

Hierarchical Refinement as a Generalization of HTN Planning

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work performed with

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- James Mason University of Maryland

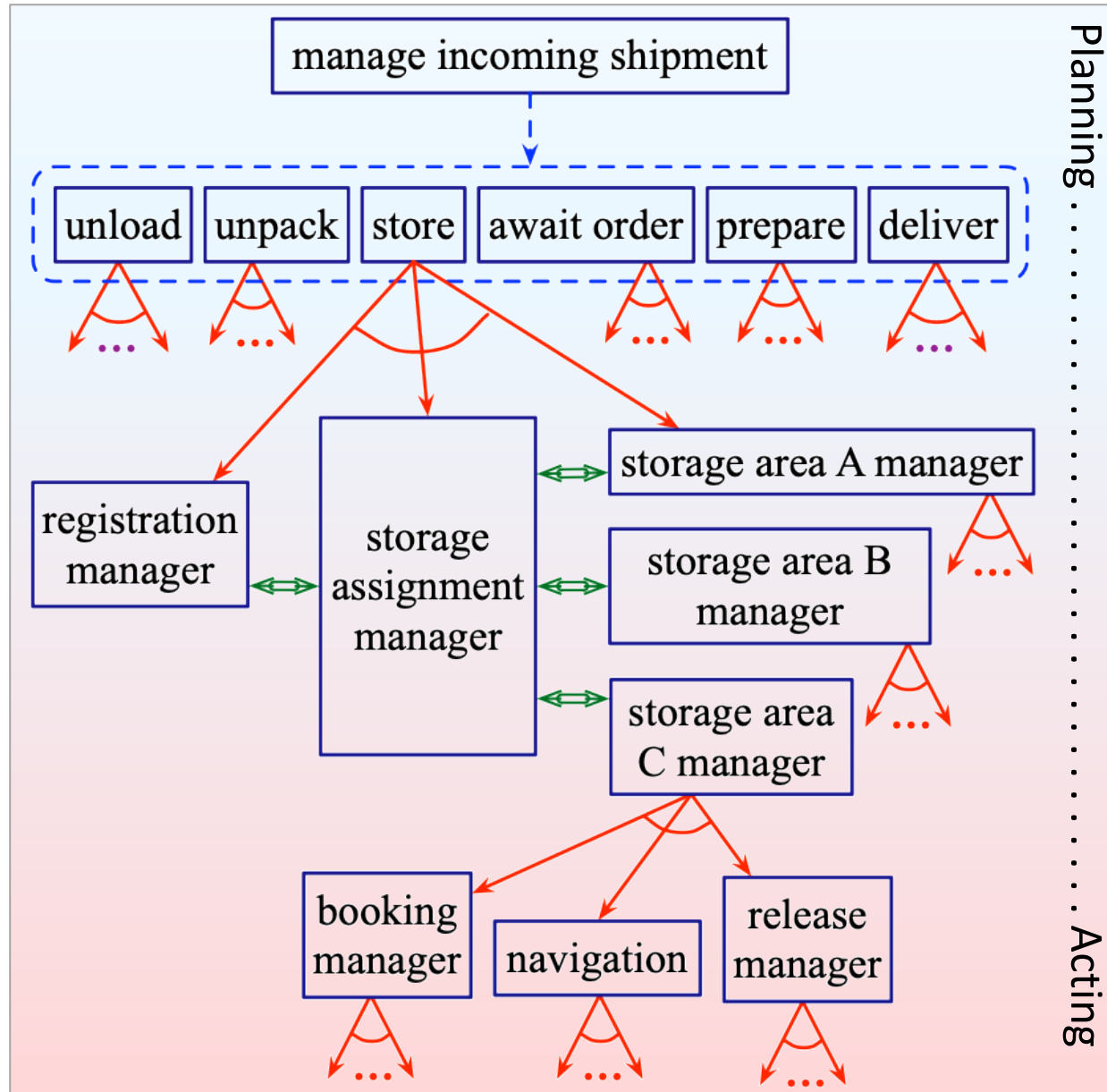
<http://www.cs.umd.edu/~nau/papers/nau2019hierarchical.pdf>

Bremen Harbor



Harbor Management Tasks

- Multiple levels of abstraction
 - Physical/managerial organization of harbor
- Upper levels:
 - Abstract tasks, can be planned in advance
- Lower levels:
 - Multiple agents
 - Partial observability
 - Dynamic change
- Continual online planning
 - Abstract and partial until more detail needed



Acting and Planning

Acting

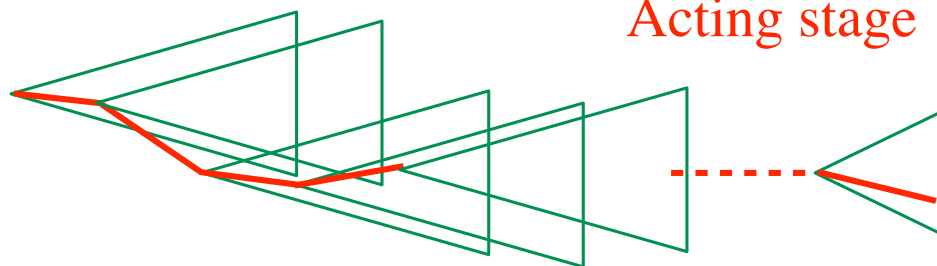
- *Performing* tasks and actions
- Use *operational models* that tell *how*
 - Dynamic, unpredictable environment
 - Adapt to context, react to events

Planning

- *Prediction + search*
- Search over predicted states, possible organizations of tasks and actions
- Use *descriptive models* to predict *what*

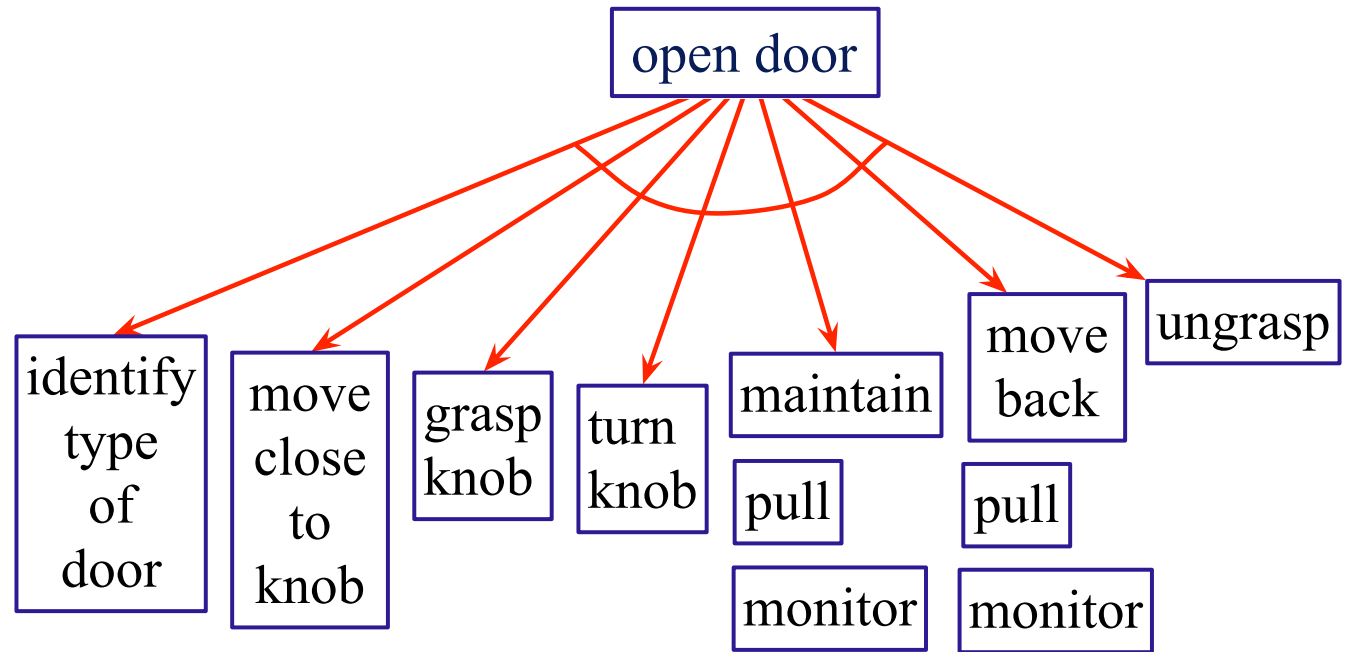
Planning stage

Acting stage



- Planning in service of acting
 - Actor asks planner for advice
- Planner runs online
 - e.g., receding horizon

