



Real World Planning and Acting

CS4246/CS5446

AI Planning and Decision Making

Sem 1, AY2021-22



Topics

- Planning as Search
 - Soundness and completeness
 - Complexity of planning (RN 11, Bibliographical and Historical Notes)
- Heuristics for planning (RN 11.3)
 - Problem relaxation and admissible heuristics
 - Domain independent planning (RN 11.3.1)
 - State abstraction in planning (RN 11.3.2)
- Hierarchical planning (RN 11.4)
 - Hierarchical task networks and HTN Planning
 - High-level actions (RN 11.4.1)
 - Searching for primitive solutions (RN 11.4.2)
 - Searching for abstract solutions (RN 11.4.3)



Solving Planning Problems

Heuristics: for classical planning
HTN: New planning model

- Planning Problem or Model
 - Appropriate abstraction of states, actions, effects, and goals (and costs and values)
- Planning Algorithm
 - Input: a problem
 - Output: a solution in the form of an action sequence
- Planning Solution
 - A **plan** or **path** from the initial state(s) to the goal state(s)
 - Any path; OR
 - An **optimal** path wrt to costs or values
 - A **goal state** that satisfies certain properties



Planning as Search

Properties and complexity analysis



Recall: Planning as Search

Source: Dana Nau: Lecture slides for *Automated Planning*

- Nearly all planning procedures are search procedures
 - Different planning procedures have different search spaces
- State-space planning
 - Each node represents a state of the world
 - A plan is a path through the space
- Forward Search
 - Prone to exploring irrelevant actions
 - Need to traverse large state-spaces
 - Average branching factor is huge!
 - Need domain-specific or domain-independent heuristics that can be derived automatically
- Backward search
 - Keep branching factor lower than forward search
 - Using state sets for searching makes it harder to come up with heuristics



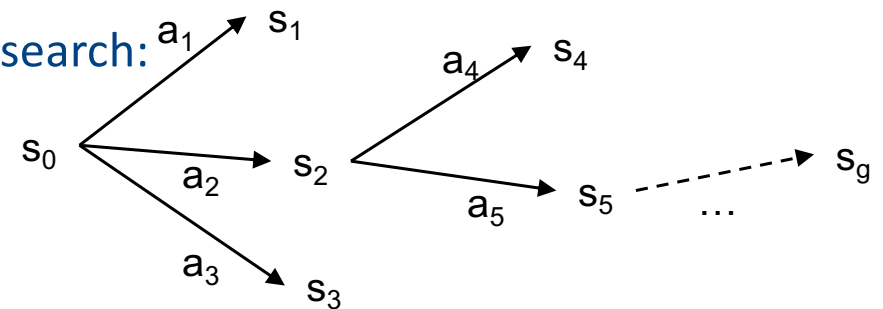
Planning Algorithm Properties

- A planning algorithm or planner is **sound**
 - For any plan generated by the planning algorithm, this plan is guaranteed to be a solution
- A planning algorithm or planner is **complete**
 - If a solution exists then the planning algorithm will return a solution
- Question: How “good” are the solutions?
 - For any plan generated by the planning algorithm, can the plan be guaranteed to be an **optimal** solution?

Deterministic Forward Search

- Some deterministic implementations of forward search:

- breadth-first search
- depth-first search
- best-first search (e.g., A^*)
- greedy search



- Breadth-first and best-first search are sound and complete

- Worst-case memory requirement is exponential in the length of the solution

- In practice, more likely to use depth-first search (DFS) or greedy search

- Worst-case memory requirement is linear in the length of the solution
- In general, sound but not complete
- But classical planning has finite no. of states, DFS can be made complete by doing loop-checking

Source: Dana Nau: Lecture slides for *Automated Planning*



Complexity of Planning

- Two decision problems:
 - **PlanSAT** –whether there exists any plan that solves a planning problem
 - **Bounded PlanSAT** –whether there is a solution of length k or less
 - For classical planning, both problems are decidable as number of states is finite
- In general:
 - Both problems are in PSPACE: solvable with polynomial amount of space
 - In many domains, Bounded PlanSAT is NP-complete; PlanSAT is in P
 - Optimal planning is usually hard, but sub-optimal planning is sometimes easy
- In real world planning:
 - Agents usually asked to find plans in specific domains, not in worst-case instances
 - To do well, need good **heuristics** or **alternate planning models**



Heuristics for Planning

Improving Efficiency



Heuristics for Planning

- Heuristic function
 - $h(s)$ estimates distance from a state s to the goal g
- Main idea
 - Find **admissible heuristic** for distance – one that does not overestimate
 - A* or other heuristic search can then find **optimal** solutions
- Approach
 - Define a **relaxed problem** that is easier to solve
 - Exact cost of solution to easier problem is **heuristic** for original problem

Types of Heuristics

- Definition and application
 - Facilitated by factored representation for states and action schemas
- Search problem
 - A graph with states as nodes and actions as edges
 - Find a path connecting initial state to goal state
- Domain independent heuristics –Why?
 - Two ways to relax the problem (make it strictly easier):
 - Add more edges – easier to find path
 - Group multiple nodes together – abstract with fewer states and easier to search
 - Prune away irrelevant branches of search tree



Heuristics of Adding Edges

- Ignore preconditions heuristic
 - Drop all preconditions from actions
- Ignore selected preconditions heuristic
 - Derive simpler measures of distance from goal
- Ignore delete list heuristic
 - Allow monotonic progress toward goal
- Caveats:
 - Finding solution to relaxed problem is still NP-hard
 - Trade-off in optimality or admissibility sometimes required
 - Expensive to calculate heuristics
 - Do not reduce state-space size



How to Define an Edge-Based Heuristic?

- Approach:

- Relax actions by removing all preconditions and all effects except goal literals
- Count minimum no. of actions required for union effects to satisfy the goal

- Note:

- An instance of the set cover problem – NP-hard

- Potential solution:

- Simple greedy algorithm guaranteed to return a set covering whose size is within a factor of $\log(n)$ of the true minimum covering
 - where n is the number of literals in the goal
- Loses guarantee of admissibility


Example: 8-Puzzle as Planning

- Planning as path search

- Game objective:


- To rearrange a given initial configuration (state) of eight numbered tiles arranged on a 3×3 board into given final or goal configuration (state)

Initial

2		3
1	8	4
7	6	5



Goal

1	2	3
8		4
7	6	5

Action(Slide(t, s_1, s_2))

Precond: $On(t, s_1) \wedge Tile(t) \wedge Blank(s_2) \wedge Adjacent(s_1, s_2)$

Effect: $On(t, s_2) \wedge Blank(s_1) \wedge \neg On(t, s_1) \wedge \neg Blank(s_2)$

Example: 8-Puzzle as Planning

- States

- A state description specifies the location of each of the eight tiles in one of the nine squares

