COMP3411/COMP9414: Artificial Intelligence

11a. Course Review

Assessment

Assessable components of the course:

Assignment 1	12%
Assignment 2	12%
Assignment 3	16%
Written Exam	60%

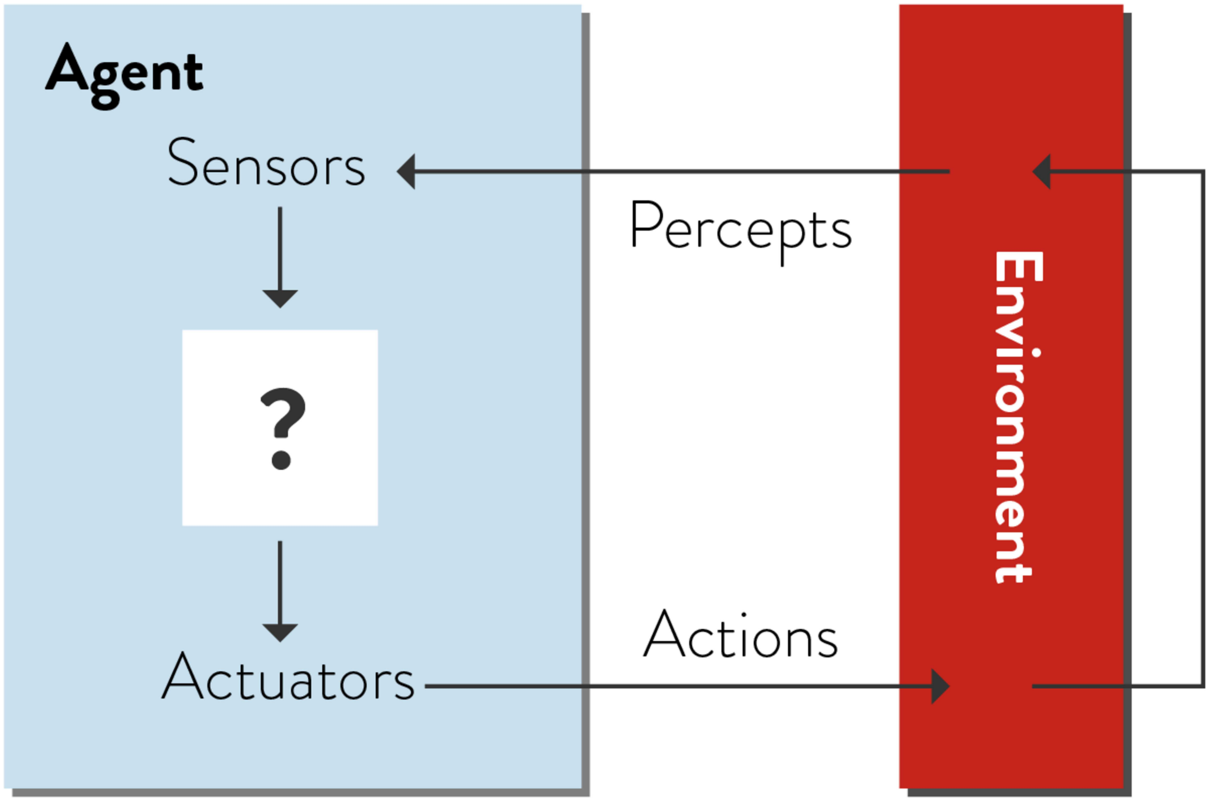
Topics Covered

- AI, Tasks, Agents & Prolog
  - What is AI?
  - Classifying Tasks
  - Agent Types
  - Prolog Programming
- Logic & Uncertainty
  - Logical Agents
  - First Order Logic
  - Uncertainty
- Solving Problems by Search
  - Path Search
  - Heuristic Path Search
  - Games
  - Constraint Satisfaction
- Learning
  - Learning and Decision Trees
  - Perceptrons & Neural Networks
  - Reinforcement Learning

Not Examinable

- Robot Motion Planning
- Evolutionary Robotics
- Computer Vision
- Deep Learning

