



COL864: Special Topics in AI

Semester I, 2022-23

Task Planning

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Outline

- Last Class
 - State Estimation
- This Class
 - Symbolic Representations for Task Planning
 - How can we represent such problems?
 - How can we (efficiently) search for a plan?
- Reference Material
 - Primary reference are the lecture notes. For basic background refer to AIMA Classical Planning Ch. 10 (Sec 10.1 - 10.3)

Acknowledgements

These slides are intended for teaching purposes only. Some material has been used/adapted from web sources and from slides by Nicholas Roy, Wolfram Burgard, Dieter Fox, Sebastian Thrun, Siddharth Srinivasa, Dan Klein, Pieter Abbeel, Max Likhachev and others.

Task Planning

- Motion planning
 - Generating collision free trajectories.
- Task Planning
 - Presence of Semantic constraints
 - Till now, generating collision free trajectories.
 - Now, consider when an action a_i must be performed before action a_j (opening a box before placing an object inside it)
 - Need to scale decision making
 - Consider an assembly task: packing objects in a container and transporting it.
 - Intuitively, we solve such problems by thinking about abstract actions “picking an object and placing in the box” assuming that precise motions can be determined later.
 - Characteristic of long-horizon tasks.
- Planning vs. Scheduling
 - Scheduling
 - Tasks are fixed (scheduling classes in a week). There may be constraints on the tasks. Don’t need to determine “which” tasks are to be done.
 - Planning
 - We need to decide “which” set of tasks or steps we need to them as well as to schedule them.



Other examples:

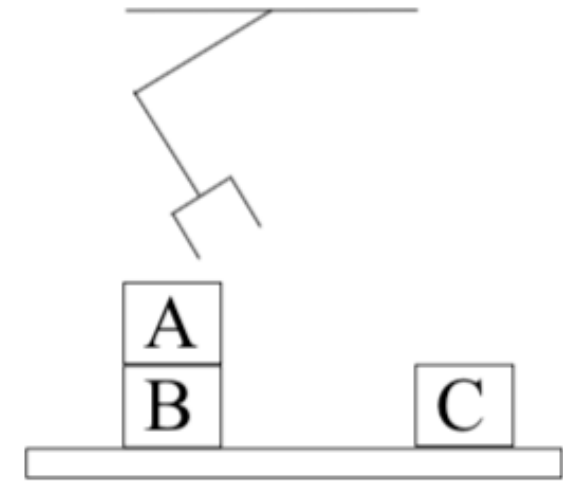
<https://www.youtube.com/watch?v=IY4PKBqp9ZM&t=179s>

Task Planning: In Essence

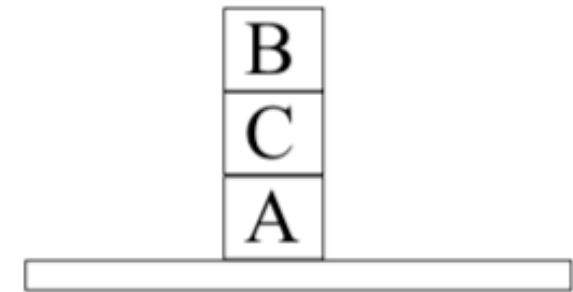
- High-level objective is to be attained by performing a sequence of actions.
- Problem is to determine if an action sequence even exists.
- If it exists then we want optimality
 - Minimizing the total number of actions.
 - Minimizing total time.
- Task Planning
 - Requires a model of the world and how an autonomous agent can interact with the world.
 - Given a particular world state, the robot can take some action to transition to another state.
 - Process of finding a task plan –
 - Autonomously reasoning about the state of the world using an internal model and coming up with a sequence of actions (or a plan) to achieve a goal.
 - Certain syntax (languages) are used to represent task planning problems.

Defining a Planning Domain

- Example: Block worlds
 - Re-order the blocks from the start state to the goal state.
 - Assume that the arm can reach/move all the top blocks.
 - Planning task: determining the order of actions.
- Abstraction
 - The precise poses of B and C are less relevant, what matters is whether B is on C or not.
 - The precise motion of the gripper is less relevant. Its symbolic effect matters, i.e., the block went on top of another.
- Symbolic Representation
 - States: “On(X, Y)” that aggregate low level positions that represent this relationship.
 - Actions: “Move(X, Y)” to denote all ways in which the robot can move X on Y.



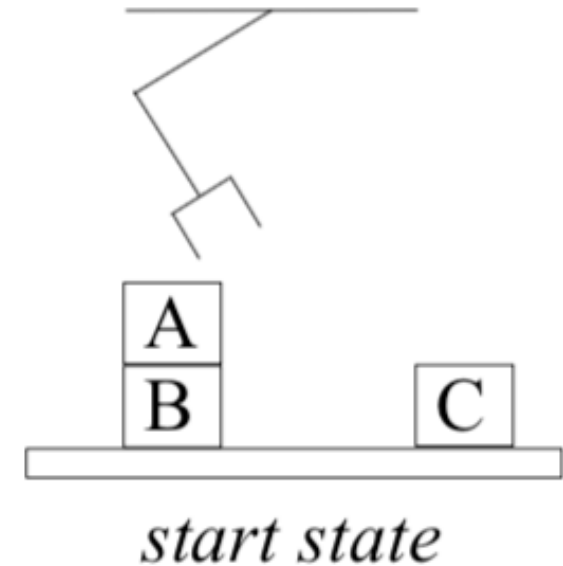
start state



goal state

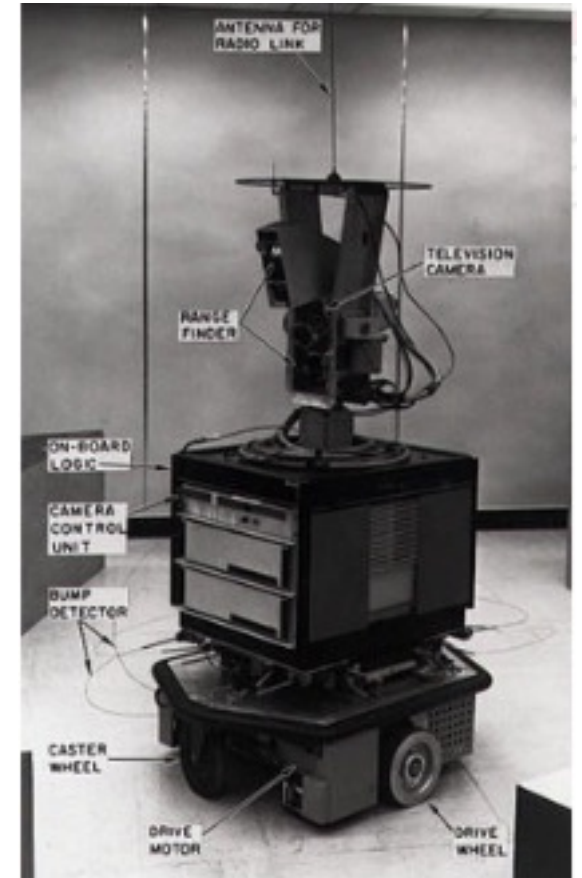
Planning Domains

- World or Domain
 - Describe the world (domain) using logic.
- Actions
 - Describe the actions available to the agent as
 - When they can be executed.
 - What happens if they are executed.
- Initial and Goal states
- Task
 - Find a plan that moves the agent from start state to goal



History: STRIPS Planning

- STRIPS: Stanford Research Institute Problem Solver
 - Represent the world using a knowledge-base of first-order logic.
 - Actions change what is currently true.
 - Describe the actions available, defined by preconditions and effects
- Planning Domain Description Language
 - Standard language for planning domains
 - International programming competitions
- Separate definitions of:
 - A domain, which describes a class of tasks.
 - Predicates and operators.
- A task, which is an instance of domain.
 - Objects. Start and goal states.
- A predicate is a first-order logic function returning True or False, given a set of objects.



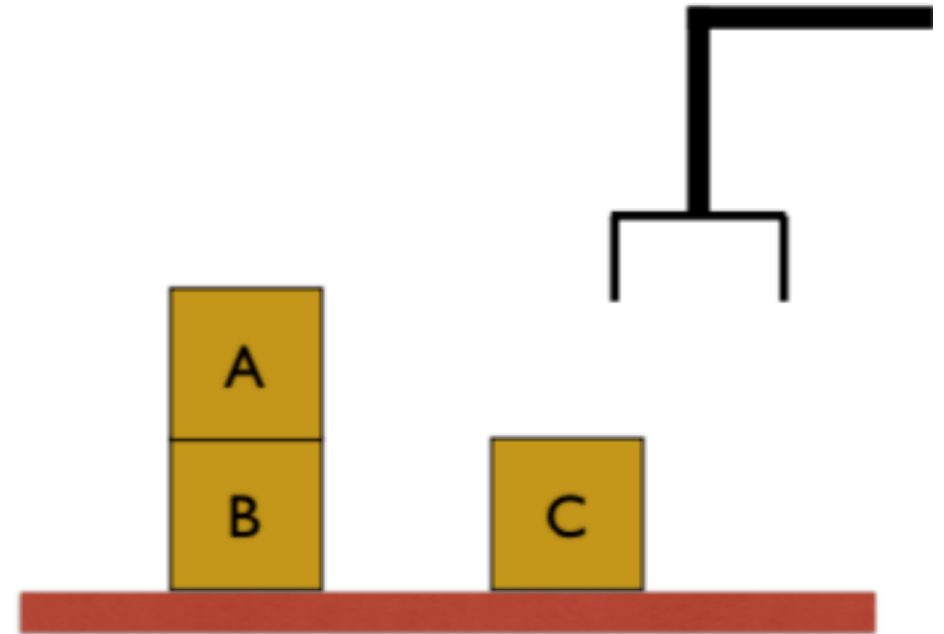
Core idea: A “task-agnostic” domain description and a “task-specific” problem

PDDL: Predicates

- A predicate returns True or False given a set of objects.

```
(define (domain blocksworld)
```

```
  (:predicates (clear ?x)  
               (on-table ?x)  
               (arm-empty)  
               (holding ?x)  
               (on ?x ?y))
```



PDDL: Operators

Operators:

- Name
- Parameters
- Preconditions
- Effects

The diagram illustrates the mapping of PDDL operator components to the `(:action pickup` definition. Colored arrows and circles are used for this purpose:

- A green arrow points from the `Name` bullet point to the `pickup` action name, which is circled in green.
- A blue arrow points from the `Parameters` bullet point to the `(?ob)` parameter, which is circled in blue.
- A red arrow points from the `Preconditions` bullet point to the `:precondition` keyword, which is circled in red.
- A purple arrow points from the `Effects` bullet point to the `:effect` keyword, which is circled in purple.

The full PDDL definition for the `pickup` action is shown below:

```
(:action pickup  
  :parameters (?ob)  
  :precondition (and (clear ?ob) (on-table ?ob) (arm-empty))  
  :effect (and (holding ?ob) (not (clear ?ob)) (not (on-table ?ob))  
               (not (arm-empty))))
```

PDDL: Problem Instance



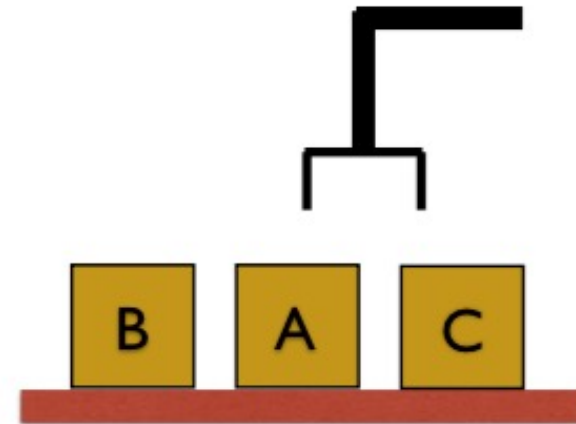
```
(define (problem pb3)
  (:domain blocksworld)
  (:objects a b c)
  (:init (on-table a) (on-table b) (on-table c)
          (clear a) (clear b) (clear c) (arm-empty))
  (:goal (and (on a b) (on b c))))
```

Start state

Goal state

PDDL: States

- A state describes the configuration of the world at a moment of time.
- A conjunction of positive literal predicates.
 - A literal is a “ground” predicate where the variables are bound to object instances.
- Closed world assumption
 - The state contains a list of literals (ground predicates) that are true.
 - The other literals not listed are assumed to be False or not true in the world.
 - This is also known as knowledge base semantics.
 - Implications
 - Avoiding the need for inference i.e., determine the state of other literals when some literals are known to be true or false.
 - No uncertainty about which actions can be executed.
 - No uncertainty about the goal.



