



AAAI 2025 Tutorial T04

Time: 2025-02-25 8:30-12:30

Location: Room 118A

Part II: Foundation Models meet Physical Agents

AAAI Tutorial: Foundation Models Meet Embodied Agents



Northwestern
University



COLUMBIA



S **Stanford**
University

Physical Agents Overview

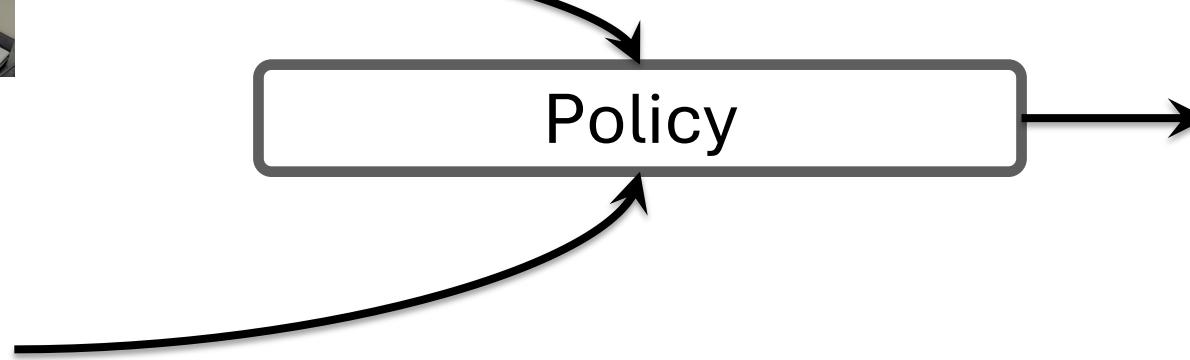


Physical Agents Overview

- Policy: $\pi(o, g) \rightarrow a$
- o : observation (images, robot proprioception, tactile, ...)
- g : goal (natural language for this tutorial)
- a : robot control commands

