Decreasing Uncertainty in Planning with State Prediction

Senka Krivic, Michael Cashmore, Daniele Magazzeni,
Bram Ridder, Sandor Szdemak and Justus Piater

https://iis.uibk.ac.at/

Problem description

Autonomous agents in complex environments

Task: Tidying up

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Example: Robotic domain

SQUIRREL Environment

SEVENTH FRAMEWORK PROGRAMME

SQUIRREL Clearing Clutter Bit by Bit

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Clearing Clutter Bit by Bit

Real-world environments

- Large number of objects and possible relations and actions
- Unknown areas and objects
- State is partially-known
- Exploration and observation are costly

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SQUIRREL Clearing Clutter Bit by Bit

Real-world environments

- Large number of objects and possible relations and actions
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- State is partially-known
- Exploration and observation are costly

But also other domains!

Planning with partially-known states

Some standard planning approaches:

- POMDP
- Contingent planners (Bonet and Geffner 2011; Hoffmann and Brafman 2005)
- Conformant planners (Smith and Weld 1998; Palacios and Geffner 2006)
- Probabilistic planners (Camacho et al. 2015)
- Replanning techniques (Brafman and Shani 2014)

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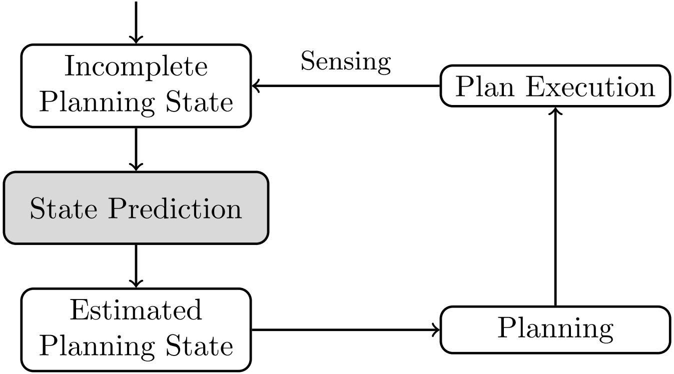
Problems with scaling!

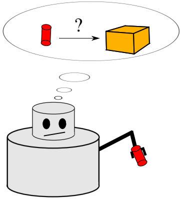
Proposed approach

Decreasing uncertainty in planning with state prediction



Proposed approach

Using experience to predict missing information



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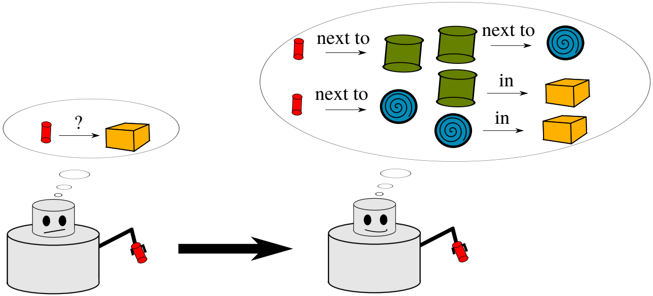

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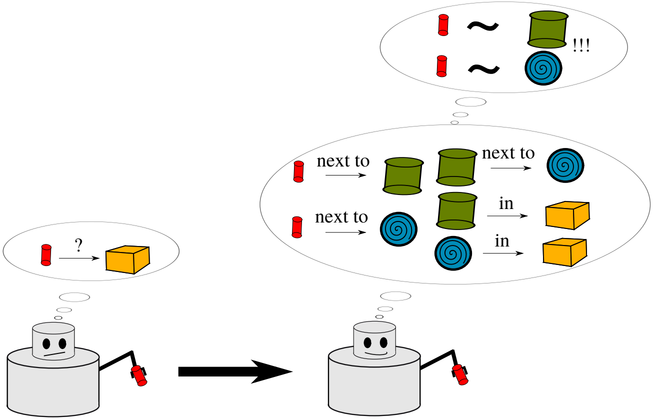

