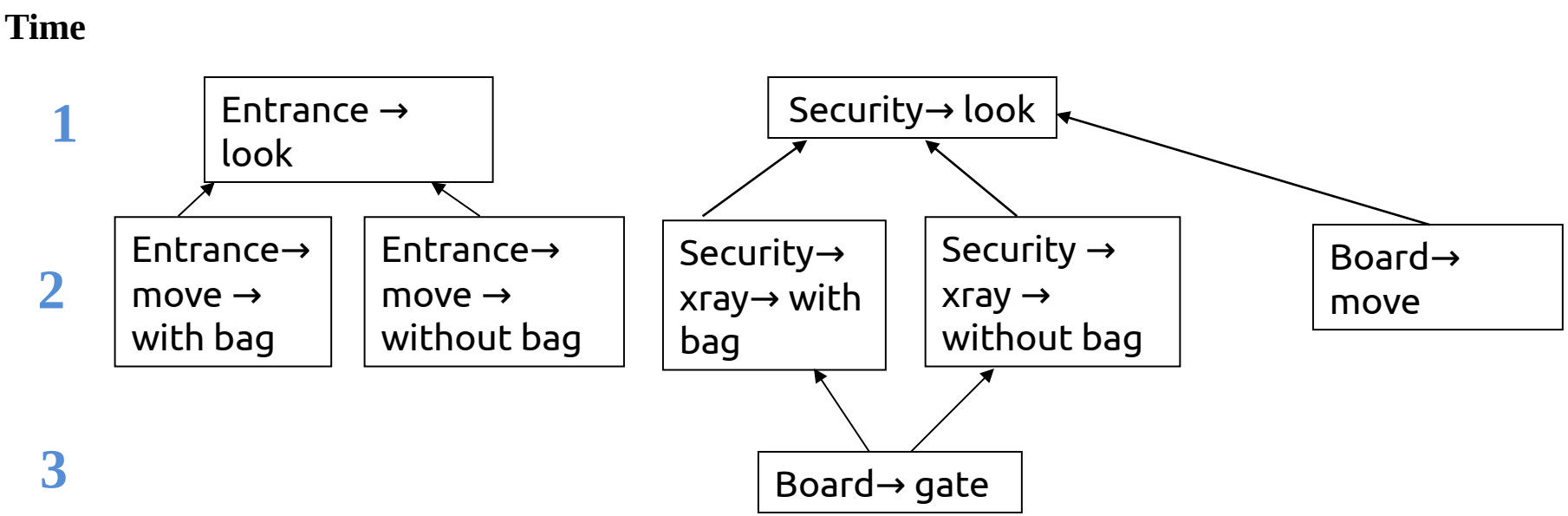
History of States



Finally

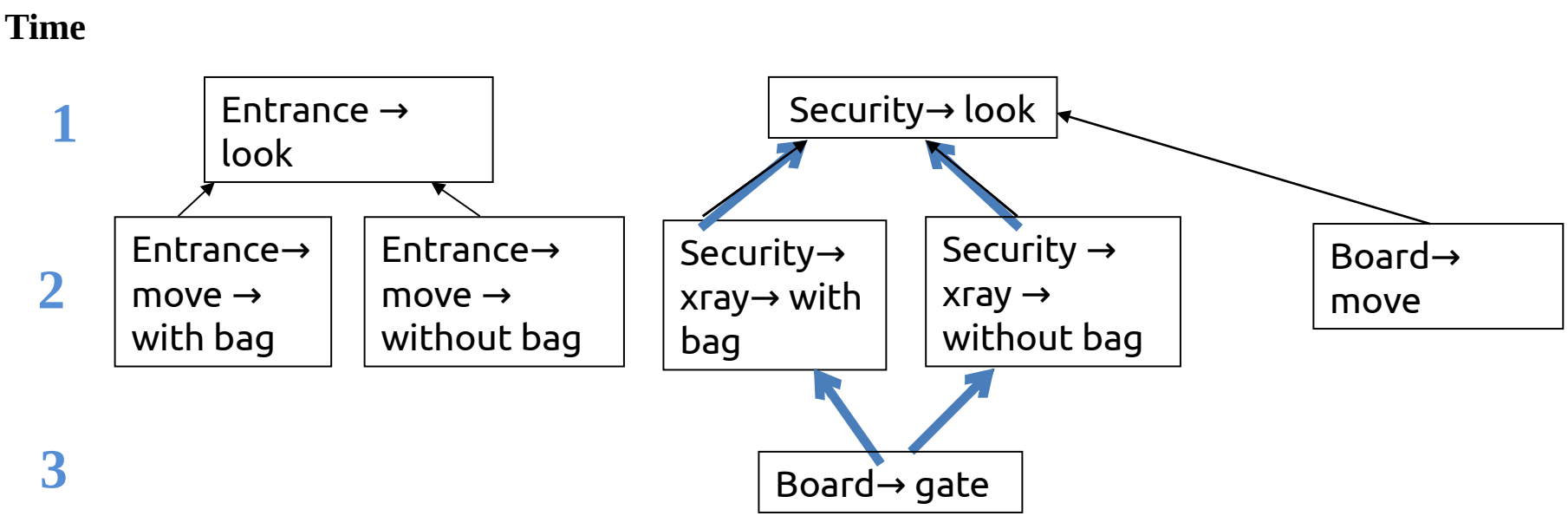
History of States Query

- Generate (or incrementally build) <u>hypotheses graph</u>
  - Vertices: denoting hypotheses at time *t*
  - Edges: connect valid continuations from *t* to *t+1*



History of States Query

- Generate (or incrementally build) hypotheses graph
  - Vertices: denoting hypotheses at time *t*
  - Edges: connect valid continuations from *t* to *t+1*
- Valid hypotheses: paths from vertices in time *t* to time *1*



SBR Highlights
[IJCAI 2005, MOO 2004-2005]

- <u>Highly efficient, Complete:</u>
  - Match observations to plan library vertices in O(1)
  - CSQ is O(M log L), M # of matches, L size of library
  - History query is polynomial:
    - Graph construction is $O(M^2)$ for each observation
    - Hypotheses extraction is $O(TM^2)$
- Extensions for interleaving, interrupting, …
- Limitation: grounded library, must fit in memory

Lazy Commitment in SBR

- Book keeping allows delaying inference
- <u>Compute only if queried</u>
  - e.g, hypotheses graph can be built only on history query
- No commitment to ranking
  - Probabilistic or decision-theoretic ranking is separate
  - SBR as filter [AAAI 2007]; PHATT, SLIM use similar approach

Mirroring
[ACS 2016, IJCAI 2017, AAAI 2018]

