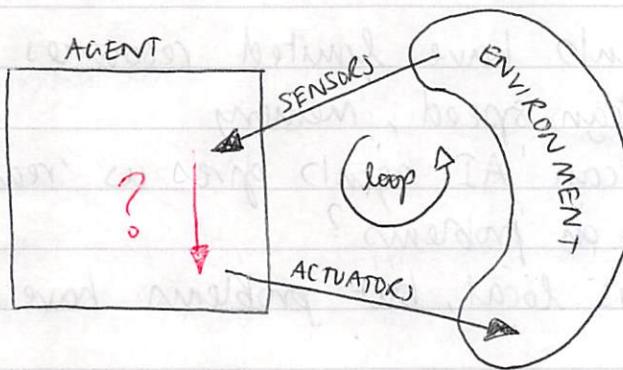


Foundations of Artificial Intelligence

* Introduction to Artificial Intelligence

- Outline:
- Agent & Environment
 - Applications of AI
 - AI and Uncertainty

* Intelligent Agent



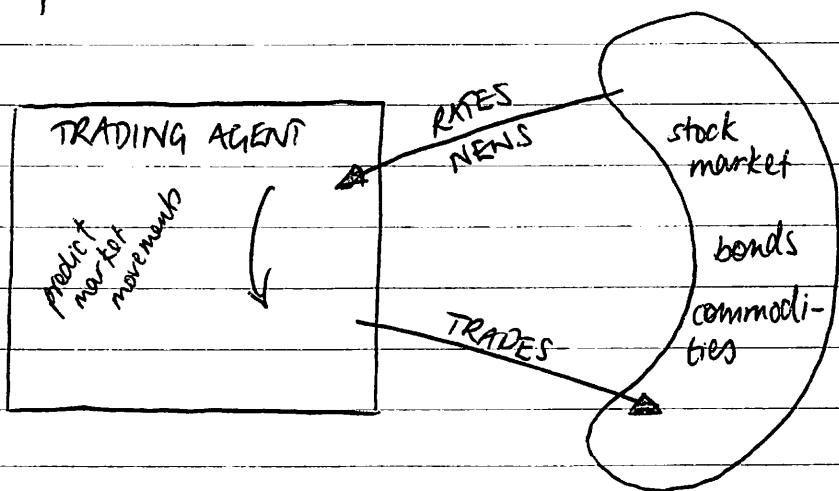
PERCEPTION ACTION CYCLE

* Applications of AI

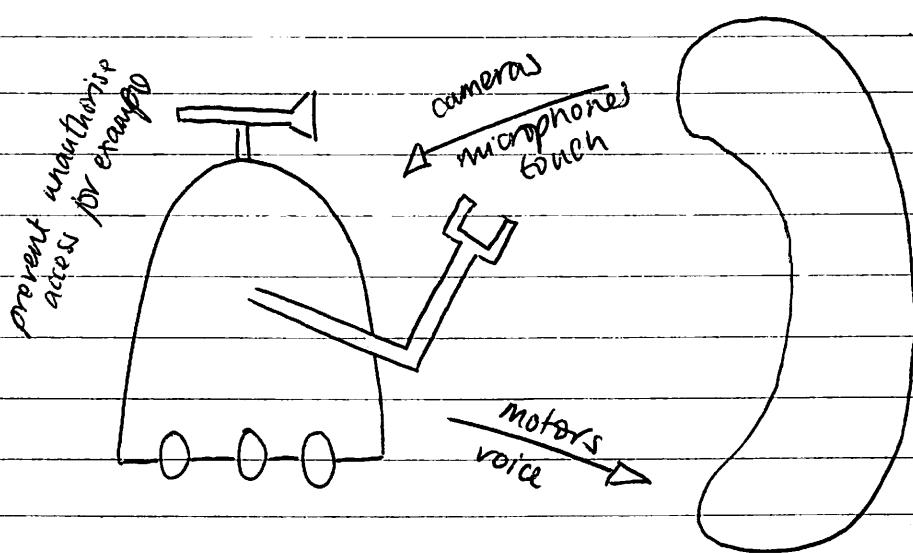
AI has successfully been used in