- Actions or operators

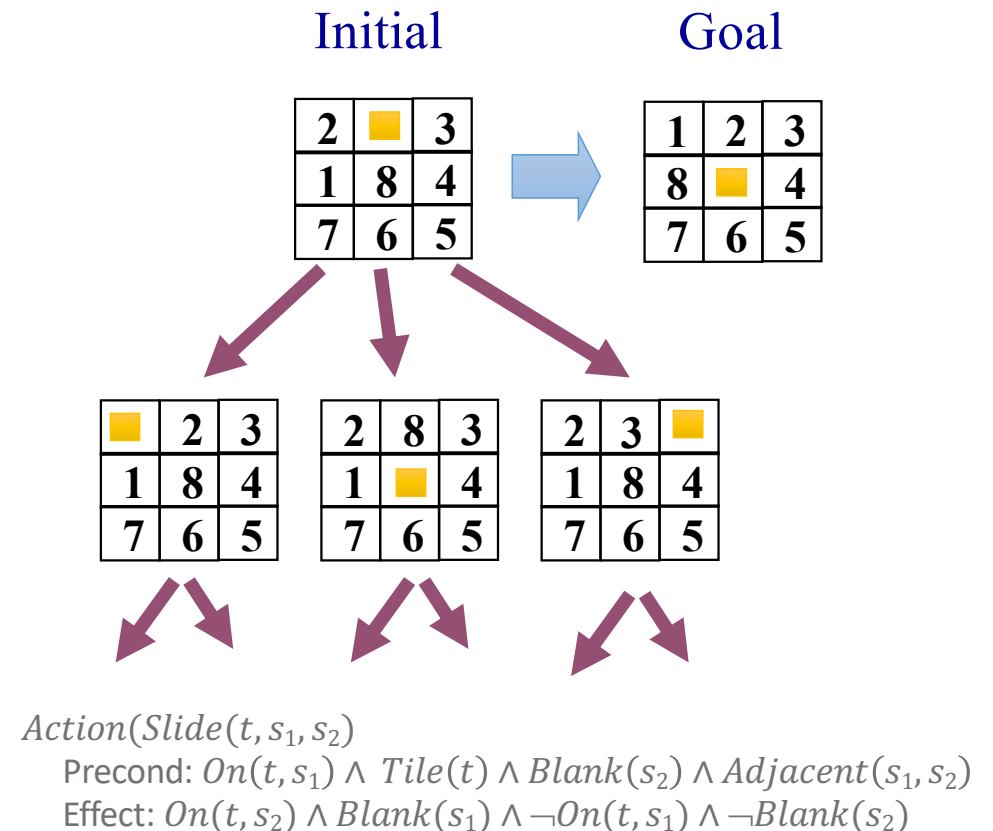
- Tile **slides** left, right, up, or down

- Goal test

- State matches the goal configuration

- Path cost

- Each step cost 1, so path cost is just the length of the path



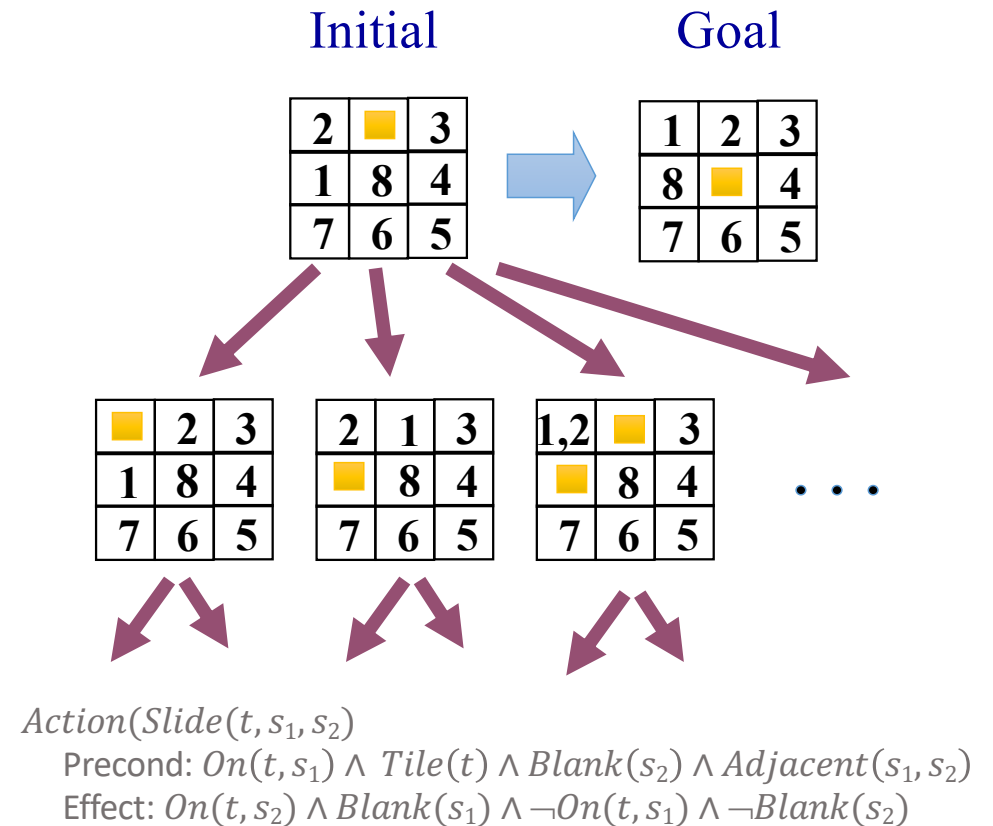


Ignore Preconditions Heuristic

- Main idea:
 - All actions become applicable in all states
 - Any single goal fluent can be achieved in one step (if there is an applicable action)
 - No. of steps required to solve relaxed problem \approx no. of unsatisfied goals
 1. Some actions may achieve multiple goals
 2. Some actions may undo the effects of others
 - Possible accurate heuristic – consider 1 and ignore 2

