

1

Turing Test: Intelligence = *Acting Humanly*

- ▶ Alan Turing (1950) “Computing Machinery and Intelligence”
 - ▶ Proposed an **imitation game**
 - ▶ Predicted that by 2000, machines could fool average person for 5 minutes, 30% of the time
- ▶ One problem: not everyone agrees on the standard proposed by the test, and whether it is meaningful
- ▶ In any case, we still haven't got there yet...
 - ▶ Loebner prize for convincing bots would award up to \$100,000 (and a gold medal) for a truly convincing interactive agent
 - ▶ No such agent has ever really been approached

▶

2

What Should an Intelligent System Do?

- ▶ Following Turing, we take an **operational** approach:

Intelligence is defined by some means of measuring performance in a set task.

- ▶ An intelligent system is one that **optimizes** some measure
- ▶ How much it changes things so that it gets closer towards the goals that have been set for it
 - ▶ The word-count of error-free text translated
 - ▶ Customer satisfaction for automated dialogue systems
 - ▶ Hours of accident free, real-time driving
 - ▶ Amount of data collected by an autonomous space-vehicle
 - ▶ ...

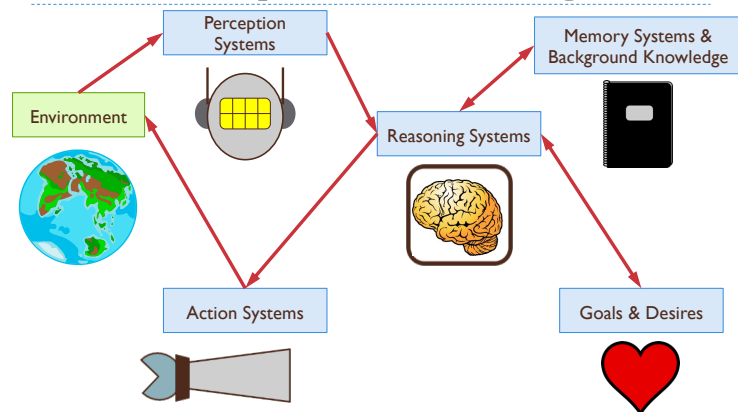
▶

3

The Agent-Based Approach to AI

4

Possible Components of an AI Agent



Artificial Intelligence (CS 131)

5

5

Judging the Best Agent

Suppose we have been given the common elements:

1. A precise performance measure
2. A sequence of world-information states (perceptions)
3. A starting knowledge-base for the agent
4. A fixed set of actions the agent can perform

The best agent is then the one that: *maximizes* the performance measure (1), when *compared to* all agents that experience the *same world* (2), and have access to the *same knowledge* (3) and have the *same actions* available (4)

Artificial Intelligence (CS 131)

6

6

Using PEAS to Describe Agents

Performance	Environment	Actuators	Sensors
-------------	-------------	-----------	---------

- ▶ **Example:** Autonomous automobile driving system
- ▶ **Performance:** Hours of safe travel, obedience to laws, minimal time to destination.
- ▶ **Environment:** Road, traffic, pedestrians, passengers.
- ▶ **Actuators:** Vehicle turning, acceleration, braking, signals.
- ▶ **Sensors:** Radar, video cameras, sonar, spoken-word interface for destinations, GPS.

Artificial Intelligence (CS 131)

7

7



Environments Vary

- ▶ **Fully observable** or **partially observable**?
 - ▶ Chess or poker?
- ▶ **Deterministic** or **stochastic**?
 - ▶ Pac-Man or Ms. Pac-Man?
- ▶ **Episodic** or **sequential**?
 - ▶ Assembly line robot or autonomous automobile?
- ▶ **Static** or **dynamic**?
 - ▶ Checkers or space exploration?
- ▶ **Discrete** or **continuous**?
 - ▶ Backgammon or robot soccer?
- ▶ **Single agent** or **multiagent**?
 - ▶ Mario game controller or NPC shooter team?