(on-table a)

(on-table b)

(on-table c)

(clear a)

(clear b)

(clear c)

(arm-empty)

PDDL: Operators

- Implicit Markov assumption.

```
(:action putdown  
  :parameters (?ob)  
  :precondition (and (holding ?ob))  
  :effect (and (clear ?ob) (arm-empty) (on-table ?ob)  
              (not (holding ?ob))))
```

PDDL: Goals

- A conjunction of literal predicates.
 - (and (on a b) (on b c))
- Predicates not listed are don't cares.
- Each goal is thus a *partial* state expression.
 - Implies a set of goal states.

Formal Specification

- Predicates P
 - A set of predicates P , each with p_n parameters.
- Objects O
- Literal predicates L
 - A set of predicates from P with bound parameters from O .
- States
 - A list of positive ground literals, $s \subseteq L$
 - Goal test : a list of positive ground literals, $g \subseteq L$
- Operator List:
 - Name
 - Parameters
 - Preconditions
 - Effects

PDDL: Action Execution

Start state:

(on-table a) (on-table b) (on-table c)
(clear a) (clear b) (clear c) (arm-empty)

Action: pickup(a)

- Check preconditions
- Decide to execute.
- Delete negative effects.
- Add positive effects.

```
(:action pickup
:parameters (?ob)
:precondition (and (clear ?ob) (on-table ?ob) (arm-empty))
:effect (and (holding ?ob) (not (clear ?ob)) (not (on-table ?ob))
(not (arm-empty))))
```

Next state:

~~(on-table a)~~ (on-table b) (on-table c)
~~(clear a)~~ (clear b) (clear c) ~~(arm-empty)~~
(holding a)

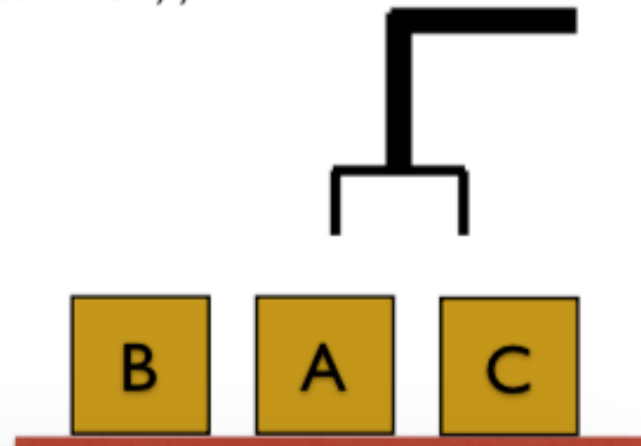
PDDL: Example

State: (on-table a) (on-table b) (on-table c)
(clear a) (clear b) (clear c) (arm-empty))

Goal: (and (on a b) (on b c))

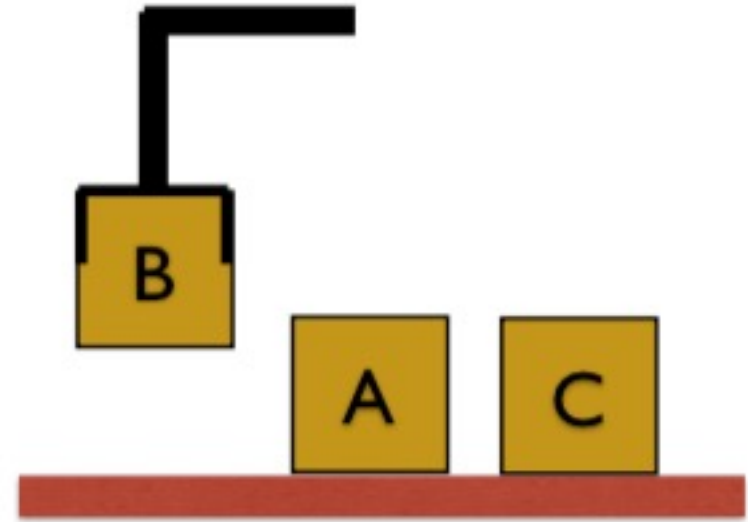
```
(:action pickup
  :parameters (?ob)
  :precondition (and (clear ?ob) (on-table ?ob) (arm-empty))
  :effect (and (holding ?ob) (not (clear ?ob))
               (not (on-table ?ob))
               (not (arm-empty))))
```

pickup(b)



PDDL: Example

after pickup(b) ...



State: (on-table a) ~~(on-table b)~~ (on-table c)
(clear a) ~~(clear b)~~ (clear c) ~~(arm-empty)~~ (holding b))
Goal: (and (on a b) (on b c))

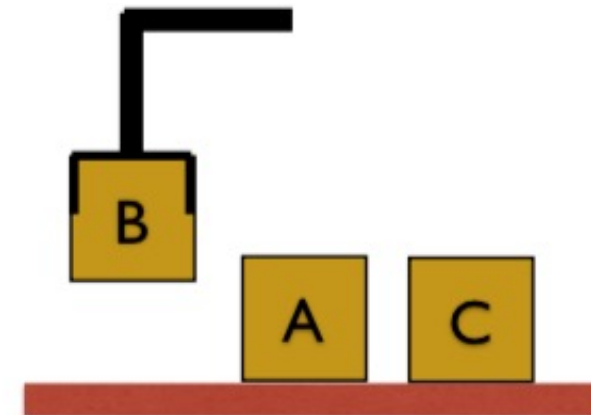
PDDL: Example

State: (on-table a) (on-table c)
(clear a) (clear c) (holding b))

Goal: (and (on a b) (on b c))

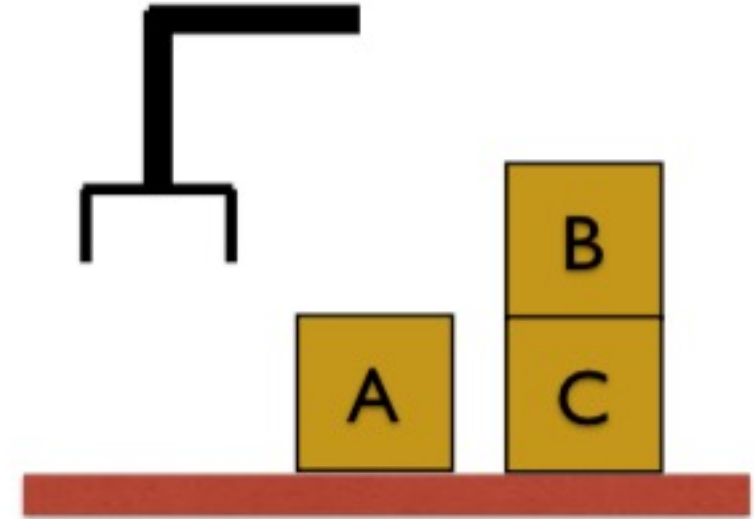
```
(:action stack
  :parameters (?ob ?underob)
  :precondition (and (clear ?underob) (holding ?ob))
  :effect (and (arm-empty) (clear ?ob) (on ?ob ?underob)
    (not (clear ?underob)) (not (holding ?ob))))
```

stack(b, c)



PDDL: Example

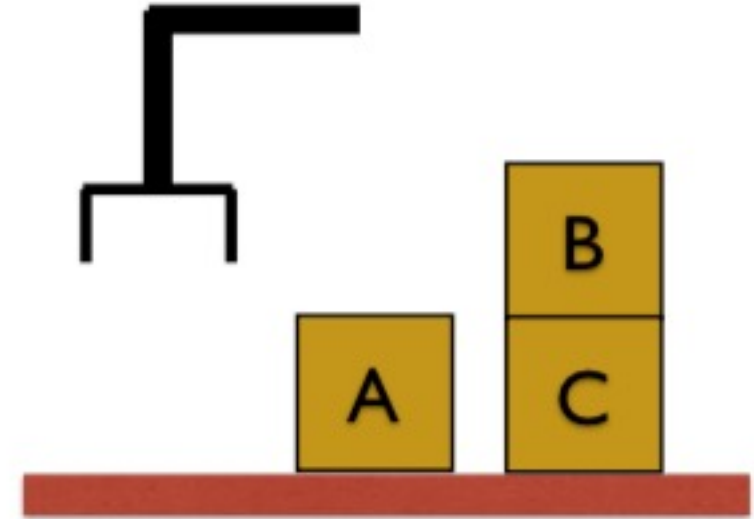
after stack(b, c) ...



State: (on-table a) (on-table c)
(clear a) ~~(clear c)~~ ~~(holding b)~~
(arm-empty) (clear b) (on b, c))
Goal: (and (on a b) (on b c))

PDDL: Example

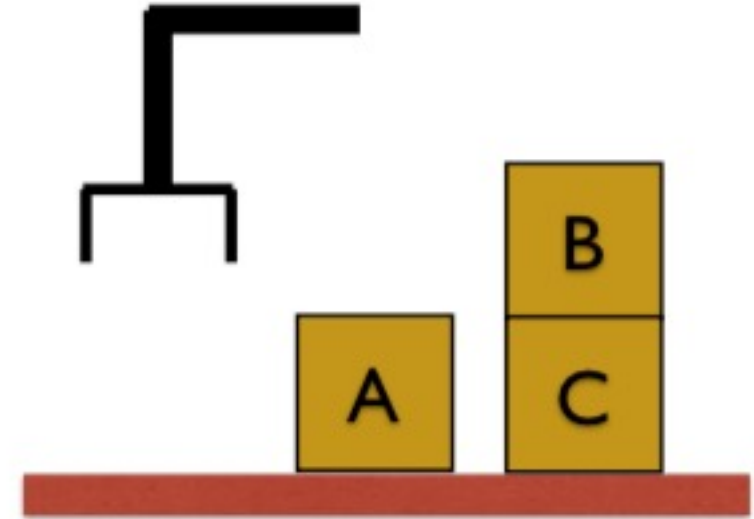
after stack(b, c) ...



State: (on-table a) (on-table c)
(clear a) ~~(clear c)~~ ~~(holding b)~~
(arm-empty) (clear b) (on b, c))
Goal: (and (on a b) (on b c))

PDDL: Example

after stack(b, c) ...



