Equipping Robot Control Programs with First-Order Probabilistic Reasoning Capabilities

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Abstract

Introduction

Applications of S.R. Models

Architectural Overview

Representation Formalisms

Learning

Inference

Integration with the Control Program

References
Abstract
Abstract

An autonomous robot system that is to act in a real-world environment is faced with the problem of having to deal with a high degree of both complexity as well as uncertainty. Therefore, robots should be equipped with a knowledge representation system that is able to soundly handle both aspects. In this paper, we thus introduce an architecture that provides a coupling between plan-based robot controllers and a probabilistic knowledge representation system based on recent developments in statistical relational learning, which possesses the required level of expressiveness and generality. We outline possible applications of the corresponding models in the context of robot control, discussing suitable representation formalisms, inference and learning methods as well as transparent extensions of a robot planning language that allow robot control programs to soundly integrate the results of probabilistic inference into their plan generation process.
Introduction
Autonomous Robot in human environments

Why is there a need for powerful Probabilistic Reasoning?

- To make reasonable predictions about the state of the environment.
- High dimensional State Estimation problems.
- Robust control programs (i.e., anticipate failures, select actions that maximize success likelihood).
- Allows the robot to extract *MEANING* behind agent interaction.
Setting the breakfast table – Uncertain Info
– Who’s eating, who sits where, who eats what, who’s going to need Utensil $x, y, z$. 

Example
The Human way –

Knowledge that Person $X$ always eats cereal.

Subconscious Heuristics for locating plates/bowls and utensils.

contextual info –

- recent activity in the kitchen
  (has someone recently run the dishwasher)
- spatial relationships

All of this information is taken into account when deciding the order in which places should be searched.

All of these decisions require reasoning under uncertainty, how can this be adapted so that a Robot can solve similar tasks.
What Does the Robot Need?

A Knowledge Representation that supports reasoning at appropriate levels of abstraction.

- The model needs to be as general as possible, and not specific to a particular instance of an environment.

First-order Languages, allow universal quantification, and abstract away concrete objects.

Anybody who eats cereal is likely to use a bowl and a tablespoon. But may use a cup or teaspoon.
SRL is a combination of:

- First Order Representations
- the semantics of probabilistic graphical models.

Q. How does this affect Real-World environments?
A. Complexity and Uncertainty.

**First Order Representations** –
Are well suited to dealing with high degrees of complexity by supporting universal rules that generalize across objects having similar properties.

**Probabilistic Models** –
Allow for representing the varying degrees of uncertainty.
- Contains a set of general First-Order sentences that describe dependencies among atomic sentences pertaining to objects belonging to particular classes.
- The strength of which is quantified by probabilistic parameters.

For any concrete set of objects belonging to the classes, the model can be compiled (via template mechanism) into a ground model that represents a full-joint probability distribution over all the ground atoms that can be constructed from the model's set of logical predicates and the set of objects it was combined with.
Suppose the template model contains only a single (weighted rule):

\[ \forall p \, \text{eats}(p, \text{Cereals}) \rightarrow \text{uses}(p, \text{Bowl}) \]

which applies to all people \( p \).

If this model is combined with a set of concrete people, e.g. \( \{\text{Nick}, \text{Ashok}\} \).

The ground model will represent the full-joint distribution over the set of possible worlds implied by the ground atoms (boolean r.v.'s)

\[
\text{eats}(\text{Nick}, \text{Cereal}), \text{uses}(\text{Nick}, \text{Bowl}), \\
\text{eats}(\text{Ashok}, \text{Cereal}), \text{uses}(\text{Ashok}, \text{Bowl})
\]

a distribution over \( 2^4 = 16 \) possible worlds.
Generally it is not possible to quantify the degree of uncertainty that applies to a particular aspect of the domain in question.

So the probabilistic parameters of the models should be learnt from data.

(Training data for parameter learning)

Note: The structure of the model
(spec. of possible dependencies in the domain)
is given by expert knowledge.
Applications of S.R. Models

Abstract

Introduction

Applications of S.R. Models

Benefits 1

Benefits 2

Architectural Overview

Representation

Formalisms

Learning

Inference

Integration with the Control Program

References
Tasks are usually under-specified.

- A Robot can fill in the missing parts of a task specification by inferring the most likely specification and adjusting its control program appropriately.
- Setting the table.
- Parametrizing a plan with knowledge represented by an retrieved from a statistical relation model is desirable in that it allows the adaptation of default plans to a concrete situation.

Context Specific Decision-Making and Plan Selection

- Given a statistical relational model that captures precisely the connection between sequences of actions and the respective contexts.
- In the absence of facts, infer a "logical" (most likely) truth value to create an appropriate plan.
Use probabilistic models to select heuristics

- Search Heuristic (for an item that is unknown) – Infer from common kitchen layouts, the most likely location of a utensil.

