

Applications of AI

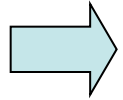
Alan Mackworth

UBC CS 322 - Intro 3

January 7, 2013

Textbook §1.5 - 1.6

Today's Lecture



Recap from last lecture

- Further Representational Dimensions
- Applications of AI

Representation and Reasoning (R&R) System

problem \Rightarrow representation \Rightarrow computation \Rightarrow representation \Rightarrow solution

- A **representation language** that allows description of
 - The environment and
 - Problems (questions/tasks) to be solved
- Computational **reasoning procedures** to
 - Compute a solution to a problem
 - E.g., an answer/sequence of actions
- How should an agent **act** given the current state of its environment and its goals?
- How should the environment be represented in order to **help** an agent **to reason effectively**?

Main Representational Dimensions Considered

Domains can be classified by the following dimensions:

- 1. **Uncertainty**
 - Deterministic vs. stochastic domains
- 2. **How many actions** does the agent need to perform?
 - Static vs. sequential domains

An important design choice is:

- 3. **Representation scheme**
 - Explicit states vs. propositions vs. relations

Features vs. States, another example

T_{11} : student 1 takes course 1

T_{12} : student 1 takes course 2

T_{21} : student 2 takes course 1

T_{22} : student 2 takes course 2

Does student 2 take course 2?

- Feature-based: Is T_{22} true?
- State-based: are we in one of the red states?

	T_{11}	T_{12}	T_{21}	T_{22}
S_0	0	0	0	0
S_1	0	0	0	1
S_2	0	0	1	0
S_3	0	0	1	1
S_4	0	1	0	0
S_5	0	1	0	1
S_6	0	1	1	0
S_7	0	1	1	1
S_8	1	0	0	0
S_9	1	0	0	1
S_{10}	1	0	1	0
S_{11}	1	0	1	1
S_{12}	1	1	0	0
S_{13}	1	1	0	1
S_{14}	1	1	1	0
S_{15}	1	1	1	1

Course overview

Course Modules \ Dimensions	Deterministic vs. Stochastic	Static vs. Sequential	States vs. Features vs. Relations
1. Search	Deterministic	Static	States
2. CSPs	Deterministic	Static	Features
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Example problems:

“find **path** in known map”

“are deliveries **feasible**?”

“what **order** to do things in to finish jobs fastest?”

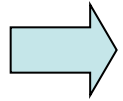
“HasCoffee(Person) **if** InRoom(Person, Room) \wedge DeliveredCoffee(Room)”

“**probability** of slipping”

“given that I may slip and the **utilities** of being late and of crashing, should I take a detour?”

Today's Lecture

- Recap from last lecture



Further Representational Dimensions

- Applications of AI

Further Dimensions of Representational Complexity

We've already discussed:

1. Deterministic versus stochastic domains
2. Static vs. Sequential domains
3. Explicit state or features or relations

Some other important dimensions of complexity:

4. Flat vs. hierarchical representation
5. Knowledge given vs. knowledge learned from experience
6. Goals vs. complex preferences
7. Single-agent vs. multi-agent
8. Perfect rationality vs. bounded rationality

4. Flat vs. hierarchical

- Should we model the whole world on the same level of abstraction?
 - Single level of abstraction: **flat**
 - Multiple levels of abstraction: **hierarchical**
- *Example: Planning a trip from here to a resort in Cancun*

Going to the airport

Take a cab

Call a cab

Lookup number

Dial number

Ride in the cab

Pay for the cab

Check in

....

- **Delivery robot:** Plan on level of cities, districts, buildings, ...
- **This course: mainly flat representations**
 - Hierarchical representations required for scaling up

5. Knowledge given vs. knowledge learned from experience

- The agent is provided with a model of the world once and for all OR
- The agent **can learn** how the world works based on experience
 - in this case, the agent often still does start out with some **prior knowledge** (no *tabula rasa!*)
- **Delivery robot**: Known/learned map, prob. of slipping, ...
- **This course**: mostly knowledge given
 - **Learning**: CPSC 340 and CPSC 422