State: (on-table a) (on-table c)
(clear a) ~~(clear c)~~ ~~(holding b)~~
(arm-empty) (clear b) (on b, c))
Goal: (and (on a b) (on b c))

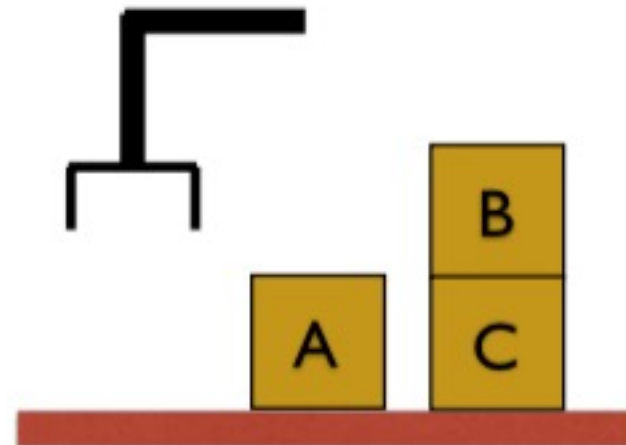
PDDL: Example

State: (on-table a) (on-table c)
(clear a) (arm-empty) (clear b) (on b, c)

Goal: (and (on a b) (on b c))

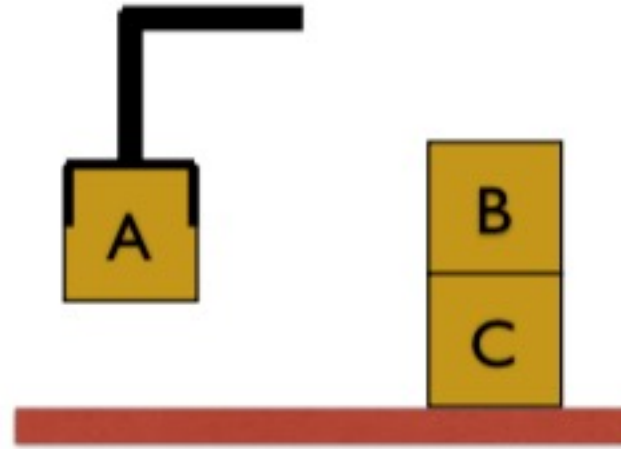
```
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  :parameters (?ob)
  :precondition (and (clear ?ob) (on-table ?ob) (arm-empty))
  :effect (and (holding ?ob) (not (clear ?ob)) (not (on-table ?ob))
              (not (arm-empty))))
```

pickup(a)



PDDL: Example

after pickup(a)



State: ~~(on-table a)~~ (on-table c)
~~(clear a)~~ ~~(arm-empty)~~ (clear b) (on b, c) (holding a)
Goal: (and (on a b) (on b c))

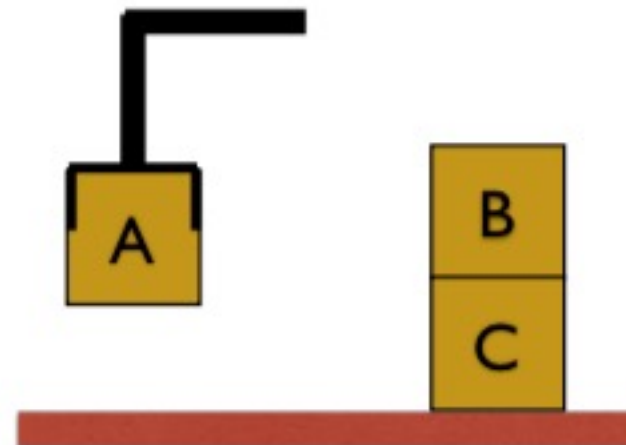
PDDL: Example

State: (on-table c)
(on b, c) (clear b) (holding a))

Goal: (and (on a b) (on b c))

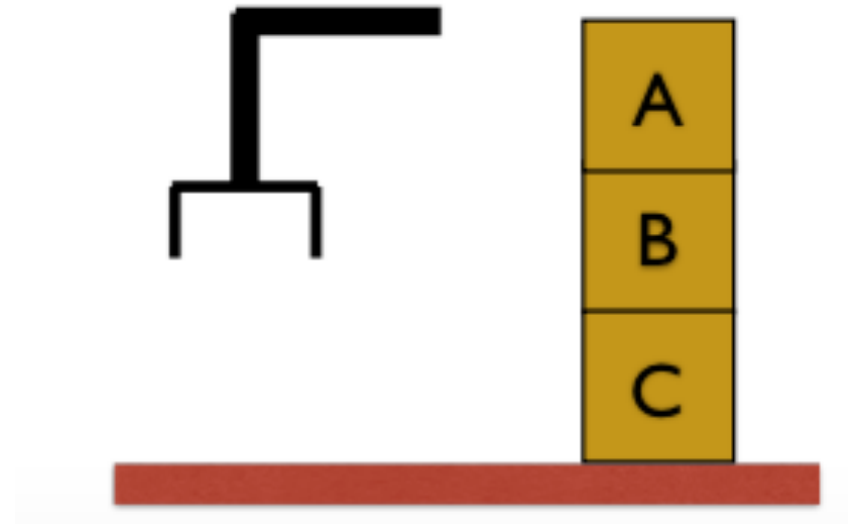
```
(:action stack
:parameters (?ob ?underob)
:precondition (and (clear ?underob) (holding ?ob))
:effect (and (arm-empty) (clear ?ob) (on ?ob ?underob)
(not (clear ?underob)) (not (holding ?ob))))
```

stack(a, b)



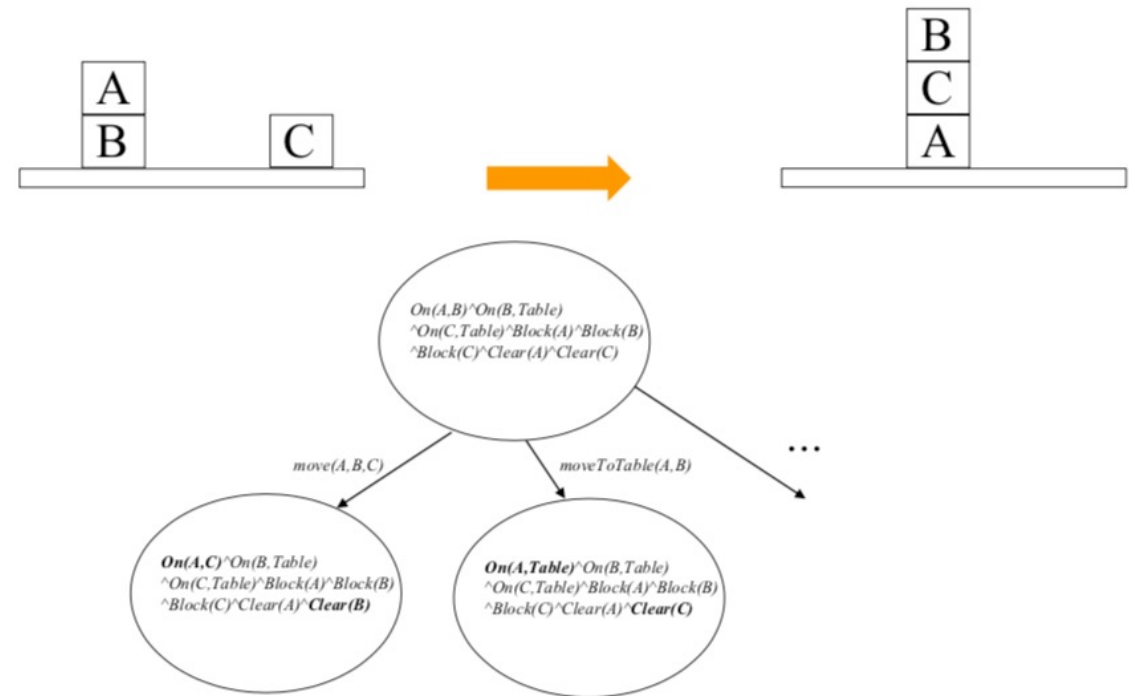
PDDL: Example

State: (on-table c)
(on a b) (clear b) (on b, c) (holding a))
Goal: (and (on a b) (on b c))



Planning: As a Graph Search

- Search Problem
 - Nodes are states
 - Actions are applicable operators
 - Goal expression as a goal test
- How to search the graph for a plan?
 - Direct search
 - Informed search
 - Domain independent heuristics.



Another Example: Object Fetching

The agent is in an indoor area. There are rooms and hallways. There are objects in the environment.

Problem: “take an apple from the shelf and put it on the table”

Example plan:

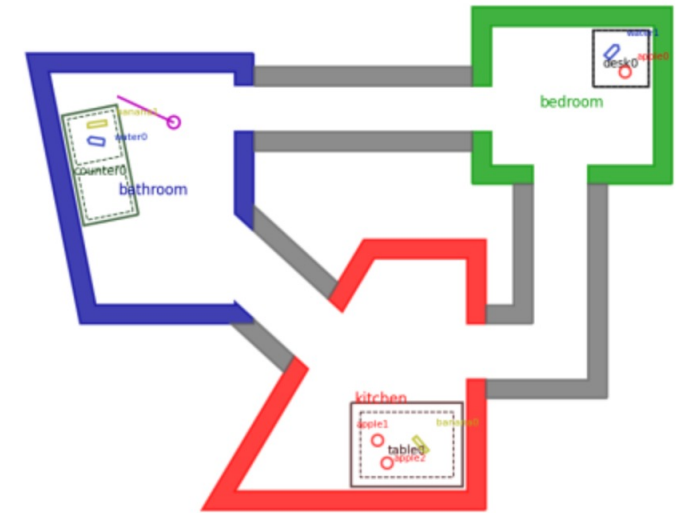
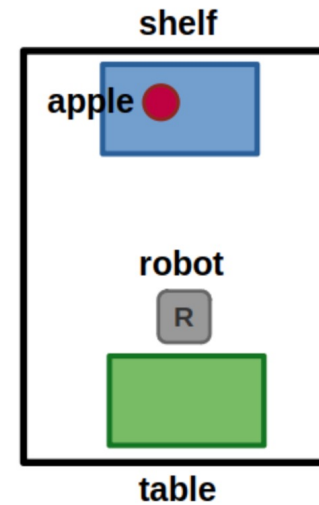
Move to the shelf

Pick up the apple

Move back to the table

Place the apple

Example courtesy Sebastian Castro



Simple task planning example world: A robot can move between a finite set of locations, and can pick and place objects at those locations.

Example: Object Fetching

- **Domain: The task-agnostic part**

- **Predicates:** (Robot ?r), (Object ?o), (Location ?loc), (At ?r ?loc), (Holding ?r ?o), etc.
- **Actions:** move(?r ?loc1 ?loc2), pick(?r ?o ?loc), place(?r ?o ?loc)

- **Problem: The task-specific part**

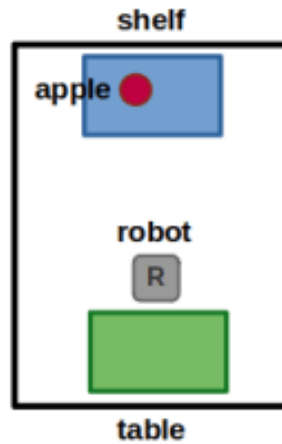
- **Objects:** (Robot robot), (Location shelf), (Location table), (Object apple)
- **Initial state:** (HandEmpty robot), (At robot table), (At apple shelf)
- **Goal specification:** (At apple table)

```
(:action move
  :parameters (?r ?loc1 ?loc2)
  :precondition (and (Robot ?r)
                    (Location ?loc1)
                    (Location ?loc2)
                    (At ?r ?loc1))
  :effect (and (At ?r ?loc2)
              (not (At ?r ?loc1)))
)
```

```
(:action pick
  :parameters (?r ?o ?loc)
  :precondition (and (Robot ?r)
                    (Obj ?o)
                    (Location ?loc)
                    (HandEmpty ?r)
                    (At ?r ?loc)
                    (At ?o ?loc))
  :effect (and (Holding ?r ?o)
              (not (HandEmpty ?r))
              (not (At ?o ?loc)))
)

(:action place
  :parameters (?r ?o ?loc)
  :precondition (and (Robot ?r)
                    (Obj ?o)
                    (Location ?loc)
                    (At ?r ?loc)
                    (not (HandEmpty ?r))
                    (Holding ?r ?o))
  :effect (and (HandEmpty ?r)
              (At ?o ?loc)
              (not (Holding ?r ?o)))
)
```

