Symposium on Explainability

WhiteBox

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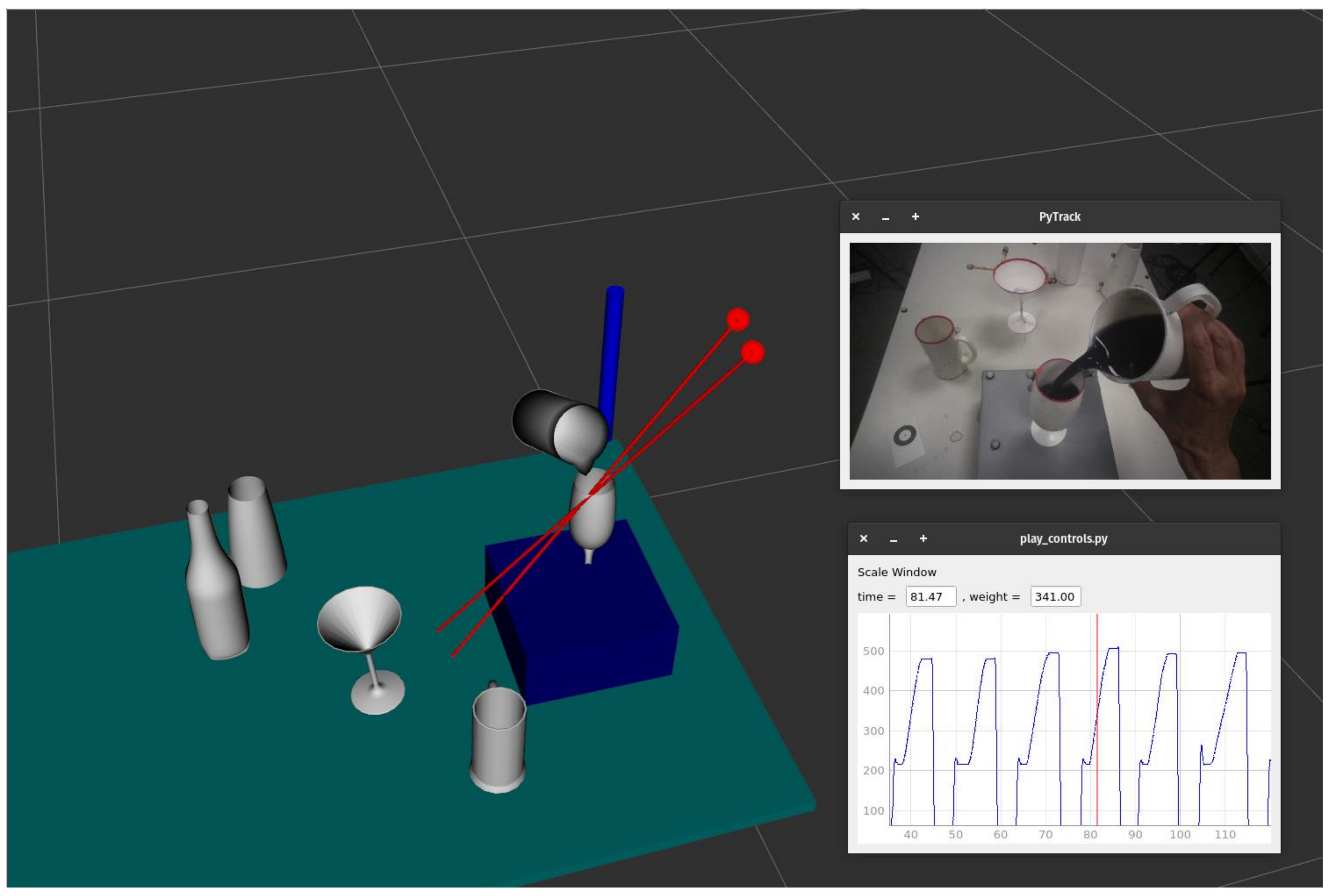
Deep black box models and probabilistic white box models inform each other

Natural visuomotor control tasks such as pouring liquids into cups are trivial for humans but are challenging to model. The goal of this project is to conduct experiments of humans pouring a liquid and provide a computational account of human sensorimotor control involving sensory uncertainty, internal model uncertainty, and action variability. By systematically comparing solutions found by Deep Reinforcement Learning (DRL) black box models and optimal control under uncertainty white box models, we aim to characterize and understand differences between these models.