Agent Model

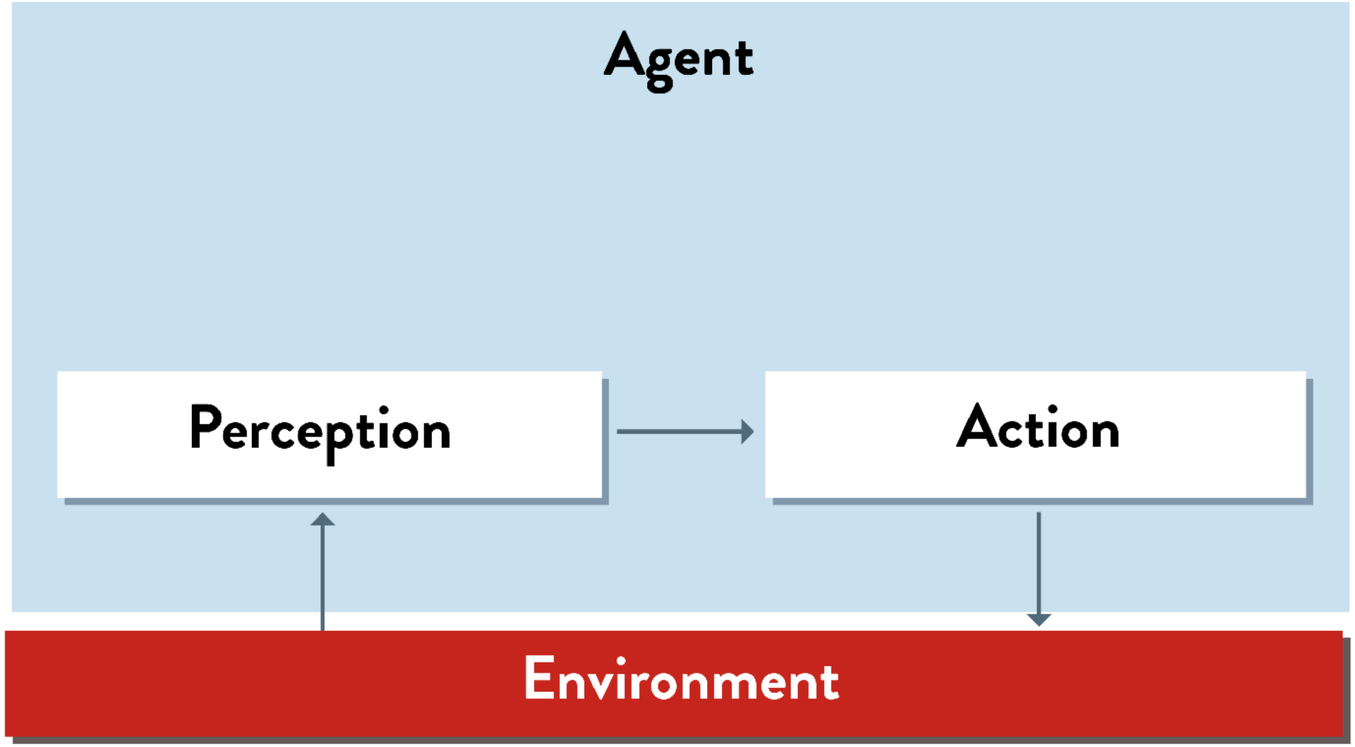


Environment types

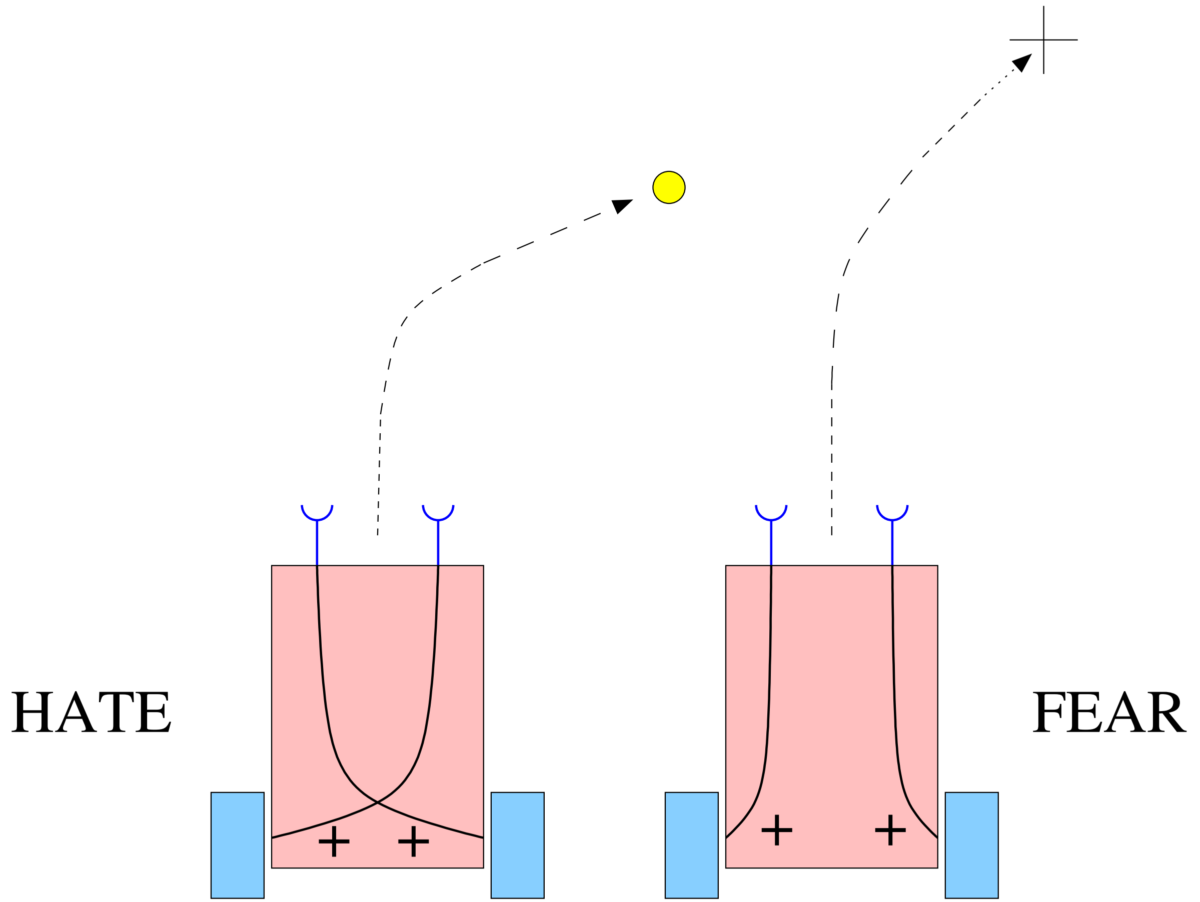
We can classify environments as:

- Simulated vs. Situated or Embodied
- Static vs. Dynamic
- Discrete vs. Continuous
- Fully Observable vs. Partially Observable
- Deterministic vs. Stochastic
- Episodic vs. Sequential
- Known vs. Unknown
- Single-Agent vs. Multi-Agent

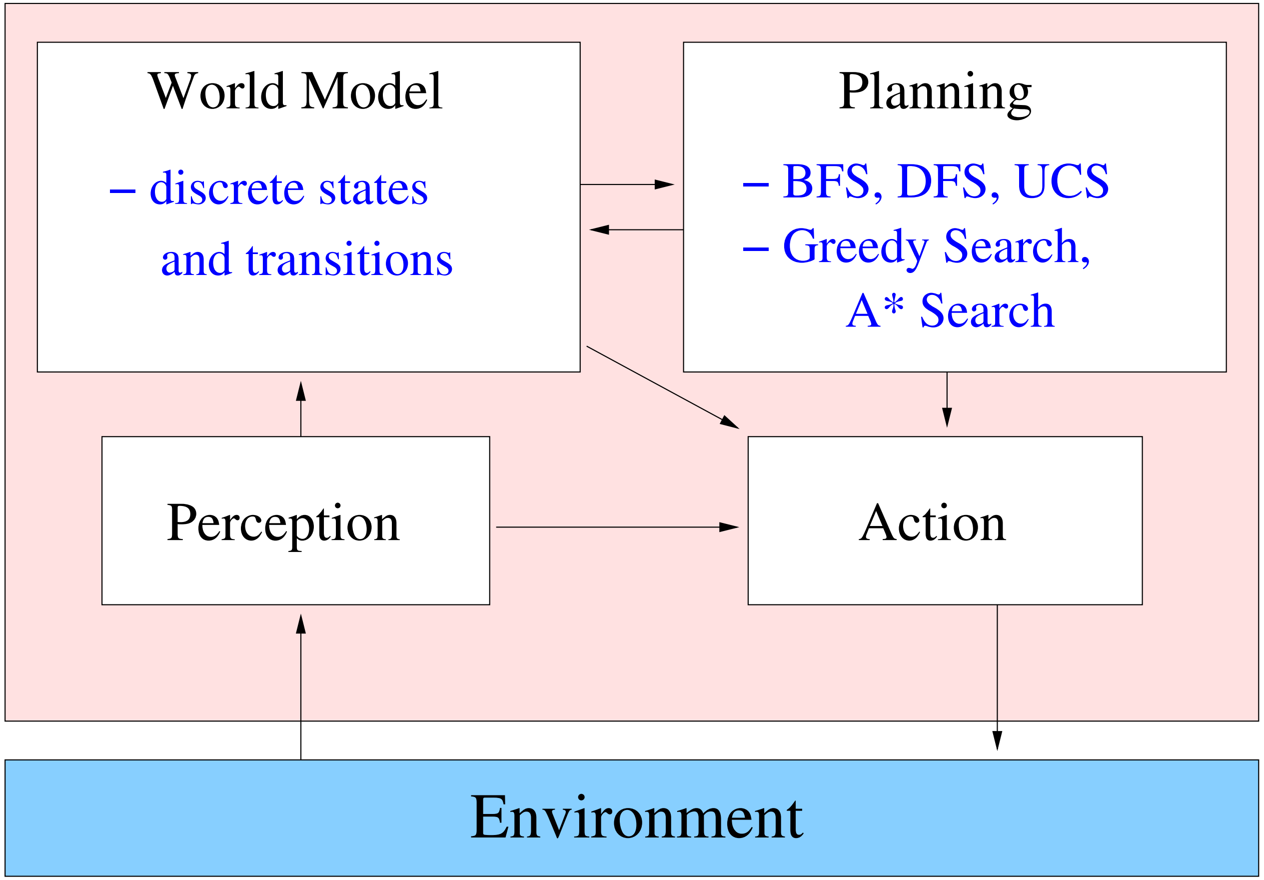
Reactive Agent



Braitenberg Vehicles



Path Search Agent



Path Search Algorithms

General Search algorithm:

- add initial state to queue
- repeat:
  - take node from front of queue
  - test if it is a goal state; if so, terminate
  - “expand” it, i.e. generate successor nodes and add them to the queue

Search strategies are distinguished by the order in which new nodes are added to the queue of nodes awaiting expansion.