- Finance
- Robotics
- Games
- Medicine
- The web

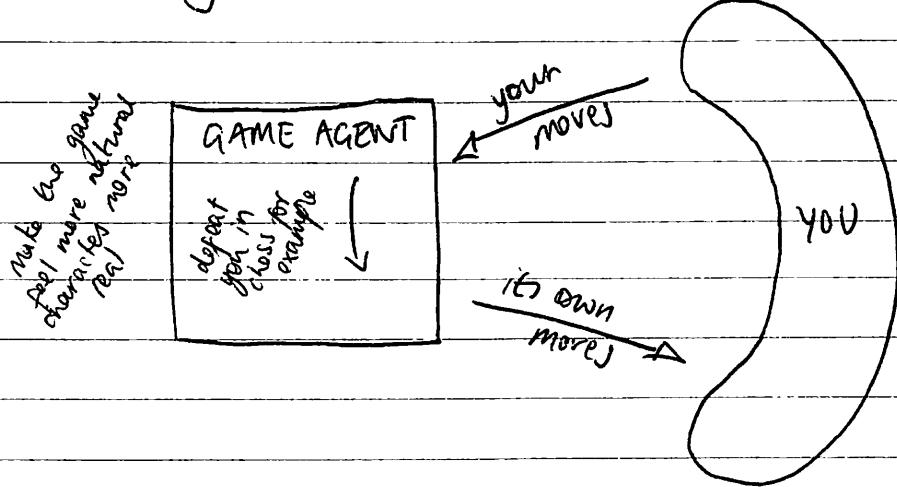
AI in finance:



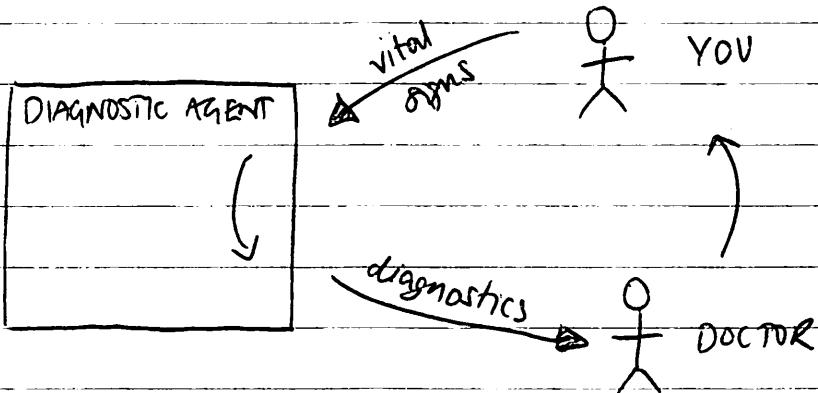
AI in robotics



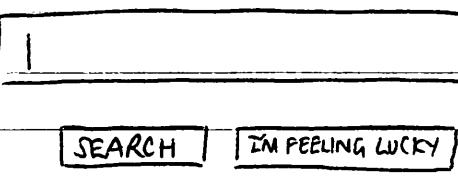
AI in games



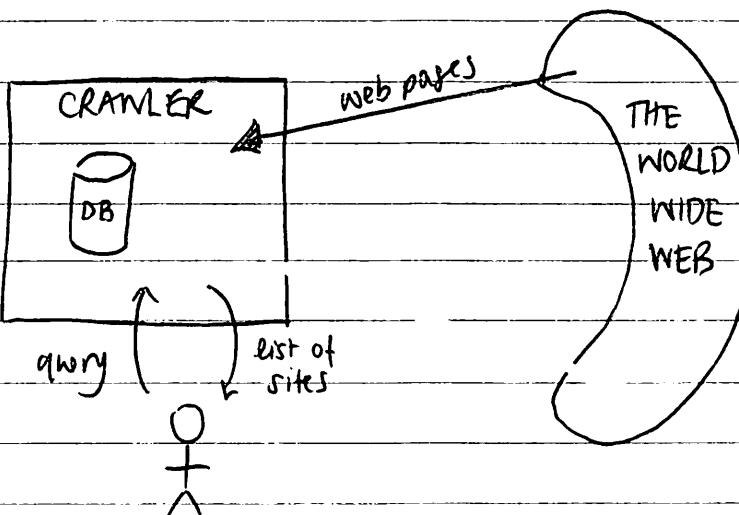
AI in medicine



AI and the web



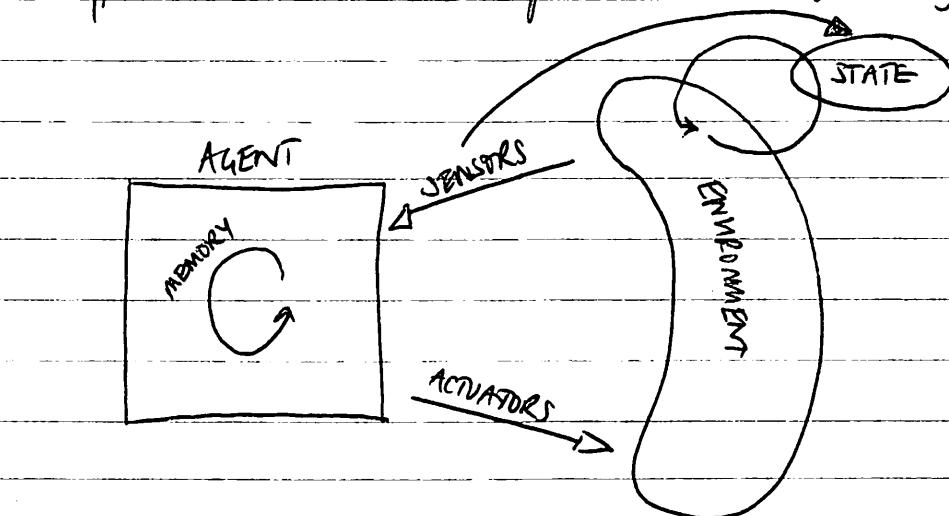
find most relevant web pages for your search



