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| Notation | | | |  |  | |
| [indicator function]  {set of unique elements}  Product | | | |  |  | |
| Week 1 | | | |  |  | |
| Week 2 | | | |  |  | |
| Week 3 Search | | | |  |  | |
| **Reflex** > **States** (search, MDPs, games) > **Variables** (CSP, Markov Networks, Bayesian Network)> **Logic**   * Search is powerful iff well understood world states and actions. So key skill is defining and decomposing problems into states * State is a summary of past actions sufficient to choose future actions optimally. State collapses tree into having only info that we use to choose future actions optimally to avoid the exponential blow ups * Search problem is an abstraction that provides a clean interface to the world to find optimality * Paradigm is the trifecta: modelling, learning (structured perceptron), inference | | | | Definition of search problem   1. Sstart Start state 2. Action(s): possible actions from states 3. Cost(s,a): cost of the action from state s 4. Succ(s,a): successor state from state s given action a 5. IsEnd(s): reached end state? | | |
| **1. Tree search**   * Enumerating all states and actions but not done in practice so we build algorithms to help instantiate a search tree. * Tree search is memory efficiency but exponential time complexity | | | | **2. DP**  DFS with reuse | | **3. UCS** The analog of DP for BFS |
| **1a. Exhaustive**  If b actions per state and max depth of D | **1b. DFS**  Key idea is backtracking search plus terminate when it finds first end state | **1c. BFS**  Key idea: explore all nodes in order of increasing depth  Space > DFS because @ lowest level have to remember the queue of nodes to explore | **1d. DFS-ID** | Definition of DP   1. Recurse 2. If already computed for s, return cached answer   Effect: recasts tree search problem as a DAG. If not DAG then DP breaks! | | 1. Expand sates close to the start 2. Use past-cost to re-use computation   Key idea: UCS enumerates sates in order of increasing past cost.  Implementation diff: UCS start to end, Djikstras all nodes |
| |  |  |  |  |  | | --- | --- | --- | --- | --- | |  | Exhaustive | DFS | BFS | DFS-ID | | Edge Cost | Any | 0 | ≥ 0 | ≥ 0 | | Time | O(bD) | O(bD) | O(bd) | O(bd) | | Space | O(D) which is small | O(D) | O(bD) > DFS | O(d) | | | | | |  |  |  | | --- | --- | --- | |  | DP | UCS | | Cycles | No | Yes | | Edge cost | Any | ≥ 0 | | Time | O(n) | O(nlogn) | | Space | ? | ? | | | |
| **4. A\*** Key idea is to distort edge costs to favour certain end states  A\* explores in order of past cost(s,a) and future cost (h(s))  Cost’(s,a) = cost(s,a) + h(succ(s,a)) –h(s)  Definition of h(s) is any estimate of future cost (s). If h(s) =0 means I’m on the optimal path. | | | |  | | |
| Week 4 MDP | | | |  |  | |
| Relationship to search. Many similarities but one main one and one minue one. Major is the transition probabilities minor is changed from minimising cost to maximising rewards.   1. succ(s,a) becomes T(s,a,s’). Transition distribution for each state, s is . Introduced via the chance nodes. 2. cost(s,a) becomes Reward(s,a,s’). Reward may be positive or negative   Definitions   * Policy: A mapping from each state s \in States to an action a \in Actions * Utility: Following a policy yields a random path. The utility of a policy is the discounted sum of the rewards on the path. This is a random variable. * Path: s0 → a1,r1,s1 → a2,r2,s2 … (action, reward, new state) * Utility: r1 + r2 + r3 + … * Value: The value of a policy at a state is the expected utility. Also known as expected utility | | | | Definition   1. Sstart Start state 2. Action(s): possible actions from states 3. T(s,a,s’): transition prob of s’ by taking action a from a 4. R(s,a,s’): reward for taking T(s,a,s’) 5. Succ(s,a): successor state from state s given action a 6. IsEnd(s): reached end state? 7. 0 ≤ ≤ 1: discount factor (default 1) | | |
| What is a solution for MDP?   * Policy * Utility | | | |  |  | |
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| Week 6 Adversarial Games | | | |  |  | |
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| Alpha beta pruning is a technique to minimise search of minimax   * When beta <= alpha then we break * The recursion is DFS. It evaluates the first leaf as a baseline. | | | |  |  | |
| Week 7 CSPs | | | |  |  | |
| Factor graphs   * Variables * Domain * Constraints/factor: scope, expression | | | |  |  | |
| Dynamic Ordering | | | |  |  | |
| Arc consistency: take forward look ahead to the extreme. Can solve large problems. Limitation: only looks at pairwise constraints (local structure) not global structures | | | |  |  | |
| Modelling: binary constraints easiest to reason about, lots of tools. Every n-ary CSP can be reduced to binary CSPs. | | | |  |  | |