Midterm Review

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Basic Uninformed Search (Summary)

Criterion	Breadth-First	Uniform-Cost	Depth-First	Depth-Limited	Iterative Deepening	Bidirectional (if applicable)
Time	b^d	b^d	b^m	b^l	b^d	$b^{d/2}$
Space	b^d	b^d	bm	bl	bd	$b^{d/2}$
Optimal?	Yes	Yes	No	No	Yes	Yes
Complete?	Yes	Yes	No	Yes, if $l \geq d$	Yes	Yes

b = branching factor
d = depth of shallowest goal state
m = depth of the search space
l = depth limit of the algorithm

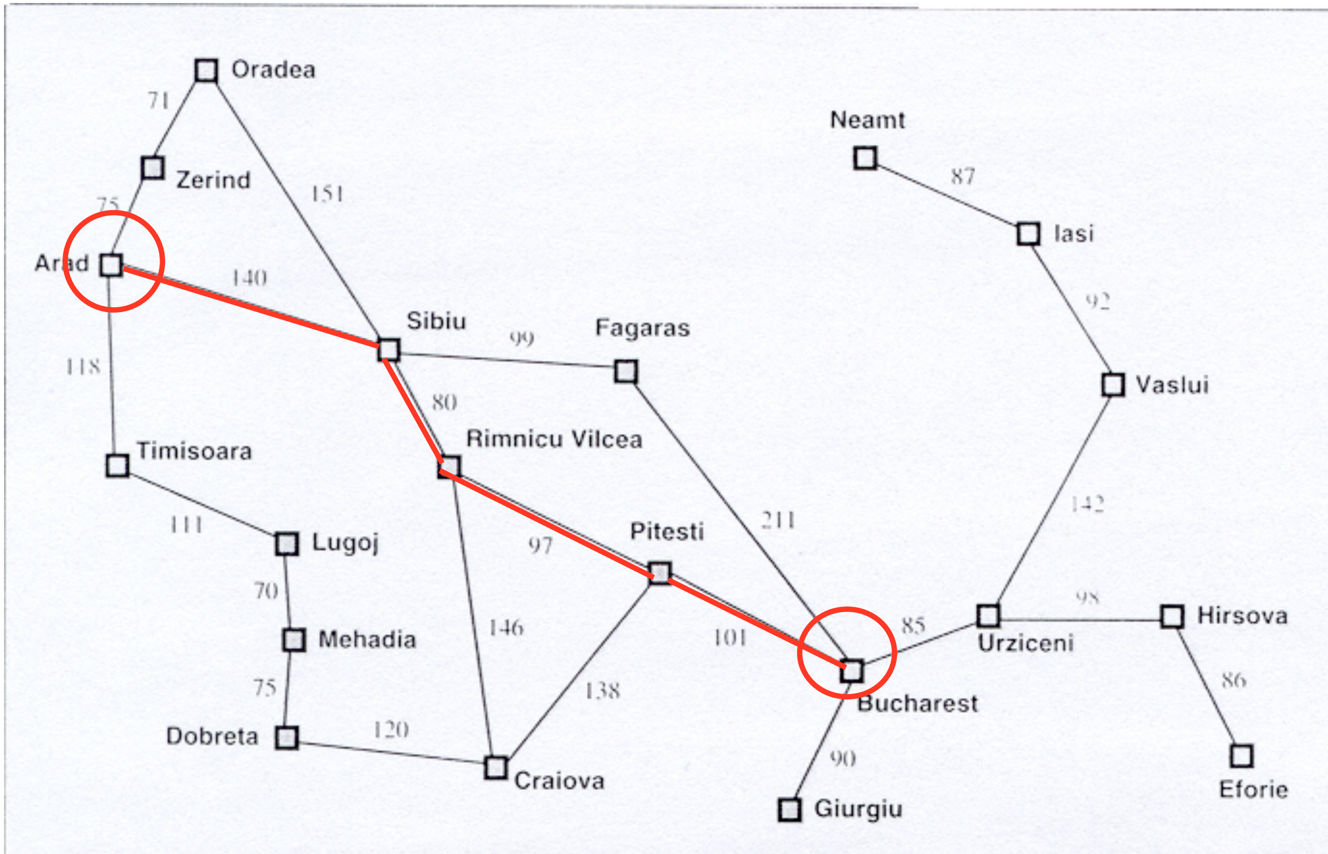
CSP Solving - Backtracking search

- Depth-first search for CSPs with single-variable assignments is called backtracking search
- Improvements:
  - Most constrained variable/Minimum Remaining Values – choose the variable with the fewest legal values
  - Least constraining variable – choose the variable that rules out the fewest values in the remaining value
  - Forward checking – Keep track of remaining legal values and terminate when a variable has no remaining legal values
  - Arc Consistency (AC3) – propagate information across arcs
  - Conflict-Directed Backjumping – maintain a conflict set and backjump to a variable that might help resolve the conflict

A* Search

function A*-SEARCH (*problem*) **returns** a solution or failure
  return BEST-FIRST-SEARCH (*problem, g+h)*

f(n) = estimated cost of the cheapest solution through n
= g(n) + h(n)



Straight–line distance to Bucharest	
Arad	366
Bucharest	0
Craiova	160
Dobreta	242
Eforie	161
Fagaras	178
Giurgiu	77
Hirsova	151
Iasi	226
Lugoj	244
Mehadia	241
Neamt	234
Oradea	380
Pitesti	98
Rimnicu Vilcea	193
Sibiu	253
Timisoara	329
Urziceni	80
Vaslui	199
Zerind	374

A* Search…

In a minimization problem, an admissible heuristic h(n) *never overestimates the real value*

(In a maximization problem, h(n) is admissible if it never *under*estimates)

Best-first search using f(n) = g(n) + h(n) and an admissible h(n) is known as *A* search*

