Physical Manipulation Planning & Learning

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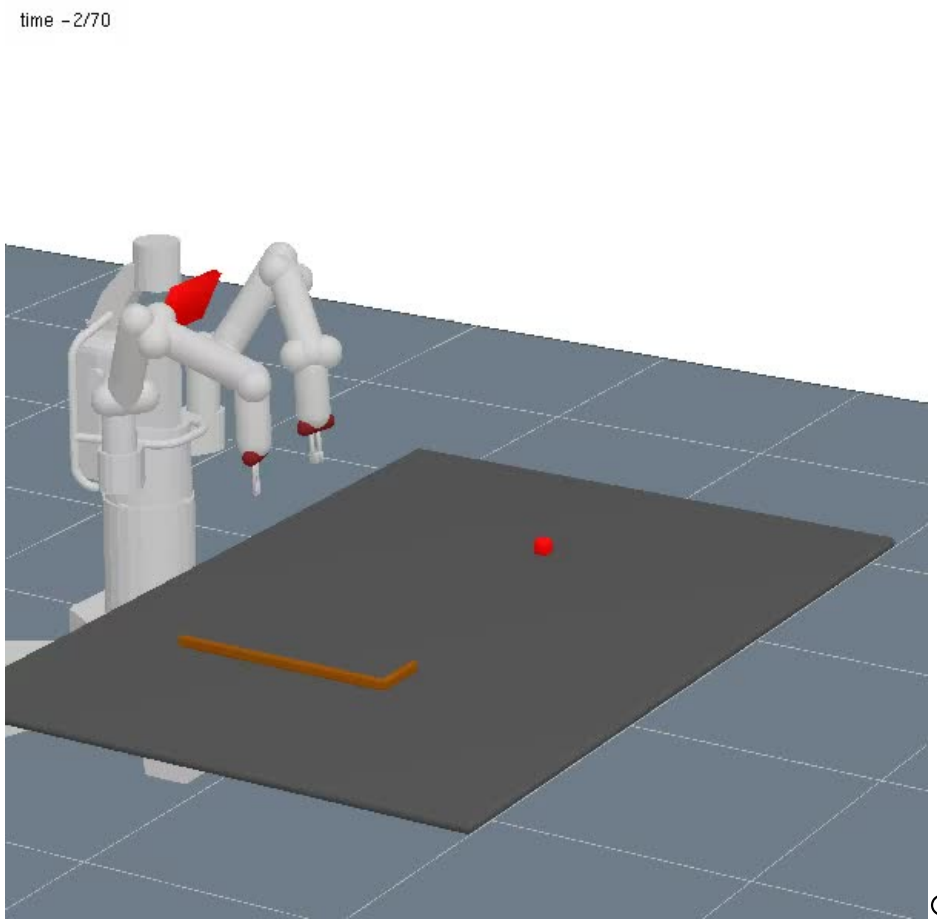
RSS workshop on Action Representation for Robot Learning, July 13, 2020

Outline

- *Describing Physics For Physical Reasoning*
- *Deep Visual Reasoning*

- Discussion

Previous work on sequential manipulation Planning



Toussaint, Allen, Smith, Tenenbaum: *Differentiable Physics and Stable Modes for Tool-Use and Manipulation Planning*. R:SS'18

How Describe Physics *For* Reasoning?

- What is a *fundamental/general/sufficient* description?
  Sufficient for general purpose physical reasoning?

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  Sufficient for general purpose physical reasoning?

- Contact-Invariant Optimization (Mordatch & Todorov, 2012)
  - constrains pose difference between *pre-defined* contact points
  - no sliding, no finding/optimizing contacts for the purpose of...

- General complementarity formulations (e.g., Posa & Tadrake, 2013)
  - Fundamentally principled and general, but remaining challenges:
  - non-smooth contact geometry switches (beyond point-ot-point)
  - multi-physics for efficiency

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- Physical Reasoning should leverage multi-physics descriptions!
  - deliberately apply different levels of simplification for different aspects of inference
  - describe physics as if it would switch laws (from Newton-Euler, to pick-and-place, to quasi-static equations)

Toussaint, Ha, Driess: *Describing Physics For Physical Reasoning: Force-based Sequential Manipulation Planning*. RAL/IROS 2020

Path-Optimization Approach

- **Logic-Geometric Program:**

$$\min_{x:[0,KT]\to\mathcal{X}} \int_0^{KT} f_{\text{path}}(\bar{x}(t))\ dt$$

$$\text{s.t.} \quad x(0) = x_0,\ h_{\text{goal}}(x(T)) = 0,$$

$$\forall_{t\in[0,T]}:\ h_{\text{path}}(\bar{x}(t), s_{k(t)}) = 0,\ g_{\text{path}}(\bar{x}(t), s_{k(t)}) \leq 0$$

$$\forall_{k\in\{1,..,K\}}:\ h_{\text{switch}}(\hat{x}(t_k), s_{k\text{-}1}, s_k) = 0,\ g_{\text{switch}}(\hat{x}(t_k), s_{k\text{-}1}, s_k) \leq 0$$