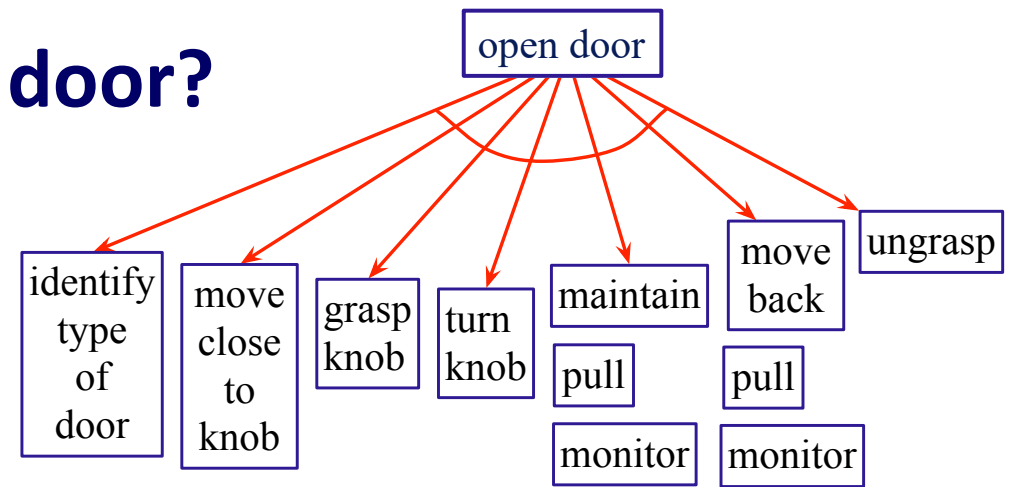
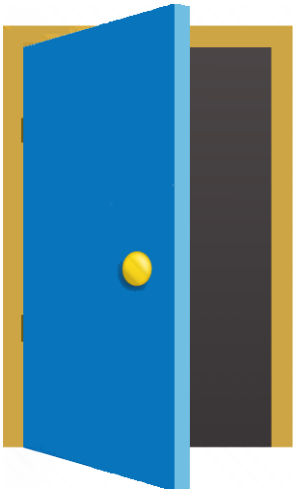
Opening a Door



- Details depends on what kind of door
 - Might not be known until acting time

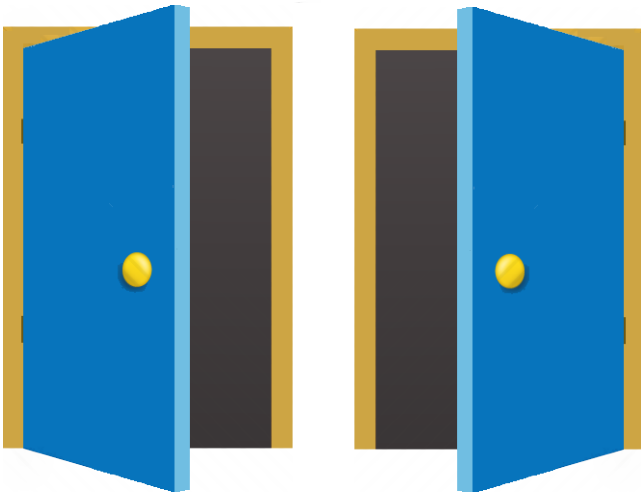
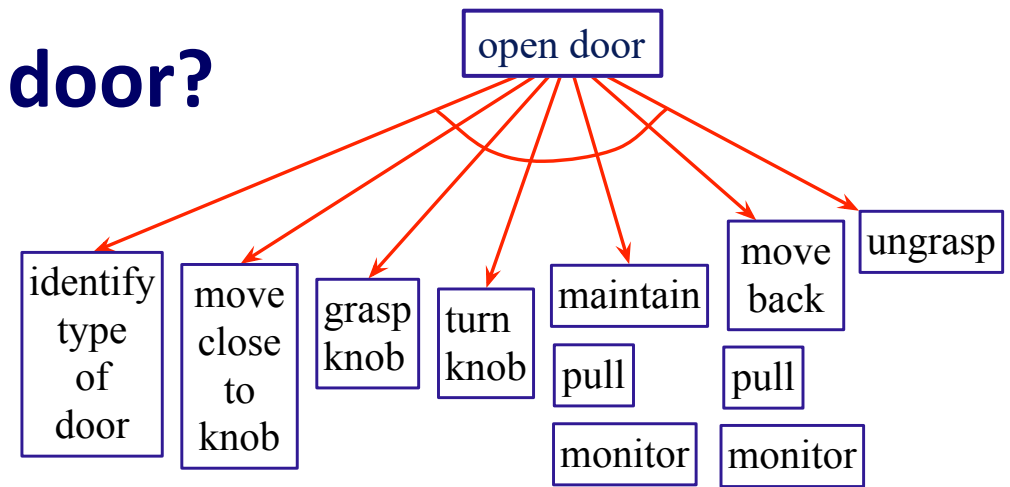
What kind of door?

➤ Sliding or hinged



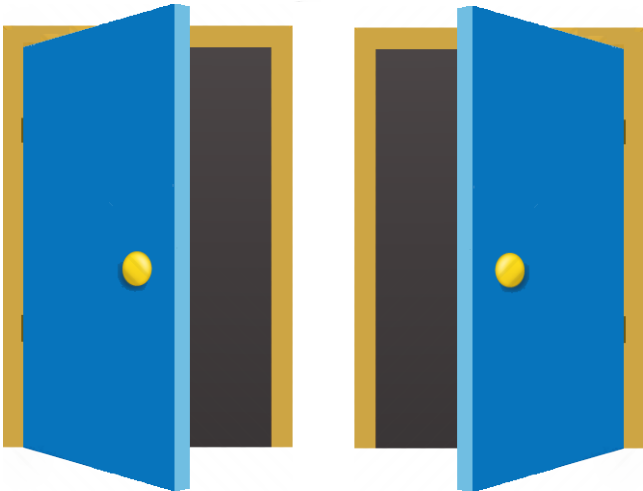
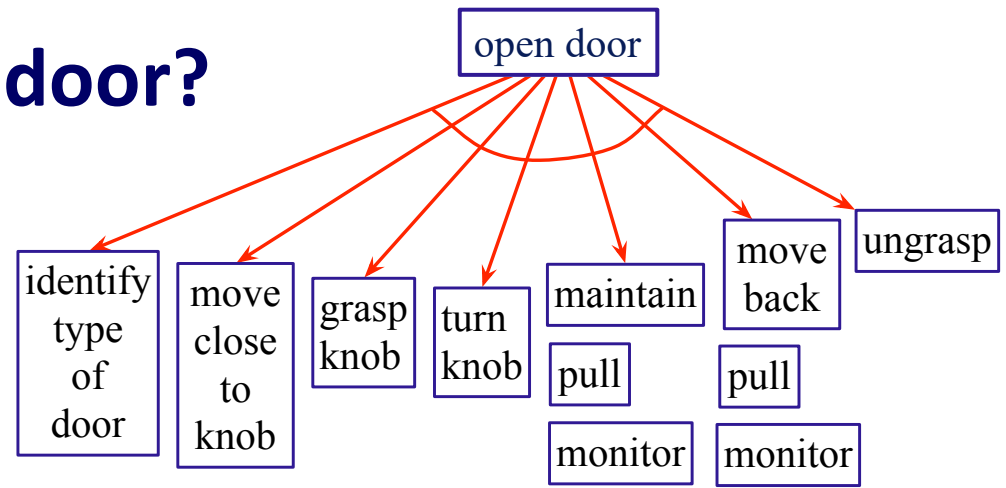
What kind of door?

- Sliding or hinged
- Hinge on left or right



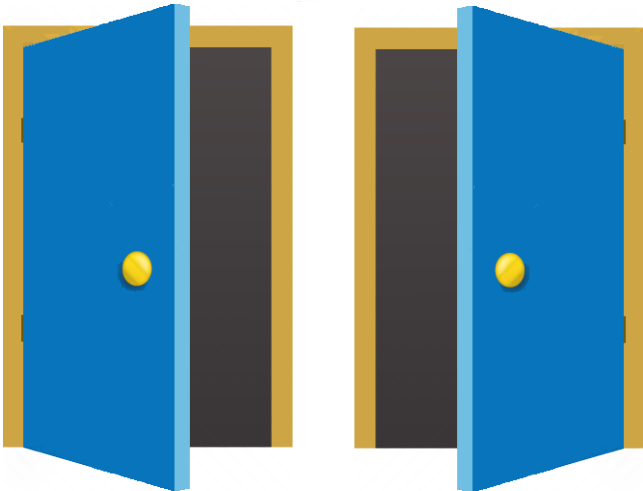
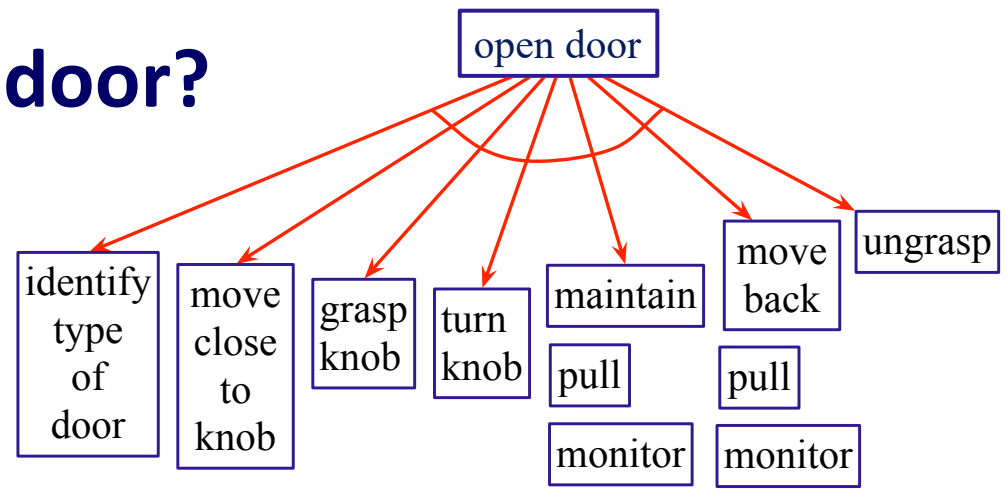
What kind of door?