Search Strategies

- BFS and DFS treat all new nodes the same way:
  - BFS add all new nodes to the back of the queue
  - DFS add all new nodes to the front of the queue
- (Seemingly) Best First Search uses an evaluation function $f()$ to order the nodes in the queue; we have seen one example of this:
  - UCS $f(n)$ = cost $g(n)$ of path from root to node n
- Informed or Heuristic search strategies incorporate into $f()$ an estimate of distance to goal
  - Greedy Search $f(n)$ = estimate $h(n)$ of cost from node n to goal
  - A* Search $f(n) = g(n) + h(n)$

Complexity Results for Uninformed Search

Criterion	Breadth-First	Uniform-Cost	Depth-First	Depth-Limited	Iterative Deepening
Time	$O(b^d)$	$O(b^{\lceil C^*/\varepsilon \rceil})$	$O(b^m)$	$O(b^k)$	$O(b^d)$
Space	$O(b^d)$	$O(b^{\lceil C^*/\varepsilon \rceil})$	$O(bm)$	$O(bk)$	$O(bd)$
Complete?	Yes[1]	Yes[2]	No	No	Yes[1]
Optimal ?	Yes[3]	Yes	No	No	Yes[3]

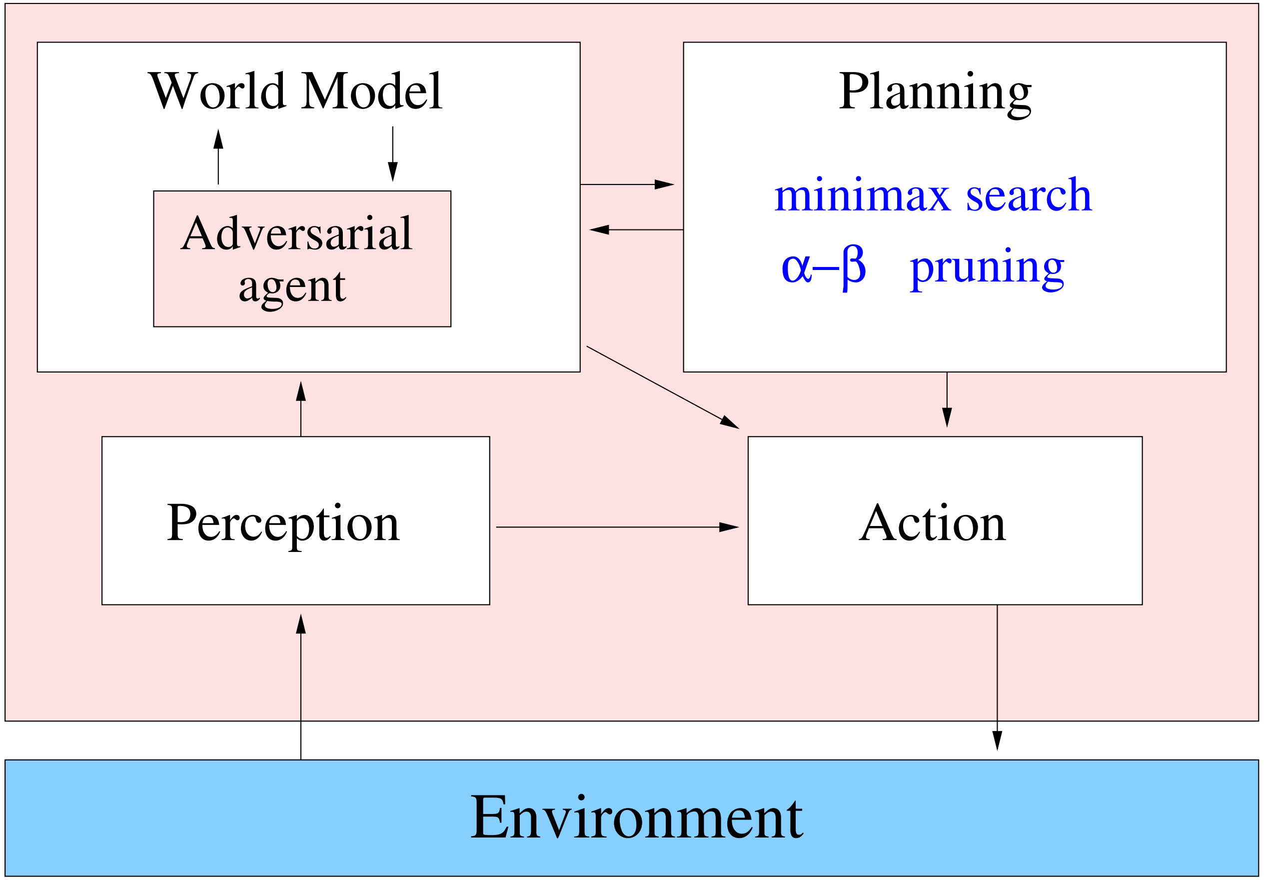
b = branching factor, d = depth of the shallowest solution,
m = maximum depth of the search tree, l = depth limit.

1 = complete if b is finite.

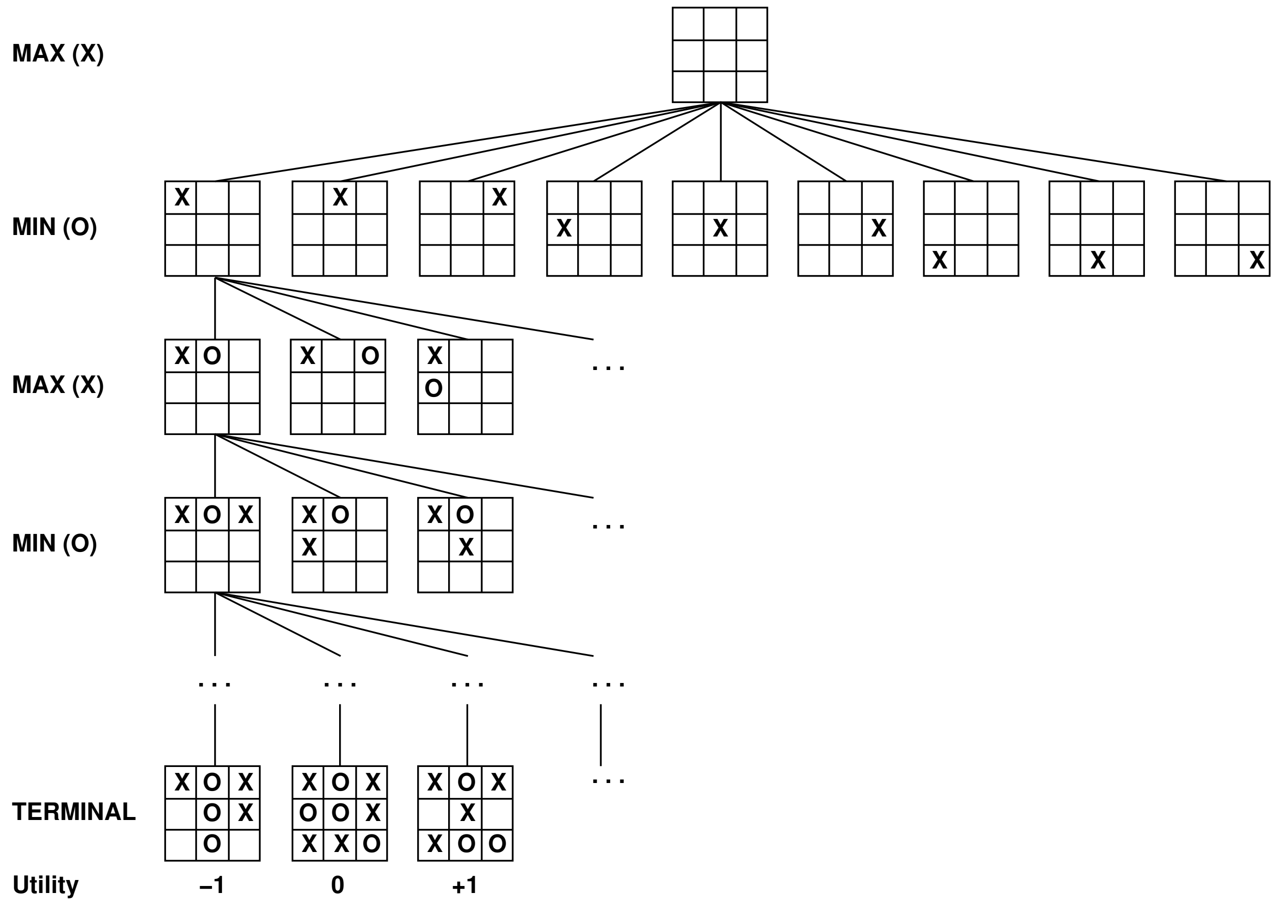
2 = complete if b is finite and step costs $\geq \varepsilon$ with $\varepsilon > 0$.