Terminology

* FULLY vs PARTIALLY observable environment

↑
what the agent can sense in any point in time is sufficient to make the optimal choice e.g. seeing all the cards on the table in a game



* DETERMINISTIC vs STOCHASTIC environment

* DISCRETE vs CONTINUOUS environments

* BENIGN vs ADVERSARIAL environments

↑
stochastic
games where there are opponents?

Example:

	PARTIALLY OBSERVABLE	STOCHASTIC	CONTINUOUS	ADVERSARIAL
Checkers				X
Poker	X	X		X
Robot Car	X	X	X	X

momentary sensing is limited

other cars are unpredictable

other drivers

AI as uncertainty management

AI = what to do when you don't know what to do?

Reasons for uncertainty

- Sensor limits
- Adversaries
- Stochastic environments
- Laziness
- Ignorance

AI is a discipline which deals with uncertainty and manages it in decision making

Examples of AI

Language translation e.g. news articles - this is done by examining many articles which are published in both languages. These are used to find the most probable translation.

Example of its use in a Chinese / English menu

Unit 1 summary

- Key application
- Intelligent agents
- Key attributes of environment
- Sources of uncertainty
- Rationality

* Knowledge-Based Artificial Intelligence

Overview:

- Conundrums in AI
- Characteristics of AI Problems & Agents
- AI in practice: Watson
- What is knowledge-based AI
- The four schools of AI

* Fundamental Conundrums of Artificial Intelligence

- Intelligent agents have limited resources
 - e.g. processing speed, memory
 - How then can AI agents give us 'real time' performance on problems?
- Computation is local, but problems have global constraints
- Logic is deductive, but many problems are not
 - How can AI agents address inductive and abductive problems?
- The world is dynamic and knowledge is limited
 - How can AI agents address new problems?
- Problem solving, learning and reasoning are complex, explanation and justification even more so
 - How can we get AI Agents to explain or justify its decisions?

* Characteristics of AI Problems

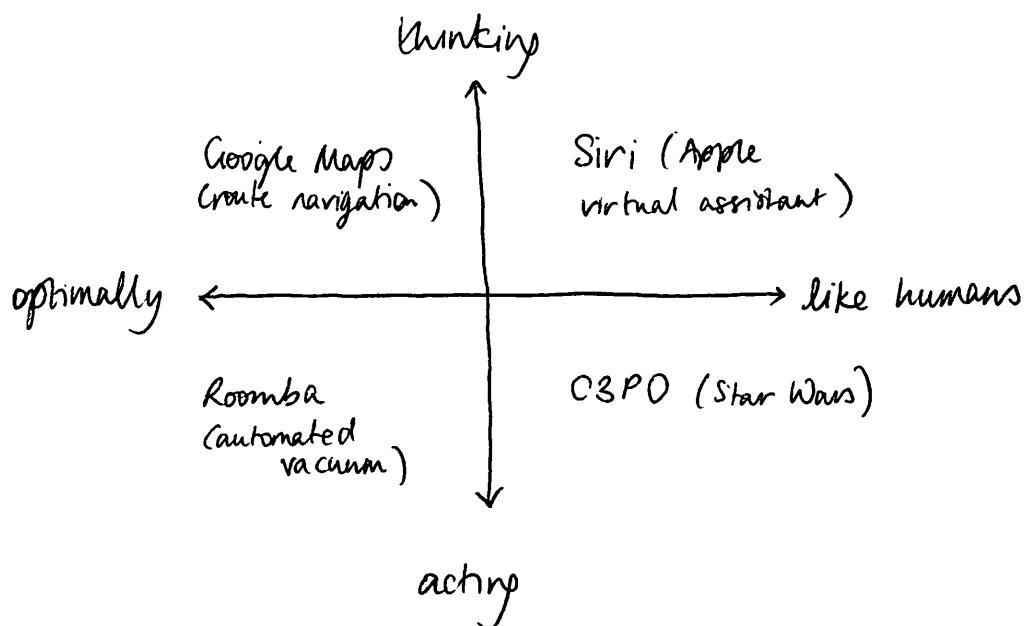
- Knowledge often arrives incrementally
- Problems exhibit recurring patterns
- Problems have multiple levels of granularity
- Many problems are computationally intractable
- The world is dynamic, knowledge is relatively static
- The world is open-ended but knowledge is limited

* Exercise : What is KBAI

Where does an autonomous vehicle fall on the spectrum?