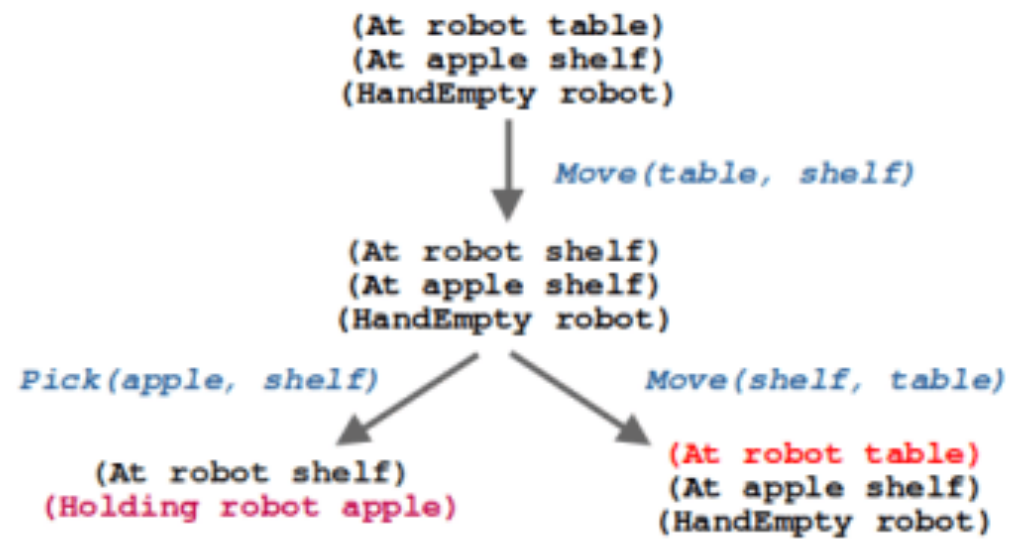
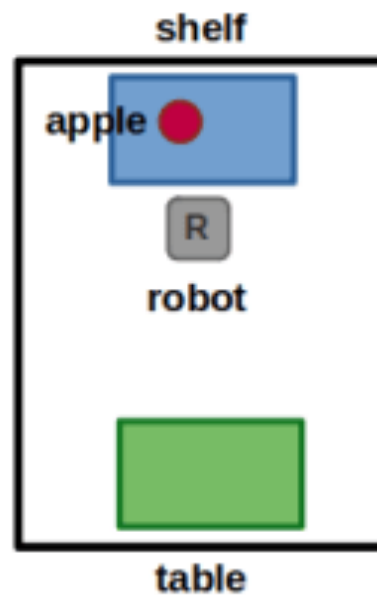
Example: Object Fetching

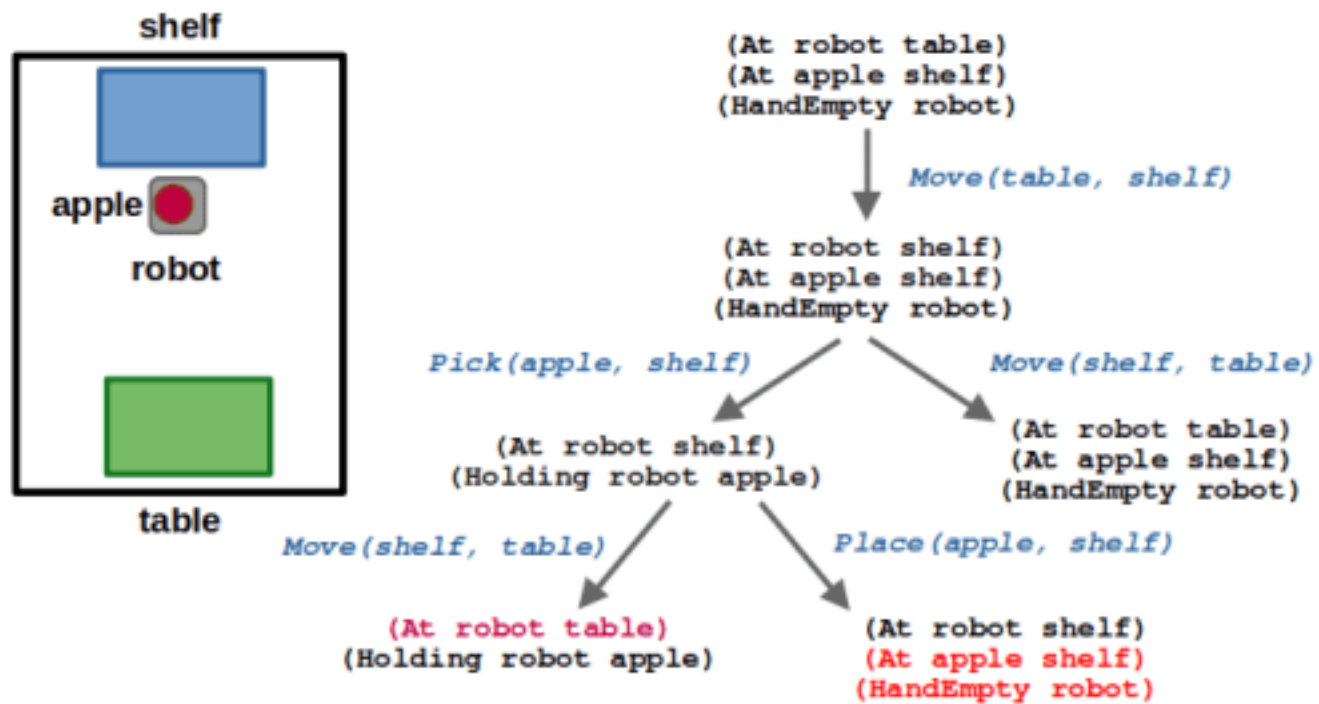


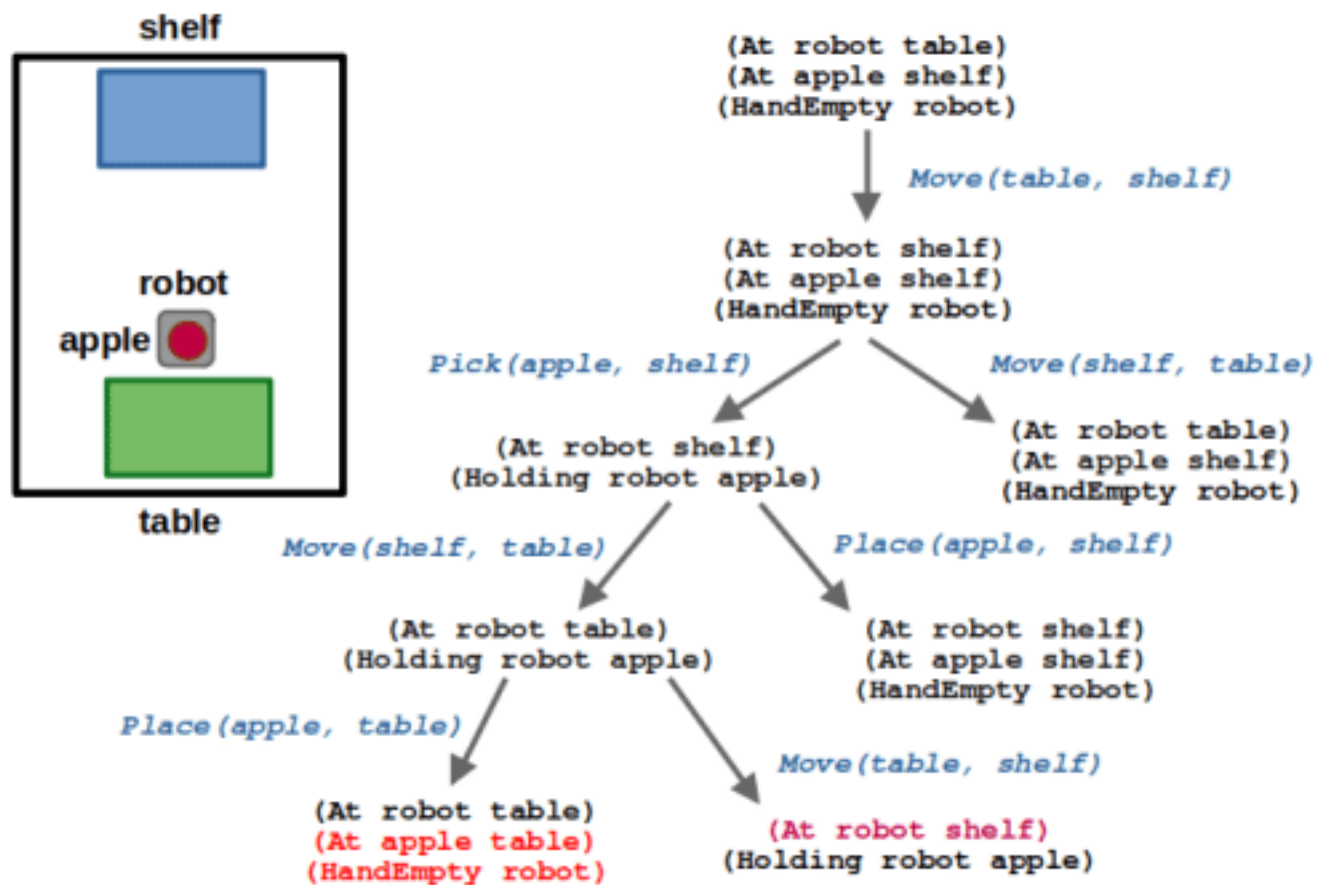
```
(At robot table)
(At apple shelf)
(HandEmpty robot)

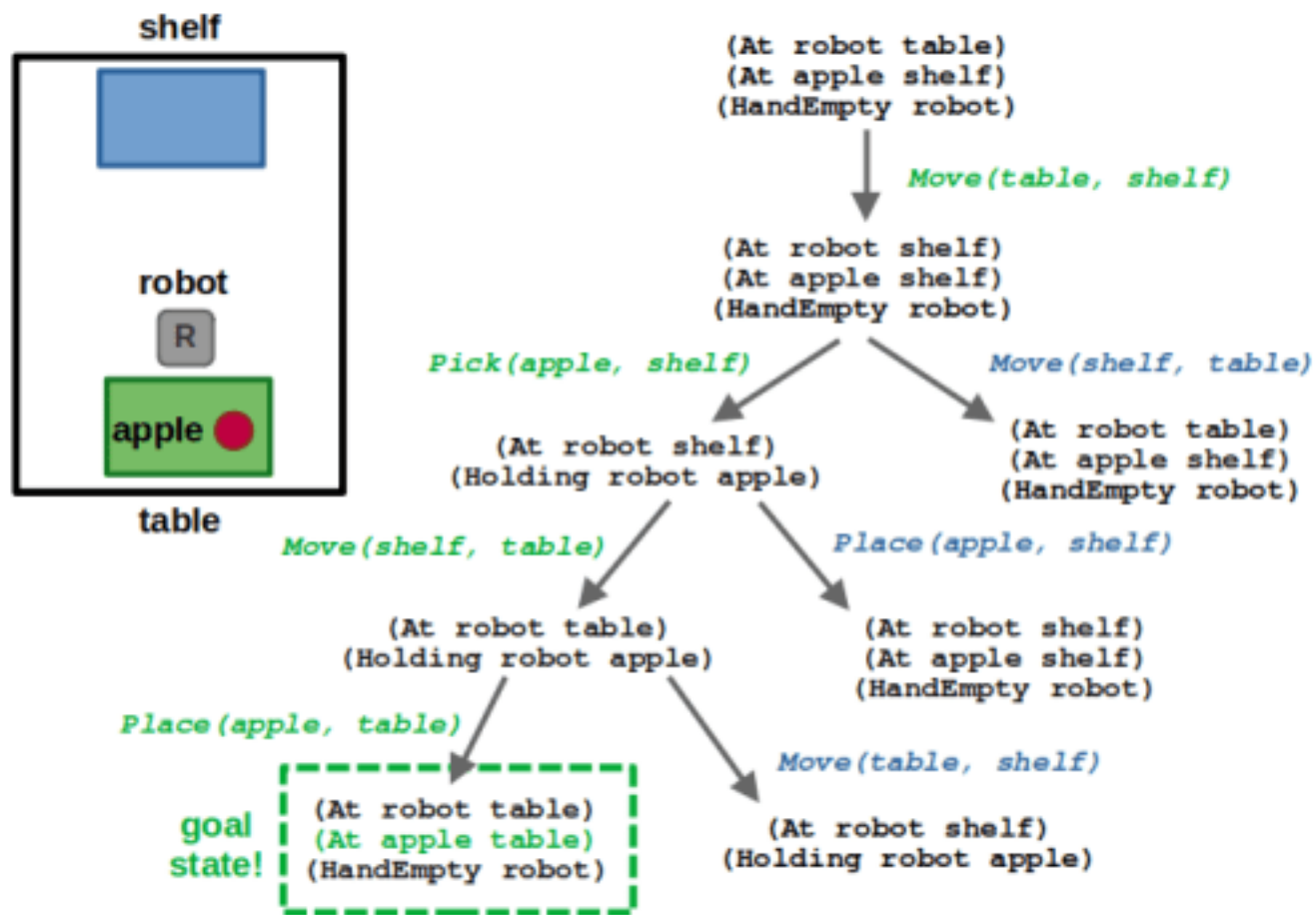
↓ Move(table, shelf)

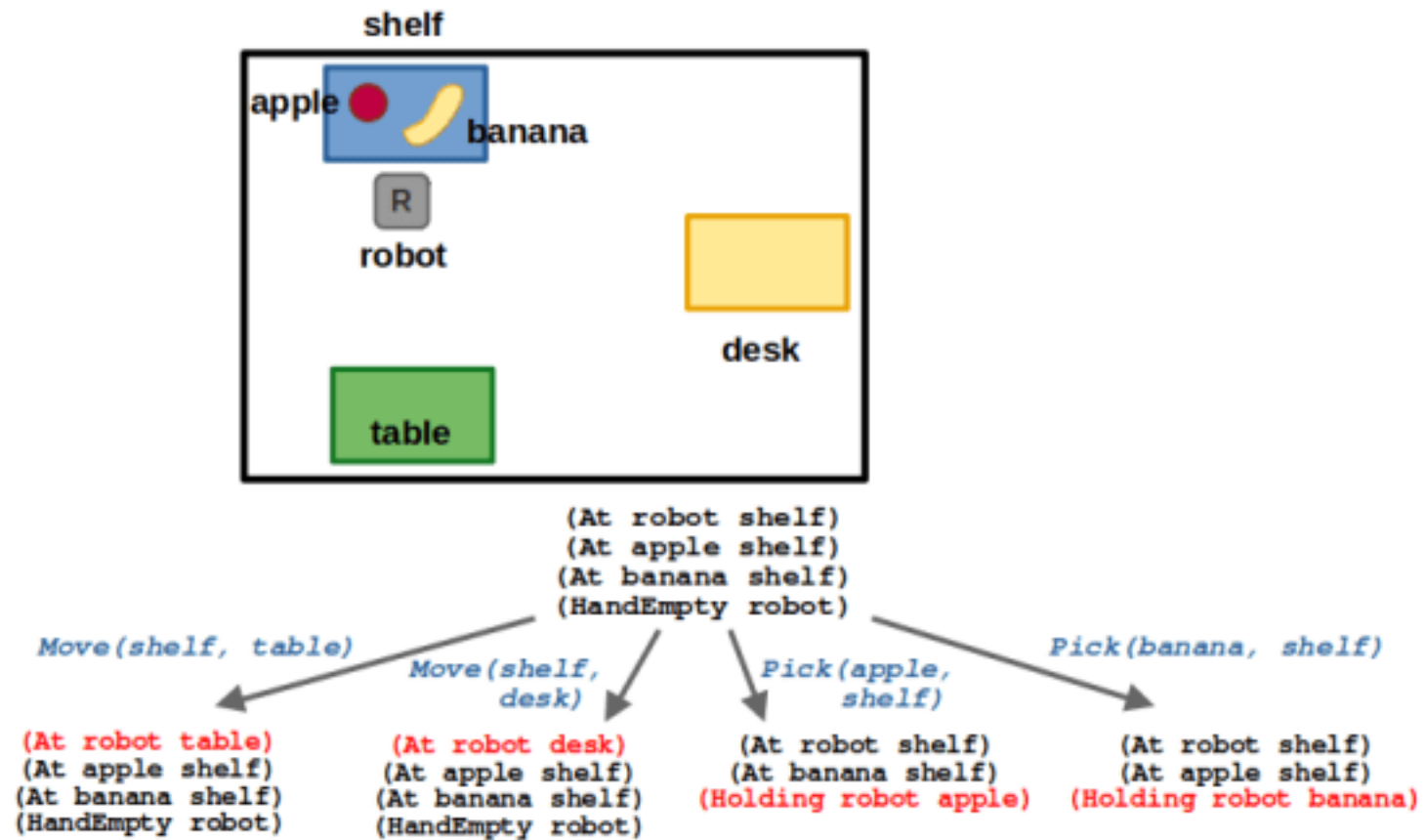
(At robot shelf)
(At apple shelf)
(HandEmpty robot)
```