- Sliding or hinged
- Hinge on left or right
- Open toward or away



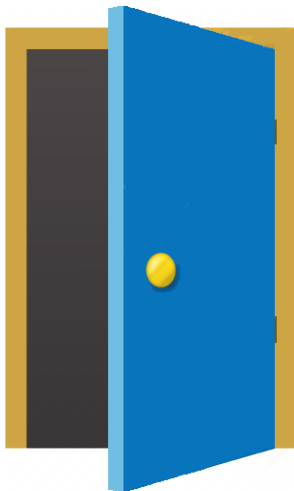
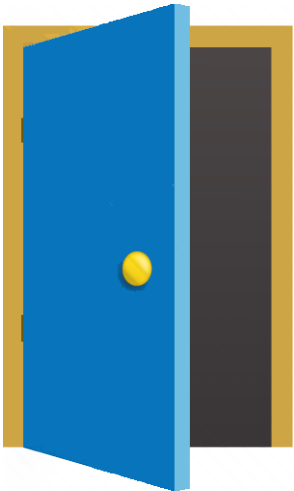
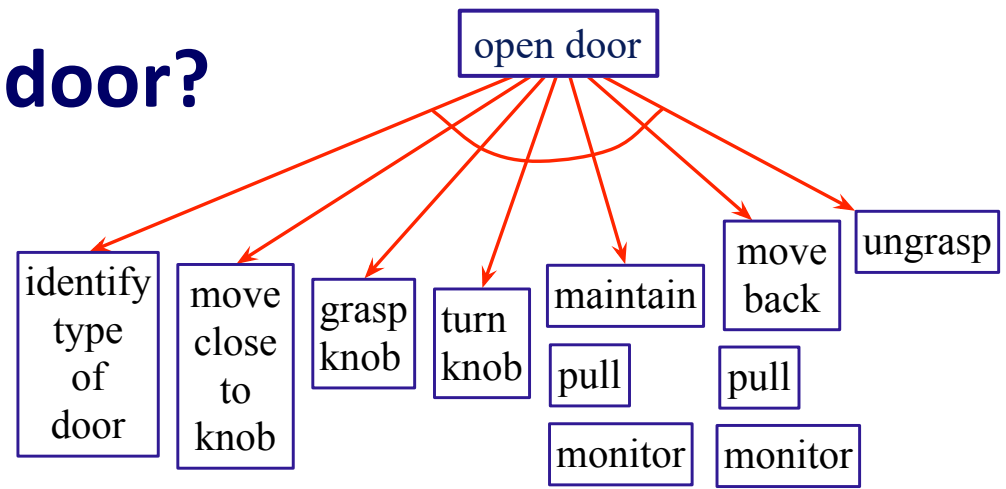
What kind of door?

- Sliding or hinged
- Hinge on left or right
- Open toward or away
- Knob, lever,



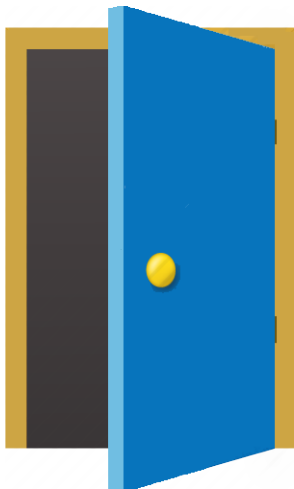
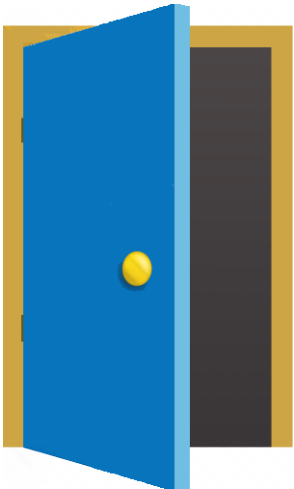
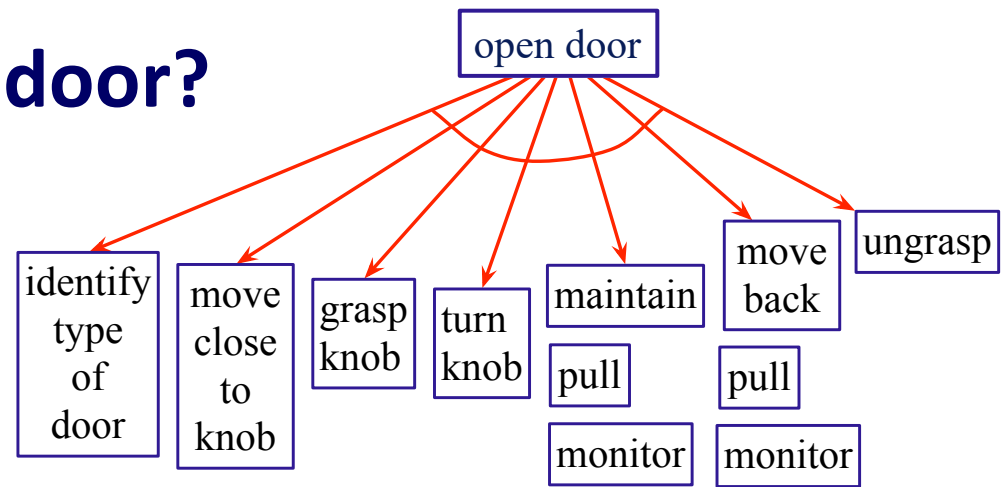
What kind of door?

- Sliding or hinged
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- Knob, lever, push bar, push plate,



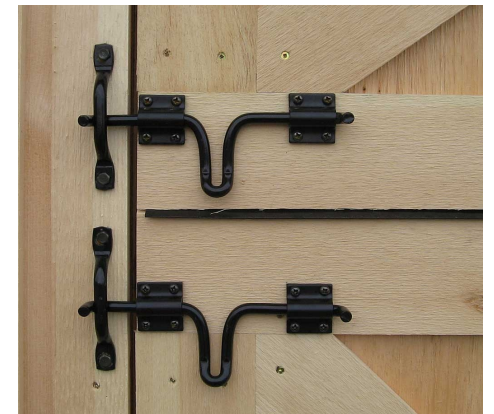
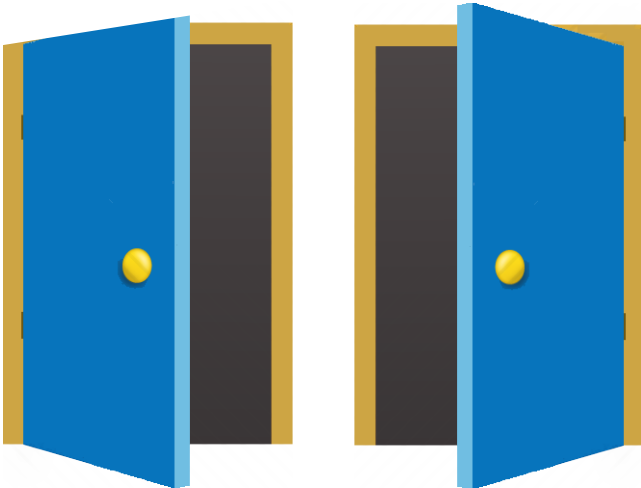
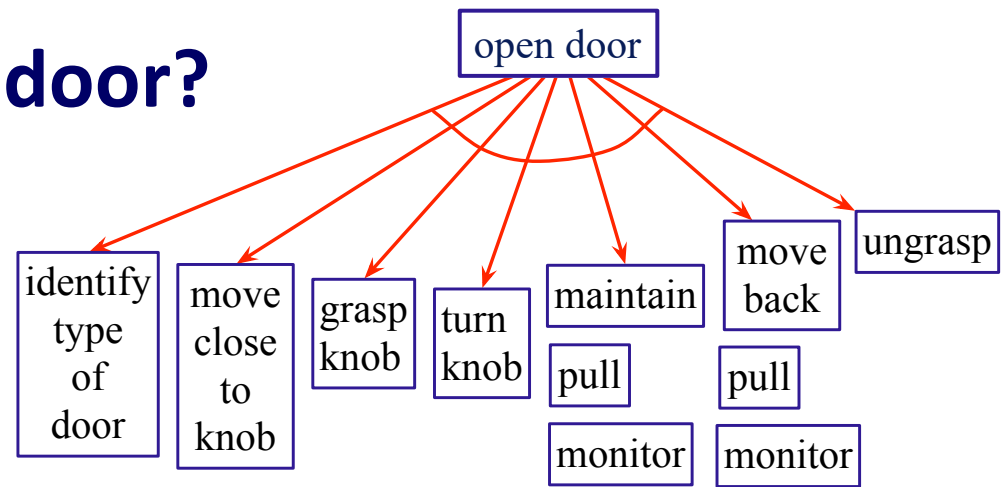
What kind of door?

- Sliding or hinged
- Hinge on left or right
- Open toward or away
- Knob, lever, push bar, push plate, pull handle, thumb latch,



What kind of door?