- Decision variables $x(t)$ in each time slice:
  - robot joint configuration $\in \mathbb{R}^n$
  - free object poses $\in SE(3)^m$
  - wrench interactions $\in \mathbb{R}^{6\cdot n_c}$
  - timing $\tau \in \mathbb{R}$ (real time interval)

Toussaint, Ha, Driess: *Describing Physics For Physical Reasoning: Force-based Sequential Manipulation Planning*. RAL/IROS 2020

Specific Models Used

- The logic skeleton decides which model is being applied to which objects in which phase ($\rightarrow$ different dofs in different phases)

- Three force exchange models:
  - General complementarity contact
  - Forced contact
  - Instantaneous contacts (impulse exchange)

- Three object dynamics models:
  - General Newton-Euler

$$\begin{pmatrix} \dot{v} \\ \dot{w} \end{pmatrix} + g - M^{-1}(F - \lambda) = 0 \qquad \text{(Newton-Euler).} \tag{1}$$

  - Quasi-static (friction λ to enforce $(\dot{v}, \dot{w}) \equiv 0$)
  - Static (e.g., stable grasp)

- Integrated in single path optimization formulation

Crucial: Point-of-Attach Parameterization

- Major pain: Dealing robustly with switching contact geometries

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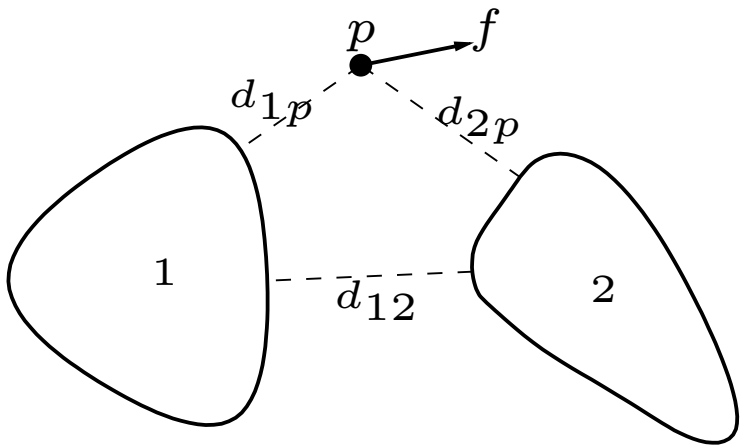
- Major pain: Dealing robustly with switching contact geometries
- Don't use **wrench** $(f, \omega) \in \mathbb{R}^6$ as decision variable, but $(f, p) \in \mathbb{R}^6$ with the **point-of-attack** $p \in \mathbb{R}^3$ $\quad (\omega = f \times p)$



Complementarity constraints:

$$d_{1p} f = 0 \ , \quad d_{2p} f = 0 \ , \quad d_{12} \geq 0$$

- Handles any contact configurations – and transitions between!
  (point-to-point, point-to-line, line-to-line, point-to-surface, line-to-surf., surf.-to-surf.)
- Related to previous work on "equivalent contact point" (Xie & Chakraborty '16)

