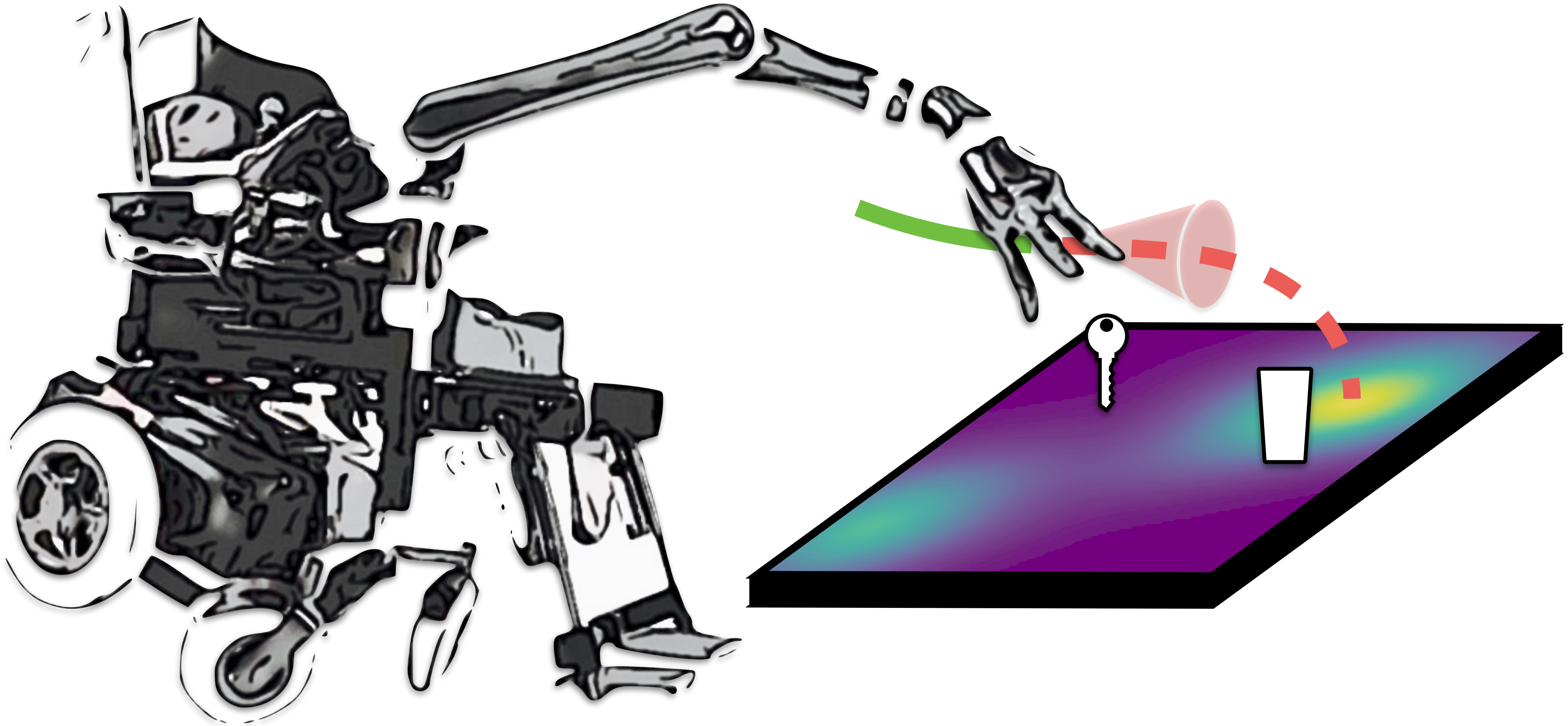
Assistive Manipulation: Reducing the Control Effort with Multi-Modal Intent Prediction



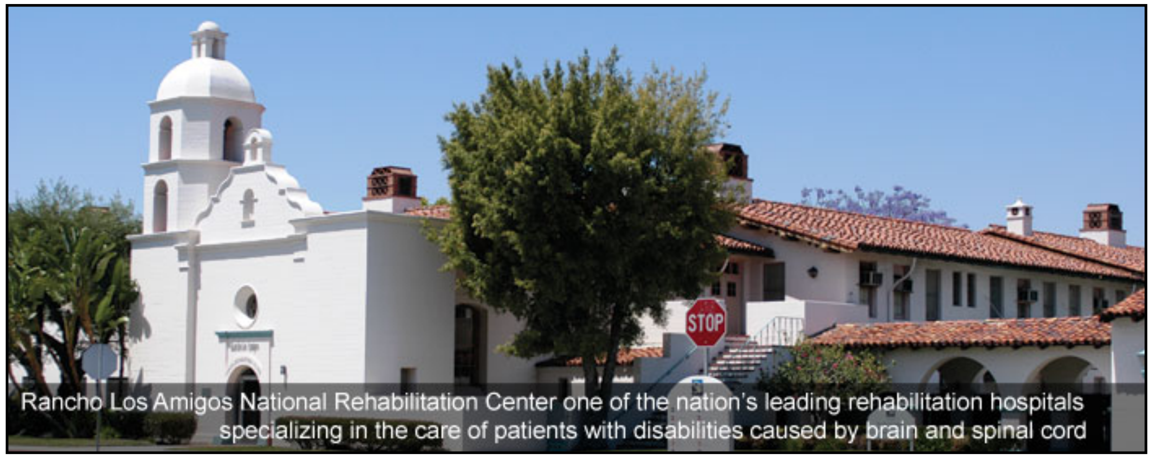
Renaud Detry – KU Leuven

https://www.nature.com/articles/nature11076

Lesson learned from a discussion with SCI Group: Lower the burden of robot operation

Challenges: charging a chair's battery, eating, picking up keys, picking up groceries, opening doors.

Major limitation of current solutions: even the simplest tasks are monopolizing the user's attention.



Our project aims to facilitate the guidance of a robot with a noisy, low-bandwidth input device

Neurobotics: blended brain-machine control for human assistance using hybrid smart systems

Pinhao Song, Ophelie Saussus, Santiago Rondón, Sofie De Schrijver, Erwin Aertbelien, Tom Theys, Renaud Detry, Peter Janssen

Funded by KU Leuven

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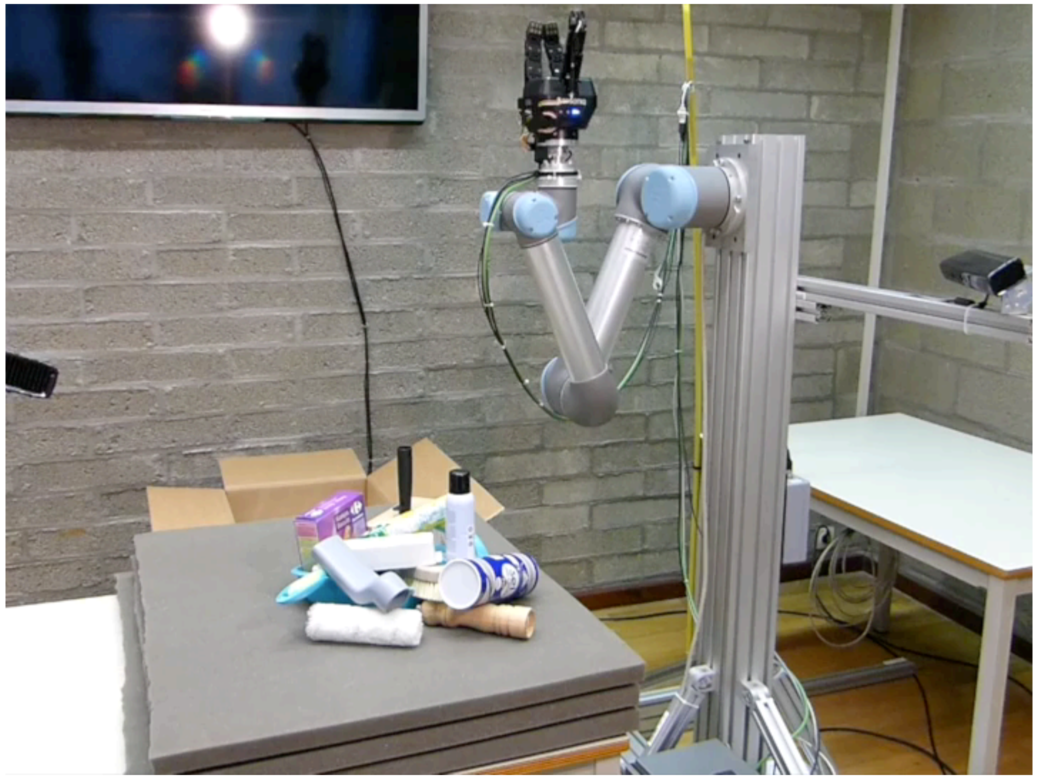
Objective: lower the burden of robot operation (with today's very capable data-driven robot models)

1: Parse user intent

2: Move robot in a direction aligned with intent



We focus on predicting user intent from the user-guided robot motion

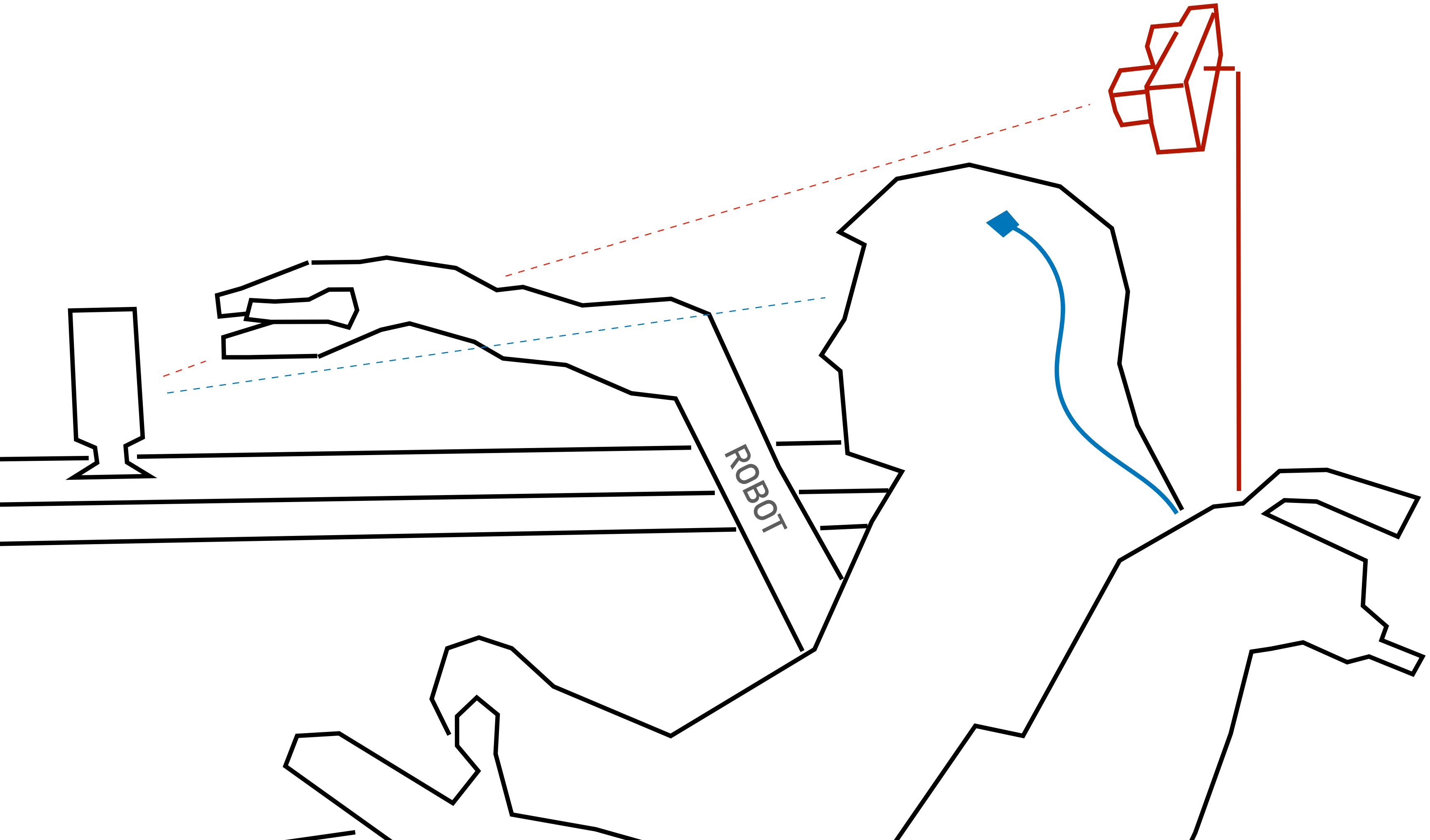
1: Parse user intent

2: Move robot in a direction aligned with intent

To understand the user's intent, we must reconcile user input with a contextual (visual) scene understanding

1. The subject initiates a reaching motion towards the desired object,

2. The robot infers the subject's intention - i.e., which object the subject intends to grasp and from where to approach.