- Sliding or hinged
- Hinge on left or right
- Open toward or away
- Knob, lever, push bar, push plate, pull handle, thumb latch, something else

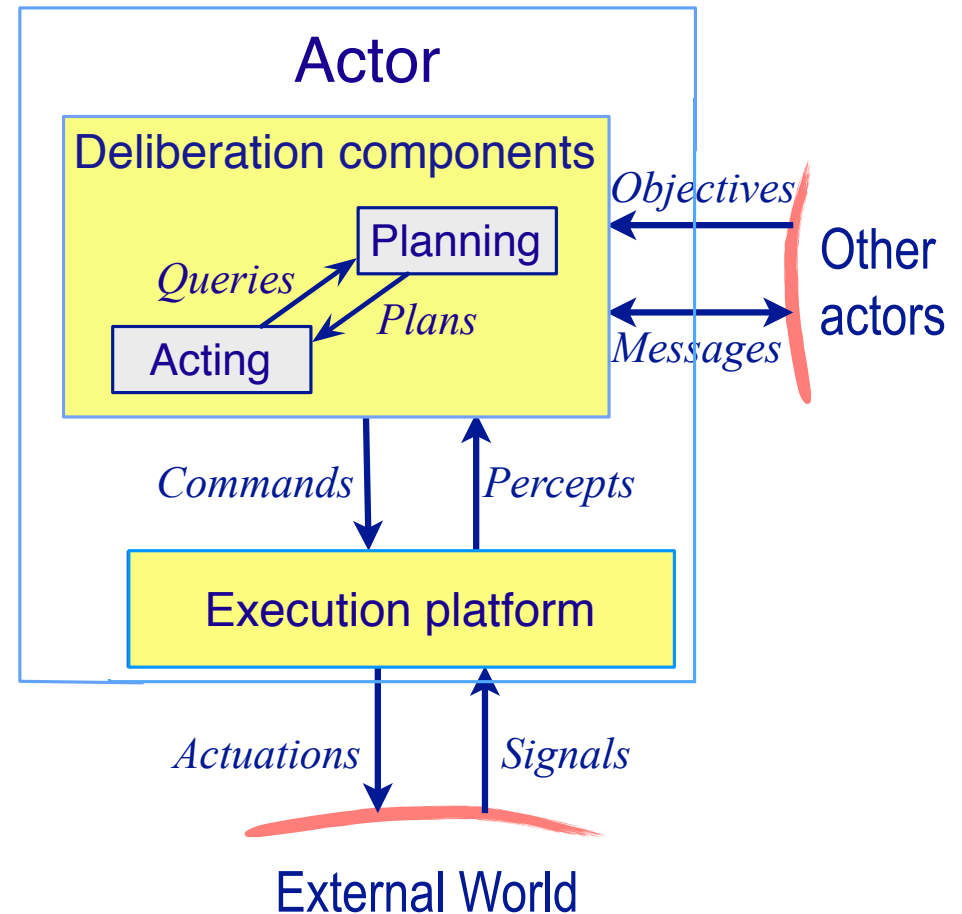


Refinement Acting

- *Task*:
 - activity for the actor to perform
- For each task, one or more *refinement methods*
 - Operational models telling how to perform the task

```
method-name(arg1, ..., argk)  
  task: task-identifier  
  pre: test  
  body: computer program  
        that may include  
        tasks and commands
```

“primitive” functions that the actor can send to its execution platform



Refinement Acting

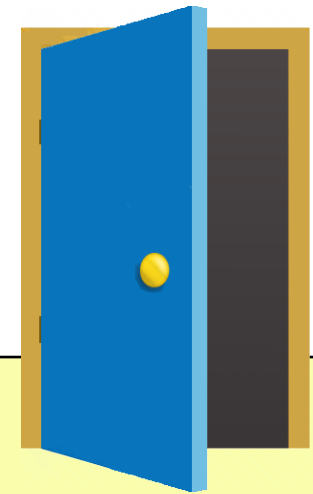
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method-name($arg_1, \dots, arg_k$)
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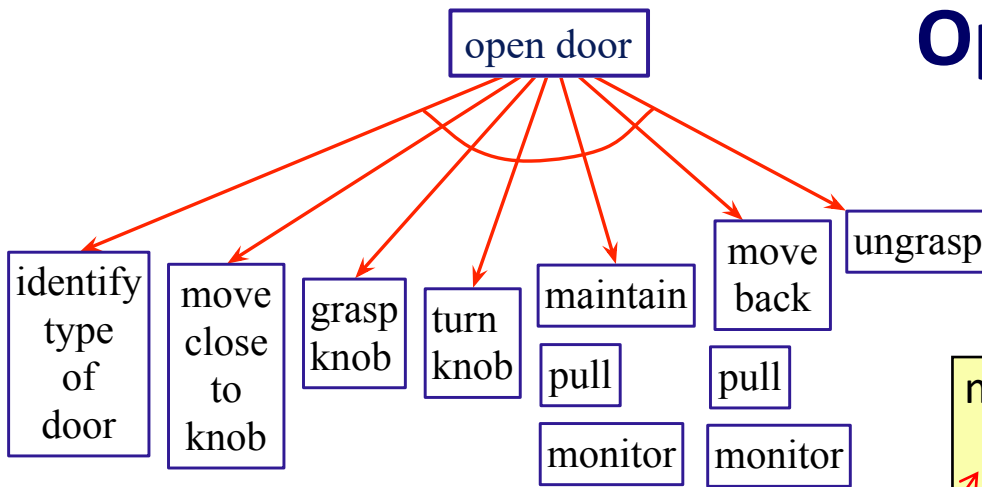
- Differences from HTN methods
 - Actor uses them reactively
 - Body is a computer program that invokes tasks, commands
 - Commands interact with external world
 - Outcomes not known in advance
 - Current state obtained using sensors, represented using state variables

“primitive” functions that the actor can send to its execution platform

Opening a Door



- What kind:
 - Hinged on left, opens toward us, knob



```

m-opendoor( $r, d, l, h$ )
  task: opendoor( $r, d$ )
  pre:  $\text{loc}(r) = l \wedge \text{road}(l, d) \wedge \text{handle}(d, h)$ 
  body:
    while  $\neg \text{reachable}(r, h)$  do
      move-close( $r, h$ )
      monitor-status( $r, d$ )
    if  $\text{door-status}(d) = \text{closed}$  then
      unlatch( $r, d$ )
      throw-wide( $r, d$ )
      end-monitor-status( $r, d$ )
    
```

```

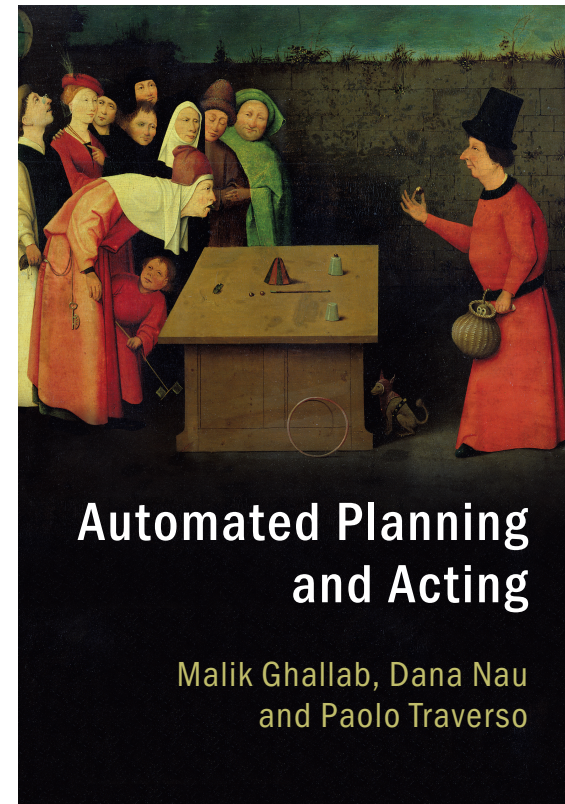
m1-unlatch( $r, d, l, o$ )
  task: unlatch( $r, d$ )
  pre:  $\text{loc}(r, l) \wedge \text{toward-side}(l, d) \wedge \text{side}(d, \text{left}) \wedge \text{type}(d, \text{rotate}) \wedge \text{handle}(d, o)$ 
  body: grasp( $r, o$ )
        turn( $r, o, \text{alpha1}$ )
        pull( $r, \text{val1}$ )
        if  $\text{door-status}(d) = \text{cracked}$  then ungrasp( $r, o$ )
        else fail
    
```

```

m1-throw-wide( $r, d, l, o$ )
  task: throw-wide( $r, d$ )
  pre:  $\text{loc}(r, l) \wedge \text{toward-side}(l, d) \wedge \text{side}(d, \text{left}) \wedge \text{type}(d, \text{rotate}) \wedge \text{handle}(d, o) \wedge \text{door-status}(d) = \text{cracked}$ 
  body: grasp( $r, o$ )
        pull( $r, \text{val1}$ )
        move-by( $r, \text{val2}$ )
    
```

RAE (Reactive Acting Engine)

- Uses refinement methods to accomplish tasks
 - Based on OpenPRS robot control architecture
- I'll give a summary
- For details:
 - Ghallab, Nau, and Traverso, *Automated Planning and Acting*, Cambridge University Press, 2016
 - Final manuscript and lecture slides freely downloadable [here](#)



RAE (Reactive Acting Engine)

