CS3243 CheatSheet

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Agents and Environment

Agent Components

Sensors and Actuators

- Sensors: information about the env
  - Percept data at timestep t, p_t
  - Percept History, $P = p_1, ..., p_t$
- Actuators: how agent interacts with environment
  set of Actions A

Agent function $f : P \rightarrow a$, where a is a selected action given P

Agent is rational if optimises performance measure (implies quantifiable objective), given

- percept seq
- prior knowledge
- set of actions
- performance measure

Note: do **not** assume agent is omniscient.

Types of agents

1. Reflex Agents
   - uses `if-else` to make decisions, direct mapping of percepts to actions
   - domain specific, impractical for large search space
2. Model-based reflex agent
   - makes decisions based on an internalised model
   - eg logical agents / bayesian networks
3. Goal Utility-based agents
   - Given state, actions and goals / utility
   - Determine seq of actions to reach goal / max utility
   - uninformed / informed search, Local Search, CSP, Adversarial Search

AI as Graph Search

- Each percept corresponds to a state in the problem (state → vertex)
- Define desired (goal) states
- After action, arrive at new state (actions are edges)
- Search space is graph

Problem Env

Fully observable	Partially observable	Whether can sense all information
Deterministic	Stochastic	Whether intermediate state can be determined based on action and state
Episodic	Sequential	episodic: action impacts current state, sequential: actions impact future states
Discrete	Continuous	for state information
Single	Multi agent	other entities that influence agent behaviour, competing or cooperating
Known	Unknown	Knowledge of agent (knowing where is goal state)
Static	Dynamic	If env will change while agent is deciding action

Path Planning

Properties

Environment

- Fully observable
- Deterministic
- Discrete
- Episodic (plan solution, not execute, but plan is formed sequentially)

Search Space

State: representation of instance of environment

Node: Element in frontier representing current path traversed

- State
- Parent Node
- Action
- Path Cost
- Depth

Goal Test function

Actions function

Action costs function (≥ 0)

Transition Model function: takes in a state, applies action, returns new state

Algo Criteria

Efficiency - space and time

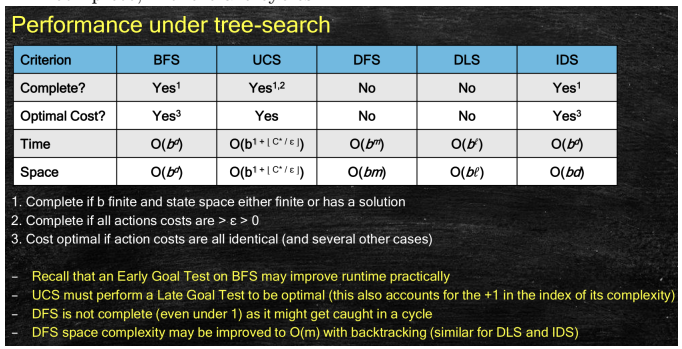
Complete - find a solution when one exists and correctly report failure when it does not

Optimal - solution with lowest path cost among all solutions

Types of search

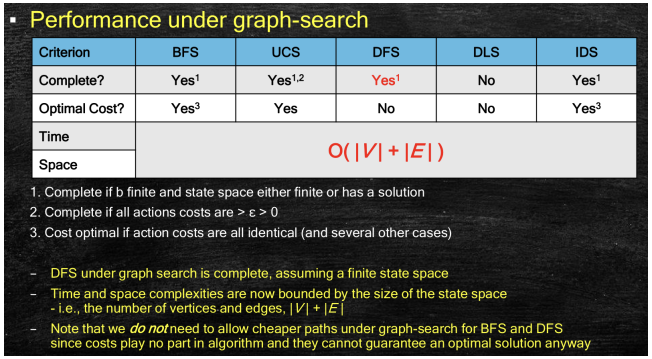
Tree Search

- No restrictions on revisiting states, allows redundant paths, including cycles
- Incomplete, if there are cycles