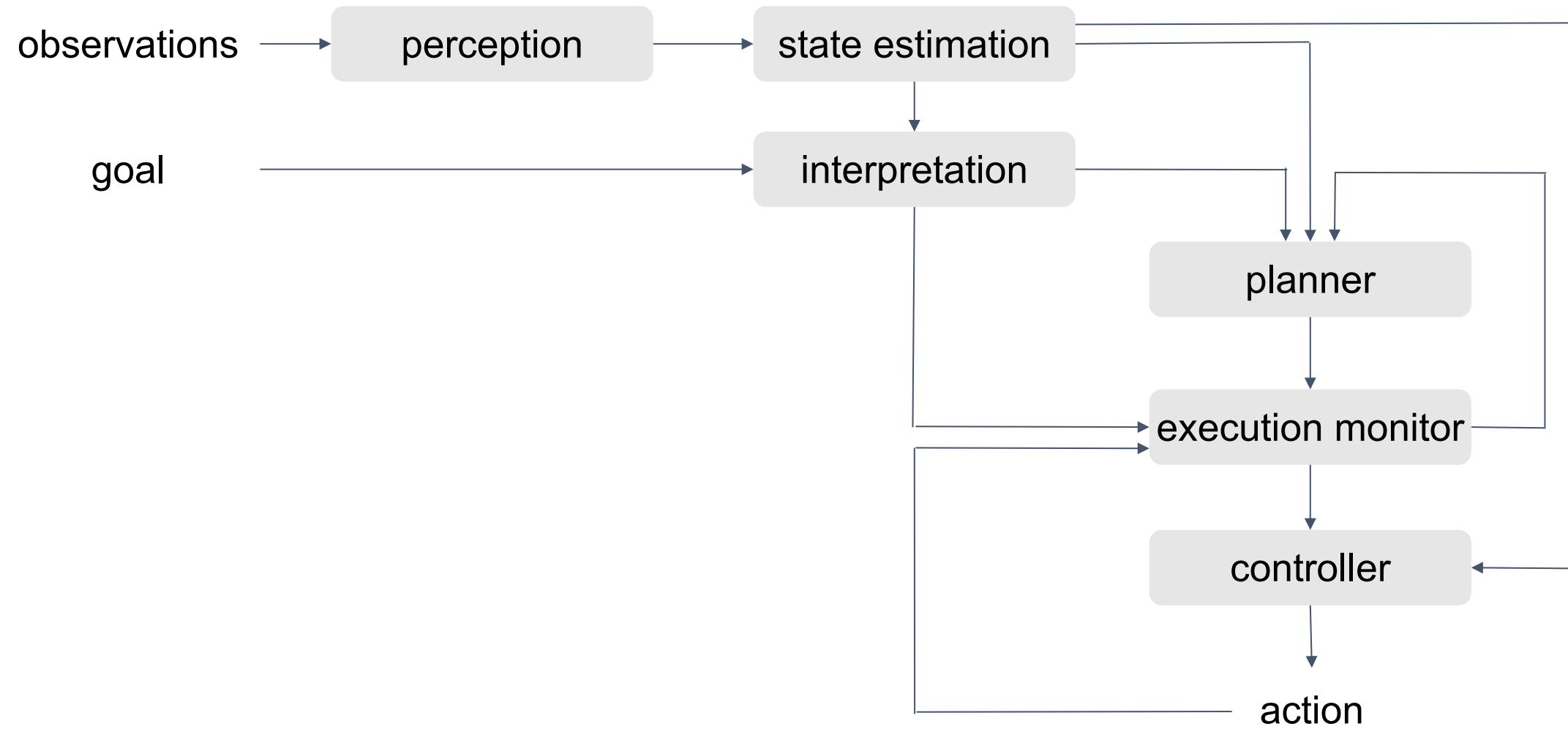


Wash the plate

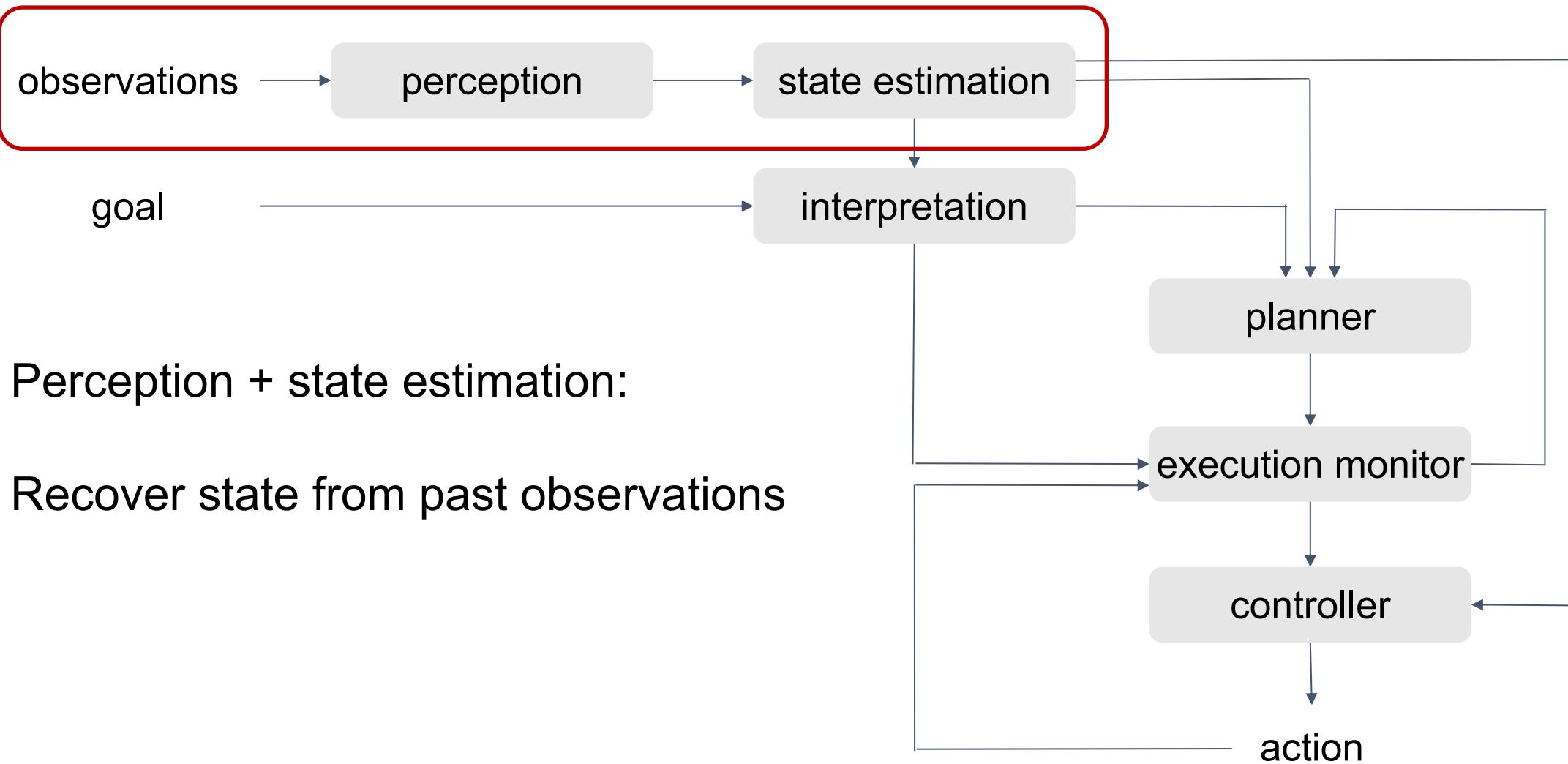


Robot Actions

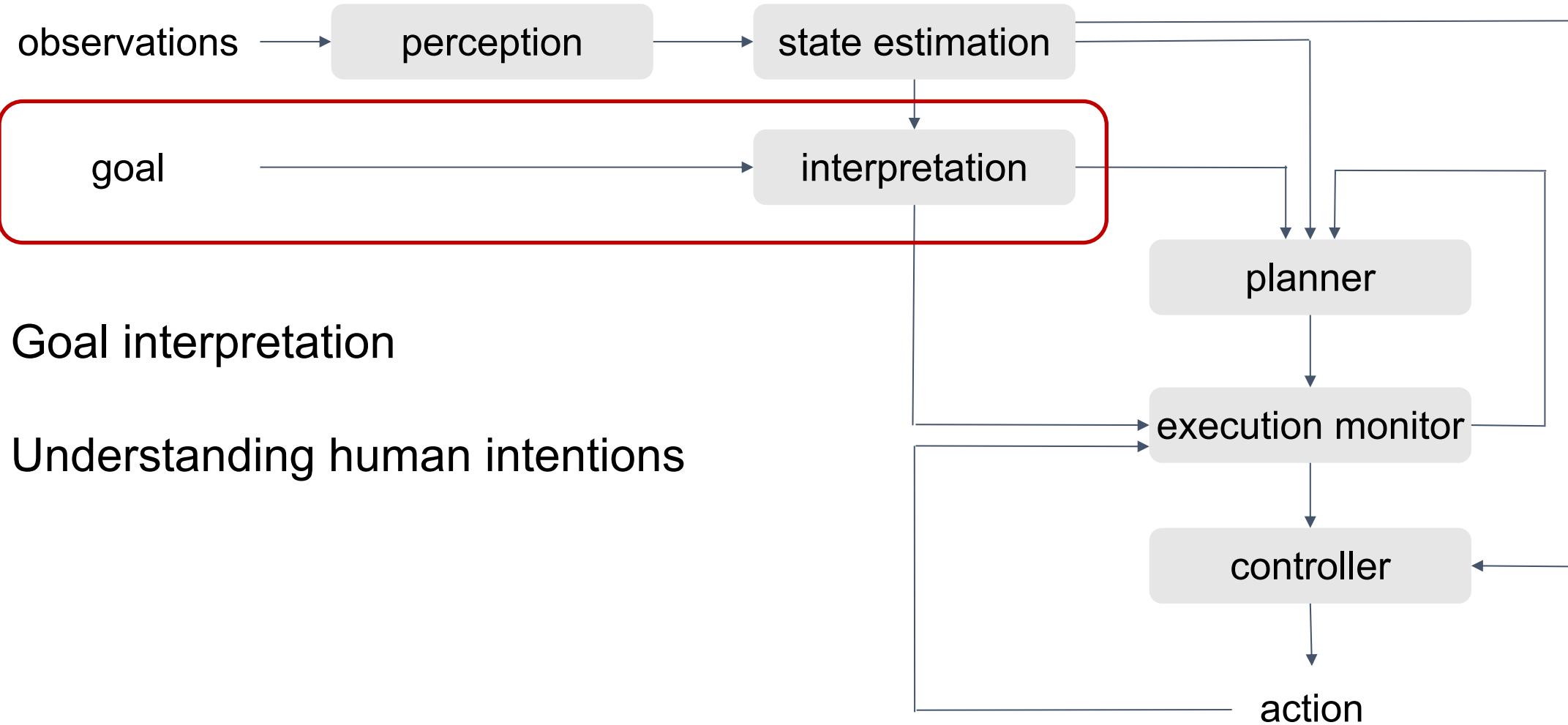
The Robot Architecture



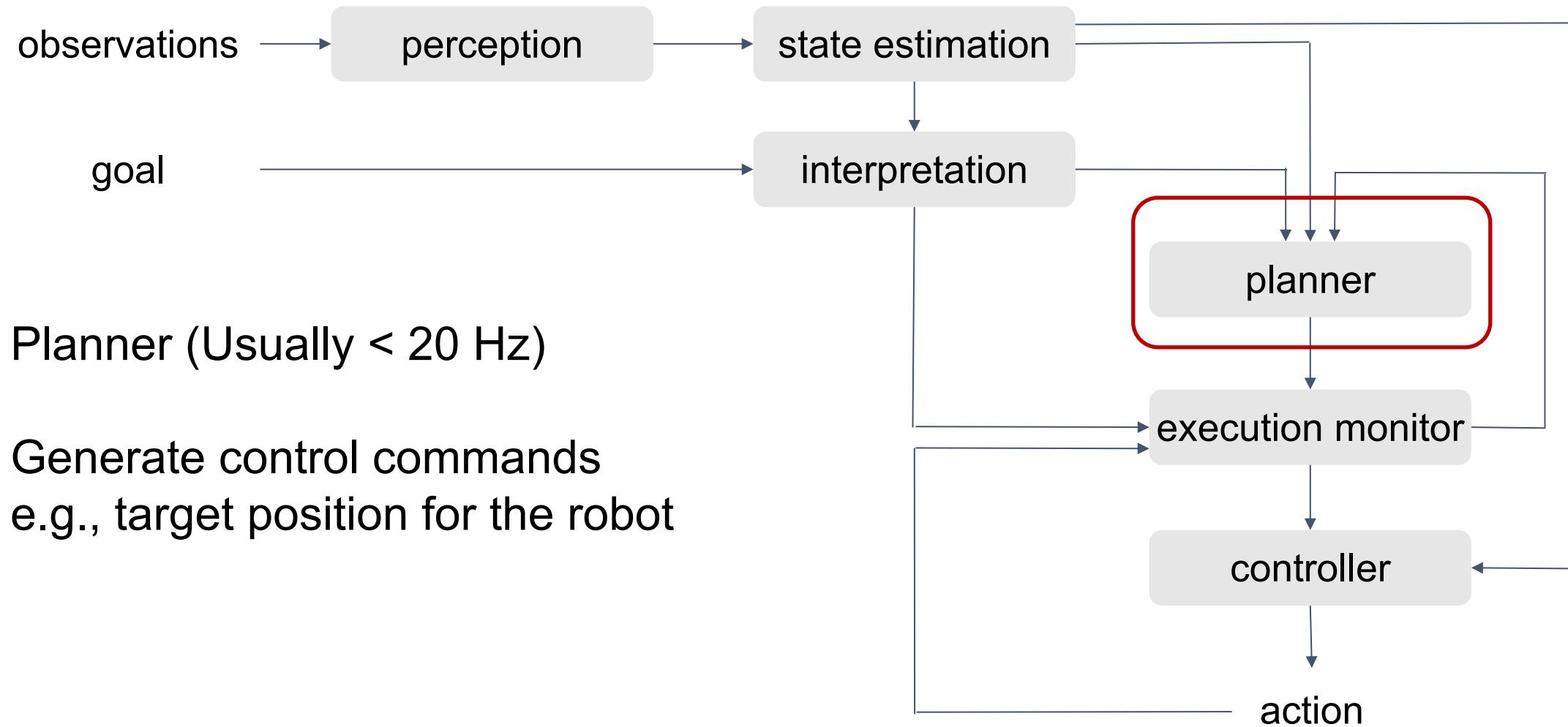
The Robot Architecture



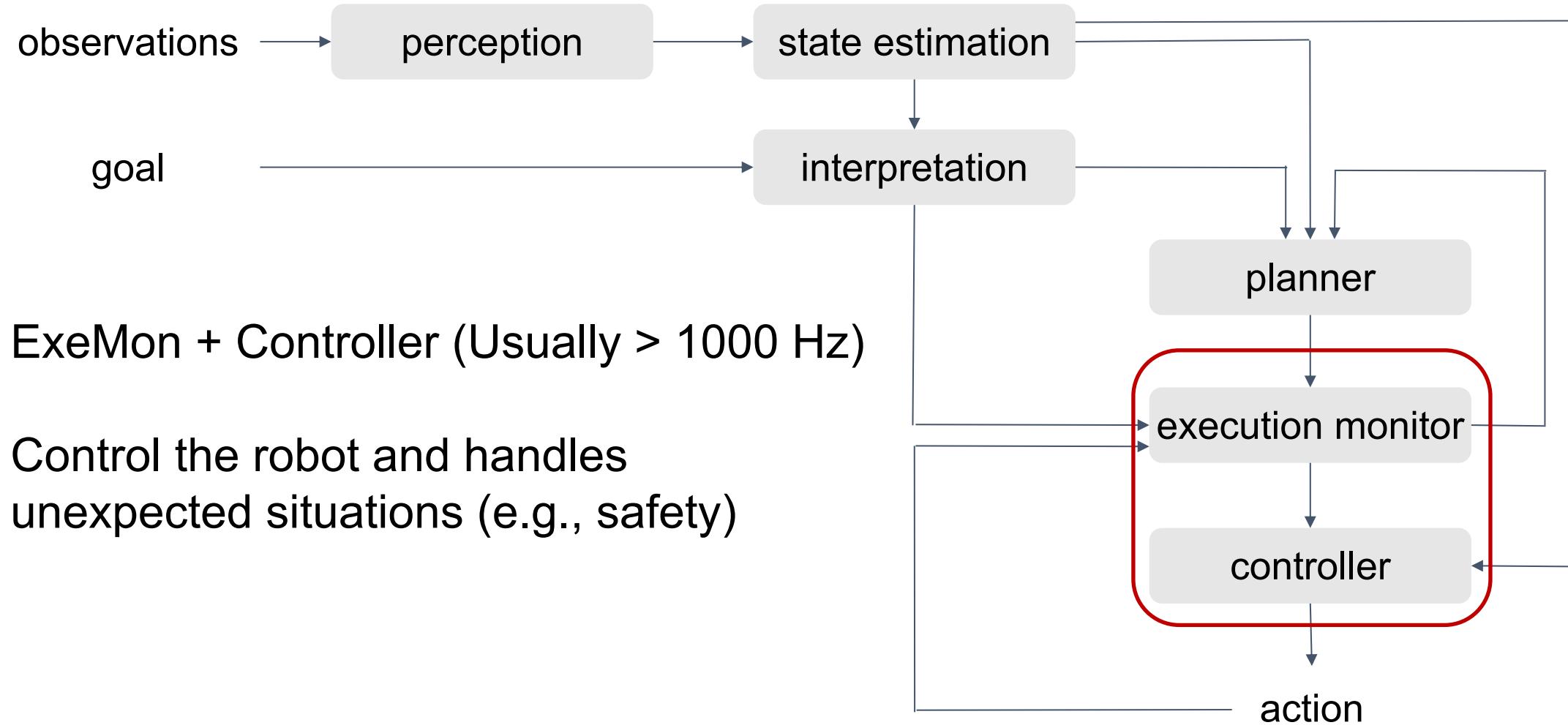
The Robot Architecture



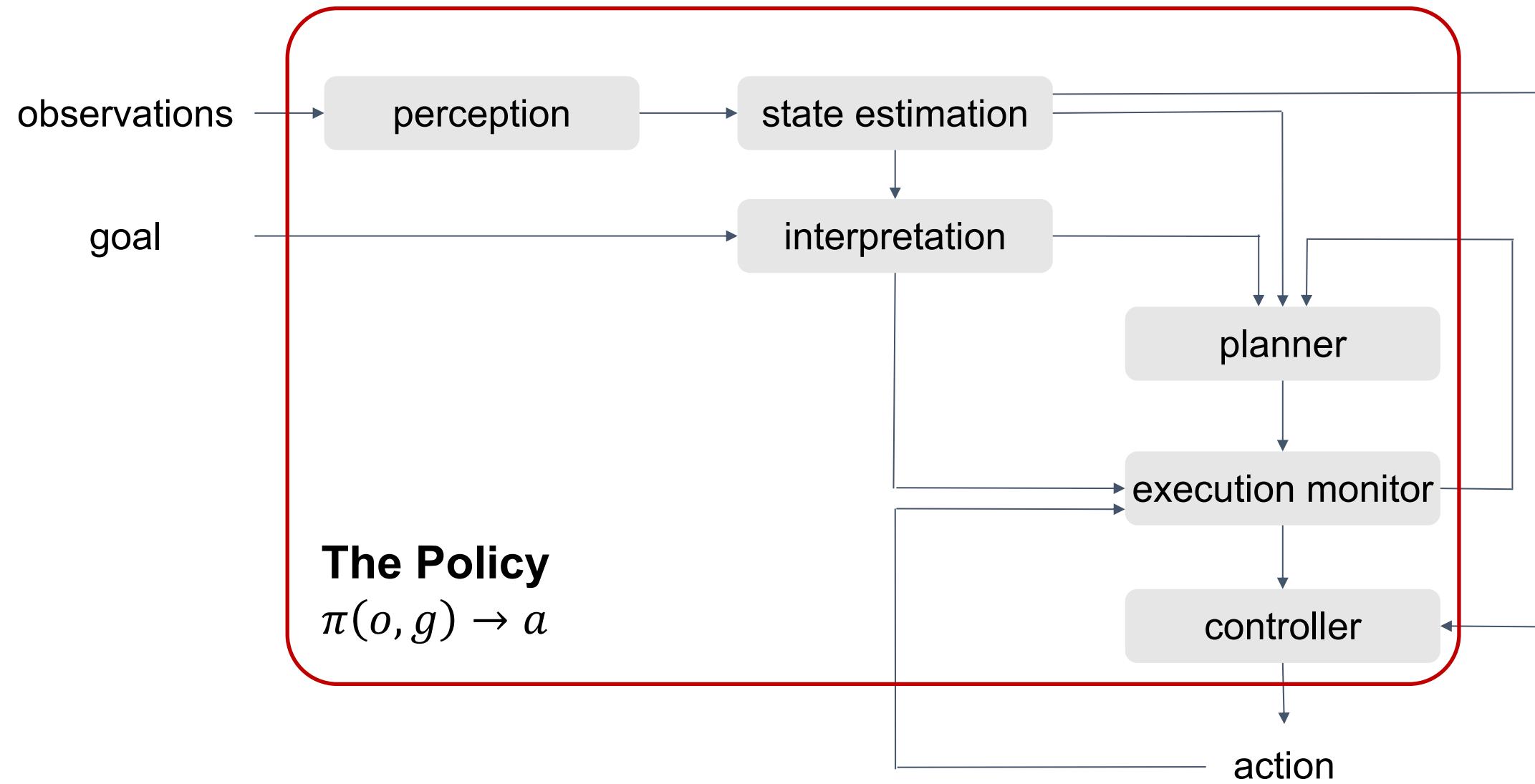
The Robot Architecture



The Robot Architecture



The Robot Architecture



- How to design and build the “state”
 - Usually involves computer vision and signal processing techniques
 - Partial observability is very salient
- How to design and build the “action”
 - Usually involves both discrete and continuous parameters
- How to design and build policies (high-level and low-level)
 - High-level: primitive functions such as pick and place
 - Low-level: primitive control commands such as target position and velocity
- How to design and build transition models and reward functions
 - Ground-truth is unknown
 - Reward functions are usually hard to define manually
 - Reward functions also need to consider human preferences