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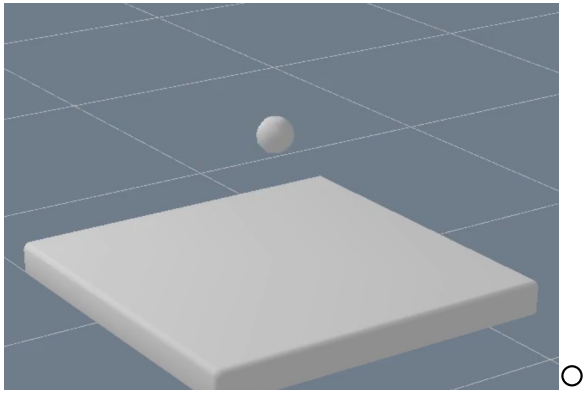
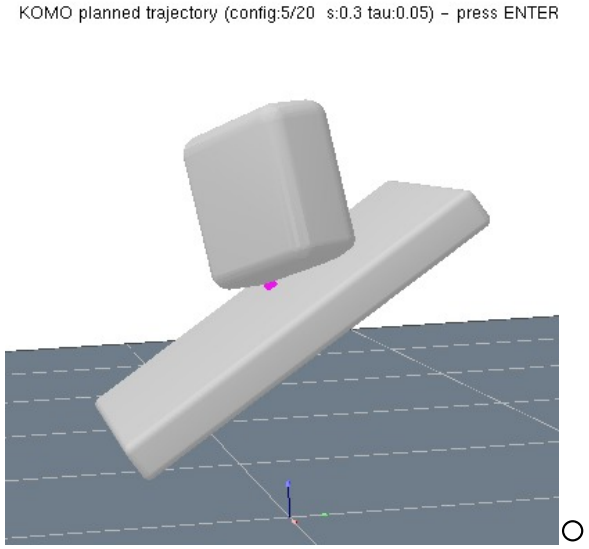
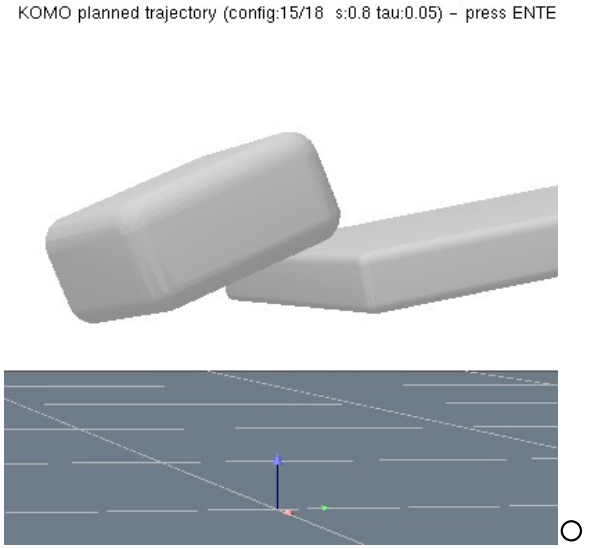
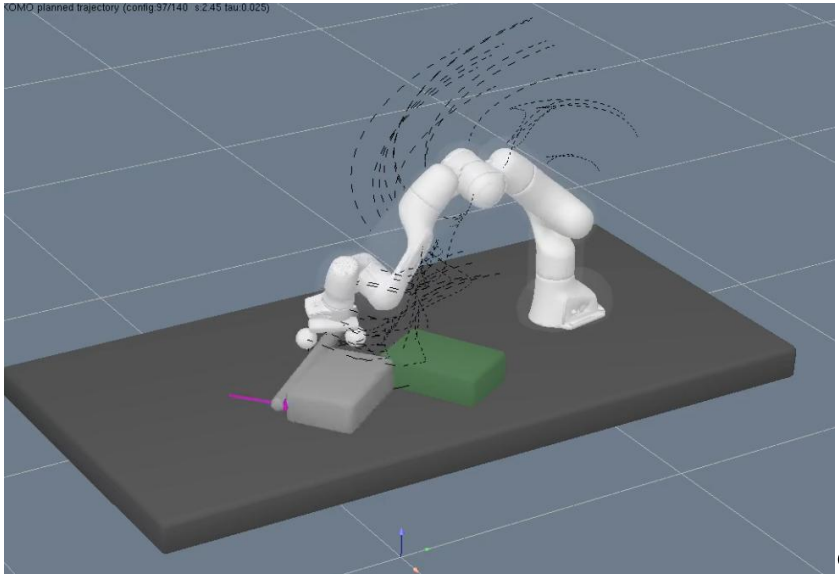
Passive Tests – Simulation via Path Optimization