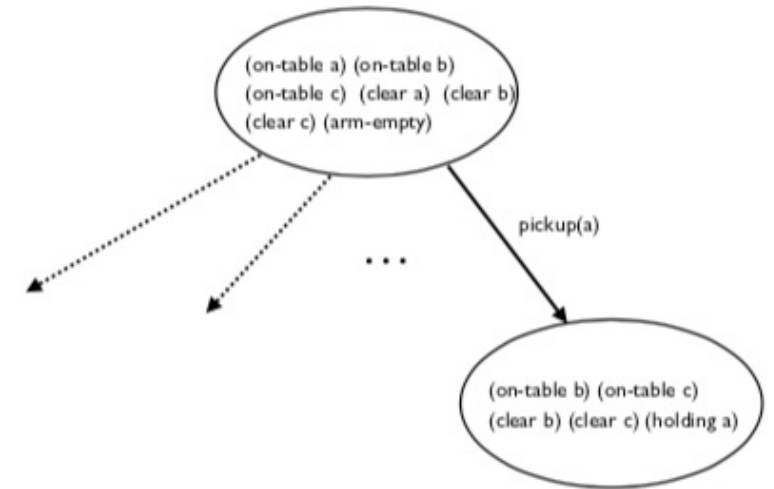




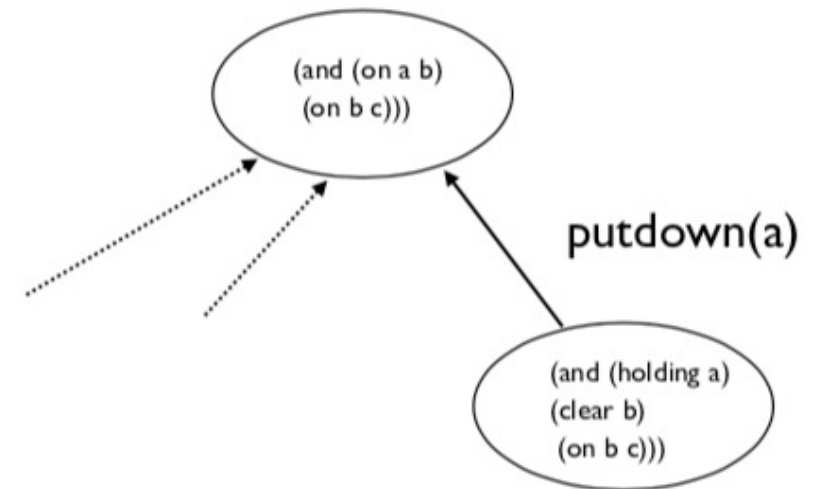
Searching for a Plan

- Forward planning
 - Begin from the initial state and examine the effects of all actions applicable on that state.
 - Determine *successor* states and continue the process till you reach the goal state.
 - Often the branching factor is large.
- Backward or regression search
 - Start at the goal state, apply actions backward until we find the sequence of actions that reaches the initial state.
 - Computes the *predecessor* state s' for a final state s reached by action a .
 - Check for only those actions that are relevant for the goal
 - At least one of the action's effects (positive or negative) should unify with the goal.
 - Often the branching factor is low.

Forward search

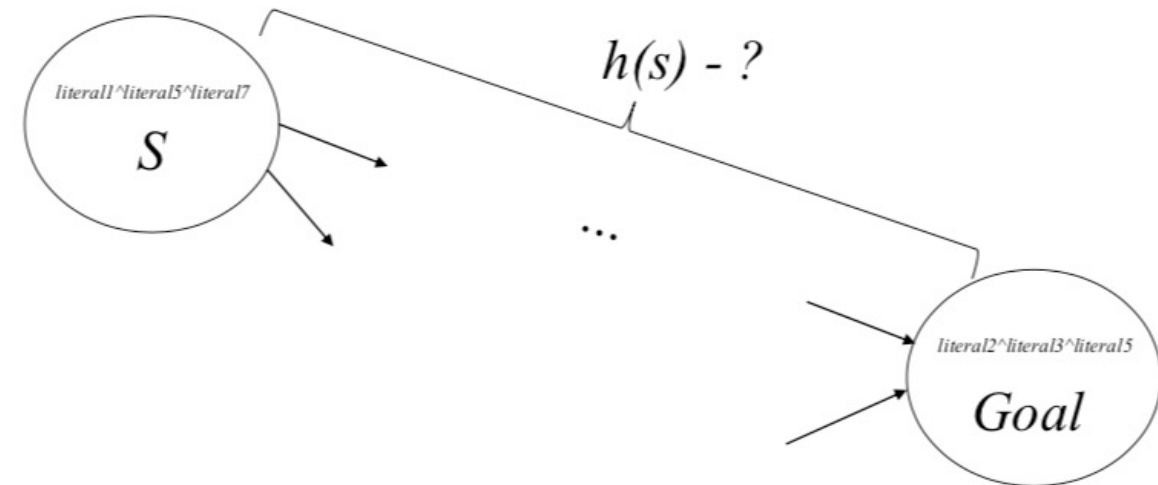


Backward search



Heuristics for Planning

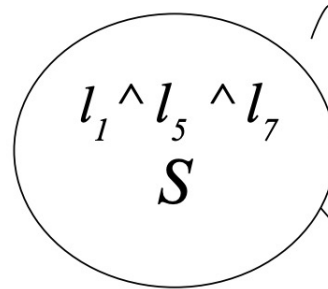
- Informed Search
 - Can try to search with A* by constructing a heuristic.
 - *Domain-specific heuristics* can be derived from the problem structure.
 - Requires careful engineering.
- *Domain-independent* heuristics
 - Once a planning problem is encoded in the PDDL form then can the search be independent of the domain.
 - The number of literals that are NOT yet satisfied.
 - The heuristic should work for any problem encoded in PDDL.



Heuristics for Planning

Heuristic I: Number of unsatisfied goals.

Is this admissible in general? No. One action may generate more than one goals. Hence, the estimate may not be a lower bound.



$h(s) - ?$



...

Question: How useful is this heuristic?

- Applicable problems
- Admissibility
- Local minima



Key idea:

$h(s) = \#$ of literals in goal not satisfied in s

i.e., $h(s) = \#$ of literals l_i such that $l_i(s) = \text{false}$ and $l_i(\text{goal}) = \text{true}$

Heuristics for Planning

Alternatively, create a relaxation of the problem.

Solve the simplified problem optimally.

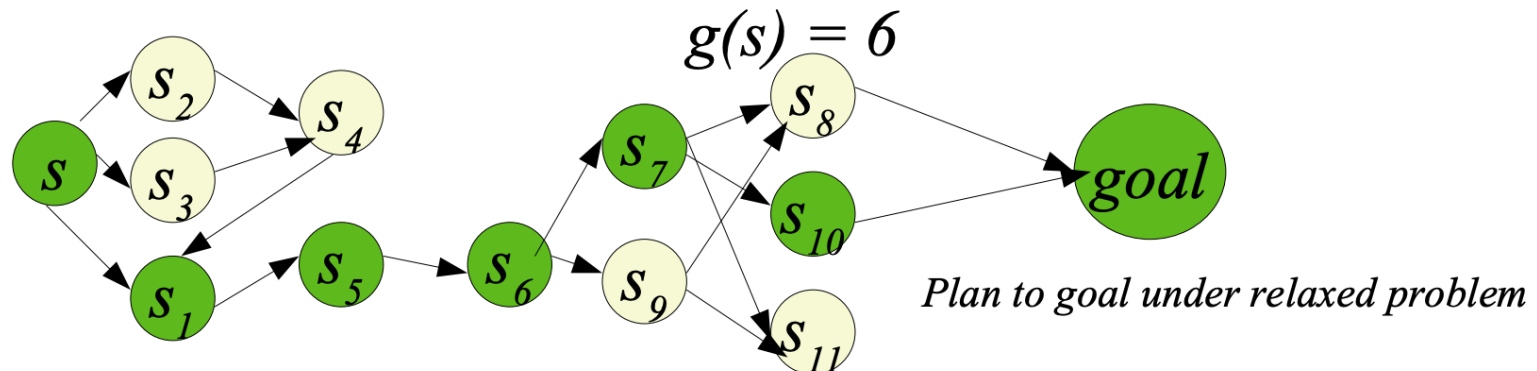
Key idea:

- 1) Compute $h(s)$ by solving a **relaxed** (simpler) problem
- 2) **empty-delete-list**: assume actions do not have any negative effects

MoveToTable(b,x)

Precond: $\text{On}(b,x) \wedge \text{Clear}(b) \wedge \text{Block}(b)$

Effect: $\text{On}(b, \text{Table}) \wedge \text{Clear}(x) \wedge \sim \text{On}(b,x)$



Heuristics by Solving Relaxed Problems

- Recap: Notion of a relaxed problem
 - Make simplifying assumption on the original planning problem i.e., address a relaxed problem.
 - Solve the relaxed problem optimally. Use the optimal plan in the relaxed problem as a heuristic for the original problem which is hard to solve.
- Heuristic Search Planner (HSP) and Fast Forward (FF) Planner use this idea
 - Relax the problem by deleting the negative effects of actions.
 - Solve the relaxed problem using a planner.