6. Goals vs. (complex) preferences

- An agent may have a **goal** that it wants to achieve
 - E.g., there is some **state or set of states** of the world that the agent wants to be in
 - E.g., there is **some proposition or set of propositions** that the agent wants to make true
- An agent may have **preferences**
 - E.g., a **preference/utility function** describes how happy the agent is in each state of the world
 - Agent's task is to reach a state which makes it as happy as possible
- Preferences can be **complex**
 - E.g., **Diagnostic assistant** faces **multi-objective problem**
 - Life expectancy, suffering, risk of side effects, costs, ...
 - **Delivery robot**: “deliver coffee!” vs “mail trumps coffee, but Chris needs coffee quickly, and don't stand in the way”
- **This course: goals and simple preferences**
 - Some scalar, e.g. linear combination of competing objectives

7. Single-agent vs. Multiagent domains

- Does the environment include other agents?
- If there are other agents whose actions affect us
 - It can be useful to explicitly model their goals and beliefs, and how they **react** to our actions
- Other agents can be: **cooperative**, **neutral**, **competitive**, or a **bit of each**
- **Delivery robot**: Are there other agents?
 - Should I coordinate with other robots?
 - Are kids out to trick me?
- **This course: only single agent scenario**
 - Multiagent problems tend to be complex
 - Exception: **deterministic 2-player games** can be formalized easily

8. Perfect rationality vs. bounded rationality

We've defined rationality as an abstract ideal

- Is the agent able to live up to this ideal?

- **Perfect rationality:**

- the agent can derive what the best course of action is

- **Bounded rationality:**

- the agent must make good decisions

- based on its perceptual, computational and memory limitations

- **Delivery robot:**

- "Find perfect plan" vs.

- "Can't spend an hour thinking (thereby delaying action) to then deliver packages a minute faster than by some standard route"

- **This course: mostly perfect rationality**

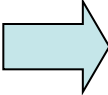
- But also consider **anytime** algorithms for optimization problems

Today's Lecture

- Recap from last lecture
- Further Representational Dimensions

 Applications of AI

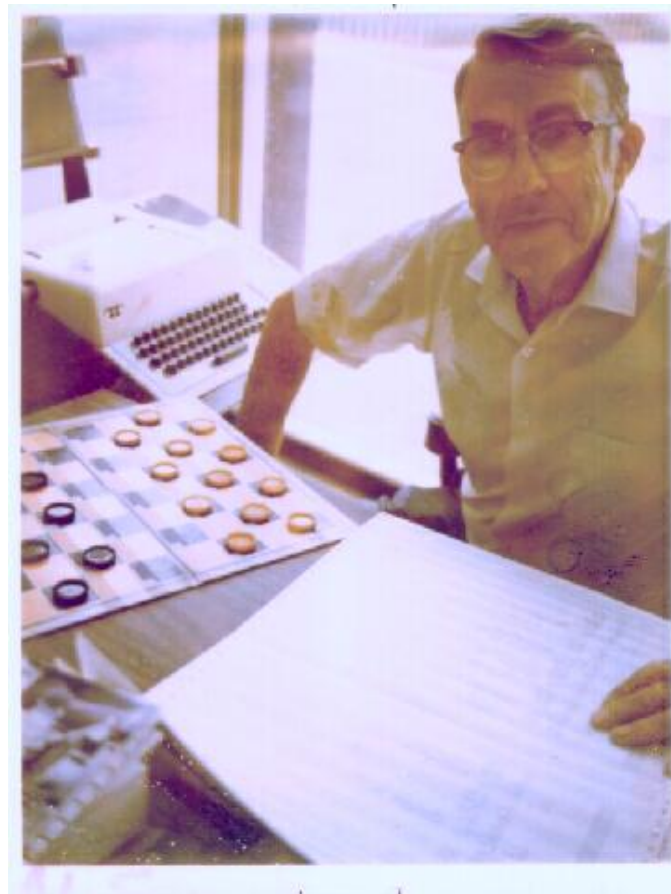
Course Map



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Search: Checkers

- Early learning work in 1950s by Arthur Samuel at IBM
- Chinook program by Jonathan Schaeffer (UofA)
 - Search to explore the space of possible moves and their consequences
 - 1994: world champion
 - 2007: declared unbeatable



Search: Chess

- In 1997, **Gary Kasparov**, the chess grandmaster and reigning world champion played against **Deep Blue**, a program written by researchers at IBM



Source: *IBM Research*



Search: Chess

- Deep Blue won 3 games, lost 2, tied 1



- 30 CPUs + 480 chess processors
- Searched 126,000,000 nodes per sec
- Generated 30 billion positions per move reaching depth 14 routinely

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CSP: Sudoku

Sudoku rules are extremely easy: Fill all empty squares so that the numbers 1 to 9 appear once in each row, column and 3x3 box.