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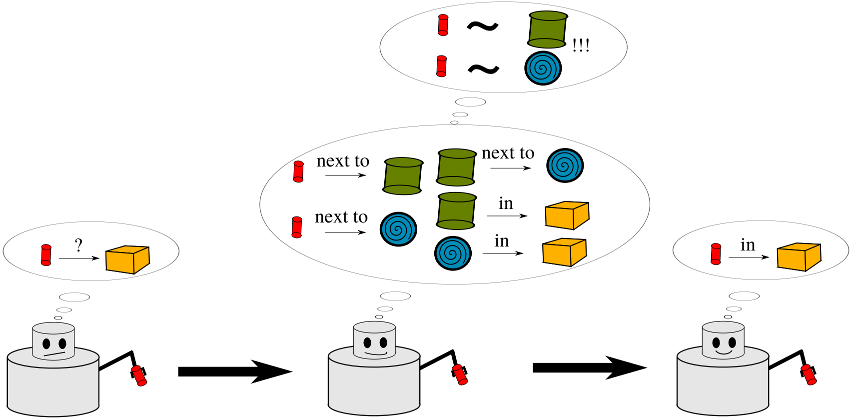
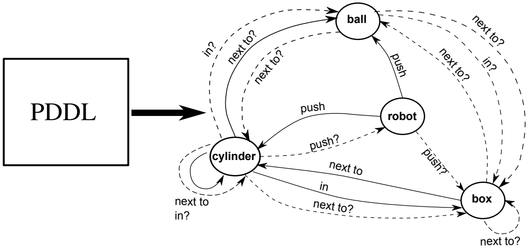


Proposed approach

Removing uncertainty with predictions

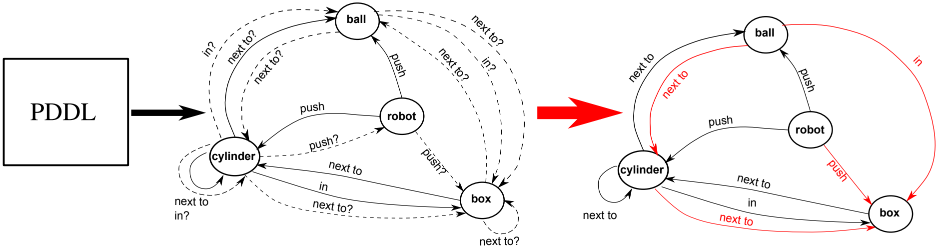
1. Representing initial state by a multigraph



Proposed approach

Removing uncertainty with predictions

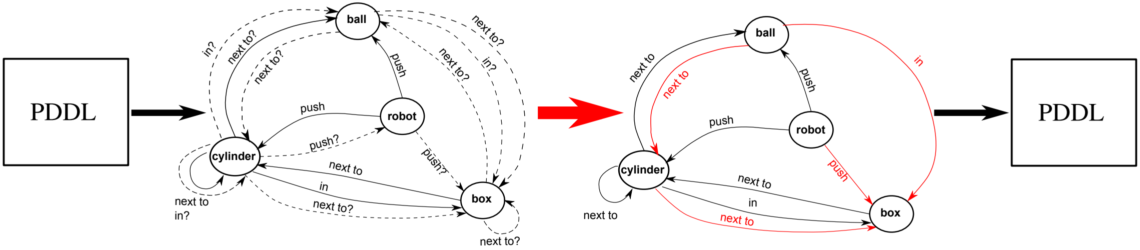
1. Representing initial state by a multigraph
2. Predicting missing edges



Proposed approach

Removing uncertainty with predictions

1. Representing initial state by a multigraph
2. Predicting missing edges
3. Translating new edges into the state



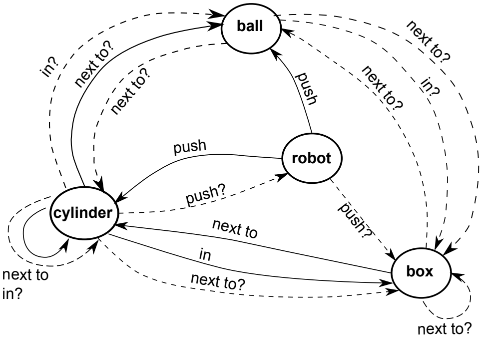
Methodology

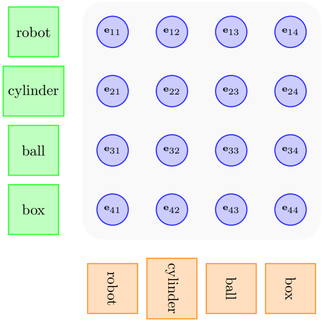
Maximum Margin Multi-Valued Regression (M^3VR)