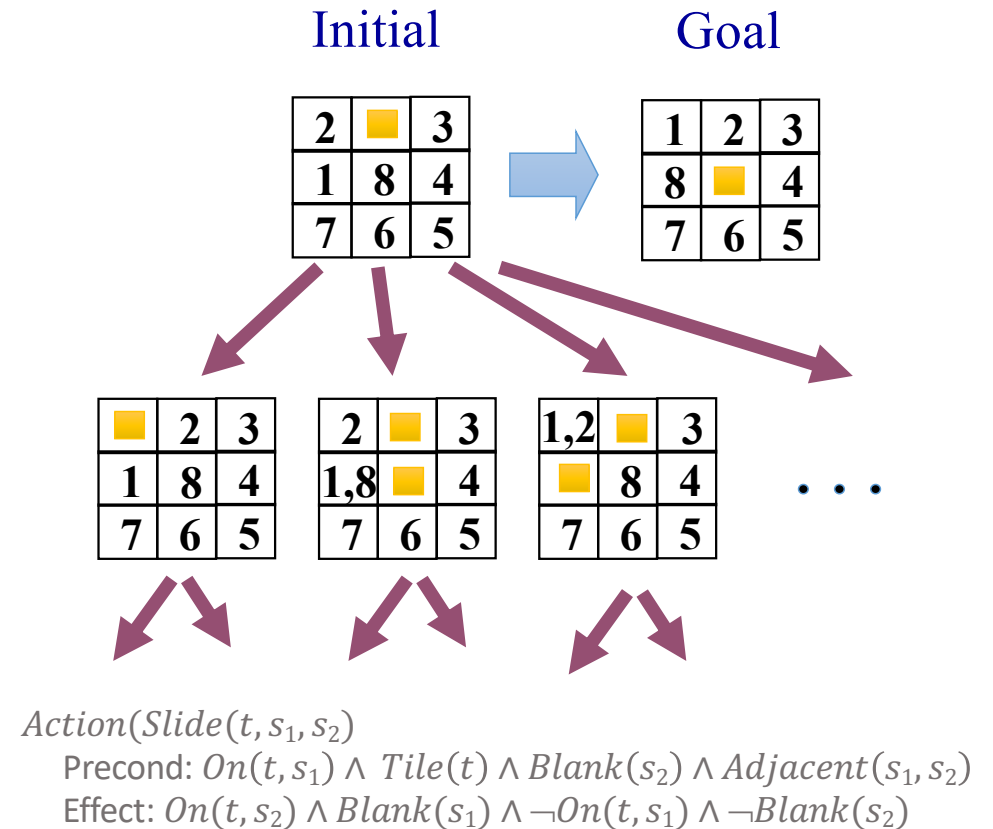
Ignore Selected Preconditions Heuristic

- Remove Preconditions
 - $Blank(s_2) \wedge Adjacent(s_1, s_2)$
- What does the heuristic do?
- What are the estimates?



Ignore Selected Preconditions Heuristic

- Remove Preconditions
 - $Blank(s_2)$
- What does the heuristic do?
- What are the estimates?
- Caveat:
 - Unclear which preconditions can be selectively ignored in general





Ignore Delete List Heuristic

- Main idea:
 - Assume only positive literals in all plans and actions
 - Remove delete list from all actions (all negative literals from effects) to make monotonic progression toward goal
 - Create a relaxed version of original problem that is easier to solve, where solution length will serve as good heuristics
 - Approximate solution can be found in polynomial time by hill-climbing

Ignore Delete Lists Heuristic

- Ignore delete lists
 - How does the problem become easier when ignore delete lists heuristic is applied to this schema?

Initial

2	■	3
1	8	4
7	6	5



Goal

1	2	3
8	■	4
7	6	5

Action(Slide(t, s_1, s_2))

Precond: $On(t, s_1) \wedge Tile(t) \wedge Blank(s_2) \wedge Adjacent(s_1, s_2)$

Effect: $On(t, s_2) \wedge Blank(s_1) \wedge \neg On(t, s_1) \wedge \neg Blank(s_2)$

Can We Do Better?

- What would **YOU** do?
 - Can planning system emulate human moves?
 - Would that help?

Initial

2	■	3
1	8	4
7	6	5



Goal

1	2	3
8	■	4
7	6	5

Action(Slide(t, s_1, s_2))

Precond: $On(t, s_1) \wedge Tile(t) \wedge Blank(s_2) \wedge Adjacent(s_1, s_2)$

Effect: $On(t, s_2) \wedge Blank(s_1) \wedge \neg On(t, s_1) \wedge \neg Blank(s_2)$



Domain-independent Pruning

- Symmetry reduction
 - Prune all symmetric branches of the search tree except for one
 - For many domains, efficiently solve intractable
- Forward pruning
 - Accept risk of pruning away an optimal solution, in order to focus search on promising branches
- Rule-out negative interactions
 - A problem has **serializable subgoals** if there exists an order of subgoals such that the planner can achieve them in that order without having to undo any of the previously achieved subgoals



Serializable Subgoals

- Planning examples in the real world:
 - Build a tower of blocks on Table, in any order
 - Switch on all n lights with independent switches, in any order
 - Remote Agent Planner that commands NASA's Deep Space One spacecraft (1998) – serializable by design – able to command spacecraft in real-time



Heuristics of State Abstraction

- State abstraction:
 - Many-to-one mapping from states in the ground representation of the problem to the abstract representation
- Main approach:
 - Ignore some fluents
 - Solution in abstract state space will be shorter than a solution in the original space – **admissible heuristic**
 - Abstract solution extensible to solution for original problem



Example: Air Cargo Transportation

- **Original problem:**
 - 10 airports, 50 planes and 200 cargos
 - Total no. of states =
- **Assumption:**
 - All cargos are just in 5 airports, instead of 10, and all cargos in the same airport have the same destination.
- **Reformulation:**
 - Drop all the irrelevant At fluents (What are the relevant ones?)
 - Total no. of states =
- **Solution:**
 - Shorter than that for original problem (admissible heuristic)
 - Extensible by adding relevant actions



Decomposition

- Main idea:
 - Divide problem into parts, solving each part independently, and then combining the parts - Key idea in defining heuristics
- How to choose the right abstraction to reduce total cost?
 - Defining abstraction, doing abstract search, mapping abstraction back to original problem
 - Can the cost be less than original planning cost?
 - Example:
 - Pattern databases – cost of creation amortized over many problem instances



Planning Cost with Abstraction

- Problem definition:
 - Suppose the goal is a set of fluents G , divided into disjoint subsets G_1, \dots, G_n .
 - Find plans P_1, \dots, P_n that solve the respective subgoals
 - What is the estimated cost of the plan for achieving all of G ?
- Heuristic estimation:
 - Think of each $Cost(P_i)$ as a heuristic estimate
 - If each subproblem uses an admissible heuristic, taking Max is admissible
- Assuming subgoal independence:
 - Sum the cost of solving each independent subgoal; if admissible, Sum is better than Max – Why?
 - Solution **optimistic** when there are negative interactions between subplans for each subgoal; e.g., action in one subplan deletes goals in another subproblem.
 - Solution **pessimistic** (not admissible) when there are positive interactions; e.g., actions in one subplan achieves goals in another subproblem



Summary

- Classical or deterministic planning
 - No consensus on the best approach; competition and cross-fertilization induce progress
- Using domain-independent heuristics
 - Transform planning problems into relaxed problem spaces
 - Effective heuristics derived with subgoal independence assumptions by:
 - relaxation of planning problem
 - pruning repeated or irrelevant branches
 - Solve with efficient algorithms



Example: FF- FastForward

- Characteristics:

- Forward state-space searcher making use of effective heuristics
- Ignore-delete-list heuristic with graph plan for heuristic estimation
- Hill-climbing search (modified to keep track of plan) with heuristic to find a solution
 - Non-standard hill-climbing algorithm: avoids local maxima by running a breadth-first search from the current state until a better one is found
 - If this fails, FF switches to greedy best-first search instead
- [Hoffmann, 2001]



