AI Knowledge representation

- Core distinction between:
  - **Declarative** representation (**WHAT**)
    - All birds can fly
    - Ducks are birds
    - Penguins are birds, but cannot fly
    - Etc
  - **Inference** (**HOW** to compute)
    - Pengi is a penguin
    - Pengi is a bird
    - Can Pengi fly?
KR general intelligence

Structured object models
wheel(w1), wheel(w2),
frame(1), connected(w1,f)...

Occlusion relations
partially_behind..

Structured models of complete scenes
lawnmower(l), dustbin(b), spatial_relation(l,b)

Commonsense, dynamic prediction models
What will probably happen if I move this table?
Finite worlds $\leftrightarrow$ probabilistic graphical model, but
  – Random variable for all ground relations, e.g. $\text{on}_{a,b}=1$
  – Need to order all objects and relations
  – No generalization over objects
Number of model parameters grows exponentially fast (in #objects and #relations) even if there is considerable structure
States are described by objects and relations; powerful representations and learning algorithms need to support that (~Prolog-like)

Figure 1.6: Data structures for FREGE. a) A state and a set of applicable actions. b) Part of the transition model ($T$).
An Logical (Machine Learning) Classic

1. TRAINS GOING EAST

1.

2.

3.

4.

5.

2. TRAINS GOING WEST

1.

2.

3.

4.

5.
Relational Representation

Example:
eastbound(t1).

Background theory:
car(t1,c1).     car(t1,c2).     car(t1,c3).     car(t1,c4).
rectangle(c1).   rectangle(c2).   rectangle(c3).   rectangle(c4).
short(c1).       long(c2).        short(c3).       long(c4).
none(c1).        none(c2).        peaked(c3).      none(c4).
two_wheels(c1).  three_wheels(c2). two_wheels(c3).  two_wheels(c4).
load(c1,l1).     load(c2,l2).       load(c3,l3).     load(c4,l4).
circle(l1).      hexagon(l2).       triangle(l3).    rectangle(l4).
one_load(l1).    one_load(l2).      one_load(l3).
three_loads(l4).

Hypothesis:
eastbound(T) :- car(T,C), short(C), not none(C).
AI started using relational KR

1970

Shakey and STRIPS planning

John McCarthy Situation Calculus
Logic dominates in linguistics and spatial/temporal data

Semantics, discourses, grammars

Spatial and Temporal formalisms
KR and AI

State-of-the-art (learning) approaches:
Based on propositional, probabilistic graphical models
In: Computer vision, (cognitive) Robotics, Linguistics, and Reinforcement Learning
An AI classic: Bioinformatics, molecules, and proteins

Examples $E$
- pos(mutagenic($m_1$))
- neg(mutagenic($m_2$))
- pos(mutagenic($m_3$))
...

Background Knowledge $B$
- molecule($m_1$)
- molecule($m_2$)
- atom($m_1$, $a_{11}$, $c$)
- atom($m_2$, $a_{21}$, $o$)
- atom($m_1$, $a_{12}$, $n$)
- atom($m_2$, $a_{22}$, $n$)
- bond($m_1$, $a_{11}$, $a_{12}$)
- bond($m_2$, $a_{21}$, $a_{22}$)
- charge($m_1$, $a_{11}$, 0.82)
- charge($m_2$, $a_{21}$, 0.82)
...
Relational representations (graphs: objects and relations)

Tasks → subsumes attribute-value
Tools → rules, decision trees, etc
Real Time Strategy Games (RTS)

This subsumes all kinds of logistics domains!

StarCraft 2 (Blizzard)
And yes... Blocks World!
Uncertainty and Learning

- Core of this course:
  - Representation
  - Inference (deduction, abduction)

- Later
  - Some uncertainty
  - Some utility
  - No learning

- Current AI:
  - Statistical Relational Learning (SRL)
  - Probabilistic Logic Learning (PLL)
  - KR+learning+probability+utility+AI+…
Uncertainty?