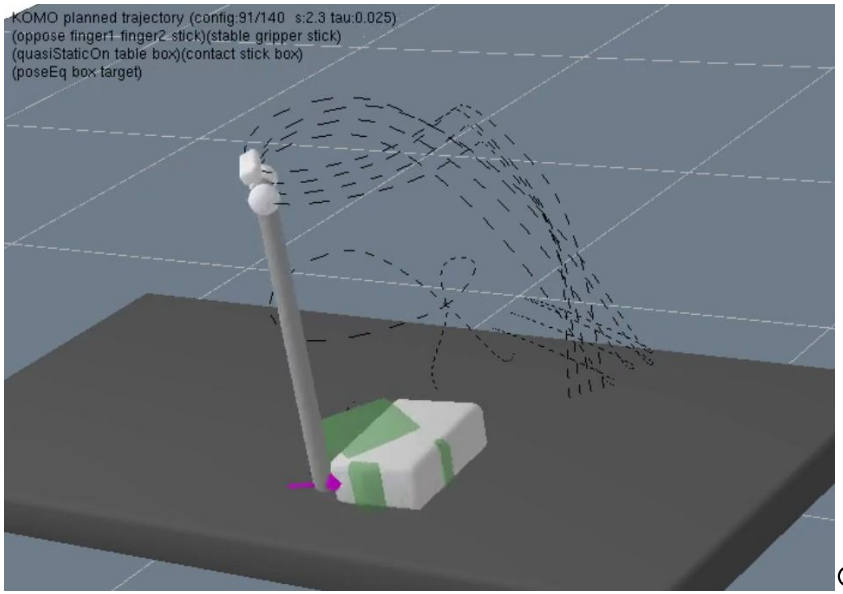






Pushing with a stick





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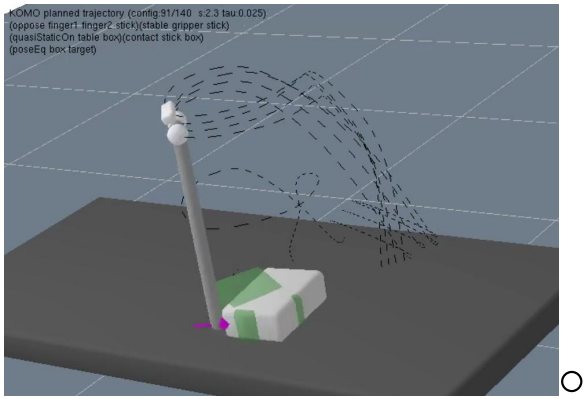

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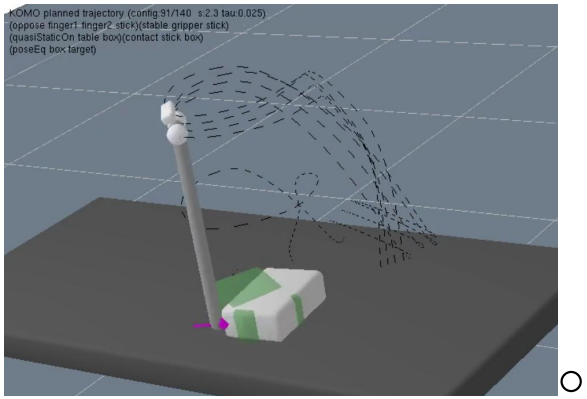

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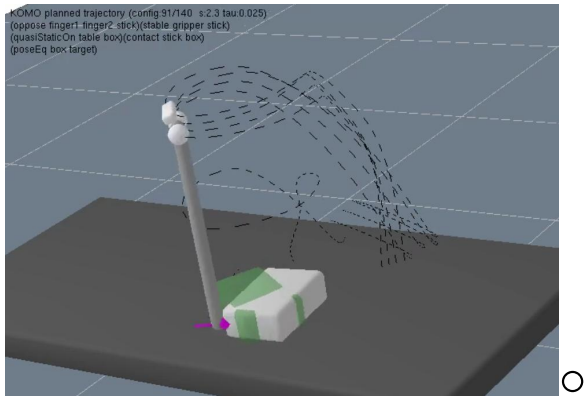

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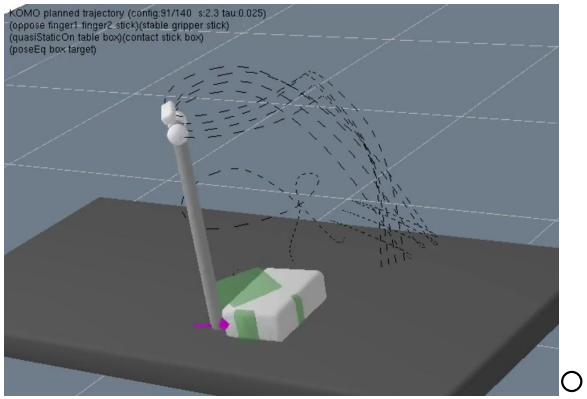

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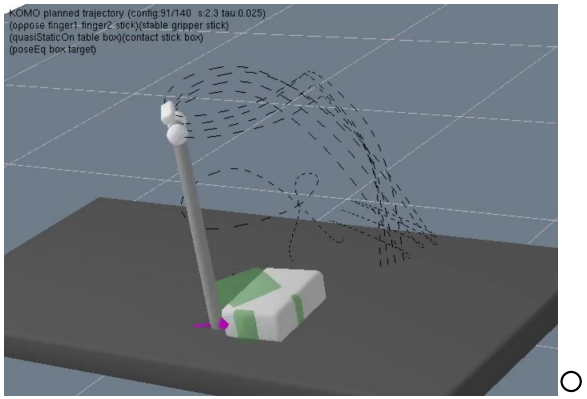

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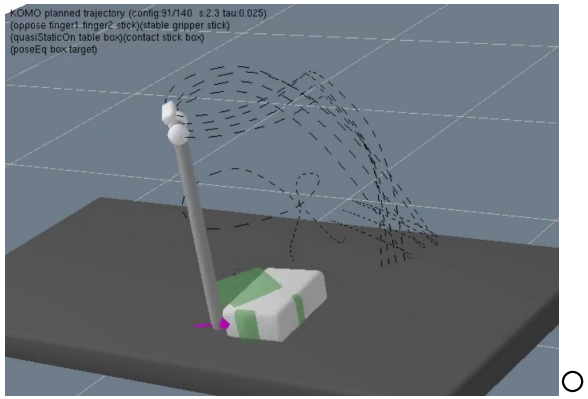

