Part D: Statistical Relational Learning for Robotics
Outline

- Rough idea of statistical relational learning
- Learning probabilistic rules $\rightarrow$ model-based relational RL
- Exploration
- Conclusions
vector space
great advances
mature ML/RL methods

hybrid, combinatorial space
great challenges
relational learning & inference
If a robot starts manipulating objects, the whole environment becomes “subject to robotics” – methods for planning, control, estimation, etc need to extend external DoFs, not only robot’s internal DoFs.
Objects & Relations

- World is composed of objects
  - objects have (changeable) properties & relations
  - the state $s$ is given by the set of all properties/relations of all objects

- Example: We have a symbolic property $\text{big}$ and relation $\text{on}$
  - In a world with 2 objects $A, B$, the state $s$ is composed of 3 variables
    \[ s = (\text{big}(A), \text{big}(B), \text{on}(A, B)) \]
  - In a world with 3 objects $A, B, C$, $s$ is composed of 6 variables:
    \[ s = (\text{big}(A), \text{big}(B), \text{big}(C), \text{on}(A, B), \text{on}(B, C), \text{on}(A, C)) \]
  - In a world with $n$ objects we have $n + n(n - 1)/2$ state variables

  *The size of the state space is exponential in # objects*
Relational models

- Relational models...
  - generalize data seen in one world (with objects \( A, B, C, \ldots \)) to another world (with objects \( D, E, \ldots \))
  - make predictions based only on the properties/relations of objects, *not their identity*
  - thereby imply a very strong type of generalization/prior which allows to efficient learn in the exponentially large space

**Object Abstraction Assumption:** *The world is made up of objects, and the effects of actions on these objects generally depend on their attributes rather than their identities.*

Pasula, Zettlemoyer & Kaelbling (ICAPS 2004)
Example: Bayesian Logic Programs

- In logic programming,
  \[
  \text{stable}(A) :\neg \ \text{on}(A,B), \ \text{big}(B)
  \]
  means "For all $A, B$ if $B$ is big and $A$ on $B$ then $A$ is stable"
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- In Bayesian Logic Programs [Kersting and de Raedt]
  \[ \text{stable}(A) :- \text{on}(A,B), \text{big}(B) \]
  means “For all \( A, B \), if \( \text{big}(B) \) and \( \text{on}(A, B) \) are random variables, then \( \text{stable}(A) \) is a random variable”
  Associated with this rule is a conditional probability table (CPT) that specifies the probability distribution over \( \text{stable}(A) \) for any possible values of \( \text{on}(A, B) \) and \( \text{big}(B) \)

- We have a knowledge representation that allows us to construct a grounded Bayesian Network for specific worlds (sets of objects); this BN will have many shared parameters.
• There exist many many more relational modelling formalisms.

   Markov Logic Networks, Probabilistic Relational Models, Relational Markov Networks, Relational Probability Trees, Stochastic Logic Programming, ...

See ECML/PKDD 2007 tutorial by Lise Getoor!

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- “Probabilistic learning & inference on 1st order logic representations”
  - very strong generalization across objects
  - in my view: the currently only way to express & learn uncertain
    knowledge about environments with objects & properties/relations

SRL + Robotics = perfect match!
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Model-based RL in the relational case

\[ D = \{ \]

\begin{align*}
\text{grab(c)} : & \quad \text{box(a) box(b) ball(c) table(d) on(a,b) on(b,d) on(c,d) inhand(nil) ...} \\
& \quad \rightarrow \text{box(a) box(b) ball(c) table(d) on(a,b) on(b,d) \neg on(c,d) inhand(c) ...} \\
\text{puton(a)} : & \quad \text{box(a) box(b) ball(c) table(d) on(a,b) on(b,d) \neg on(c,d) inhand(c) ...} \\
& \quad \rightarrow \text{box(a) box(b) ball(c) table(d) on(a,b) on(b,d) on(c,a) inhand(nil) ...} \\
\text{puton(b)} : & \quad \text{box(a) box(b) ball(c) table(d) on(a,b) on(b,d) on(c,a) inhand(nil) ...} \\
& \quad \rightarrow \text{box(a) box(b) ball(c) table(d) on(a,b) on(b,d) on(c,a) inhand(nil) ...} \\
\text{grab(b)} : & \quad \text{box(a) box(b) ball(c) table(d) on(a,b) on(b,d) on(c,a) inhand(nil) ...} \\
& \quad \rightarrow \text{box(a) box(b) ball(c) table(d) on(a,d) \neg on(b,d) on(c,d) inhand(b) ...} \\
& \quad \vdots \\
\} \\