Classical Planning Today

- Classical Planning research: Examples:
 - Families of systems in use – Heuristic Search Planner (HSP), Fast Forward (FF), Fast Downward
 - <https://planning.wiki/ref/planners/>
- International Planning Competitions
 - <https://www.icaps-conference.org/competitions/>
 - FastForward (FF) [Hoffmann, 2001] was the winner in the 2002 International Planning Competition (IPC)
 - SATPlan was the winner in the 2004 and 2006 IPC
 - IPC 2014 was won by SymBA*, based on bidirectional search using heuristics and abstraction.
 - IPC 2018 was won by Delfi, using deep learning to select a planner from a collection of planners including Fast Downward (uses forward search) with various heuristics and SymBA*
 - IPC 2020 – Hierarchical planning!
- Classical Planning in practice: Examples
 - Commercial video games [Neufeld, X., et al., 2019]
 - AI planning for enterprise [Sohrabi, S., 2019]
 - Space exploration [Estlin, T., et al. 07] [Rabideau, G., et al., 2020]



Hierarchical Planning and Acting

Manage complexity



Examples

- **Example 1:**

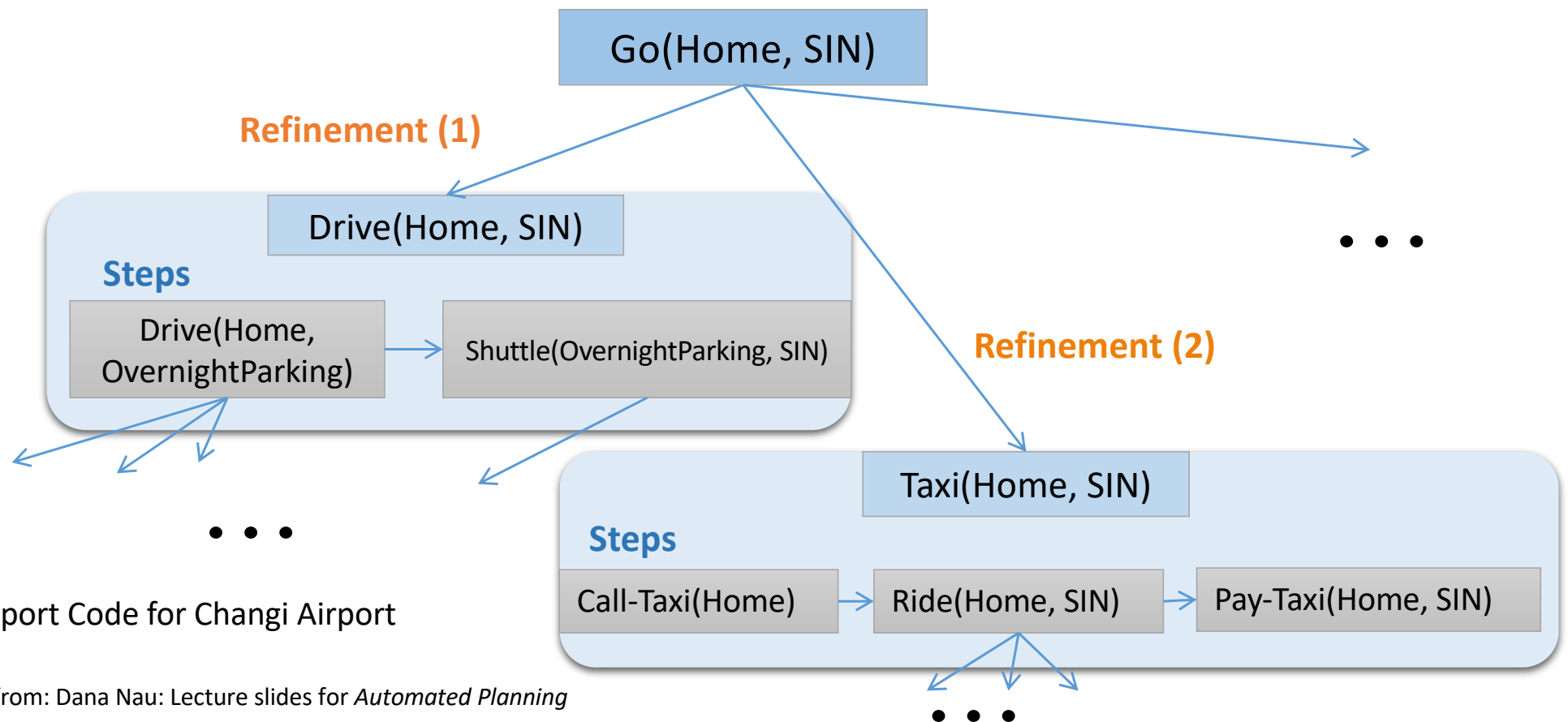
How to go to CS4246 lecture from home?

- Solution: Go to COM1 from home, find lecture hall
- Solution: take MRT, change to internal bus, get off, find SR 2.
- Solution: Switch on laptop, launch Zoom, join lecture

- **Example 2:**

How to land on the Jezero Crater of Mars from X space station?