Sudoku Puzzle

	9	3	6	2	8	1	4	
	6						5	
	3			1			9	
	5		8		2		7	
	4			7			6	
	8						3	
	1	7	5	9	3	4	2	

Sudoku Solution

2	7	1	9	5	4	6	8	3
5	9	3	6	2	8	1	4	7
4	6	8	1	3	7	2	5	9
7	3	6	4	1	5	8	9	2
1	5	9	8	6	2	3	7	4
8	4	2	3	7	9	5	6	1
9	8	5	2	4	1	7	3	6
6	1	7	5	9	3	4	2	8
3	2	4	7	8	6	9	1	5

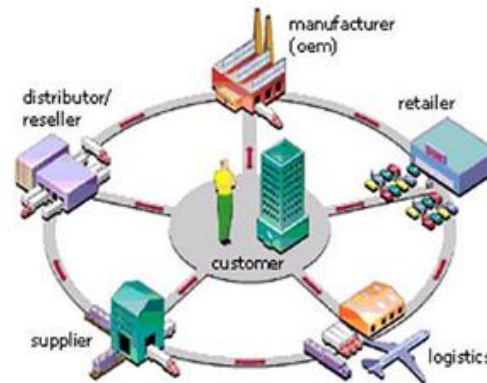
Constraint optimization problems

- Optimization under side constraints (similar to CSP)
- E.g. mixed integer programming (software: **IBM CPLEX**)
 - **Linear** program: $\max c^T x$ such that $Ax \leq b$
 - **Mixed integer** program: additional constraints, $x_i \in \mathbb{Z}$ (integers)
 - NP-hard, widely used in operations research and in industry



Transportation/Logistics:

SNCF, United Airlines
UPS, United States
Postal Service, ...



Supply chain
management

software:
Oracle, SAP, ...

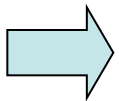


Production planning
and optimization:

Airbus, Dell,
Thyssen,
Toyota, Nissan, ...

Course Map

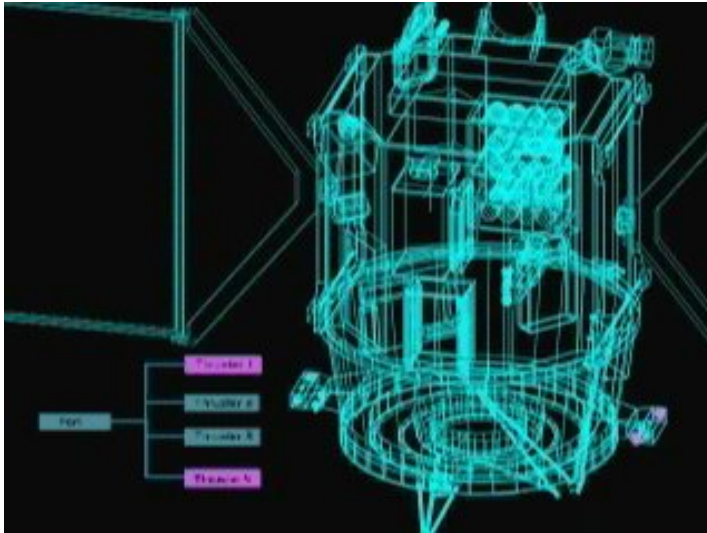
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Planning: Spacecraft Control

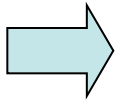
NASA: Deep Space One spacecraft

- operated autonomously for two days in May, 1999:
 - determined its precise position using stars and asteroids despite a malfunctioning ultraviolet detector
 - planned the necessary course adjustment
 - fired the ion propulsion system to make this adjustment



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Logic: Cyc

- AI project that started 1984 with the objective
 - to codify, in machine-usable form, millions of pieces of knowledge that comprise human common sense
- Logic reasoning procedures, e.g.
 - Every tree is a plant
 - Plants die eventually
 - Therefore, every tree dies eventually
- Criticisms include
 - Difficulty of adding knowledge manually
 - Non-scalability
 - Empirical evaluation - no benchmarks