3 = optimal if actions all have the same cost.

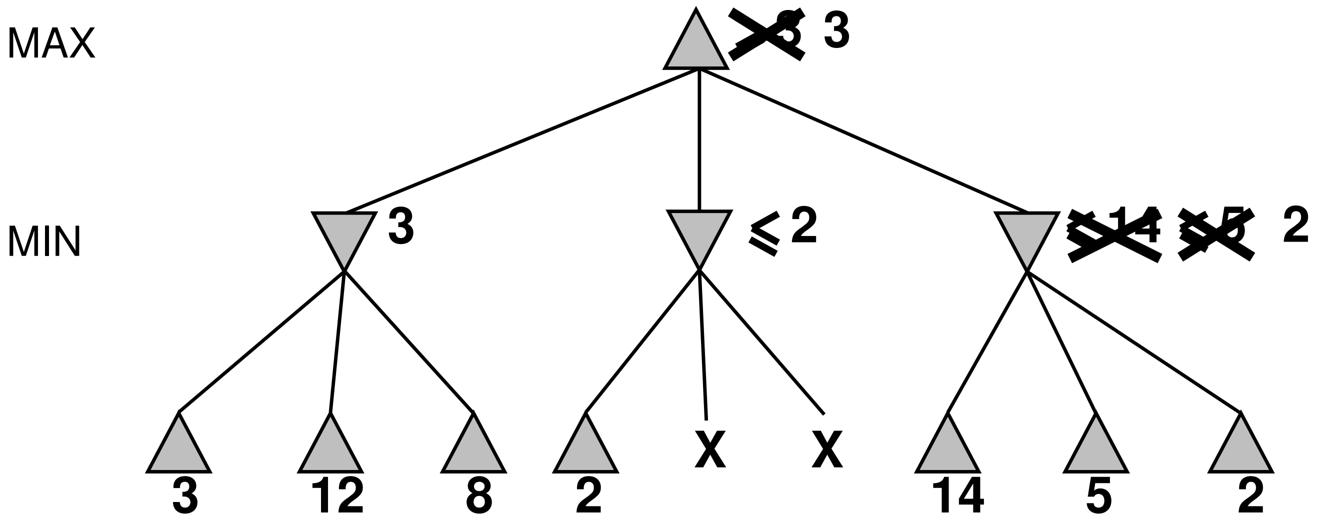
Game Search Agent



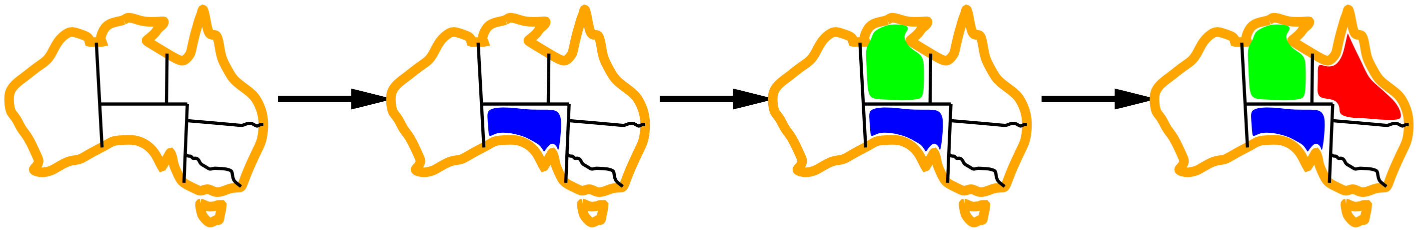
Minimax Search



α-β pruning

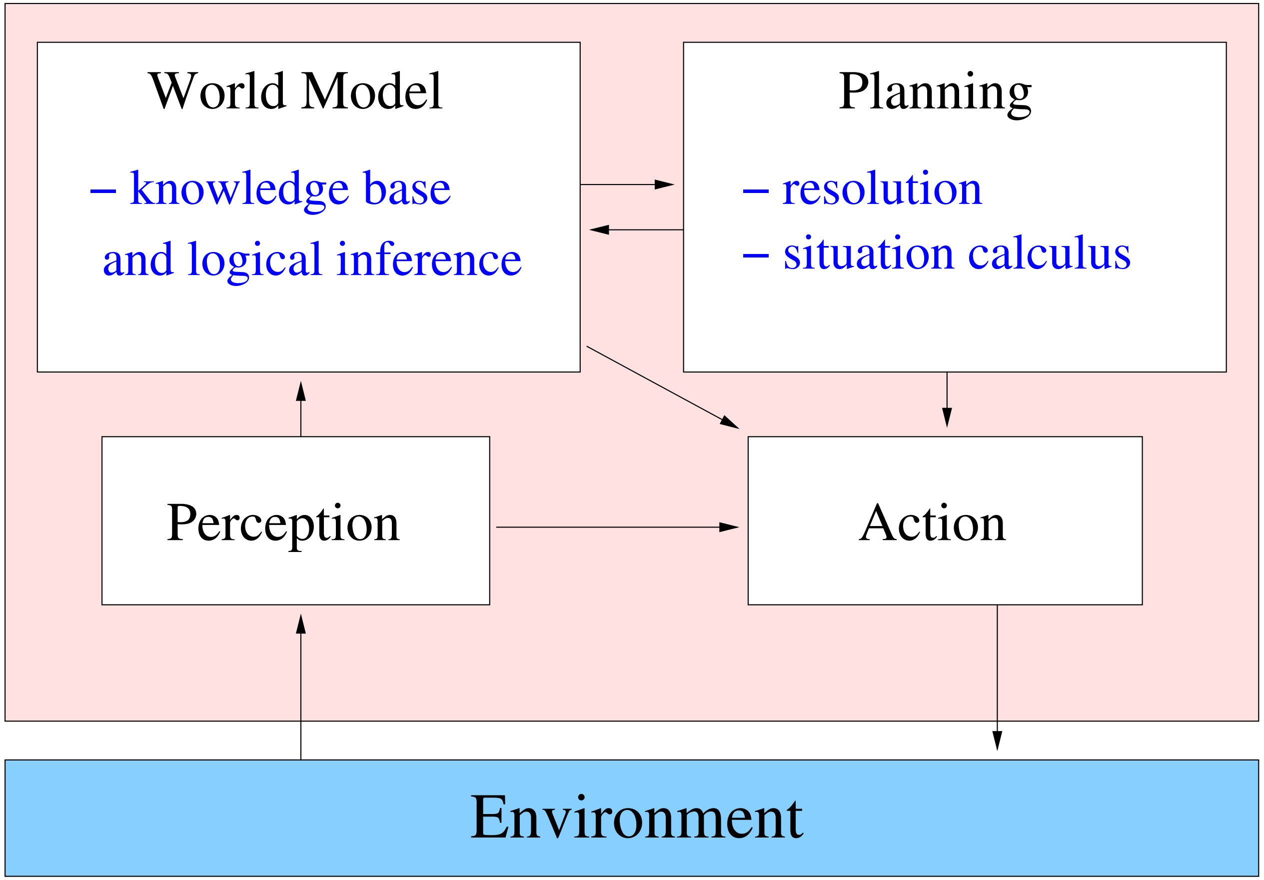


Constraint Satisfaction Problems



- backtracking search
- enhancements to backtracking search
- local search
  - hill climbing
  - simulated annealing

Logical Agent



Propositional Logic

A sentence is valid if it is true in all models,
e.g. TRUE, $A \vee \neg A$, $A \Rightarrow A$, $(A \wedge (A \Rightarrow B)) \Rightarrow B$