Autonomous vehicles are in the acting optimally quadrant

* Exercise : The four schools of AI



* Problem Solving

- Outline :
- What is a problem?
 - Example: Route finding
 - State spaces

Unit 2 : Problem Solving

Theory and technology of building agents to plan ahead and solve problems

Definition of a problem

- Initial state
- Actions ($s \rightarrow \{a_1, a_2, a_3, \dots\}$) could be state dependent
- Result ($s, a \rightarrow s'$)
- GoalTest ($s \rightarrow \text{true/false}$)
- PathCost ($s \xrightarrow{a} s \xrightarrow{a} s' \dots \rightarrow n$) → n (the cost)
- StepCost ($s, a, s' \rightarrow n$)

Example: Driving from one city to another
convert map of roads to a graph move along edges - you have the frontier, explored and unexplored areas

Function : TREE.SEARCH (problem) :

frontier = {[initial]}

loop :

 if frontier is empty : return FAIL

 path = remove-choice (frontier)

 s = path.end

 if s is a goal : return path

 for a in actions:

 add [path + a \rightarrow Result (s, a)]

 to frontier

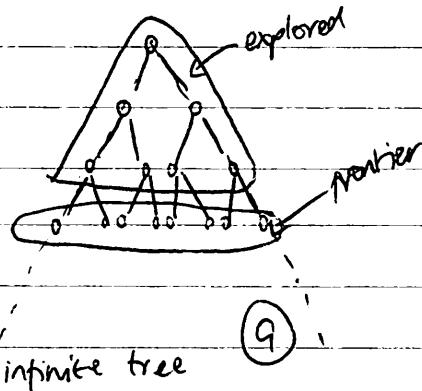
In general the goal test is applied when we remove the path from the frontier not when it's added to the frontier

- Breadth first search : explore the shortest paths first (where edges are all 1)

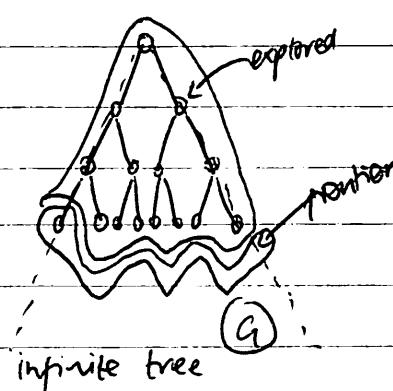
- Cheapest first search : explore the cheapest path first (where the edges have assigned costs)

- Depth first search: explore the longest path first (where edges are all 1)

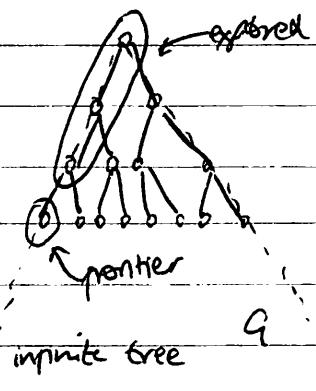
BREADTH FIRST
SEARCH



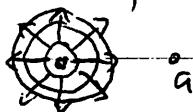
CHEAPEST FIRST
SEARCH



DEPTH FIRST
SEARCH



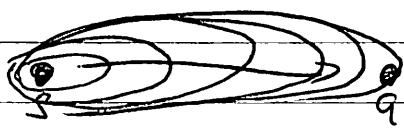
- complete - guaranteed to find the goal if it's at some finite place in an infinite tree
- search area expand uniformly in all directions i.e.



cheaper storage
costs frontier and explored only contain n nodes

- * Greedy-best first search \rightarrow uses estimated distance from goal to decide which direction to expand its search in. This is good but doesn't find the optimal if there are barriers in the search paths

The idea is we want to get the optimal solution faster!



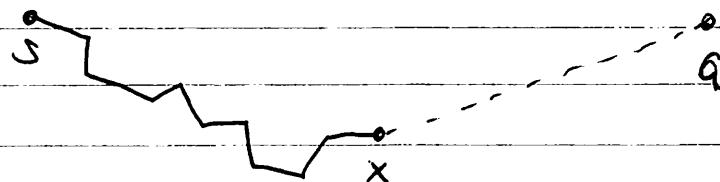
A* search : Best estimated total path cost first

expanding the paths which have the minimum value of the function f

$$f = g + h$$

$g(\text{path})$ = path cost

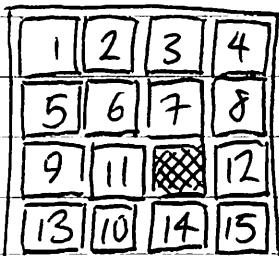
$h(\text{path}) = h(s)$ = estimated distance to goal



A* finds the lowest cost path if :

- $h(s) \leq$ true cost
- i.e. • h never overestimates
- h is optimistic
- h is admissible