Artificial Intelligence (CS 131)

8

8



Performance Measures Vary

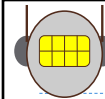
- ▶ **Goal-directed performance:** a single end-point that is either achieved, or not, no matter how it is done
 - ▶ Winning a game of robot soccer
 - ▶ Clearing all levels in Pac-Man
 - ▶ Vacuuming the living room
- ▶ **Utility-directed performance:** a numerical measure, which can be achieved in greater or lesser amounts
 - ▶ Driving a vehicle safely while arriving at finish in the least time
 - ▶ Achieving the highest level of customer satisfaction ratings
 - ▶ Exploring the greatest number of square kilometers of Mars while returning the most varied set of rock samples



Artificial Intelligence (CS 131)

9

9



Agents Vary

- ▶ **Reflex agents:** pre-programmed routines for dealing with any situation they perceive in their environment
 - ▶ Construction robots
 - ▶ Roomba vacuums
 - ▶ Video-game NPC controllers
- ▶ **Memory agents:** keep track of the world around them as they perceive it over time, and build up more complex knowledge & action possibilities
 - ▶ Autonomous vehicles
 - ▶ Spoken dialogue systems
- ▶ **Reasoning agents:** represent knowledge of world and do explicit problem solving
 - ▶ Chess playing programs
 - ▶ Space exploration systems
- ▶ **Adaptive agents:** can change their behavior over time
 - ▶ Learning agents for game play
 - ▶ Preference-learning automated assistants



Artificial Intelligence (CS 131)

10

10

Using Search to Solve AI Problems

11

Basic Search Techniques for AI

- ▶ **Search** is a common method for solving AI problems
 - ▶ Allows precise problem formulations
 - ▶ Solves a variety of problems directly
 - ▶ Provides a simple and direct algorithm
- ▶ We will first consider some **uninformed** search methods
 - ▶ No special information about the problem used
 - ▶ Automatic, simple ways of choosing how search will proceed
 - ▶ Technique relies heavily on proper problem formulation
 - ▶ A range of algorithms, with different **performance profiles**



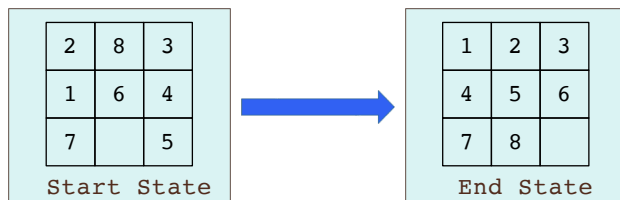
Artificial Intelligence (CS 131)

12

12

Sample Problems for Search

- Simple puzzles, like 8-puzzle:



- Cryptarithmic problems:

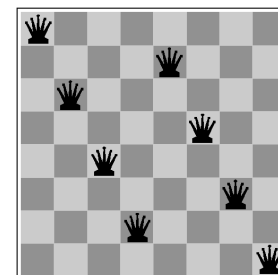


Artificial Intelligence (CS 131) 13

13

The n -Queens Problem

- Place n Queens on an $(n \times n)$ chessboard, so that no two attack (are in line with) one another
 - Popular algorithmic benchmark
 - Solved via **search** for $n \leq 500,000$
 - Can be solved **mathematically** using work of Hoffman, Loessi, & Moore (1969) for any values of $n > 3$



(Not a solution!
Can you find one?)

Artificial Intelligence (CS 131) 14

14

Real Examples

- A large number of problems of real interest can be solved using search techniques:
 - Theorem proving in math and logic
 - Combinatorial optimization in chip design
 - Robot navigation and path planning
 - Resource scheduling in computing
 - Complex game play
- Solving such problems involves re-formulating them so search techniques can be applied

Artificial Intelligence (CS 131) 15

15

Formalizing a Search Problem

- States:** the set of all things to search through
- Initial state:** where we starts
- Goal states/tests:** how we know we've reached solution
- Actions:** what things we can do to change the state, moving along some **path** in our **search-space**
- Transition model:** what happens when we take some action a in some state s_1 (i.e., state s_2 we end up in)
- Action cost function:** what it costs (if anything) to take our actions, moving from state to state

Artificial Intelligence (CS 131) 16

16

Solving a Search Problem

- ▶ A **solution** to a search problem is a sequence of actions that generates a complete path from a starting state to a goal state
- ▶ An **optimal** solution is one that has minimal overall cost
- ▶ This leads to a couple of questions:
 1. How do we *balance* the cost of a solution with the cost of doing the search itself?
 2. How do we *measure* these costs?