- Even known items can rely on a search
  Ex. Is what I’m looking for in the dishwasher
  Has . . . moved the item to another spot.
Architectural Overview
Probabilistic Reasoning Engine interacts with the Robot Controller using RPC’s. Plan Based Controller is implemented on top of an extended version of the Lisp dialect, RPL.

- It stores known facts about entities in the environment in a KB which can be used to provide evidence to the probabilistic reasoner.
When the Control Program is faced with a situation in which probabilistic inference is necessary e.g. an under-specified task it query’s the p.r. system by issuing a request consisting of:

- the name of the model to use
- a list of evidence variables (taken from KB)
- a list of query variables (variables are logical ground atoms)
The ProbCog reasoner, which manages a pool of probabilistic models, then processes the request by:

- instantiating the selected model for the given set of objects
- running the inference method
- returning the inference results in a reply.
The Robot Controller then processes the returned probabilities by applying suitable operators:

- thresholding, or
- argmax

and uses the processed result to parametrize its plans or modify its control program in general.
Problem: Setting the table.
In KB: 3 people will be participating \{Moo Moo, Piggy, and Blue\}
These are members of Nick’s family that are known to the model.

Goal: To set the table the following info is needed:
- what utensils to put at which seat.

If info regarding what utensils people will probably use, and their seating order, then the robot has the information that it needs.

This translates to the following probabilistic query:

\[
P(sitsAtIn(?p, ?pl, M), usesAnyIn(?p, ?u, M) |
\]
\[
\text{mealT}(M, \text{Breakfast}) \land \text{day}(M, \text{Saturday}) \land
\]
\[
\text{takesPartIn}(P1, M) \land \text{name}(P1, \text{MooMoo}) \land
\]
\[
\text{takesPartIn}(P2, M) \land \text{name}(P2, \text{Piggy}) \land
\]
\[
\text{takesPartIn}(P3, M) \land \text{name}(P3, \text{Blue}))
\]
Representation Formalisms
A representation formalism that combines first-order logic with undirected probabilistic graphical models.

**Logical Language** – FOL

**Probabilistic Language:** – Markov Networks

**Syntax:** FO formulas with weights

**Semantics:** Templates for Markov net features

**Learning:**

**Parameters:** Generative or discriminative

**Structure:** Inductive Logic Programming with arbitrary clauses and MAP score

**Inference:**

**Maximum a Posteriori Probability (MAP):** Weighted satisfiability

**Marginal:** MCMC with moves proposed by SAT solver

Partial grounding + lazy inference

FROM: Pedro Dominigos Dept of Computer Science & Engr.
University of Washington.
The expressiveness of MLN’s does come at a price.

- learning is generally more problematic
- inference becomes more expensive and is therefore less well suited to near real-time applications.

Despite these drawbacks. MLN’s are useful when expressiveness is key.

When the added expressiveness is not needed. They use a representation based on directed graphical models.

Use BLN’s (Bayesian Logic Networks).
The *ProbCog* framework supports the conversion of BLNs to MLNs. This means that:

- Learning algorithms applicable to BLNs can be used to learn MLNs, and
- Inference algorithms for MLNs can be used for BLNs.

The support for conversions allows the extension of models with constraints unsupported by BLNs as needed, transforming them to MLNs and continuing the modelling process in the richer representation language.
Learning
Note: The structure of the model (specification of possible dependencies), is given by a knowledge engineer.
The structure on the previous slide can be translated into either:

**conditional dependencies**  – MFrags

**logical formulas**  – features of MLNs

The ProbCog learning stage uses a training database containing a list of ground atoms (atomic sentences that directly correspond to sensory observations) in order to learn the model parameters that most appropriately explain the observations that were made.

**Q.** How to obtain a training database?

**A.** Use sensors.
<table>
<thead>
<tr>
<th>Data</th>
<th>Sensor</th>
<th>Time</th>
<th>Generated atoms</th>
</tr>
</thead>
<tbody>
<tr>
<td>ID_Cup3</td>
<td>RFID:Cupboard₁</td>
<td>t</td>
<td>performed(P₁, A₁, S₁)</td>
</tr>
<tr>
<td>ID_Cup3</td>
<td>RFID:Glove&lt;sub&gt;P₁&lt;/sub&gt;</td>
<td>t+x</td>
<td>actionₜ(A₁, Pickup)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>place(A₁, Cupboard₁)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>involves(A₁, Cup₃)</td>
</tr>
<tr>
<td>ID_Cup₃</td>
<td>RFID:Table</td>
<td>t+x+y</td>
<td>succ(S₁, S₂)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>performed(P₁, A₂, S₂)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>actionₜ(A₂, Putdown)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>place(A₂, Table)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>involves(A₂, Cup₃)</td>
</tr>
</tbody>
</table>
The learning algorithms that yield parameters from the gathered training data are based on either ML or MAP estimation.

In MLNs learning needs to be done approximately.