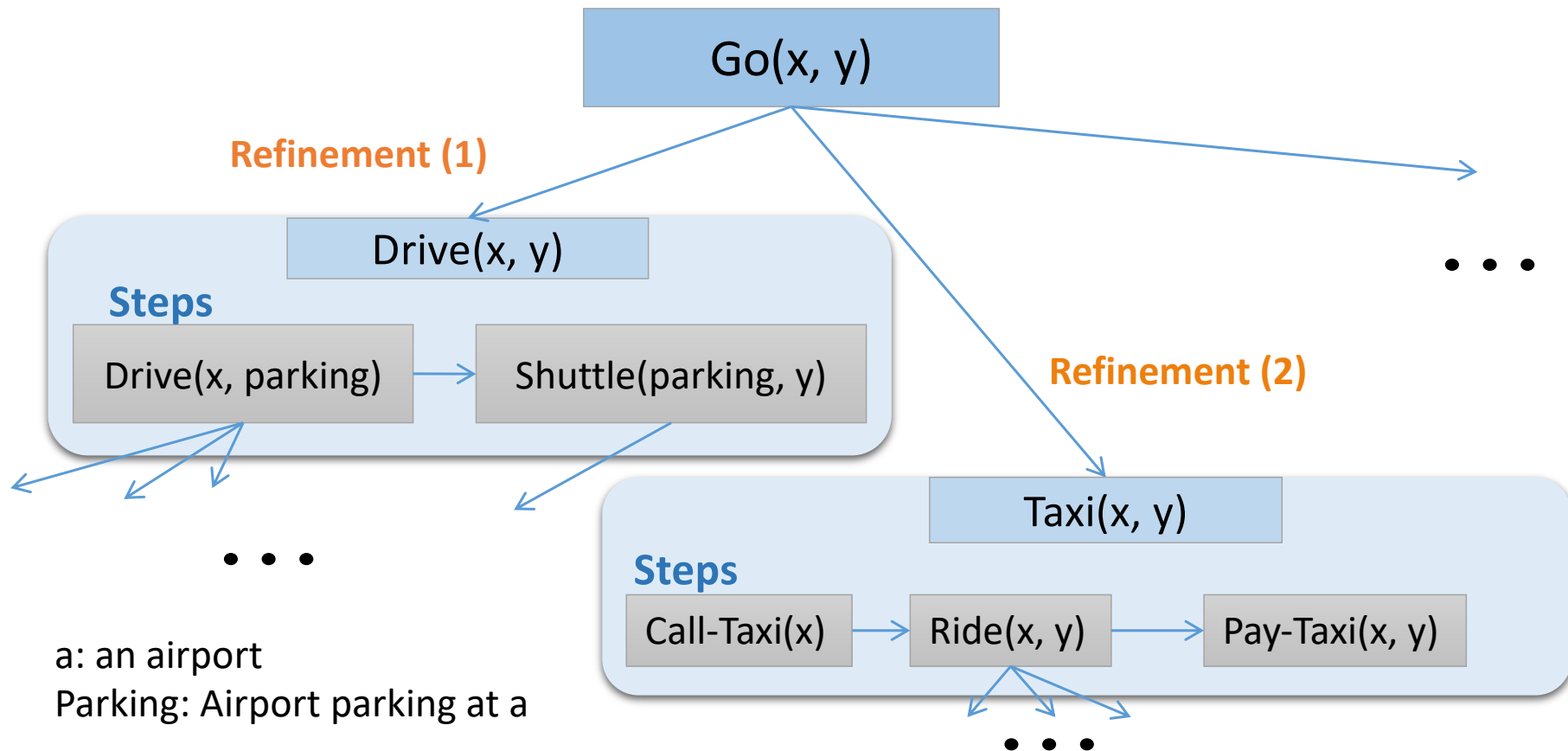
Example: Going to Changi Airport



SIN: Airport Code for Changi Airport

Adapted from: Dana Nau: Lecture slides for *Automated Planning*

Example: Going to an airport





Managing Complexity in Planning

- Hierarchical decomposition
 - Division of **tasks** into different **subtasks** at next level
 - At each level focus only a small number of tasks
- Deferred planning
 - Planning can occur before and during plan execution
 - Particular action can remain at an abstract level prior to the execution phase



Hierarchical Decomposition

- Key benefits
 - At each level of hierarchy, a **task** is reduced to a small number of **subtasks** or **activities** at the next lower level
 - Computational cost of finding the correct way to arrange activities for current problem is small
- Examples
 - Software components, subroutines
 - Military, government, and corporations



Hierarchical Task Networks

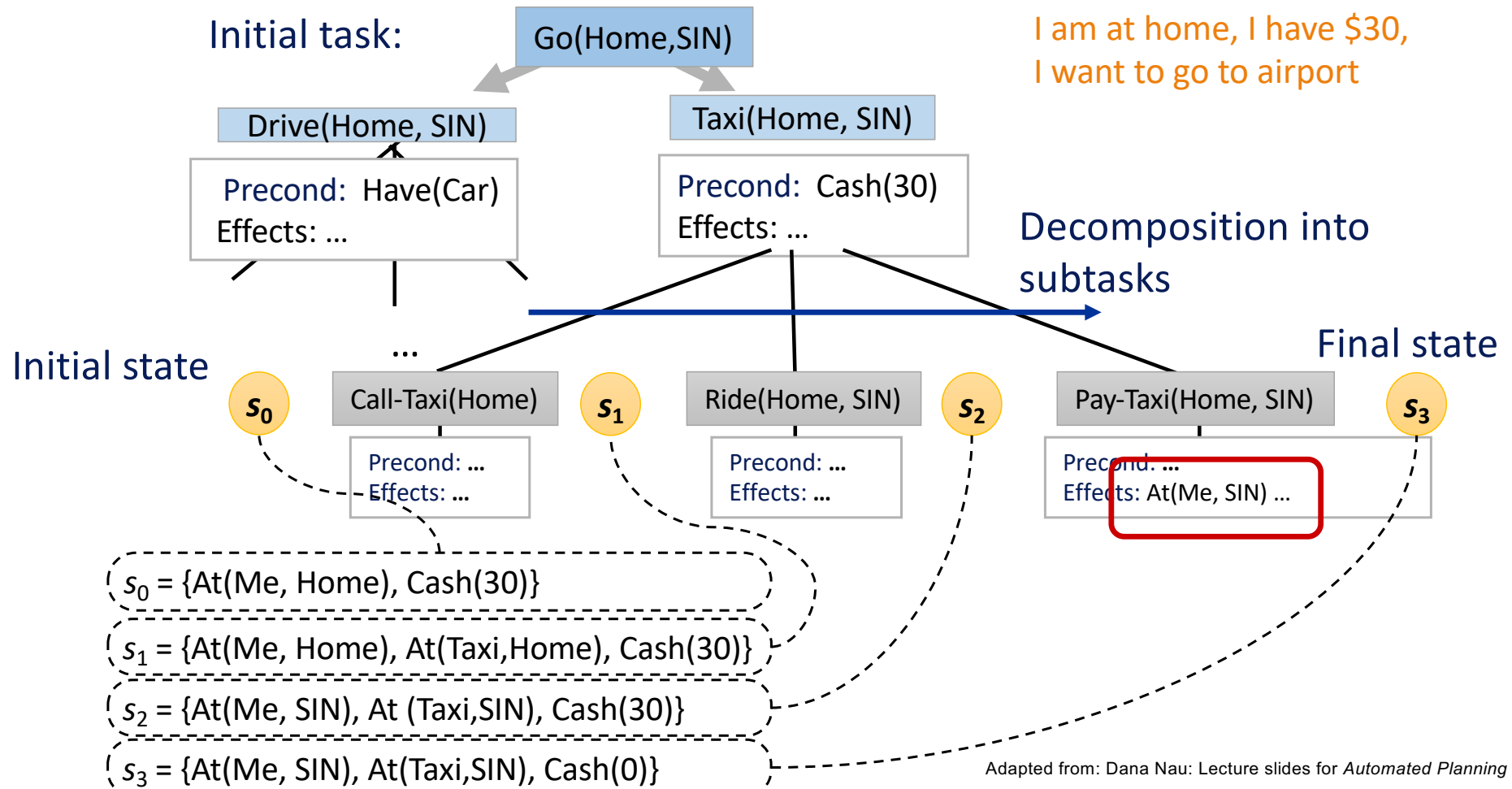
- Hierarchical task networks (HTNs)
 - A formalism to help understand hierarchical decomposition
 - A planning model that manages complexity through task abstractions
- Key concept
 - High-level actions (HLAs)
- Assumptions
 - Full observability
 - Deterministic
 - Availability of primitive actions with standard precondition-effect schemas
 - Main ideas are general in problem solving and planning and decision making



HTN Planning

- Planning Problem or Model
 - HLAs, action schemas, initial state, task list
- Planning Algorithm – How?
 - Input: a problem
 - Output: a solution in the form of an action sequence
- Planning Solution
 - Any executable plan generated by recursively applying:
 - HLA to nonprimitive tasks
 - Actions to primitive tasks
 - A goal state that satisfies certain properties

Example: Going to Changi Airport





High-Level Actions (HLAs)

- Definition

- Each HLA has one or more **refinements** into a sequence of actions
- Each (refined) action can be an HLA or a primitive action
- Recursive refinement may be needed

- Meaning

- HLAs and their refinements embody knowledge about **how to do things**
e.g., Go(Home, SIN) – drive or take a taxi



Implementation

- HLA implementation
 - An HLA refinement that contains only primitive actions
- High-level plan implementation
 - High-level plan – a sequence of HLAs
 - Concatenate implementations of each HLA in the sequence
- Observation
 - Given the precondition-effect definitions of each primitive action, can directly determine whether any given implementation of a high-level plan achieves the goal.