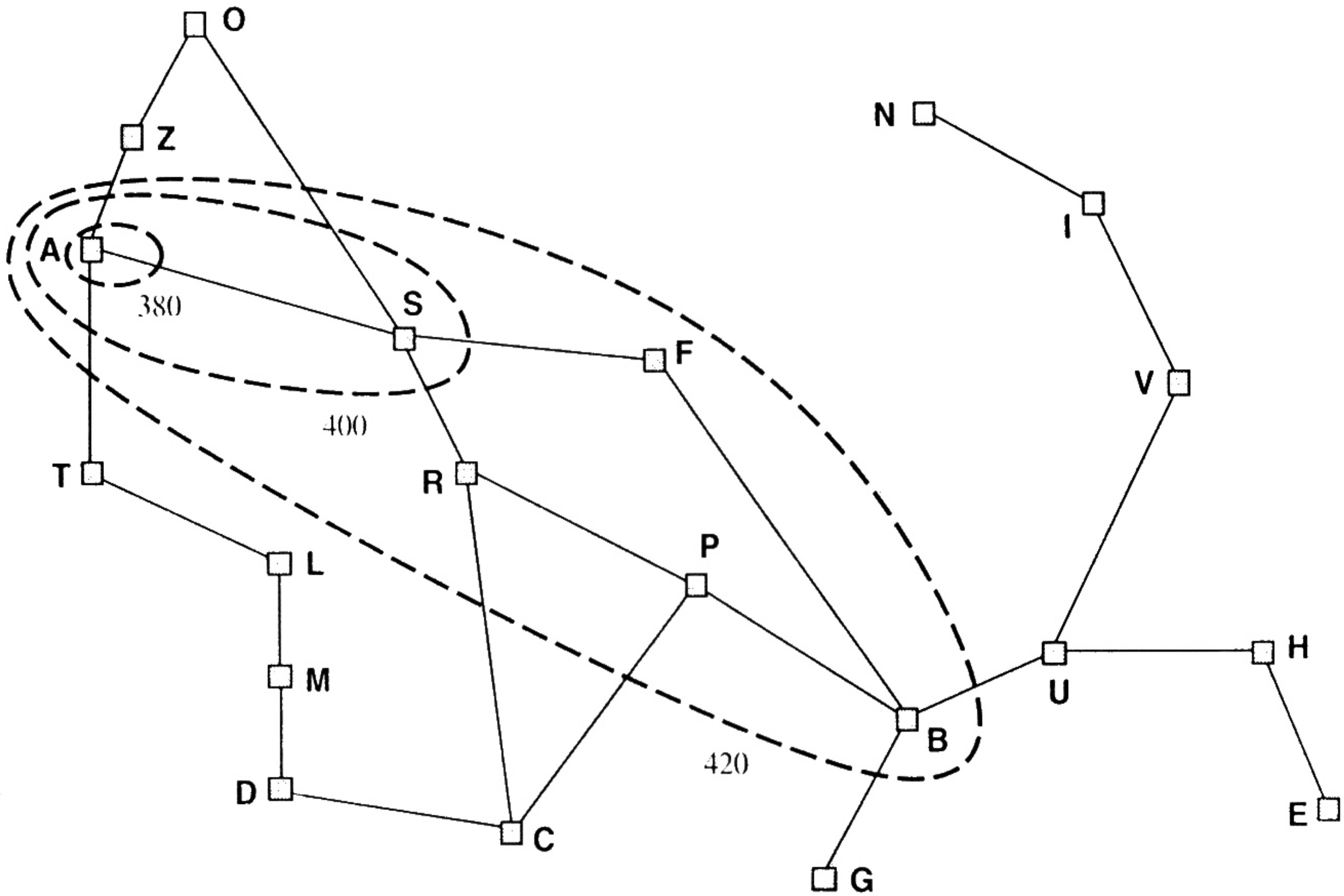
A* tree search is complete & optimal

Iterative Deepening A* (IDA*)

```
function IDA*(problem) returns a solution sequence
  inputs: problem, a problem
  static: f-limit, the current f-COST limit
          root, a node

  root ← MAKE-NODE(INITIAL-STATE[problem])
  f-limit ← f-COST(root)
  loop do
       solution, f-limit ← DFS-CONTOUR(root,f-limit)
       if solution is non-null then return solution
       if f-limit = ∞ then return failure; end

function DFS-CONTOUR(node,f-limit) returns a solution sequence and a new f-COST limit
  inputs: node, a node
           f-limit, the current f-COST limit
  static: next-f, the f-COST limit for the next contour, initially ∞

  if f-COST[node] > f-limit then return null, f-COST[node]
  if GOAL-TEST[problem](STATE[node]) then return node, f-limit
  for each node s in SUCCESSOR(node) do
     solution, new-f ← DFS-CONTOUR(s,f-limit)
     if solution is non-null then return solution, f-limit
     next-f ← MIN(next-f, new-f); end
  return null, next-f
```

f-COST[*node*] = g[*node*] + h[*node*]

A* vs. IDA*



Map of Romania showing contours at $f = 380$, $f = 400$ and $f = 420$, with Arad as the start sate. Nodes inside a given contour have f-costs lower than the contour value.