1: "What are the possible actions given visible objects?"

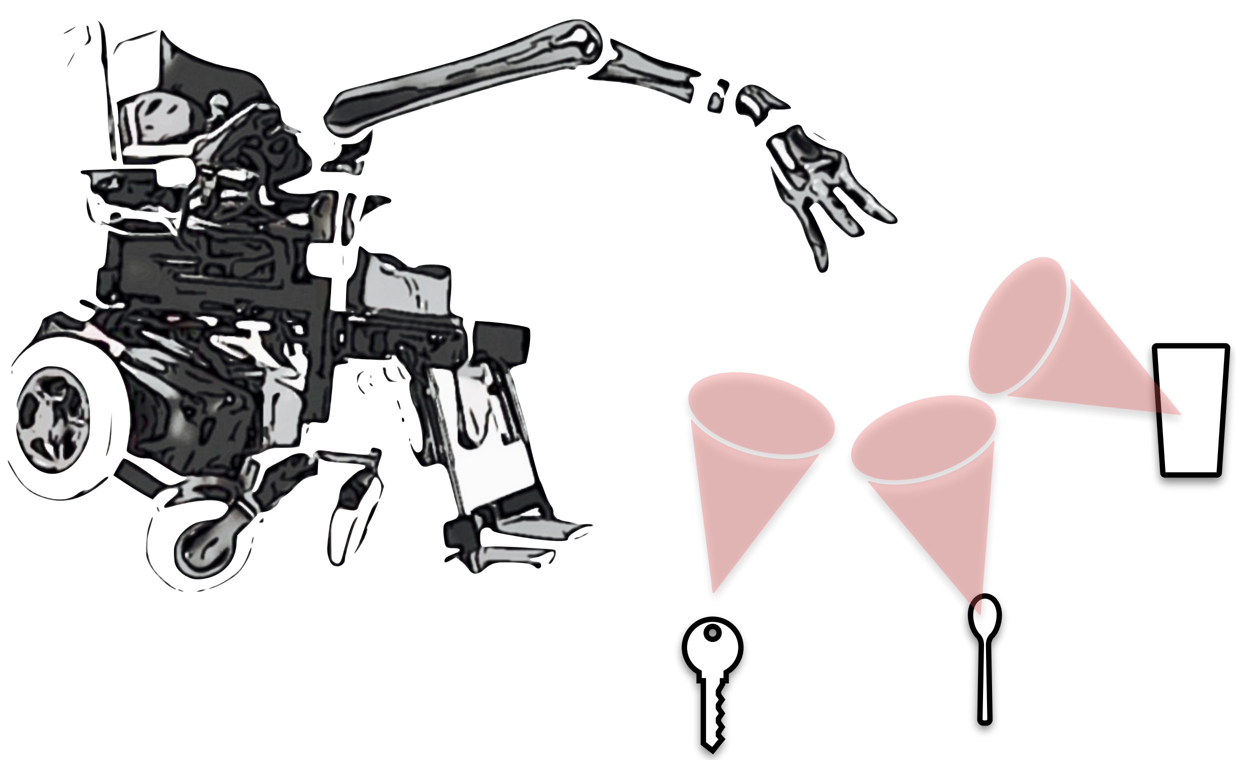
1. The subject initiates a reaching motion towards the desired object,

2. The robot infers the subject's intention - i.e., which object the subject intends to grasp and from where to approach.

1: "What are the possible actions given visible objects?"
→ Robot inventories all possible actions offered by what it sees

2: "Where is the user headed?"
→ Robot infers plausible targets given onset of motion (decoded from brain signals)

3: "What does the subject want?"
Merging 1 and 2 yields an unambiguous target



2: “What action is the subject attempting?”

1. The subject initiates a reaching motion towards the desired object,

2. The robot infers the subject’s intention - i.e., which object the subject intends to grasp and from where to approach.

1: “What are the possible actions given visible objects?”

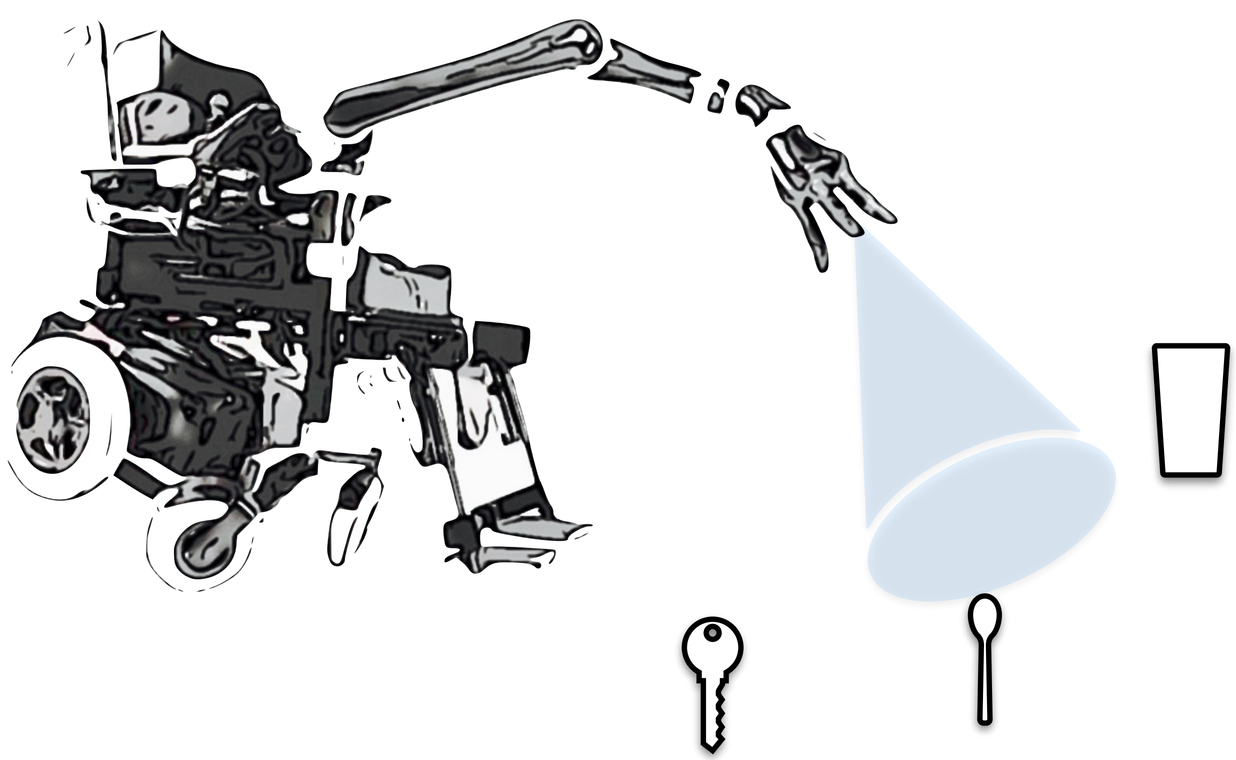
→ Robot inventories all possible actions offered by what it sees

2: “Where is the user headed?”

→ Robot infers plausible targets given onset of motion (decoded from brain signals)

3: *“What does the subject want?”*

Merging 1 and 2 yields an unambiguous target



3: Reconcile 1 and 2 to infer intent and derive a control command

1. The subject initiates a reaching motion towards the desired object,
2. The robot infers the subject's intention - i.e., which object the subject intends to grasp and from where to approach.

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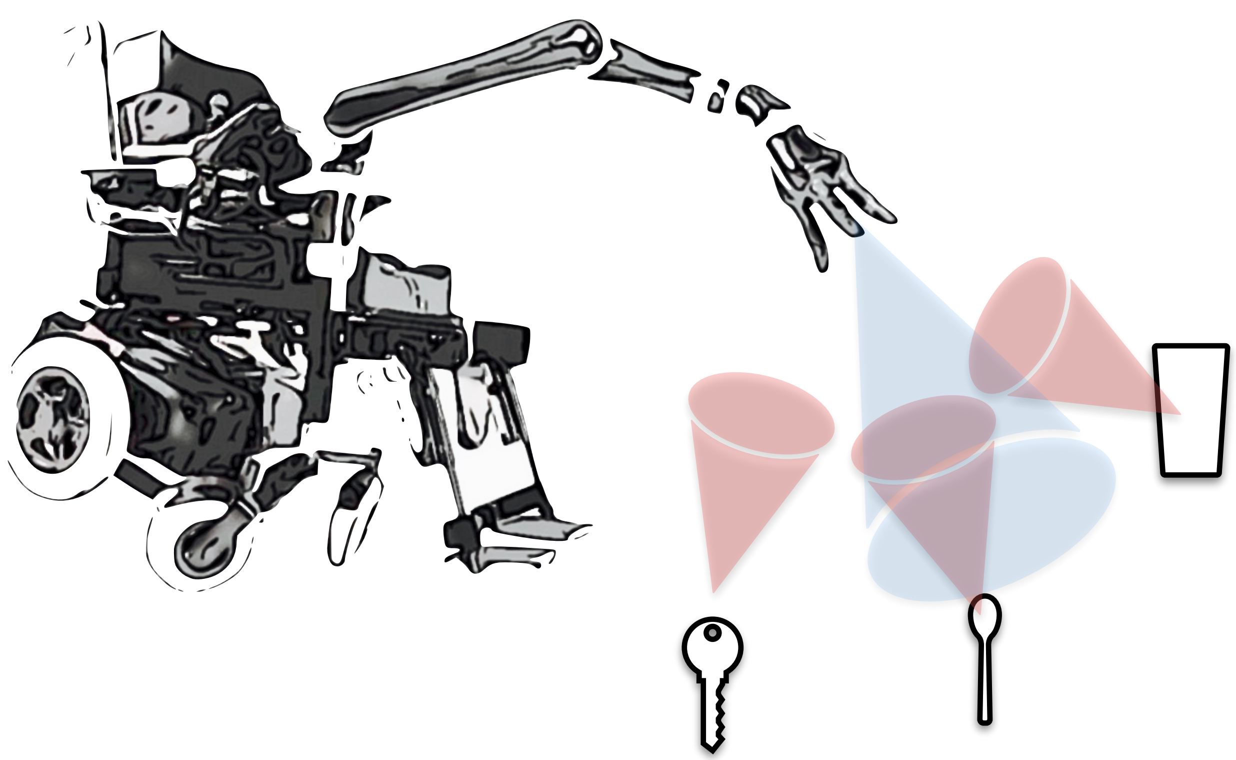


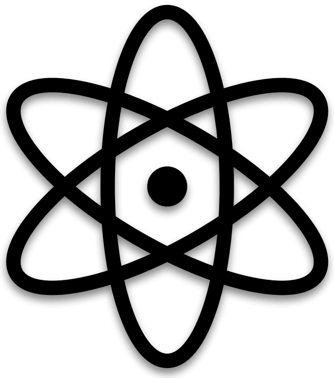
3: "*What does the subject want?*"