Agenda: $\{stack \sigma_1, \dots, stack \sigma_n\}$

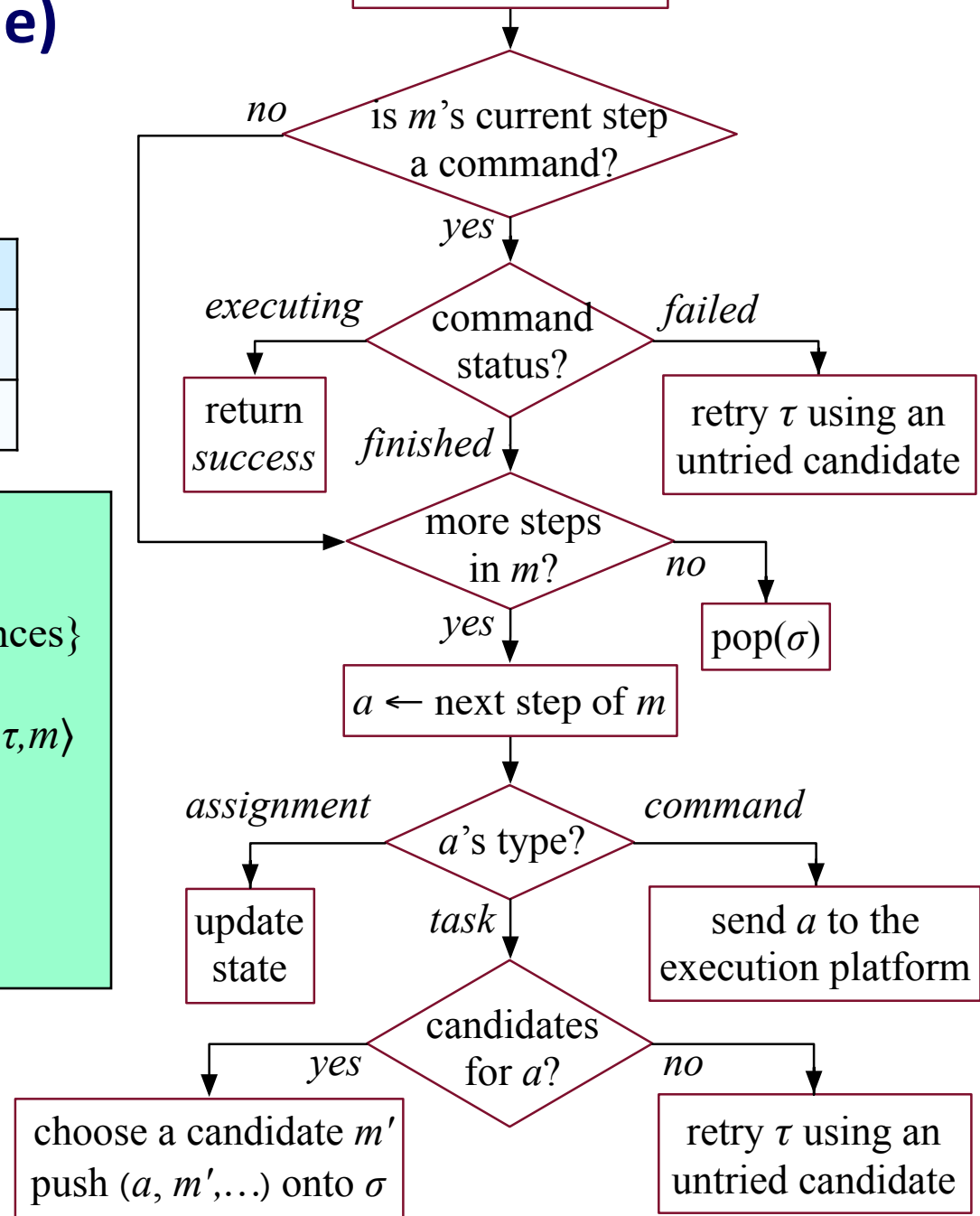
Like program execution stacks

$stack =$	(sub-subtask, method, ...)
	(subtask, method, ...)
	(task, method, ...)

loop:

for every new external task or event τ
Candidates = {applicable method instances}
 choose $m \in \text{Candidates}$
 create refinement stack σ , initially just $\langle \tau, m \rangle$
 add σ to *Agenda*
 for each stack σ in *Agenda*
 Progress(σ)
 if σ is finished, remove it from *Agenda*

Progress(σ): $(\tau, m, \dots) \leftarrow \text{top}(\sigma)$



RAE (Reactive Acting Engine)

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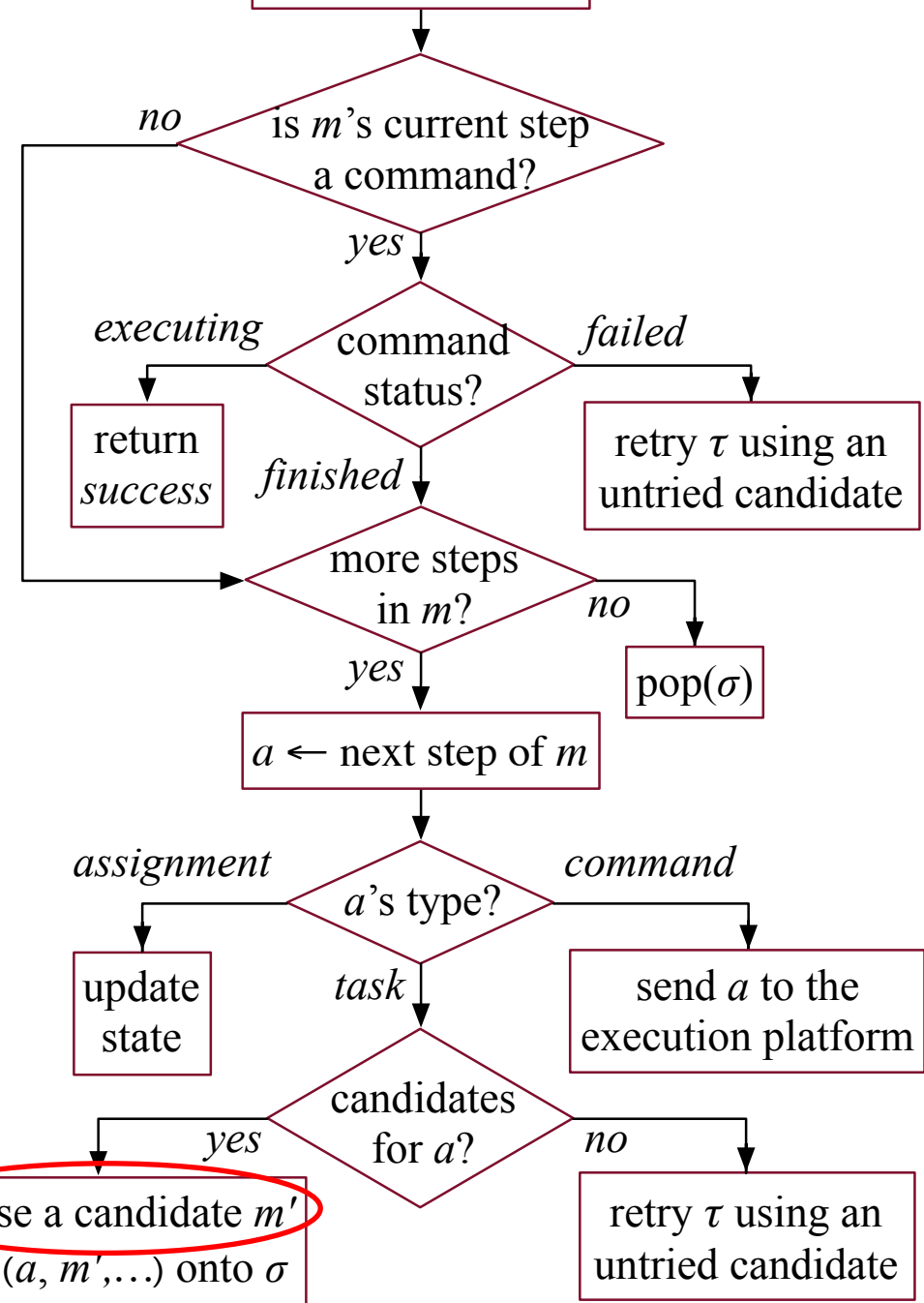
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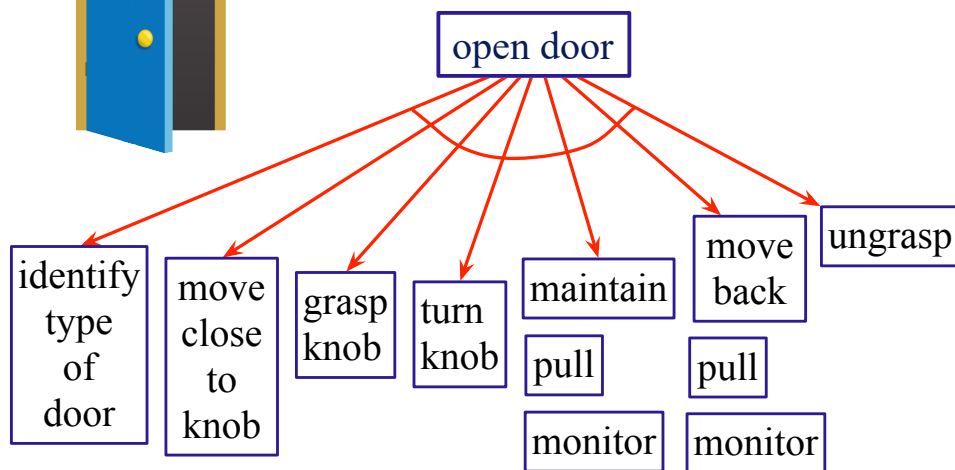
if σ is finished, remove it from *Agenda*

- Get advice from a planner

Progress(σ): $(\tau, m, \dots) \leftarrow \text{top}(\sigma)$



How to Do the Planning?