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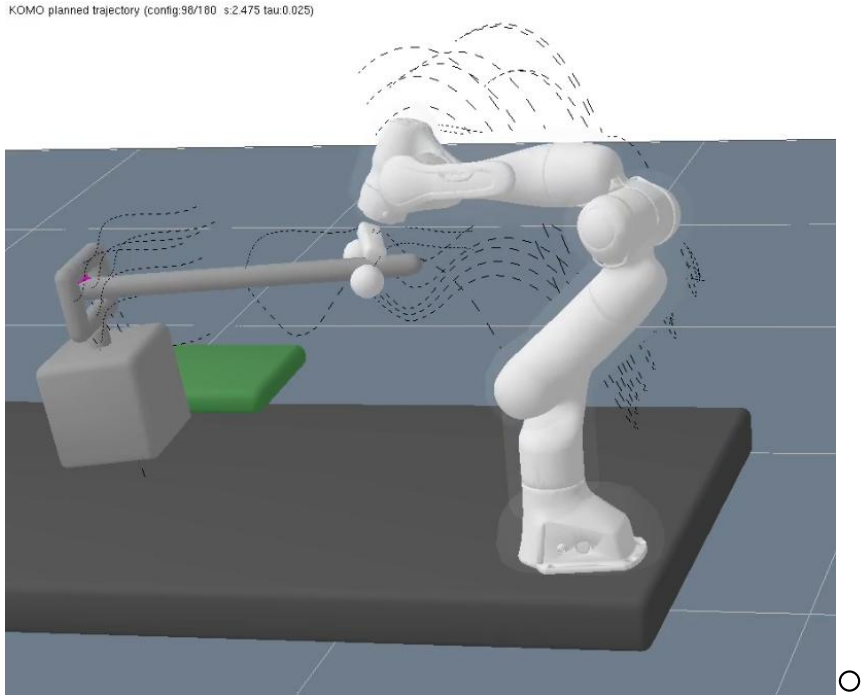
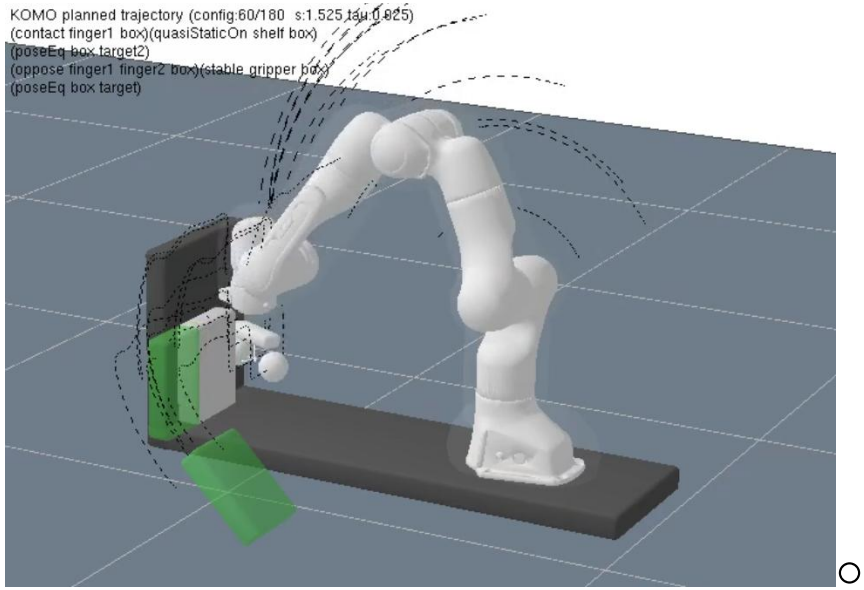
Lifting a box



Grabbing a book from a shelf



Limitations

- Needs 10-40 seconds for full paths
- Local optima! (Basic ongoing work on integrating sampling...)
- *Skeletons are given* in these examples

$\rightarrow$ Use this as a means to generate data!

Learning

Learning to predict full solutions

- From a **visual** scene encoding, directly predict a solution skeleton!