Validity is connected to inference via the Deduction Theorem:
$KB \models \alpha$ if and only if $(KB \Rightarrow \alpha)$ is valid

A sentence is satisfiable if it is true in some model
e.g. $A \vee B$, C

A sentence is unsatisfiable if it is true in no models
e.g. $A \wedge \neg A$

Satisfiability is connected to inference via the following:
$KB \models \alpha$ if and only if $(KB \wedge \neg\alpha)$ is unsatisfiable
i.e. prove α by *reductio ad absurdum*

Truth Tables

P	Q	$\neg P$	$P \wedge Q$	$P \vee Q$	$P \Rightarrow Q$
F	F	T	F	F	T
F	T	T	F	T	T
T	F	F	F	T	F
T	T	F	T	T	T

Resolution

Conjunctive Normal Form (CNF – universal)

conjunction of $\underbrace{\text{disjunctions of literals}}_{\text{clauses}}$

e.g. $(A \vee \neg B) \wedge (B \vee \neg C \vee \neg D)$

Resolution inference rule (for CNF): complete for propositional logic

$$\frac{\ell_1 \vee \cdots \vee \ell_k, \qquad m_1 \vee \cdots \vee m_n}{\ell_1 \vee \cdots \vee \ell_{i-1} \vee \ell_{i+1} \vee \cdots \vee \ell_k \vee m_1 \vee \cdots \vee m_{j-1} \vee m_{j+1} \vee \cdots \vee m_n}$$

where ℓ_i and m_j are complementary literals. e.g.

$$\frac{P_{1,3} \vee P_{2,2}, \qquad \neg P_{2,2}}{P_{1,3}}$$

Resolution is sound and complete for propositional logic.

First Order Logic

Constants	$Gold, Wumpus, [1,2], [3,1]$, etc.
Predicates	$Adjacent(), Smell(), Breeze(), At()$
Functions	$Result()$
Variables	$x,\ y,\ a,\ t, \ldots$
Connectives	$\land\ \lor\ \neg\ \Rightarrow\ \Leftrightarrow$
Equality	$=$
Quantifiers	$\forall\ \exists$

Sentences

Brothers are siblings

$\forall x, y\; Brother(x,y) \Rightarrow Sibling(x,y)$

"Sibling" is symmetric

$\forall x, y\; Sibling(x,y) \Leftrightarrow Sibling(y,x)$

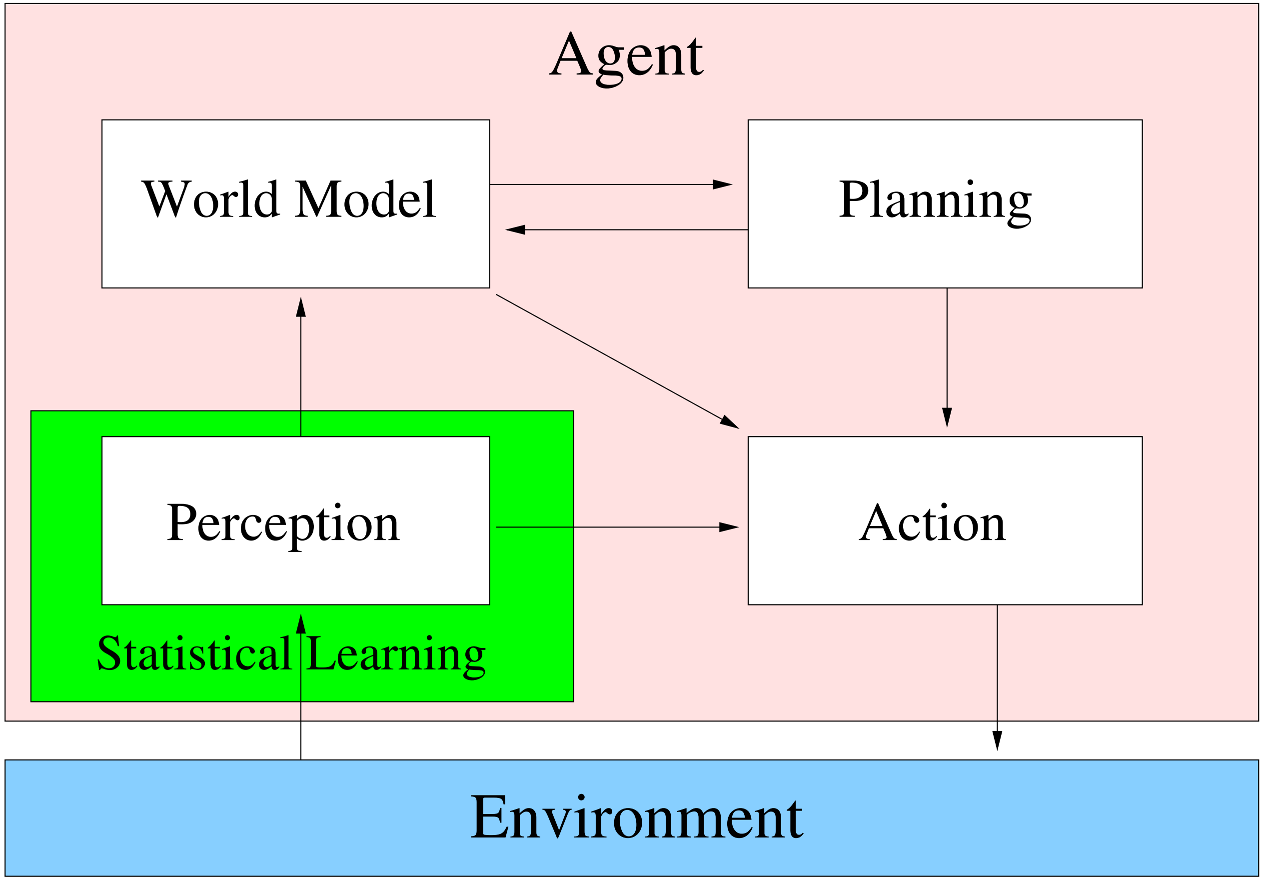
One's mother is one's female parent

$\forall x, y\; Mother(x,y) \Leftrightarrow (Female(x) \wedge Parent(x,y))$

A first cousin is a child of a parent's sibling

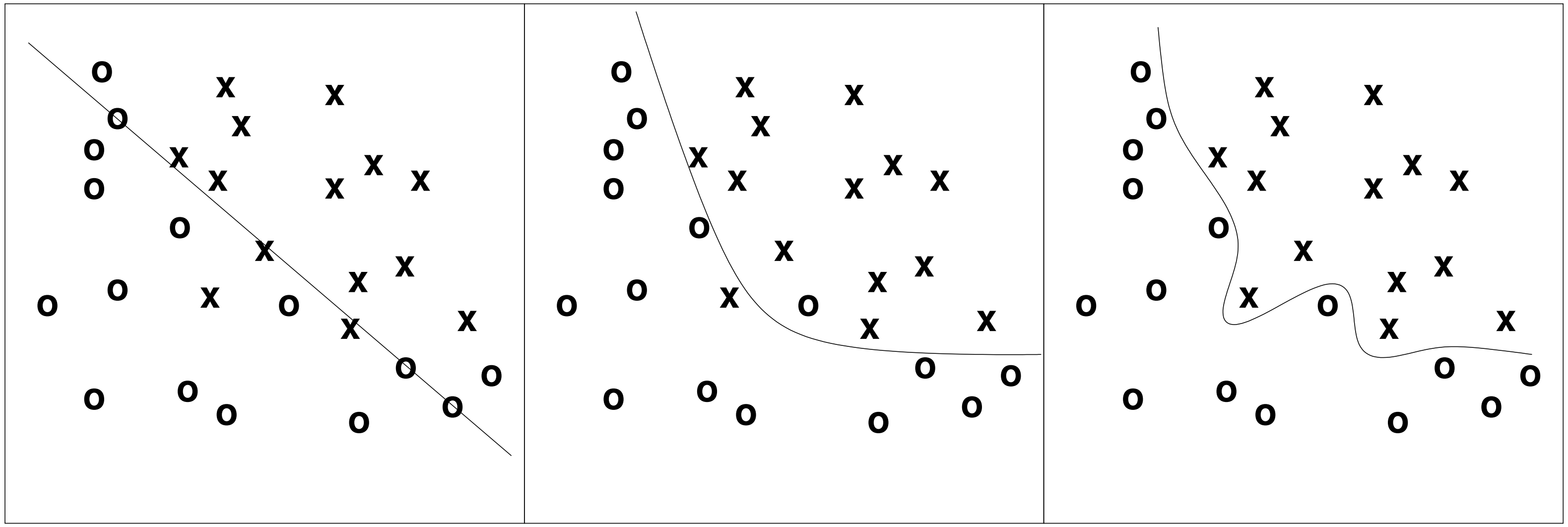
$\forall x, y FirstCousin(x,y) \Leftrightarrow \exists p, ps\; Parent(p,x) \wedge Sibling(ps,p) \wedge Parent(ps,y)$