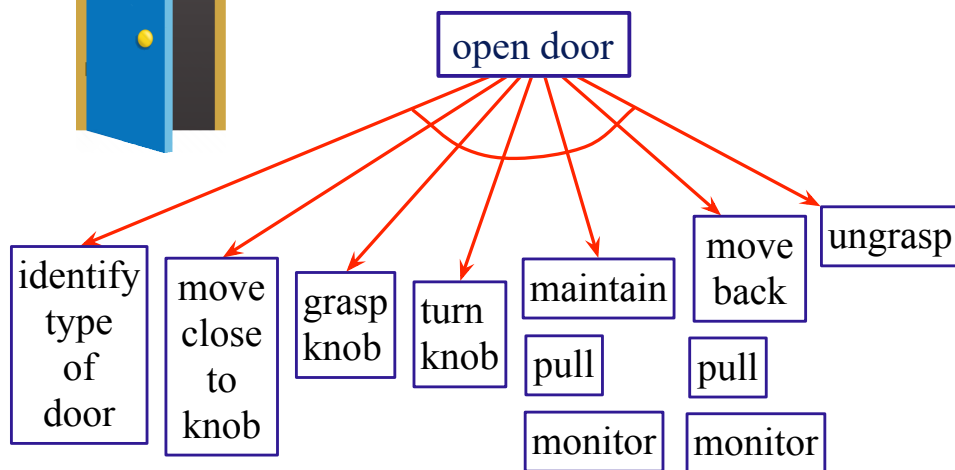


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    if door-status(d) = closed then
      unlatch(r,d)
      throw-wide(r,d)
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```

- In the book: SeRPE planner
 - Extends the SHOP algorithm to reason about refinement methods
 - Executes code in the method's body, but
 - Descriptive models of commands
 - Classical actions, abstract state
 - To backtrack from a method *m*:
 - Revert to state when *m* was chosen

How to Do the Planning?



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- In the book: SeRPE planner
 - Extends the SHOP algorithm to reason about refinement methods
 - Executes code in the method's body, but
 - Descriptive models of commands
 - Classical actions, abstract state
 - To backtrack from a method *m*:
 - Revert to state when *m* was chosen
- Classical actions don't represent
 - Nondeterministic outcomes, partial observability, exogenous events, durations, predicted future events, overlapping actions and events, ...
 - Sometimes OK, but often not

Acting and Planning

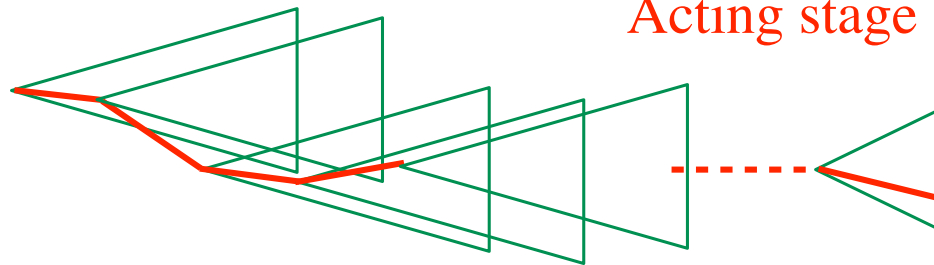
Acting

- *Performing* tasks and actions
- Use *operational models* that tell *how*
 - Dynamic, unpredictable environment
 - Adapt to context, react to events

Planning

- *Prediction + search*
- Search over predicted states, possible organizations of tasks and actions
- Use *descriptive models* to predict *what*

Consistency?



Acting and Planning

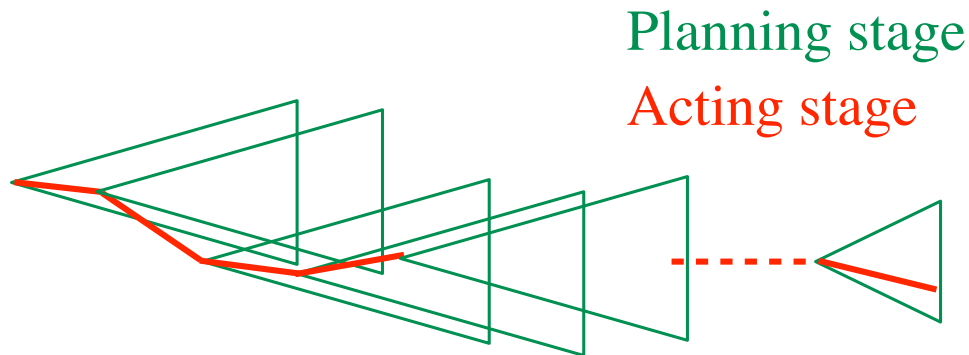
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Planning

- *Prediction + search*
- Search over predicted states, possible organizations of tasks and actions
- ~~Use *descriptive models* to predict *what*~~

Simulated execution of
actor's operational models



Why should we think this will work?

- Why does AI planning use descriptive models?
 - (1) AI planners search a huge search space, need fast predictions
 - (2) Effort required to create detailed operational models
 - Especially if you aren't a domain expert
-
- Problems aren't as bad as they used to be
 - (1) Like HTN methods, the operational models focus the search
 - Computers have gotten more powerful
 - Compute detailed simulations more quickly
 - e.g., fast physics-based simulations
 - (2) Real-world actors will already include control software
 - May be able to use it as refinement methods

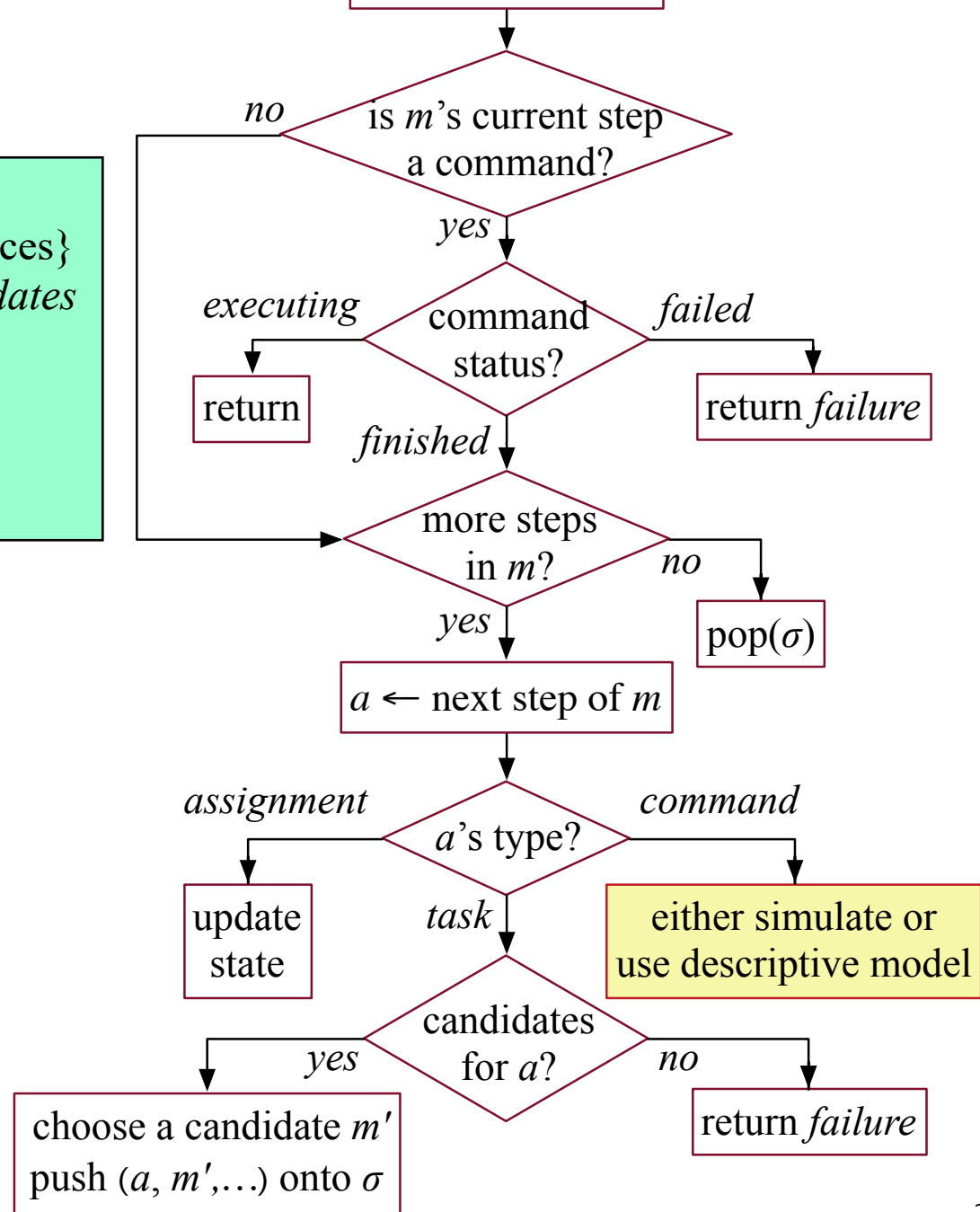
RAEplan

- Simulate RAE on a single task

RAEplan(task τ):

$Candidates = \{\text{applicable method instances}\}$
 nondeterministically choose $m \in Candidates$
 create refinement stack σ for τ and m
 loop while $Progress(\sigma) \neq failure$
 if σ is completed then return m
 return *failure*

