## Learning Action Models: Qualitative Approach

Thomas Bolander, DTU Compute, Tech Univ of Denmark Joint work with: Nina Gierasimczuk, ILLC, Amsterdam (based on paper to appear at LORI 2015)


## Introduction

What our paper is about:

- Formal learning theory applied to dynamic epistemic logic (DEL).
- First paper to study the problem of learnability of action models in DEL.
- The goal is build agents that can learn to plan.

Our results are only the first few unsteady baby steps in action model learning. The really interesting stuff is all the future work...


## DEL by example: A hidden coin toss

We use the action models of DEL [Baltag et al., 1998] with added postconditions (ontic actions) as in [Ditmarsch et al., 2008].

Let $b$ mean "the coin faces the black side up".


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## Observations, streams and identifiability

- Agents learn actions (action models) by a stream (infinite sequence) of observations ( $s, s^{\prime}$ ) for that action: when executing the action in state $s$, state $s^{\prime}$ will result.
- Finite identifiability: after a finite sequence of observations, the agent says "stop" and identifies the correct action model.
- Identifiability in the limit: after a finite sequence of observations, the agent settles on a particular action model and never changes her mind (but is never able to say "stop").

Example. Possible stream on language with a single proposition $p$ :

$$
(\emptyset,\{p\}),(\{p\}, \emptyset),(\emptyset,\{p\}),(\{p\}, \emptyset),(\emptyset,\{p\}),(\{p\}, \emptyset), \ldots
$$

## Basic results on learnability

Restrictions on action models (actions) imposed in all of the following (including all results):

- Only fully observable actions: partially observable are not learnable in the strict sense.
- Only propositional actions: all preconditions of all events are formulas of propositional logic (not epistemic formulas).


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Theorem 1. The set of deterministic actions is finitely identifiable.
Theorem 2. The set of (possibly non-deterministic) actions is not finitely identifiable, only identifiable in the limit.

## Learning actions via update: precondition-free atomic actions



Left: Initial action model containing all possible postconditions. The blue and red sets correspond to possible observations.
Right: The action model after receiving the observation $(\{q\},\{p, q\})$.

## Learning actions via update: (non-atomic) deterministic actions with maximal preconditions

Maximal preconditions: all preconditions are maximally consistent conjunctions of propositional literals (e.g. $p \wedge \neg q$ in the language over $\{p, q\}$ ).

Examples in the language over a single proposition $\{p\}$.

$$
\begin{array}{ll}
\langle p, \top\rangle & \langle\neg p, \top\rangle \\
\langle p, \neg p\rangle & \langle\neg p, p\rangle
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## Learning actions via update: deterministic actions with minimal preconditions

A simple update is no longer sufficient. But sufficient to always conjecture the set of minimal events using the following order:

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e \leq e^{\prime} \quad:=\operatorname{pre}\left(e^{\prime}\right) \models \operatorname{pre}(e) \text { and } \operatorname{post}\left(e^{\prime}\right) \models \operatorname{post}(e)
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Example. $\langle p, r\rangle \leq\langle p \wedge q, r \wedge s\rangle$. (Ockham's razor, cf. Kevin's talk!) Important: All non-minimal events are preserved "in the background". Example. Learning the functioning of an $n$-bit counter. Case $n=2$ :

Current action model:
Current state of counter:
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Resulting action model: $n+1$ events (instead of $2^{n}$ as in the case of maximal preconditions).

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## Future work:

- Extended classes of actions: arbitrary pre- and post-conditions, partial observability, multiple agents (joint learning).
- Computational complexity.
- Proactive learning (using consecutive streams).
- Ultimate goal: general learning-and-planning agents.