Graph Search

- Maintain `reached` hash table
- Add nodes to `reached` hash table on push
- Only add new node to frontier (and `reached`) if
  1. state represented has not been reached before
  2. path to state already reached is cheaper than the stored one



Limited Graph Search V1

- Uses `reached` hash table
- Adds to `reached` on push to frontier
- Only pushes to frontier when not in `reached`

Limited Graph Search V2

- Similar to V1
- Adds notes to `reached` on pop from frontier
- Does not check if path is cheaper than stored one
- Not optimal for UCS or A*

Uninformed Search

BFS - Queue

Time: $O(b^d)$

Space: $O(b^d)$

Complete: Yes if finite search space or contains solution

Optimal: No unless costs uniform

b: branching factor

d: depth of shallowest goal

Can be optimised with early goal test (goal test on push to frontier instead of pop)

UCS aka Dijkstra - PQ, path cost

Time: $O(b^e)$

Space: $O(b^e)$

Complete: Yes if finite search space or contains solution

Optimal: Yes, tree, graph and limited V2

e: $1 + \lfloor \frac{C*}{\epsilon} \rfloor$, where C* is the optimal path cost

ϵ: small positive constant, smallest action cost

DFS - Stack

Time: $O(b^m)$

Space: $O(bm)$

Complete: No, unless finite search space

Optimal: No

m: max depth

Note: space can be improved to $O(m)$ by using backtracking (assume fixed order of actions)

Depth Limited Search (DLS)

DFS with depth limit l

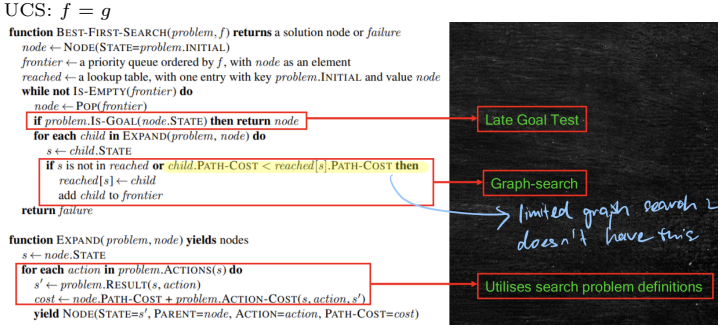
Time: $O(b^l)$
Space: $O(bl)$
Complete / Optimal: No

Iterative Deepening Search (IDS)
Use DLS recursively, each time increasing l by 1
- Completeness of BFS with space complexity of DFS

Overhead: rerun top levels many times ($\sim 11\%$)
- Nodes generated by DLS: $O(b^0 + b^1 + ... + b^l)$
- Nodes generated by IDS: $O((d+1)b^0 + db^1 + ... + b^d)$

Time: $O(b^d)$
Space: $O(bd)$
Complete: same as BFS
Optimal: same as BFS

Informed Search
Use domain knowledge to estimate cost from s to G using heuristic function h
Define evaluation function f to be used as priority function in PQ
UCS: $f = g$



Greedy Best First Search
Explore state that you estimate is closest to a goal
Evaluation fn: $f(n) = h(n)$
Optimal: not optimal as does not take into consideration cost of path travelled (one node very close to goal but high cost to get to adjacent to start node)
Tree Search: Incomplete, stuck between 2 nodes with lowest h values
Graph Search: Complete, if search space is finite

A* Search
Evaluation fn: $f(n) = g(n) + h(n)$
Optimality:
Admissible heuristic: Tree Search, Graph Search
Consistent heursitic: Tree, Graph, Limited Graph V2
A* and Graph Search costly due to updates (need update descendants)

Heuristics
Admissible Heuristics
$\forall n, h(n) \leq h^*(n)$
- $h(n)$ never overestimates the cost
- $h(n) = 0$ at goal

Consistent Heuristics
$\forall n, n', h(n) \leq cost(n, a, n') + h(n')$
- f costs monotonically increasing along a path

Dominance
if $\forall n, h_1(n) \geq h_2(n)$, then h_1 dominates h_2
- if h_1 is also admissible: h_1 closer to h^*, h_1 more efficient than h_2

Note: for 3243, h_1 and h_2 need not be admissible

Creating heuristics
- Want efficient h, close to $O(1)$
- Want admissible, consistent harder

Relaxing the problem
- relaxing constraints gives admissible heuristics
- relaxing more constraints creates less dominant heuristics

Top Down Approach
- What dependent variable do I want to model / approx
- What are the independent variables that help to calculate these

Bottom up Approach
- What variables can you efficiently calculate?
- What can these variables model?