▶ Artificial Intelligence (CS 131) 17

17

Important Assumption: Non-negative Costs

- ▶ The text (p. 65) notes that in all search problems considered, it is assumed that the cost of any search step is always some **positive value** $c > 0$, and total cost is just the **sum**
- ▶ Why is this important?
 1. If the cost of actions can be *any* value, what does an “optimal” algorithm need to do?
 - ▶ Note: since a negative “cost” is actually a *reward*, this would mean that there is no upper limit on rewards we could get
 2. What if negative costs *are* allowed, but there is a *lower bound*, so every cost is $c \geq -\epsilon$, for some fixed value ϵ ?
 - ▶ How does this affect search where infinite looping solutions are *not* allowed? What about when infinite loops *are* allowed?

▶ Artificial Intelligence (CS 131) 18

18

The 8-Puzzle Problem

7	2	4
5		6
8	3	1

Start State

	1	2
3	4	5
6	7	8

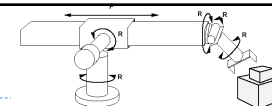
Goal State

- ▶ **States:** arrangements of tiles
 - ▶ Integer sequences like: $\langle 7, 2, 4, 5, 0, 6, 8, 3, 1 \rangle$
 - ▶ Gives $9! = 9 \times 8 \times 7 \times \dots \times 2 \times 1 = 362880$ states
- ▶ **Goal:** sequence $\langle 0, 1, 2, 3, 4, 5, 6, 7, 8 \rangle$
- ▶ **Actions:** move blank tile in one of 4 directions
 - ▶ Not all moves always available
- ▶ **Transitions:** deterministic transitions from state to state
- ▶ **Path cost:** 1 unit per move (why?)

▶ Artificial Intelligence (CS 131) 19

19

Robotic Assembly



- ▶ Robot arm tasked to build a specific object out of known parts
- ▶ **States:** combinations of positions for arm and object to build
 - ▶ Robotic joint angles
 - ▶ Location and orientation of each part
 - ▶ Is the space continuous? How do we handle this?
- ▶ **Goal:** Assembled object
 - ▶ How do we distinguish one of many?
- ▶ **Actions:** continuous arm movements, $\text{config}_1 \rightarrow \text{config}_2$
- ▶ **Transitions:** changes of the state of robot and parts, given actions
 - ▶ Deterministic or not?
- ▶ **Path cost:** looking for most efficient solution
 - ▶ Time to construct entire object?
 - ▶ Most reliable solution?

▶ Artificial Intelligence (CS 131) 20

20

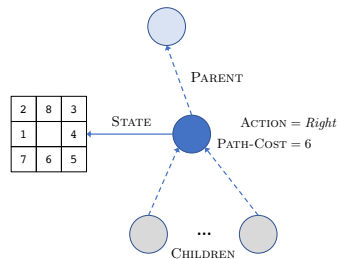
Search Trees

- ▶ A search tree represents a process using a **graph**

- ▶ Nodes in the graph represent search up to some point

- ▶ Nodes contain information:

1. Current *state* of problem
2. *Action* taken to get into state
3. *Path-cost* to get to that state
4. Link back to *parent*, i.e. the previous step in the search-path (for back-tracking purposes)



Artificial Intelligence (CS 131) 21

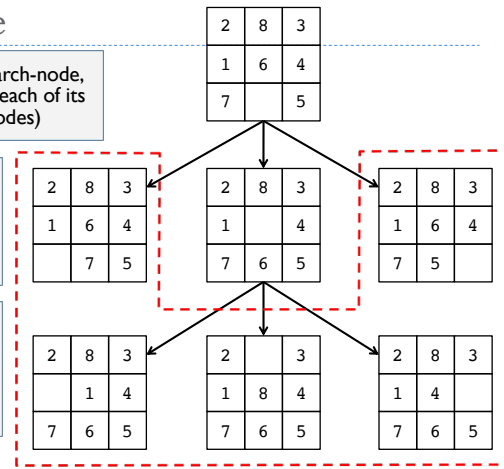
21

An Example

When we examine a search-node, we **expand** it, producing each of its **successors** (next nodes)