Go(Home,SIN)

Drive(Home, SIN)

Taxi(Home, SIN)

Precond: Have(Car)

Precond: Cash(30)

Effects: ...

Effects: ...

Decomposition into subtasks

Final state

Initial state

 S_0

Call-Taxi(Home)

 S_1

Ride(Home, SIN)

S2

Pay-Taxi(Home, SIN)

S₃

~~Precond. ..~~
~~Effects: ...~~

~~Precond. ...~~
Effects: ...

Precond. ...
Effects: At(Me, SIN) ...

$$s_0 = \{\text{At}(\text{Me}, \text{Home}), \text{Cash}(30)\}$$
$$s_1 = \{\text{At}(\text{Me}, \text{Home}), \text{At}(\text{Taxi}, \text{Home}), \text{Cash}(30)\}$$
$$s_2 = \{At(Me, SIN), At(Taxi, SIN), Cash(30)\}$$
$$s_3 = \{At(Me, SIN), At(Taxi, SIN), Cash(0)\}$$

Adapted from: Dana Nau: Lecture slides for *Automated Planning*



Planning with HLAs

- Definition

- Achieves the goal from a given state if at least one of its implementations achieves the goal from that state

- Note

- Not all implementations need to achieve the goal
- The agent **decides** which implementation to execute

- Question:

- How is this different from **nondeterministic** planning?



Planning with HLAs

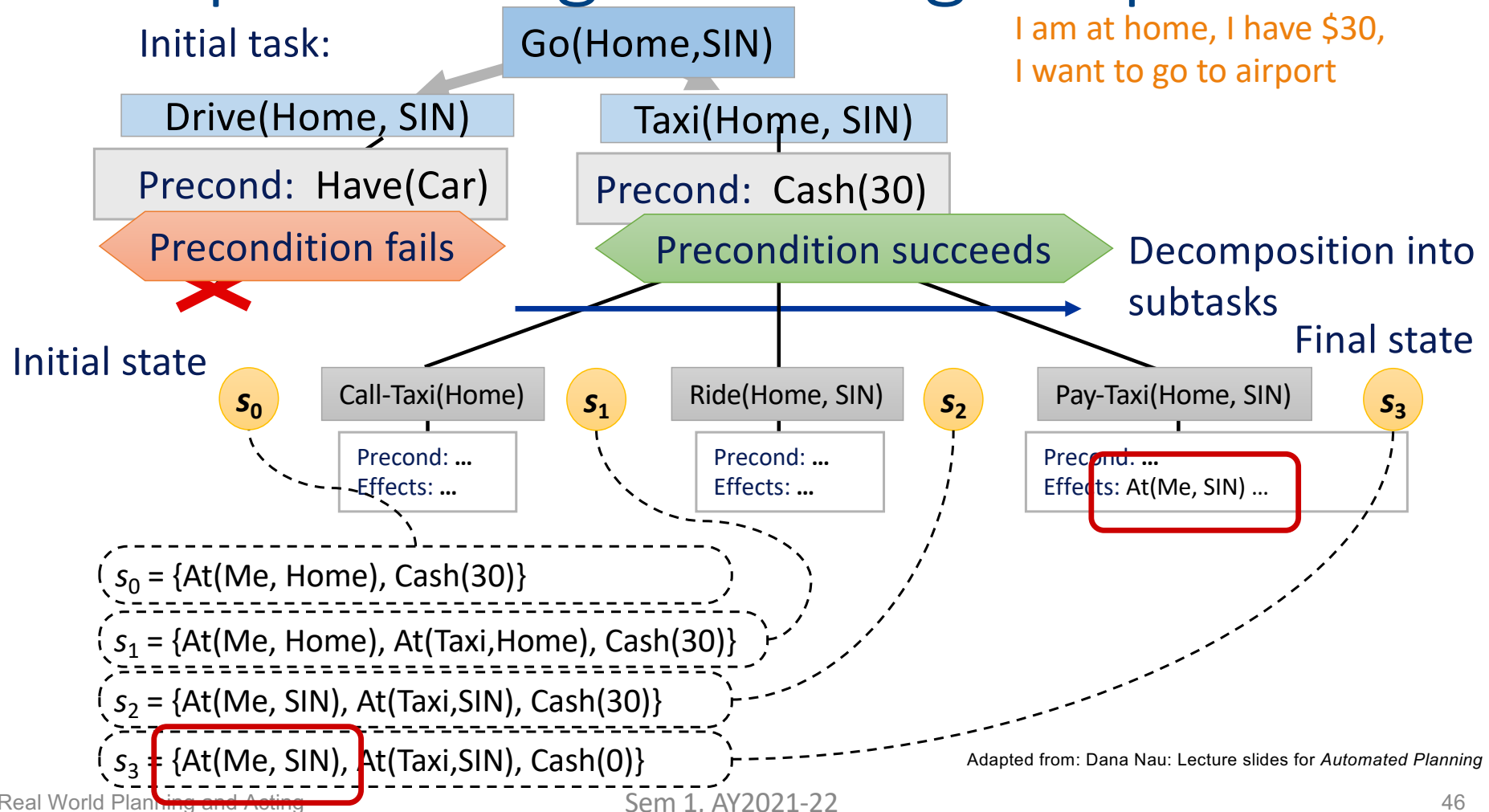
- With one HLA implementation
 - Compute preconditions and effects of HLA from those of the implementation
 - Treat HLA exactly as if it were a primitive action
- Observation
 - Right collection of HLAs can reduce time complexity of (blind) search from exponential to linear in solution depth
 - Devising an appropriate collection of HLAs is **HARD!**
- With multiple HLA implementations
 - Search among implementations for one that works; **OR**
 - Reason directly about the HLAs - enables derivation of provably correct abstract plans, without having to consider their implementations



Hierarchical Planning as Search

Searching for Primitive Solutions

Example: Going to Changi Airport





Searching for Primitive Solutions

- HTN Planning
 - Start with top level action *Act*
 - Find an implementation of *Act* that achieves the goal
- Hierarchical planning algorithm
 - Repeatedly choose an HLA in current plan and replace with refinement
 - Until the plan achieves the goal
- Example:
 - Breadth-first search tree
 - Plans are considered in order of depth of nesting of the refinements, rather than number of primitive steps
 - Can use graph-search, depth-first, and iterative deepening



Generic Planning Framework

- Classical planning definition:
 - For each primitive action ai :
 - Provide one refinement of Act with steps – $[ai, Act]$
 - Create recursive definition of Act to add actions
 - Final refinement:
 - steps – empty, precondition – goal, effect – null
- Algorithm:
 - Repeatedly choose an HLA in the current plan
 - Replace it with one of its refinements
 - Until the plan achieves the goal