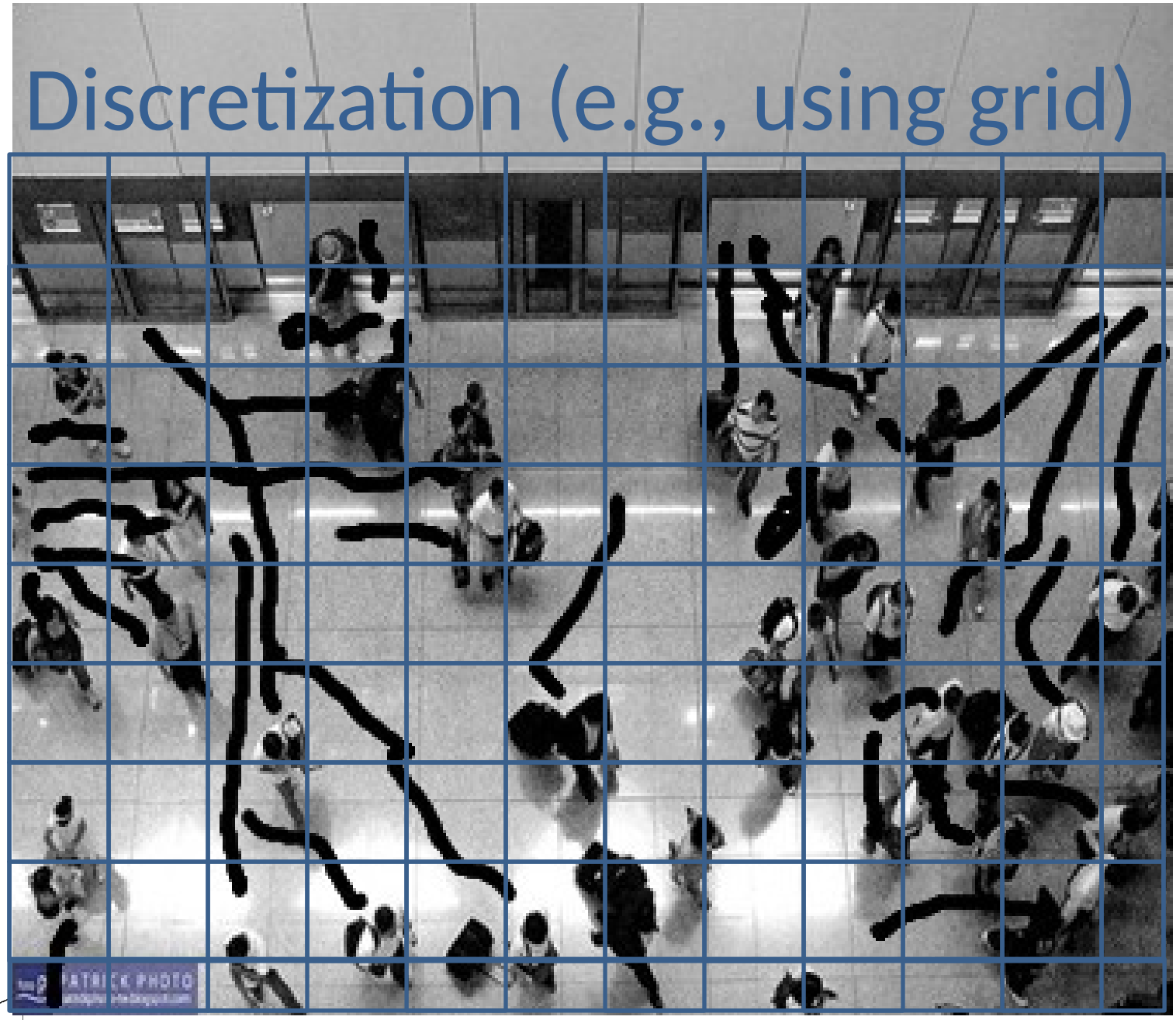
Observations and Plans are in Continuous Space

gestures, motions, goal locations: <u>trajectories</u>

Security Camera Image

Tracked Trajectories

Discretization (e.g., using grid)