Local Search Problems
- Only have goal test, but not values in goal state
- Want goal state values, not interested in path
- Greedy not systematic
- Space Complexity: $O(b)$, only store node and successors

State formulation
- All states have all components of solution
- no partially filled states
- Each state is a potential solution
- "guess" a soltion
- "check" its value
- make "systematic guess" by moving to states of higher value (higher value closer to goal)

Steepest Ascent Hill Climbing Algorithm

```
current = initial state
while true:
    neighbour = highest-valued successor of current
    if value(neighbour) ≤ value(current) return current
    current = neighbour
```

- Only store current state
- On each iteration, find successor that **improves** on current state
- Requires `actions` and `transitions` to determine successor
- Requires `value`: a way to assign each state a value ($f(n) = -h(n)$)
- If none exists, return current state as the bes option
- **Can fail**, may reutrn non-goal state
- may fail at local maxima, shouldder plateau, ridge

Variants
- Sideways move: replace $\leq$ with $<$
- Can traverse shoulder
- Stochastic hill climbing: chooses randomly among states with values better than current
-try to prevent getting stuck at local maxima
- First Choice: handles high b by randonly generating successors and choosing first one that is better
- Similar to stochastic, handles high b
- Random restart: add outer loop which randomly picks new start state until solution found
- Guaranteed to find solution

Analysis
let p_1 be probability of success, n_1 be number of steps of expected solution, n_2 be no. of steps of expected failure

$$\text{Expected Computation} = n_1 + \frac{1-p_1}{p_1} * n_2$$

Local Beam Search
Algo:
1. Begin with k random starts
2. Each iteration generate successors for all k states
3. Repeat with best k among all successors unless goal found

Better than k parallel random restarts → best k among **all** successors, not best from each set of successors, k times

Stochastic Beam Search
Similar to stochastic hill climbing

Constraint Satisfaction Problem
Systematic search unlike LSP greedy search

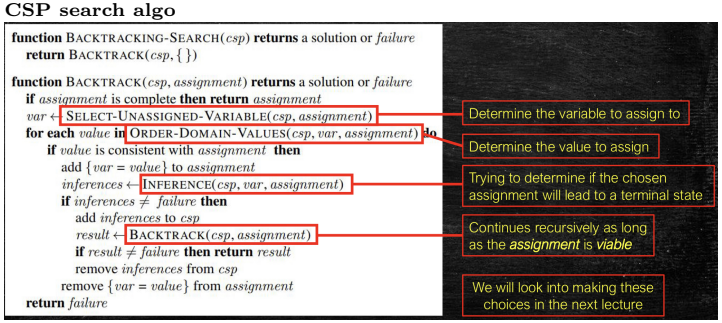
Formulating CSP
State Representation:
- Variables: $X = x_1, x_2, ..., x_n$
- Domains: $D = d_1, d_2, ..., d_n$
- such that x_i has domain d_i
- Initial State: all variables unassigned
- Intermediate State: partial assignment

Goal Test
- Constraints: $C = c_1, c_2, ..., c_m$
- Each c_i describes necessary relationship rel, between set of variables $scope$
- eg. $scope = (x_1, x_2)$ and $rel = x_1 > x_2$
- constraints can be unary, binary, global

Actions and Transitions
- costs and evaluation function not utilised

Objective: find complete and consistent assignment
- complete: all variables assigned
- consistent: all constraints in C satisfied

CSP search algo



- Use DFS as solutions are all at max depth
- Each level assign to only one variable, not all because order does not matter (prunes tree)
- Backtrack when there are no legal assignments