Hierarchical Search

function HIERARCHICAL-SEARCH(*problem, hierarchy*) **returns** a solution or *failure*

frontier \leftarrow a FIFO queue with [*Act*] as the only element

while *true* **do**

if IS-EMPTY(*frontier*) **then return** *failure*

plan \leftarrow POP(*frontier*) // chooses the shallowest plan in frontier

hla \leftarrow the first HLA in *plan*, or *null* if none

prefix, suffix \leftarrow the action subsequences before and after *hla* in *plan*

outcome \leftarrow RESULT(*problem*.INITIAL, *prefix*)

if *hla* is *null* **then** // so plan is primitive and outcome is its result

if *problem*.IS-GOAL(*outcome*) **then return** *plan*

else for each *sequence* **in** REFINEMENTS(*hla, outcome, hierarchy*) **do**

 add APPEND(*prefix, sequence, suffix*) to *frontier*

Source: RN Figure 11.8



Hierarchical Search

- Main idea:
 - Explore space of sequences that conform to knowledge in the HLA library about how things are to be done
 - Knowledge encoded in action sequences in each refinement and in the preconditions of the refinements
- Practical impact:
 - Can generate huge plans with little search
 - e.g., O-PLAN to develop production plans for HITACHI (Bell and Tate 1995)
 - Hierarchically structured – easier for human to understand



Complexity Analysis

- Assumption
 - A planning problem has a solution with d primitive actions.
- For non-hierarchical, forward state-space planner
 - With b allowable actions at each state, cost is $O(b^d)$
- For HTN planner
 - Suppose each nonprimitive action has r possible refinements, each into k actions at the next lower level
 - So $r^{(d-1)(k-1)}$ possible regular decomposition trees could be constructed (see details in RN 11.4.2)
- Observation
 - Small r and large k - library of HLAs with small number of refinements each yielding a long action sequence - May be hard to construct!



Proving Plan Properties

Searching for Abstract Solutions

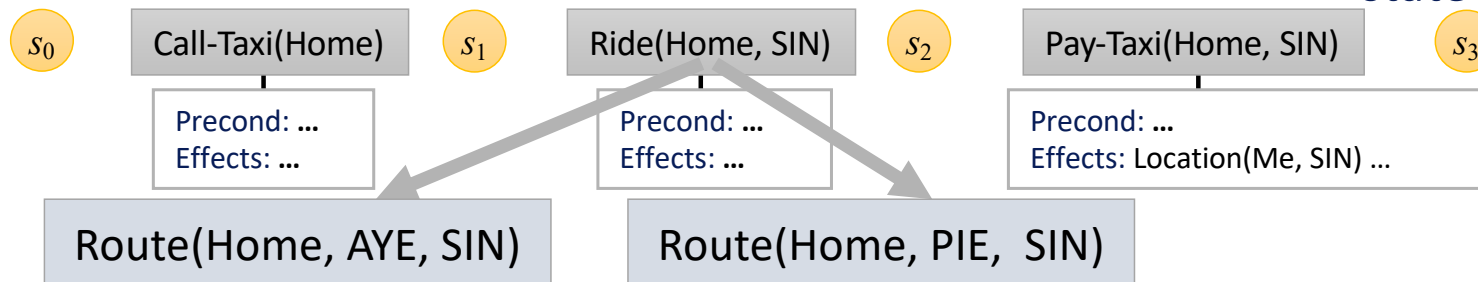
Motivation

- Example:

- We should determine if a high-level plan can get one to the airport, without going through all the specific details like precise route or alighting terminal
[Call-Taxi(Home), Ride(Home, SIN), Pay-Taxi(SIN)]

Initial
state

Final
state





Searching for Abstract Solutions

- Approach

- Write precondition-effect description of the HLAs
- Prove that the high-level plan achieves the goal
- Work in small search space of high-level actions
- Refine committed plan to achieve exponential reduction



Searching for Abstract Solutions

- Downward refinement property (of HLA descriptions)
 - Through description of the steps:
 - Every high-level plan that “claims” to achieve the goal achieves the goal
 - At least one implementation achieves the goal
- Main challenges
 - How to write HLAs with downward refinement property?
 - How to write HLAs with multiple implementations?
 - How to describe effects of an action that can be implemented in many different ways?
- Key idea
 - Determine if **reachable sets** of a sequence of HLAs in the plan overlap with goals



Reachable Set

- Reachable set of an HLA

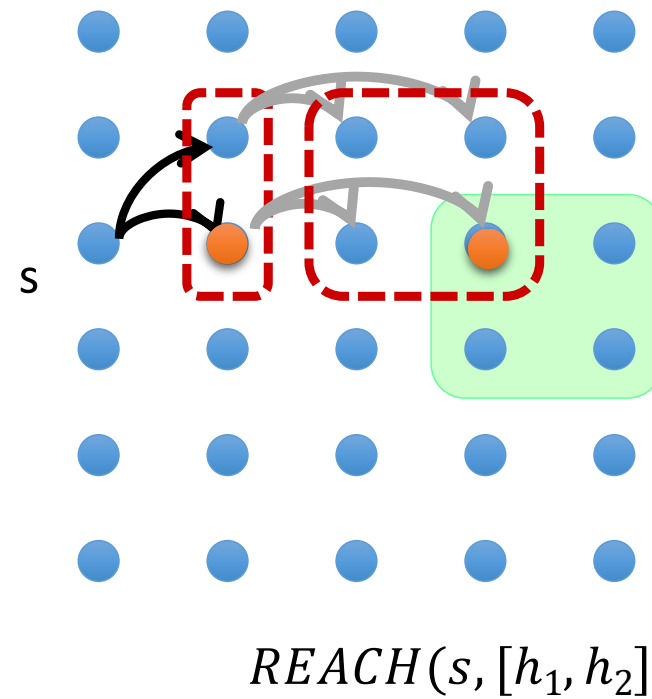
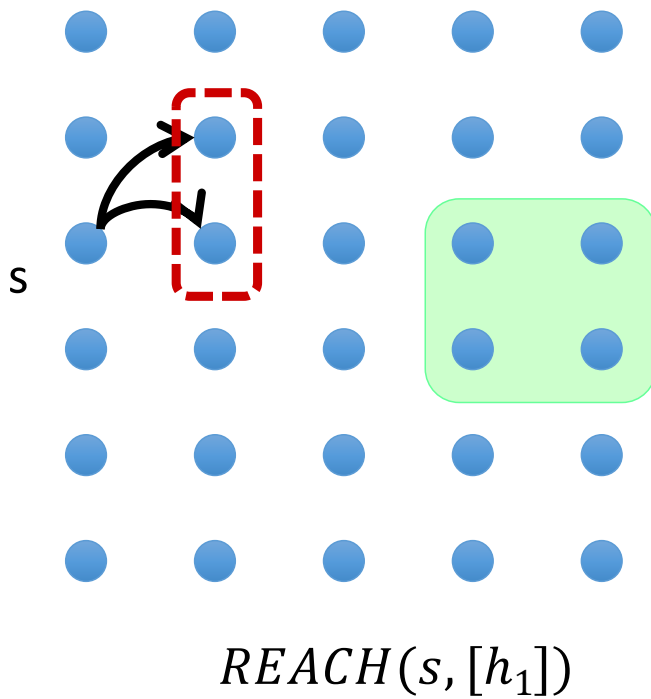
- Given a state s and an HLA h : $REACH(s, h)$ is the set of states **reachable by** any of the HLA's implementations