Driess, Ha, Toussaint: *Deep Visual Reasoning: Learning to Predict Action Sequences for Task and Motion Planning from an Initial Scene Image*. RSS 2020

`RSS paper #3`

Danny Driess

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Learning to predict full solutions

- From a **visual** scene encoding, directly predict a solution skeleton!
- ...estimate a very strong **heuristic** over discrete decisions
- but **generalize** “1st order” (across objects)

Driess, Ha, Toussaint: *Deep Visual Reasoning: Learning to Predict Action Sequences for Task and Motion Planning from an Initial Scene Image*. RSS 2020

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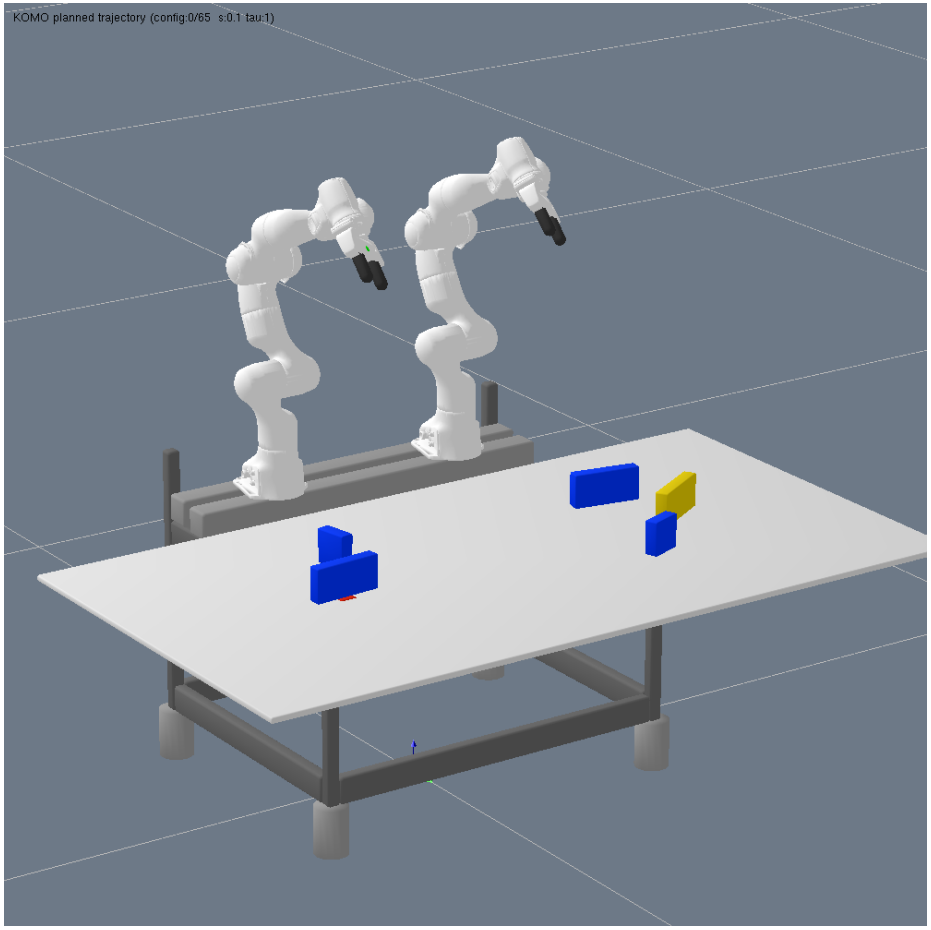
Example



- Approx. 500,000 leaf nodes up to depth 6

Approach

- Raw data $D = \{\left(S^i, g^i, a^i_{1:K^i}, F^i\right)\}_{i=1}^n$ with scene S^i, goal g^i, skeleton $a^i_{1:K^i}$, feasibility F^i