Logic: Cyc

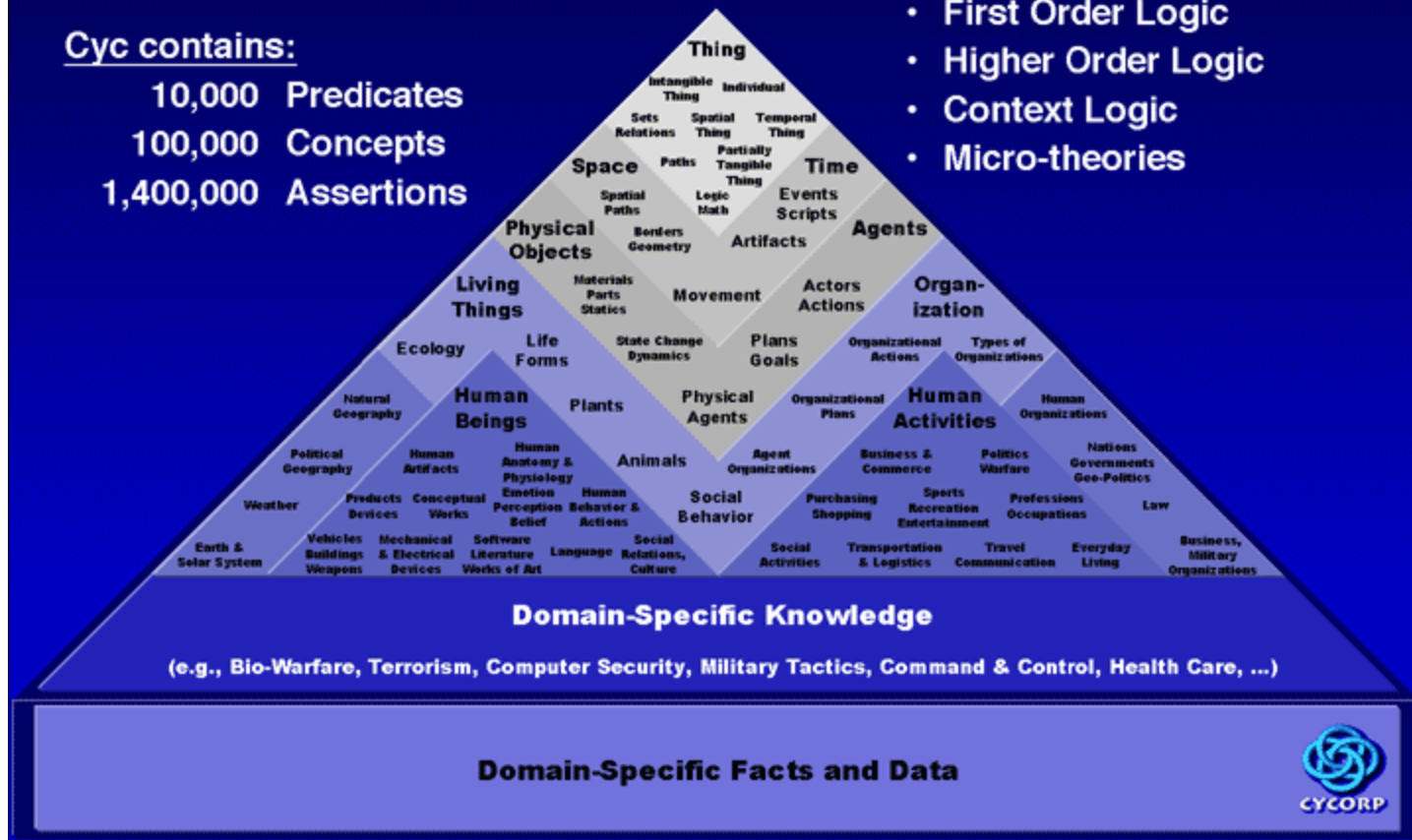
Cyc Ontology & Knowledge Base

Cyc contains:

10,000 Predicates
 100,000 Concepts
 1,400,000 Assertions

Represented in:

- First Order Logic
- Higher Order Logic
- Context Logic
- Micro-theories



CSP/logic: formal verification



Hardware verification
(e.g. IBM, Intel)

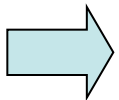


Software verification
(small to medium programs)

Most progress in the last 10 years based on
encodings into propositional satisfiability (SAT)