\bullet \text{ How can we learn a predictive model } P(x' \mid u, x) \text{ for this data?} \\
\text{With } n = 20 \text{ objects, state space is } > 2^{n^2} \approx 10^{120}
Learning probabilistic rules

Pasula, Zettlemoyer & Kaelbling: Learning probabilistic relational planning rules (ICAPS 2004)

• **Compress** this data into probabilistic relational rules:

\[
\text{grab}(X) : \ on(X,Y), \ block(Y), \ table(Z)
\]

\[
\rightarrow \begin{cases} 
0.7 &: \ inhand(X), \ \neg on(X,Y) \\
0.2 &: \ on(X,Z), \ \neg on(X,Y) \\
0.1 &: \ \text{noise}
\end{cases}
\]

• Find a rule set that maximizes *(likelihood - description length)*
Role of uncertainty in learning these rules

- Introducing uncertainty in the rules not only allows us to model stochastic worlds, it enables to compress/regularize and thereby learn strongly generalizing models!

- A core problem with deterministic AI is learning deterministic models.
Role of uncertainty in learning these rules

⇒ uncertainty ↔ regularization ↔ compression & abstraction

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uncertainty enables learning!
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Planning as inference in relational domains

- Once the model is learnt, using it (planning) is hard

- SST & UCT do not scale with # objects

→ Use Planning-as-Inference:

\[ \text{model depending on: situation relevance} \]

one representation good for learning, another good for planning

(Lang & Toussaint, JAIR 2010)
Planning as inference in relational domains

(we’re using factored frontier for approx. inference)

→ Advances in **Lifted Inference** will translate to better robot manipulation planning.
Application

Random exploration:

Real-world:

Planning:

Online explore-exploit:

Lang & Toussaint: Planning with Noisy Probabilistic Relational Rules (JAIR 2010)
Toussaint et al: Integrated motor control, planning, grasping and high-level reasoning in a blocks world using probabilistic inference (ICRA 2010)
Lang, Toussaint & Kersting: Exploration in Relational Worlds (ECML 2010)
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Relational Exploration

• The state space is inherently exponential in the # objects. How could we realize strategies like $E^3$ or R-max in relational domains?

"smoothed empirical density"
Relational Exploration

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- Key insight:

  strong generalization of model

  \[ \iff \]

  strong implication on what is considered novel is explored

For instance, if you’ve seen a red, green and yellow ball rolling, will you explore whether the blue ball also rolls? Or rather explore something totally different, like dropping a blue box?
Relational Exploration

- Transfer *Explicit Explore or Exploit* ($E^3$) to Relational Domains

- Representations to formulate an “empirical distribution” (non-novelty)

\[
\begin{align*}
\text{propositional} & \quad P(s) \propto c_D(s) \\
\text{distance based} & \quad P_d(s) \propto \exp\left\{ - \min_{(s_e, a_e, s_e') \in D} d(s, s_e)^2 \right\} \\
\text{predicate-based} & \quad P_p(s) \propto c_p(s) \ I(s \models p) + c_{\neg p}(s) \ I(s \models \neg p) \\
\text{context-based} & \quad P_\phi(s) \propto \sum_{\phi \in \Phi} c_D(\phi) \ I(\exists \sigma : s \models \sigma(\phi)) \\
\text{ (contexts} & \leftrightarrow \text{ set of LHSs of rules) }
\end{align*}
\]
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Online Relational explore-exploit:

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- Statistical Relational Learning addresses only one aspect of such a prior: objects. There is much more:

  static:
  - 3D Geometry
  - Kinematics (rigid b., DoFs)
  - Controllability

  dynamic:
  - things don’t float in the air
  - small things on top of large
  - implausible forces

  semantic:
  - a car in a kitchen is unlikely

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Relational Learning in Robotics

- A popular science article:

  *I, algorithm: A new dawn for artificial intelligence*
  (Anil Ananthaswamy, NewScientist, January 2011)

  Talks of “probabilistic programming, which combines the logical underpinnings of the old AI with the power of statistics and probability.” Cites Stuart Russel as “It’s a natural unification of two of the most powerful theories that have been developed to understand the world and reason about it.” and Josh Tenenbaum as “It’s definitely spring”.

20/23
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• My impression: Exactly these kinds of developments give new hope for Robots to explore, learn and plan in our natural world, composed of objects.
Kaelbling & Tomás Lozano-Pérez: Hierarchical Task and Motion Planning in the Now (ICRA 2011)
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thanks for your attention!