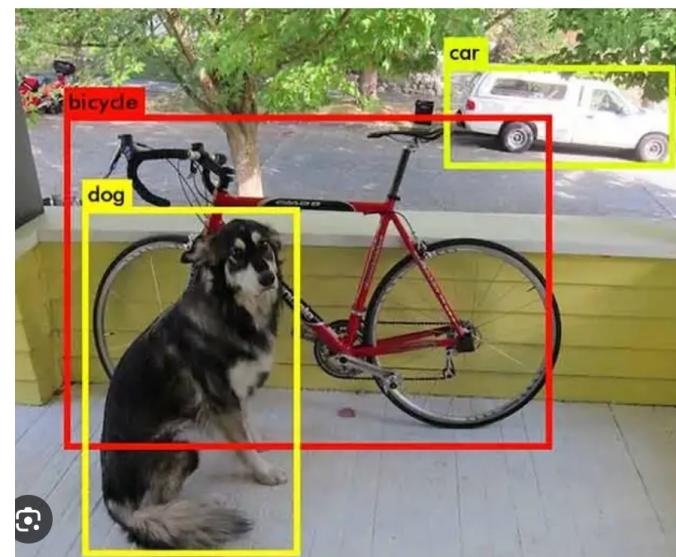
- How to design and build the “state”
 - Usually involves computer vision and signal processing techniques
 - Partial observability is very salient

- In this tutorial, we will focus on obtaining representations about “objects”

Vision Techniques



Segmentation



Detection



Tracking



Image-to-3D

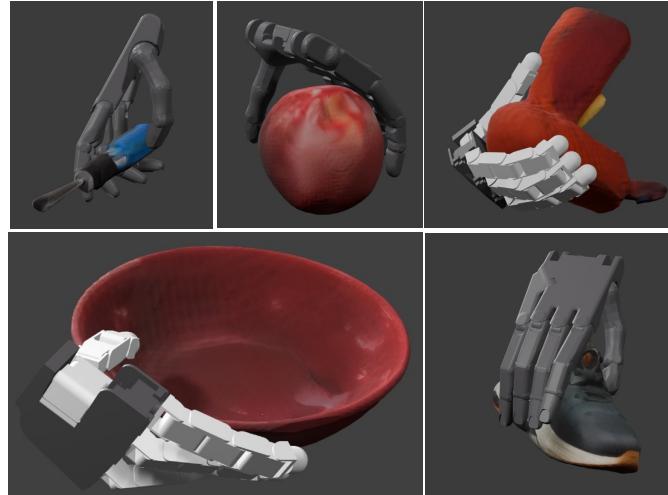
laptop, monitor, keyboard, mouse, cup, tissues, watch, cables, headphones, notebook, pen, stand, lamp, papers, toy, desk, chair



describe the objects in this image -- just give a one word generic prompt for each object that you see in this image.

- ☐ **Accurate 3D scene understanding** is crucial for reliable manipulation in real environments

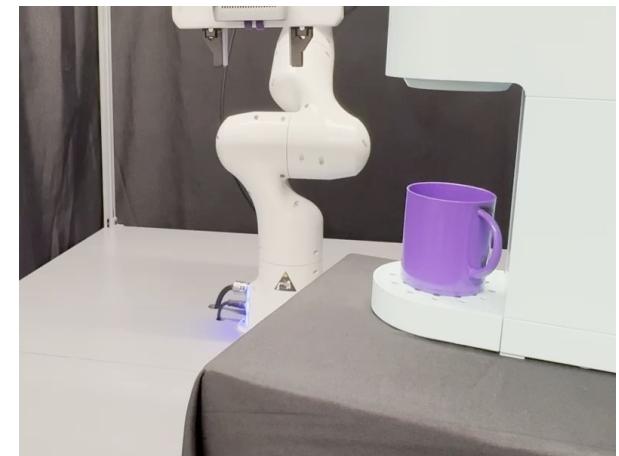
Grasping



Collision Avoidance



Reliable Placing



- ❑ Different tasks were usually studied individually
 - ❑ Different tasks rely on different datasets (e.g., fixed vocabulary object detection)
 - ❑ Trend: Training on very large datasets for broad coverage
-
- ❑ Although they are called “vision FM” but they are designed to solve one particular task

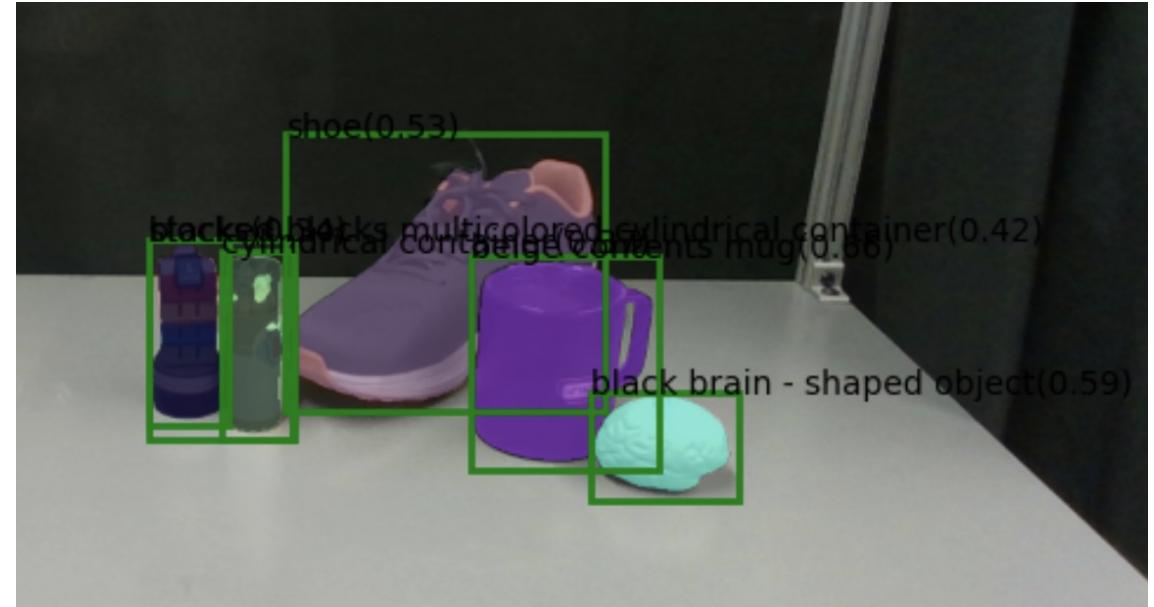
Input: RGBD Captures



Object Detection



- ❑ Three commonly used object detection modules:
- ❑ Category-agnostic: Segment-Anything
- ❑ Category-specific: Mask-RCNN
- ❑ Category-specific and open-vocabulary: Grounding-DINO



**Need to know
categories to be
detected**

Kirillov et al., “Segment Anything,” ICCV, 2023

He et al., “Mask R-CNN,” ICCV, 2017.