- Semi-supervised learning
- Partially-given multigraph representing relations
- Large-scale problems
- Sparse, skewed, imbalanced and inhomogeneous datasets
- Kernel based method used in different applications:
  - Enzyme function prediction (Astikainen et al. 2011)
  - Movies recommender system (Ghazanfar et al. 2012)
  - Affordance predictions (Szedmak et al. 2014)
  - Completing incomplete multigraphs (Krivic et al. 2015)

Methodology

Exploiting knowledge to predict missing edges





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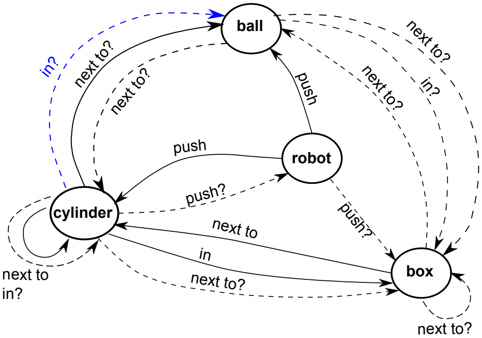

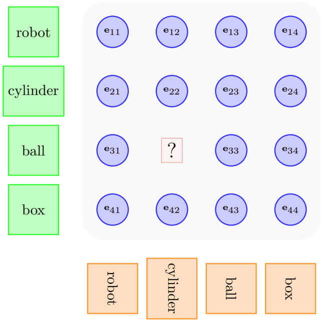

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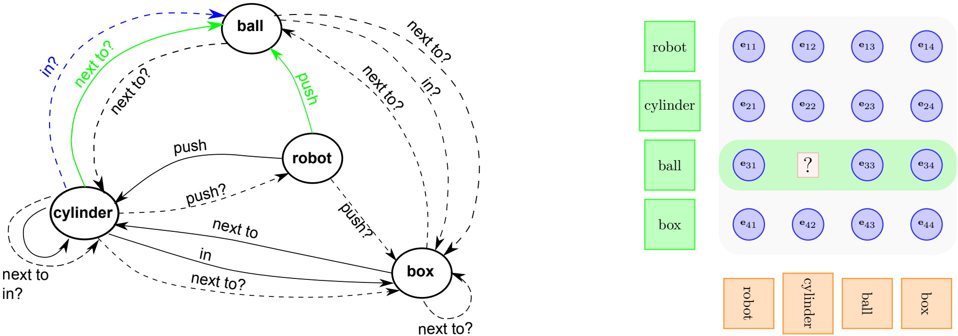

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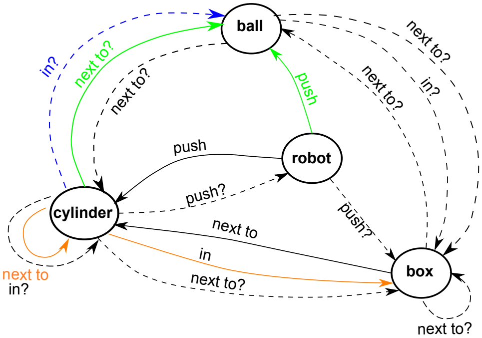

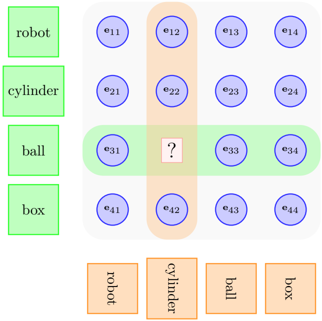

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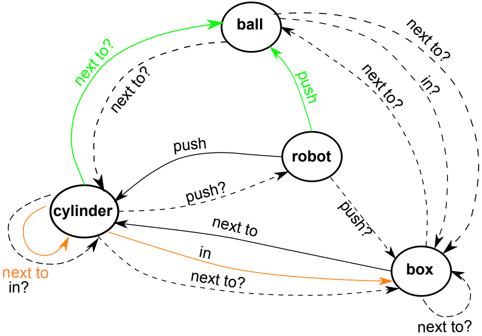