Progress(σ): $(\tau, m, \dots) \leftarrow \text{top}(\sigma)$



RAEplan

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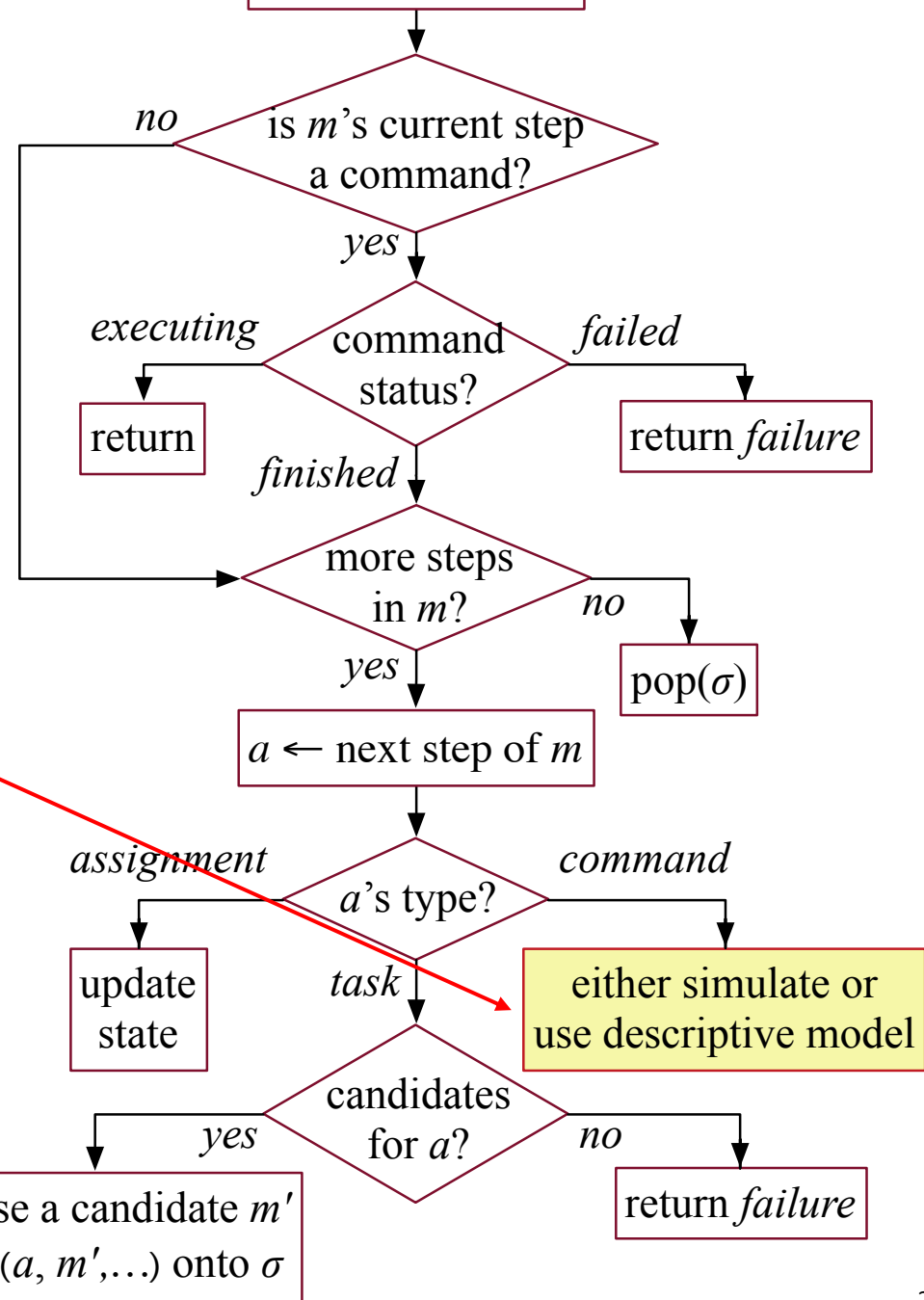
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What control strategy?

How to handle nondeterministic outcomes?

choose a candidate m'
 push $(a, m', \dots)$ onto σ

Progress(σ): $(\tau, m, \dots) \leftarrow \text{top}(\sigma)$



RAEplan

- Simulate RAE on a single task

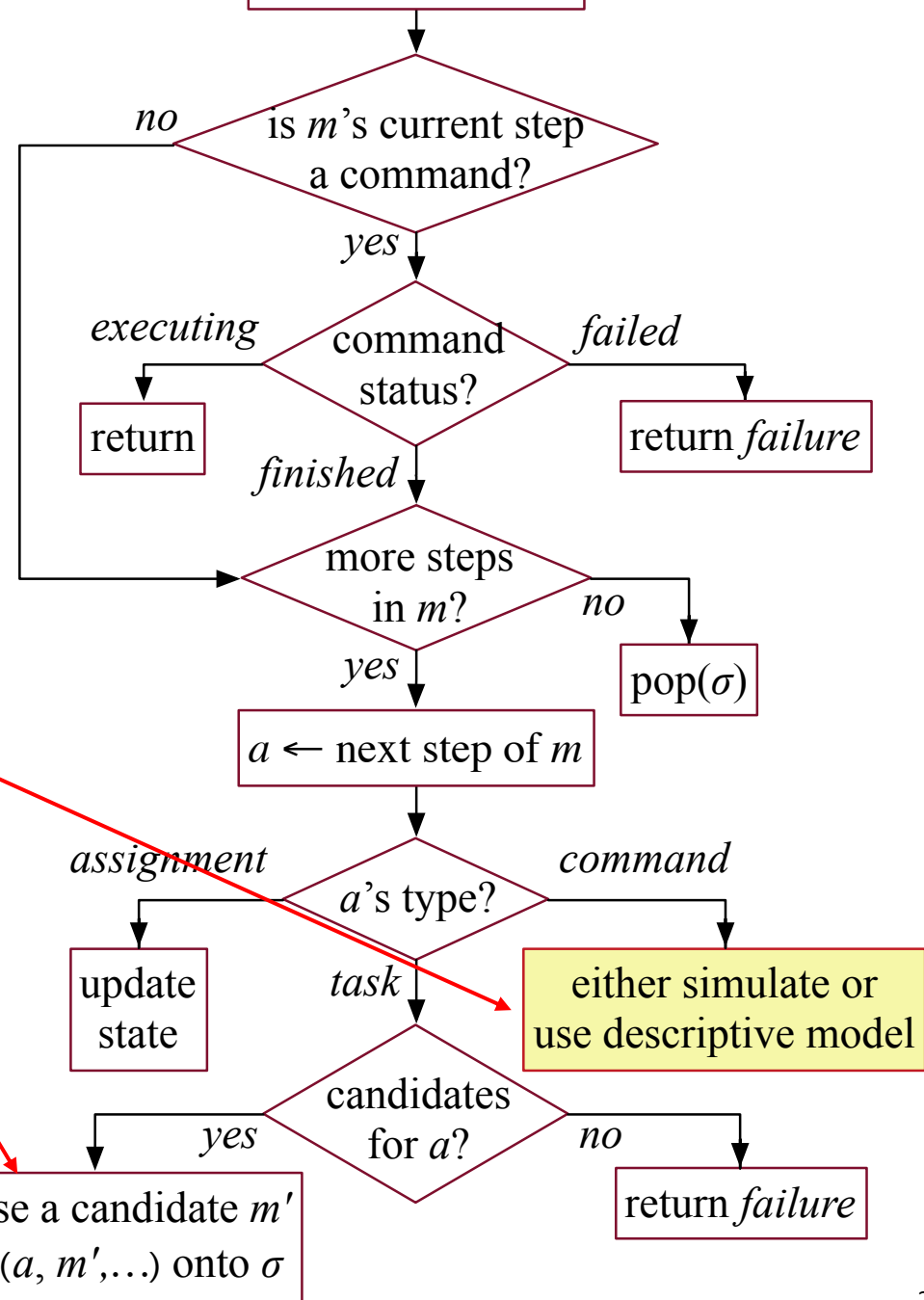
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Idea 1:
backtracking

- Backtrack over method's body
- Was easy in SHOP
 - backtrack over the task list
- In RAEplan, need to backtrack over code
- A group of students worked on this for several months, didn't get it to work

Progress(σ): $(\tau, m, \dots) \leftarrow \text{top}(\sigma)$



RAEplan

- Simulate RAE on a single task

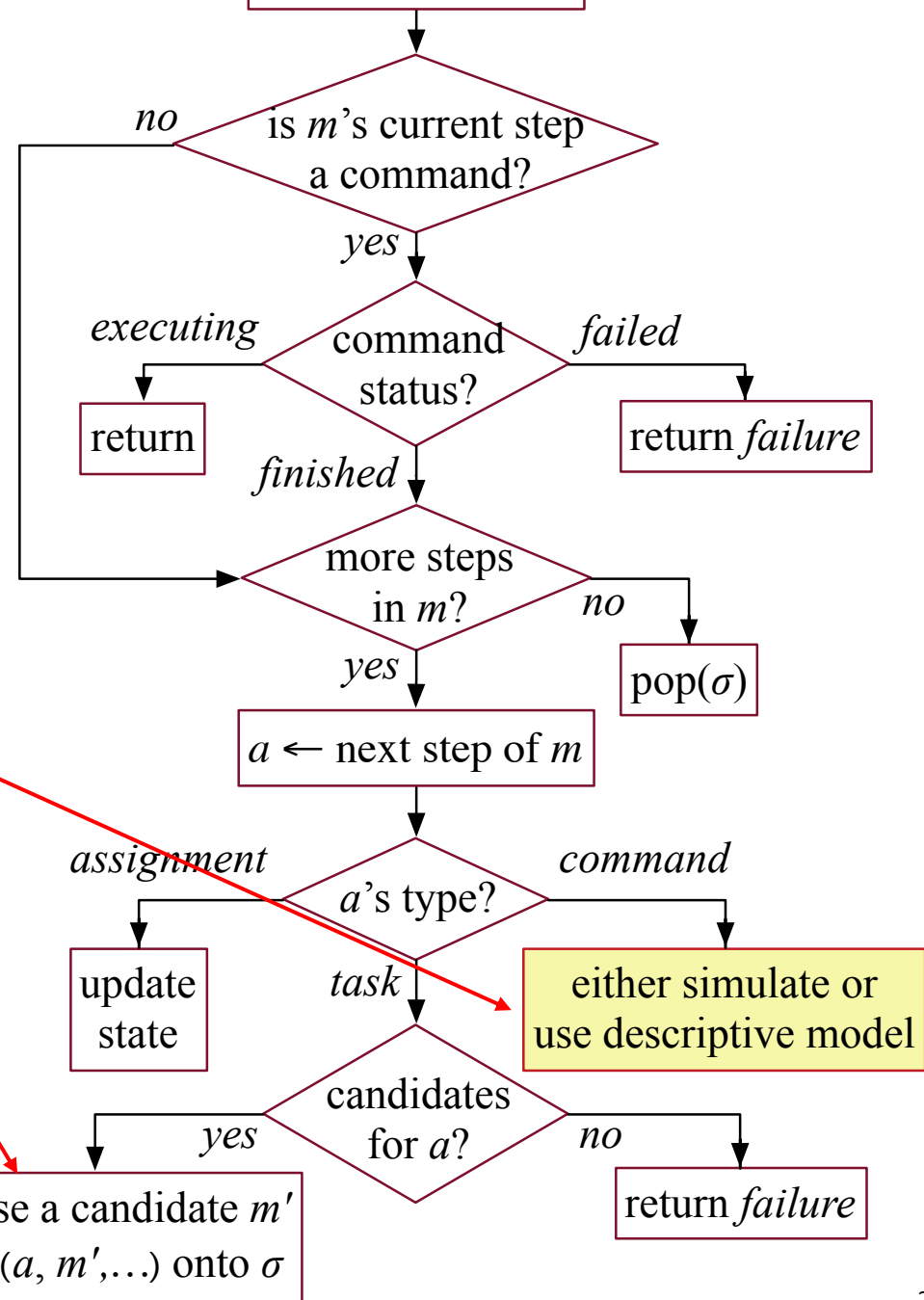
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Idea 2:
multithreading