Liu et al., “Grounding DINO: Marrying DINO with Grounded Pre-Training for Open-Set Object Detection,” arXiv, 2023.

Image to 3D Models

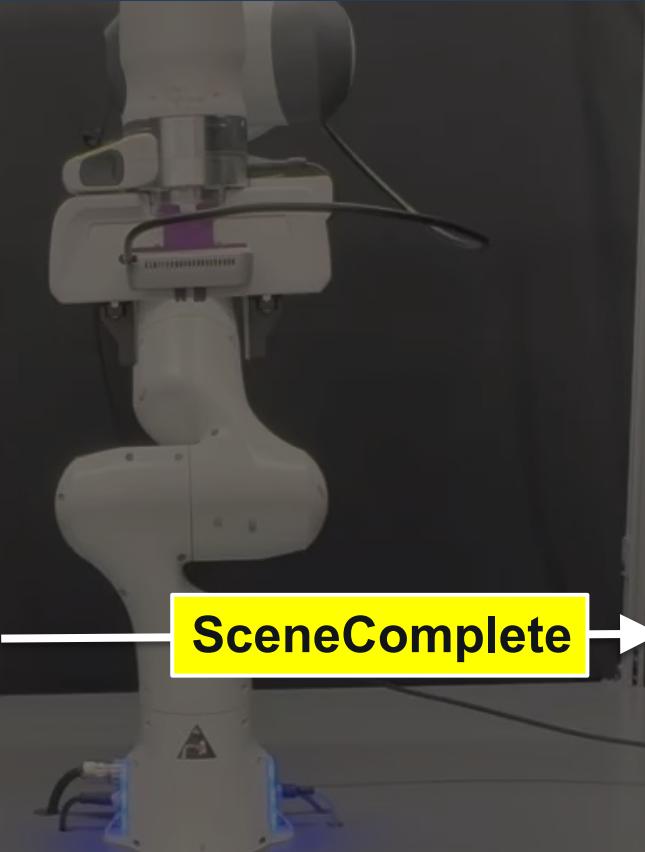


- ❑ Many existing models: RGB -> 3D
- ❑ Zero-1-to-3, InstantMesh, Instant3D

- ❑ Caveat: Usually they don't work well with partial object images (need inpainting)
- ❑ Many methods work better if we know the name of the object

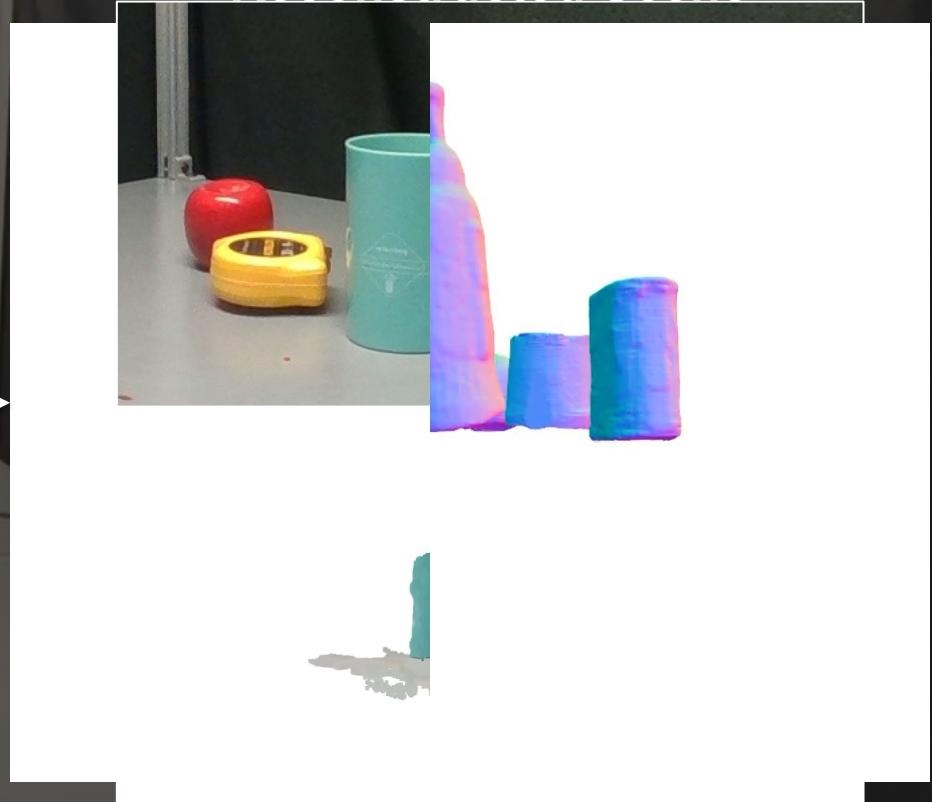
Liu et al., “Zero-1-to-3: Zero-shot One Image to 3D Object,” ICCV, 2023.
Xu et al., “InstantMesh: Efficient 3D Mesh Generation from a Single Image with Sparse-view Large Reconstruction Models,” arXiv, 2024.
Li et al., “Instant3D: Fast Text-to-3D with Sparse-View Generation and Large Reconstruction Model,” arXiv, 2023.

- ❑ Shape completion methods usually only work with RGB images
- ❑ So they don't know the actual "size" of the 3D shape
- ❑ After obtaining the mesh for an object, we need to back-project it
- ❑ Keyword: pointcloud registration



**SceneComplete takes a single-view RGB-D input
and constructs a complete, segmented, 3D model of a scene**

Scene Captured by the Robot
Reconstructed Scene



- ❑ While the object is being moved, we need to keep track of it!
- ❑ Otherwise we won't know object correspondences across states
- ❑ Three commonly used tracking modules:
- ❑ Mask tracker: Segment-Anything 2



Ravi et al., "SAM 2: Segment Anything in Images and Videos," ICLR, 2025.

Doersch et al., "TAPIR: Tracking Any Point with per-frame Initialization and temporal Refinement," arXiv, 2023.

Karaev et al., "CoTracker: It is Better to Track Together," ECCV, 2024.

Wen et al., "FoundationPose: Unified 6D Pose Estimation and Tracking of Novel Objects," CVPR, 2024.

- ❑ While the object is being moved, we need to keep track of it!
- ❑ Otherwise we won't know object correspondences across states

- ❑ Three commonly used tracking modules:
- ❑ Mask tracker: Segment-Anything 2
- ❑ Point tracker: Track-Any-Point,
CoTracker2



Ravi et al., "SAM 2: Segment Anything in Images and Videos," ICLR, 2025.

Doersch et al., "TAPIR: Tracking Any Point with per-frame Initialization and temporal Refinement," arXiv, 2023.