- Real world domains
- Vision, Robotics, Linguistics
- Noisy sensor data
- Most things are uncertain!

- Use logic for knowledge representation
- Add uncertainty

- Often upgrades of probabilistic graphical models (e.g. Bayesian networks)
Upgrading: The Alphabet of SRL

Probabilistic logics (Nilsson, Halpern, Bacchus)
Knowledge-Based Model Construction (KBMC)
Stochastic Logic Programs (SLP)
Logic programs with annotated disjunctions (LPAD)
Causal Process logic (CP-Logic)
Probabilistic Relational Models (PRM)
Statistical Relational Models (SRM)
Bayesian Logic Networks (BLN)
Bayesian Logic Programs (BLP)
Relational Markov Models (RMM)
Markov Logic Networks (MLN)
Relational Decision Networks (RDN)
Relational Dependency Networks (RDN)
Bayesian Logic (BLOG)

Many SRL systems Started as an attempt to **upgrade** a particular propositional learning /probabilistic model. (e.g. BN, CRF, MRF, ME, DBN, HMM, ..)

---

### SCFG/SLP

\[
\begin{align*}
\ldots & 1:s(A,B) :- n(A,C), v(C,D), n(D,B). \\
& 0.4:n([joe\mid T],T). \quad 0.6:n([kim\mid T],T). \\
& 0.3:v([sees\mid T],T). \quad 0.7:v([likes\mid T],T).
\end{align*}
\]
Computational Logic + AI

Computational, probabilistic logic + learning →
high-level/cognitive **vision**, high-level **robotics**, Spatial/natural **language** grounding

**Additional**
Decision-theoretic planning, abductive logic
DT-Problog

**Now @ICRA’12**

**Best paper award @ICPRAM’12**

In journal TCLP@ACM

ON(\text{book,table})
IN(\text{table, living room})
IN(\text{book,living room})?
People Tracking

person(p1). ...
person(p5).

group(p4,p5).
KR for AI cognitive robotics

(a) Logical formalism
(LOC(SELF2735)
(OBJ16837)(OBJ27298)
(OBJ392138)
(ISA(SELFROBOT)
(OBJ1DESK)(OBJ2CHAIR)
(OBJ3DOOR)
(DEF(ROBOTxx)(DESKxx)..)

(b) Representation with indexicals
(AHEAD '<1>)
(DISTANCE(BETWEEN SELF '<2>)
(FREEPATH SELF '<3>)
(CAN-EXIT '<4>)

(c) Internal world model?
Relational/Cognitive Robotics

package1 next-to package2

action:: deliver(package1,kitchen)

package6

on

package7

@KULeuve
KR for modern robotics
Relations in High-Level Vision

Bottom-up, hierarchical approach to understanding and semantically segmenting images of houses

(L. Antanas, M. van Otterlo, J. Oramas, T. Tuytelaars, L. De Raedt, ILP-2010)
**Spatial (language)**

**Spatial surroundings of the robot:**

- near(arm, table),
- distance(robot, door, 10.3),
- \( P(\text{succ} | \text{forward}) = 0.9 \), ....

**Instructions:**

“Move to the first table on your left, and pick the object nearest to the edge of it”

Involves high-level vision, planning, manipulation, etc.
In addition to relations: Uncertainty

- Many domains (inc. linguistics) exhibit
  - Structure in terms of objects and relations
  - Highly statistical and ambiguous problems

I saw the man with a telescope  
I saw the man with a telescope

Hier in Otterlo kun je mooie dingen zien. 
Martijn van Otterlo woont in Leuven..... maar, Otterlo heeft een nieuw stadhuis, maar nu is Leuven jaloers. Mr. Mark van Otterlo zei dat dat gerechtvaardigd was.