Statistical Learning Agent



Ockham’s Razor

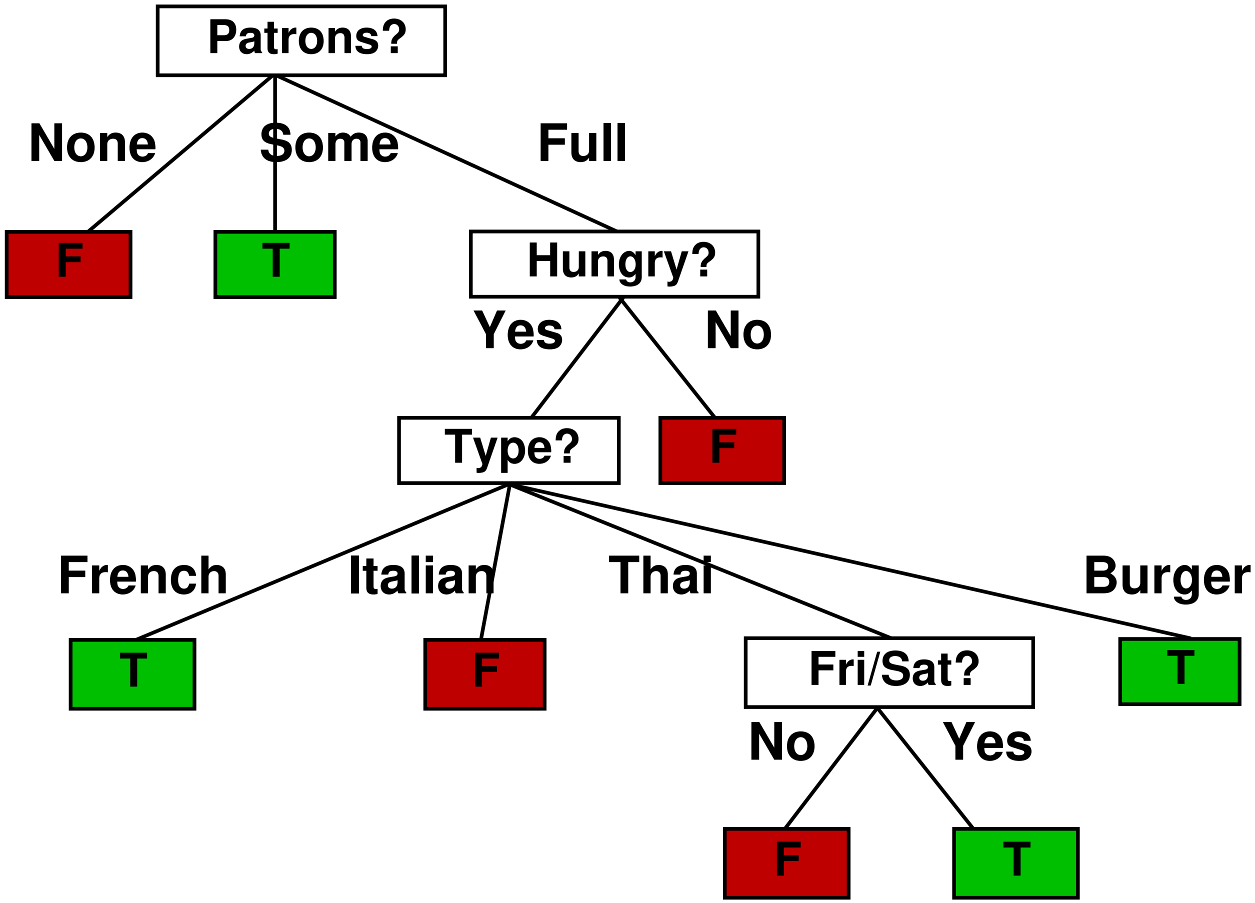
“The most likely hypothesis is the simplest one consistent with the data.”



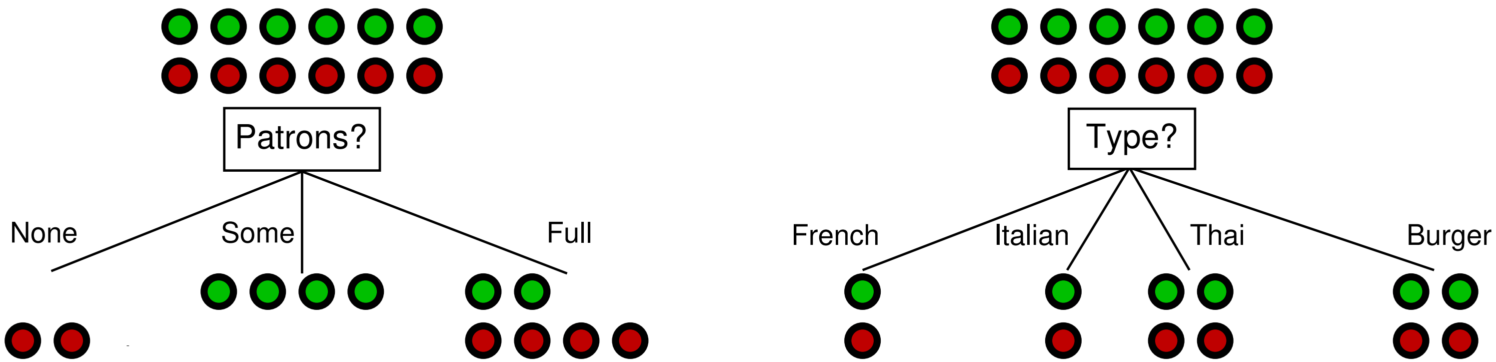
inadequate good compromise over-fitting

Since there can be noise in the measurements, in practice need to make a tradeoff between simplicity of the hypothesis and how well it fits the data.

Decision Tree



Choosing an Attribute



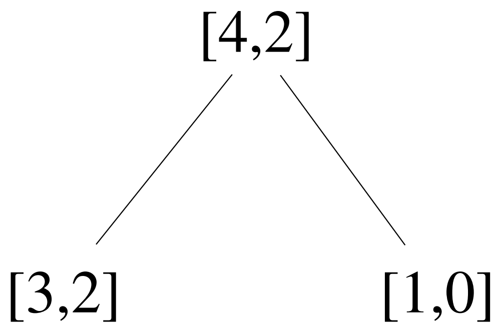
Patrons is a “more informative” attribute than Type, because it splits the examples more nearly into sets that are “all positive” or “all negative”.

This notion of “informativeness” can be quantified using the mathematical concept of “entropy”.

A parsimonious tree can be built by minimizing the entropy at each step.

Minimal Error Pruning

Should the children of this node be pruned or not?