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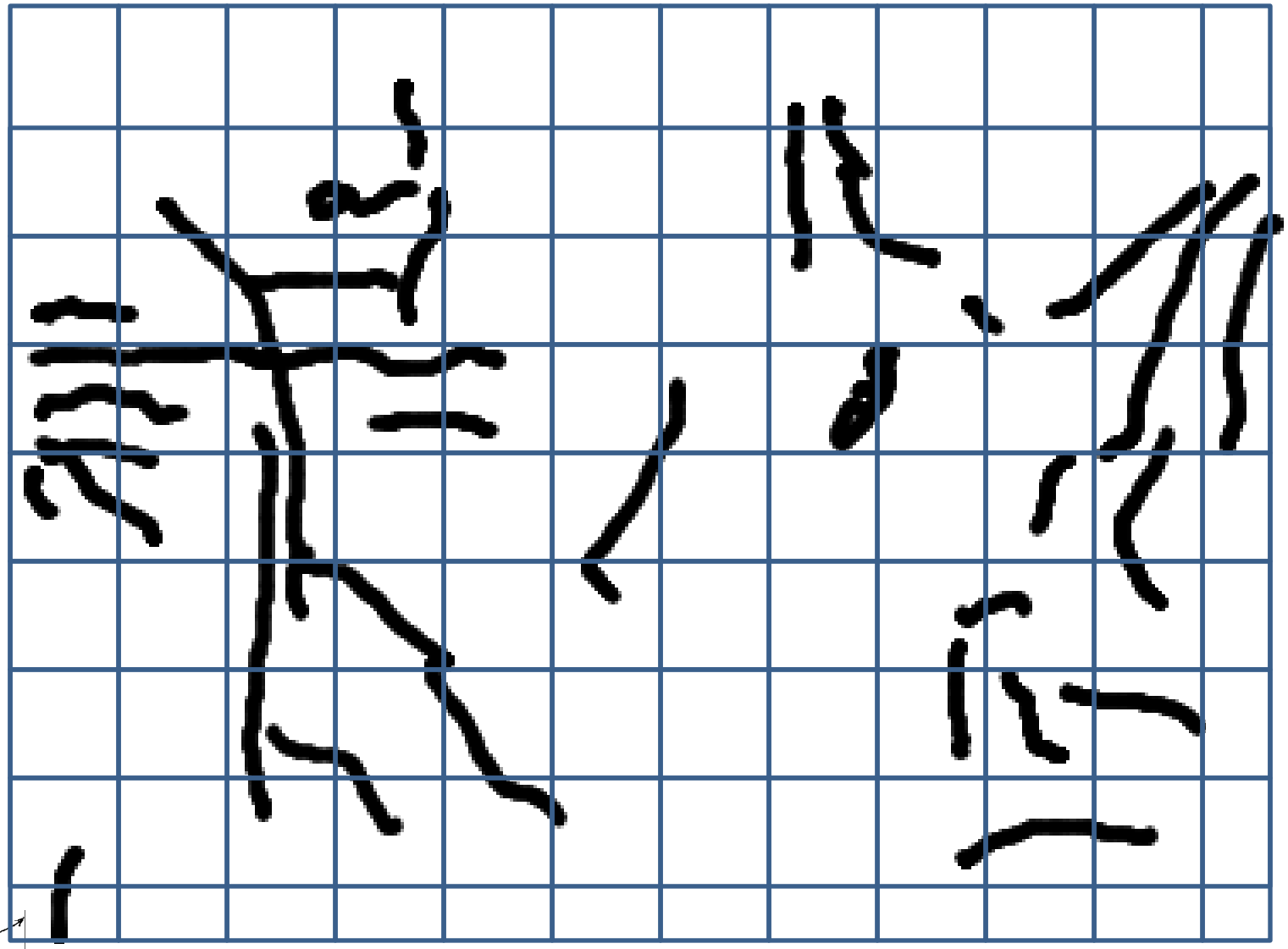
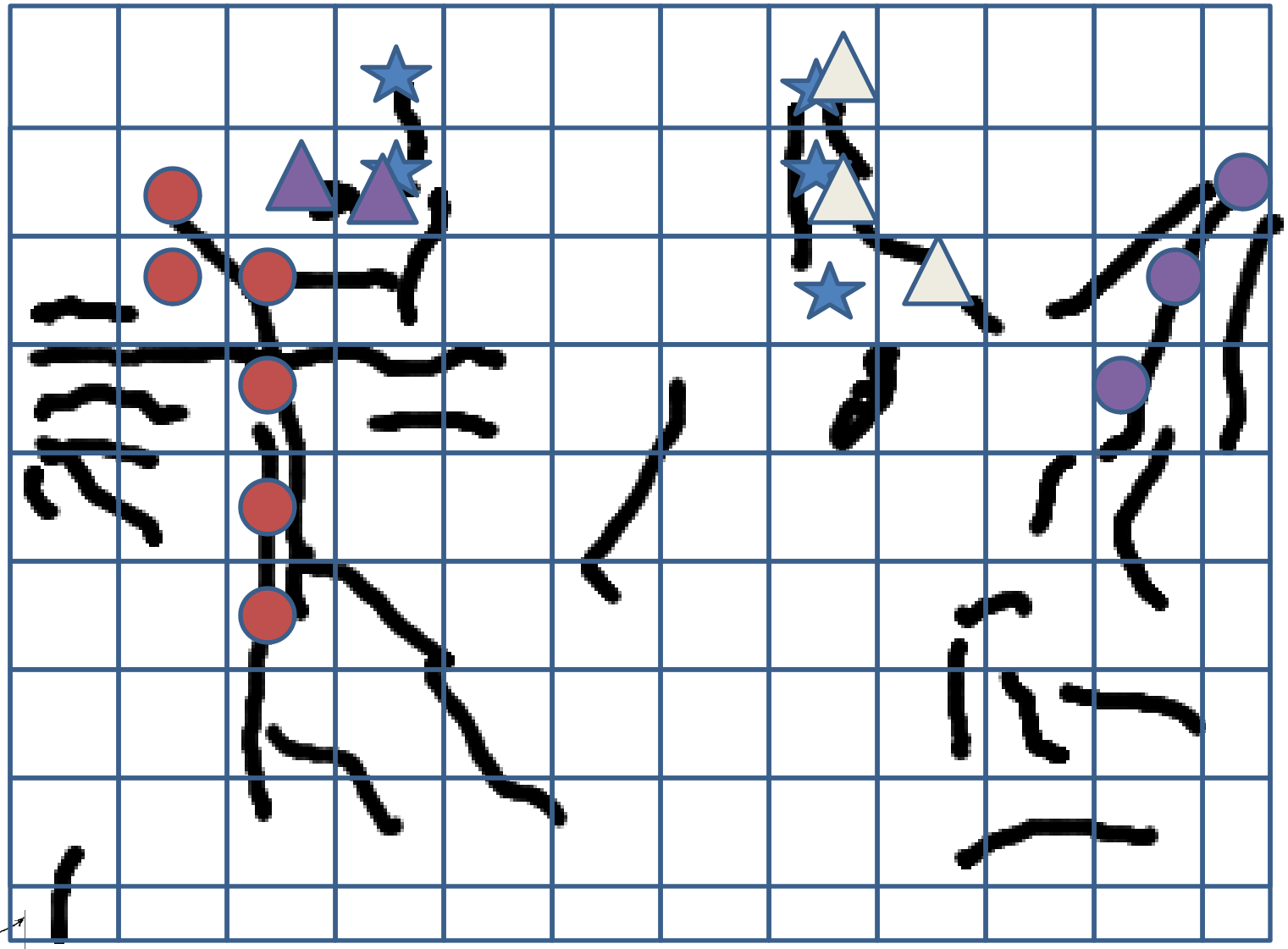