The book is on the table
The book lies on the table
The book is supported by the table
The book is about a table
The book has a table of contents
The book contains a table of contents
Jeopardy and Watson
Dynamics: CPTL
(Thon, Landwehr, De Raedt 2010)

\[
\begin{align*}
&b_1, \ldots b_n \rightarrow h_1 : p_1 \lor \ldots \lor h_m : p_m \\
&\text{cause (past)} \quad \text{effect (future)}
\end{align*}
\]

conquer a city which is close:

\[
\text{city}(C, \text{Owner}), \text{city}(C2, \text{Attacker}), \text{close}(C, C2) \rightarrow
\text{conquest}(\text{Attacker}, C) : p \lor \text{nil} : (1 - p)
\]
Again (AIPSML): Decision networks

<table>
<thead>
<tr>
<th>Weather</th>
<th>Umbrella</th>
<th>Utility</th>
</tr>
</thead>
<tbody>
<tr>
<td>norain</td>
<td>takeIt</td>
<td>20</td>
</tr>
<tr>
<td>norain</td>
<td>leaveIt</td>
<td>100</td>
</tr>
<tr>
<td>rain</td>
<td>takeIt</td>
<td>70</td>
</tr>
<tr>
<td>rain</td>
<td>leaveIt</td>
<td>0</td>
</tr>
</tbody>
</table>

\[ P(\text{Weather} = \text{rain}) = 0.3 \]
Relational Reinforcement Learning

Representation and generalization in terms of **objects** and **relations**
Logical learning, reasoning, planning

Decision-theoretic planning
Reinforcement learning

Before state-of-the-art was **propositional**

**Logic** for abduction/deduction/induction
**Probability** for uncertainty
**Utility** for optimality and learning

→ decision-theoretic high-level cognition

IOS Press (2009)
Original RRL approach by Dzeroski, De Raedt and Blockeel (ICML 98)

Episode based, tree induction (batch), Q-learning
Small, deterministic Blocks Worlds

```
qvalue(0) :-
    action(move(A,B)) , goal(on(C,D)) ,
    on(C,D), !.
qvalue(1) :-
    action(move(A,B)) , goal(on(C,D)) ,
    action(move(C,D)), !.
qvalue(0.9) :-
    action(move(A,B)) , goal(on(C,D)) ,
    action(move(D,B)), !.
qvalue(0.81).
```

```
qvalue(0.81).
    action(move(c,floor)).
    goal(on(a,b)).
    clear(c).
    on(c,b).
    on(b,a).
    on(a,floor).
qvalue(0.9).
    action(move(b,c)).
    goal(on(a,b)).
    clear(b).
    on(b,c).
    on(a,floor).
    on(c,floor).
qvalue(1.0).
    action(move(a,b)).
    goal(on(a,b)).
    clear(a).
    on(b,a).
    on(a,floor).
    on(c,floor).
qvalue(0.0).
    action(move(a,floor)).
    goal(on(a,b)).
    clear(a).
```


DT-Problog (AAAI-2010)
Van den Broeck/Thon/van Otterlo/De Raedt
Decision-theoretic Prolog

Decision Facts
? :: umbrella.
? :: raincoat.

Probabilistic Facts
0.3 :: rainy.
0.5 :: windy.

Background Knowledge

dry :- rainy, umbrella, not(broken_umbrella).
dry :- rainy, raincoat.
dry :- not(rainy).

broken_umbrella :- umbrella, rainy, windy.

Utility Facts
umbrella => -2.
raincoat => -20.
dry => 60.
broken_umbrella => -40.
Probabilistic Facts
0.3 :: buy_trust(_, _).
0.2 :: buy_marketing(_).

Background Knowledge
buys(X) :-
    trusts(X, Y),
    buys(Y),
    buy_trust(X, Y).

buys(X) :-
    marketed(X),
    buy_marketing(X).
Probabilistic Facts
...
Background Knowledge
...
Decisions
? :: marketed(P) :- person(P).

Utility Facts
buys(P) => 5 :- person(P).
marketed(P) => -3 :- person(P).
eindslide