Experimental Setup

- Collecting human visuomotor control data in a pouring task
- Setup includes:
  - Motion capture system to track object motions
  - Weighing scale to track liquid level
  - Mobile eye tracker for eye movement tracking & first-person video
- Subjects were instructed to pour without any specific guidance
- Various jug and cup combinations were used in the experiment

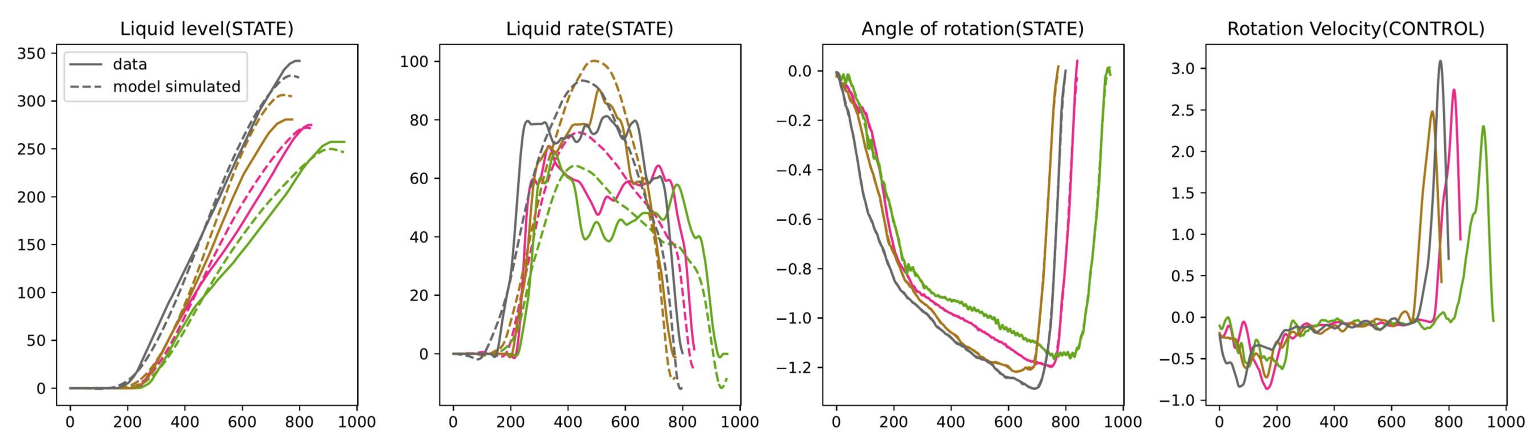
Human Pouring Control Data



White Box Approach

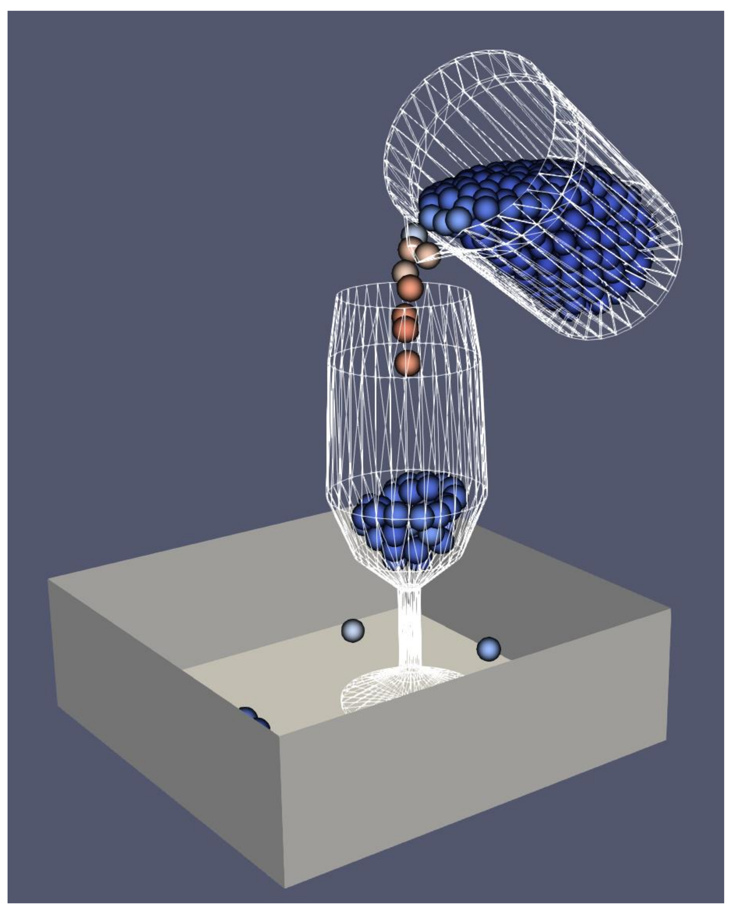
- Optimal control under uncertainty models of human sensorimotor behavior are the gold standard but require a specification of the underlying dynamics [2]
- Deriving pouring dynamics from first principles is non-trivial
- The underlying dynamics were discovered using system identification methods
- Ongoing work in applying optimal control methods to recover policies while considering signal-dependent noise (iLQG[3], MPC) and tuning costs to resemble human behavior
- Ongoing work to directly infer costs from observed behavior [4]