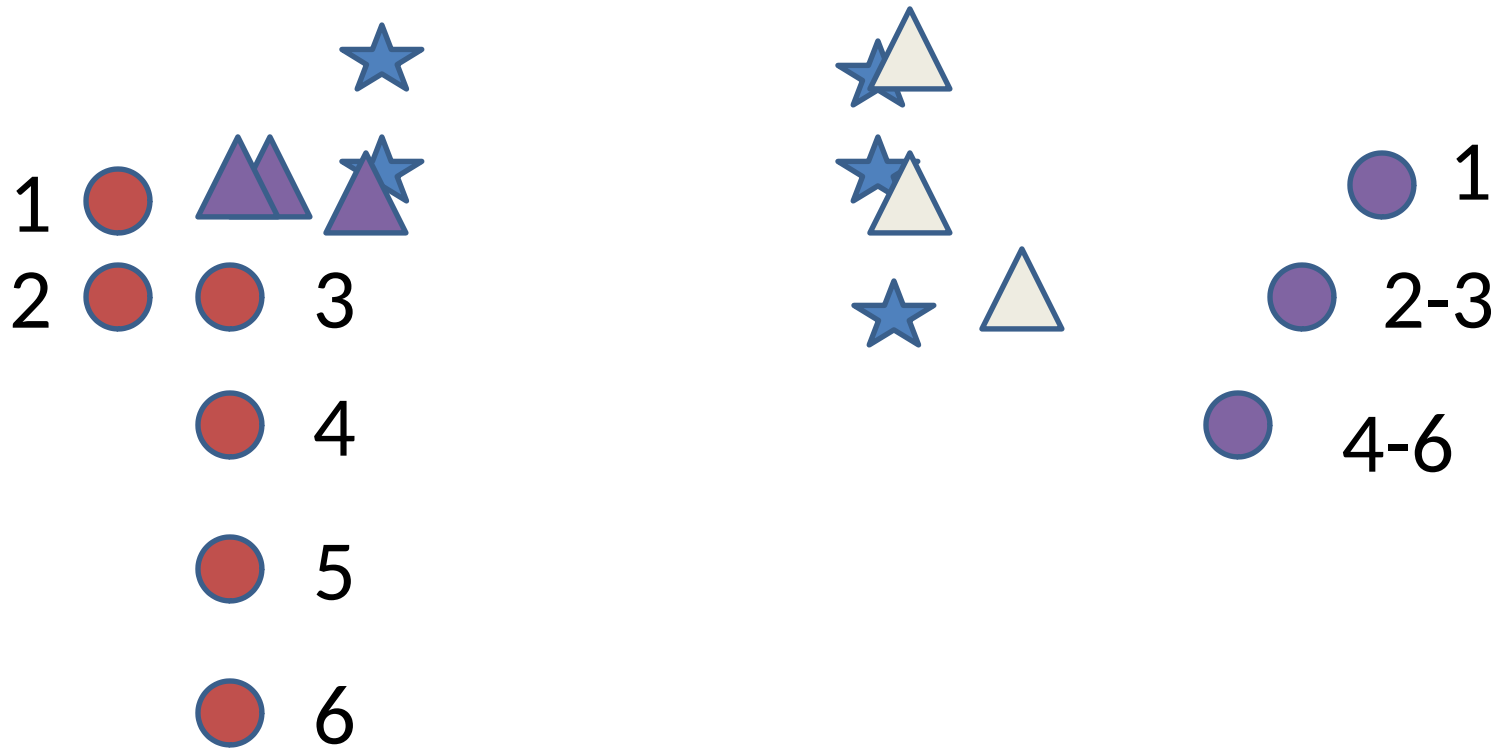