Merging 1 and 2 yields an unambiguous target

Outline

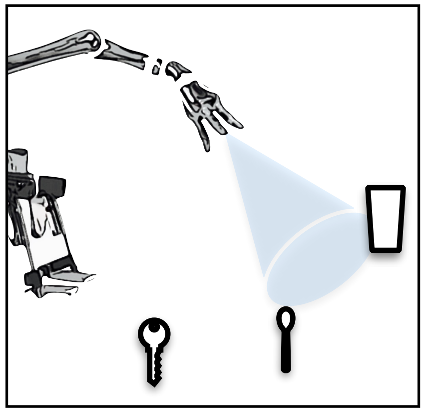
State of Art

Innovation: dynamics and multimodality



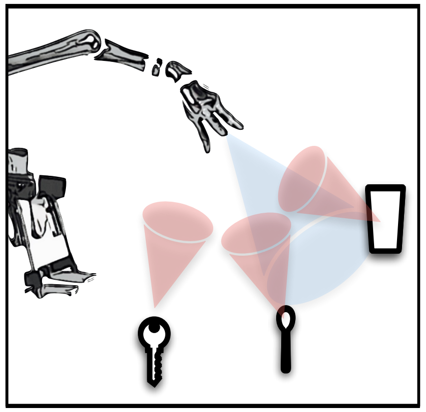
Motion Prediction

From the user's motion onset



Intention Prediction

Motion prediction + goal assessment



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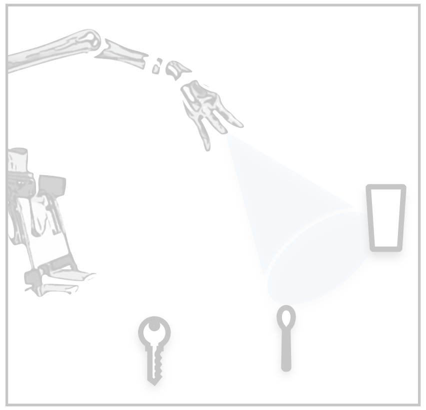

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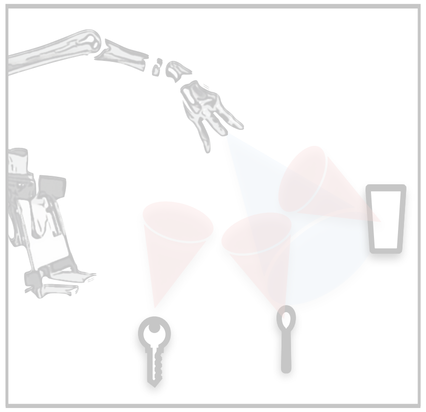
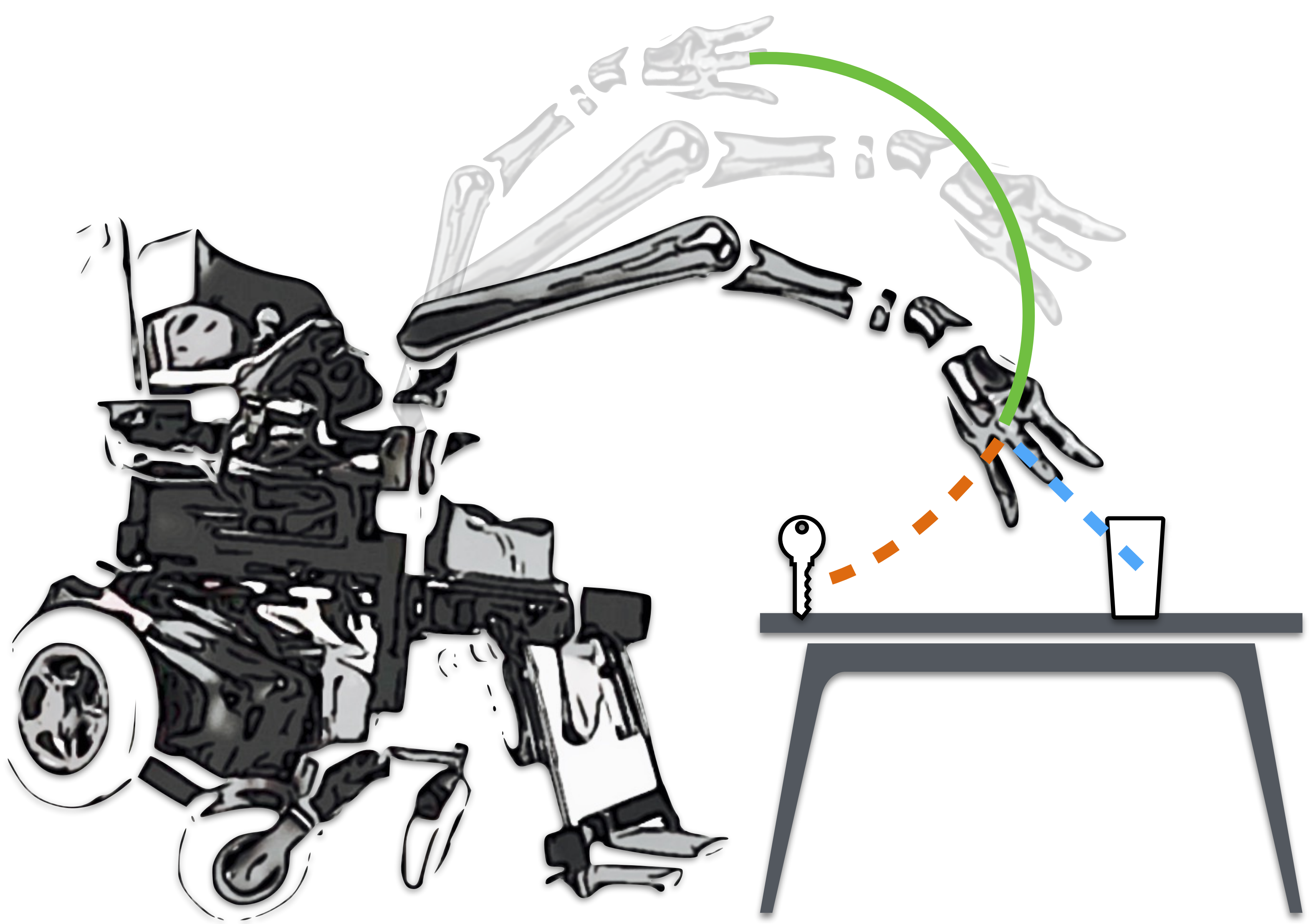
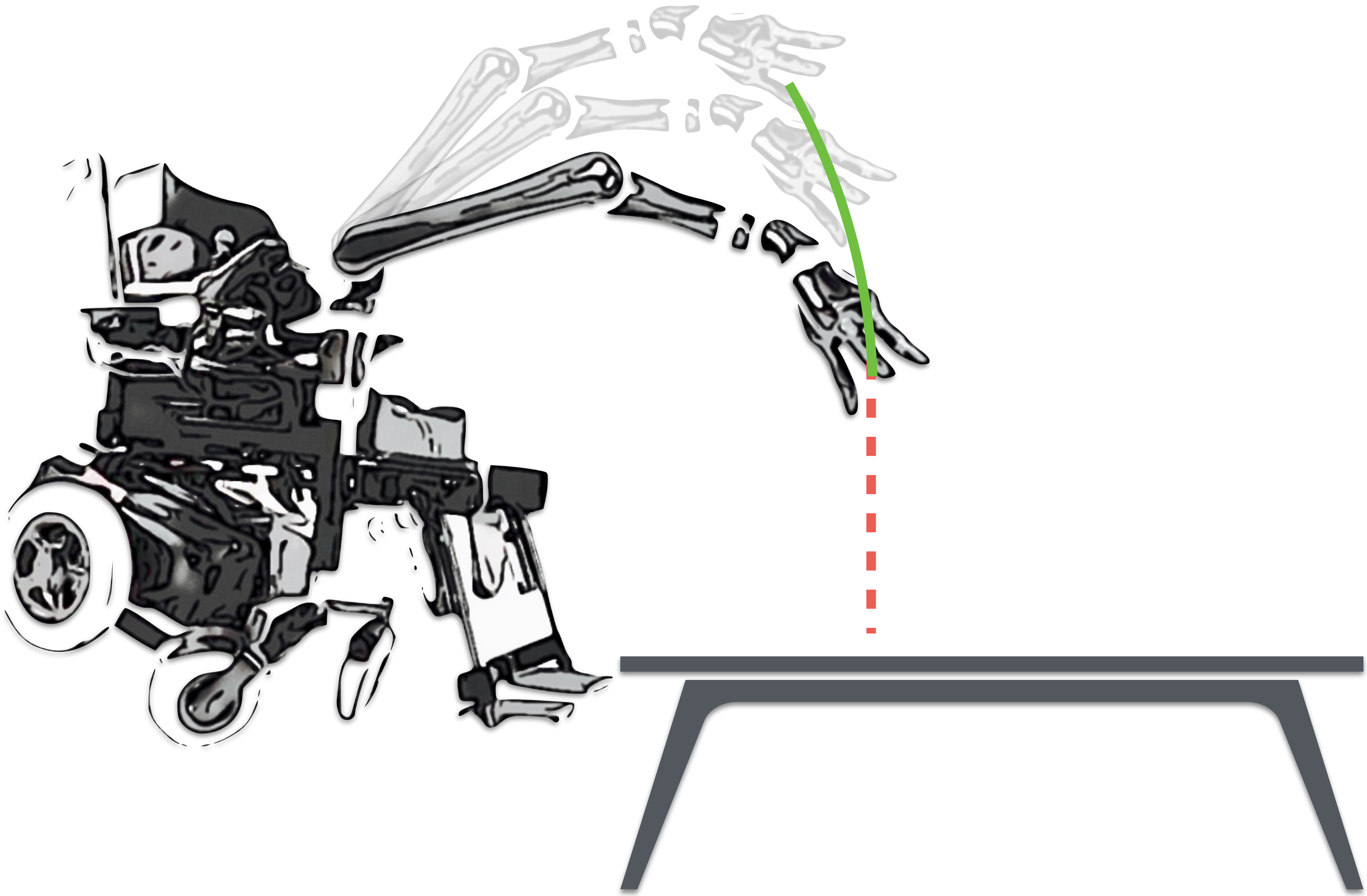


We improve the state of art by leveraging motion dynamics



We improve the state of art by modeling a trajectory distribution



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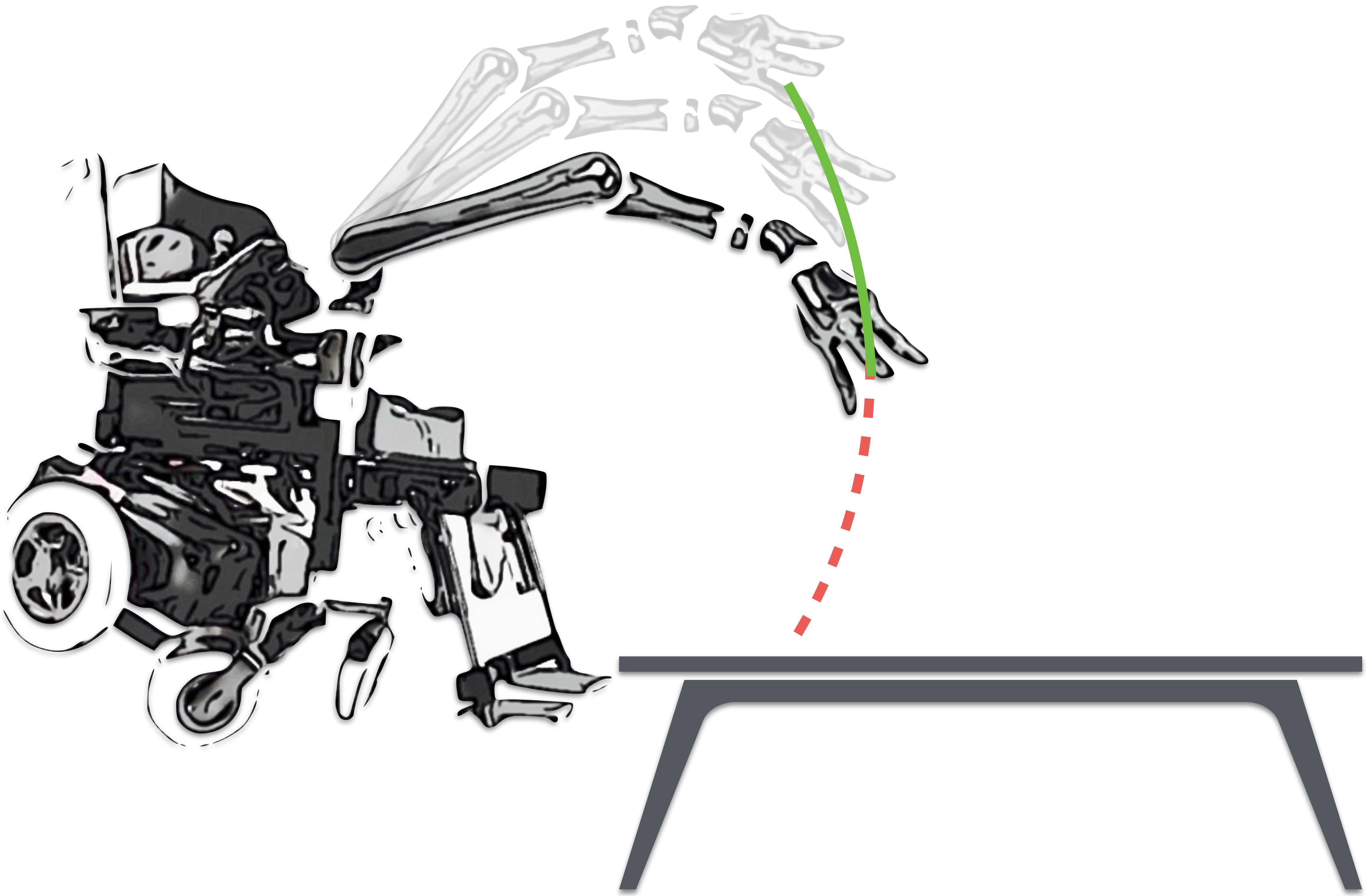