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Reasoning under Uncertainty

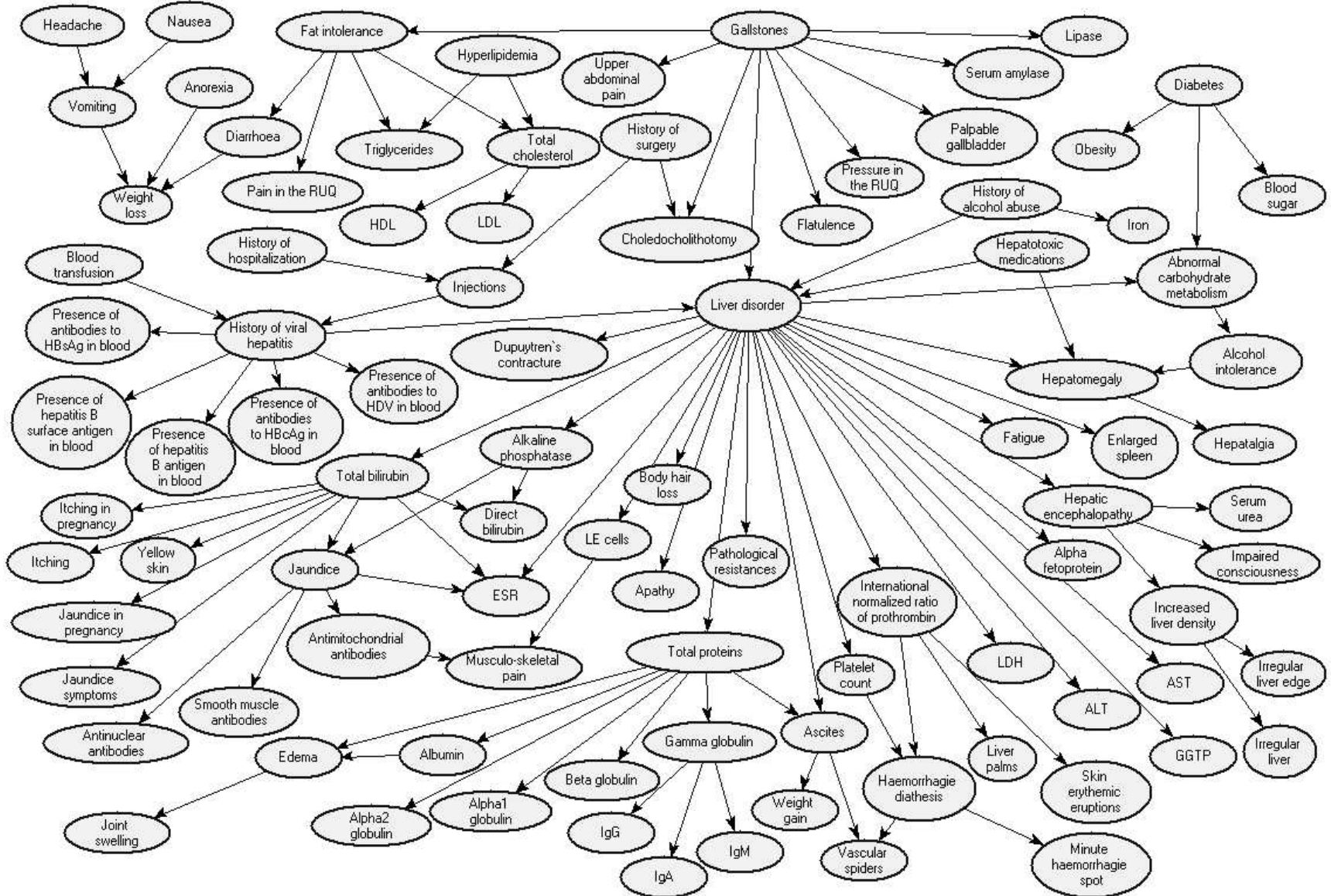
Sample application: Microsoft Kinect

- Sensor: IR camera for depth perception sensing projected pattern
- Noise: no fixed reference points; movements in the background



Source:
Microsoft
& YouTube

Uncertainty/Decision Theory: Diagnosis



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Decision Theory: Decision Support Systems

E.g., **Computational Sustainability**

- New interdisciplinary field, **AI** is a key component
 - Models and methods for **decision making** concerning the **management and allocation of resources**
 - to solve most challenging problems related to **sustainability**
- Often **constraint optimization problems**. E.g.
 - **Energy**: when and where to produce green energy most economically?
 - Which parcels of land to purchase to **protect endangered species**?
 - **Urban planning**: how to use budget for best development in 30 years?