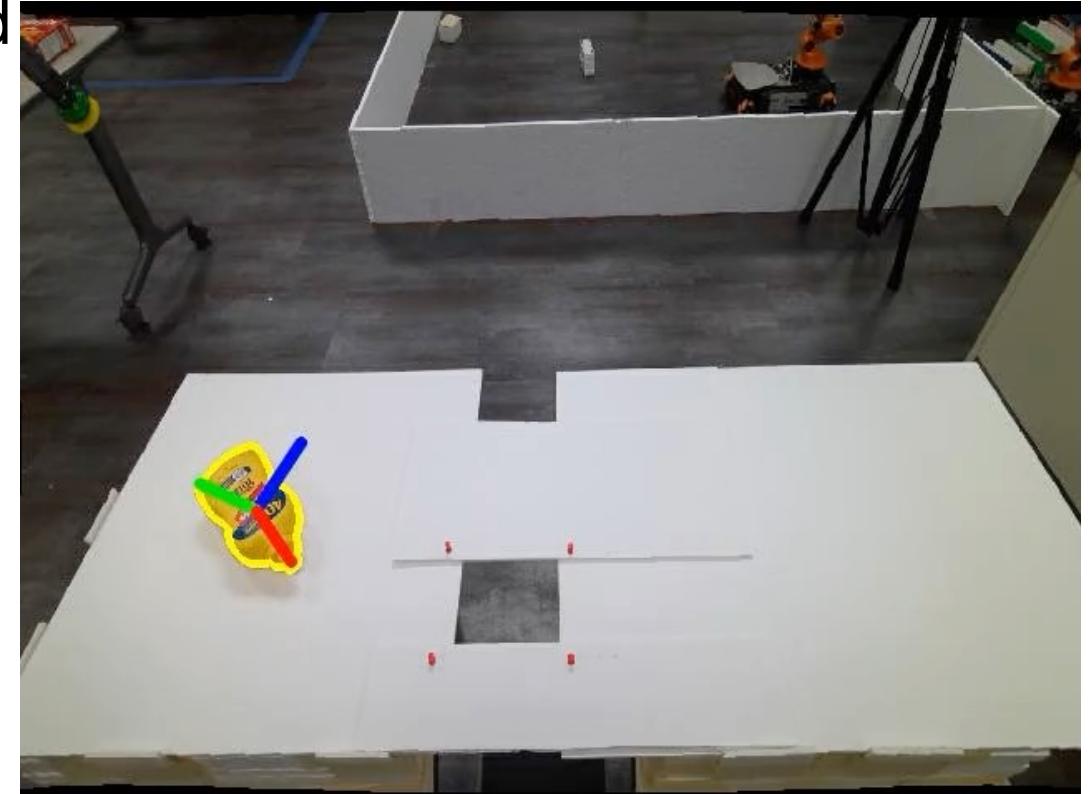
Karaev et al., "CoTracker: It is Better to Track Together," ECCV, 2024.

Wen et al., "FoundationPose: Unified 6D Pose Estimation and Tracking of Novel Objects," CVPR, 2024.

Object Tracking

- ❑ While the object is being moved, we need to keep track of it!
- ❑ Otherwise we won't know object correspondences across states

- ❑ Three commonly used tracking modules:
- ❑ Mask tracker: Segment-Anything 2
- ❑ Point tracker: Track-Any-Point, CoTracker2
- ❑ Pose tracker: Foundation Pose



Ravi et al., "SAM 2: Segment Anything in Images and Videos," ICLR, 2025.

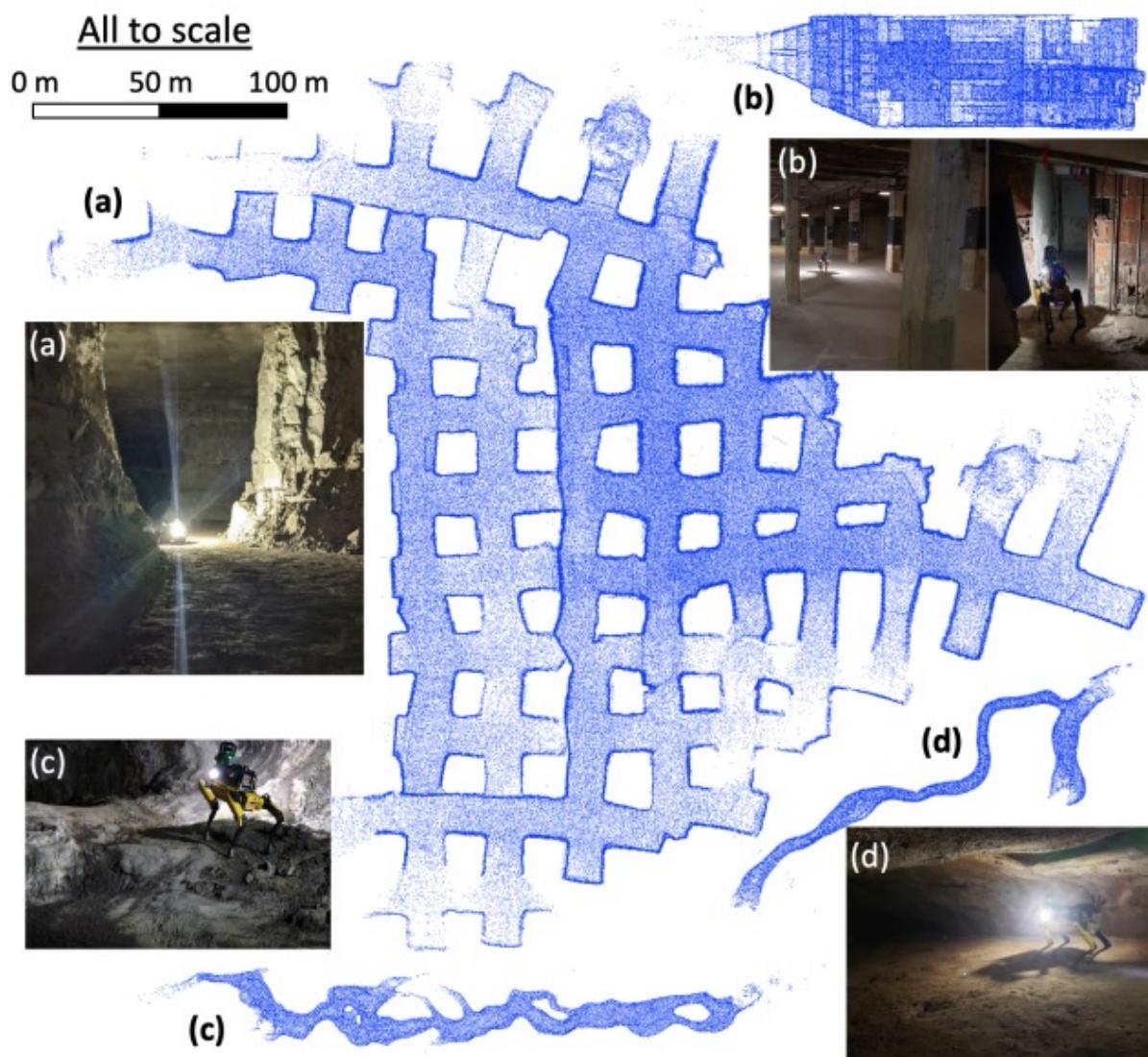
Doersch et al., "TAPIR: Tracking Any Point with per-frame Initialization and temporal Refinement," arXiv, 2023.

Karaev et al., "CoTracker: It is Better to Track Together," ECCV, 2024.

Wen et al., "FoundationPose: Unified 6D Pose Estimation and Tracking of Novel Objects," CVPR, 2024.