- The learning problem itself is ill-posed in the sense that there is not a single optimal solution.

Q. How do the author’s tackle this problem?

Their implementations of learning algorithms for MLNs allow the use of constrained optimization to impose necessary integrity conditions on the distributions.

Solution #2.
The problem can also be circumvented by learning in the BLN framework and then translating the model to a MLN.

- provided that the dependency structure can be captured by the BLN.

Q. Why does this work.
BLNs make the causal structure explicit, which makes ML easier because it reduces to counting occurrences of parent-child configurations in the data.
This is a part of an MFragment of the table setting model indicating the condition distribution of the predicate

\[ \text{consumesAnyIn}(\text{person}, \text{food}, \text{meal}) \]
Inference
There are high demands on the reasoning capabilities of the system. (Real-time).

Probabilistic Inference is NP-Hard, and exact inference is "realistically" infeasible.

So the authors resort to the following approximate inference techniques:

**independent sampling**

**MCMC** – Markov chain Monte Carlo

A class of algorithms for sampling from probability distributions based on constructing a Markov chain that has the desired distribution as its equilibrium distribution. The state of the chain after a large number of steps is then used as a sample from the desired distribution. The quality of the sample improves as the number of steps increases.

**loopy belief propagation**
The ProbCog supports various sampling algorithms.

As long as domains lack deterministic dependencies and queries involve few evidence variables, standard methods such as:

- likelihood weighting
- Gibbs sampling (MCMC algo)

In the presence of unlikely evidence, it's important to explicitly incorporate the evidence into the sampling procedure if acceptable convergence rates are to be reached:

- sampling backward from the evidence – backward simulation
- propagating the effect of evidence variables before proceeding with forward sampling –
  - importance sampling based on evidence-prepropagation
  - EPIS-BN
The only inference algorithm with acceptable results is:

**MC-SAT** – combines ideas from MCMC and satisfiability.
Is based on Markov logic, which defines Markov networks using weighted clauses in FOL.

From **MCMC** – MC-SAT – is a slice sampler with an auxiliary variable per clause, and with a satisfiability-based method for sampling the original variables given the auxiliary ones.

From **SAT** – MC-SAT – wraps a procedure around the SampleSAT uniform sampler that enables it to sample from highly non-uniform distributions over satisfying assignments.

**Author Adaptations**
- cardinality constraints – (the number of objects that an object/group can be related to)
- fully maintaining model structure – do not decompose complex formulas into clauses.
Consider the query:

\[ P(sitsAtIn(?p, ?pl, M), usesAnyIn(?p, ?u, M) \mid \]
\[ mealT(M, Breakfast) \land day(M, Saturday) \land \]
\[ takesPartIn(P1, M) \land name(P1, MooMoo) \land \]
\[ takesPartIn(P2, M) \land name(P2, Piggy) \land \]
\[ takesPartIn(P3, M) \land name(P3, Blue) \]
Integration with the Control Program
How is the Probabilistic Reasoning system integrated into the plan language (RPL), which is used for controlling the kitchen robot.

Plans written in RPL are the basis of a transformational planning system.

The plan language needs to make use of highly declarative language constructs such as:

**with-failure-handling** – indicating failure handling and failure recovering code.

**at-location** – execution of plan steps at a specific location.

Note: RPL like every Lisp-like language, provides a powerful mechanism to extend the language with new commands.

Note: RPL also allows the addition of new special forms (e.g. for establishing variable bindings)
RPL is extended with a new declarative language construct `likely-yet`.

It’s analogous to the Lisp special from let, establishing a binding of variables to tuples of atoms and the corresponding probabilities within the current lexical context, based on a set of queries and a set of evidences.

Several applications of the resulting probability distributions are conceivable:

- decisions may be based directly on probabilities
- or the user may be interested in a list of the most likely atoms to parametrize a plan.
Likely-yet provides support for post-processing returned probability distributions.

When querying seat locations: argmax Utensils should be post-processed by a threshold operator
Abstract

Introduction

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Architectural Overview

Representation Formalisms

Learning

Inference

Integration with the Control Program

Int. 1

Int. 2

Int. 3

Example

References

```
likely = let

(query

'(sitsAtIn ?person ?seating -location M)

:argmax ?person)

(utensils

:query '(usesAnyIn ?person ?utensil M)

:threshold 0.05)

:evidence

'((takesPartIn P1 M) (name P1 "Anna")

(takesPartIn P2 M) (name P2 "Bert")

(takesPartIn P3 M) (name P3 "Dorothy")

(mealT M "Breakfast")))

(with-designators

((table '(the entity (name kitchen -table))))

(for-all-matching

(lambda ((?person ?place ?m)

(?person ?entity -type ?m))

(with-designators

((obj (an entity (type ,entity -type)

(status unused))

(seat (a location (on ,table)

(place ,place))))

(achieve (entity -on -entity

obj table

seat))))

(cross-product places utensil))))
```
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