Discretization (e.g., using grid)



Resulting Observations



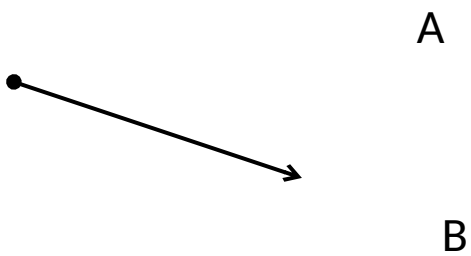
Early Commitment to Discretization

<u>Theorem **1**:</u>

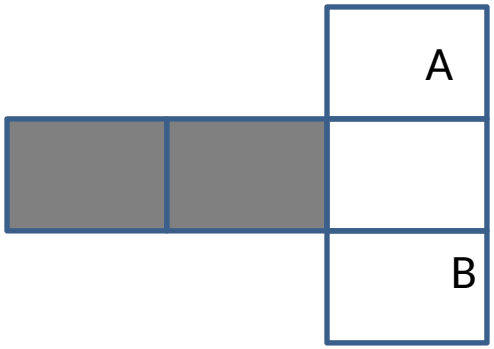
For any discretization, can find case where it fails

What is the goal of the agent?

A or B?



Continuous Version



Discrete Version

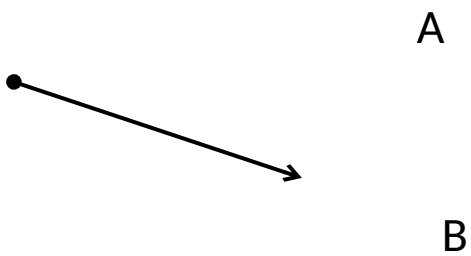
Late Commitment to Discretization

<u>Theorem **2**:</u>

For any case, can find discretization where it succeeds

What is the goal of the agent?

A or B?



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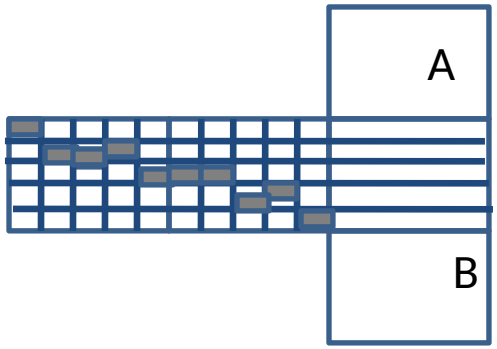


Discrete Version

Challenge:
Allow Late Commitment to Discretization

- Plan recognition libraries <u>require</u> early commitment
  - Hierarchical structures, grammars, HMMs and variants

- Plan recognition by planning (PRP) has potential
  - Generates hypotheses ad-hoc, <u>after</u> getting observations
  - Expensive for online recognition