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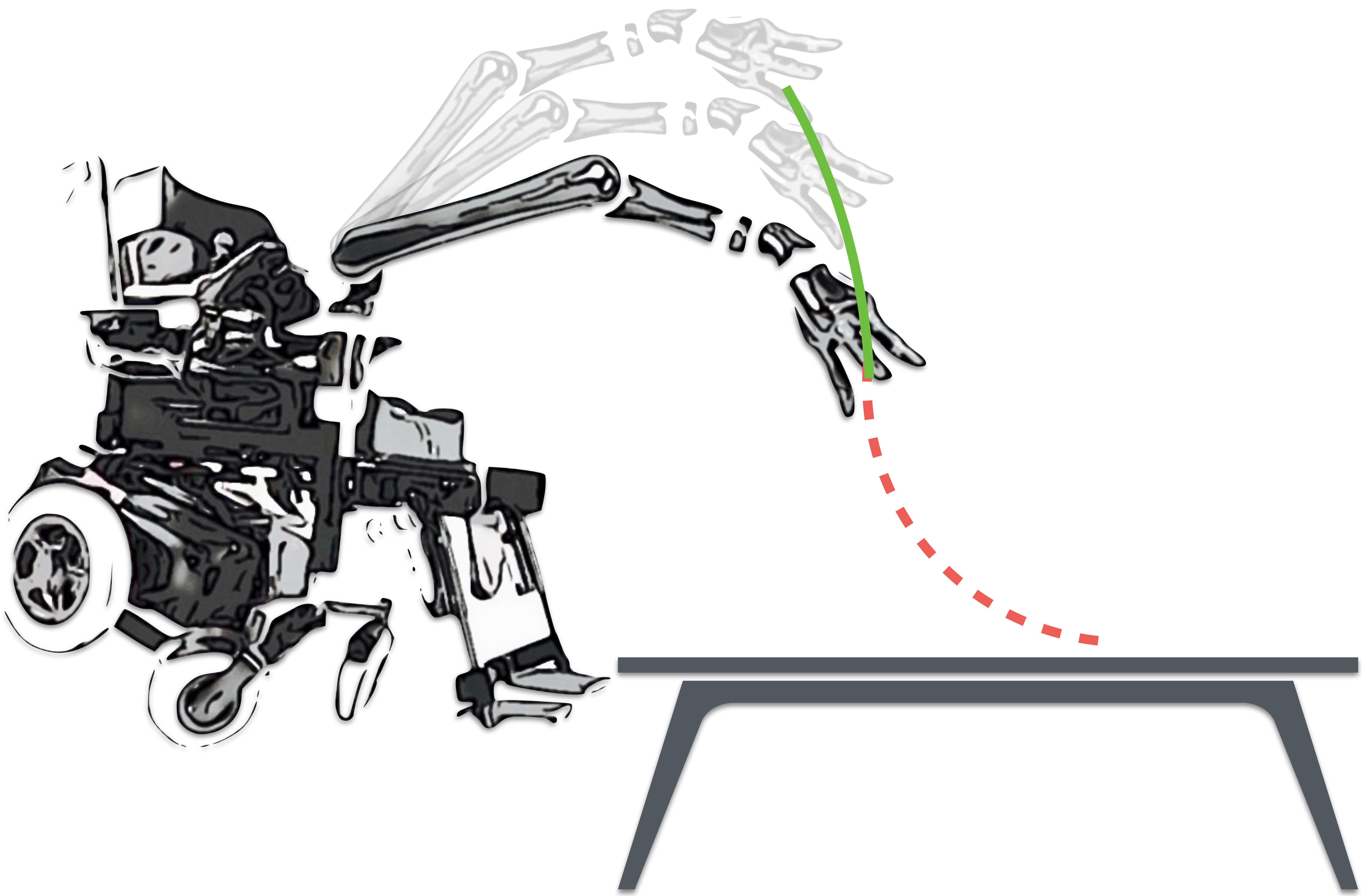

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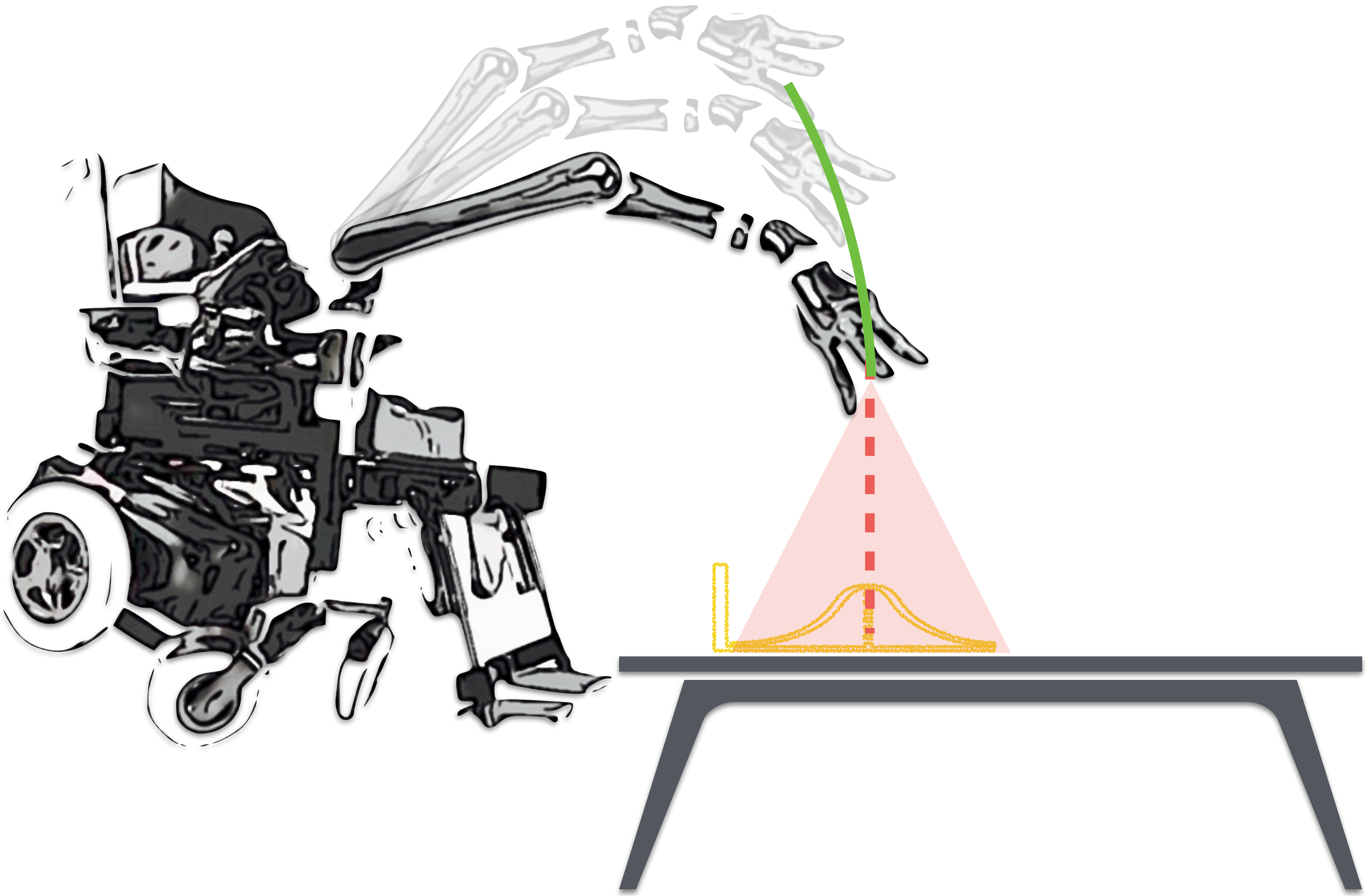
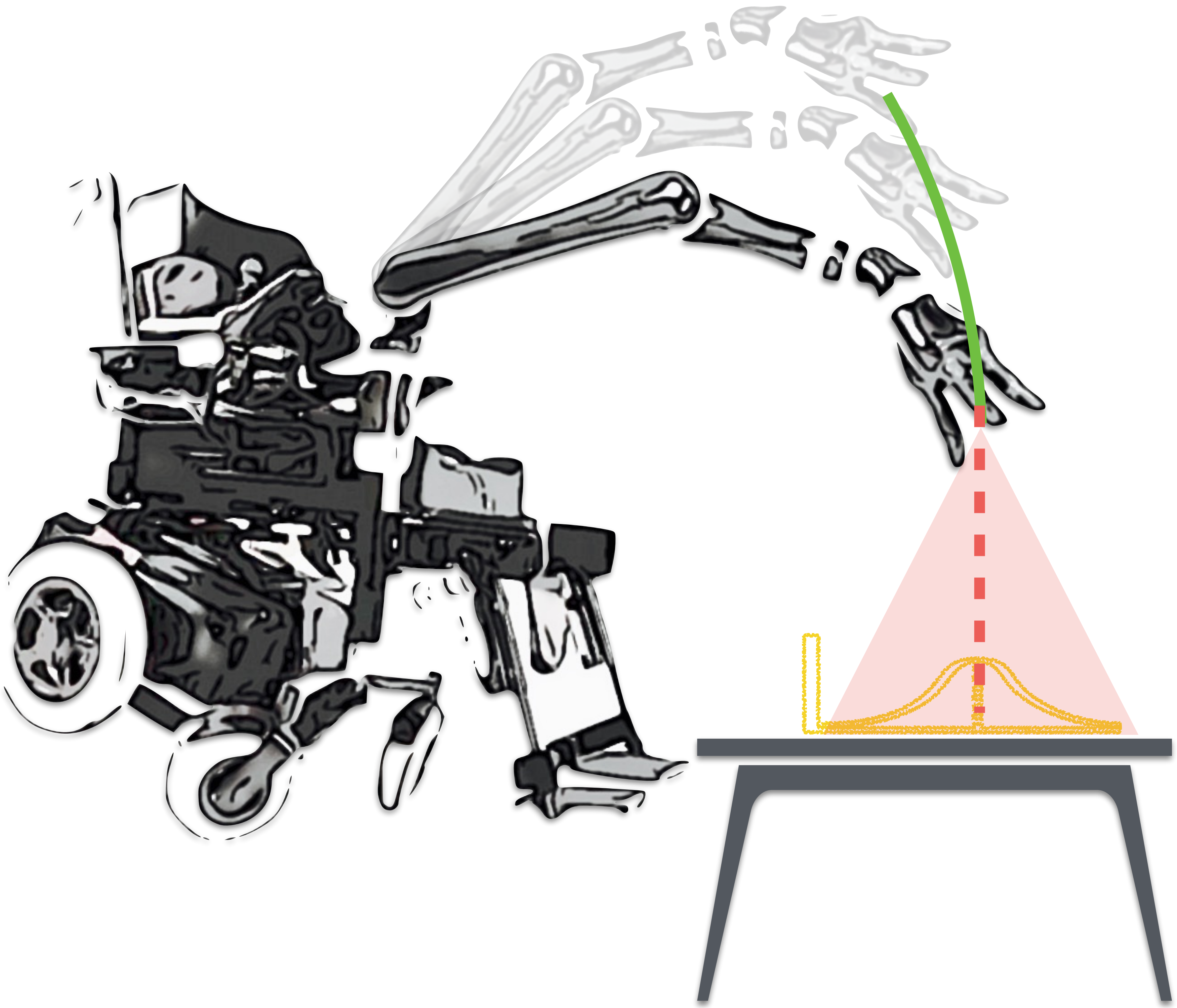