Create problem relaxations by
ignoring the delete list.

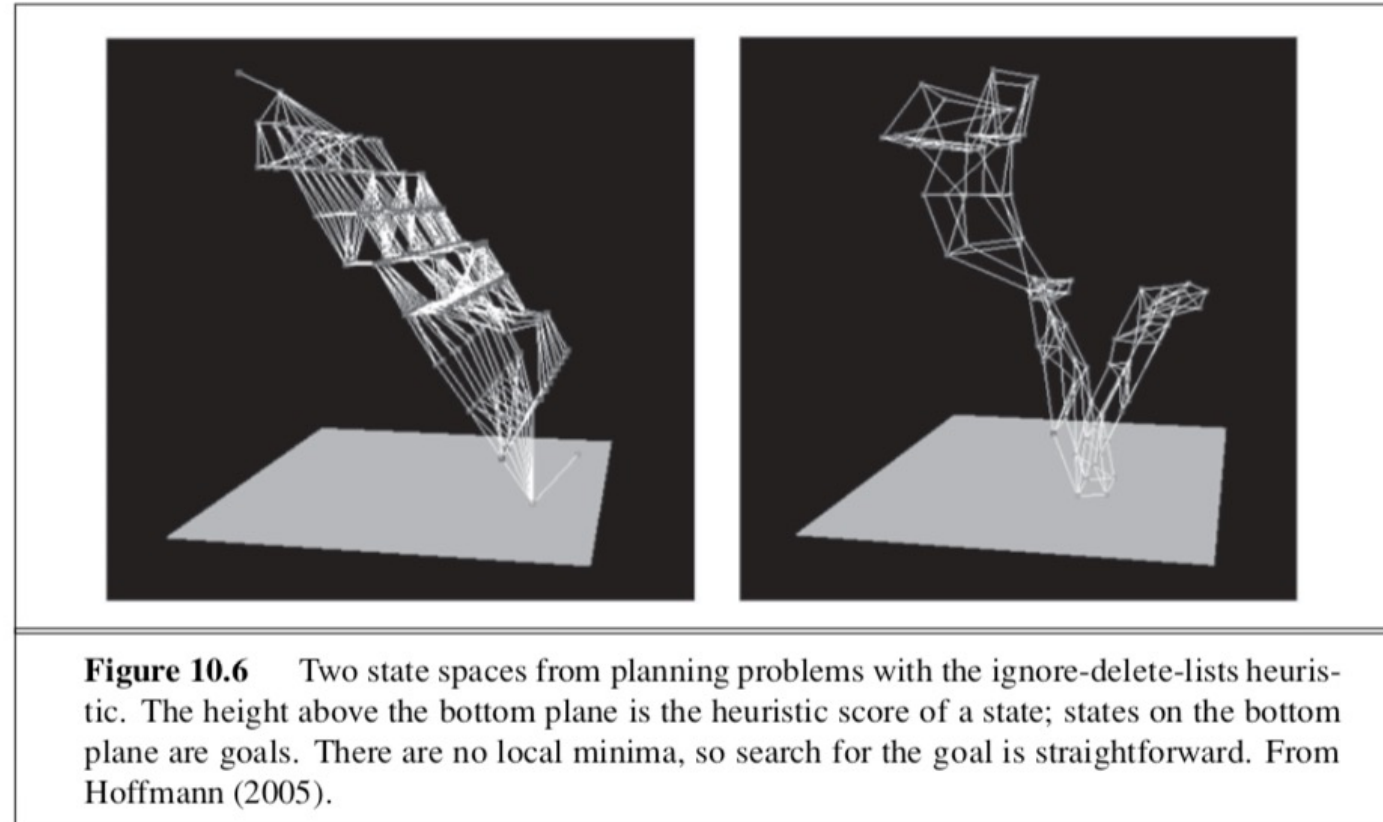
```
(:action pickup
:parameters (?ob)
:precondition (and (clear ?ob) (on-table ?ob) (arm-empty))
:effect (and (holding ?ob) (not (clear ?ob)) (not (on-table ?ob))
(not (arm-empty))))
```


Heuristic Search Planning

- Deleting negative effects of actions leads to a relaxation of the problem.
- Setup
 - Goal: conjunction of positive literals.
 - Actions
 - Precondition (conjunction of positive literals)
 - Effects (adds and deletes)
- *Monotonic* progress towards the goal
 - Each action execution monotonically adds the applicable actions.
 - Once a literal is made true, it is not deleted. Progress made is not undone.
 - When the delete effects are ignored then some of the the complex interactions between actions is ignored
 - Intuitively, If there is an action that deletes the preconditions for another action then the plan length will be longer as effort is needed to set the deleted predicate as true.
 - By ignoring delete effects, the problem gets relaxed as the actual plan is going to be at least as long.
- Heuristic Search Planning System
 - Core idea: Search for a plan making use of the “heuristic” computed from solving the “relaxed” problem. In essence, convert a planning problem to a search problem guided by a heuristic.
 - Domain independent, i.e., when the problem is expressed in PDDL format, the heuristic can be constructed automatically.

Heuristic Search Planning

- Problem: Even the relaxed problem may be hard to solve
 - Still NP hard to compute the optimal solution in the relaxed problem
 - Solution: Approximate solution can be found via hill climbing.
- Figure
 - Visualizes state space for two problems using the ignore delete list heuristic.
 - Dots (states), edges (actions) and height (heuristic cost).
 - Lower the heuristic cost, the closer we are to the goal.
 - Hill climbing search will provide an approximate solution.
- HSP Planner (Bonet and Geffner) build on this idea.
- <https://bonetblai.github.io/reports/hsp-aij.pdf>



Planning Graphs

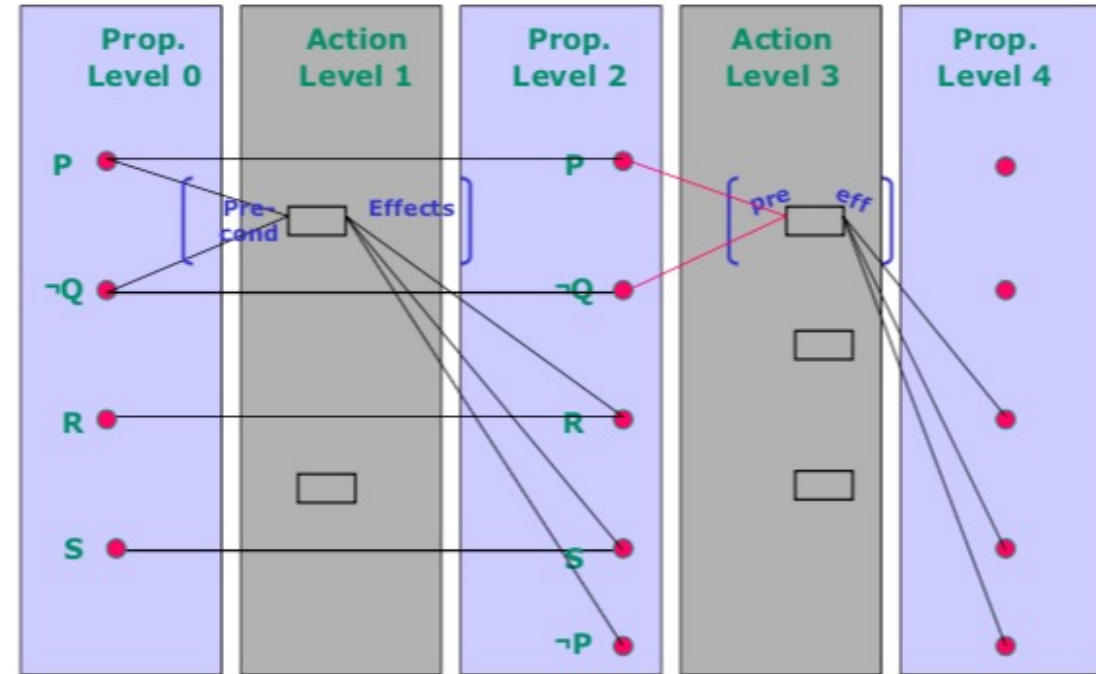
- A planning problem asks if we can reach a goal state from the initial state.
- If we have a tree of all possible actions from the initial state to successor states and so on.
- We can determine if there is a plan from start to the goal.
- ***Problem: this tree is exponential in size.***

Planning Graphs

- Planning graph is a polynomial-size approximation to this tree.
 - Trade off is that the planning graph indicates states that can ***possibly*** be reached.
- **It cannot definitively answer if the goal G is attainable from s_0**
 - *But, it can estimate how many steps it takes to reach G .*
- The estimate is always correct when it reports the goal is not reachable.
 - It never overestimates the number of steps (hence an admissible heuristic)
- Where are planning graphs used?
 - Used for obtaining heuristic values (estimating the cost of obtaining a goal)
 - Used for determining a plan (GraphPlan)

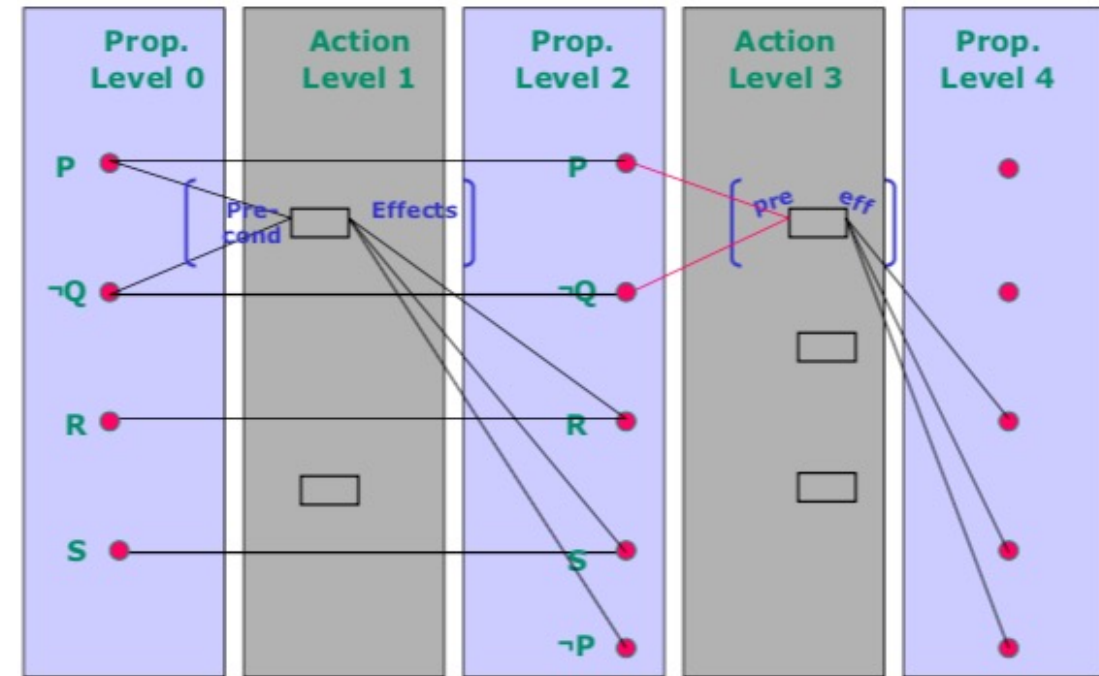
Planning Graphs

- Construction
 - Layered Graph: states and actions
 - S_i contains all the literals that "could" hold at time i .
 - A_i contains all the actions that "could" have their pre-conditions satisfied at time i .
 - **No variables.**
 - All grounded literals and grounded actions.