Left child has class frequencies [2,4]

$$E = 1 - \frac{n+1}{N+k} = 1 - \frac{4+1}{6+2} = 0.375$$

Right child has $E = 0.333$

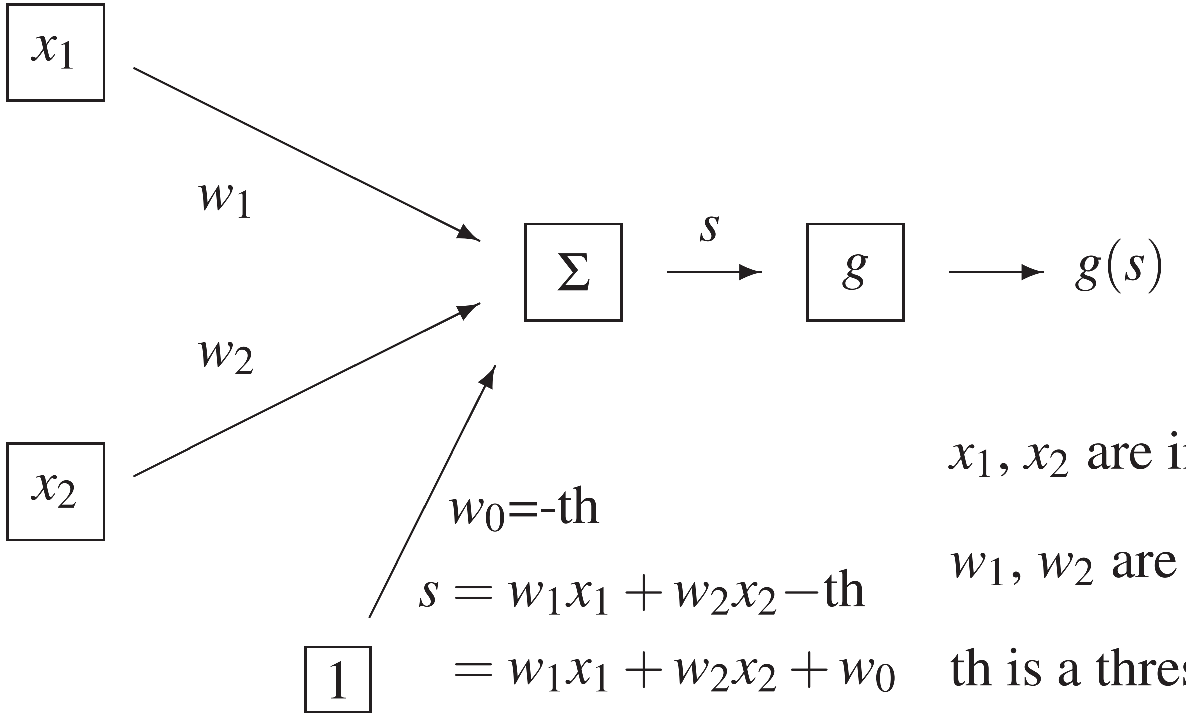
Parent node has $E = 0.444$

Average for Left and Right child is

$$E = \frac{6}{7}(0.375) + \frac{1}{6}(0.333) = 0.413$$

Since $0.413 > 0.375$, children should be pruned.

Rosenblatt Perceptron



$$s = w_1x_1 + w_2x_2 - \text{th}$$
$$= w_1x_1 + w_2x_2 + w_0$$

x_1, x_2 are inputs

w_1, w_2 are synaptic weights

th is a threshold

w_0 is a **bias** weight

g is transfer function

Perceptron Learning Rule

Adjust the weights as each input is presented.

recall: $s = w_1 x_1 + w_2 x_2 + w_0$

if $g(s) = 0$ but should be 1,

$$
\begin{aligned}
w_k &\leftarrow w_k + \eta\, x_k \\
w_0 &\leftarrow w_0 + \eta
\end{aligned}
$$

$$\text{so} \quad s \leftarrow s + \eta\,(1 + \sum_k x_k^2)$$

if $g(s) = 1$ but should be 0,

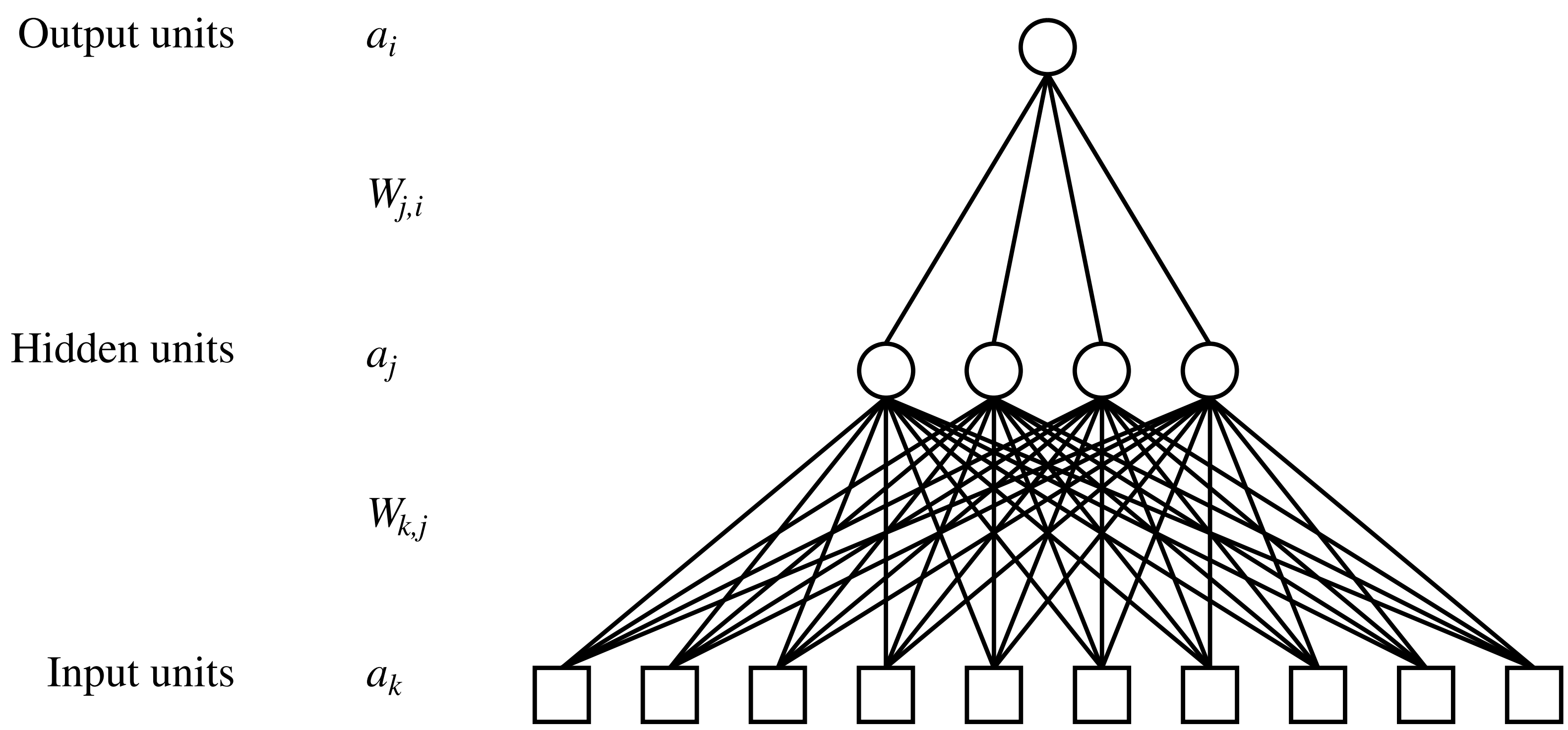
$$
\begin{aligned}
w_k &\leftarrow w_k - \eta\, x_k \\
w_0 &\leftarrow w_0 - \eta
\end{aligned}
$$

$$\text{so} \quad s \leftarrow s - \eta\,(1 + \sum_k x_k^2)$$

otherwise, weights are unchanged. ($\eta > 0$ is called the **learning rate**)

Theorem: This will eventually learn to classify the data correctly, as long as they are **linearly separable**.