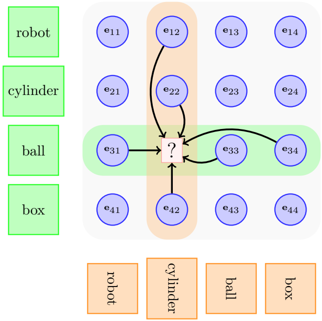

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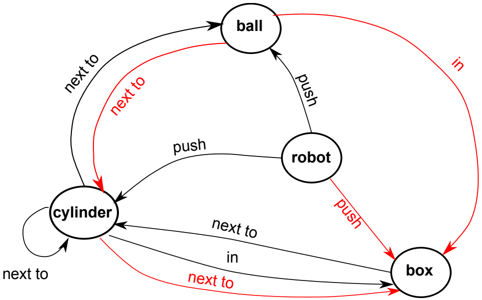
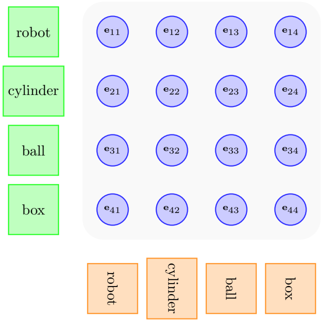
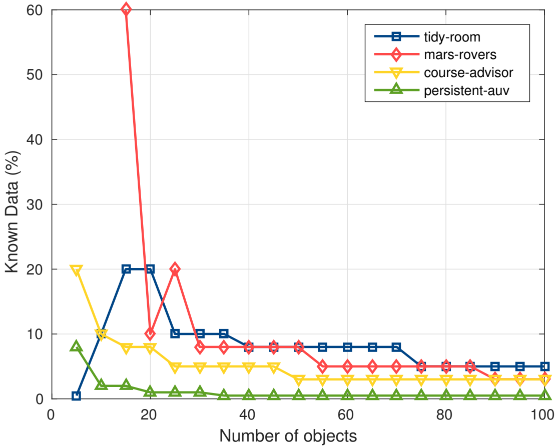




Experimental results

Minimal percentage of initial knowledge ensuring prediction accuracy $\geq 90\%$

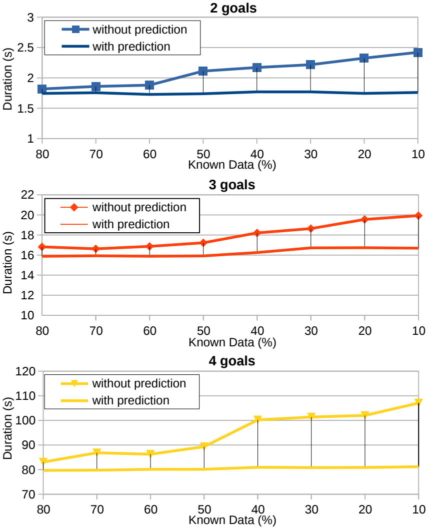


- **Domains**
  - ’tidy-room’
  - ’course-advisor’ (Guerin et al)
  - ’mars-rovers’ (Cassandra et al.)
  - ’persistent-auv’ (Palomeras et al.)
- 10-cross-fold validation
- 20% knowledge was taken as the lowest boundary for planning

Experimental results

Evaluating with conditional planning

- ’tidy-room’ domain, 20 objects
- planner CLG (Albore and Geffner 2009)
- number of goals 2-6 in the planning task
- 10-cross-fold validation
- Average time for planning with prediction: 89 [s]



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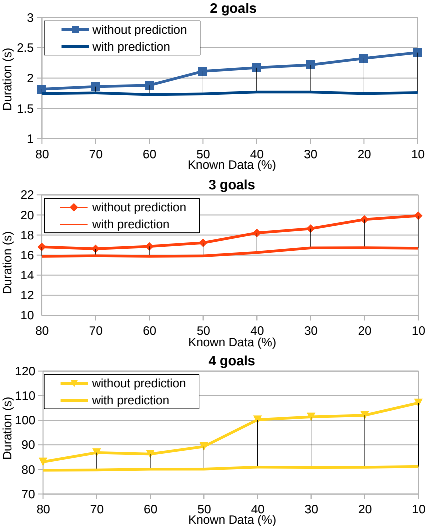
- number of goals 2-6 in the planning task
- 10-cross-fold validation
- Average time for planning with prediction: 89 $[s]$
- Plans with 5 and 6 goals are not solved without prediction!



Conclusions

1. Decreasing uncertainty in the planning state using the existing state knowledge
2. Prediction improves planning performance and scalability
3. With 20% knowledge of the state the accuracy of the complete state prediction is 90%

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Code: `github.com/Senka2112/IJCAI2017`

Thank you for your attention!