* Sliding blocks puzzle / 15 puzzle



heuristics

$h_1 = \# \text{ misplaced blocks}$

$h_2 = \text{sum}(\text{distances of blocks})$
from correct posn

both these heuristics are admissible

$h_1 \leq \# \text{ moves required fix it}$

$h_2 \leq \# \text{ " " " " }^*$

$h_2 \geq h_1$ so h_2 is a better heuristic

A block can move $A \rightarrow B$
if (A adjacent to B) and (B is blank)

↓

removing this gives h_2

removing both conditions gives h_1

Take $h = \max(h_1, h_2)$

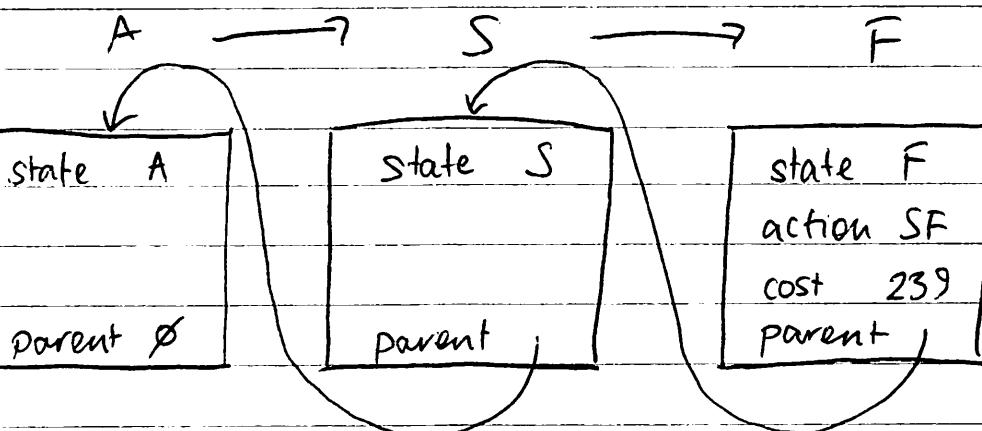
heuristic calculation can have a cost too.

removing conditions only relaxes the problem
so resulting heuristics can only underestimate
the cost

This illustrates how an algorithm can be
devised to come up with the estimated
cost heuristic

Problem-solving technology works when...

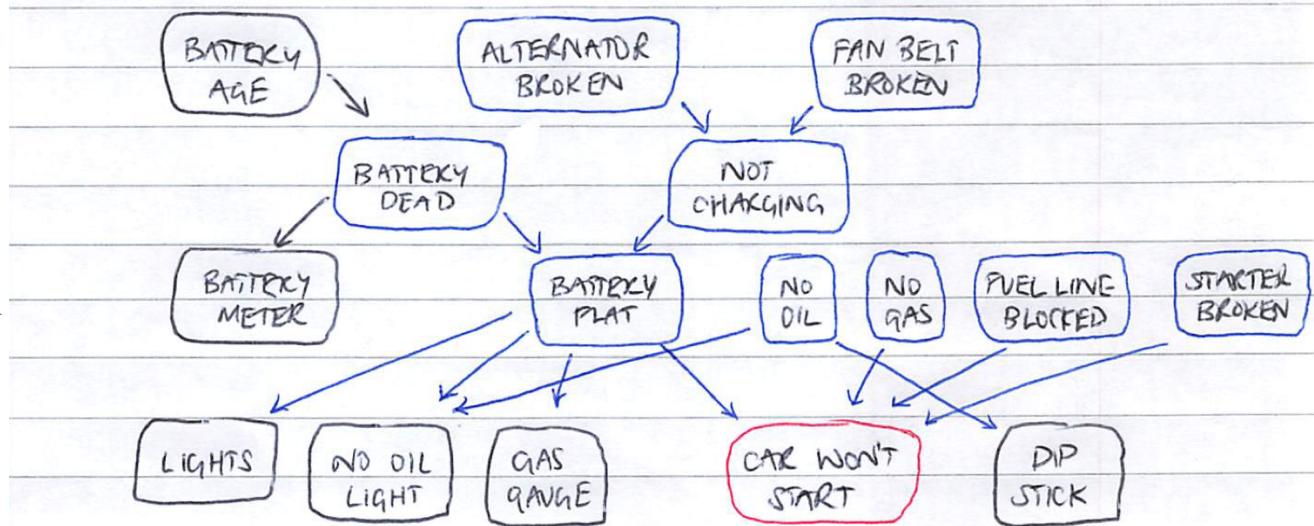
- Fully observable
- Known domain -
- Discrete
- Deterministic
- Static - no external influences on the environment



* Probability in AI

- Outline :
- Example : Bayes Network
 - Conditional Probability
 - Total Probability
 - Joint Probability
 - Bayes Rule

Bayes Networks



- Bayes network assist you in reasoning from observable variables
- Child node is influenced by the Parent in a non-deterministic way

* This course:

- Binary events
- Probability
- Simple Bayes Networks
- Conditional Independence
- Bayesian Networks
- D-separation
- Parameter Count
- Inference

* Bayes Networks are used in

- Diagnosis
- Prediction
- Machine Learning (Finance, Google, Robotics)
- Particle filters
- Hidden Markov Models (HMM)
- MDP / POMDPs
- Kalman Filters

* Probabilities:

$$P(A) = p \quad P(\neg A) = 1-p$$

Independence

$$X \perp Y \Rightarrow \underbrace{P(X)P(Y)}_{\text{marginals}} = \underbrace{P(X,Y)}_{\text{joint}}$$

Dependence

$$P(Y) = \sum_i P(Y|X=i)P(X=i) \quad \text{Total Probability}$$

$$P(\neg X|Y) = 1 - P(X|Y)$$

$$\text{but } P(X|\neg Y) \neq 1 - P(X|Y)$$

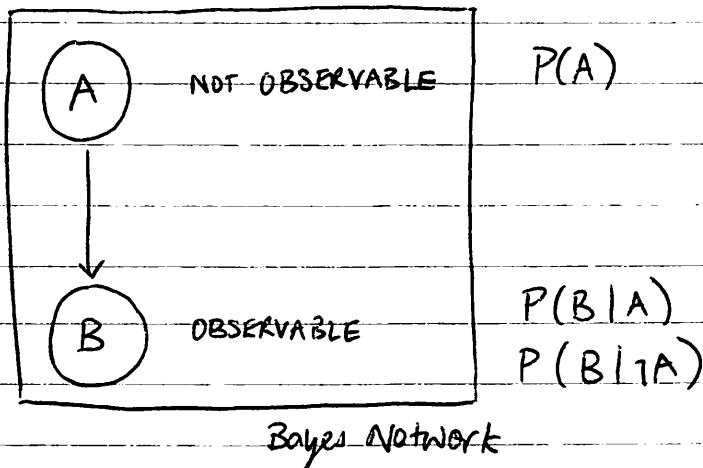
* Bayes Rule

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)} \quad \begin{matrix} \text{POSTERIOR} \\ \text{LIKELIHOOD} \end{matrix} \quad \begin{matrix} \leftarrow \text{PRIOR} \\ \text{MARGINAL LIKELIHOOD} \end{matrix}$$

||

Here B is the evidence
that A has happened or
is the case

$$\underbrace{\sum_a P(B|A=a) P(A=a)}_{\text{total probability}}$$



Diagnostic Reasoning : $P(A|B)$
 $P(\neg A|\neg B)$

* More complex Bayes Networks

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)} \quad P(\neg A|B) = \frac{P(B|\neg A) P(\neg A)}{P(B)}$$

$$P(A|B) + P(\neg A|B) = 1$$

$$P'(A|B) = P(B|A) P(A)$$

$$P(A|B) = \eta P'(A|B)$$

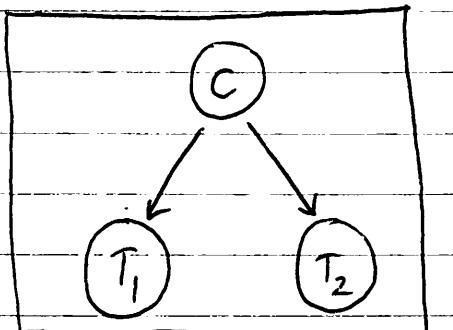
$$P'(\neg A|B) = P(B|\neg A) P(\neg A)$$

$$P(\neg A|B) = \eta P'(\neg A|B)$$

$$\eta = [P'(A|B) + P'(\neg A|B)]^{-1}$$

η is called a 'pseudo probability'

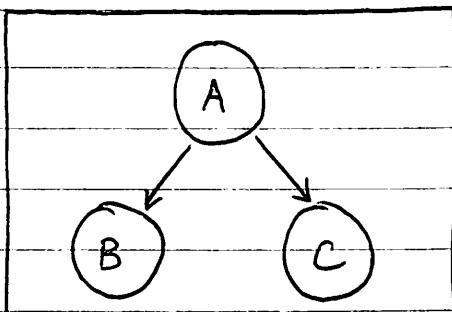
* Conditional Independence



Now let's assume the test for cancer is taken twice

* Conditional Independence

$$P(T_2 | C \cap T_1) = P(T_2 | C)$$



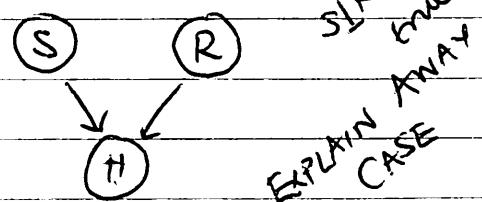
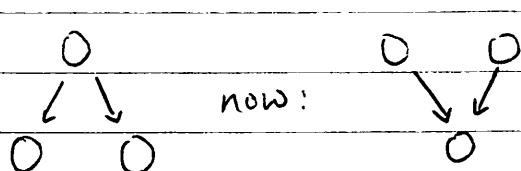
Given A
 $B \perp C$
 i.e. $\underline{B} \perp C | A$