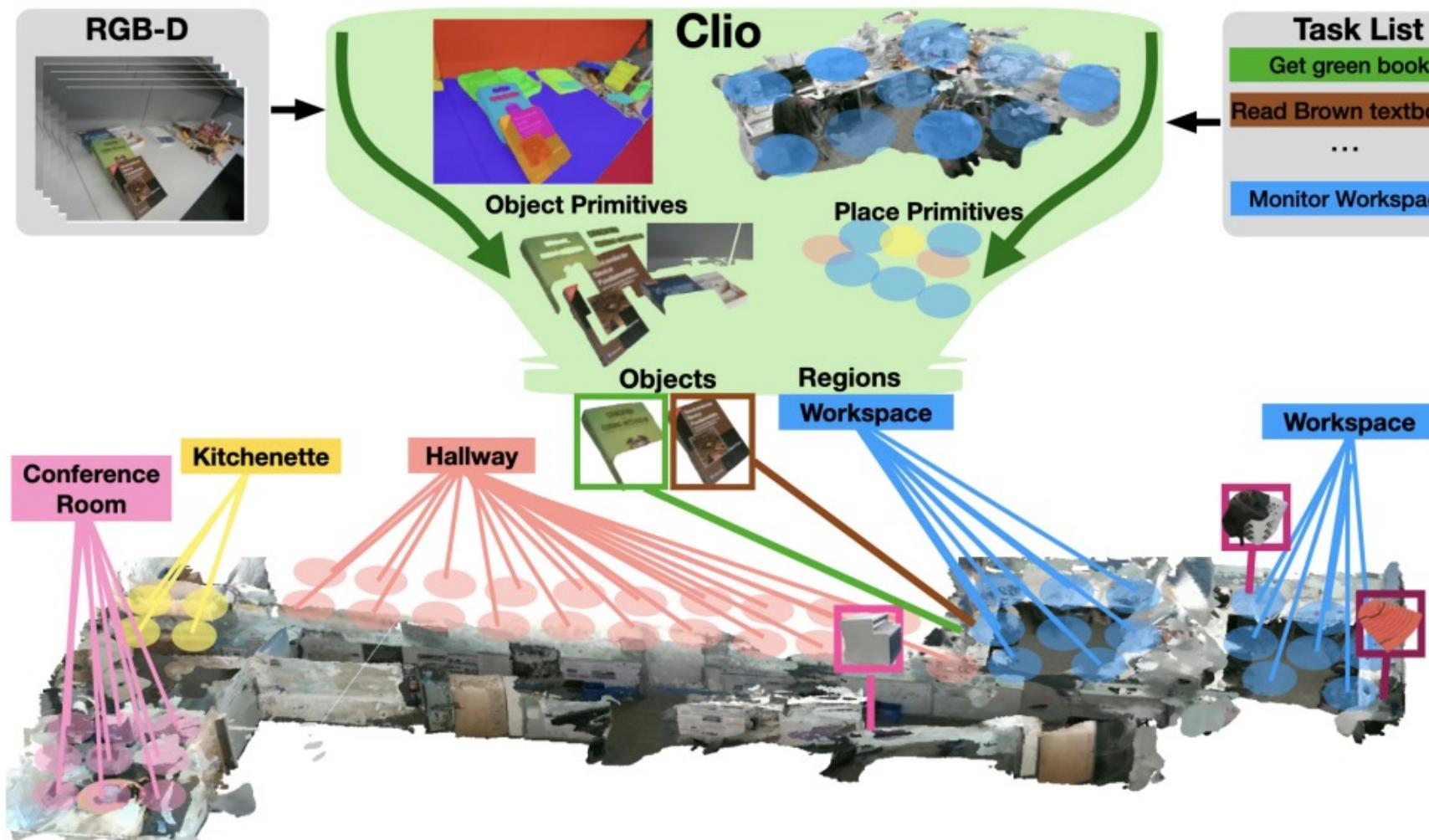
- ❑ Many 2D and 3D computer vision techniques are needed to build an object-centric state representation
- ❑ Now we have better and better foundation models for ALL of them
- ❑ However, we still don't have a “single” foundation model for all tasks
- ❑ Moreover, many models are not tuned for robotics purposes
- ❑ Different planning and control algorithms may need different levels of details

Advanced: Spatial Localization and Mapping



Reinke et al., "LOCUS 2.0: Robust and Computationally Efficient Lidar Odometry for Real-Time 3D Mapping," R-AL, 2022.

Advanced: Object-Centric SLAM



Maggio et al., "Clio: Real-time Task-Driven Open-Set 3D Scene Graphs," R-AL, 2024.

Advanced: Segmentation Under-Specification



- Depending on the task, you need to segment objects at different granularities

Advanced: Segmentation Uncertainty



- Interaction is usually needed to dis-ambiguate

Hypothesis $\hat{h}_{(1)1}$



Hypothesis $\hat{h}_{(1)2}$



Many Other Frontier Topics in Perception

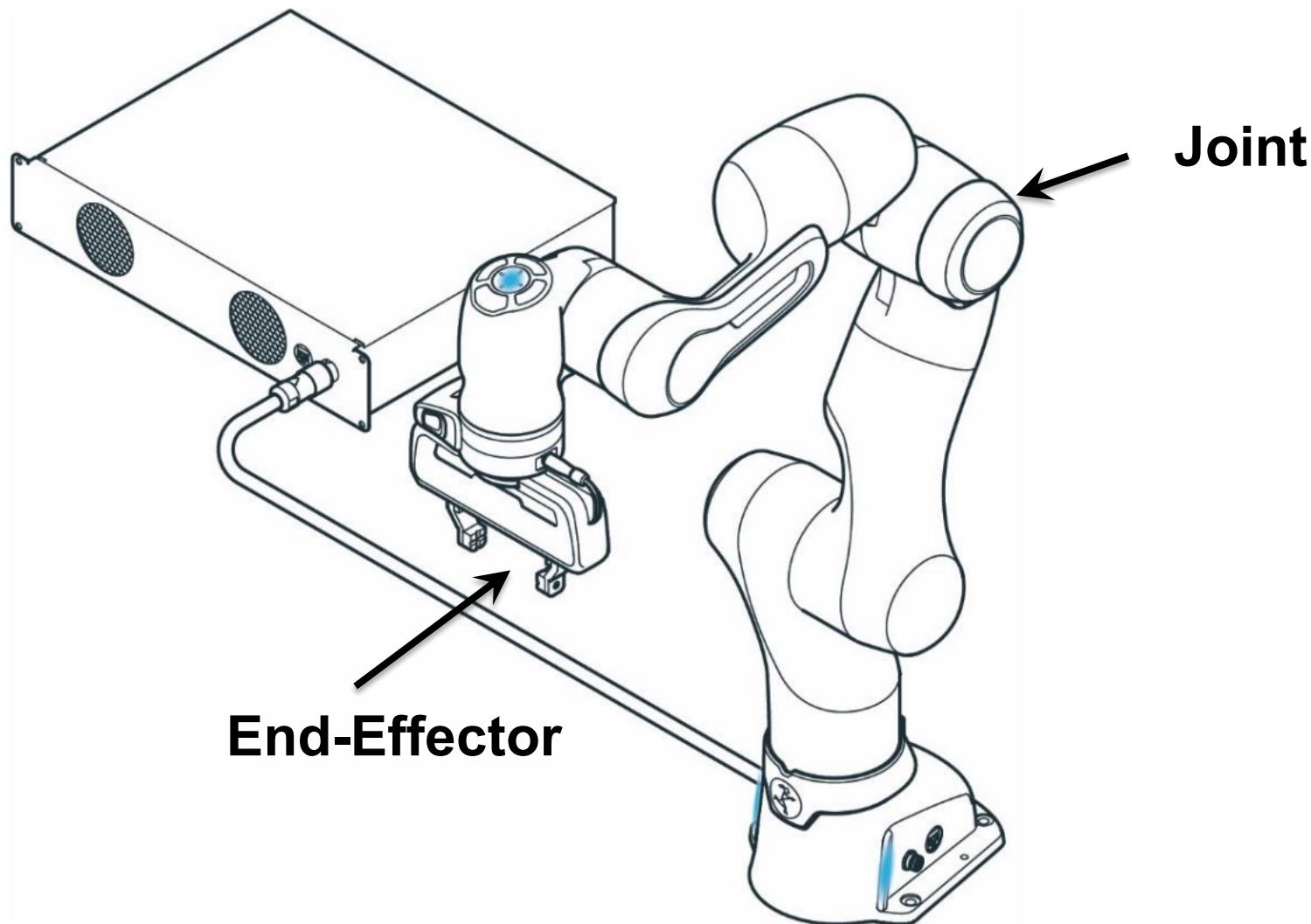


- ❑ Depth sensor denoising
- ❑ Articulated object perception
- ❑ Active sensing of physical properties
- ❑ SLAM with dynamic objects
- ❑ Task-driven representation of uncertainty

- Most systems involve a two-level design: high-level and low-level

- ❑ **Lowest-Level Action:** how much current should I apply?
- ❑ Usually run at >1000Hz