Multi-Layer Neural Networks



Gradient Descent

We define an **error function** E to be (half) the sum over all input patterns of the square of the difference between actual output and desired output

$$E = \frac{1}{2}\sum(z-t)^2$$

If we think of E as height, it defines an error **landscape** on the weight space. The aim is to find a set of weights for which E is very low.
This is done by moving in the steepest downhill direction.

$$w \leftarrow w - \eta\,\frac{\partial E}{\partial w}$$

Parameter η is called the learning rate.

Probability and Uncertainty

	toothache		$\neg$ *toothache*	
	catch	$\neg$ *catch*	*catch*	$\neg$ *catch*
cavity	**.108**	**.012**	**.072**	**.008**
$\neg$ *cavity*	**.016**	**.064**	**.144**	**.576**

$$P(\neg \texttt{cavity} \mid \texttt{toothache}) = \frac{P(\neg \texttt{cavity} \wedge \texttt{toothache})}{P(\texttt{toothache})}$$

$$= \frac{0.016 + 0.064}{0.108 + 0.012 + 0.016 + 0.064} = 0.4$$

Bayes' Rule

Product rule $P(a \wedge b) = P(a|b)P(b) = P(b|a)P(a)$

$$\rightarrow \text{Bayes' rule } P(a|b) = \frac{P(b|a)P(a)}{P(b)}$$

Useful for assessing diagnostic probability from causal probability:

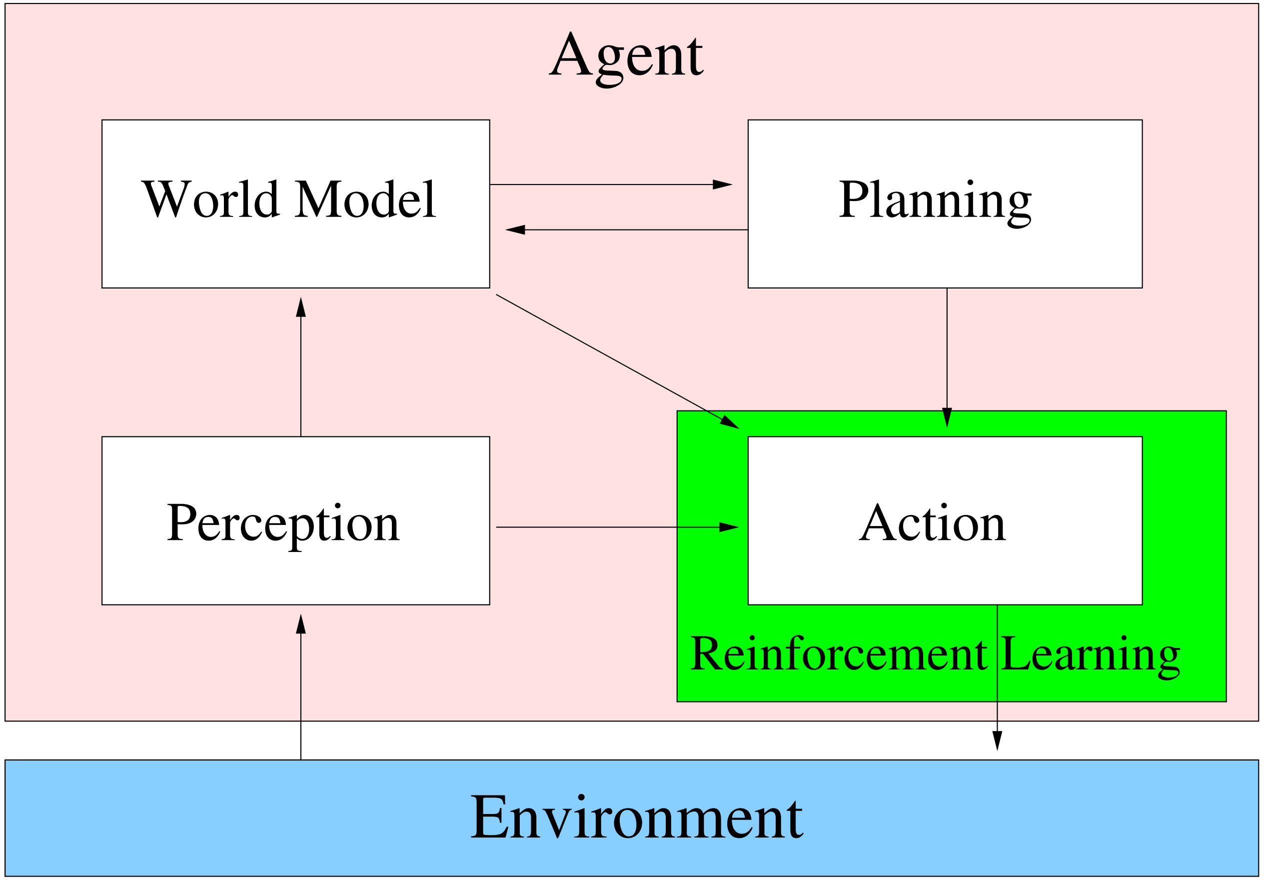
$$P(\text{Cause}|\text{Effect}) = \frac{P(\text{Effect}|\text{Cause})P(\text{Cause})}{P(\text{Effect})}$$

e.g., let M be meningitis, S be stiff neck:

$$P(m|s) = \frac{P(s|m)P(m)}{P(s)} = \frac{0.8 \times 0.0001}{0.1} = 0.0008$$

Note: posterior probability of meningitis still very small!

Reinforcement Learning Agent



Q-Learning

For each $s \in S$, let $V^*(s)$ be the maximum discounted reward obtainable from s, and let $Q(s,a)$ be the discounted reward available by first doing action a and then acting optimally.

Then the optimal policy is

$$\pi^*(s) = \mathrm{argmax}_a Q(s,a)$$

where
$$Q(s,a) = r(s,a) + \gamma V^*(\delta(s,a))$$

then
$$V^*(s) = \max_a Q(s,a),$$

so
$$Q(s,a) = r(s,a) + \gamma \max_b Q(\delta(s,a),b)$$

which allows us to iteratively approximate Q by

$$\hat{Q}(s,a) \leftarrow r + \gamma \max_b \hat{Q}(\delta(s,a),b)$$

Final Exam

- similar to Tutorial Questions, but in Multiple Choice format
- Questions 1-24 one mark each, Questaions 25-40 two marks each
- for each question, choose the ONE BEST Answer
- no marks taken off for wrong answers
- all modules covered in roughly equal proportion
- quick questions are at the beginning; longer questions at the end

Sample 1-mark Question

Completeness of a search algorithm answers the question:

(a) Is the algorithm guaranteed to find a solution when there is one?

(b) Does the strategy find the solution that has the lowest path cost of all solutions?

(c) How long does it take to find a solution?

(d) How much memory is needed to perform the search?

Sample 2-mark Question

Consider this joint probability distribution:

	short		$\neg$ short	
	wide	$\neg$ wide	wide	$\neg$ wide
striped	0.07	0.05	0.08	0.12
$\neg$ striped	0.14	0.17	0.12	0.25

Compute (to two decimal places): Prob(short $\vee$ $\neg$ wide $|$ striped)

(a) 0.50

(b) 0.63

(c) 0.75

(d) 0.80

Beyond COMP9414/3411

- COMP9444 Neural Networks and Deep Learning
- COMP9417 Machine Learning and Data Mining
- COMP4418 Knowledge Representation and Reasoning
- COMP3431 Robotic Software Architecture
- COMP9517 Machine Vision
- 4th Year Thesis topics

UNSW myExperience Survey

Please remember to fill in the UNSW myExperience Survey.

COMP3411/9414/9814 Artificial Intelligence

QUESTIONS?

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GOOD LUCK!