PRP in Continuous Domains

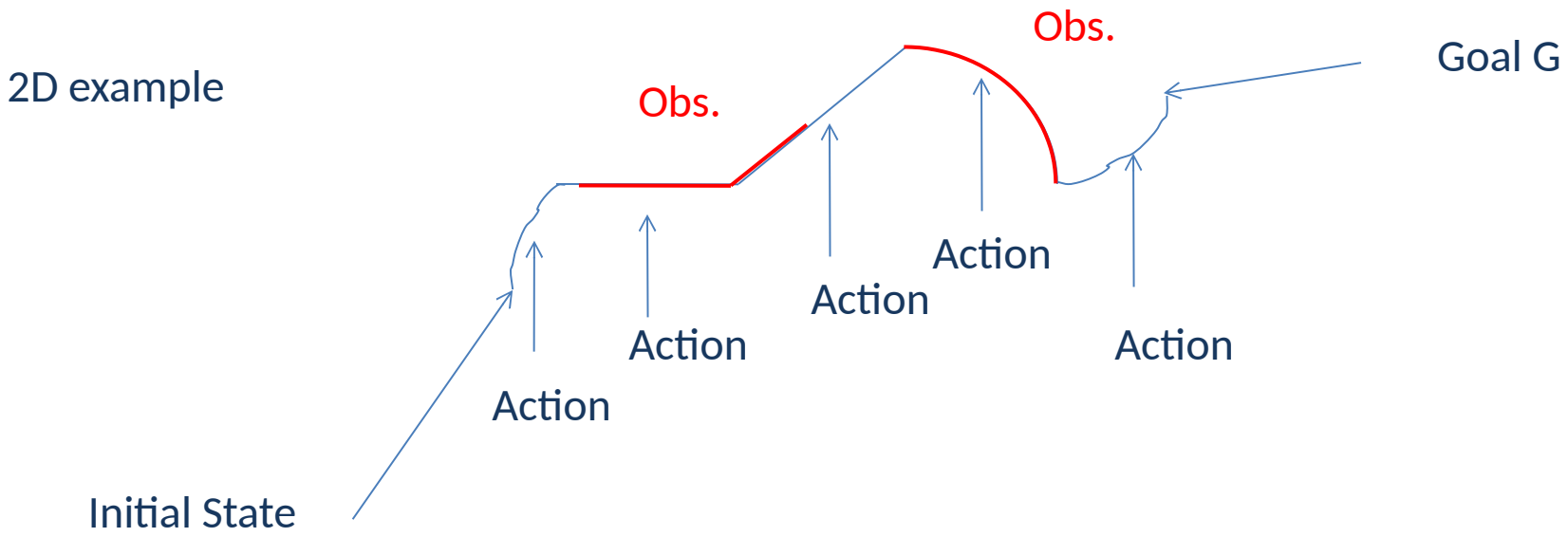
- Observations are of continuous actions?
  - Requires domain theory describing continuous domains
- Requires planner that can work in continuous domains
  - Lots of these in OMPL (Open Motion Planning Lib)
  - **But cannot compute path that "deviates from O"**

Mirroring [IJCAI 17, AAAI 18]

- Revised procedure for ranking hypotheses
  - Optimal plan (plan(G)) vs observed plan (plan(G+O))
  - Closer to formulation in [R&G 2009] (abandoned?)
- Generalize planning domain theories
  - Actions generate trajectories, not single final state
- Online recognition
  - 2T planner calls, each goal ✉ (T+1) planner calls each
  - Heuristics can improve performance (guaranteed)

Plan Recognition Problems

- Given $R = \langle W, I, G, O \rangle$
  - W domain; I initial state; G set of possible goals; O observations
- Find plans in W, from I to a goal in G, <u>that match O</u>



Plans in Domain W

<u>Plan: sequence of actions</u>

- States defined using fluents (numerical values allowed)
  - e.g., *on(A,B)=true*, *fuel-remaining(robot)=50.33*, *pos-x(r)=4.5*

- *Actions: <u>trajectories</u> of state-changes*
  - $\delta(s_{BEG},a) = (S_{BEG},\ldots,S_{END})$
  - $S_i = (S_{i-1} \backslash DEL_a(S_i)) \oplus ADD_a(S_i)$
  - Proper generalization of STRIPS actions