We improve the state of art by modeling a multi-modal trajectory distribution



Top-down view:

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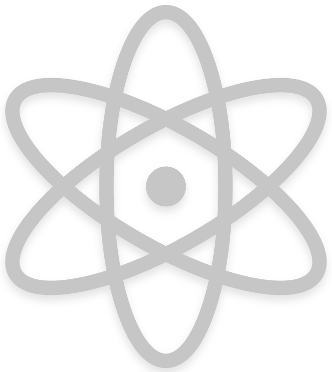

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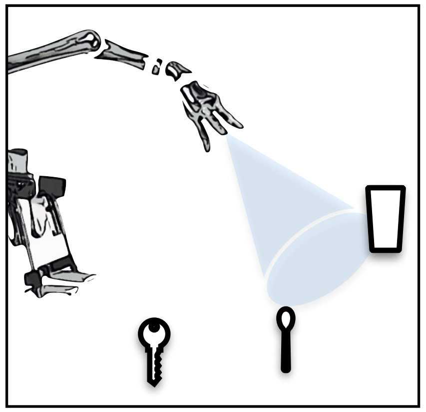
From the user's motion onset



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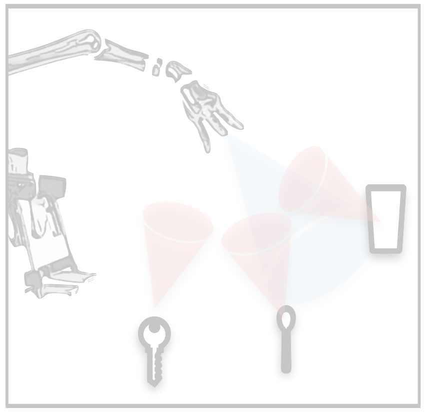
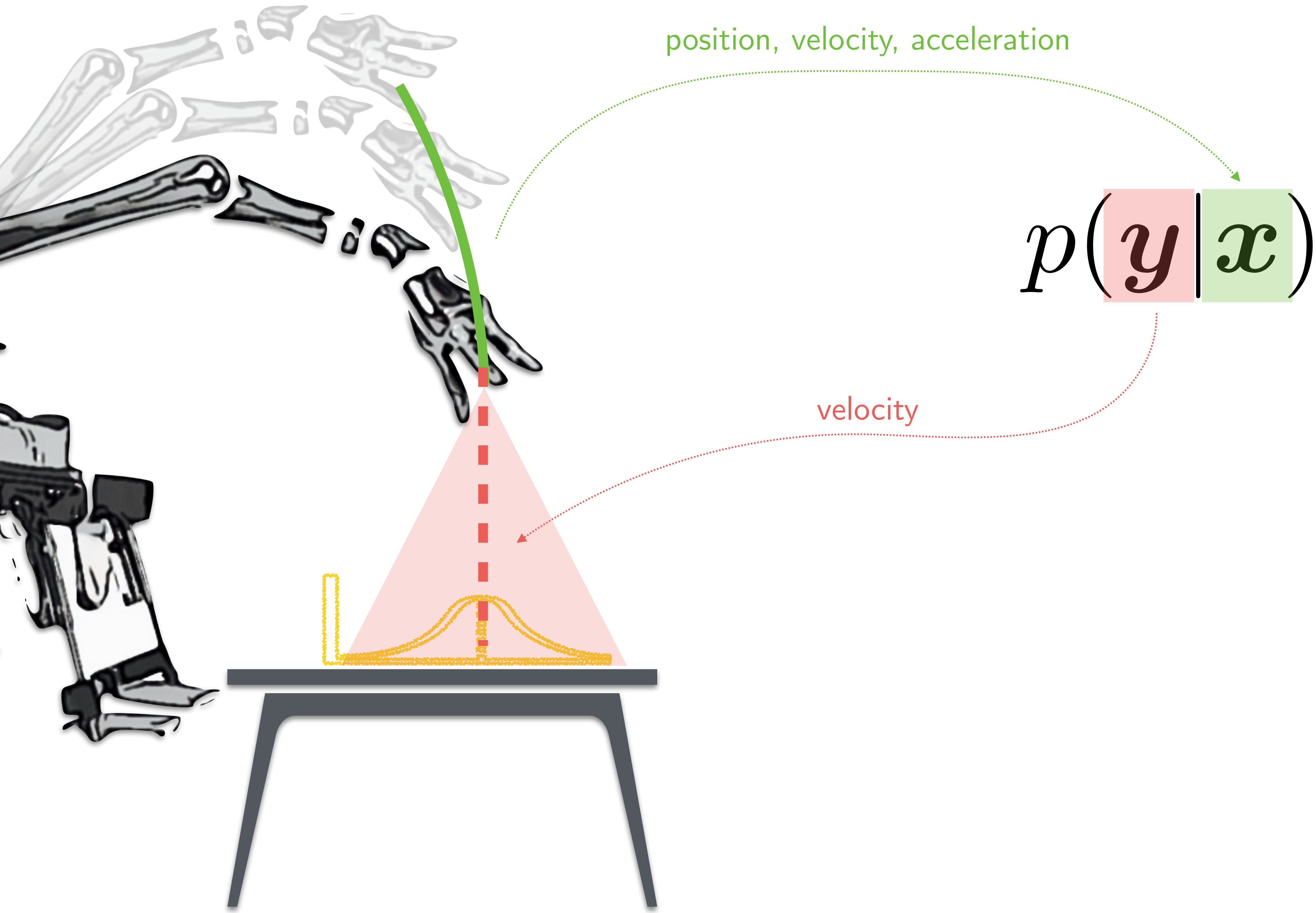
Motion prediction + goal assessment

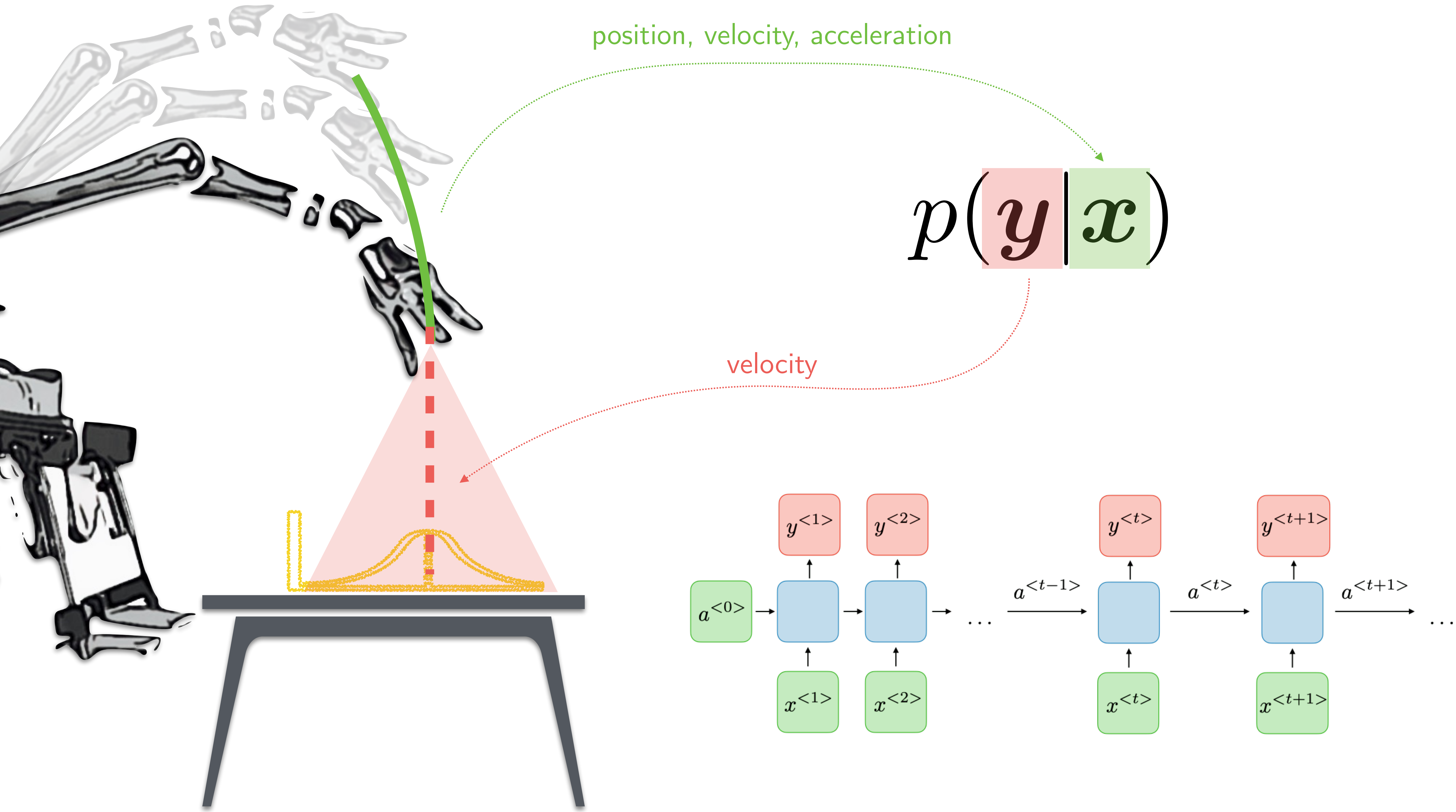


Our trajectory model encodes motion dynamics



$$p(\boldsymbol{y} \mid \boldsymbol{x})$$

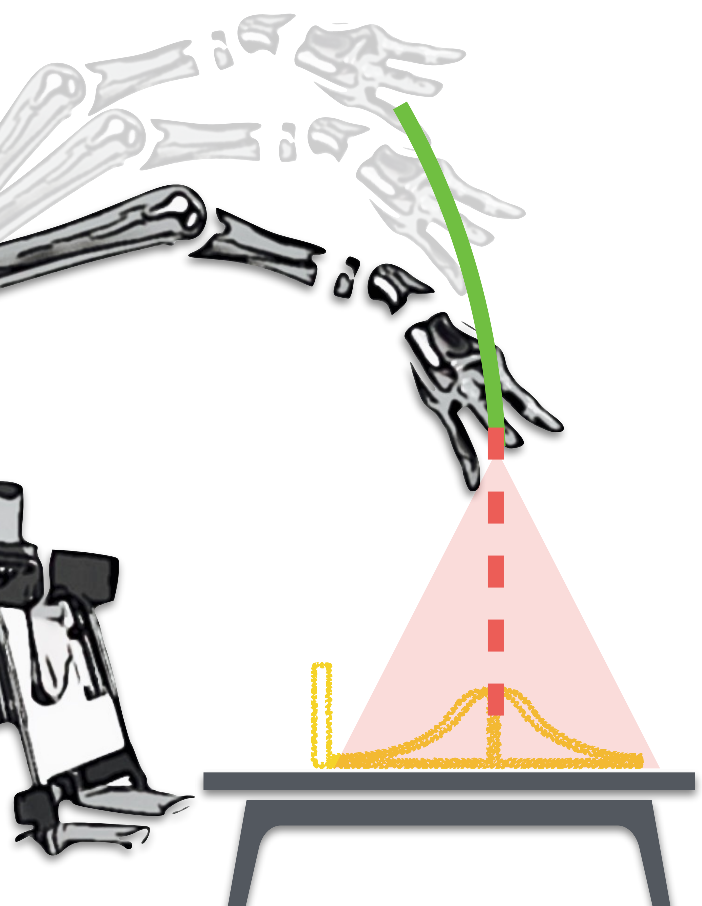
Our trajectory model encodes motion dynamics using recurrent neural networks

