### 1 Rational Agents

**Agent:** Perceives via sensors, acts via actuators

Rational: Maximizes expected performance given percepts

and knowledge ( $\neq$  omniscient)

Most challenging env: Partially observable, nondetermin-

istic, strategic, dynamic, continuous, multi-agent

### 2 Search Fundamentals

Problem: State space, initial state, actions, goal test, path

costs

**Solution:** Action sequence from initial  $\rightarrow$  goal state

### 2.1 Search Criteria

Complete: Finds solution if exists

Optimal: Lowest path cost

Complexity: b (branching), d (goal depth), m (max depth)

#### 2.2 Uninformed Search

**BFS:** layer by layer

**UCS:** Priority queue by path cost to node n: g(n)

**DFS:** deepest node first

**IDS:** DFS with increasing depth limits **Bidirectional:** Forward+backward search

## 3 CSPs

Variables:  $\{x_1, \ldots, x_n\}$ , Domains:  $\{dom_1, \ldots, dom_n\}$ ,

Constraints: Allowable value combinations

Solution: Complete value assignment

# 3.1 Backtracking Heuristics

**Most-Constrained Var:** Fewest remaining values, red. *b* **Most-Constraining Var:** Most constraints on unassigned, tie-breaker for (1)

**Least-Constraining Value:** Prefer value that rules out fewest choices for neighbors

### 3.2 Inference

Forward Checking: Delete inconsistent neighbor values, backtrack if any variables domain becomes empty

Arc Consistency (AC-3):  $\forall x \in X, \exists y \in Y \text{ satisfying constraint, } O(d^3n^2), \text{ NP-hard}$ 

# 3.3 Exploiting Structure

**Disconn.** components of contraint graph can be solved independently

**Tree CSPs:**  $O(nd^2)$  with topological node order which enforces are consistency (value assign. from root) (Almost-TCSPs: cutset conditioning (break loops in graph) and tree decomposition (connected subproblems organized as tree))

### 4 Informed Search

**Heuristic** h(n) estimates cheapest cost to goal from node n **Consistent** iff it is less than or equal to the actual cost of action a (overly optimistic) (implies admissibility)

#### 4.1 Best-First Variants

**Greedy:** f(n) = h(n), fast but incomplete/non-optimal

**A\*:** f(n) = g(n) + h(n) (UCS + Best-First)

- Complete/optimal if h admissible:  $h(n) \leq h^*(n)$
- Graph-search optimal if h consistent,  $h(s) h(s') \le c(a)$
- Exponential space complexity

**IDA\*:** f-cost cutoff, memory efficient

# 4.2 Local Search (if goal path irrelevant)

**Hill-climbing:** Move to best neighbor state, issues: local maxima/plateaus/ridges

Simulated annealing: Accept bad moves with decreasing probability (temperature T)

Genetic algorithms: Population evolution: fitness func for individuals, selection, crossover, mutation

#### 5 Games

Game: Initial state, operators (legal moves), terminal test, utility function (outcome of game)

**Properties:** States fully accessible, contingency problem, huge state space

### 5.1 Minimax

DFS game tree, MAX maximizes, MIN minimizes utility Use evaluation function for non-terminals (prefer quiescent positions) to avoid horizon effect

# 5.2 Alpha-Beta Pruning

 $\alpha$ : best MAX value,  $\beta$ : best MIN value so far Prune when  $\alpha \geq \beta$  (both MIN and MAX), Best case:  $b \to \sqrt{b}$  (depends on move ordering)

#### 5.3 Chance Games

Add chance nodes: value =  $\sum P(\text{outcome}) \times \text{value}(\text{outcome})$ 

# 6 Propositional Logic

Syntax: Literals, clauses (disjunctions), Semantics: Truth interpretations Entailment: KB  $\models \alpha$  if  $\alpha$  true in all KB models

#### 6.1 CNF Conversion

- 1. Eliminate  $\Rightarrow$ ,  $\Leftrightarrow$ :  $\alpha \Rightarrow \beta$  becomes  $(\neg \alpha \lor \beta)$
- 2. Move  $\neg$  inward:  $\neg(\alpha \land \beta)$  becomes  $(\neg \alpha \lor \neg \beta)$
- 3. Distribute  $\vee$  over  $\wedge$ :  $(\alpha \wedge \beta) \vee \gamma$  becomes  $(\alpha \vee \gamma) \wedge (\beta \vee \gamma)$