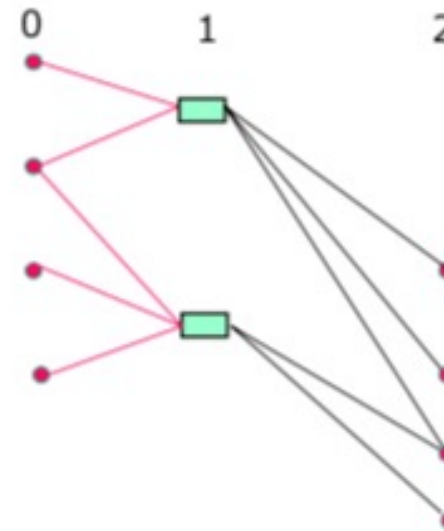
Planning Graphs

- What does a planning graph encode?
 - A planning graph only records a restricted subset of negative interactions between actions.
 - Allows “**quick**” **elimination** of some impossible alternatives in the search process.
 - Not all inconsistencies are recorded. Only obvious flaws.
 - The level at which a literal **appears** is a good estimate of how difficult it is to attain a literal from the initial state.

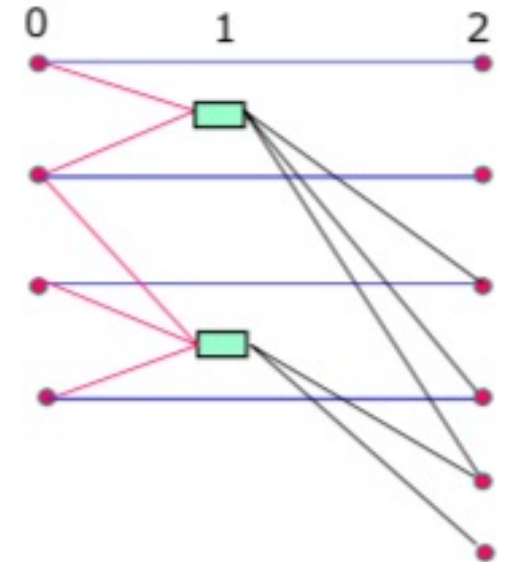


Planning graph: Construction

- Start with the initial state (given)
- Add applicable actions and effects
 - Add actions with satisfied pre-conditions
 - Add all effects of actions at previous levels
 - The action layer will contain all actions whose pre-conditions are satisfied.
- Add maintenance actions
 - Ensures that once a literal is reached it is “maintained” in the planning graph for every subsequence layer.



Add actions with satisfied pre-conditions

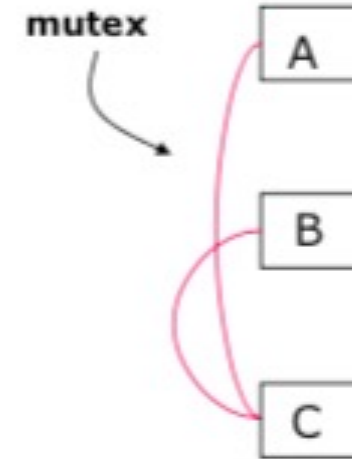


Add maintenance operations.

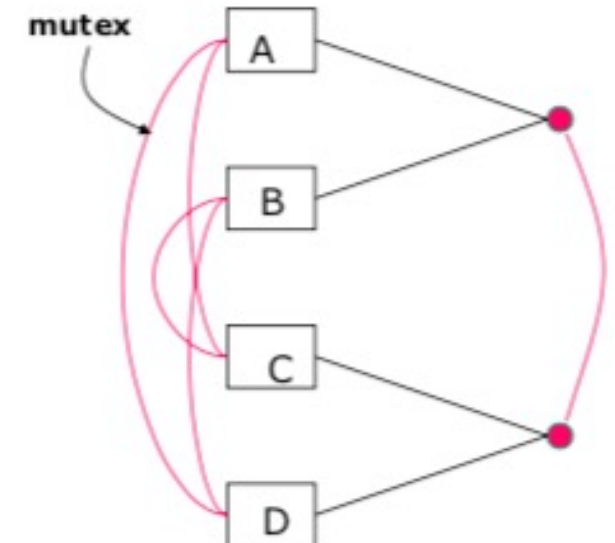
Mutually Exclusive Actions

- Two action instances at level i are mutex if:
 - Inconsistent effects
 - The effect of one action is negation of another.
 - Interference
 - One action deletes the precondition of another.
 - Competing needs
 - The actions have preconditions that are mutex at level $i-1$
- What do the mutexes model?
 - Some conditions under which two actions cannot be performed together (i.e., only one of them must be selected)
 - Detection of certain obvious flaws (there may be other conflicts that are not encoded by the planning graph)

Actions considered as mutex



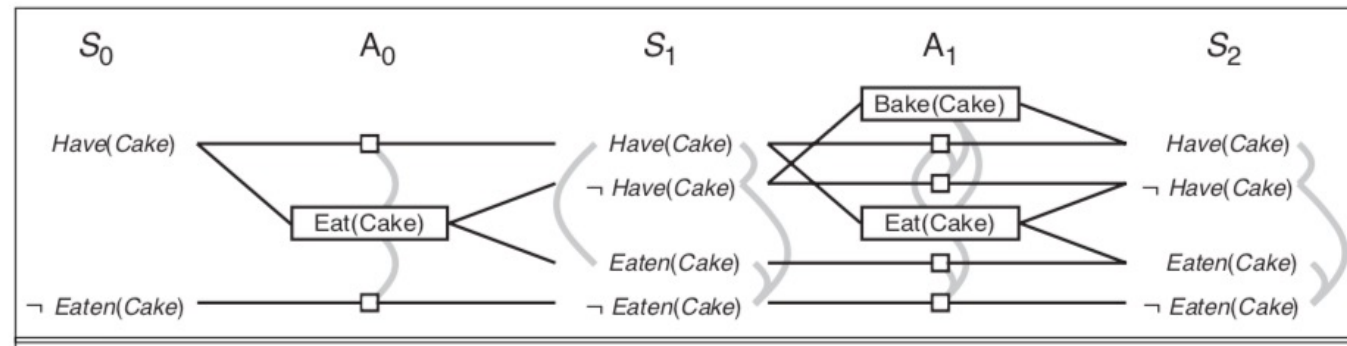
Inconsistent support



Mutually Exclusive Actions

- Inconsistent effects
 - Eat(Cake) and the persistence of Have(cake) have inconsistent effects.
- Interference
 - Eat(Cake) interferes with the persistence of Have(Cake) by negating its pre-conditions.
 - Eat(Cake) and persistence of not Eaten(Cake) are mutex.
- Competing needs
 - Bake(Cake) and Eat(Cake) are mutex because they compete on the value of the Have(Cake) precondition.

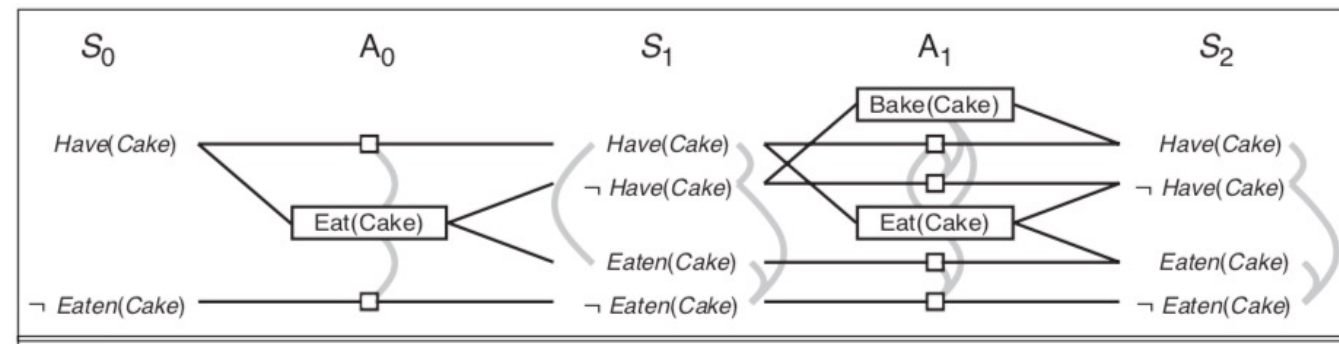
Init(Have(Cake))
Goal(Have(Cake) \wedge Eaten(Cake))
Action(Eat(Cake))
PRECOND: Have(Cake)
EFFECT: \neg Have(Cake) \wedge Eaten(Cake))
Action(Bake(Cake))
PRECOND: \neg Have(Cake)
EFFECT: Have(Cake))



Mutually Exclusive Propositions

- Two propositions at level i are mutex if:
 - Negation of each other
 - They are negations of one another
 - Inconsistent support
 - All ways of achieving the propositions at level $i-1$ are pairwise mutex. All pairs of actions that can lead to these literals cannot occur together.
- Example
 - Inconsistent support
 - $\text{Have}(\text{Cake})$ and $\text{Eaten}(\text{Cake})$ are mutex in S_1 because the only way of attaining $\text{Have}(\text{Cake})$ which is maintenance action is mutex with the only way of achieving $\text{Eaten}(\text{Cake})$ which is $\text{Eat}(\text{Cake})$

$\text{Init}(\text{Have}(\text{Cake}))$
 $\text{Goal}(\text{Have}(\text{Cake}) \wedge \text{Eaten}(\text{Cake}))$
 $\text{Action}(\text{Eat}(\text{Cake}))$
 PRECOND: $\text{Have}(\text{Cake})$
 EFFECT: $\neg \text{Have}(\text{Cake}) \wedge \text{Eaten}(\text{Cake})$
 $\text{Action}(\text{Bake}(\text{Cake}))$
 PRECOND: $\neg \text{Have}(\text{Cake})$
 EFFECT: $\text{Have}(\text{Cake})$



Planning Graphs for Heuristic Estimation

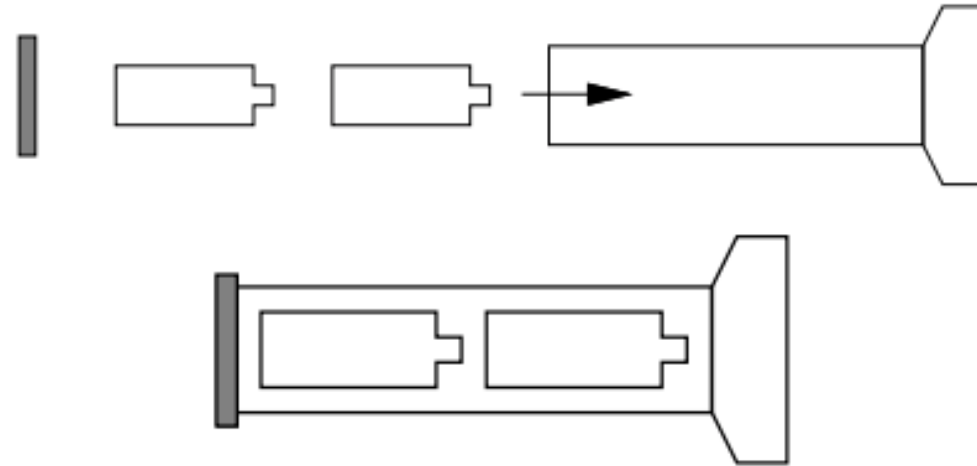
- Level-cost of a goal literal (atom)
 - Cost of attaining any goal g_i from a state s as the level at which g_i first appears in the planning graph constructed from the initial state s .
 - Encodes the difficulty to making a literal true. This estimate can be used to estimate the “*cost to go*” from a current state s to the goal, serving as a heuristic.
 - If any goal literal fails to appear in the final level of the planning graph, then the problem is unsolvable.
 - The planning graph is polynomial in size (hence tractable to compute)

Heuristic Cost of Attaining Conjunctive Goals

- **Max-level** heuristic
 - Maximum level cost of any of the goals (admissible but not accurate)
- **Level-sum** heuristic
 - Sum of the level costs of the goals
- **Set-level** heuristics
 - Level at which all the literals in the conjunctive goal appear in the planning graph without any pair of them being mutually exclusive.
- The Fast Forward (FF) Planning System (Hoffman et al.) uses the planning graph to provide a heuristic estimate while searching for a plan.
 - <http://www.cs.toronto.edu/~sheila/2542/w06/readings/ffplan01.pdf>
 - The idea is similar to HSP planning system. The idea is still one of converting the planning problem to a heuristic-guided search. But the heuristic comes from the planning graph instead of computing via the HSP approach.