- Too many parallel processes

Progress(σ): $(\tau, m, \dots) \leftarrow \text{top}(\sigma)$



choose a candidate m'
 push $(a, m', \dots)$ onto σ

either simulate or
 use descriptive model

RAEplan

- Simulate RAE on a single task

RAEplan(task τ):

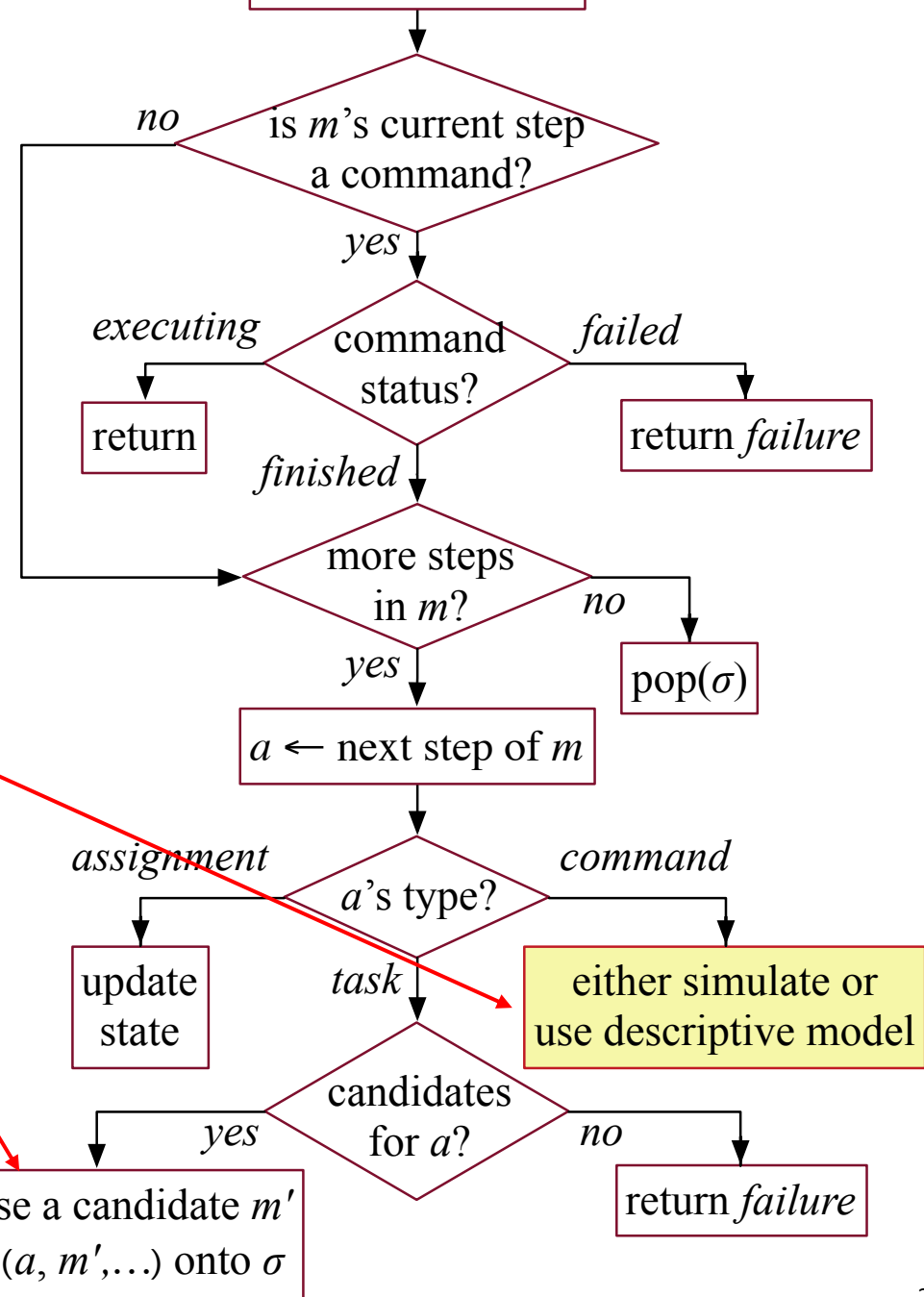
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 create refinement stack σ for τ and m
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 return *failure*

Idea 3:
Monte Carlo rollouts

- Multiple runs
 - Random outcomes in each run
- Return the method m that gives the highest expected utility

Patra, Traverso, Ghallab, and Nau. [Acting and planning using operational models](#). *AAAI*, 2019

Progress(σ): $(\tau, m, \dots) \leftarrow \text{top}(\sigma)$



Summary of Experimental Results

Domain	Dynamic events	Dead ends	Sensing	Robot collaboration	Concurrent tasks
CR	✓	✓	✓	—	✓
EE	✓	✓	—	✓	✓
SD	✓	—	—	✓	✓
IP	✓	—	—	✓	✓

- Four different domains, different combinations of characteristics
- Evaluation criteria:
 - Efficiency, successes vs failures, how many retries
- Result: planning helps
 - RAE operated better with RAEplan than without
 - RAE operated better with more planning than with less planning

Patra, Traverso, Ghallab, and Nau. Acting and planning using operational models. *AAAI*, 2019

Summary

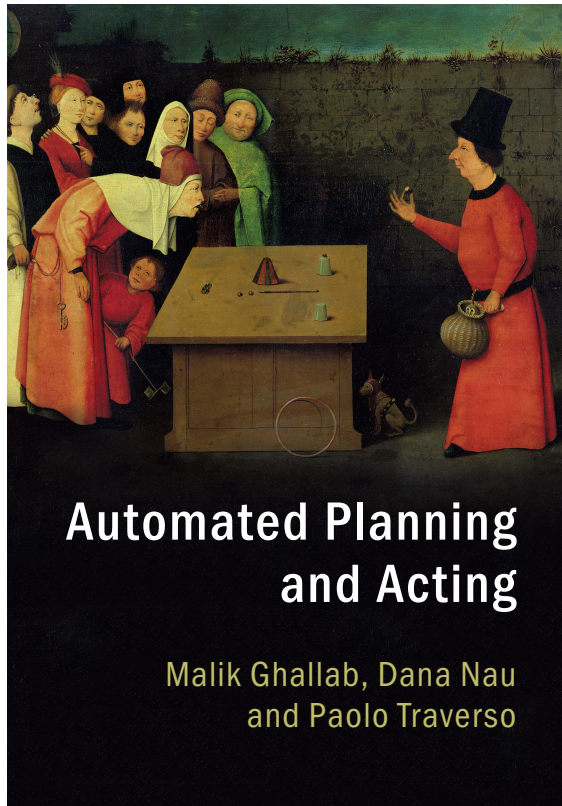
- Continual online planning, in service of acting
- Descriptive vs. operational models
- Refinement methods
 - Generalization of HTN methods
 - State variables
 - Body is a computer program that includes tasks, commands
 - Commands interact with environment
 - Outcomes not known in advance
 - Used in two ways
 - Reactively in RAE
 - Predictively in RAEplan
- Experimental results with RAE, RAEplan
 - More planning → better acting

Limitations and Future Work

- How to get the operational models?
 - Earlier, I said, “Real-world actors may already include operational models”
 - OK if the actor is RAE, OpenPRS, ...
 - Otherwise, might not be in a form we can use
 - Currently, only alternative is to write them ourselves
 - Develop learning algorithms to do this?
- Experiments were done in “toy domains”
 - Want to test the approach in real planning problems
- Ongoing project with US Naval Research Laboratory
 - Use RAE, RAEplan for recovery from attacks on software-defined networks
 - They’re writing the refinement methods
 - We plan to modify RAE, RAEplan to meet their needs

Links

- Ghallab, Nau, and Traverso, *Automated Planning and Acting*, Cambridge University Press, 2016
 - [Final manuscript, lecture slides](#)



- Patra, Traverso, Ghallab, and Nau. [Acting and planning using operational models](#). *AAAI*, 2019
- [RAE and RAEplan source code](#)
 - 3-clause BSD license
 - Caveat: software still under development