**CNF:** 
$$\bigwedge_{i=1}^{n} \left(\bigvee_{j=1}^{m_i} l_{i,j}\right)$$
, **DNF:**  $\bigvee_{i=1}^{n} \left(\bigwedge_{j=1}^{m_i} l_{i,j}\right)$ 

# 6.2 Resolution (derive formulae from KB)

**Goal:** Prove KB  $\models \alpha$  by showing KB  $\cup \{\neg \alpha\}$  unsatisfiable

**Req:** All sentences in CNF

**Rule:** From  $C_1 \cup \{l\}, C_2 \cup \{\neg l\}$  derive resolvent  $C_1 \cup C_2$ 

Empty clause □ proves unsatisfiability

## 7 Boolean Satisfiability Problem (SAT)

**Goal:** Find satisfying assignment (model) for CNF formula or prove none exists.

#### **7.1 DPLL**

Given a set of clauses  $\Delta$  over a set of variables  $\Sigma$ :

- 1. If  $\Delta = \emptyset$  return "satisfiable"
- 2. If  $\square \in \Delta$  return "unsatisfiable"
- 3. Unit propagation: assign unit clause literals, recurse
- 4. Split: try both values for unassigned variable, recurse

### **7.2 CDCL**

Enhances DPLL with conflict analysis, clause learning and backjumping.

# 8 Action Planning

Goal: Find action sequence to achieve goals.

#### 8.1 STRIPS

States: Sets of true propositions (closed world assumption)

**Actions:** Preconditions + effects (add/delete lists)

**Planning task:**  $\langle S, O, I, G \rangle$  (states, operators, initial, goal)

# **8.2 PDDL**

Standard planning language, extends STRIPS with typing, conditional effects, numerical resources

# 8.3 Algorithms

**Progression:** Forward search from initial state **Regression:** Backward search from goal

# 9 Probability / Decisions

**Prior:** P(A), **Posterior:** P(A|B)

**Product rule:**  $P(A \wedge B) = P(A|B)P(B)$ 

**Independence:** P(a|b) = P(a) iff  $P(a \land b) = P(a)P(b)$ 

Bayes' Rule:

$$P(\text{cause}|\text{effect}) = \frac{P(\text{effect}|\text{cause})P(\text{cause})}{P(\text{effect})}$$

#### 9.1 Bayesian Networks

Structure: Directed Acyclic Graph, nodes = variables, 13.1 Search Complexities edges = dependencies

**Joint distribution:**  $P(x_1, ..., x_n) = \prod_{i=1}^n P(x_i|\text{parents}(x_i))$ **Inference:** Generally NP-hard,  $O(2^n)$ . Linear for polytrees. Conditional Independence: Node independent of nondescendants given parents

# 10 (Action) Decision Theory

**Utility:** U(S) assigns values to states

Axioms: Orderability, Transitivity, Continuity

**MEU:**  $EU(A|E) = \sum_{i} P(\text{Result}(A) = i|\text{Do}(A), E)U(i)$  (rational agent maximizes MEU)

### 10.1 MDPs

Components: States S, actions A, transitions P(s'|s,a), rewards R(s)

**Policy:**  $\pi(s)$  maps states  $\rightarrow$  actions (goal: find  $\pi*$ )

### 10.2 Bellman Equation

$$U(s) = R(s) + \gamma \max_{a} \sum_{s'} P(s'|s, a)U(s')$$

$$\pi(s) = \arg\max_{a} \sum_{s'} P(s'|s, a) U(s')$$

## 10.3 Algorithms

Value iteration:  $U'(s) \leftarrow R(s) + \gamma \max_{a} \sum_{s'} P(s'|s, a) U(s')$ **Policy iteration:** Alternate evaluation + improvement

# 11 Machine Learning

Ockhams razor: Choose simplest hypothesis consistent with the data

### 11.1 Decision Trees

**Algorithm:** Greedy divide-and-conquer

- 1. Same class  $\rightarrow$  leaf
- 2. Select best attribute (max info gain)
- 3. Recurse
- Entropy:  $I(P(y_1), ..., P(y_n)) = \sum_{i=1}^{n} -P(y_i) \log_2 P(y_i)$
- Evaluation: Separate training/test sets

# 12 Deep Learning

Multiple layers learn feature hierarchies

### 12.1 MLPs

Structure: Input, hidden, output layers Training: Minimize loss with SGD + backpropagation