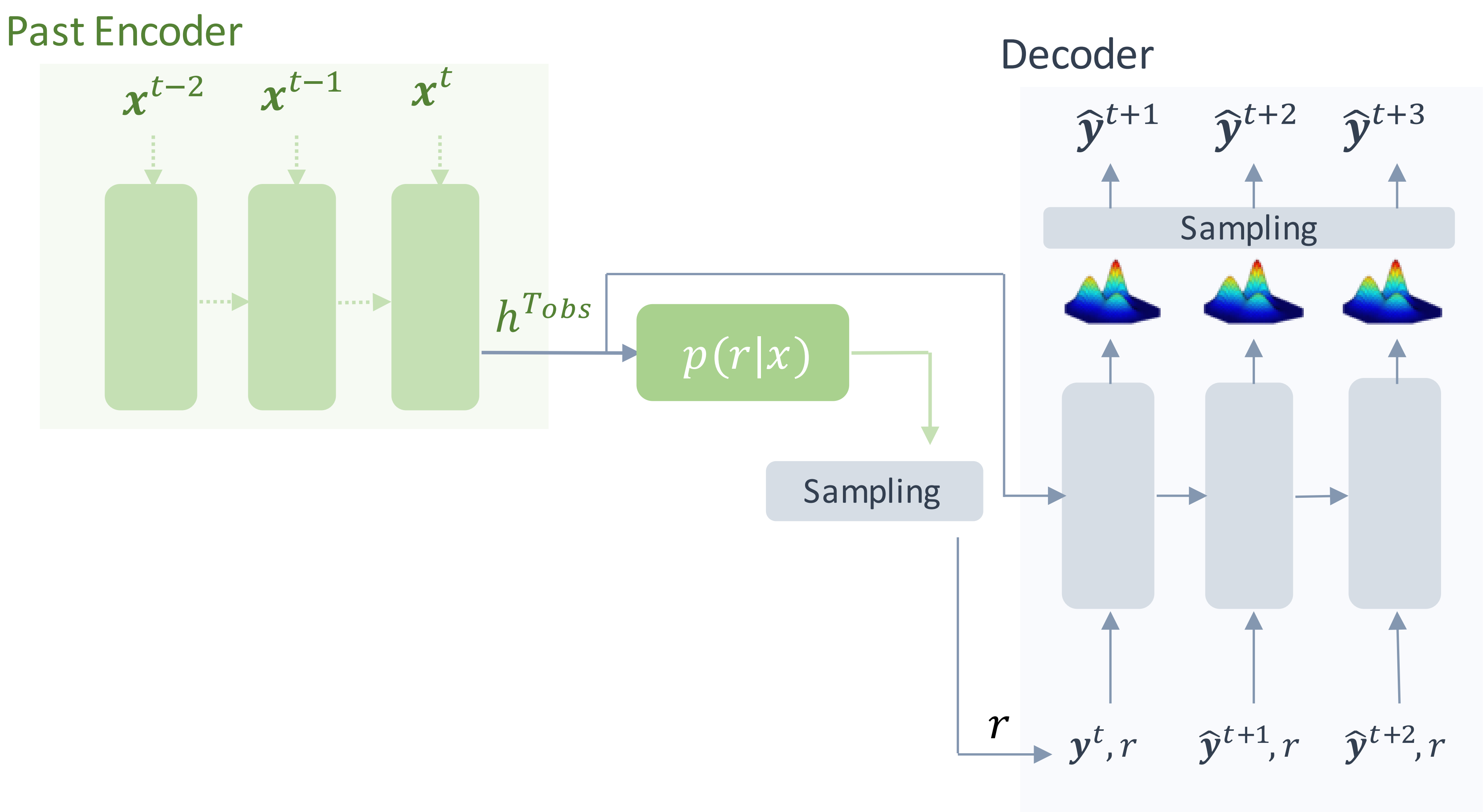


https://stanford.edu/~shervine/teaching/cs-230/cheatsheet-recurrent-neural-networks

We introduce a latent variable r, to facilitate the encoding of a low-dimensional, multi-modal representation of trajectory data

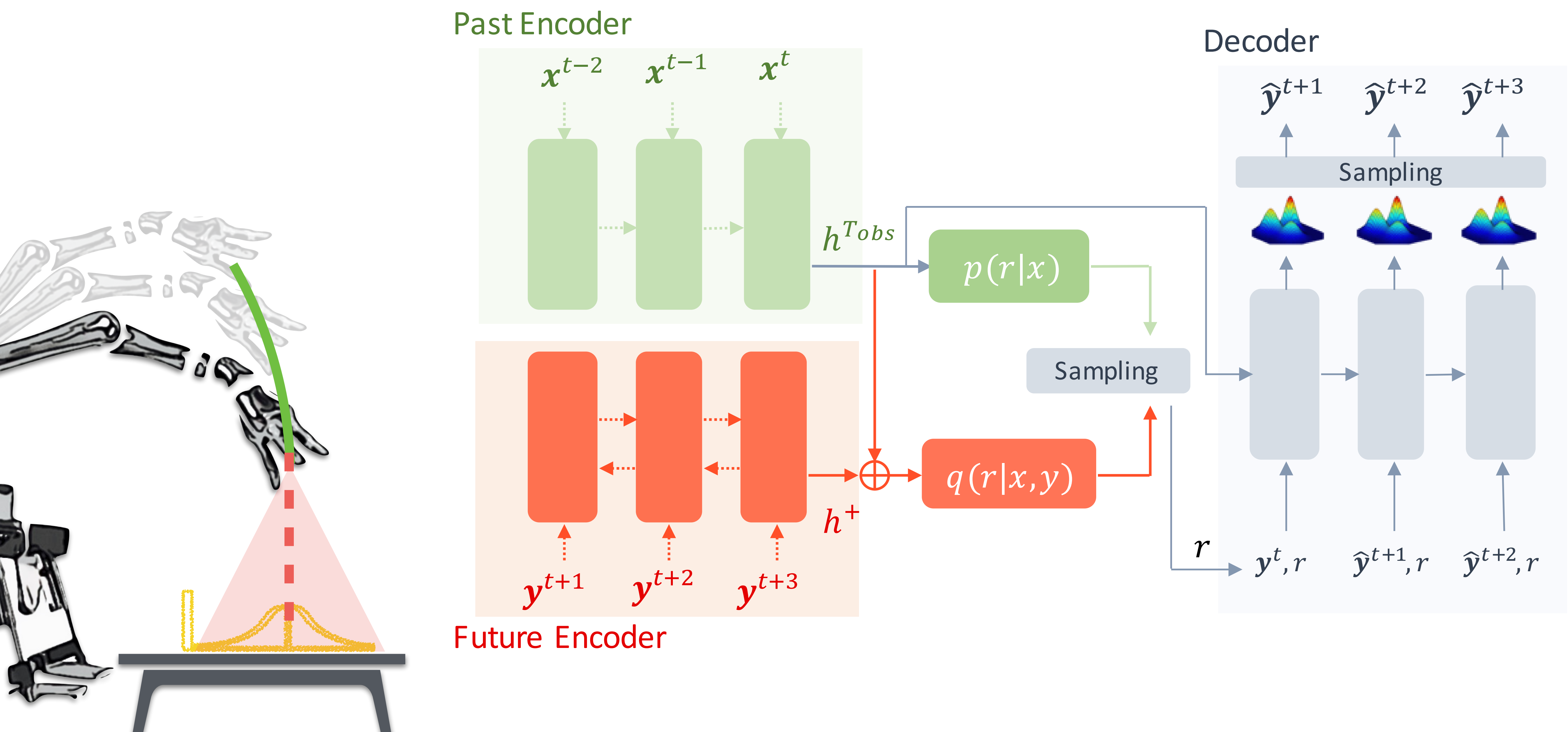
$$p(\boldsymbol{y}|\boldsymbol{x}) = \sum_{\boldsymbol{r}} p_{\psi}(\boldsymbol{y}|\boldsymbol{x}, \boldsymbol{r}) p_{\theta}(\boldsymbol{r}|\boldsymbol{x})$$





This model identifies to a CVAE.
We approximate $p_\theta(r|x)$ with $q(r|x,y)$.

$$p(\boldsymbol{y}|\boldsymbol{x}) = \sum_{\boldsymbol{r}} p_\psi(\boldsymbol{y}|\boldsymbol{x},\boldsymbol{r})\,p_\theta(\boldsymbol{r}|\boldsymbol{x})$$



We call our model *Robot Trajectron* ("RT")

Robot Trajectron: Trajectory Prediction-based Shared Control for Robot Manipulation

Pinhao Song[1], Pengteng Li[4], Erwin Aertbeliën[1,2], Renaud Detry[1,3]

ICRA2024 YOKOHAMA | JAPAN

***Abstract*— We address the problem of (a) predicting the trajectory of an arm reaching motion, based on a few seconds of the motion's onset, and (b) leveraging this predictor to facilitate shared-control manipulation tasks, by reducing the**

that goal [1], [2], [3], which does not always hold true. Furthermore, most intent estimators rely on position-based methods, which consider only the distance between gripper *position* (past or predicted) and each goal to infer the user's

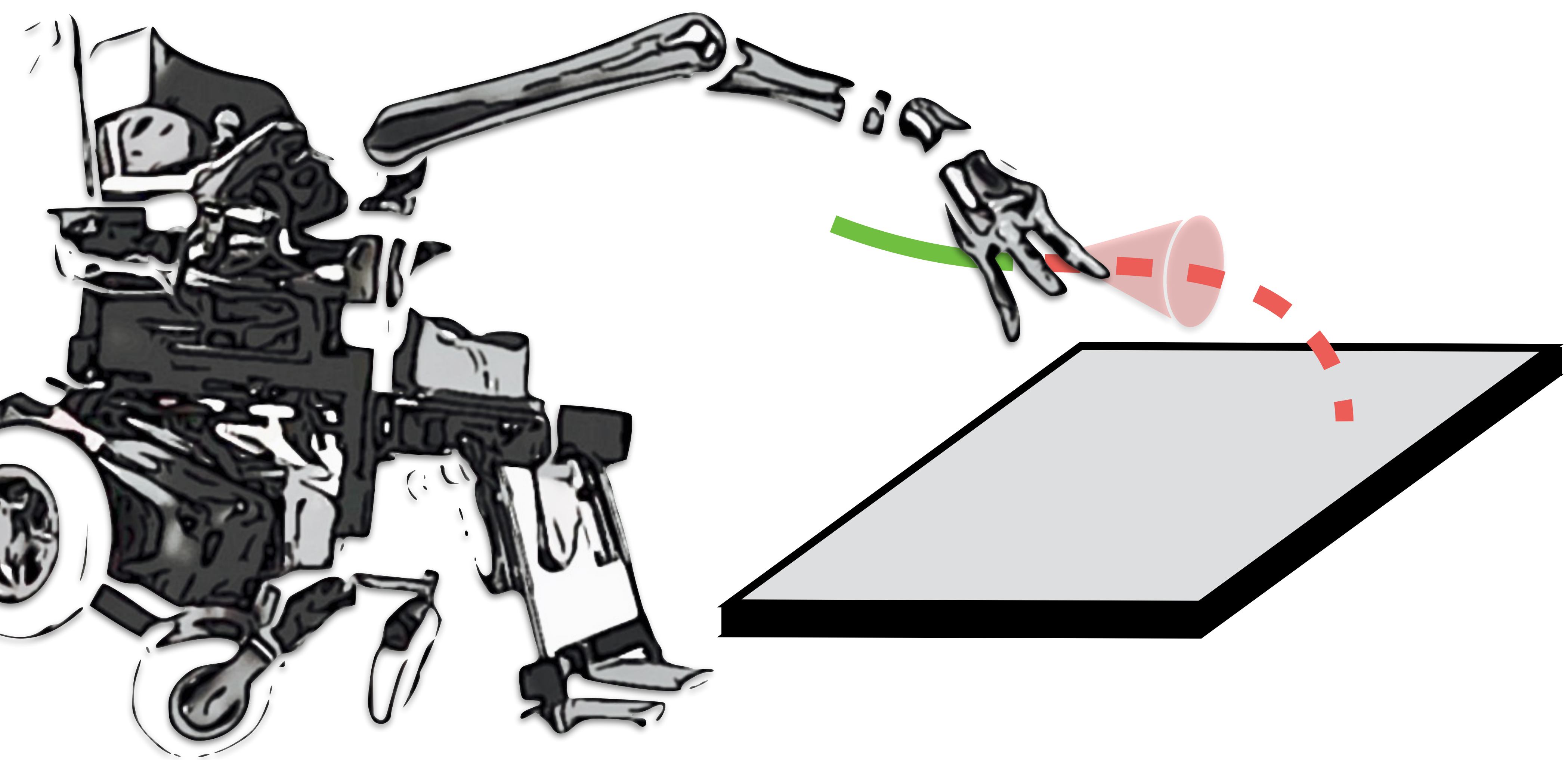
Inspired by "Boris Ivanovic, Marco Pavone
The Trajectron: Probabilistic Multi-Agent Trajectory Modeling With Dynamic Spatiotemporal Graphs"

Our Experiments showed that RT outperforms a direct LSTM on a trajectory prediction task.