Note: $B \perp C | A \not\Rightarrow B \perp C$

and

$B \perp C \not\Rightarrow B \perp C | A$

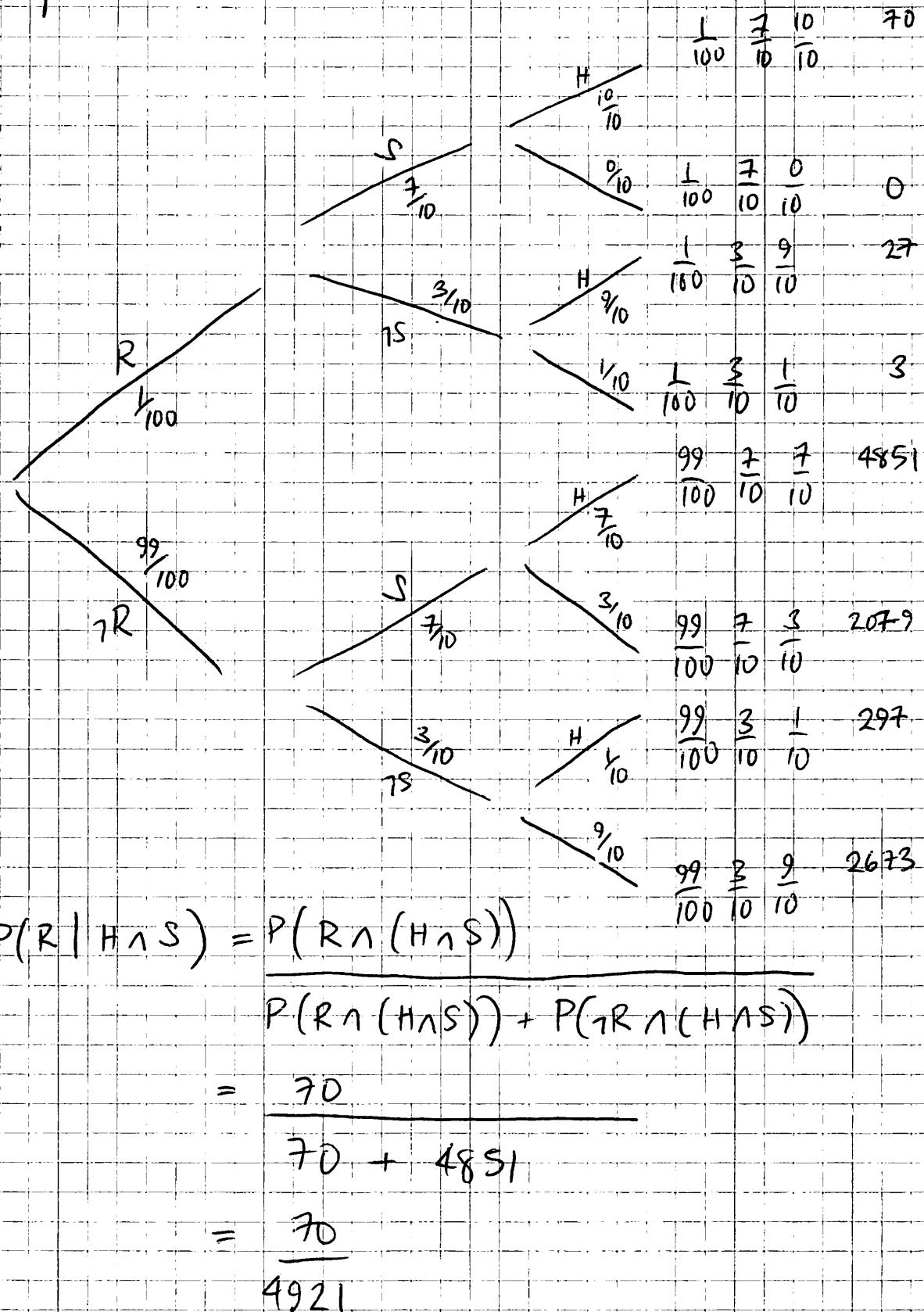
Different type of Bayes Network



$$\begin{aligned} P(S) &= P(\text{sunny}) = \frac{7}{10} \\ P(R) &= P(\text{raise}) = \frac{5}{100} \\ P(H) &= P(\text{happy}) \end{aligned}$$

$$\left\{ \begin{array}{l} P(H | R \cap S) = 1 \\ P(H | R \cap \neg S) = \frac{2}{10} \\ P(H | \neg R \cap S) = \frac{7}{10} \\ P(H | \neg R \cap \neg S) = \frac{1}{10} \end{array} \right.$$