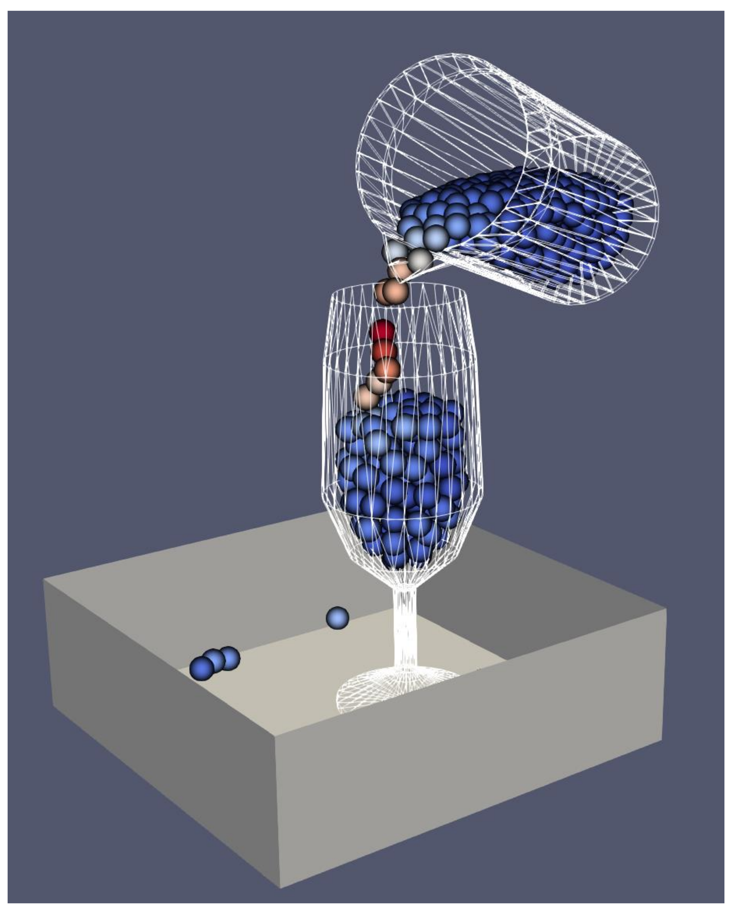
$$
\begin{aligned}
\dot{w}(t) &= \dot{w}(t) \\
\ddot{w}(t) &= -2.9\dot{w}(t) - 1447.41\theta(t) + 2.55\theta_{\mathrm{vel}}(t) + 0.97w(t)\theta(t) - 1.82\dot{w}(t)\theta(t) - 73.38\theta^2(t) \\
&\quad -50.35\theta(t)\theta_{\mathrm{vel}}(t) - 8.27\theta_{\mathrm{vel}}^2(t) + 1418.6\sin(\theta(t)) - 3.164\sin(\theta_{\mathrm{vel}}(t)) \\
\dot{\theta}(t) &= \theta_{\mathrm{vel}}(t)
\end{aligned}
$$



Black Box Approach

- Deep Reinforcement Learning algorithms can be used to learn sequential actions in pouring
- A specialized DNN [5] that learns complex rigid/non-rigid body interactions is trained on human pouring data adapted to the simulation environment
- Since the learnt environment model is fully differentiable, optimal control methods can be applied to recover pouring policies
- Ongoing work to train multiple Deep RL agents to do pouring in the simulation environment
- Physics based simulation SplishSplash [1]





[1] https://github.com/InteractiveComputerGraphics/SPlisHSPlasH
[2] Todorov, 2005
[3] Todorov & Li, 2005
[4] Straub, Schultheis, et al (2023).
[5] DPI-net, Li et al, ICLR(2019)

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