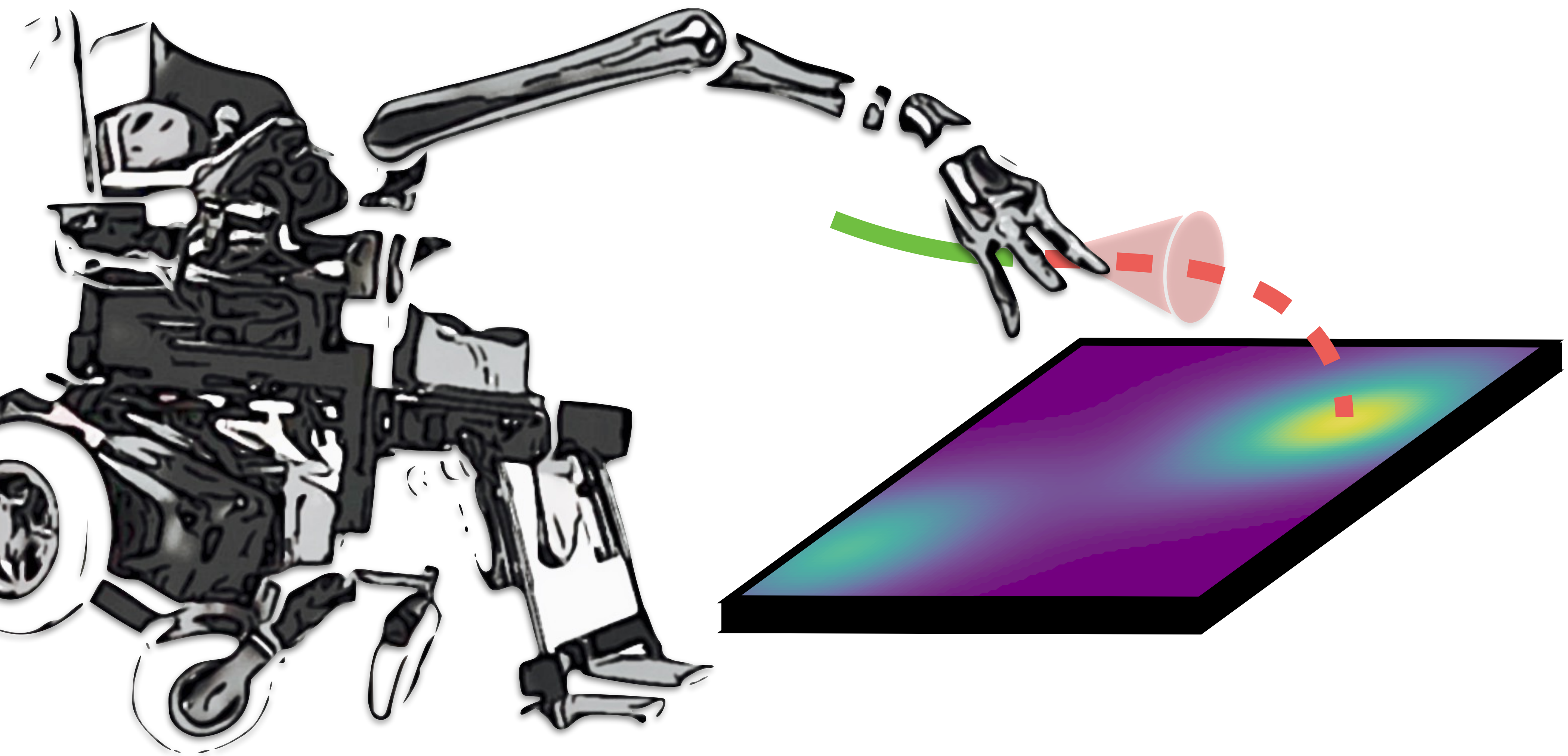
RT trained on 100k trajectories collected in sim.

Method	Most likely (mm)	
	ADE	FDE
Vanilla LSTM [29]	136.95	115.47
Robot Trajectron	30.58	49.94

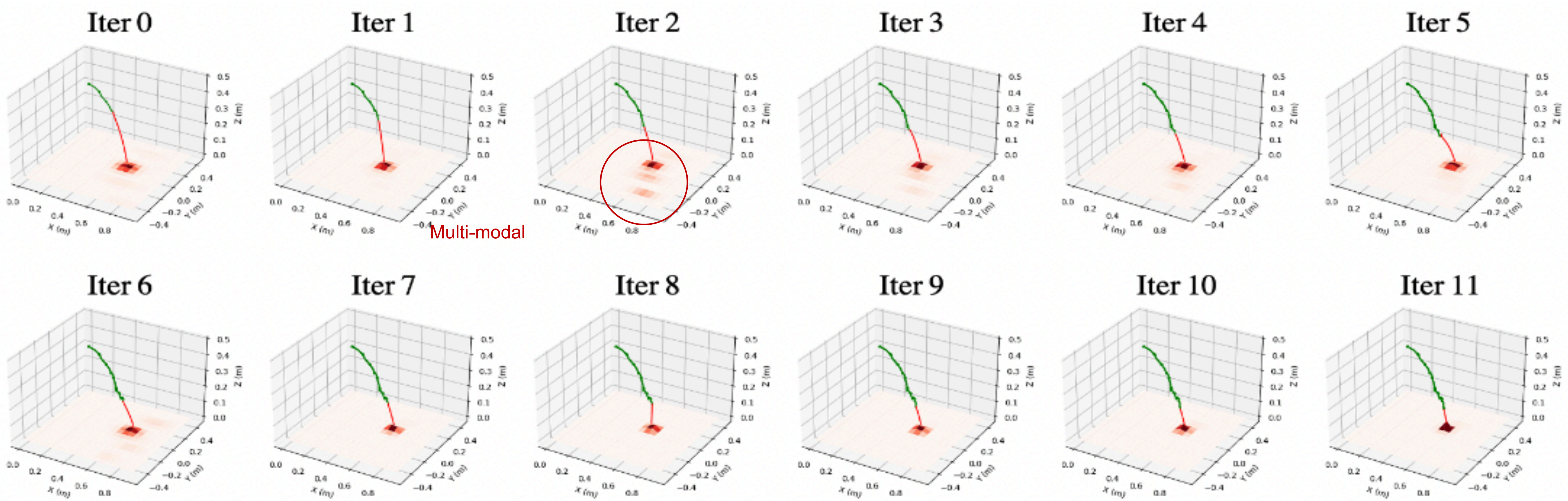
In a tabletop scenario, trajectory forecasts can be intersected with the table plane



Similarly, RT's probabilistic motion predictions can be projected onto the table plane



Our sim experiments demonstrate RT's multi-modal prediction capacity



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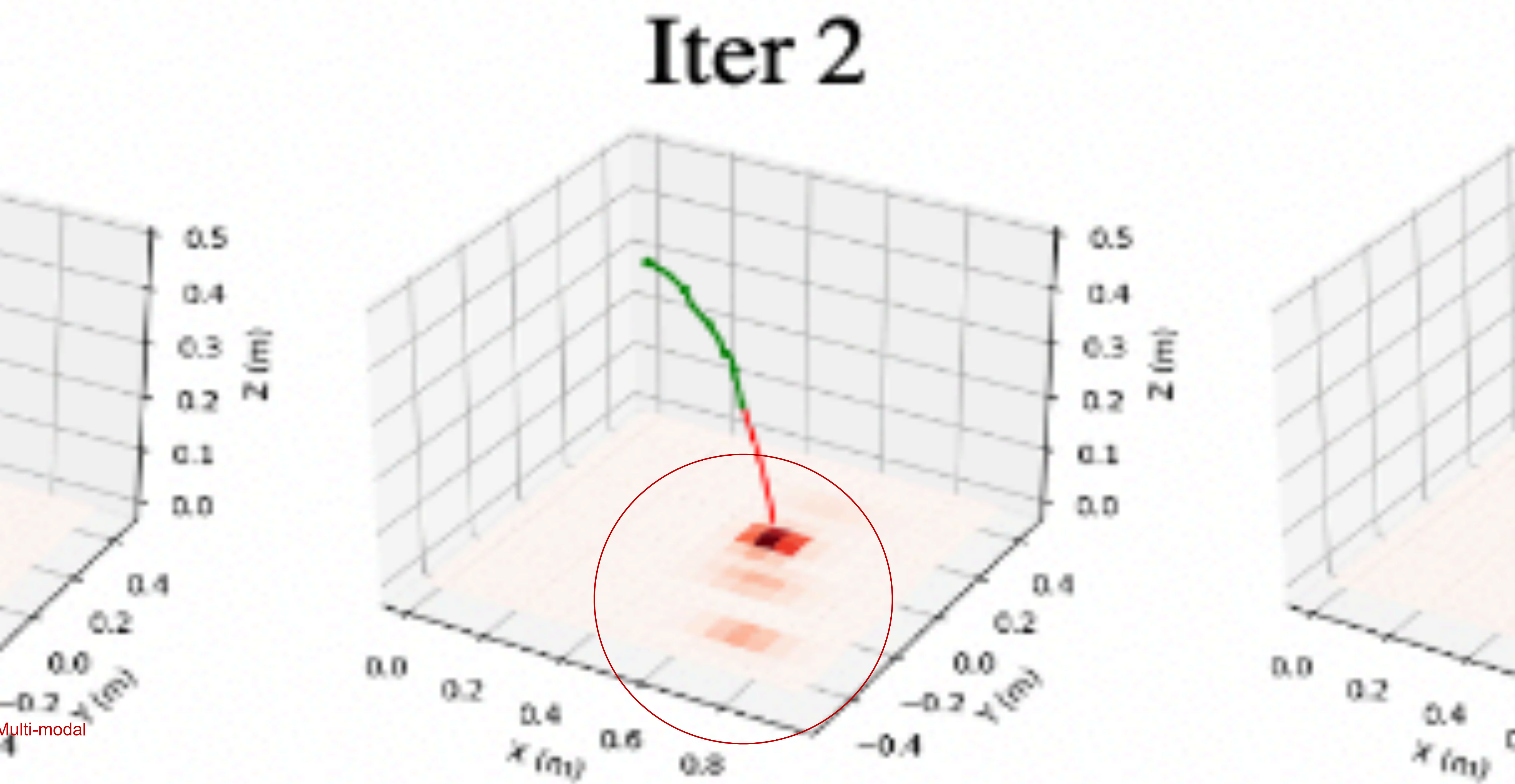

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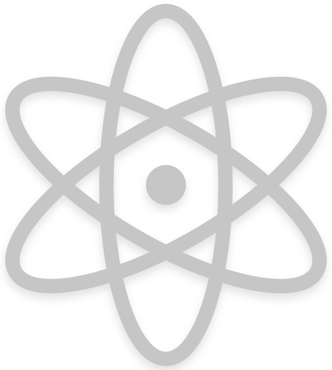

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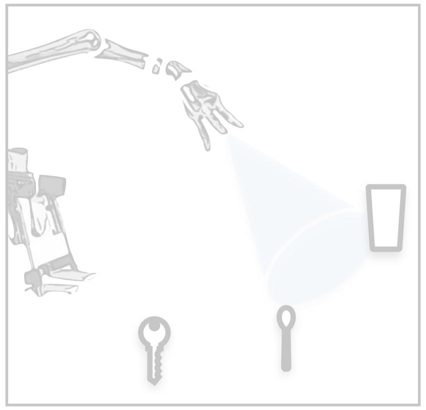