Example



$$P(R | H \cap S) = \frac{P(R \cap (H \cap S))}{P(R \cap (H \cap S)) + P(\text{GR} \cap (H \cap S))}$$

$$= \frac{70}{70 + 4851}$$

$$= \frac{70}{4921}$$

$$\text{Bayes Formula} \Rightarrow \frac{P(H \cap S | R) P(R)}{P(H \cap S)}$$

$$= \frac{\frac{70}{100} \times \frac{1}{100}}{\frac{70}{10000} + \frac{4851}{10000}} = \frac{70}{4921} = \frac{1}{703}$$

* Characteristics of AI Agents

- Agents have limited computing power
- Agents have limited sensors
- Agents have limited attention
- Computational logic is fundamentally deductive
- AI agents' knowledge is incomplete relative to the world

* Exercise: What are AI problems?

- Answering questions on Jeopardy
- Configuring the dimensions for the basement of a new house
- Tying Shoelaces
- Deciding on the route to a new destination
- Making sense of a news broadcast
- Designing a robot that walks on water
- Establishing whether a flower pot can be used as a drinking cup
- Deciding whether or not a new animal is a bird

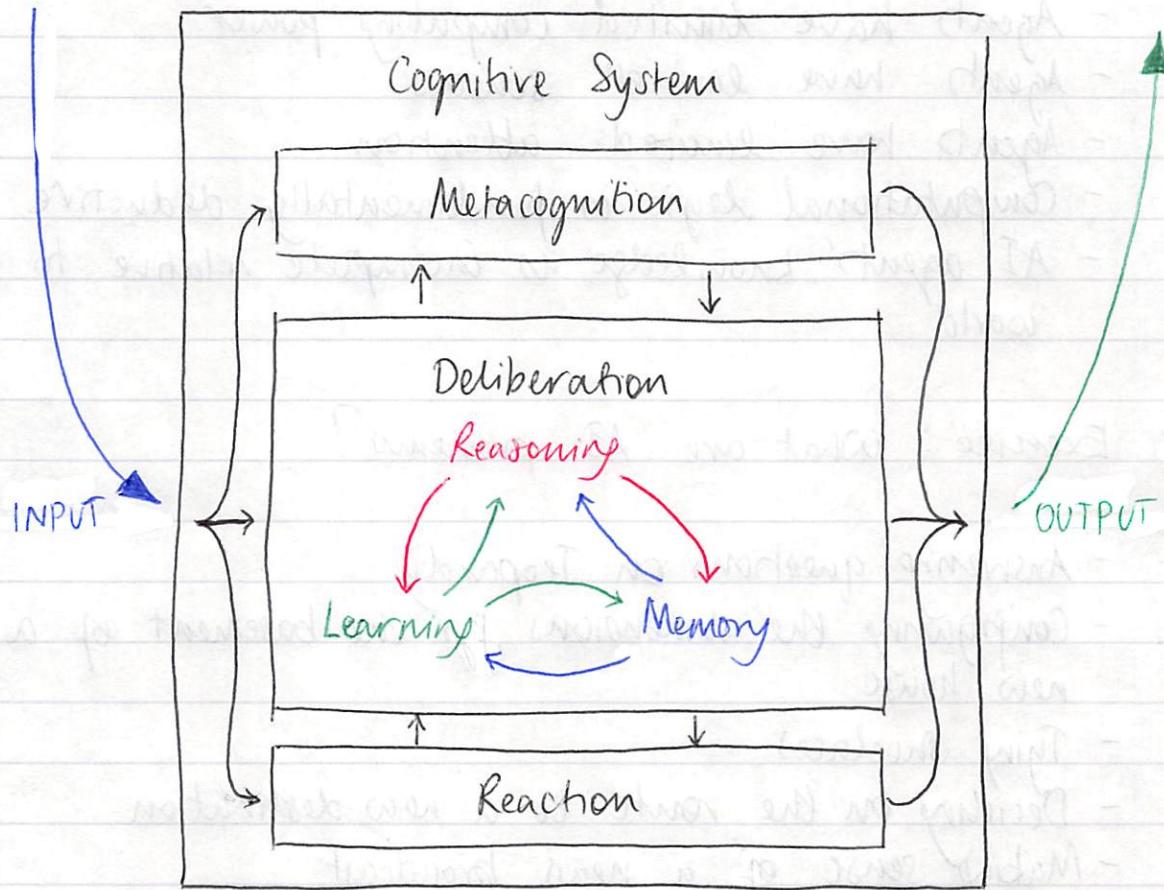
An AI agent could be designed to solve any problem that a human can.

* AI in Practice: Watson (IBM's Jeopardy player)

Watson needs to be able to:

- Read clue
- Search knowledge base
- Decide on an answer
- Phrase the answer as a question.

* What is Knowledge-Based AI?



* Foundations: The four schools of AI