Finding good plan hypotheses

- Want: plan hypothesis $\pi_R = \text{argmax } P(\pi|O)$
  - Intuitively – "best matches the observations"

- We want matching that maximizes

$$P(\pi|O) = \beta\, P(O|\pi)\, P(\pi)$$

$$= \beta\, \underbrace{P(O|\pi)}_{\text{Obs., given plan}}\, \underbrace{P(\pi|g)}_{\text{Plan, given goal}}\, \underbrace{P(g)}_{\text{Prior on goal}}$$

Focus: Maximize $P(O|\pi)$, $P(\pi|g)$

How to maximize $P(O|\pi)$, $P(\pi|g)$:

<u>Two principles:</u>

- $P(O|\pi)$ [obs. given plan]: prefer <u>plans matching obs.</u>
  - Minimize *Error*(π, O): Accumulated distance between π and O
  - <u>$P(O|\pi)$</u> = 1 / (1+Error(π, O))

- $P(\pi|g)$ [plan given goal]: <u>prefer optimal plans</u>
  - Assume rationality of observed
  - Higher <u>$P(\pi|g)$</u> when π <u>**closer**</u> to ideal plan π^*
  - Defined as (normalized) ratio between costs of π and π^*

How to maximize $P(O|\pi)$, $P(\pi|g)$: Shortcut

<u>Two principles:</u>

- $P(O|\pi)$ [obs. given plan]: prefer <u>plans matching obs.</u>
  - Minimize *Error*(π, O): Accumulated distance between π and O
  - <u>$P(O|\pi)$</u> = 1 / (1+Error(π, O))

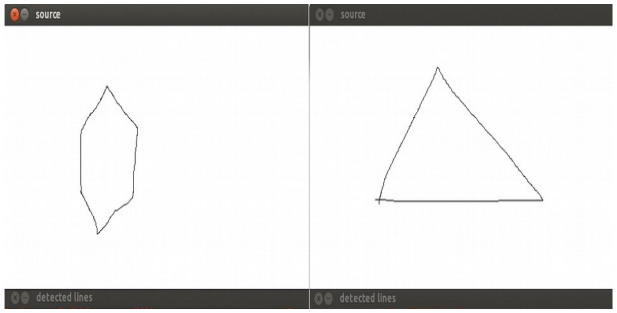
    = 1 when perfect = plan that goes through obs.

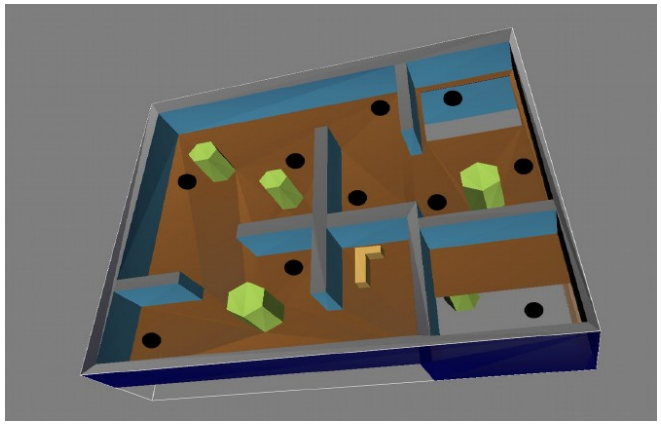
- $P(\pi|g)$ [plan given goal]: <u>prefer optimal plans</u>
  - Assume rationality of observed
  - Higher <u>$P(\pi|g)$</u> when π **<u>closer</u>** to ideal plan π^*
  - Defined as (normalized) ratio between costs of π and π^*

Calls to planner

Domains

- Motion planners in OMPL [Şucan et al. 2012]
- Polygon drawing planner [Vered et al. 2016]
- ROS MoveBase standard navigation package





Summary: Lazy is Good

- Late commitment to discretization: a MUST
  - Remember the theorems (and shown experimentally)
  - Mirroring: a novel form of PRP allowed this
- Late commitment to computing queries: Efficient
- Promising: distinguish queries in PRP
  - Ignore (most of) the past [Masters & Sardina 2017]
  - Pre-computing [Marting et al. 2015, Pereira et al. 2016, 2017]
- Thanks: Friendly organizers and atmosphere at PAIR

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