Example: flashlight domain

- Problem involves putting batteries into a torchlight.



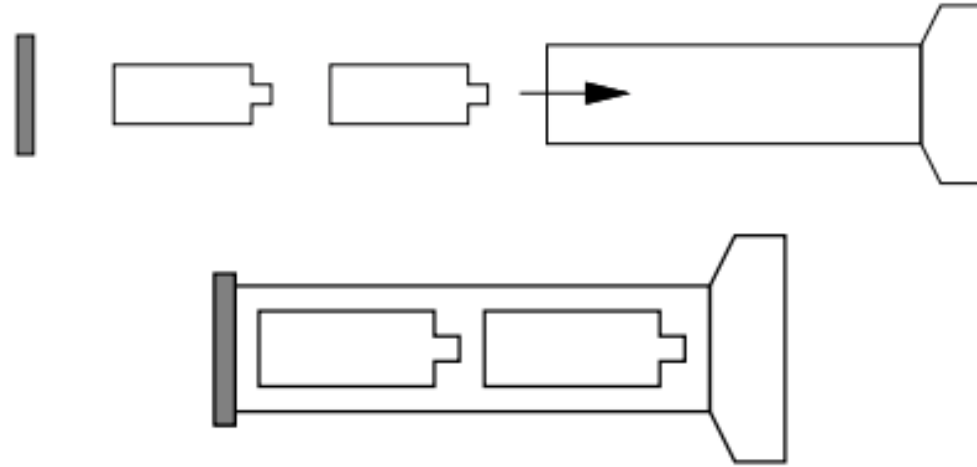
Object
Instances

$I = \{Battery1, Battery2, Cap, Flashlight\}$

Actions

Name	Preconditions	Effects
<i>PlaceCap</i>	$\{\neg On(Cap, Flashlight)\}$	$\{On(Cap, Flashlight)\}$
<i>RemoveCap</i>	$\{On(Cap, Flashlight)\}$	$\{\neg On(Cap, Flashlight)\}$
<i>Insert(i)</i>	$\{\neg On(Cap, Flashlight), \neg In(i, Flashlight)\}$	$\{In(i, Flashlight)\}$

Example: flashlight domain



Initial State $S = (On(Cap, Flashlight), \neg In(Battery1, Flashlight) \neg In(Battery2, Flashlight))$

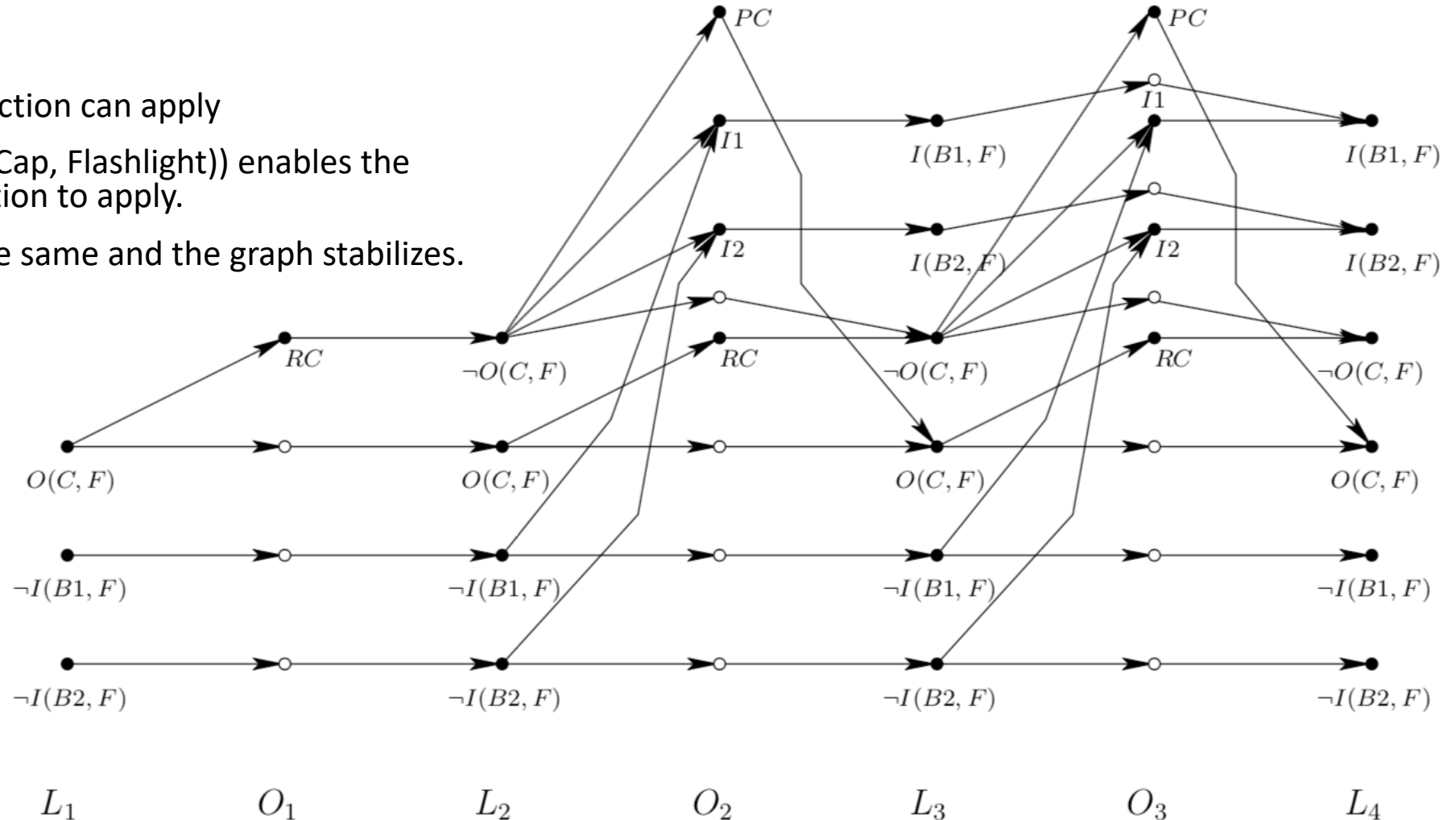
Goal $G = \{On(Cap, Flashlight), In(Battery1, Flashlight), In(Battery2, Flashlight)\},$

Plan $(RemoveCap, Insert(Battery1), Insert(Battery2), PlaceCap)$

Example: flashlight domain

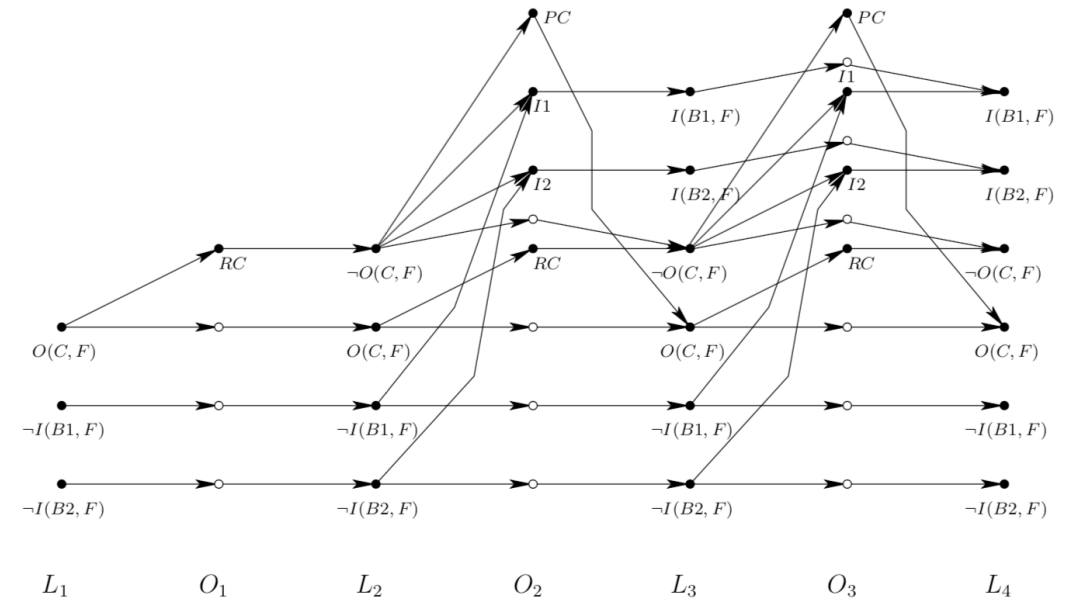
Planning graph

- In L1 only remove cap action can apply
- Appearance of $\text{Not}(\text{On}(\text{Cap}, \text{Flashlight}))$ enables the battery insertion operation to apply.
- Finally, L3 and L4 are the same and the graph stabilizes.



Graph Plan: Using Planning Graphs for Obtaining the Plan

- Central Idea
 - Use the planning graph to extract a plan
 - Instead of using the graph for providing a heuristic.
- Graph Plan
 - Look for a plan of depth K.
 - Then search for a solution.
 - If you succeed return a plan, else increase the plan depth to K+1



- Interleaves graph extension and plan search
- Once all the goals appear as non-mutex in the graph then call a plan search.

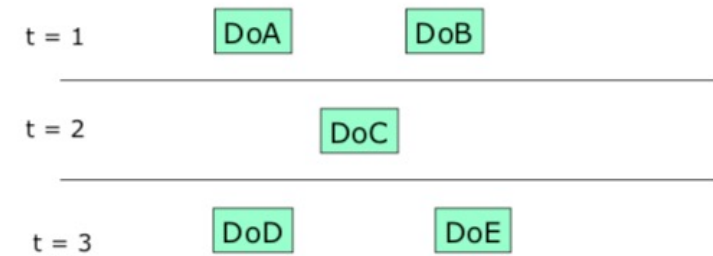
Extracting the Plan

- There can be several actions in an action layer.
- How to extract the plan?
 - Start from layer k and search backwards.
 - Perform an And/Or search.
 - All literals in the target state are to be satisfied (AND part)
 - Try the possible operators under mutex constraints (OR part). Note: mutex says that some actions cannot take place together, we need to select between them.

Planning graph has multiple actions at a level.

A plan of depth k

- has k times steps
- may have multiple parallel actions per time step



Procedure for plan extraction

- If all the literals in the goal appear at the deepest level and not mutex, then search for a solution for each subgoal at level i
 - For each subgoal at level i
 - Choose an action to achieve it
 - If it's mutex with another action, Fail
 - Repeat for preconditions at level i-2

Lots more to planning! Hierarchical Planning

There is whole lot more to planning!

Complex tasks may be decomposed hierarchically and then refined.

Key idea:

Not every action needs to be fully planned out from the beginning!

1. Plan at a high level
2. Work out details as needed