At each stage, we choose an unexpanded **leaf node**, typically avoiding repeats

The set of leaf nodes that have not been expanded yet is the **search frontier**



Artificial Intelligence (CS 131) 22

22

A General Search Technique

Image source: [Russell & Norvig \(2021\)](#)

```
function BEST-FIRST-SEARCH(problem, f) returns a solution node or failure
  node ← NODE(STATE=problem.INITIAL)
  frontier ← a priority queue ordered by f, with node as an element
  reached ← a lookup table, with one entry with key problem.INITIAL and value node
  while not IS-EMPTY(frontier) do
    node ← POP(frontier)
    if problem.IS-GOAL(node.STATE) then return node
    for each child in EXPAND(problem, node) do
      s ← child.STATE
      if s is not in reached or child.PATH-COST < reached[s].PATH-COST then
        reached[s] ← child
        add child to frontier
  return failure
```

- ▶ Every search starts from the specified **initial state** of the problem
- ▶ In order to track our progress, we keep track of two sets of nodes:
 1. **Frontier**: nodes we know about, but haven't **expanded** yet (our initial state goes into the frontier at the start of search)
 2. **Reached**: nodes we have already expanded

Artificial Intelligence (CS 131) 23

23

A General Search Technique

Image source: [Russell & Norvig \(2021\)](#)

```
function BEST-FIRST-SEARCH(problem, f) returns a solution node or failure
  node ← NODE(STATE=problem.INITIAL)
  frontier ← a priority queue ordered by f, with node as an element
  reached ← a lookup table, with one entry with key problem.INITIAL and value node
  while not IS-EMPTY(frontier) do
    node ← POP(frontier)
    if problem.IS-GOAL(node.STATE) then return node
    for each child in EXPAND(problem, node) do
      s ← child.STATE
      if s is not in reached or child.PATH-COST < reached[s].PATH-COST then
        reached[s] ← child
        add child to frontier
  return failure
```

- ▶ At each step, so long as we still have something left in the frontier:
 1. We grab the next node in the frontier; these will be ordered by some **priority function** that defines their order
 2. We run our **goal-test** on the node: if we hit the goal, we are done!

Artificial Intelligence (CS 131) 24

24

A General Search Technique

Image source: [Russell & Norvig \(2021\)](#)

```

function BEST-FIRST-SEARCH(problem, f) returns a solution node or failure
  node ← NODE(STATE=problem.INITIAL)
  frontier ← a priority queue ordered by f, with node as an element
  reached ← a lookup table, with one entry with key problem.INITIAL and value node
  while not IS-EMPTY(frontier) do
    node ← POP(frontier)
    if problem.IS-GOAL(node.STATE) then return node
    for each child in EXPAND(problem, node) do
      s ← child.STATE
      if s is not in reached or child.PATH-COST < reached[s].PATH-COST then
        reached[s] ← child
        add child to frontier
  return failure
    
```

- ▶ If we haven't reached the goal, we **expand** our node to get the other nodes that we can reach based upon our various **actions**
- ▶ We add any new node to the frontier if:
 1. It is a **brand-new** node, with a state we haven't seen, OR
 2. We have seen the state before, but have a **lower path-cost** (the new version replaces any older version in the frontier)

Artificial Intelligence (CS 131) 25

25

A General Search Technique

Image source: [Russell & Norvig \(2021\)](#)

```

function BEST-FIRST-SEARCH(problem, f) returns a solution node or failure
  node ← NODE(STATE=problem.INITIAL)
  frontier ← a priority queue ordered by f, with node as an element
  reached ← a lookup table, with one entry with key problem.INITIAL and value node
  while not IS-EMPTY(frontier) do
    node ← POP(frontier)
    if problem.IS-GOAL(node.STATE) then return node
    for each child in EXPAND(problem, node) do
      s ← child.STATE
      if s is not in reached or child.PATH-COST < reached[s].PATH-COST then
        reached[s] ← child
        add child to frontier
  return failure
    
```

Some searches fail!

- ▶ No algorithm solves every problem
- ▶ If the frontier becomes **empty**, we have expanded every node we can reach in the search, without ever passing our goal-test

Artificial Intelligence (CS 131) 26

26