Approach

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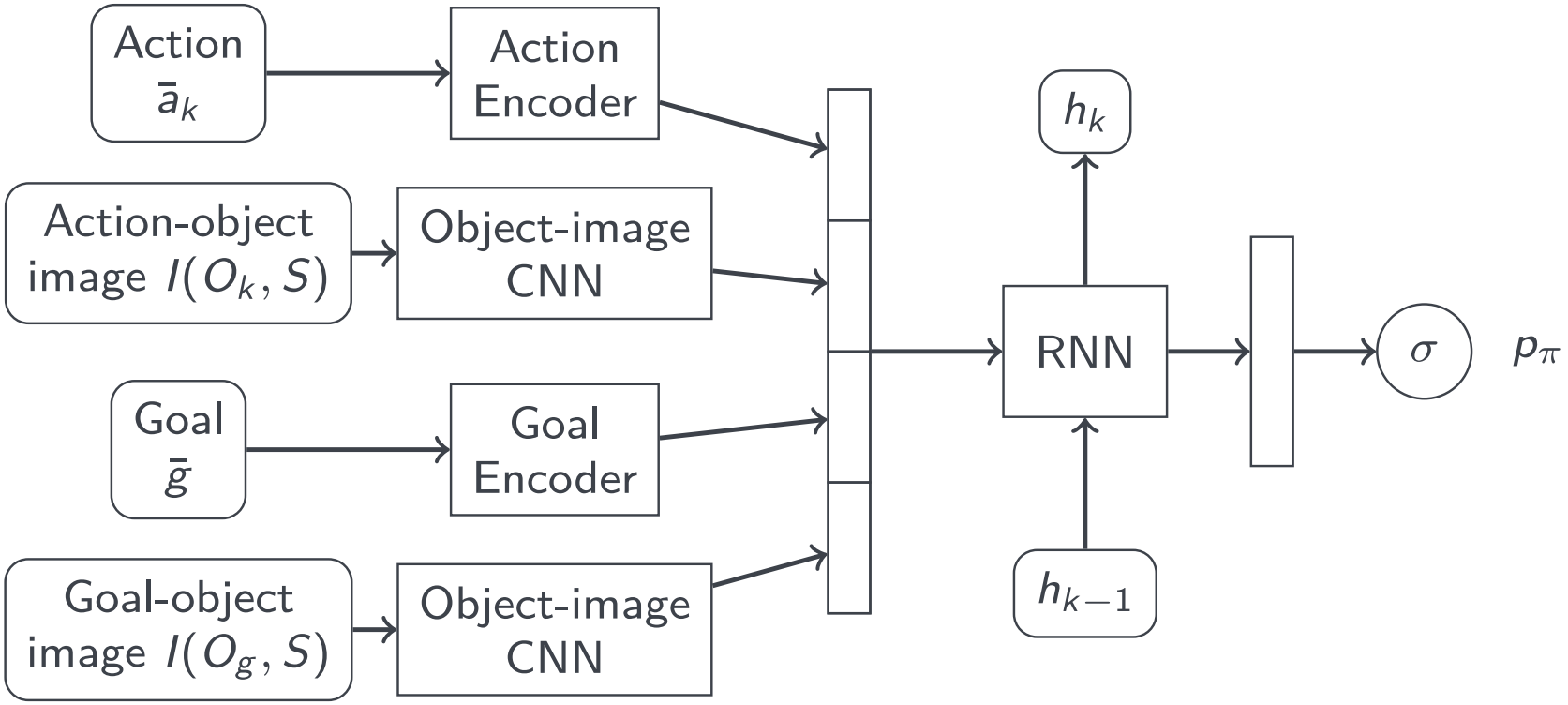
- **Sequence training data** $\mathcal{D} = \{(S^i, g^i, a^i_{1:K^i}, f^i)\}_{i=1}^n$ with $f^i = f^i_{1:K}$:

$$f^i_j = \begin{cases} 1 & F^i = 1 \\ 1 & \exists \left(S^l, a^l_{1:K^l}, g^l, F^l\right) \in D \quad \text{s.t.} \quad F^l = 1,\ g^l = g^i,\ a^l_{1:j} = a^i_{1:j} \\ 0 & \text{else} \end{cases}$$