Planning Under Uncertainty

Helicopter control: MDP, reinforcement learning



Source:
*Andrew
Ng*

Planning Under Uncertainty

Autonomous driving:

DARPA Urban Challenge - Stanford's Junior



Source:
*Sebastian
Thrun*

Planning Under Uncertainty

- Autonomous driving: Dickmanns (1986), Google, Audi, Toyota, Mercedes-Benz, ...
- Self-driving cars are now street legal in Florida, California and Nevada.



Image source:
geek.com

Military applications: ethical issues

- Robot soldiers
 - Existing: robot dog carrying heavy materials for soldiers in the field
 - The technology is there
- Unmanned airplanes
- Missile tracking
- Surveillance
- ...



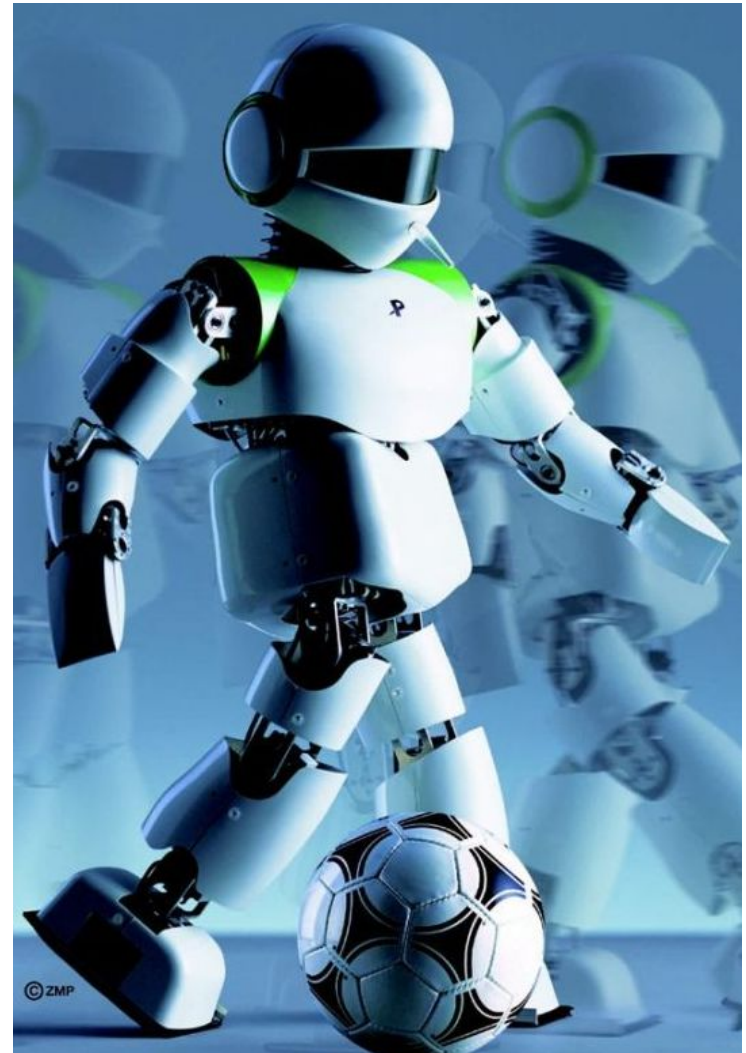
Image Source: Boston Dynamics

Multiagent Systems: Robot Soccer



Source: RoboCup web site

RoboCup



The Dynamites: Two on Two



World's First Soccer Playing Robots (UBC, 1993)

Robot Soccer: Humanoids



Source:
Darmstadt Dribbling Dackels
40

Summary(1)

We would like most general agents possible, but to start with we need to **restrict scope**:

4. Flat representations (vs. hierarchical)
5. Knowledge given (vs. knowledge learned)
6. Goals and simple preferences (vs. complex preferences)
7. Single-agent scenarios (vs. multi-agent scenarios)
8. Perfect rationality (vs. bounded rationality)

Extensions we **will** cover:

1. Deterministic versus **stochastic** domains
2. Static vs. **Sequential** domains
3. Representation: **Explicit state** or **features** or **relations**

Summary(2)

- Huge diversity of applications
- More than I could possibly show here
- We shall focus on their common foundations

Coming up ...

- For Friday, 1pm: Assignment 0
 - Available on Connect
 - Section 1.5 & 1.6 in the textbook will be particularly helpful
- We'll start the search module: *read Sections 3.0-3.4*
- Please continue to bring coloured cards (we shall use them next class)