### 13 Quick Reference

Criterion	Breadth-	Uniform-	Depth-	Depth-	Iterative	Bidirectional
	First	Cost	First	Limited	Deepening	(if applicable)
Complete?	Yesa	Yes <sup>a,b</sup>	No	No	Yesa	Yes <sup>a,d</sup>
Time	$O(b^d)$	$O(b^{1+\lfloor C^*/\epsilon \rfloor})$	$O(b^m)$	$O(b^l)$	$O(b^d)$	$O(b^{d/2})$
Space	$O(b^d)$	$O(b^{1+\lfloor C^*/\epsilon \rfloor})$	O(bm)	O(bl)	O(bd)	$O(b^{d/2})$
Optimal?	Yes <sup>c</sup>	Yes	No	No	Yes <sup>c</sup>	Yes <sup>c,d</sup>

- branching factor
- depth of solution
- maximum depth of the search tree
- cost of the optimal solution minimal cost of an action

- a b is finite
- b if step costs not less than  $\epsilon$
- c if step costs are all identical
- d if both directions use breadth-first search

## 13.2 Probability Rules

$$P(A \cup B) = P(A) + P(B) - P(A \cap B)$$

 $P(A|B) = \frac{P(A \cap B)}{P(B)}$  if P(B) > 0

If mutually exclusive:  $P(A \cap B) = 0$ 

If independent: P(A|B) = P(A)

## 13.3 Logic Equivalences

$$\neg (A \wedge B) \equiv (\neg A \vee \neg B)$$
 (De Morgan)

$$\neg (A \lor B) \equiv (\neg A \land \neg B)$$
 (De Morgan)

$$(A \Rightarrow B) \equiv (\neg A \lor B)$$

$$(A \Leftrightarrow B) \equiv ((A \Rightarrow B) \land (B \Rightarrow A))$$

# 13.4 AC-3 Step-by-Step

For each arc  $(X_i, X_i)$ : Remove values from  $dom(X_i)$  that have no supporting value in  $dom(X_i)$ . If domain becomes empty, return inconsistent.

# 13.5 CNF Conversion Examples

$$\phi \Leftrightarrow \psi \equiv (\phi \Rightarrow \psi) \land (\psi \Rightarrow \phi) \equiv (\neg \phi \lor \psi) \land (\neg \psi \lor \phi)$$

## 13.6 Resolution Steps

To prove  $KB \models \alpha$  show that  $K \cup \{\neg \alpha\} \models \bot$ :

- 1. Add  $\neg \alpha$  to KB
- 2. Convert all to CNF clauses
- 3. Apply resolution rule until  $\square$  derived
- 4. If  $\square$  found  $\Rightarrow$  KB  $\models \alpha$

# 13.7 MDP Value Update

$$U^{t+1}(s) = R(s) + \gamma \max_{a} \sum_{s'} P(s'|s, a) U^{t}(s')$$

# 13.8 MDP Policy Improvement

- 1. Policy evaluation, given policy  $\pi_t$  calc. utilities  $U_t = U^{\pi_t}$
- 2. Policy improvement

$$\pi_{t+1}(s) = \operatorname{argmax}_a \sum_{s'} P(s'|s, a) U_t(s')$$

### 13.9 Information Gain Calculation

 $Gain(A) = Entropy(S) - \sum_{v} \frac{|S_v|}{|S|} Entropy(S_v)$ where  $S_v = \text{subset}$  with attribute A = v

Entropy:  $H(S) = -\sum_{i} p_{i} \log_{2} p_{i}$ 

### 13.10 Alpha-Beta Pruning Rules

Initialize root with  $\alpha = -\infty$ ,  $\beta = \infty$ 

Prune if  $\beta < \alpha$ 

Update:  $\alpha = \max(\alpha, value)$  at MAX

Update:  $\beta = \min(\beta, value)$  at MIN

## 13.11 CSP Arc Consistency

Arc  $X \to Y$  consistent if:  $\forall x \in D_X, \exists y \in D_Y$  such that (x,y)satisfies constraint

### 13.12 Misc

If two events A and B are unconditionally independent, they may not be conditionally independent given another event C.

If two DTs are equally accurate, the one with fewer nodes is preferrable since it is less prone to overfitting.

ML: Manual feature engineering, simpler models, perform well on structured data and simpler problems, requires less computational power

**DL:** Automatically learns features from data, can handle large complex datasets by learning hierarchical features and using deep architectures, requires a lot more computational power

**NOTE:** Predicate Logic (PL1) missing