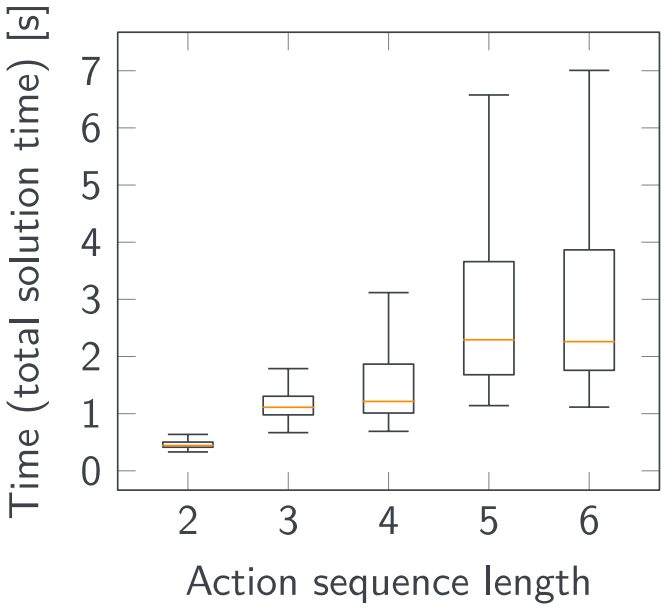
Network Architecture

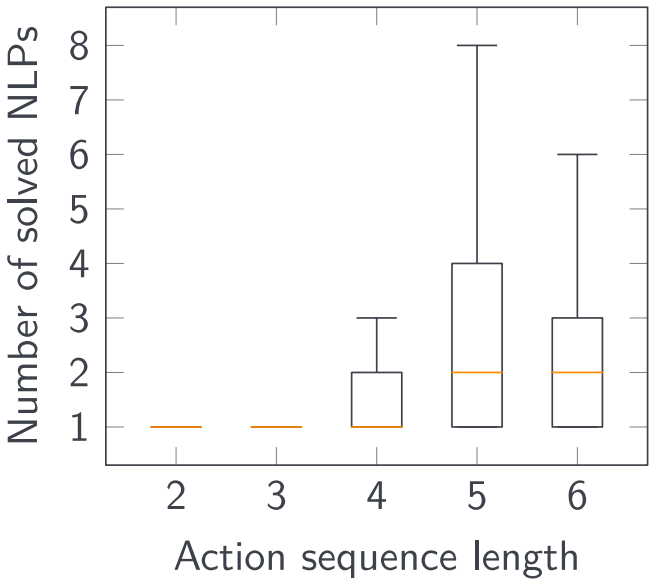


$$
\begin{aligned}
(p_\pi, h_k) &= \pi_{\text{NN}}\big(\bar{a}_k, I(O_k, S), \bar{g}, I(O_g, S), h_{k-1}\big) \\
&= \pi\big(a_k, g, a_{1:k-1}, S\big)
\end{aligned}
$$

- Separate encoding of predicates $\bar{a}, \bar{g}$ and references O (as masks)

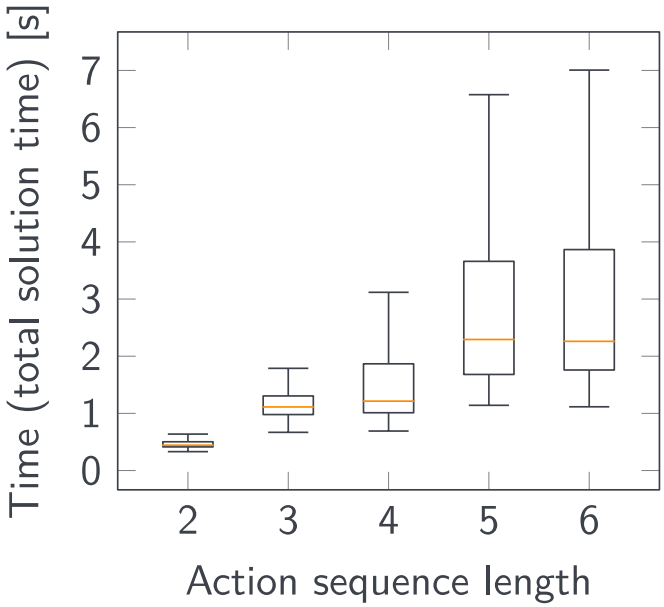
Results

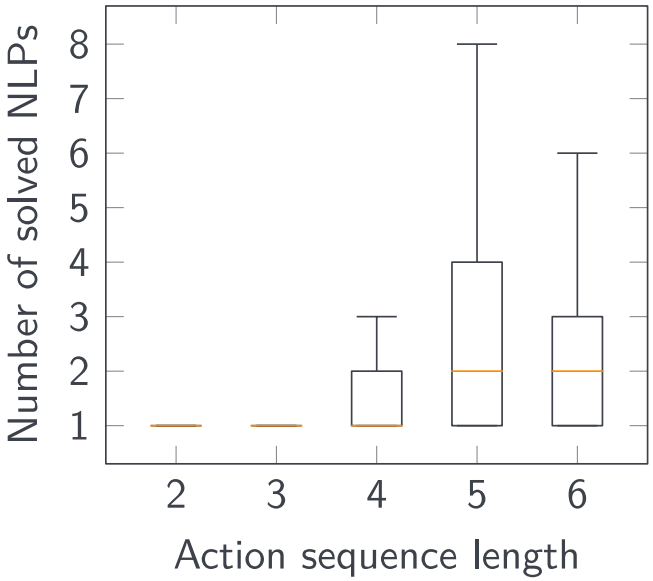




- Usually the first proposed action sequence is feasible

Results


Time (total solution time) [s]
0
1
2
3
4
5
6
7
2
3
4
5
6
Action sequence length


Number of solved NLPs
1
2
3
4
5
6
7
8
2
3
4
5
6
Action sequence length

Discussion

“Action Representation for Robot Learning”

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- "TAMP with feedback controllers" (Russ Tedrake)
  - these controllers are the action representation we want

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"Action Representation for Robot Learning"

- "TAMP with feedback controllers" (Russ Tedrake)
  - these controllers are the action representation we want

- "several efforts explore [approaches where] actions are mapped into low level robot commands by the analytic controller"

  " new paradigm that bridges robot learning and advanced robot control"

  analytic control + high-level learning?
  learning control + high-level physical reasoning?

(of course, it's not either or..)

Thanks

- *for your attention!*

- *Describing Physics For Physical Reasoning:* (IROS/RAL '20) `arxiv`
- *Deep Visual Reasoning:* (RSS '20) `paper #3`

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Jung-Su Ha

- Code for Physics LGP:
  `https://github.com/MarcToussaint/`