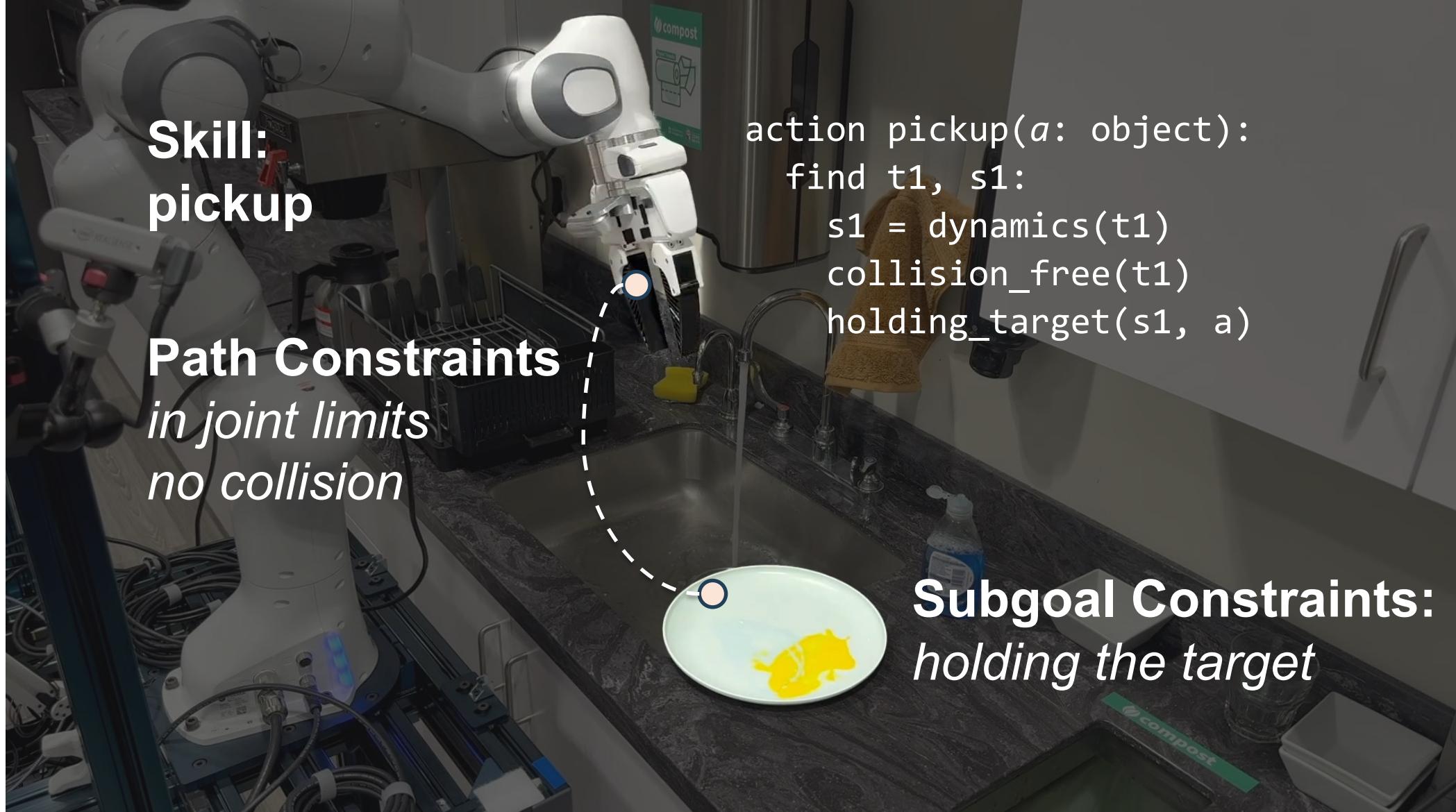
- ❑ **“Low-Level” Action:**
 - target position / velocity for the robot joints
 - target position / velocity for the robot end-effector

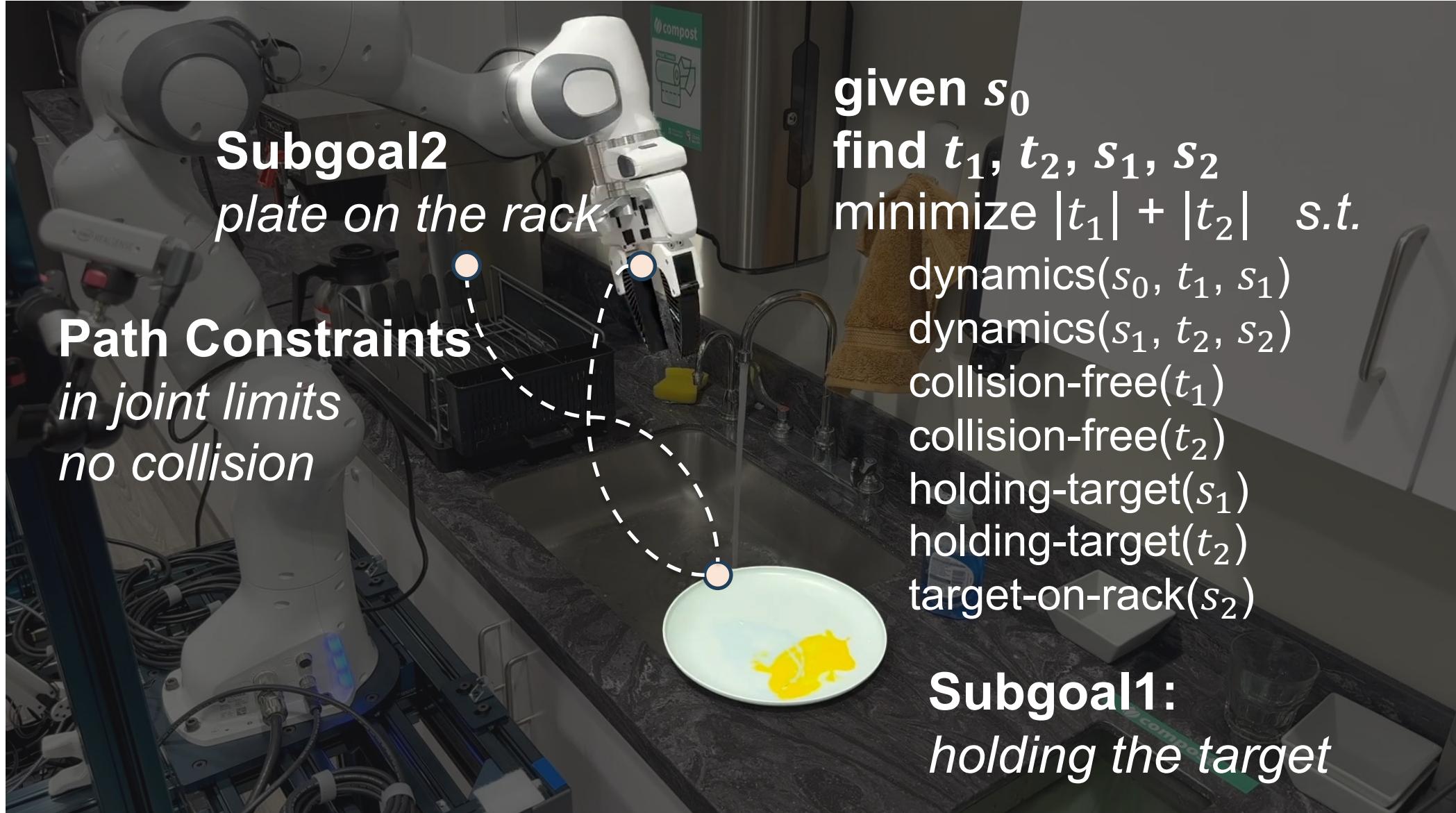


- ❑ **High-Level Actions** are usually object-centric
- ❑ Different algorithms may use different granularities

```
action grasp(object):  
    grasp_pos = find_grasp(object)  
    traj = find_trajectory(current_pos(), grasp_pos)  
    execute(traj)  
    close_gripper()
```

```
action place(object, surface):  
    place_pos = find_place(object, surface)  
    traj = find_trajectory(current_pos(), place_pos)  
    execute(traj)  
    open_gripper()
```





- **Low-level action:** joint and end-effector commands
- **High-level action :** object-centric commands
- **Integrated low-level and high-level action:** usually based on constrained optimization frameworks

- How to react to human perturbation and other endogenous events in a multi-level system?
- Simple solution, but usually not scalable: perform action selection at all layers at a high frequency