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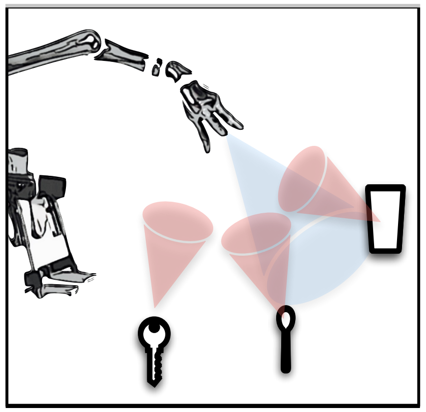
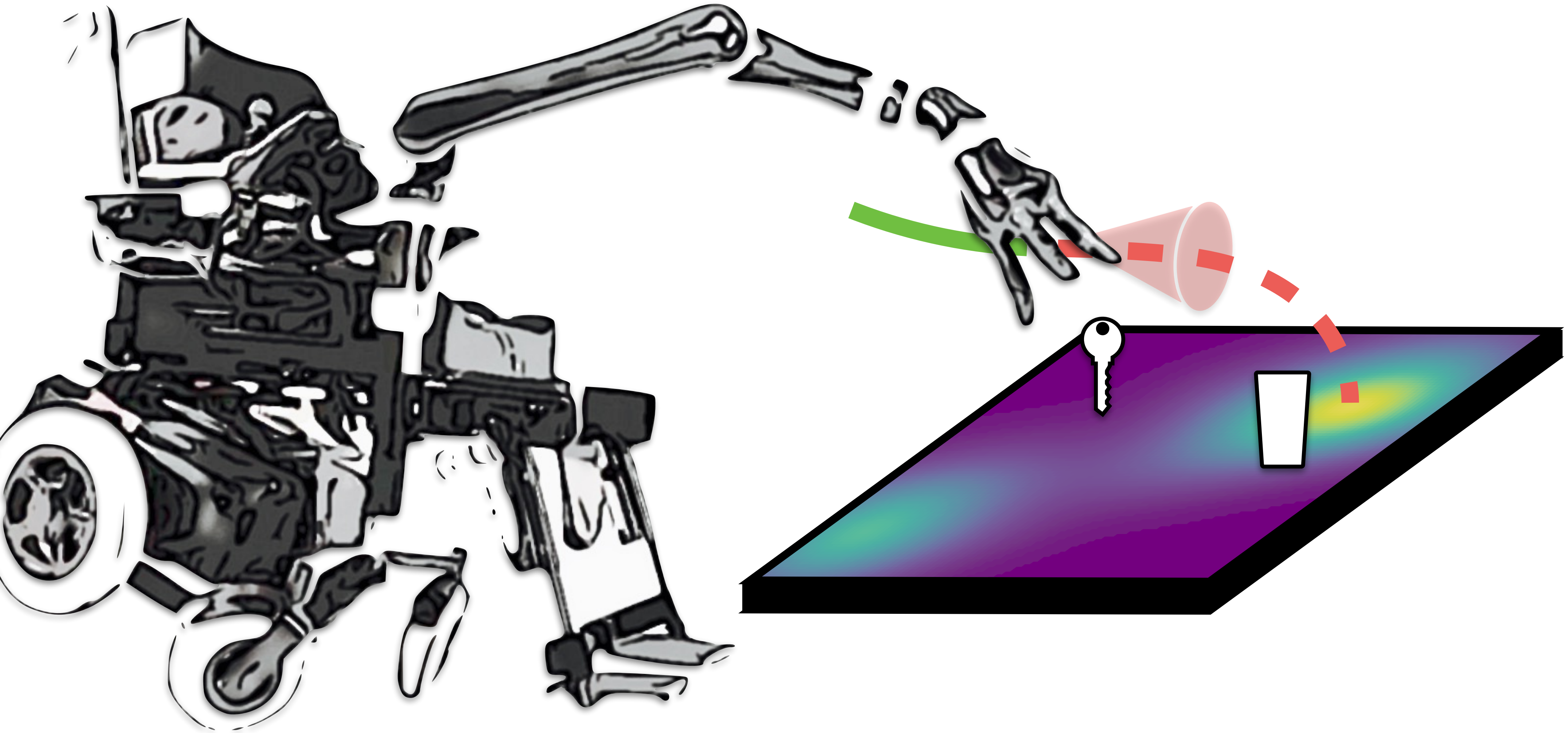
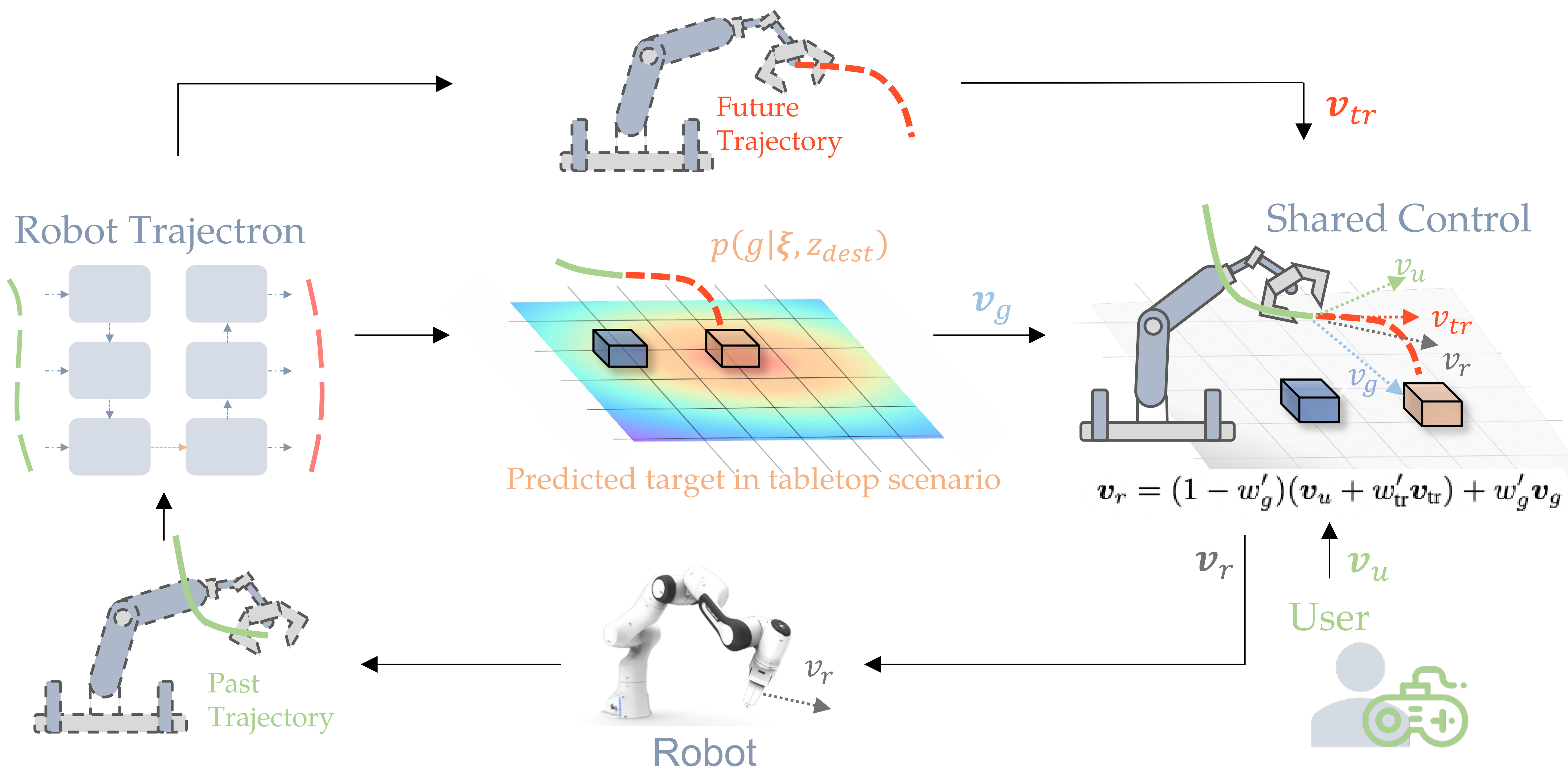


Table-plane projections allow us to intuitively reconcile goal locations and trajectory forecasts

Implicit Grasp Diffusion: Bridging the Gap between Dense Prediction and Sampling-based Grasping
Pinhao Song, Pengteng Li, Renaud Detry – CoRL 2024



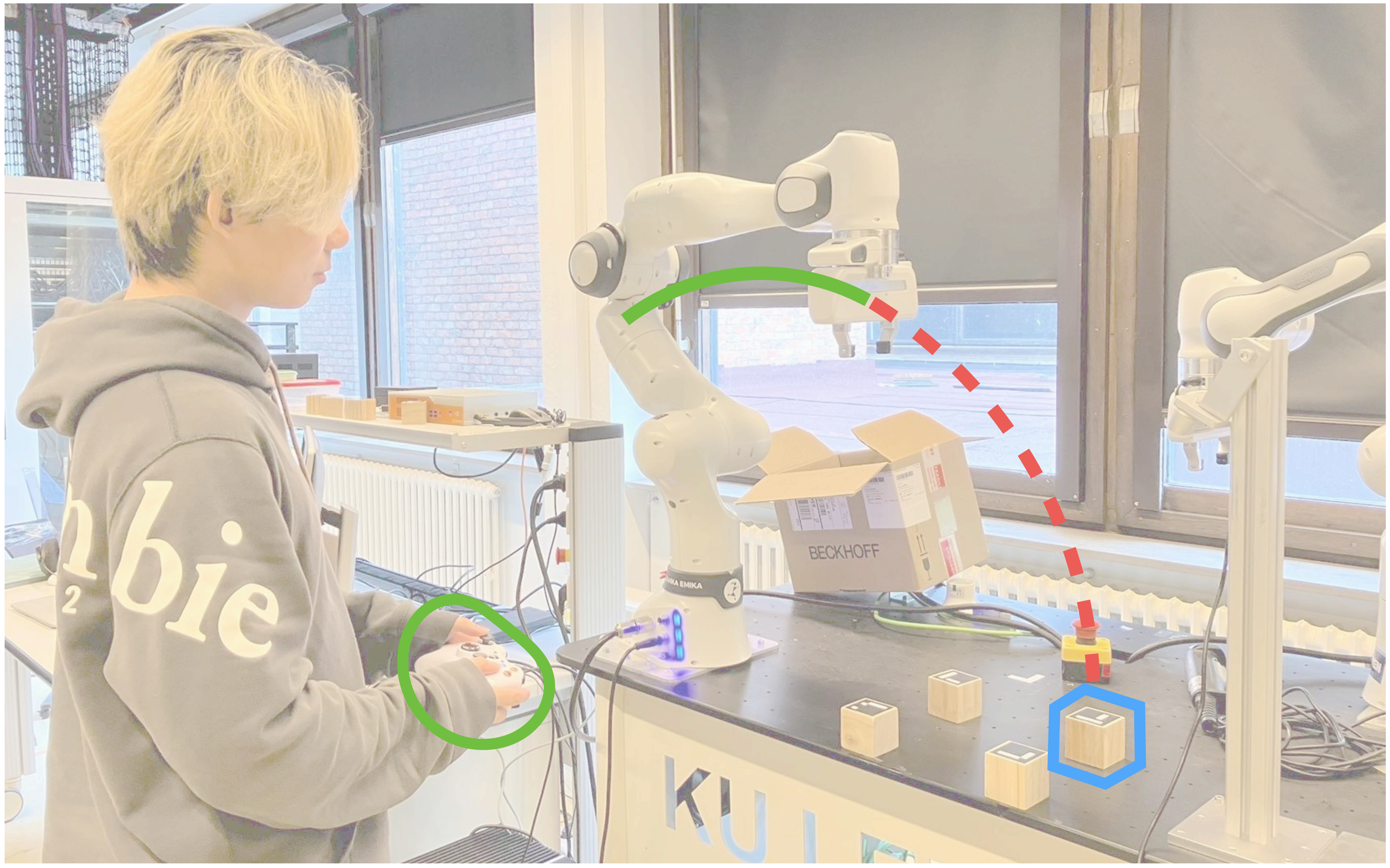
We leveraged RT to assemble a simple shared controller that combines user input, motion forecasts and goal locations



Our simple RT-based shared controller performs on-par with MaxEnt IOC, a state-of-art shared-control method

- **Subjects**: 10, from local community
- **Objets**: 4 small cubes equipped with ArUCo markers
- **Task**: the subject was required to gradually approach one object
- **Baseline 1**: no assistance (direct teleoperation)
- **Baseline 2**: MaxEnt IOC [1]

Method	Time (sec)	Input	Average l_{tr} (m)
Teleop. [3]	9.36±0.71	41.8±2.8	2.452±0.246
MaxEnt IOC [3]	7.24±0.33	33.8±1.2	2.007±0.060
Robot Trajectron	7.17±0.43	33.8±1.3	1.981±0.092



[1] Gottardi, A., Tortora, S., Tosello, E., & Menegatti, E. (2022). Shared control in robot teleoperation with improved potential fields. *IEEE Transactions on Human-Machine Systems*, *52*(3), 410-422.

Robot Trajectron ("RT") is a motion dynamics model that with multi-modal motion forecasting capabilities

Pinhao Song, Pengteng Li, Erwin Aertbelien, and Renaud Detry. *Robot Trajectron: Trajectory Prediction-based Shared Control for Robot Manipulation.* ICRA 2024.