- Reachable set of a sequence of HLAs

- Reachable set of a sequence of HLAs $[h_1, h_2]$ is the union of all the reachable sets obtained by applying h_2 in each state in the reachable set of h_1 :

$$REACH(s, [h_1, h_2]) = \cup_{s' \in REACH(s, h_1)} REACH(s', h_2)$$

Example



Source: RN: Fig 11.6



High-Level Planning

- Practical implications
 - Agent can choose element of the reachable set it ends up in when it executes the HLA
 - HLA with multiple refinements is more “powerful” than the same with fewer refinements
- High-level plan
 - A sequence of HLAs
 - Achieves goal if its reachable set intersects set of goal states
 - Otherwise, the plan does not work
- Search algorithm
 - Search among high-level plans
 - Look for one whose reachable set intersects goal
 - Once that happens, commit to that abstract plan
 - Focus on refining the plan further



Representing HLA Effects

- Effects as reachable sets
 - As reachable set for each possible initial state
 - Represent changes made to each fluent or state variable
- Recall: Primitive action
 - Can add or delete a fluent or variable or leave it unchanged
- HLA
 - Can also control variable value, depending on implementation chosen
 - Description derivable, in principle, from descriptions of its refinements, such that the downward refinement property holds



Representing Reachable Set

- Notations:

- \sim means possibly, if the agent chooses
- E.g., $\tilde{+}A$ means “possibly add A ”, i.e., either leave A unchanged or make it True

- Questions:

- What do $\simeq A$ and $\tilde{\pm}A$ mean?

- Example

Go(Home, SIN) with two refinements

- *Drive(Home, SIN)* and *Taxi(Home, SIN)*
- Possibly delete *Cash* (if agent decides to take a taxi)
- So should have effect $\simeq \text{Cash}$



Example

- Consider:
 - Schemas for HLAs h_1 and h_2 :
 - Action (h_1 , Precond: $\neg A$, Effect: $A \wedge \simeq B$)
 - Action (h_2 , Precond: $\neg B$, Effect: $\tilde{+}A \wedge \tilde{\pm}C$)
- Meaning:
 - h_1 adds A and possibly delete B
 - h_2 possibly adds A and has full control over C
- Exercise:
 - If only B is true in the initial state and goal is $A \wedge C$
 - What sequence of HLAs will achieve the goal?



Summary

- Hierarchical planning
 - Using abstraction to manage complexity
 - Planning as refinements
 - Planning in abstract space
- HTN Planning
 - Focus on tasks instead of goals
 - Use hierarchical decomposition and delayed planning ideas to manage complexity
- Searching for primitive actions
 - Recursive refinement
- Search for abstract actions
 - Downward refinement property
 - Check if reachable set intersects with goals



Example: PANDA

- The PANDA framework for hierarchical planning
 - <https://rdcu.be/cn6Ra>
 - Höller, D., et al., *The PANDA Framework for Hierarchical Planning*. KI - Künstliche Intelligenz, 2021.
 - Höller, D., et al., *HDDL: An Extension to PDDL for Expressing Hierarchical Planning Problems*. Proceedings of the AAAI Conference on Artificial Intelligence, 2020. **34**(06): p. 9883-9891.



HTN Planning Today

- Key idea
 - Construct plan library (knowledge base) of known methods for implementing complex, HLAs
- Approach
 - Learn planning methods from problem-solving experience
 - Save used plan in library as a method for task-specific HLA implementation
 - Accumulate knowledge over time
 - Generalize methods, eliminating problem-specific details, keeping key elements of the plan
- In practice:
 - Many real-world applications; ideas adopted in modern day planning and reinforcement learning
 - Old HTN planners: Noah, Nonlin, O-Plan, SIPE, SIPE-2, SHOP, SHOP2
 - Fast Downward (Helmert 2006) won 2004 IPC; uses hierarchical decomposition of planning tasks to derive heuristics with delayed evaluation in best first search
 - New research trends in hierarchical planning and hierarchical reinforcement learning



Homework

- Readings:

- Heuristics: RN: 11.3
- Hierarchical: RN: 11.4
- Summary: RN: 11.7
- Complexity: RN Chapter 11, Bibliographical and Historical Notes (last page)

- Reviews:

- RN: 3.3, 3.5, 3.6 (Review of search and heuristics in problem solving)



References

- Content:
 - Nau, Dana. Lecture Slides from Automate Planning: Licensed under the Creative Commons Attribution-NonCommercial-ShareAlike License: <http://creativecommons.org/licenses/by-nc-sa/2.0/>
- Classical planning systems: (Journal articles publicly available online or through NUS Library e-Resources)
 - Hoffmann, J. and B. Nebel, *The FF planning system: fast plan generation through heuristic search*. J. Artif. Int. Res., 2001. **14**(1): p. 253–302.
 - Helmert, M., *The fast downward planning system*. J. Artif. Int. Res., 2006. **26**(1): p. 191–246.
 - Georgievski, I. and M. Aiello, *HTN planning: Overview, comparison, and beyond*. Artificial Intelligence, 2015. **222**: p. 124-156.
- Classical planning in the Real World:
 - Neufeld, X., et al., Building a Planner: A Survey of Planning Systems Used in Commercial Video Games. IEEE Transactions on Games, 2019. 11(2): p. 91-108. <https://ieeexplore.ieee.org/document/8214211>
 - Sohrabi, S., AI Planning for Enterprise: Putting Theory Into Practice, in Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI-19. 2019, International Joint Conferences on Artificial Intelligence Organization. p. 6408--6410. <https://www.ijcai.org/proceedings/2019/0897.pdf>
 - Estlin, T., et al. *Increased Mars Rover Autonomy using AI Planning, Scheduling and Execution*. in *Proceedings 2007 IEEE International Conference on Robotics and Automation*. 2007. https://ai.jpl.nasa.gov/public/documents/papers/estlin_icra07_marsrover.pdf
 - Rabideau, G.; Wong, V.; Gaines, D.; Agrawal, J.; Chien, S.; Kuhn, S.; Fosse, E.; and Biehl, J. [Onboard Automated Scheduling for the Mars 2020 Rover](#). In *Proceedings of the International Symposium on Artificial Intelligence, Robotics and Automation for Space, of i-SAIRAS'2020*, Noordwijk, NL, 2020. European Space Agency https://ai.jpl.nasa.gov/public/documents/papers/M2020_OBP_i-SAIRAS2020_camera.pdf