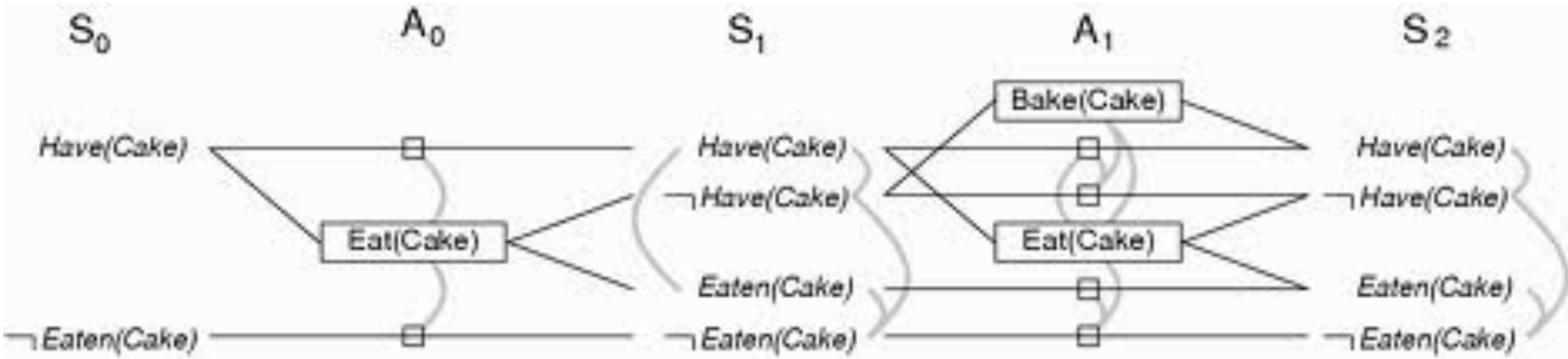
LP, IP, MIP, WDP, etc …

- Topics you should know at a high level:
  - LP: visual representation of simplex
  - (M)IP: Branch and cut (what are cuts? Why do we use them?)
    - Cuts should *separate* LP optimum from integer points
    - Gomory cuts:
      - Let the columns of $A \in \Re^{m \times n}$ be denoted by $\{a_1, a_2, \ldots a_n\}$
      - $S = \{x \in \mathbb{Z}^n_+ \mid Ax \leq b\}$.
        1. Choose nonnegative multipliers $u \in \Re^m_+$
        2. $u^T Ax \leq u^T b$ is a valid inequality ($\sum_{j \in N} u^T a_j x_j \leq u^T b$).
        3. $\sum_{j \in N} \lfloor u^T a_j \rfloor x_j \leq u^T b$ (Since $x \geq 0$).
        4. $\sum_{j \in N} \lfloor u^T a_j \rfloor x_j \leq \lfloor u^T b \rfloor$ is valid for X since $\lfloor u^T a_j \rfloor x_j$ is an integer
- Topics you should know well:
  - Formulating a combinatorial search problem as an IP/MIP (think HW2, P2)
  - (M)IP: Branch and bound (upper bounds, lower bounds, proving optimality)
  - Principle of least commitment (stay flexible)

Planning Review

- STRIPS – basic representation
- Linear Planning – work on one goal at a time. Solve goal completely before moving onto the next one.
  - Reduces search space since goals are solved one at time.
  - But this leads to incompleteness [Sussman Anomaly]
  - Planner's efficiency is sensitive to goal orderings
  - Concrete implementation as an algorithm: GPS [look over example in slides]
- Partial-Order Planning – only constrain the ordering in the problem only as much as you need to at the current moment.
  - Sound and complete whereas Linear Planning is only sound
- Graph plan – try to "preprocess" the search using a planning graph
- SatPlan – generate boolean SAT formula for plan
  - What was the limitation?

Planning Graph



Adds a level until either a solution is found by EXTRACT-SOLUTION [either CSP or backwards search] or no solution exists.

Mutex Rules for Actions

- Mutex between two actions at a given level:
  - Inconsistent effects: One action negates the effect of the other
  - Interference: One of the effects of an action is the negation of a precondition of the other
  - Competing needs: One of the preconditions of one action is mutually exclusive with a precondition of the other.

Mutex Rules for Literals

- Literals negation of the other [easy]
- Inconsistent support – if each possible pair of actions from the prior action graph level that could achieve the two literals is mutually exclusive.
  - Check to see if pairs of actions that produce literals are mutex on the past action level.
  - Look at Book example